A Dynamic Programming Model for Joint Optimization of Electric Drayage Truck Operations and Charging Stations Planning at Ports

Xuanke Wu, Yunteng Zhang, and Yuche Chen

***Abstract*— The adoption of electric vehicles at ports is a promising approach to achieve sustainability goals. However, realizing the full potential of this strategy depends on effective coordination between infrastructure planning and operational scheduling. In this paper, we propose a joint optimization framework that can co-optimize these two components to minimize the overall system cost. To capture the dynamic nature of scheduling decisions, we model the problem using dynamic programming techniques. Our model accounts for the spatial and temporal heterogeneities of charging and driving costs for different truck trips. To evaluate the effectiveness of our proposed framework, we conducted an empirical study at the Port of Los Angeles and Port of Long Beach. Specifically, we aimed to fulfill 5% of the daily 20-foot equivalent unit containers using electric drayage trucks. Our model identified the optimal number of electric trucks, charging stations, and truck schedules required to meet the container throughput requirement. We also analyzed the cost per container as a function of daily throughput level for various scenarios. Our findings provide insights on how to determine charger supply based on daily throughputs at ports, and how to choose the appropriate ratios of electric trucks and battery sizes in the truck fleet under different throughput and electric price cases.**

***Index Terms*— Truck operation scheduling, dynamic programming, electric truck.**

I. Introduction

CARGO shipping has contributed a significant amount of particulate matter, oxides of nitrogen, and sulfur oxide emissions [1], [2] While shipping emissions primarily occur at sea, the most noticeable and health-damaging effects are typically experienced in port areas and nearby cities [3]. In particular, the drayage trucks used for transporting goods within ports make a significant contribution to the air pollution in and around port areas [4]. The electrification of port drayage fleets is widely recognized as a promising approach to mitigate emissions at ports [5]. Trucks can be classified into two main categories: light-duty trucks and heavy-duty trucks. The electrification process for these two types of trucks differs significantly. Light-duty trucks are defined as trucks with a gross vehicle weight of up to 3,860 kg and a payload capacity of up to 1,815 kg. They are primarily used for passenger transportation and household goods delivery. In recent years, several car manufacturers have introduced, or announced plans to introduce, electric light-duty trucks such as Ford's electric F-150, Rivian's R1T, and General Motors' Hummer EV. These electric light-duty trucks offer driving ranges between 200 to 350 miles, which is sufficient for most of the daily usage of light-duty trucks. As a result, there is a growing trend in the adoption and penetration of light-duty trucks in the market. However, the situation is markedly different for the electric heavy-duty truck market. Heavy-duty trucks are defined as trucks with a gross vehicle weight exceeding 12,000 kg and are primarily used for long-haul freight transportation (such as interstate transportation) and short-haul goods movement (such as drayage trucks in port areas). Currently, there are very few electric heavy-duty truck models available in the market, including BYD's 8TT, Volvo VNR, and Daimler eCascadia. These trucks offer driving ranges between 70-120 miles, with battery sizes ranging from 200 to 300 kWh. Most of the electric heavy-duty trucks planned for introduction by 2030-2035 are expected to have a battery size of at least 500 kWh and a mileage range above 200 miles. The current market offerings of heavy-duty trucks, as well as their battery specifications, clearly demonstrate that limited driving range remains a significant obstacle to the widespread adoption of electric trucks. This is especially true for the adoption of electric drayage trucks in port areas [6]. Many port authorities, including those in Los Angeles and Long Beach, have considered deploying electric drayage trucks in their jurisdictions as a solution to air quality issues. However, they have all acknowledged the limitations of driving range and the lack of experience in managing electric truck fleets [4], [5]. For this reason, it is crucial to efficiently plan, manage, and operate electric heavy-duty trucks and charging infrastructure to ensure the successful adoption of electric trucks in port areas [7], [8], [9].

There is a body of literature dedicated to managing and operating electric cars and their charging infrastructure. Numerous studies have investigated routing problems in various real-world scenarios, with the goal of maximizing passenger flow while minimizing fleet size and operating

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costs. Specifically, many of these studies have addressed the mileage range challenges for electric cars in passenger transportation, taking into account factors such as driving range and charging features. Some studies have focused on developing routing strategies that consider charging functions [10], [11], [12], [13], [30], [39], [40], [42]. For example, Montoya et al. [14] extended classical electric vehicle routing problems to consider non-linear charging functions, i.e. state of charge level is not linearly increased with charging time. They developed a mixed-integer programming method and converted the non-linear feature of charging into a series of linear constraints. Other studies investigated assigning electric vehicles for predetermined routes considering charging facility locations [15], [16], [17]. And other studies focused on co-optimization of charging infrastructure management and electric vehicle operations [37], [38].

And yet other studies focused on minimizing charging costs by optimizing recharging schedules and specifications of charging, such as charger power and battery size [18], [19], [20]. Though these studies are interesting, they do not apply to drayage truck planning and operating optimization. Drayage truck operation has challenges in 1) sequential decision making, given that drayage trucks must frequently move between locations in port areas; 2) freight transportation is different from passenger transportation because the goods are normally heterogeneous products and require different transport truck types and movement distances can vary significantly.

Limited studies studied electric trucks. Sassi and Oulamara [21], developed models for optimally assigning electric trucks to predetermined routes and scheduling charging activities at a single depot. Vahdani and Shahramfard [22] developed a dual-objective optimization model to solve for assignment of trucks and forklifts for a multidoor, cross-dock problem. Schiffer and Walther [23] developed a robust optimization to coordinate plan charging location and truck routing for freight transportation. They find that the coordinated decision process can improve system performance and reduce system costs. Above relevant studies of electric trucks focus on determining routes and charging locations for long-haul freight transportation. But drayage trucks have features of frequent movements and frequent acceleration/deceleration within a confined area [24]. These features makes the time-dependent operating decision to be critical in drayage truck fleet management.

There are limited studies related to drayage truck operations and management. There are some studies related to truck appointment systems for drayage truck operations in ports and Huynh et al. [25] summarized these studies. Drayage truck appointment studies focus on optimally coordinating arrival time among drayage trucks to arrive at port terminals. And most drayage appointment studies focus on the one-time arrival of trucks, which means each truck (normally belonging to different companies) only comes to the terminal one time per day to transport containers. For example, Chen et al. [26] developed an integer programming framework to optimally spread the terminal arrival time of a fleet of drayage trucks to reduce waiting time at terminal gates. It does not consider the sequential decision of drayage truck operations. Phan and Kim [27] proposed a decentralized decision-making model for the terminal to coordinate the arrival time of drayage trucks from different companies. The paper formulated drayage truck negotiations with equilibrium constraints. But the paper still focuses on one-time arrival per day for each drayage truck. Above literature failed to consider sequential decision-making of drayage truck movements within the port terminal during the day. Other relevant studies investigate trip characteristics of drayage trucks. For example, You and Ritchie [28] analyzed drayage truck driving data in Los Angles Port and showed trip length, trip average speed, and trip types of drayage trucks during a typical day of operation. Prohaska et al. [29] conducted a similar study on the drayage truck driving behavior of Long Beach Port. These studies provide informative drayage truck driving data, but they do not consider optimizing drayage truck fleet management given the driving data. There is even no relevant study on electric drayage truck operation and planning optimization. Some studies look at the feasibility of deploying electric drayage trucks and analyzed the installation and operating cost of charging stations at port areas [4], [5]. These studies provide useful information but are not directly relevant to operation and planning.

The above literature review indicates a gap in research on electric drayage truck operation at ports, which is crucial for achieving sustainability. Drayage truck operations have unique challenges that require sequential decision-making for efficient management and optimization, including frequent movements and dynamic task types. Relevant studies on electric cars and buses are not directly applicable due to differences in passenger and freight transportation. Similarly, studies on electric long-haul trucks do not consider time-dependent decisions. Existing drayage truck studies either focus on appointment systems or cost-benefit analysis, which do not address sequential decision-making. Thus, there is a need for robust methods to design decision-making processes for electric drayage truck operation and charging activities.

This paper presents a novel approach to addressing the knowledge gap in the literature surrounding the deployment of electric drayage trucks in port areas. Our proposed solution is a joint optimization framework that integrates fleet planning and operation decisions for electric drayage trucks. We utilize a mixed-integer dynamical programming model to optimize infrastructure planning decisions such as charging supply and truck battery size, as well as sequential daily operational decisions such as delivery activities and charging schedules. We aim to minimize system costs and improve operating efficiency. Our contribution to the literature lies in the development of a robust mathematical optimization framework capable of determining intra-day trip and charging activities for trucks of various battery sizes. Finally, we provide a case study based in the Los Angeles Ports to demonstrate the effectiveness of our framework.

II. Methodology

Drayage trucks are utilized for local transportation of cargo and empty containers between shipping terminals and nearby warehouses or distribution centers. The electrification of port drayage trucks entails decision-making at two stages:

(a) planning stage, which involves determining the number and type of electric drayage trucks to be deployed as well as the number of charging stations required within the port; and (b) operation stage, which involves designing the daily activities of electric trucks to meet container throughput requirements. Decisions made during the planning stage regarding trucks and charging stations not only affect planning costs but also determine the availability of trucks and charging stations during the operation stage. During the operation stage, the following decisions must be made on a daily basis:

(1) How many trucks should be assigned to take transport tasks in each period?
(2) Which type of delivery should they make: inland, intermediate, or near-dock?
(3) When should batteries get charged, considering the electricity price during peak and off-peak hours?
(4) How can trucks avoid unnecessary idling?

The decision-making process is divided into two levels, with the upper level responsible for determining the allocation of resources, and the lower level responsible for determining how these resources will be utilized. The overall aim is to minimize the total cost.

We build a bilevel mixed-integer optimization model, from a central operator perspective, to find optimal decisions at the upper-level planning stage (number of electric drayage trucks, charging stations) and lower-level operations stage at hourly resolution (scheduling operational activities) while fulfilling container throughput requirements. Specifically, the lower-level operations stage includes a sequential truck activity decision during each scheduling hour. The decision of one truck at one scheduling hour will be influenced by prior decisions of that truck and other trucks (through charging station availability). This sequential decision-making can be solved using a dynamic programming method. The overall objective is to achieve a minimum summation of infrastructure and operating costs.

With the notation defined in Table I, we can define some functions and then introduce the bilevel optimization model. There are three types of decision variables, i.e., the total number of electric drayage trucks to purchase, y_I, the total number of charging stations to install, y_K, and daily decision $x_{n,i}^a$. $x_{n,i}^a = 1$ is a binary variable, and it equals 1 if truck i is conducting activity a in period n. There are a total of 6 activities, thus, a can be 1 to 6 each corresponds to different activities as shown in Table I. Dynamic programming algorithm requires definitions of status variables, which include truck battery state of charge (SOC) $S_{n,i}$ and vehicle delivery remaining hour $R_{n,i}$. The transition function of SOC status variable is $S_{n+1,i} = S_{n,i} - \sum_{a=1,2,3} \gamma_i^a \cdot x_{n,i}^a + \gamma_i^4 \cdot x_{n,i}^4$, which subtracts delivery consumption from the previous stage SOC or add charged battery capacity. The transition function for vehicle delivery remaining hour is $R_{n+1,i} = R_{n,i} + \sum_{a=1,2,3} x_{n,i}^a \cdot (h_a - 1) - x_{n,i}^6$. In operational stages, decisions are made in every stage (i.e., one hour), but vehicle delivery can take several hours. Thus $R_{n,i}$ is used to record the number of remaining hours for a truck delivery trip. $R_{n,i}$ equals 0 when truck i finishes a delivery trip and back to port at *n-1* or a truck is not choosing any delivery trip (i.e., $a \neq 1, 2, 3$).

The objective as shown in Equation (1) contains planning costs and the sum of daily operation cost over 5 years. The planning cost is defined as $\boldsymbol{\varphi_c}(\mathbf{y_I}, \mathbf{y_K}) = c_I \cdot y_I + c_K \cdot y_K$, i.e. cost of purchasing y_I electric drayage truck and installing y_K charging station. The daily operational cost $\varphi_g(y_I, y_K)$ is compromised by two parts, $\sum_{n=1}^{N} \sum_{i=1}^{y_I} \sum_a \beta_n^a \cdot x_{n,i}^a$, refers to the total operating cost associated with charging, waiting, and delivery activities, and $\sum_{n=1}^{N} \sum_{i=1}^{y_I} \varepsilon_n \cdot x_{n,i}^4 \cdot (S_{n,i} - S_{n-1,i})$, refers to the total charging cost, wherein $(S_{n,i} - S_{n-1,i})$ refers to the change in battery state of charge (SOC) from period $n-1$ to n. The daily container throughput is defined as $\varphi_T^a(y_I, y_K) = \sum_{n=1}^{N} \sum_{i=1}^{y_I} x_{n,i}^a$ which counts containers delivered by all trucks over periods within a day.

$$Minimize\ W = \varphi_c(y_I, y_K) + \varphi_g(y_I, y_K) \tag{1}$$

$$\text{Subject to} \quad \varphi_T^a(y_I, y_K) \geq T_a, a = 1, 2, 3 \tag{2}$$

$$\sum_{a=1}^{6} x_{n,i}^a = 1, \forall i, n \tag{3}$$

$$\sum_{i=1}^{y_I} x_{n,i}^4 \leq y_K, \forall n \tag{4}$$

$$L_i - \left(S_{n,i} - \gamma_i^a\right) \leq M \cdot \left(1 - x_{n,i}^a\right), \quad a = 1, 2, 3, \forall i, n \tag{5}$$

$$S_{n,i} + \gamma_i^4 \cdot x_{n,i}^4 - U_i \leq \mathrm{M} \cdot \left(1 - x_{n,i}^4\right), \forall i, n \tag{6}$$

Equations (2) to (6) are constraints. Equation (2) ensures the minimum daily container throughput T_a is met. Equation (3) ensures that truck i can perform only one activity in any period n. Equation (4) guarantees that at any period n, the number of charging trucks does not exceed the available charging stations. Equation (5) controls electric trucks' decisions when their battery state of charge is low. It prevents a truck to choose any type of delivery activity if the completion of delivery will result in a battery level below the minimum level. Equation (6) states the battery level of a truck cannot exceed battery capacity.

For operation cost $\varphi_g(y_I, y_K)$, the decision space is $N \cdot y_I$, wherein N is the number of decision periods and y_I is the number of decisions to be made in each period. The computational demand exponentially expands with an increase in the dimensionality of the decision space. A dynamic programming model can significantly reduce the computational power required for solving the model compared with traditional programming models when the problem has inherent characteristics like a dynamic nature [19], [30], [31]. We approach the second stage operating cost minimization problem with a multiperiod dynamic programming model and convert the one-time $N \cdot y_I$ decision space into N sequential period decisions with only y_I decisions to be made in each period. Specifically, we define the value function $Z_n(\mathcal{S}_\mathbf{n})$ as the minimum operational cost from period 1 to n with the state set $\mathcal{S}_\mathbf{n}$. Therefore, the objective function in operation stage $\varphi_g(y_I, y_K)$ equals $Z_N(\mathcal{S}_\mathbf{N})$. According to Bellman's principle of optimality [32], n-stage decision-making can be considered a process of the first n-1 stages plus the last n^{th} stage. Thus, we can define the recursive value function

TABLE I
NOTATION AND NOMENCLATURE

Parameters	Description
$\boldsymbol{n}$	Index of time stage in the operational decision process, $n=\{1,\ldots,N\}$
$\boldsymbol{i}$	Index of vehicle, $i=\{1,\ldots., y_I\}$
$\boldsymbol{a}$	Index of activity decision by vehicles, a={1: long-distance delivery, 2: middle-distance delivery, 3: short-distance delivery, 4: charging, 5: idling, 6: a vehicle is on a delivery trip}
$\boldsymbol{c_I}$	The unit cost associated with the type of truck, \$/truck
$\boldsymbol{c_K}$	The unit cost of building an electric charging station, \$/station
$\boldsymbol{\beta_n^a}$	a=1, 2, 3: delivery associated cost at stage n, \$/hour a=4, 5: labor cost associated with charging or idling at stage n, \$/hour
$\boldsymbol{\varepsilon_n}$	Electricity associated cost at stage n (peak/off-peak hours), \$/hour
$\boldsymbol{\gamma_i^a}$	a=1, 2, 3: energy consumption associated with deliveries for vehicle i, kWh a=4: battery energy recovery while charging for vehicle i, kWh
$\boldsymbol{h_a}$	a=1, 2, 3: required hours for deliveries, hours
$\boldsymbol{U_i}$	Battery capacity for vehicle i, kWh
$\boldsymbol{L_i}$	Battery minimum level for vehicle i, kWh
$\boldsymbol{T_a}$	a=1, 2, 3: required daily throughput for deliveries, TEUs
Value functions	
$\boldsymbol{\varphi_c(y_I, y_K)}$	$\boldsymbol{\varphi_c}(\boldsymbol{y_I}, \boldsymbol{y_K}) = c_I \cdot y_I + c_K \cdot y_K$ Infrastructure cost for y_I electric trucks and y_K charging stations
$\boldsymbol{\varphi_g(y_I, y_K)}$	$\varphi_g(y_I, y_K) = \sum_{n=1}^{N}\sum_{i=1}^{y_I}\sum_a \beta_n^a \cdot x_{n,i}^a + \sum_{n=1}^{N}\sum_{i=1}^{y_I} \varepsilon_n \cdot x_{n,i}^4 \cdot (S_{n,i} - S_{n-1,i})$ Operational cost when daily throughput is met of y_I electric trucks and y_K charging stations
$\boldsymbol{\varphi_T^a(y_I, y_K)}$	$\varphi_T^a(y_I, y_K) = \sum_{n=1}^{N}\sum_{i=1}^{y_I} x_{n,i}^a, a = 1,2,3.$ Operational daily throughputs under y_I electric trucks and y_K charging stations
Decision variables	
$\boldsymbol{y_I}$	Total number of trucks to purchase, including large and small
$\boldsymbol{y_K}$	Total number of electricity chargers to install
$\boldsymbol{x_{n,i}^a}$	Binary variable, whether vehicle i takes activity decision a at stage n
Status variable	
$\boldsymbol{\mathcal{S}_n}$	State of charge of all vehicles at stage n, $\mathcal{S}_n = \left(S_{n,1}, \ldots S_{n,i} \ldots, S_{n,y_I}\right)^T$, specifically, $S_{1,i} = U_i$ and $S_{n,i} \in (L_i, U_i), \forall\, i, n$ $S_{n+1,i} = S_{n,i} - \sum_{a=1,2,3} \gamma_i^a \cdot x_{n,i}^a + \gamma_i^4 \cdot x_{n,i}^4, \forall\, i, n$
$\boldsymbol{R_{n,i}}$	The remaining hours that vehicle i is out for delivery, specifically, $R_{1,i} = 0$ $R_{n+1,i} = R_{n,i} + \sum_{a=1,2,3} x_{n,i}^a \cdot (h_a - 1) - x_{n,i}^6, \forall\, i, n$

$Z_n(S_n)$ as

$$Z_n(\mathcal{S}_\mathbf{n}) = \min_{x_{n,i}^a}\left\{Z_{n-1}(\mathcal{S}_{\mathbf{n-1}}) + \sum_{i=1}^{y_I}\sum_a \beta_n^a \cdot x_{n,i}^a + \sum_{i=1}^{y_I} \varepsilon_n \cdot x_{n,i}^4 \cdot \left(S_{n,i} - S_{n-1,i}\right)\right\} \quad (7)$$

The boundary conditions are $Z_0(\mathcal{S}_\mathbf{0}) = 0$, which means no operating costs are incurred before the operation stage starts, and $S_{0,i} = U_i$, which assumes all trucks start with a fully charged status. The solution process of the dynamic programming algorithm starts with stage $n = 1$. Since $Z_0(\mathcal{S}_\mathbf{0}) = 0$ and $S_{0,i} = U_i$, $Z_1(\mathcal{S}_\mathbf{1}) = \min_{x_{n,i}^a}\left\{\sum_{i=1}^{y_I}\sum_a \beta_1^a \cdot x_{1,i}^a + \sum_{i=1}^{y_I} \varepsilon_1 \cdot x_{1,i}^4 \cdot \left(S_{1,i} - U_i\right)\right\}$. This becomes a standard linear programming problem to find the optimal truck activities decision variables of $x_{n,i}^a$. Once $x_{n,i}^a$ are determined, the state variable set, $\mathcal{S}_\mathbf{2}$ (state of charging at beginning of stage 2), can be calculated. At stage 2, the model will determine the truck activities in this stage based on trucks' state of charging levels $\mathcal{S}_\mathbf{2}$. The truck activities will be optimized to minimize the sum of previous stages' costs, i.e. $Z_1(\mathcal{S}_\mathbf{1})$, and current stage costs, i.e. the remaining part in Equation (7). The algorithm will continue until it traverses all stages.

We implement our proposed model on a case study at the Port of Long Beach and Port of Los Angeles and build the model based on empirical input parameters (see Table II). The input for daily port throughput is 1,299 TEU containers, which is 5% of the total containers processed at San Pedro Bay Port Complex (a combination of the Port of Los Angeles and Port of Long Beach), the largest port in the United States. We assume three tiers of delivery trips, with round trip distances of 4 miles, 22 miles, and 108 miles. This categorization is based on a study conducted by the National Renewable Energy Laboratory [29] using more than 36,000 miles of

TABLE II
SUMMARY OF INPUT PARAMETERS

Parameter	Value	Reference
Vehicle parameters		
Battery sizes of electric trucks	Truck Type 1: 250 kWh Truck Type 2: 500 kWh	250 kWh [33] for regular trucks. 500 kWh [34] for high-end trucks.
Cost parameters		
Cost of electric truck	250 kWh: $288,000 500 kWh: $360,000	The study conducted for the ports of Long Beach and Los Angeles [35].
Cost of charging station	$105,000 (including installation and materials)	Assuming 200kW direct current fast charging [35].
Cost of electricity	$0.28 per kWh (off-peak) $0.56 per kWh (peak)	Los Angeles Department of Water and Power's time-of-use rate plans.
Labor and maintenance costs for the delivery, charging and waiting	Delivery: • Labor: $9.8/hour • Charging and waiting: $4.9/hour	Cost assumptions are consistent with the technical report of electrification for the ports of Los Angeles and Long Beach [4].
Budget period	5 years	Often used for infrastructure ownership and financing analysis [4].
Operation parameters		
Truck operation hours	4 to 12 a.m.	
Minimum Container throughput	1,299 TEUs/day TEU: 20-foot equivalent unit.	5% of total TEU throughput at the Port of Long Beach and Port of Los Angeles.
Round-trip delivery distance/time/% of TEUs	Near dock: 4mi/1hr / 10% Intermediate: 22mi/2hr/50% Inland: 108mi/4hr/40%	Average distance, time, and percentage of TEUs for three tiers of trips based on a real-world study at ports of Long Beach and Los Angeles [29].
Round-trip delivery energy consumption (truck type 1 / type 2)	Near dock: 7kWh/10kWh Intermediate: 53 kWh/66kWh Inland: 146kWh/162kWh	Average distance, time, and energy consumption for three tiers of trips based on a real-world study at Port of Long Beach [29]; note the type 2 truck (500 kWh) energy consumption per trip is larger because type 2 trucks are heavier and thus, require more energy for propulsion
Charging station power	150 kW	Assumptions from a technical report of electrification for ports of Los Angeles and Long Beach [4].
Initial truck battery state of charge	100%	All electrics are assumed to be fully charged during the no-activity time of 12 am-4 am.

in-use drayage truck data collected at the Port of Los Angeles and Port of Long Beach. The tier 1 drayage truck trip covers most of the port area and near-dock trips, which transfer containers between shipping carriers. The tier 2 trip is referred to as an intermediate trip, which mainly transfers containers to railyard or similar facilities that are relatively close to ports. The tier 3 trip is an inland trip, which transports containers from arriving ships to warehouses at inland locations and delivers containers to final locations using long-haul trucks. The laboratory report provides data such as trip distance, duration, and percentage of 20-foot equivalent units (TEUs) for each tier of drayage truck trips based on real-world data.

III. CASE STUDY AND RESULTS

We run the dynamic programming model to solve for optimal planning and operation decisions for the port electric drayage truck optimization that satisfies the 1299 TEUs per day throughput requirement. The composition of TEUs is 129 (inland), 640 (intermediate), and 530 (near-dock).

We tried to search for optimal solutions for various scenarios considering different battery size trucks. The results in Table III show that, in Scenario#1, there are at least 140 trucks with normal battery sizes (250 kWh) and 51 charging stations needed for daily TEU transport requirements. The infrastructure cost is $45,675,000, and the 5-year operating cost reaches $74,692,359, making a total 5-year cost of $120,367,359, i.e., $50.8 per TEU. If only considering trucks with large battery sizes (500 kWh, see Scenario#2), it requires 125 trucks and 22 charging stations, with a higher average cost of $52.9 per TEU over a 5-year budget period. This is because larger battery size trucks are heavier and have higher energy consumption rates, which contribute to a higher operation cost. Therefore, to take both advantages of higher endurance mileages from the large batter-size trucks and lower energy consumption

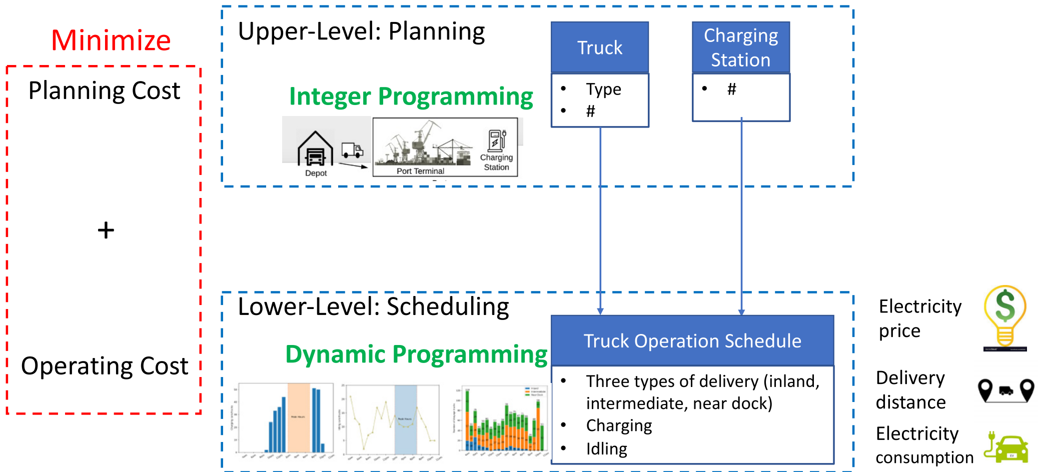

Fig. 1. Flowchart of concept.

TABLE III
TRUCKS, CHARGING STATIONS AND COSTS UNDER DIFFERENT SCENARIOS

Scenarios	1	2	3
# of 500 kWh battery trucks	0	125	60
# of 250 kWh battery trucks	140	0	70
# of chargers	51	22	34
Infrastructure cost	$46 m	$47 m	$45 m
Operation cost	$75 m	$78 m	$ 75m
Total	$120 m	$125 m	$119 m
Per-TEU cost	$50.8	$52.9	$49.1

rates from the regular ones, Scenario#3 comes to the most economically friendly solution in our case studies with a combination of two types of trucks, 60 large battery size trucks and 70 normal battery size trucks with 34 charging stations, whose average 5-year budget cost is only $49.1 per TEU. We believe this solution with a combination of two types of trucks can achieve of balance between truck usage and charging infrastructure demand. The model prefers the 250 kWh trucks over 500-kWh truck because of the lower cost. But the 250-kWh truck needs to be charged in higher frequency and demands more chargers (as shown when comparing results of Scenario 1 and 2). The results of Scenario 3 is the combination that can achieve minimum cost while satisfying the TEU throughput requirements.

In addition to minimizing the total cost, the model also generates an optimal daily operating schedule. We only present the optimal operation decisions for Scenario #1, which consists of 140 regular size battery (250 kWh) trucks and 51 charging stations. Fig. 2 summarizes the three types of delivery decisions made at each stage. Trucks that are either on delivery trips or are charging or idling are excluded, and the number of charging and idling activities for trucks are reported in Fig. 3 and Fig. 4, respectively. For instance, if 20 trucks decide to make inland deliveries at 4 a.m., they will not be counted repeatedly between 5 to 8 a.m., as an inland round trip usually takes 4 hours.

In Fig. 3, we can observe the number of trucks charging over the operation period. The results indicate that no trucks are scheduled to charge during peak hours, which is between 2 to 7 p.m. This finding is reasonable since electricity rates

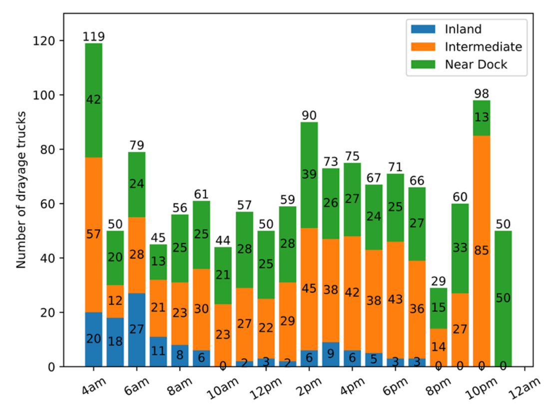

Fig. 2. The number of deliveries as a function of operating periods.

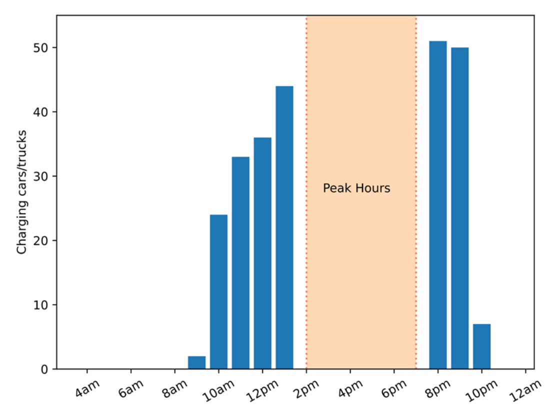

Fig. 3. The number of charging stations as a function of operating periods.

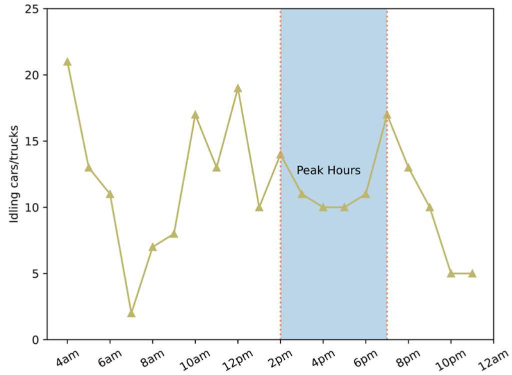

Fig. 4. The number of trucks in idling status as a function of operating periods.

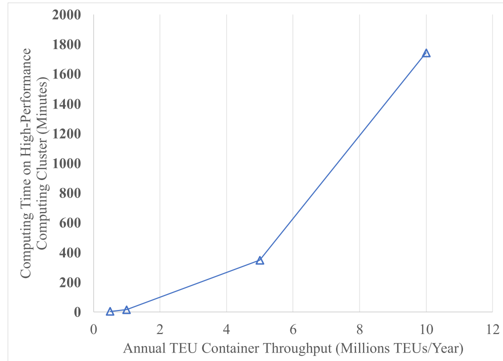

Fig. 5. Computation time (minutes) on high-performance computing cluster as a function of annual TEU container throughput.

TABLE IV
TIME DISTRIBUTION OF TRUCK ACTIVITIES IN A DAILY OPERATION

Activity	Throughput	Hours	Time Percentage
Inland delivery	129 TEUs	516 hr	18%
Intermediate delivery	640 TEUs	1,280 hr	46%
Near-dock delivery	530 TEUs	530 hr	19%
Charging	--	247 hr	9%
Idling	--	227 hr	8%
Total	1,299 TEUs	2,800 hr	100%

during peak hours are twice as high as off-peak hours. The optimized results demonstrate an increasing number of trucks charging before peak hours and a high charging volume during the first two hours after the peak hours. Moreover, during peak hours, there is a notable increase in the number of trucks delivering TEU activities at 2 p.m. (Fig. 2), which reduces the number of trucks idling at the port due to low battery status (see Fig. 4).

Fig. 4 shows the number of trucks that are in idle status as a function of time. Several reasons can lead to an idling decision at each stage. One is that after several deliveries, the truck's battery cannot afford another delivery before getting charged; however, when there are not enough chargers, drivers have no other choice but to wait. Another possible reason is that the model will proactively reserve some trucks idling at the beginning in case that a high charging volume will be encountered when they all return to the port and need charging at the same time. For example, at the beginning of 4 a.m., 21 trucks, accounting for 15% of the total fleet, are purposely assigned idling for the second reason while there is a spike in the number of idling trucks at 7 p.m., and in this case, they are more likely waiting to get charged because the charging stations are limited (see the high-level of charging volumes in Fig. 3 at 8 and 9 p.m.).

Table IV presents the time distribution of each activity. We can see three kinds of deliveries, inland, intermediate, and near-dock deliveries, take up the most time each day, accounting for 83%, whereas charging and idling almost equally share the rest of the time, at 9% and 8%, respectively. This implies that the optimal operation schedule makes the most use of time and truck capacities to accomplish the TEU transport requirements.

The optimization program is executed on the Hyperion, a high-performance computing (HPC) cluster provided by the University of South Carolina. Each node on the HPC cluster has 28 cores with a computing speed of 2.8 GHz and a memory of 128GB, which enables parallel computing. The program takes ∼5 minutes to determine the optimal fleet size, charging station, and daily activity schedules for a daily throughput of 1299 TEUs (i.e., 500,000 annual TEUs), which represents around 5% of the total TEUs processed at the Port of LA, the largest port in the United States. To evaluate the scalability of the model, we increased the daily throughput to 10%, 25%, 50%, and 100% of LA's TEUs, and we present the corresponding computation time in Fig. 5.

Our framework offers practical applications for ports that are considering the adoption of electric drayage trucks. By utilizing our bilevel model, ports can effectively determine the optimal size and composition of the truck fleet, along with the required number of chargers, to accommodate any desired level of throughput using electric trucks. A notable example is the Port of LA, the largest port in the US, which currently handles an annual throughput of 10 million TEUs, as illustrated in Fig. 5. Employing our model on the Hyperion HPC cluster, the planning decisions and corresponding daily operational schedules for the entire port's drayage electrification can be determined within approximately 3 hours. Additionally, the lower-level dynamic programming-based schedule optimization model can be executed in just 1-2 minutes. This enables port authorities to easily adapt their daily schedules in response to changes in the availability of charging stations and electric trucks, facilitating efficient and flexible operations.

IV. CONCLUSION

The primary objective of this paper is to present a novel bi-level mixed-integer programming model. This model efficiently addresses the optimization of infrastructure planning decisions, encompassing factors such as charging supply, truck battery size, delivery activities, and charging schedules. The overarching goal is to minimize the overall costs associated with port electrification. To tackle the complex decision-making process spanning multiple periods, we have devised a dynamic programming model. This approach effectively mitigates computational demands and reduces the problem's dimensionality by decomposing it into a series of recursive subproblems.

To demonstrate the applicability of our model, we implemented a numeric experiment to plan and schedule 5% of daily container throughput at the Port of Long Beach and Port of Los Angeles, the two largest ports in the United States. The results show that the algorithm helps saving emissions from drayage trucks. More specifically, it saves 0.62 ton of $PM_{2.5}$, 112.12 tons of NO_x, 0.45 ton of SO_x, 38.28 tons of CO and 47,860.22 tons of estimated CO_2 per year (estimated from heavy-duty and diesel-fueled trucks with an equivalent 5% amount of TEU transport mileage, i.e., 72,356 mi/day [36]). In this study, we established certain assumptions regarding key factors such as truck battery size, charging station quantity, electricity price, energy consumption rate, and various operational and infrastructure costs. These assumptions were based on relevant research conducted on electric drayage trucks at ports. By leveraging our proposed model, we were able to determine the optimal fleet size and number of charging stations required to minimize system costs while achieving the desired daily container throughput. Furthermore, the model generated delivery and charging schedules for the truck fleet with a granularity of 1 hour. These schedules were optimized to avoid charging activities during periods of peak electricity prices in the afternoon, while prioritizing deliveries during the early morning and late evening to mitigate traffic congestion. Additionally, we performed a comparative analysis of scenarios involving electric trucks with different battery sizes, specifically 500 kWh and 250 kWh.

The findings presented in this paper hold significant practical implications for the electrification of drayage trucks in ports. Firstly, it emphasizes the importance of aligning the size of the electric truck fleet with the port's daily throughput, thus enabling optimal planning of charging stations and daily operational schedules. Secondly, determining the appropriate battery size for electric trucks necessitates a comprehensive cost-benefit analysis that takes into account factors such as typical drayage truck trips, local traffic conditions, and the availability of charging infrastructure. Lastly, the cost-effectiveness of port electrification is greatly influenced by electricity prices, underscoring the need for careful consideration in this aspect. To investigate these implications, we conducted a series of experiments with varying throughput levels using a high-performance computing cluster. The results indicate that as the annual throughput rises from 500,000 TEUs (5% of the Port of Los Angeles' throughput) to 10 million TEUs (100%), the computation time increases from 5 minutes to approximately 3 hours. In addition, the use of electric drayage trucks has the potential to significantly reduce vehicle emissions, improving air quality in and around ports. Our findings reveal that when electric drayage trucks are deployed to handle 5% of TEU throughput at the Port of Los Angeles, 72,365 miles of diesel truck mileage are replaced with electricity.

We acknowledge certain limitations in our current model and propose several avenues for future research to address these limitations. One limitation pertains to the time resolution of the model, which is currently set at 1 hour. This may result in some inflexibility in scheduling planning. To overcome this constraint, a promising future direction is to enhance the granularity of the modeling period, potentially reducing it to 30 minutes or even 15 minutes. This increased resolution would allow for more flexible and precise operational scheduling.

Another limitation of our model is its reliance on fixed truck trip distance/time and energy consumption per trip for three types of shipments. This assumption may not accurately reflect real-time traffic conditions. To tackle this limitation, a prospective research direction involves incorporating the stochastic nature of these parameters. This could be achieved by analyzing large volumes of real-time traffic data and truck energy consumption data. By doing so, the model would be better equipped to account for dynamic and varying traffic conditions, thus providing more realistic and accurate optimization outcomes.

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