Routing of Battery Electric Heavy-Duty Trucks for Drayage Operations

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16. Abstract

California has a long history of reducing greenhouse gas (GHG) emissions, and has been working to accelerate the adoption of battery electric heavy-duty trucks (BEHDTs). Unlike diesel heavy-duty trucks (DHDTs), which have hundreds of miles of range per refill, BEHDTs have a restricted, load-dependent driving range, which makes charging planning an important role in the use of BEHDTs as an alternative to DHDTs. This research study investigates a mixed fleet drayage routing problem (MFDRP) with non-linear charging times. The study extends existing mixed fleet drayage routing models by considering multiple charging locations and allowing for more flexible routes for freight pickup and delivery. We formulate the MFDRP as a mixed integer programming model. After linearization and variable elimination, the model can be solved by commercial optimization solvers. However, the model becomes inefficient to solve when the problem size increases. Therefore, we develop a modified adaptive large neighborhood search algorithm, which can solve the problem with hundreds of units of demand in a few CPU minutes. Finally, we simulate one-day drayage operations with different BEHDT shares in the fleet for the years 2022, 2025, and 2030 to assess the potential for substituting DHDTs with BEHDTs. The numerical experiments indicate that employing BEHDTs as substitutes for DHDTs will increase the fleet size under the same level of demand. To reach the maximum share of BEHDTs in the truck fleet, the fleet size increases by 47.2%, 3.4%, and 3.4% in 2022, 2025, and 2030, respectively. Over 50% (90%) CO_2 (NO_x) emission reductions can be achieved by employing BEHDTs to the maximum share in the fleet.

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EXECUTIVE SUMMARY

California has a long history of reducing GHG and NO_x emissions. To meet the aggressive GHG reduction targets, California has been working on reducing truck emissions by accelerating the adoption of zero-emission trucks. One major area where zero-emission vehicles (ZEVs) may be employed is in drayage operations because of the disproportionate emission share in the transport sector. With the development of truck manufacturers, battery electric heavy-duty trucks (BEHDT) are available on the market, which provides an alternative option other than diesel heavy-duty trucks (DHDTs).

However, existing studies related to ZEVs mainly focused on light-duty vehicles. Limited research attention has been paid to the applications of BEHDTs in drayage operations. This research fills the gap and examines the potential to gradually adopt BEHDTs. We study different mixtures of diesel trucks and BEHDTs under various scenarios from 2022 to 2030 based on the best available estimations of developments in the battery industry.

We first formulate the mixed fleet drayage routing problem as a non-linear mixed integer programming problem. Followed by the model linearization and variable elimination, the model can be solved using commercial optimization solvers. However, the model cannot be solved efficiently when the problem size increases. Therefore, we develop a modified adaptive large neighborhood search heuristic to improve computational performance.

The potential of substituting BEHDTs for DHDTs in daily drayage operations is investigated in this study. We simulate scenarios with different BEHDT shares in the operating fleet to explore the impact of employing BEHDTs for 2022, 2025, and 2030. The results indicate that, currently, BEHDTs are not practical as substitutes for DHDTs due to their range limits. In order to meet the demand with a large percentage of BEHDTs in the truck fleet, the number of trucks need to increase by 47.2%. However, as BEHDT performance improves, in 2025 and 2030, the fleet size only increases by 3% in order to reach the maximum BEHDT share in the fleet. This makes BEHDTs a potential alternative solution for daily drayage operations since substituting BEHDTs for DHDTs in the fleet can lead to a reduction of over 50% in CO_2 emissions and 90% in NO_x emissions, as long as there is sufficient charging infrastructure outside the depot.

1. Introduction

In the last decade, globalization and urbanization have significantly increased the size of the international trade market. Global trade reached $28.5 trillion in 2021 and kept growing in the first two quarters of 2022 [1]. With a conservative estimation of 2.6 annual growth, the global heavy-duty truck (HDT) fleet size will exceed 64 million by 2050 [2]. The demand for transportation accounted for 7.7 percent of the GDP in 2020, and the transport sector accounted for 27 percent of greenhouse gases (GHG) and 56 percent of NO_x, among which trucks generated 22 percent of GHGs and 32 percent of NO_x [3]. Much of this consists of container shipping, which is used for 90 percent of the commodities in the United States [4].

California established GHG reduction goals in 2006, the only state to have done so to date. It enacted AB 32 and set a goal of reducing GHG emissions below the 1990 level by 2020, cutting them by 30 percent. Later, California enacted SB 32 to further reduce GHG emissions by another 10 percent by 2030. The law does not state specific approaches or requirements for reaching the GHG reduction goal, but a more efficient freight movement system is a clear avenue for consideration, given its disproportionate GHG share in the transport sector.

One of the most promising directions for reducing GHG emissions in the trucking industry is adopting zero-emission trucks in freight operations. Burke and Sinha investigated the zero-emission HDT markets [5]. Their report indicated that although both hydrogen fuel cells and batteries can be used as alternative fueling options, battery electric heavy-duty trucks (BEHDTs) are the only zero-emission HDTs currently available on the market, while hydrogen cells are still in the testing stage. Thus, this project focuses on BEHDTs as the substitute for traditional diesel heavy duty trucks (DHDTs).

We further focus on drayage service, a short-haul pickup and delivery service for transporting freight among ports, warehouses, and other facilities. The drayage operation problem is a special case for the capacitated pickup and delivery problems with all trucks having the same capacity (single container) since an HDT can carry one empty or loaded container or drive without a container.

The project is built on an earlier work by Giuliano et al. [6]. They developed an optimization model and tested it using real-world data collected from the Ports of Los Angeles and Long Beach. However, they simplified truck trips by assuming trips must start and end at the port and may only have one or two stops outside the port. In addition, they assumed that the port was the only charging location available. Figure 1 shows the two types of trips in their work.

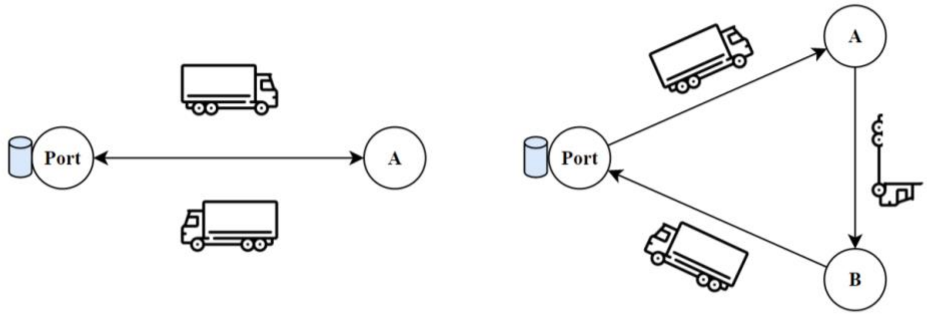

Figure 1. Two restricted routing patterns

However, charging stations can also be considered outside the port to improve the BEHDTs' routing potentials. Figure 2 is a possible one-day route for a BEHDT. The BEDHT starts at the depot. It first conducts a few pickups and deliveries (demand satisfaction trips). As the battery level goes down, the BEDHT visits charging station C (charging trip) and then continues its pickup and delivery. By the end of the day, the truck goes back to the depot.

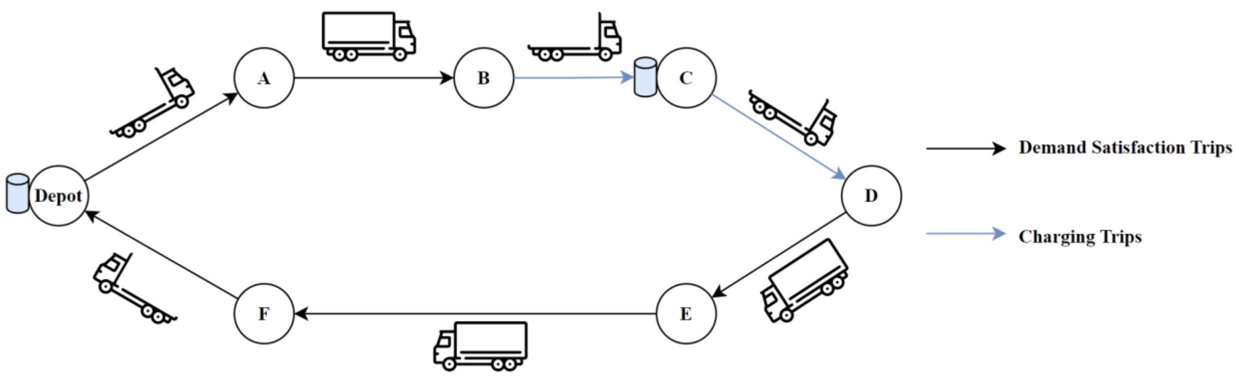

Figure 2. A more realistic BEHDT route

The major contributions of this study are as follows:

1) We consider charging locations outside the depot with non-linear charging times for BEHDTs.
2) We consider load-dependent energy consumptions to simulate a more realistic scenario for BEHDTs.
3) We propose an adaptive large neighborhood search (ALNS) algorithm to solve real-world size problems.

The rest of the report is structured as follows. In Section 2, a literature review of routing for drayage operations is provided. A mixed-integer programming (MIP) model is presented in Section 3, including linearizing the MIP, and introducing additional cuts to improve the solving time. In Section 4, a modified ALNS is presented to efficiently solve the proposed problem. In Section 5, the experimental results of our approaches are presented. We test our approach on both randomly generated small-size datasets and practical-size datasets from the Ports of Los Angeles and Long Beach. Section 6 offers conclusions and implications for future research.

2. Literature Review

The drayage routing problem is a variation of the pickup and delivery problem (PDP) with all vehicles' capacity equal to one. The goal is to minimize the cost of regional freight movements. Prior research on drayage services has typically used the multi-traveling salesperson problem (m-TSP) formulations [7–11]. Most of the earlier work focused on minimizing the travel distance for freight pickup and delivery. Jula et al. proposed an exact method for small-size problems with dynamic programming and a genetic algorithm for large-size problems [7]. Zhang et al. formulated the m-TSP with multi-depots [10]. They developed a reactive tabu search to solve the model and solved small-scale problems optimally. Instead of purely minimizing travel distance for daily drayage operations, Zhang et al. extended their model by considering trucks as a limited resource [11]. The model was solved by a window partition method inspired by Wang and Regan [9].

Due to globalization and economic prosperity, freight movements have been increasing during the past decades, leading to social issues associated with air pollution, especially in GHG emissions, NO_x, and particulates. Erdoğan and Miller-Hooks introduced the green vehicle routing problem (GVRP) to the literature to address the need to consider emissions while optimizing vehicle routes [12]. They formulated GVRP as a MIP and solved the problem with a modified saving algorithm and a heuristic to improve the initial solution.

Lin et al. conducted a comprehensive survey of GVRPs [13]. They indicated that GVRP should consider heterogeneous fleets instead of identical vehicles. Behnke and Kirschstein formulated the GVRP with heterogeneous fleets. Instead of searching for the shortest path, they calculate the emission-minimal path for each vehicle class [14]. Koyuncu and Yavuz proposed two GVRP formulations with node- and arc-duplicating forms [15]. They compared both models' computational performance under various refueling policies, mixed fleets, and charging locations. Another variation of the mixed fleet vehicle routing problem is considering a heterogeneous driving range which was introduced by Juan et al. [16]. A more recent study on the multi-range VRP by Eskandarpour et al. [17] separated the objective function into monetary costs and environmental impacts. They applied a large neighborhood search to solve their optimization model. Bruglieri et al. investigated the GVRP with capacitated fuel stations with constant refueling time [18].

Asghari and Mirzapour Al-e-hashem summarized the most recent studies of GVRP [19]. One of the future directions was to consider various energy consumption rates for electric battery vehicles. As a greener substitute for DHDTs, researchers extended the GVRP by considering battery powered trucks. Elangovan et al. analyzed the GHG emissions for diesel and electric light-duty trucks [20]. The results showed that electric light-duty trucks emitted about 30 percent less GHGs and consumed 66 percent less energy than diesel light-duty trucks.

Unlike commercial pickup and delivery service with small packages and commodities, drayage operations are containerized. The HDTs' driving range depends on the carrying loads, and BEHDTs are particularly sensitive, ranging from 70 miles to 100 miles. Based on payload, Giuliano et al. interviewed BEDHT drivers and found that range limitations significantly curtail the tasks they can undertake [6]. This suggests the need for charge planning to employ BEHDTs in drayage operations.

The electric vehicle routing problem (EVRP), an extension of the VRP that considers the limited driving range for electric vehicles and charging stations, is an extensively studied problem. Lin et al. presented a general EVRP formulation that minimized fleet size, travel time, and energy costs [21]. Pelletier et al. extended the EVRP into the stochastic world with uncertain energy consumption [22]. They formulated the problem as a robust optimization problem and developed a large neighborhood search heuristic to solve it. Because electric vehicles usually have strict limits on working time with a relatively long re-charging time, electric vehicle drivers tend to visit charging stations as few times as possible. As a result, full recharging policies are commonly accepted in the literature [23–26].

Felipe et al. considered heterogeneous charging facilities for electric vehicles [27]. Recent EVRP studies have considered the possibility of battery swapping [28–30], but the high cost and large capacity of the batteries for BEHDTs make it difficult to perform in practice. In this study, we use a concave piecewise-linear function to calculate charging times for BEHDTs, since researchers have widely used piecewise linear approximations as the charging function [31–33].

Most EVRPs cannot be solved optimally since VRP itself has been known to be NP-hard. Exact methods such as branch-and-cut [34], branch-and-price [24], and the MIP-based reduction procedure [35] can solve small-scale problems optimally. However, for large instances, an optimal solution cannot be obtained within a reasonable amount of computational time. Therefore, most of the studies in the literature have used heuristics to solve their models. Tabu search is a class of local search methods that have been used in different variations of VRPs. The most successful variation is adaptive large neighborhood search proposed by Ropke and Pisinger [36], which studies show is one of the most effective metaheuristics for solving vehicle routing problems [37–40]. In this study, we propose a modified Tabu search to efficiently solve our mathematical formulation.

3. Mixed Fleet Drayage Routing Problem

In this section, we first describe the mixed fleet drayage routing problem (MFDRP) and formulate the problem as a MIP model. Since the formulated MIP model contains a few non-linear constraints, model linearization is also presented in this section, followed by model preprocessing with variable eliminations.

3.1 Problem Formulation

We use an arc-based formulation for the MFDRP. In this report, we consider two types of trucks. A set D represents available DHDTs and a set E represents all the BEHDTs. Unlike a DHDT, which has a range of hundreds of miles per refill, under the current battery technology, a BEHDT has a more limited range between charging and the range depends on the loading state of the truck. Therefore, we assume only BEHDTs need to be charged during working hours. In addition, all the trucks start and end at the truck depot.

The problem is defined on a directed graph $G = (V, A)$ with a vertex set $V = \{0,1, \dots, n, n + 1, \dots, n + m, n + m + 1\}$ and an arc set $A = \{(i, j)|i \neq j \ and \ i, j \in V\}$. In addition, both the vertices 0 and $n + m + 1$ represent the truck departure depot and arrival depot, respectively, although in reality both can represent the same physical location. $C = \{1, \dots, n\}$ is the customer location set and $F = \{n + 1, \dots, n + m\}$ is the location set of charging stations. A sample network is given in Figure 3.

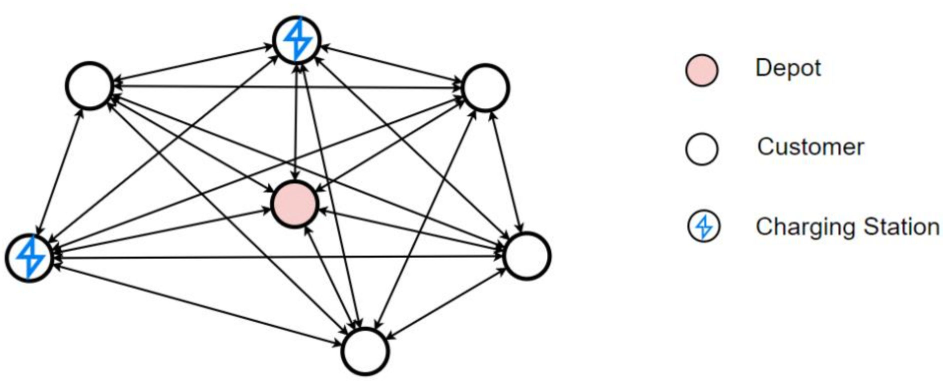

Figure 3. A sample network

Each location i ($i \in V$) is associated with a quadruple $\{q_i, w_i, s_i, \bar{r}_i\}$ where $q_i \in \{-1,0,1\}$ represents the loading state and $q_i = 1(-1)$ means a pickup (drop-off) of a container at location i, and $q_i = 0$ means no pickup or drop-off at location i (e.g., only charging occurs at location i); $w_i \in \{0, \gamma_e, \gamma_l\}$ represents the load weight where γ_e is the weight for an empty container and γ_l is the weight for a loaded container; s_i represents the service time; and binary indicator $\bar{r}_i$ represents whether a BEHDT can be charged at location i. To simplify the model, we assume that a truck can only conduct one of the following three tasks at each non-depot location: pickup, drop-off, or charging. However, the modeling framework allows for multiple tasks at the same location by copying the node. In this way, only a single task is applied at each node. Binary variable $x_{i,j}^d = 1$ if and only if arc (i,j) is traveled by a DHDT $d \in D$; binary variable $x_{i,j}^e = 1$ if and only if arc (i,j) is traveled by a BEHDT $e \in E$. Due to the range limitation on BEHDTs, we introduce binary variable r_i^e to determine if truck e recharges at location i and non-negative variable b_i^e to keep track of truck e's battery level upon arrival at location i. Non-negative variable z_i^k represents the arrival time of truck k $(k \in D \cup E)$ at location i. Since BEHDTs have disparate power consumption rates under different loading states, we introduce a default battery consumption rate p, a load-dependent consumption rate p', and a variable l_i^k which represents the container loading states at location i for truck k. Figure 4 provides battery consumption rates for BEHDT under different load states.

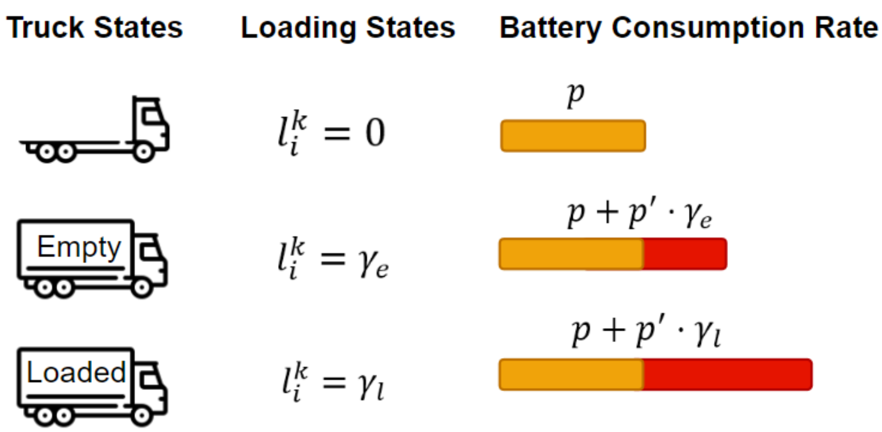

Figure 4. Battery consumption rates under different states

The notation used in the report is as follows:

Sets

- K The set of all the trucks
- D The set of DHDTs, $D \in K$
- E The set of BEHDTs, $E \in K$
- V The set of locations, $V = \{0,1,\dots,n+m+1\}$
- C The set of customers, $C = \{1,\dots,n\}$
- F The set of charging stations, $F = \{n+1,\dots,n+m\}$
- A The set of arcs in the network
- Ω The set of emissions, $\Omega = \{\mathrm{CO_2}, \mathrm{NO_x}\}$, with set index ω

Parameters

- p The default hourly battery consumption rate
- p' The load dependent hourly battery consumption rate
- $t_{i,j}$ Travel time on arc (i,j)
- $a_{i,j}$ Distance of arc (i,j)
- q_i Loading state at location i

w_i Load weight at location i

s_i Service time at location i

$\bar{r}_i$ Charging station indicator for location i

c_0^d The daily DHDT employment cost

c_0^e The daily BEHDT employment cost

c_1^d The DHDT fuel cost per mile

c_1^e The BEHDT charging cost per mile

c_ω^d The Emission cost of DHDT for pollutant ω

c_ω^e The Emission cost of BEHDT for pollutant ω

$\bar{z}$ The maximum working time for truck drivers

Variables

$x_{i,j}^k$ Binary variable for a truck k traveling on arc (i,j), $k \in K$

z_i^k Arrival time at location i for truck k, $k \in K$

l_i^k Truck k's container loading state when leaving location i , $k \in K$

r_i^e Binary indicator for BEHDT e recharging at location i, $e \in E$

b_i^e Battery level for BEHDT e upon arriving at location j, $e \in E$

The MFDRP can be formulated as,

$$\min_{x_{i,j}^d, x_{i,j}^e} \left(c_0^d \sum_{d \in D} \sum_{j \in C} x_{0,j}^d + c_0^e \sum_{e \in E} \sum_{j \in C} x_{0,j}^e \right) + \left(\sum_{(i,j) \in A} a_{i,j} \left((c_1^d + \sum_{\omega \in \Omega} c_\omega^d) \sum_{d \in D} x_{i,j}^d + (c_1^e + \sum_{\omega \in \Omega} c_\omega^e) \sum_{e \in E} x_{i,j}^e \right) \right) \quad (1)$$

Subject to

$$\sum_{j \in V} \sum_{k \in K} x_{i,j}^k = 1 \qquad \forall i \in C \qquad (2)$$

$$\sum_{i \in V} x_{i,j}^k - \sum_{i \in V} x_{j,i}^k = 0 \qquad \forall j \in C \cup F, k \in K \qquad (3)$$

$$x_{i,0}^k = x_{n+m+1,i}^k = 0 \qquad \forall i \in C \cup F, k \in K \qquad (4)$$

$$\sum_{i \in C \cup F} x_{0,i}^k = \sum_{i \in C \cup F} x_{i,n+m+1}^k \quad \forall k \in K \qquad (5)$$

$$r_i^e \le \bar{r}_i \qquad \forall i \in V, e \in E \qquad (6)$$

$$x_{i,j}^e \left((1 - r_i^e) b_i^e + r_i^e - t_{i,j}(p + p' l_i^e) \right) \le b_j^e \qquad \forall j \in V \backslash \{0\}, i \in V, e \in E \qquad (7)$$

$$b_0^e = 1 \qquad \forall e \in E \qquad (8)$$

$$b_i^e \ge 0 \qquad \forall i \in V, e \in E \qquad (9)$$

$$x_{i,j}^d \left(z_i^d + s_i + t_{i,j} \right) \le z_j^d \qquad \forall i,j \in V, d \in D \qquad (10)$$

$$x_{i,j}^{e}\left(z_i^e + r_i^e \cdot f(b_i^e\ ) + s_i + t_{i,j}\right) \le z_j^e \qquad \forall i,j \in V, e \in E \qquad (11)$$

$$z_{n+1}^k - z_0^k \le \bar{z} \qquad \forall k \in K \qquad (12)$$

$$z_0^k = 0 \qquad \forall k \in K \qquad (13)$$

$$x_{i,j}^k\left(l_i^k + q_j \cdot \mathrm{w_j}\right) \le l_j^k \qquad \forall i \in V, j \in V\backslash\{0\}, k \in K \qquad (14)$$

$$x_{i,j}^k l_i^k = 0 \qquad \forall k \in K, i \in V, q_j > 0 \qquad (15)$$

$$l_0^k = 0 \qquad \forall k \in K \qquad (16)$$

$$l_i^k \ge 0 \qquad \forall i \in V, k \in K \qquad (17)$$

$$x_{i,j}^k \in \{0,1\} \qquad \forall (i,j) \in A, k \in K \qquad (18)$$

$$r_i^e \in \{0,1\} \qquad \forall i \in V, e \in E \qquad (19)$$

$$z_i^k \in R \qquad \forall i \in V, k \in K \qquad (20)$$

The objective function (1) is to minimize the cost for one day's drayage operation, including daily truck employment costs, fuel costs, and emission costs. Constraints $(2-5)$ are the traditional vehicle routing constraints such as demand satisfaction constraints and flow conservation constraints. Constraint (6) indicates that charging only occurs at locations with charging stations. Constraint (7) defines the remaining battery level of a BEHDT upon arrival at location j. The constraint only becomes effective only when truck e travels on arc (i,j). When $x_{i,j}^e = 1$, the remaining battery for truck e after traveling arc (i,j) can be represented as follows:

$$b_j^e = \begin{cases} b_i^e - t_{i,j}(p + p' l_i^e) & if\ r_i^e = 0 \\ 1 - t_{i,j}(p + p' l_i^e) & if\ r_i^e = 1 \end{cases} \qquad (21)$$

The battery consumption rate on arc (i,j) is determined by the container load state of truck e when leaving location i. Constraint (8) states that all the BEHDTs are fully charged in the truck depot at the beginning of the day. Constraint (9) ensures every BEHDT can arrive at the next destination with a non-negative battery level. Constraints $(10-11)$ keep track of the arrival time for all the trucks as well as eliminating sub-tours. In constraint (11), f is the charging time function, which depends on the battery level of BEHDT e upon arrival at location i. In this report, we assume a piece-wise linear charging function in our experiments. Constraints $(12-13)$ bound the working time for all the trucks. Constraints $(14-17)$ are the truck capacity constraints. The rest of the constraints are domain constraints.

3.2 Model Linearization

The proposed MFDRP has a few non-linear constraints (7), (10), (11), (14) and (15). All these constraints share one property: the non-linear terms have at most one non-negative continuous variable multiplied by multiple binary variables. We linearize our model using the following approach.

Model Linearization: The expression $y = u\sum_{i=1}^{N} v_i$, where u is a non-negative variable with a maximum value of U and v_i are binary variables, can be linearized by introducing the following constraints:

$$y \le Uv_i \qquad \forall i \in \{1,2,\dots,N\} \tag{22}$$

$$y \le u \tag{23}$$

$$y \ge u + U\left(-N + \sum_{i=1}^{N} v_i\right) \tag{24}$$

$$y \ge 0 \tag{25}$$

3.3 Preprocess of the MFDRP Model

To improve the formulation of the proposed model, we first eliminate variables based on feasibility rules. Then we strengthen the formulation by eliminating symmetric solutions.

3.3.1 Variable Eliminations

The first elimination rule is based on the truck capacity. A location i can have three types of freight loads: loaded container, empty container, and no container. By constraints $(14-17)$, once a truck picks up a container, it cannot pick up other containers before dropping off the current load. It is worth noting that BEHDTs can visit charging stations at any time. Therefore, variable $x_{i,j}^{k}$ and arc (i,j) are eliminated if the following condition holds:

$$\begin{cases} q_j > 0 \; if \; q_i > 0 \\ q_j < 0 \; if \; q_i < 0 \end{cases} \qquad \forall i \in C \tag{26}$$

The second elimination rule is based on BEHDT range. Variable $x_{i,j}^{e}$ is eliminated if arc (i,j) satisfies the following conditions.

$$\begin{cases} \underset{i\prime\in V}{min}\, t_{i',i}p + t_{i,j} * (p + p') + \underset{j'\in F\cup\{n+1\}}{\min} t_{j,j'}p > 1 & if \; q_i = 1 \\ \underset{i\prime\in V}{min}\, t_{i',i}p + t_{i,j}(p + p'\gamma) + \underset{j'\in F\cup\{n+1\}}{\min} t_{j,j'}p > 1 & if \; q_i = \gamma \\ \underset{i\prime\in V}{min}\, t_{i',i}(p + p') + t_{i,j}p + \underset{j'\in F\cup\{n+1\}}{\min} t_{j,j'}p > 1 & if \; q_i = -1 \\ \underset{i\prime\in V}{min}\, t_{i',i}(p + p'\gamma) + t_{i,j}p + \underset{j'\in F\cup\{n+1\}}{\min} t_{j,j'}p > 1 & if \; q_i = -\gamma \end{cases} \quad \forall i \in C, j \in C \tag{27}$$

These four conditions are the cases that a BEHDT traveling on arc (i,j) connects two customer locations. Taking the first condition as an example, the first term represents the minimum battery consumption on prior arc (i',i). The second term is the battery consumption on arc (i,j). The last term is the minimum battery consumption that allows the BEHDT to reach the nearest charging station or depot. These three trips cannot exceed the battery limit. Otherwise, arc (i,j) is not a valid arc for a BEHDT in the model.

3.3.2 Eliminating Symmetry

Although two different types of trucks are employed in the model, trucks in the same truck set are homogeneous, meaning all the DHDTs are the same and all the BEHDTs are the same. In this case, multiple solutions can be made identical by switching the numbering of the trucks. To avoid the symmetry of the solutions, we label DHDTs and BEHDTs using numerical values. DHDTs are numbered from one to $|D|$, followed by BEHDTs from $|D|+1$ to $|D|+|E|$. Additional constraints $(28-29)$ are introduced to force trucks with smaller labels to be employed first.

$$\sum_{i\in V} x_{0,i}^{d} \leq \sum_{i\in V} x_{0,i}^{d-1} \qquad \forall d \in \{2,3,\dots,|D|\} \tag{28}$$

$$\sum_{i\in V} x_{0,i}^{e} \leq \sum_{i\in V} x_{0,i}^{e-1} \qquad \forall e \in \{|D|+2,|D|+3,\dots,|D|+|E|\} \tag{29}$$

4. Solution Approach

Although the proposed MFDRP can be solved optimally by commercial solvers, it takes hours to even find feasible solutions for problems of practical size. Therefore, we propose a modified ALNS heuristic to solve the problem. There are two main steps to solve the MFDRP with ALNS, (1) find an initial feasible solution, and (2) explore neighborhoods of the current solution and move towards a better solution.

4.1 Initial Solution Construction

In the proposed model, containers may be empty or loaded. Before constructing truck routes, we first match supply and demand based on container types. The formal definition of a matched supply and demand (also referred as task) is the following:

$$\tau = (o, d, \xi)$$

where o is a supply node, d is a demand node, and ξ is a binary indicator for the demand type (i.e., $\xi = 0$ for empty container demand and $\xi = 1$ for loaded container demand).

There are many ways to match supply and demand. For example, the distance between a supply node i and a demand node j can be considered as the preferences for pair (i, j), which turns the matching problem into a stable marriage problem and can be solved by the Gale-Shapley algorithm [41]. Once all the customer nodes have been matched, we store every matched task τ into a task list (T) and use the following algorithm for initial solution construction.

Algorithm 1: Initial Solution Construction

Step 0. $D = \{\}, k = 0.$

Step 1. $k = k + 1$

Step 2. Introduce a new truck k with its schedule $\pi_k = []$ and initialize the truck location $\iota = 0$

Step 3. Search for the nearest $task$ s.t.

$$\tau^* = (o^*, d^*, \xi^*) = \arg \min_{(o,d,\xi)\in \mathrm{T}} a_{\iota,\mathrm{o}}$$

Step 4. If working time for truck k with $\tau^* \leq \bar{z}$:

Append τ^* to π_k

Remove τ^* from T

Update truck location $\iota = d^*$

Else:

Append truck k to D

Go to Step 1

Step 5. If T is not empty, go to Step 3, else STOP.

For initial solution construction, only DHDTs are used in the system. *Algorithm 1* is a greedy algorithm for solving a bin-packing problem. In this algorithm, trucks are considered as capacitated bins with limited working time. Each ordered list π_k holds the truck schedule for truck k. Every time a new truck is introduced into the system, it will search for the nearest remaining τ^* in T based on the truck's last location. If the current truck can finish τ^* and return to the depot within $\bar{z}$, we append τ^* to the ordered list and remove τ^* from the task list T. Otherwise, the truck is added to the diesel truck set D and a new truck $k+1$ is introduced to the system to take the remaining tasks. The algorithm stops when all tasks are assigned.

4.2 Modified ALNS

The ALNS is adapted from Dessouky et al. [38]. The modified ALNS in our study considers truck substituting between DHDTs and BEHDTs. In addition, we introduce charging station insertion and task re-match operations in our ALNS. The framework of our ALNS is given in Figure 5.

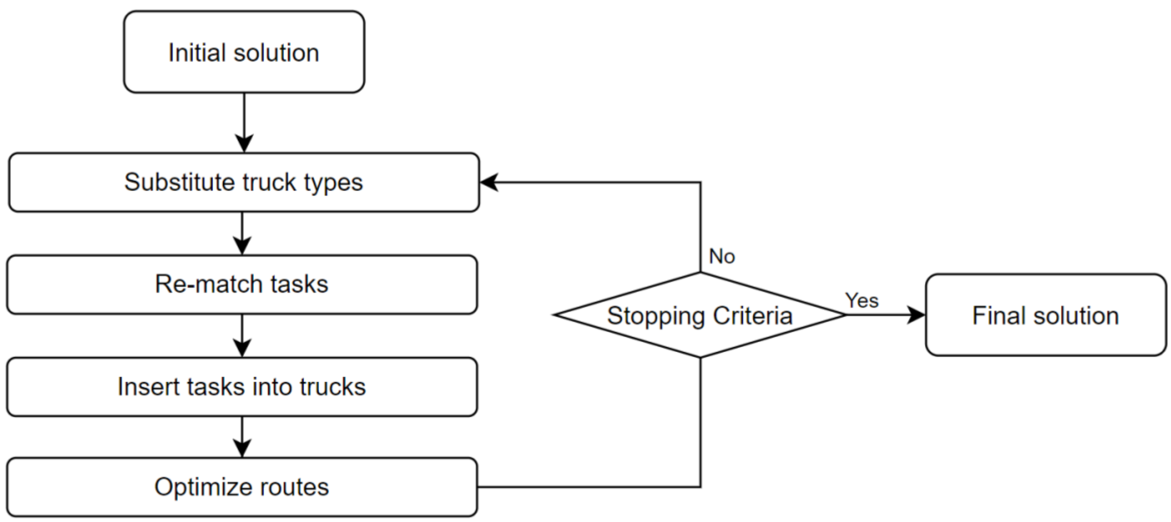

Figure 5. Solution framework for our ALNS

4.2.1 Substitute Truck Types

After running *Algorithm 1*, only DHDT routes are generated. Figure 6 shows a truck route in the initial solution.

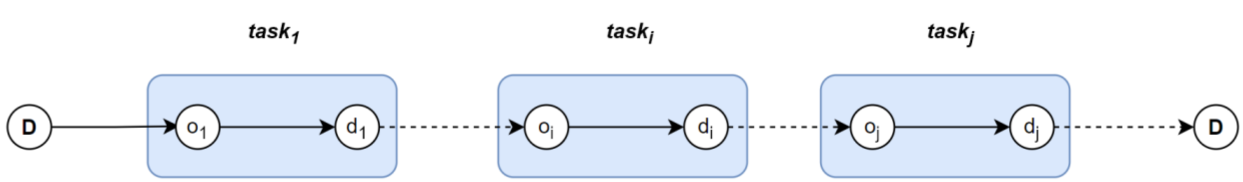

Figure 6. A truck route in the initial solution

When we substitute a BEHDT for a DHDT, charging station insertions are necessary to ensure non-negative battery levels for the BEHDT. Figure 7 gives two types of charging station insertions, within and between task insertions. In addition, because the charging time for BEHDTs is non-negligible, we cut off tasks that exceed the working time limit and add them back into the task list T. On the other hand, when substituting a BEHDT for a DHDT, we only need to eliminate all the charging stations along the route.

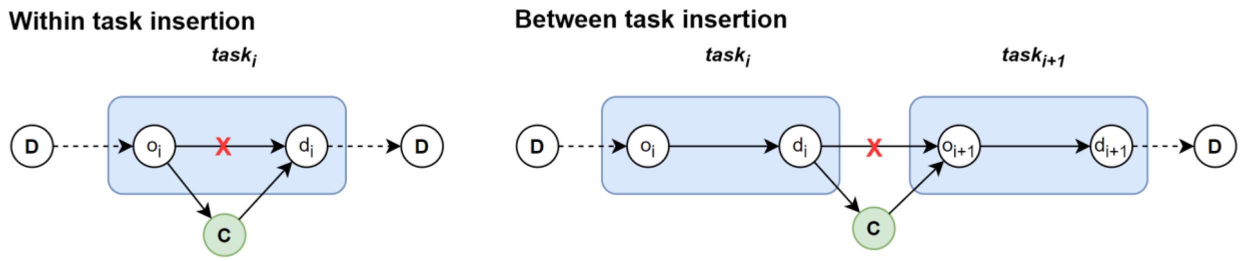

Figure 7. Two types of charging insertions

4.2.2 Re-match Tasks

Initially, all the tasks are generated in a greedy manner only considering the distance between supply and demand nodes. It is easy to see such a matching might lead to a sub-optimal solution and trap the model solution in a local minima. Therefore, it is necessary to re-match supply and demand nodes along the procedure. In each iteration, trucks that have less than δ tasks will be removed from the truck sets. These tasks will be added back to the task list T. Before inserting these unassigned tasks to trucks, in each iteration with a certain probability ρ, we randomly remove η tasks from all the trucks and add them back to the task list T and rematch these tasks.

4.2.3 Insert Tasks into Trucks

At this point, if the task list T is not empty, we need to insert tasks into existing trucks or employ additional trucks to ensure demand satisfaction.

4.2.4 Optimize Routes

For each DHDT, we minimize its travel distance with working time limit constraints. For each BEHDT, additional battery constraints are considered when determining its routes. Although finding the best route for every truck is a TSP which is NP-hard, the best route can be found fast when each truck can have at most $\frac{\bar{z}}{s_i}$ tasks. In practice, a truck usually serves less than twenty customers in daily drayage operations.

4.2.5 Stopping Criteria

The heuristic terminates when the following two conditions hold:

1) The maximum number of iterations (Ψ) is reached.
2) The improvement between successive iterations is not greater than Δ.

4.2.6 Complete ALNS Heuristic

The solution to the problem is a collection of truck routes for DHDTs and BEHDTs which are stored in D and E, respectively. Two functions are used in the ALNS (1) C_{sys} is a function that calculates the system costs based on the truck routes in D and E, and (2) g is a function that calculates travel distances for any truck k. The complete ALNS heuristic is given in Algorithm 2.

Algorithm 2: Modified ALNS

Step 0. Set $\psi = 0$, $E = \{\}$, $\bar{d} = \frac{c_0^e - c_0^d}{c_1^d - c_1^e + \sum_{\omega \in \Omega}(c_\omega^d - c_\omega^e)}$,

Step 1. $\chi^* = (D, E)$, $\mathrm{K}^* = C_{sys}(D, E)$, $\psi^* = 1$,

Step 2. For truck k in D:

    If $g(k) > \bar{d}$:

        Remove truck k from D

        Insert charging stations into π_k with greedy insertion

        If working time for truck $k > \bar{z}$:

            Cut off the tasks that exceed $\bar{z}$ and add these tasks to T

            Add k to E

    Else if truck k has less than δ tasks:

        Add all the tasks in truck k to T

        Remove truck k from D

Step 3. For truck k in E:

    If $g(k) \leq \bar{d}$:

        Remove truck k from E

        Remove charging stations from π_k

        Add k to D

Step 4. With probability ρ, randomly remove η tasks from all trucks to T and re-match OD pairs for all $\tau \in \mathrm{T}$ based on the demand type

Step 5. While T is not empty:

    Select a τ' from T

    If τ' can be inserted into any active truck $k \in D \cup E$:

        Insert τ' into π_k

    Else:

        Assign τ' to a new truck

Step 6. Optimize routes for all active trucks

Step 7. If $C_{sys}(D, E) \leq \mathrm{K}^*$:

$\chi^* = (D, E)$

$\mathrm{K}^* = C_{sys}(D, E)$

$\psi^* = \psi$

Step 8. $\psi = \psi + 1$

Step 9. If $\psi - \psi^* \geq \Delta$ or $\psi = \Psi$, STOP; otherwise go to Step 2.

The algorithm starts with the solution generated by Algorithm 1. In Step 0, we initialize a few parameters, where ψ is the iteration counter, E is the set for BEHDTs, and $\bar{d}$ is the travel distance threshold for substituting a DHDT to a BEDHT. In Step 1, we introduce χ^* to store the best solution, K^* to store the minimum system cost, and ψ^* to store the iteration that finds the best solution. Step 2 and Step 3 are the truck type substituting process. If a DHDT travels more than the threshold $\bar{d}$, we substitute the DHDT to a BEHDT, perform charging station insertions, and cut off tasks that exceed the working time limit $\bar{z}$. If a DHDT travels less than $\bar{d}$ and has fewer than δ tasks, it is removed from the system and its tasks are added back to the task list T. On the other hand, if a BEHDT travels less than $\bar{d}$, it is substituted back to a DHDT by removing all charging stations on its route. Step 4 is the task re-matching process. In each iteration, there is a probability ρ of performing a re-match for the remaining tasks in T. Every time a re-match happens, additional δ tasks are added back to T from the truck routes to better explore the solution space and escape from a local minima. In Step 5, we try to insert the remaining tasks in T into existing trucks. Every time a task cannot be inserted into existing trucks, it is assigned to a new truck. Step 6 is the route optimization procedure, which finds the best route for each individual truck. In Step 7, the best solution is updated if the system costs in the current iteration is lower than the minimum system costs. We then update the iteration number and check the stopping criteria.

5. Numerical Experiments

In this section, we present the numerical results of small-size and practical-size instances. Most of the parameters are taken from Giuliano et al.'s study [42]. We first run the modified ALNS on small instances, which can also be solved by a standard commercial optimization solver Gurobi using the MFDRP formulation. The optimal solutions obtained from the Gurobi solver are also considered as benchmark cases to show the effectiveness of the proposed ALNS heuristic. Then, we use the modified ALNS to solve practical size problems to explore the potential of employing BEHDTs in drayage operations in years 2022, 2025, and 2030.

All the numerical experiments are conducted on a square grid map with randomly generated customer and charging station nodes on the map. The depot is located at the center of the map. All the trucks start and end at the depot. DHDTs are assumed to be able to finish one-day operations without refueling and BEHDTs are fully charged at the beginning of the day. Once a BEHDT arrives at a charging station, it cannot leave the station until it is fully charged. We use a two-stage charging model in this study. The battery has a faster (slow) charging speed v_1 (v_2) before (after) the battery level threshold, as shown in Figure 8. We assume all the trucks are driving on well-maintained roads with an average speed of 40 mph. The service time for all customer nodes is half an hour.

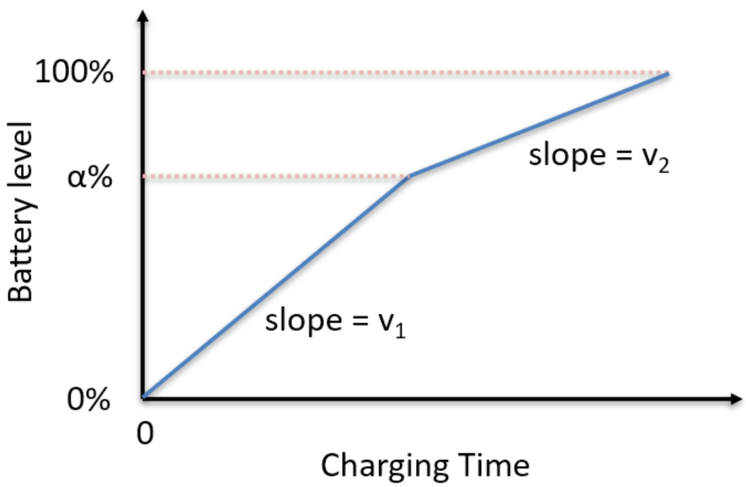

Figure 8. Charging curve

All simulated experiments are solved on a computer with an Intel i7-12800H CPU of 4.8 GHz and a RAM of 64 GB. All the scripts are programmed in Python 3.8. The MFDRP model is solved by Gurobi 9.5.2 with Python API.

5.1 Experiments with Small-size Instances

As a non-linear MIP model, the MFDRP cannot be efficiently solved by state-of-the-art commercial optimization solvers when the problem size is large. However, for very small instances, the model can be solved optimally within 4 CPU minutes. A 50 miles by 50 miles grid map is generated with 8-12 customer nodes and 2 charging station nodes. The location of the customer and charging station nodes are randomly generated on the map. All the small cases are solved with Gurobi 9.5.2 as well as the modified ALNS. We record the best solution found within 2 CPU hours for all the experiments. The parameters that are used in this section can be found in the Appendix.

Table 1. Small instances results

Name	Gurobi Solver				ALNS			
	Obj	LB	Gap	Time (s)	Obj	Gap	Imp	Time (s)
4F4E2C1	836.74	836.74	0.00%	209.0	836.74	0.00%	0.00%	3.2
4F4E2C2	822.81	822.81	0.00%	74.9	828.93	0.74%	-0.74%	2.9
4F4E2C3	818.16	818.16	0.00%	148.0	818.16	0.00%	0.00%	3.3
4F4E2C4	860.54	860.47	0.01%	88.8	867.18	0.77%	-0.77%	2.8
4F4E2C5	770.68	770.68	0.00%	216.3	779.63	1.15%	-1.16%	1.8
Avg	**821.79**	**821.77**	**0.00%**	**147.4**	**826.13**	**0.53%**	**-0.54%**	**2.8**
6F4E2C1	770.71	243.43	68.41%	7200.0	770.71	68.41%	0.00%	8.3
6F4E2C2	835.80	270.85	67.59%	7200.0	873.01	68.98%	-4.45%	4.3
6F4E2C3	831.95	303.65	63.50%	7200.0	872.57	65.20%	-4.88%	3.8
6F4E2C4	816.84	238.85	70.76%	7200.0	835.44	71.41%	-2.28%	3.2
6F4E2C5	776.94	230.31	70.36%	7200.0	770.30	70.10%	0.85%	4.6
Avg	**806.45**	**257.42**	**68.13%**	**7200.0**	**824.40**	**68.82%**	**-2.15%**	**4.84**
8F4E2C1	1115.21	223.09	80.00%	7200.0	830.39	73.13%	25.54%	7.8
8F4E2C2	1206.20	305.24	74.69%	7200.0	1251.97	75.62%	-3.79%	10.2
8F4E2C3	1168.02	318.66	72.72%	7200.0	867.79	63.28%	25.70%	4.6
8F4E2C4	1248.14	332.73	73.34%	7200.0	1299.55	74.40%	-4.12%	9.2
8F4E2C5	1266.20	339.48	73.19%	7200.0	1283.10	73.54%	-1.33%	5.7
Avg	**1200.76**	**303.84**	**74.79%**	**7200.0**	**1106.56**	**71.99%**	**8.40%**	**7.5**

Table 1 shows the numerical results for the small instances. In total, we conducted 15 instances with three different settings and each setting has five randomly generated instances. The instance name shows the types of nodes on the map. For example, instance 8F4E2C1 means it is the first instance with eight loaded container demand nodes, four empty container demand nodes, and two charging station nodes. The first group of columns is the numerical results retrieved directly from the Gurobi solver. Within the group, the first column (Obj) shows the objective function value of the best solution found; the second column (LB) is the best lower bound; the third column (Gap) is the optimality gap between the best objective function value and the best lower bound; the fourth column (Time) is the solving time in seconds for the Gurobi solver. The second group of columns is the results from our ALNS. Since ALNS does not provide any lower bounds in the solving procedure, we compare the results with the solver solution and calculate improvements (Imp) compared to the best solution from the Gurobi solver. As shown in Table 1, all the cases under 4F4E2C can be solved optimally within a few hundred seconds by the Gurobi solver, while ALNS can also solve these cases nearly optimally within a few seconds. However, when the problem size increases, the solver performance drops down significantly. None of them can be solved optimally within two CPU hours. Although ALNS consistently solves the problem in a matter of seconds and provides good quality solutions. In some instances, such as 6F4E2C5, 8F4E2C1, and 8F4E2C3, ALNS even outperforms the best solution from the solver.

5.2 Experiments with Practical-size Instances

In this section, we conduct simulations to explore the potential of substituting DHDTs with BEHDTs from different aspects including the fleet size, travel distances, and emissions. In addition, three years (2022, 2025, and 2030) are considered in our experiments. For each target year, we considered three situations including (1) all trucks are DHDTs (Max-DHDTs), (2) nearly half of the trucks are BEHDTs (Mid-Point), and (3) all trucks are BEHDTs (Max-BEHDTs). In total, we have nine groups of experiments. The year 2022 with all DHDTs is considered as our base case. We modify parameters from Giuliano et al.'s work [42], which provides comprehensive information including daily employment costs, emission rates, and battery capacity improvements for both DHDTs and BEHDTs for years 2022, 2025 and 2030. Other parameters are listed in the Appendix.

Similar to Giuliano et al. [42], we study scenarios with daily demand for empty and loaded containers as 135 and 176 respectively. We randomly generate demand nodes on the map in each experiment and run five replications under each setting.

As seen in Figure 9, in 2022, to satisfy the daily demand, the Max-DHDTs scenario requires 71.6 trucks on average. As the share of BEHDTs increases, the fleet size increases significantly. To reach the maximum BEHDT share in the truck fleet, there is a 47.2% increase in the fleet size, and the average fleet size becomes 105.4. Additional trucks are needed due to the range limitations and extra charging time. The fleet size for reaching maximum BEHDT share reduces sharply over the target years as battery technology improves. In 2025 and 2030, the fleet sizes both increased by 3.4% to reach the maximum BEHDT share in the fleet.

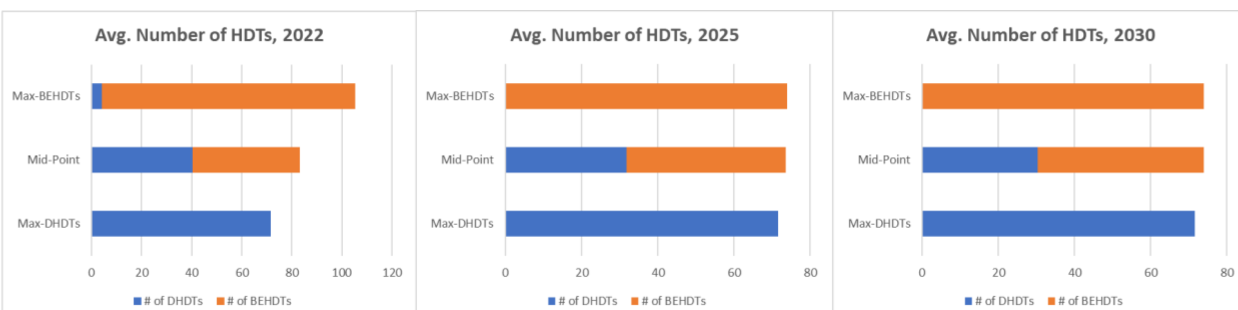

Figure 9. Avg. number of HDTs required for each target year

Figure 10 provides the truck miles for daily demand satisfaction. In 2022, the truck miles increase as the BEHDT share increases. These extra truck miles are caused by detours for charging. In 2025, we still can see a slightly increase in the truck miles under different scenarios. However, in 2030, the truck miles are very similar under different scenarios. As battery technology significantly improves in future years, there is less need to charge during the workday. Thus, there is less need to take detours for charging during working time.

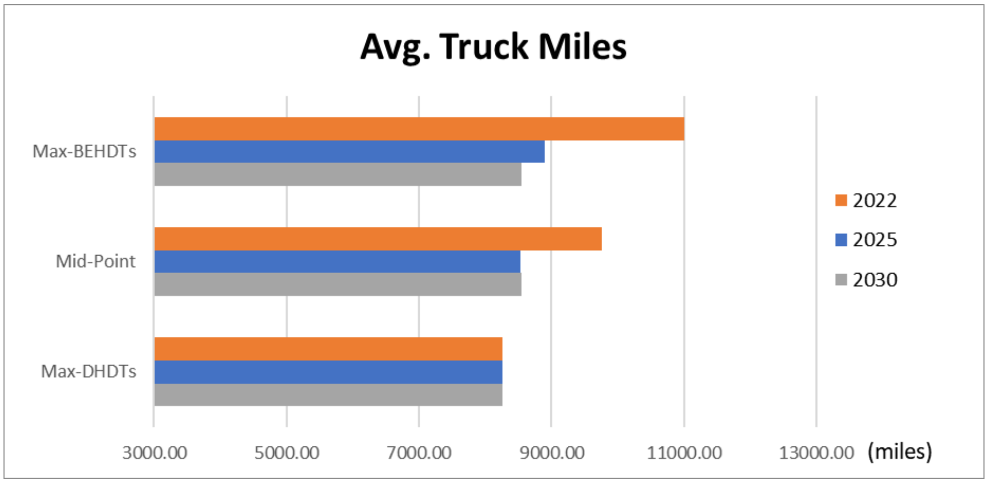

Figure 10. Avg. truck miles required for each target year

Table 2 shows the emissions reductions relative to the Max-DHDT scenario for each target year. In all target years, the Max-BEHDT scenario has the most emissions savings. In 2022, over 50% reductions in CO_2 emissions and 93% reductions in NO_x can be achieved by employing BEHDTs in the fleet. In 2025 and 2030, with fewer BEHDT charging detours, CO_2 emissions can be reduced by an additional 10%. In addition, NO_x emissions can be reduced to zero when only using BEHDTs in drayage operations.

Table 2. Net daily emissions savings, relative to Max-DHDTs

Pollutant	Year	Mid-point		Max-BEHDTs	
		Net saving (kg)	% of saving	Net saving (kg)	% of saving
CO_2	2022	3531.63	14.5%	12375.98	50.9%
	2025	8655.44	40.2%	13249.23	61.5%
	2030	7254.03	37.6%	11864.52	61.4%
NO_X	2022	4.90	31.1%	14.78	93.6%
	2025	5.07	64.0%	7.94	100.0%
	2030	4.92	62.0%	7.94	100.0%

6. Conclusion

In this project, we examine the potential of employing BEHDTs in daily drayage operations as a substitute for DHDTs. We consider multiple charging locations on the map with non-linear charging time for BEHDTs. We first formulate the MFDRP as a non-linear MIP and then improve the formulation with linearization and variable elimination. Then, a modified ALNS is proposed to solve the problem in a more efficient way. The effectiveness of the proposed ALNS is shown in small-size instances. We conduct randomized experiments based on data from the Port of Los Angeles and Long Beach. The results indicate that:

a) Employing BEHDTs as substitutes for DHDTs will increase the fleet size under the same level of demand, especially given today's battery technology. To reach the maximum BEHDT share in the fleet, the fleet size increases by 47.2%, 3.4%, and 3.4% in 2022, 2025, and 2030, respectively.

b) Additional truck miles caused by employing BEHDTs decrease as battery technology improves. In 2022, there is a 33% increase in truck miles when the maximum BEHDT share in the fleet is reached. These additional truck miles are caused by BEHDT charging detours. With improved battery capacity, BEHDTs are able to travel longer per charge, requiring fewer detours for charging.

c) Significant emission reductions can be achieved by employing BEHDTs as substitutes for DHDTs. In 2022, up to 50.9% of CO_2 emissions can be reduced by employing BEHDTs. In 2025 and 2030, an additional 10% of CO_2 emissions can be saved with fewer truck miles. Since BEHDTs do not emit NO_x, zero NO_x emissions can be achieved in drayage operations when only using BEHDTs to transport freight.

There are several limitations to the study. First, we assume all the HDTs drive at a constant speed. In the real world, traffic conditions are dynamic. One future direction could be incorporating dynamic traffic network states into the model. For example, traffic simulation models can be introduced to better approximate the transportation network states and traffic flow conditions. Second, we do not consider capital costs for infrastructure construction and assume sufficient charging infrastructure outside the depot. One extension of this study could also determine the best allocations for charging facilities. Third, in this study, we conducted experiments on randomly generated datasets to simulate the drayage system. Future work can collect data from logistics companies in the San Pedro Bay area and test our approach on more realistic datasets. Finally, more research can be done to investigate the latest commercially available BEHDT ranges and charging times using higher power electric charging systems.

7. References

1. UNCTAD. *Global Trade Update*. 2022.
2. Mulholland, E., J. Teter, P. Cazzola, Z. McDonald, and B. P. Ó Gallachóir. The Long Haul towards Decarbonising Road Freight – A Global Assessment to 2050. *Applied Energy*, Vol. 216, 2018, pp. 678–693. https://doi.org/10.1016/j.apenergy.2018.01.058.
3. US EPA, O. Fast Facts on Transportation Greenhouse Gas Emissions. https://www.epa.gov/greenvehicles/fast-facts-transportation-greenhouse-gas-emissions. Accessed Feb. 7, 2022.
4. Kilian, L., N. K. Nomikos, and X. Zhou. Container Trade and the U.S. Recovery. https://papers.ssrn.com/abstract=3963305. Accessed Oct. 30, 2022.
5. Burke, A. Technology, Sustainability, and Marketing of Battery Electric and Hydrogen Fuel Cell Medium-Duty and Heavy-Duty Trucks and Buses in 2020-2040. 2020. https://doi.org/10.7922/G2H993FJ.
6. Giuliano, G., M. Dessouky, S. Dexter, J. Fang, S. Hu, S. Steimetz, T. O'Brien, M. Miller, and L. Fulton. Developing Markets for Zero Emission Vehicles in Short Haul Goods Movement. 2020. https://doi.org/10.7922/G2DN43BT.
7. Jula, H., M. Dessouky, P. Ioannou, and A. Chassiakos. Container Movement by Trucks in Metropolitan Networks: Modeling and Optimization. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 41, No. 3, 2005, pp. 235–259. https://doi.org/10.1016/j.tre.2004.03.003.
8. Shiri, S., and N. Huynh. Assessment of U.S. Chassis Supply Models on Drayage Productivity and Air Emissions. *Transportation Research Part D: Transport and Environment*, Vol. 61, 2018, pp. 174–203. https://doi.org/10.1016/j.trd.2017.04.024.
9. Wang, X., and A. C. Regan. Local Truckload Pickup and Delivery with Hard Time Window Constraints. *Transportation Research Part B: Methodological*, Vol. 36, No. 2, 2002, pp. 97–112. https://doi.org/10.1016/S0965-8564(00)00037-9.
10. Zhang, R., W. Y. Yun, and I. Moon. A Reactive Tabu Search Algorithm for the Multi-Depot Container Truck Transportation Problem. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 45, No. 6, 2009, pp. 904–914. https://doi.org/10.1016/j.tre.2009.04.012.
11. Zhang, R., W. Y. Yun, and H. Kopfer. Heuristic-Based Truck Scheduling for Inland Container Transportation. *OR Spectrum*, Vol. 32, No. 3, 2010, pp. 787–808. https://doi.org/10.1007/s00291-010-0193-4.
12. Erdoğan, S., and E. Miller-Hooks. A Green Vehicle Routing Problem. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 48, No. 1, 2012, pp. 100–114. https://doi.org/10.1016/j.tre.2011.08.001.

13. Lin, C., K. L. Choy, G. T. S. Ho, S. H. Chung, and H. Y. Lam. Survey of Green Vehicle Routing Problem: Past and Future Trends. *Expert Systems with Applications*, Vol. 41, No. 4, Part 1, 2014, pp. 1118–1138. https://doi.org/10.1016/j.eswa.2013.07.107.

14. Behnke, M., and T. Kirschstein. The Impact of Path Selection on GHG Emissions in City Logistics. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 106, 2017, pp. 320–336. https://doi.org/10.1016/j.tre.2017.08.011.

15. Koyuncu, I., and M. Yavuz. Duplicating Nodes or Arcs in Green Vehicle Routing: A Computational Comparison of Two Formulations. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 122, 2019, pp. 605–623. https://doi.org/10.1016/j.tre.2018.11.003.

16. Juan, A. A., J. Goentzel, and T. Bektaş. Routing Fleets with Multiple Driving Ranges: Is It Possible to Use Greener Fleet Configurations? *Applied Soft Computing*, Vol. 21, 2014, pp. 84–94. https://doi.org/10.1016/j.asoc.2014.03.012.

17. Eskandarpour, M., D. Ouelhadj, S. Hatami, A. A. Juan, and B. Khosravi. Enhanced Multi-Directional Local Search for the Bi-Objective Heterogeneous Vehicle Routing Problem with Multiple Driving Ranges. *European Journal of Operational Research*, Vol. 277, No. 2, 2019, pp. 479–491. https://doi.org/10.1016/j.ejor.2019.02.048.

18. Bruglieri, M., S. Mancini, and O. Pisacane. The Green Vehicle Routing Problem with Capacitated Alternative Fuel Stations. *Computers & Operations Research*, Vol. 112, 2019, p. 104759. https://doi.org/10.1016/j.cor.2019.07.017.

19. Asghari, M., and S. M. J. Mirzapour Al-e-hashem. Green Vehicle Routing Problem: A State-of-the-Art Review. *International Journal of Production Economics*, Vol. 231, 2021, p. 107899. https://doi.org/10.1016/j.ijpe.2020.107899.

20. Elangovan, R., O. Kanwhen, Z. Dong, A. Mohamed, and R. Rojas-Cessa. Comparative Analysis of Energy Use and Greenhouse Gas Emission of Diesel and Electric Trucks for Food Distribution in Gowanus District of New York City. *Frontiers in Big Data*, Vol. 4, 2021, p. 693820. https://doi.org/10.3389/fdata.2021.693820.

21. Lin, J., W. Zhou, and O. Wolfson. Electric Vehicle Routing Problem. *Transportation Research Procedia*, Vol. 12, 2016, pp. 508–521. https://doi.org/10.1016/j.trpro.2016.02.007.

22. Pelletier, S., O. Jabali, and G. Laporte. The Electric Vehicle Routing Problem with Energy Consumption Uncertainty. *Transportation Research Part B: Methodological*, Vol. 126, 2019, pp. 225–255. https://doi.org/10.1016/j.trb.2019.06.006.

23. Wen, M., E. Linde, S. Ropke, P. Mirchandani, and A. Larsen. An Adaptive Large Neighborhood Search Heuristic for the Electric Vehicle Scheduling Problem. *Computers & Operations Research*, Vol. 76, 2016, pp. 73–83. https://doi.org/10.1016/j.cor.2016.06.013.

24. Yu, Y., S. Wang, J. Wang, and M. Huang. A Branch-and-Price Algorithm for the Heterogeneous Fleet Green Vehicle Routing Problem with Time Windows. *Transportation Research Part B: Methodological*, Vol. 122, 2019, pp. 511–527. https://doi.org/10.1016/j.trb.2019.03.009.

25. Zhang, S., Y. Gajpal, S. S. Appadoo, and M. M. S. Abdulkader. Electric Vehicle Routing Problem with Recharging Stations for Minimizing Energy Consumption. *International Journal of Production Economics*, Vol. 203, 2018, pp. 404–413. https://doi.org/10.1016/j.ijpe.2018.07.016.
26. Zhao, M., and Y. Lu. A Heuristic Approach for a Real-World Electric Vehicle Routing Problem. *Algorithms*, Vol. 12, No. 2, 2019, p. 45. https://doi.org/10.3390/a12020045.
27. Felipe, Á., M. T. Ortuño, G. Righini, and G. Tirado. A Heuristic Approach for the Green Vehicle Routing Problem with Multiple Technologies and Partial Recharges. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 71, 2014, pp. 111–128. https://doi.org/10.1016/j.tre.2014.09.003.
28. Ban, M., Z. Zhang, C. Li, Z. Li, and Y. Liu. Optimal Scheduling for Electric Vehicle Battery Swapping-Charging System Based on Nanogrids. *International Journal of Electrical Power & Energy Systems*, Vol. 130, 2021, p. 106967. https://doi.org/10.1016/j.ijepes.2021.106967.
29. Hof, J., M. Schneider, and D. Goeke. Solving the Battery Swap Station Location-Routing Problem with Capacitated Electric Vehicles Using an AVNS Algorithm for Vehicle-Routing Problems with Intermediate Stops. *Transportation Research Part B: Methodological*, Vol. 97, 2017, pp. 102–112. https://doi.org/10.1016/j.trb.2016.11.009.
30. Masmoudi, M. A., M. Hosny, E. Demir, K. N. Genikomsakis, and N. Cheikhrouhou. The Dial-a-Ride Problem with Electric Vehicles and Battery Swapping Stations. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 118, 2018, pp. 392–420. https://doi.org/10.1016/j.tre.2018.08.005.
31. Keskin, M., G. Laporte, and B. Çatay. Electric Vehicle Routing Problem with Time-Dependent Waiting Times at Recharging Stations. *Computers & Operations Research*, Vol. 107, 2019, pp. 77–94. https://doi.org/10.1016/j.cor.2019.02.014.
32. Pelletier, S., O. Jabali, G. Laporte, and M. Veneroni. Battery Degradation and Behaviour for Electric Vehicles: Review and Numerical Analyses of Several Models. *Transportation Research Part B: Methodological*, Vol. 103, 2017, pp. 158–187. https://doi.org/10.1016/j.trb.2017.01.020.
33. Szablowski, L., and P. Bralewski. Impact of Development of Infrastructure for Charging Electric Vehicles on Power Demand in the National Power System. *Civil and Environmental Engineering Reports*, Vol. 29, 2019, pp. 66–91. https://doi.org/10.2478/ceer-2019-0006.
34. Koç, Ç., and I. Karaoglan. The Green Vehicle Routing Problem: A Heuristic Based Exact Solution Approach. *Applied Soft Computing*, Vol. 39, 2016, pp. 154–164. https://doi.org/10.1016/j.asoc.2015.10.064.
35. Leggieri, V., and M. Haouari. A Practical Solution Approach for the Green Vehicle Routing Problem. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 104, 2017, pp. 97–112. https://doi.org/10.1016/j.tre.2017.06.003.

36. Ropke, S., and D. Pisinger. An Adaptive Large Neighborhood Search Heuristic for the Pickup and Delivery Problem with Time Windows. *Transportation Science*, Vol. 40, 2006, pp. 455–472. https://doi.org/10.1287/trsc.1050.0135.

37. Demir, E., T. Bektaş, and G. Laporte. An Adaptive Large Neighborhood Search Heuristic for the Pollution-Routing Problem. *European Journal of Operational Research*, Vol. 223, No. 2, 2012, pp. 346–359. https://doi.org/10.1016/j.ejor.2012.06.044.

38. Dessouky, M. M., S. Carvajal, and S. Yao. Congestion Reduction Through Efficient Empty Container Movement Under Stochastic Demand. No. NCST-USC-RR-20-19, 2020. https://doi.org/10.7922/G2W09464.

39. Lahyani, R., A.-L. Gouguenheim, and L. C. Coelho. A Hybrid Adaptive Large Neighbourhood Search for Multi-Depot Open Vehicle Routing Problems. *International Journal of Production Research*, Vol. 57, No. 22, 2019, pp. 6963–6976. https://doi.org/10.1080/00207543.2019.1572929.

40. Shao, Y., and M. Dessouky. A Routing Model and Solution Approach for Alternative Fuel Vehicles with Consideration of the Fixed Fueling Time. *Computers & Industrial Engineering*, Vol. 142, 2020, p. 106364. https://doi.org/10.1016/j.cie.2020.106364.

41. Gale, D., and L. S. Shapley. College Admissions and the Stability of Marriage. *The American Mathematical Monthly*, Vol. 69, No. 1, 1962, pp. 9–15. https://doi.org/10.2307/2312726.

42. Giuliano, G., M. Dessouky, S. Dexter, J. Fang, S. Hu, and M. Miller. Heavy-Duty Trucks: The Challenge of Getting to Zero. *Transportation Research Part D: Transport and Environment*, Vol. 93, 2021, p. 102742. https://doi.org/10.1016/j.trd.2021.102742.

8. Data Summary

Products of Research

The primary date source was publicly available from the report “Developing Markets for Zero-Emission Vehicles in Goods Movement” (Giuliano et al., 2018), which was supported by the National Center for Sustainable Transportation. Also, randomly generated data sets were used in this study.

Data Format and Content

All research products will be available online in digital form. Manuscript will appear in a common document-viewing format, such as PDF, and supplemental materials such as tables and numerical data will be in a tabular format such as Microsoft Excel spreadsheets, CSV files.

Data Access and Sharing

The data can be found at Dataverse: https://doi.org/10.7910/DVN/ZWMXVK

Reuse and Redistribution

USC's policy is to encourage, wherever appropriate, research data to be shared with the public through internet access. This public access will be regulated by the university to protect privacy and confidentiality concerns, as well to respect any proprietary or intellectual property rights. Administrators will consult with the university's legal office to address any concerns on a case-by-case basis, if necessary. Terms of use will include requirements of attribution along with disclaimers of liability in connection with any use or distribution of the research data, which may be conditioned under some circumstances.

9. Appendix

Table A1. Parameters for small-size instances

c_0^d	300
c_0^e	360
c_1^d	0.58
c_1^e	0.38
$c_{co_2}^d$	0.1
$c_{NO_x}^d$	0.5
$c_{co_2}^e$	0
$c_{NO_x}^d$	0
$\bar{z}$	8
Ψ	400
Δ	200
β	0.3
η	4
δ	2
v_1	0.8
v_2	0.2
α	80

Table A2. Parameters for practical-size instances

Year	2022	2025	2030
c_0^d	150	150	150
c_0^e	380	250	180
c_1^d	1.36	1.26	1.16
c_1^e	0.49	0.50	0.47
$c_{co_2}^d$	0.1501	0.1329	0.1191
$c_{NO_x}^d$	0.0010	0.0005	0.0005
$c_{co_2}^e$	0.0506	0.0475	0.0444
$c_{NO_x}^d$	0	0	0
Ψ	1000		
Δ	400		
β	0.3		
η	4		
δ	2		
$\bar{z}$	8		
v_1	0.8		
v_2	0.2		
α	80		