Heavy-Duty Trucks: The Challenge of Getting to Zero

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ABSTRACT

This research considers strategies that will reduce truck emissions and achieve public health and GHG reduction targets. Freight shipments in urban areas are increasing throughout the world as a result of globalization, rising incomes, and shifting patterns of production and consumption. Urban freight shipments are overwhelmingly made by trucks, which generate significant negative impacts on human health and contribute to GHG emissions. We examine the potential of zero emission heavy-duty trucks (ZEHDTs). We use simulation modeling and case studies to explore the impacts of using battery electric heavy-duty trucks (BEHDTs) and natural gas hybrid heavy-duty trucks (hybrid HDTs) in freight operations, taking into account differences in performance and refueling. We estimate impacts for 2020, 2025, and 2030. BEHDT applications are limited in the near term due to range and charging limitations, but as BEHDT performance improves and prices go down, they are viable for a larger segment of the market. Hybrid vehicles are the most cost-effective alternative for reducing air toxics, but BEHDTs reduce air toxics the most by 2025. Subsidies and charging infrastructure investment would be required to promote use of BEHDTs.

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1. Introduction

Freight shipments are increasing throughout the world as a result of globalization, rising incomes, and shifting patterns of production and consumption. At the national scale freight demand is largely a function of GDP per capita. Given expected economic growth, it is estimated that the global heavy-duty truck fleet will increase by a factor of 2.6 to 64 million by 2050 (Mulholland et al., 2018). Trucks generate a disproportionate share of GHGs. The transport sector in the US accounts for 28% of greenhouse gases, second only to industry. Trucks account for 23% of the transport sector share (USEPA, 2018b). Trucks also contribute disproportionately to air toxics. The US transport sector accounts for nearly 56% of NOX and 22% of VOC, the precursors to smog and ozone (USEPA, 2018a). The transport sector also accounts for almost 20% of particulates. Trucks account for about one third of NOX and 30% of particulates from the transport sector.[1]

California has a long history of air quality regulation, and with passage of AB 32 in 2006 became the first state to establish GHG reduction targets and a comprehensive program for achieving them. California however still has some of the most serious air quality problems in the nation. Five counties have had more than 100 days per year of unhealthful air quality (USEPA Air Quality Index over 100) every year since 2014.[2] Air pollution is a major environmental justice problem; some of the worst air quality "hot spots" are in locations with high shares of minority and low income populations. The combination of aggressive GHG reduction targets, the increasing share of pollutants generated by trucks, and environmental justice problems surrounding the state's ports, has led to aggressive efforts to reduce truck emissions. Through a series of regulations, subsidies from the state's cap and trade program, and state funded demonstration programs, California is seeking to accelerate the adoption of zero emission (ZE) and near zero emission (NZE) trucks. A major target is the short-haul trucking sector.

California's efforts provide a unique opportunity to examine performance of zero and near zero trucks and evaluate their promise for broader adoption. If California's targets are to be met, ZEVs and NZEVs must be adequate substitutes for the conventional diesel truck, either via price and performance or subsidies. We use simulation and case studies to explore the potential of heavy-duty ZEs and NZEs in short-haul trucking in three target years: 2020, 2025, and 2030. We compare battery electric (BEHDT), hybrid, and conventional diesel heavy-duty trucks. There is a growing literature on alternative fuel HDTs. Our study contributes in the following ways: 1) we start with a base case that is informed by experience using BEHDTs and hybrids in drayage service; 2) we account for the limited availability of recharging facilities; 3) we account for the effect of differences in performance operations, and 4) we develop a two stage solution approach for the vehicle routing problem that solves the distance minimization problem as a minimum cost flow problem, and then solves the minimum fleet size problem as a bin packing problem.

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[1] Calculated by authors from USEPA Air Pollution Emissions Trend Data, 2018a.
[2] USEPA, AirCompare, https://www3.epa.gov/aircompare/#trends

We compare costs and air quality benefits across a set of scenarios based on the simulations. We find that natural gas hybrid trucks are the most cost-effective, while battery electric trucks reduce emissions the most after 2025. We conduct two case studies of short-haul firms to compare to the simulation results.

The remainder of this paper is organized as follows. First we review the literature on zero and near zero heavy-duty trucks. We then present our research approach, simulation model, and data. We follow with results on fleet size, emissions, and costs for scenarios and target years. We then present a cost effectiveness comparison of hybrid and BEHDT relative to diesel. The last part of the analysis is two case studies to extend some of the simulation model results. We close with conclusions and policy implications.

2. Heavy-duty ZE and NZE trucks

There is growing interest in the potential of shifting to zero or near zero trucks in response to the expected growth of freight demand and the contribution of trucks to air pollution and GHG emissions. Studies based on global demand show that the freight sector would need an array of mitigation strategies including cleaner fuel vehicles to achieve significant CO_2 reductions (Mulholland et al., 2018).

Near zero emission heavy-duty trucks include a variety of hybrid technologies, with a small battery energy source that allows for short periods of electricity propulsion paired with an internal combustion engine (ICE) powered by conventional diesel or alternative fuels. Hybrid HDTs have approximately the same performance characteristics as a conventional diesel truck. The range is 300 miles or more, and refueling is accomplished within several minutes. The difference from conventional diesel or diesel hybrid is fuel availability, as no alternative fuel is as widely available as diesel. Alternative fuel hybrids began to be commercially available in the mid-2010s.

Zero emission HDTs include battery electric (BE) and hydrogen fuel cell. Battery electric HDTs are at present the only ZEHDT commercially available. Hydrogen fuel cell HDTs are in the testing stage. BEHDTs are limited by battery technology. Battery technology is improving quickly, but electricity from batteries still has low energy density. The more powerful the battery, the larger and heavier it must be. Currently HDT batteries weigh about 6,000 lbs (Burke and Sinha, 2020).

There is a large literature on alternative fuel vehicles, but most focuses on passenger vehicles. Heavy duty trucks and buses are less well studied (Giuliano, White and Dexter,2018). Within the literature on heavy duty vehicles, topics include forecasts of future performance and of future market penetration (e.g. IEA 2017; CEC 2017), assessments of potential markets, and alternative fuel HDT performance, policy strategies for achieving market penetration goals (e.g. Elhedhli and Merrick, 2012; Norsworthy and Craft, 2013; Quak and Nesterova, 2014). For this paper we focus on the most relevant literature, potential markets and HDT performance.

2.1   *Potential market*

Most studies of the potential market for BEHDTs are technical; they assume a trend of battery technology improvement as well as the infrastructure needed to support BEHDTs, and monetary costs are not considered. Cabukoglu et al (2018) used data from the Swiss truck VMT tax system

to estimate the potential of BEHDT for the entire domestic truck freight system. They estimated CO_2 reductions from various scenarios that allow for battery swapping, exceeding gross vehicle weight limits, and rapid advancement in battery technology. They assumed the required infrastructure, and no costs were considered. Their study showed that without these assumptions, the potential market was quite small (12% of freight demand). CO_2 reductions were less than proportional with market penetration, as the BEHDTs replaced lower mileage diesel trips. Liimatainen et al. (2019) conducted a comparative analysis of potential markets for Switzerland and Finland using EU truck survey data. Assuming recharging available everywhere and the capacity for two 8-hour shifts per day, the load became the limiting factor. They found more market potential for Switzerland, because Finland commodities tended to be heavier, and heavier loads were permitted.

Most recently, Burke and Sinha (2020) conducted an analysis of BE and fuel cell trucks and buses in California. They used total cost of ownership (TCO) to compare alternative fuel vehicles with diesel as the base case. They assumed a 150-mile effective range for short-haul, widely available charging (fueling) infrastructure, and a one to one substitution between diesel and BEHDT (e.g. all work within the short-haul market is interchangeable, regardless of load, operating conditions, etc.). They used a breakeven analysis to determine the purchase and fuel prices that would result in the same TCO as for diesel. Results showed that purchase price must decline, cost of electricity or hydrogen must be low, and battery technology must improve rapidly in order to achieve the state's targets.

2.2   Zero emission HDT performance

Research on ZE HDT performance is limited, because the first demonstrations included only a few test vehicles, and the second wave of demonstrations are in progress. Heavy-duty ZEVs were first introduced in the transit bus market. By 2015 there were 40 electric transit buses in operation, compared to 16 planned and active demonstrations for HDTs (Giuliano et al., 2018).

A comprehensive review of demonstrations as of 2018 yields the following findings (Giuliano et al., 2020). Medium-duty electric vehicles have been used successfully in widespread demonstrations yet are still only suitable for limited applications where ranges are fairly short, and vehicles return to a home-base to recharge regularly. For BEHDTs, demonstration projects showed operating ranges of between 70-100 miles per charge, varying significantly depending on payload and operating conditions. Due to range restrictions, these vehicles also require additional attention to routing and refueling. Reliability and durability of battery-based systems were found to have steadily improved in recent years. A critical factor in BEHDT deployment is charging infrastructure, which does not yet exist. Another concern is the draw on the power grid from trucks, particularly if they are required to refuel during the day and are geographically clustered.

Estimates of purchase cost of BEHDTs are highly speculative due to low production volumes. The cost of battery electric trucks for drayage operation is estimated at approximately three times that of diesel alternatives. While battery electric trucks would have lower per mile refueling costs, their limited range means that the amortization costs would be spread over fewer productive miles driven per day.

2.3   Using simulation to examine market for ZE HDTs

Another approach to evaluating the potential for ZE HDTs is using optimization to identify the cost and emission minimizing solution for a given set of freight demands. Research on ZE truck routing evolved from the well-studied vehicle routing problem (VRP) and the green logistics problem. The VRP focuses on minimizing the total distance traveled by all vehicles in the operation while the green logistics problem focuses more on cost optimization and greenhouse gas (GHG) emission reduction (Demir et al., 2013). In response to rapid development of battery technology, studies have examined vehicle routing with ZE trucks using electric batteries (Dammak and Dhouib, 2019). Lin et al. (2016) incorporated travel time minimization, energy cost minimization and fleet size minimization into their optimal electric vehicle (EV) routing strategy. They applied an exact method in solving their formulated problem. Others like Schneider et al. (2014) used an approximate method when their objective is to minimize the travel length as well as the number of vehicles used. Due to the range anxiety of BEHDTs and the high vehicle cost compared to traditional diesel fueled vehicles, researchers tend to include additional objectives into their models while routing BEHDTs. Davis and Figliozzi (2013) integrated four models in their research which added vehicle range maximization and energy estimation to the classic objectives as mentioned above.

3. Research approach

In this study we combine and advance the above threads of the literature. We use data from local short-haul operations and from BEHDTs currently in use to ground our research in actual short-haul freight operations and performance of BEHDTs in the short-haul environment. We study a specific routing problem for drayage operations where trucks depart from the port and visit a destination and possibly visit another destination on their return trip to the port. We make use of the special structure of this routing problem to solve the distance minimization problem as a minimum cost flow problem. Then, given this minimum distance we solve the minimum fleet size problem as a bin packing problem. The simulation model is based on survey data from the Los Angeles and Long Beach ports.

We use the model output to estimate costs and air pollution savings for various combinations of diesel, hybrid, and BEHDT fleets. We generate scenarios for 2020, 2025, and 2030. The 2020 scenario is based on actual operation of alternative fuel HDTs currently in demonstration. The 2025 and 2030 scenarios are based on best available estimates of improvements in battery technology. The scenarios compare conventional diesel, CNG hybrid, and BEHDTs. We therefore capture both the technical and cost aspects of these comparisons. Finally, we conduct two case studies of short-haul firms to further refine simulation results. We use data on truck assignments and tours to estimate what share of each firm's operations could be served with BEHDTs.
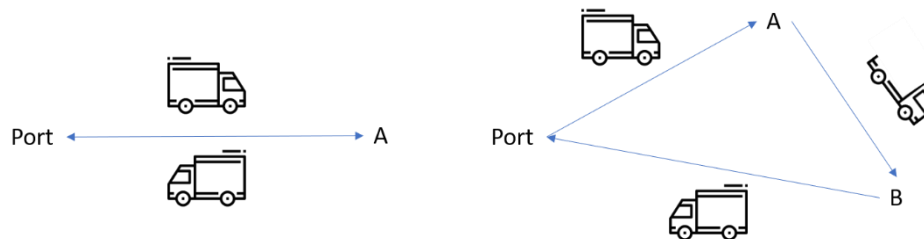
4. Simulation model

We use for simulation a simple case of drayage operations in which all trips start and end at the ports. Trips may have one stop (single pickup/delivery) or two stops. In the case of two stops, there is no demand between them, meaning that the truck is empty when traveling from the first to the second stop. Figure 1 shows the types of trips that a truck is allowed to make. The

problem objective is to minimize the total miles travelled and fleet size to serve the demand. We make the following assumptions:

- All trips are round trips and start and end at the port.
- Demand is the number of containers, and demand only exists between the port and the other locations. The containers are either fully loaded or empty.
- All trucks operate under one of three states: no container, empty container, or fully loaded container.
- Trucks have different power consumption rates for each different operating state.
- Although for both ZEV and diesel trucks we account for the weight in computing the fuel consumption and emissions, the model assumes that all truck types can carry the same cargo load capacity.
- All ZEVs are battery powered and the charging stations are located within the port.
- There are no refueling detours for any truck.

Figure 1. Two Types of Trips a Truck can Travel

The simulation model generates the following: 1) The total vehicle miles travelled required to satisfy the daily demand; 2) the number of vehicles (diesel, NG hybrid, and BET) required; 3) the corresponding pollutant and GHG emissions

4.1   Model formulation

Instead of solving the problem using a single model, we use a two-stage approach. See Figure 2. We first formulate a minimum cost circulation problem which outputs the minimum total miles travelled to satisfy the total demand and the optimal trips for the trucks to travel. Then, we take the optimal trips as an input into a bin-packing problem to minimize the fleet size.

Figure 2. Two-stage Model Formulation Approach
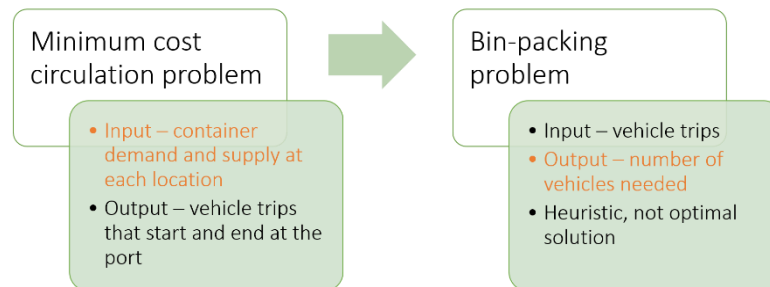
The two sub-problems, minimum cost circulation and bin-packing problems, are well known problems in the optimization literature. The minimum cost circulation problem can be

formulated into a linear programming problem (LP) and solved by a standard LP solver. The bin-packing problem, on the other hand, is NP-hard which means there are no optimal algorithms that can solve this problem in polynomial time. Therefore, we adapt a heuristic algorithm which can produce good enough solutions in fast computation time.

4.1.1   The Minimum Cost Circulation Problem

First, we list the notation we use for this sub-problem.

V: the set of vertices, each v_i stands for a location and v_0 is the port
V':   a copy of V where v_i' stands for a location and v_0' stands for the port
E: the set of edges, each edge is denoted by uv or (u, v) with $u, v \in V \cup V'$
d_{uv}:   the demand from u to v
c_{uv}:   the cost for edge uv
f_{uv}:   the flow (demand) for edge uv

Figure 3 illustrates the network that is constructed. Originally, we have the set of vertices V representing the port and the locations. An edge exists between v_0 and v_i if v_i has container demands from the port. Then we make a copy of V, which is V'. An edge exists between v_i' and v_0' if v_i' delivers containers to the port. After that, we link all the edges between $\{v_i\}_{i=1}^n$ and $\{v_i'\}_{i=1}^n$ such that they form a complete bi-partite graph. Finally, we link edge $v_0'v_0$ to make the network a circulation network.

The cost for any edge $uv \in E$ is the distance (in miles) between the location u and the location v. Notice that $c_{v_iv_i'}$ is 0 for all $i = 1, \ldots, n$ because v_i' and v_i represent the same location.

Figure 3. The Constructed Network
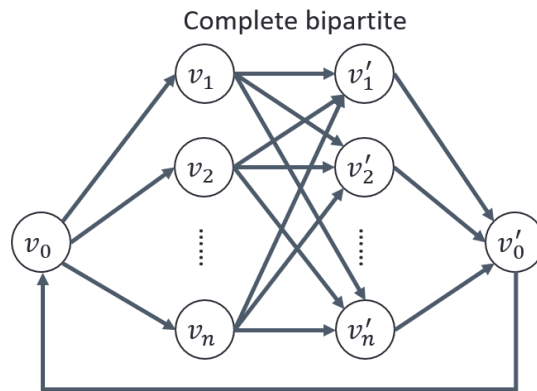
Based on the network above, we develop the following mathematical model. Notice that f_{uv} are the decision variables.

$$\min \sum_{uv \in E} c_{uv} f_{uv}$$

$$s.t. \sum_{v \in V \cup V'} f_{uv} = \sum_{v \in V \cup V'} f_{vu}, \forall u \in V \cup V'$$

$$f_{v_0 v_i} \geq d_{v_0 v_i} \quad \forall i = 1, \ldots, n$$

$$\sum_{j=1}^{n} f_{v_j v_i'} \geq d_{v_i' i v_0} \quad \forall i = 1, \ldots, n$$

$$f_{uv} \geq 0, \forall uv \in E$$

The first set of constraints are the flow conservation constraints and the second set of constraints ensures that demand is met. We use the Gurobi software to solve our linear program model since it is widely used (Kelso, 2015) and it has sufficient support packages for a variety of problem types and algorithms compared to other software (2019 Linear Programming Software Survey Results).

4.1.2   The Bin-packing Problem

Recall that the output for the minimum cost circulation problem is a set of optimized vehicle trips. We want to assign the trips to trucks such that the number of trucks is minimized. This is exactly the same as the bin-packing problem where items (trips) are packed (assigned) into bins (trucks) and the objective is to use as few bins (trucks) as possible. Figure 4 illustrates how minimizing the fleet size is actually a bin-packing problem. The slight deviation from the standard bin-packing problem is that the refueling process needs to be also inserted during the day.

Figure 4. The Bin-packing Illustration
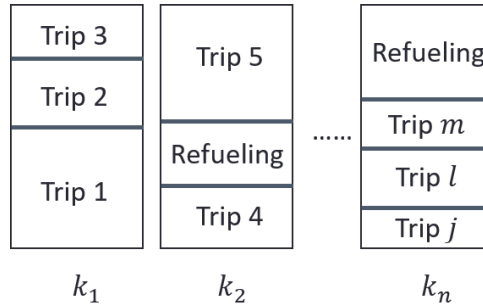
Suppose there are in total n trucks and j trips. The notation we use for this problem is listed below.

r_i: the range for truck i in terms of travel time
t_j: the operation time required for trip j
T: the working hours limit for each truck
h_i: the refueling time for truck i
k_i: $k_i = 1$ if truck i is used, and 0 otherwise
x_{ij}:   the indicator of whether truck i is assigned to trip j

We can formulate this problem into a mixed integer linear programming problem (MILP) as shown below. Notice that k_i and x_{ij} are the decision variables. In presenting the formulation, we treat the refueling (h_i) as a constant for ease of understanding of the model. However, in actuality, the refueling time depends on the day's usage and especially for BEHDT cannot be

treated as a constant time. Thus, our solution procedure takes these factors in account in determining the refueling time and we discuss this computation after presenting the formulation.

$$\min \sum_{i=1}^{n} k_i$$

$$s.t. \ h_i + \sum_{j=1}^{m} t_j x_{ij} \leq Tk_i, \forall i = 1,2,\dots,n$$

$$t_j x_{ij} \leq r_i, \forall i = 1,2,\dots,n \ \ \forall j = 1,2,\dots,m$$

$$\sum_{i=1}^{n} x_{ij} = 1, \forall j = 1,2,\dots,m$$

$$k_i = 0 \ or \ 1, \forall i = 1,2,\dots,n$$

$$x_{ij} = 0 \ or \ 1, \forall i = 1,2,\dots,n \ \forall j = 1,2,\dots,m$$

The objective of the formulation is to minimize the total number of trucks needed to serve the demand. The first set of constraints ensures that the operating time for each truck does not exceed the working time limit. The second set of constraints ensures that every trip assigned to the truck does not exceed its corresponding range. The third set of constraints ensures that every trip is served by one truck.

To solve this problem, we adapt a heuristic algorithm called the subset sum algorithm (Pisinger and Toth, 1998). The idea of this base algorithm is to recursively pick unpacked items such that the summation of their value is maximized and fits the capacity constraint of a bin. Gupta and Ho (1999) conducted an empirical study to show that this algorithm outperforms some of the other well known algorithms for solving the bin-packing problem. Epstein et al. (2009) studied this intuitive algorithm to better understand its approximation ratio. Then, Epstein and Kleiman (2011) adapted this algorithm for a selfish bin-packing problem. Zhang et al. (2018) used this algorithm to solve their packing problem within a cost-sharing mechanism. To adapt this base algorithm in our context, unassigned trips are selected such that the summation of their travel times is maximized and fits the time constraint of a truck. Additionally, we augment this algorithm by considering the refueling times between trips. After the assignment of a trip to a truck and if the remaining fuel level is less than the range of this assigned trip, then the refueling time is added to this truck. The computation of the refueling time is described in the next section. Since the battery depletion rate depends on whether the truck is loaded or not, the amount of time required to recharge the battery also depends on the nature of the trips.

4.2   Simulation model data
We obtained survey data from the Port of Long Beach and Port of Los Angeles that contains origins and destinations for container demands across the years 2010-2012. The data includes origins, destinations, direction, and container status (fully loaded or empty). We drew a sample of 10 days of data and generated an average daily demand. The daily average demand includes 135 empty and 176 loaded containers across 94 locations.

We select parameters based on the best available information for the vehicle technologies. The year 2020 is our base case, and we use actual data from existing field demonstrations for the 2020 parameters. These parameters are not the same as those published by vehicle manufacturers, but rather represent performance experienced in the demonstrations. Therefore 2020 is our best estimate of real world operating conditions We use the best available predictions on technology improvements for 2025 and 2030. We run the simulation model for diesel and BEHDT, as hybrids have the same performance characteristics as diesel in short-haul application. Selected parameters and assumptions are given in Table 1. The full list of parameters is available in Appendix A.   We assume constant travel times which is based on multiplying the average travel speed by the distance of the trip. The average speed depends on the length of the trip. If the trip is less than 5 miles an average speed of 20 mph is used; otherwise an average speed of 45 mph is used. We assume all the vehicles are operating on well maintained roads.

Table 1: Selected simulation model parameters

Common to all trucks	
Speed: 20 mph for trips < or = 5 miles; 45 mph otherwise	
Daily operation: one 8-hr shift per truck	
Diesel	**BEHDT**
Range (miles)	**Loaded/empty/no container**
>300 mi all years	Year 2020: 60/85/100 Year 2025: 156/250/328 Year 2030: 204/323/433
Refueling time	
15 min	3 hours for 0-80%; + 2hours for 80-100%
Battery capacity (kwh)	
N/A	Year 2020: 240 Year 2025: 525 Year 2030: 650

Diesel trucks are assumed to be fully fueled at the beginning of day. BEHDT trucks are assumed to be fully charged. Refueling during the day is added if the trips assigned to the truck exceeds its fuel range. The fueling process for diesel trucks is rather short and relatively independent of the fuel level; hence refueling time is treated as a constant. For BEHDT trucks, refueling time depends on the charge level at the time of refueling, and charge level depends on the load. Also, the solution procedure does not allow depletion of the battery to fall below 20% to prevent the battery from degenerating too quickly.

5. Results

5.1   Simulation model results: fleet size

All simulations are solved using python with Gurobi API. They are conducted on a computer with an Intel i7-4720HQ CPU of 2.60GHz and a RAM of 8 GB. We conduct simulations for each target year using the same set of demands. Since the performance of hybrid electric and diesel trucks is the same for short-haul, we simulate diesel only and the results for the diesel case will be

applied to the hybrid electric case, e.g. having the same number of vehicles. For each target year we estimated the outcomes of an increasing share of BE trucks until the maximum possible share is reached. The maximum possible share is the point at which the required trips can no longer be performed by BETs because of range and charging constraints.   Figure 5 shows the results. For this set of demands, an all diesel fleet would require 19 trucks. As the share of BETs increases, the fleet size increases, reflecting the additional trucks required due to range and charge time limitations of BETs. The number of additional trucks required declines sharply over the target years as BET performance improves. In 2020, the maximum possible BET share is 75%, which requires a total of 36 trucks. By 2030, the maximum possible share is 96% and requires 23 vehicles. We note that these results are optimistic because we assume all truck types have the same load capacity.

Figure 5: Number of trucks required for each target year
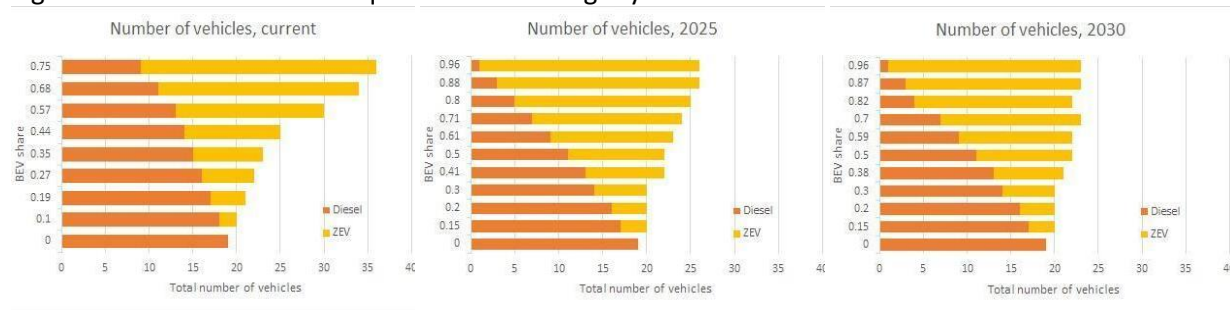
5.2   Simulation model results: emissions

We use the simulation results to estimate benefits and costs of using diesel, NG hybrid or BEHDTs. We use the following scenarios for each target year: all diesel, all hybrid, midpoint BET (the middle ZEV penetration in Figure 5), and maximum BET (largest possible BET penetration). The simulation results give total vehicles, miles, and load status.

For benefits we consider reductions in $PM_{2.5}$, NO_X, and CO_2.   The estimation of drayage truck emissions includes tailpipe emissions of criteria pollutants but full well-to-wheels emissions of greenhouse gases. Air toxic impacts are local, while GHG emissions from any part of the fuel pathway negatively impact climate change. We use several sources to develop emission rates: the 2018 San Pedro Bay Ports Clean Air Action Plan (CAAP) (San Pedro Bay Ports, 2019) and CARB target year estimates; Zhu (2014) for fuel economy and carbon intensity of each fuel.

CO2 emissions (gCO2e/mi) are calculated using the carbon intensity for each fuel in gCO2e/MJ, the conversions MJ/GDE and MJ/kWh, and the fuel economy for each truck (mi/GDE or kWh/mi). The carbon intensity for each fuel is 100.45 (diesel), 79.21 (natural gas), and 93.75 (electricity). We use the factors 146.5 MJ/GDE and 3.6 MJ/kWh. Emissions rates are given in Table 2.

The fuel economy for diesel, battery electric, and natural gas hybrid trucks were calculated using the Advisor simulation model (Burke and Zhao 2015) on a port drayage drive cycle (Prohaska, Konan, Kelly and Lemmert, 2016). The simulation included vehicle component (e.g. engine, battery, power electronics) characterizations with efficiencies that improved from 2020 through 2030. The assumed improvement of battery electric truck component efficiencies were less than

that for the diesel or natural gas hybrid trucks. The fuel improvement decreases the overall carbon emissions from 2020 to 2030.

Table 2: Emission Rates for Diesel Trucks, NG Hybrid Trucks and ZEVs

Vehicle Technology	Criteria Pollutant Emissions		CO_2 Emissions
	$PM_{2.5}$ (g/mile)	NO_x (g/mile)	CO_2 (g/mile)
Diesel Present	0.01	1.91	2943.0
Diesel 2025	0.005	0.96	2605.0
Diesel 2030	0.005	0.96	2336.0
NG Hybrid Present	0.008	0.16	2100.0
NG Hybrid 2025	0.004	0.16	1859.0
NG Hybrid 2030	0.004	0.16	1667.0
ZEV Present	0	0	992.0
ZEV 2025	0	0	932.0
ZEV 2030	0	0	871.0

Figure 6 gives daily emissions for each scenario and target year. For all emissions except NO_x in 2020, the maximum BET alternative dominates in every year, but at the price of increasing the total number of vehicles required. Hybrid and mid-point BETs have offsetting advantages. Hybrid does better for NO_x in 2020, midpoint BET does better for $PM_{2.5}$, and hybrid does better for CO_2 throughout. The difference between hybrid and midpoint BET is the result of the large number diesel trucks that remain in the mixed fleet. Note that Figure 6 gives estimates per day. We annualize these estimates to make comparisons with costs.

Figure 6: Emissions and total vehicles per day for four vehicle scenarios, each target year
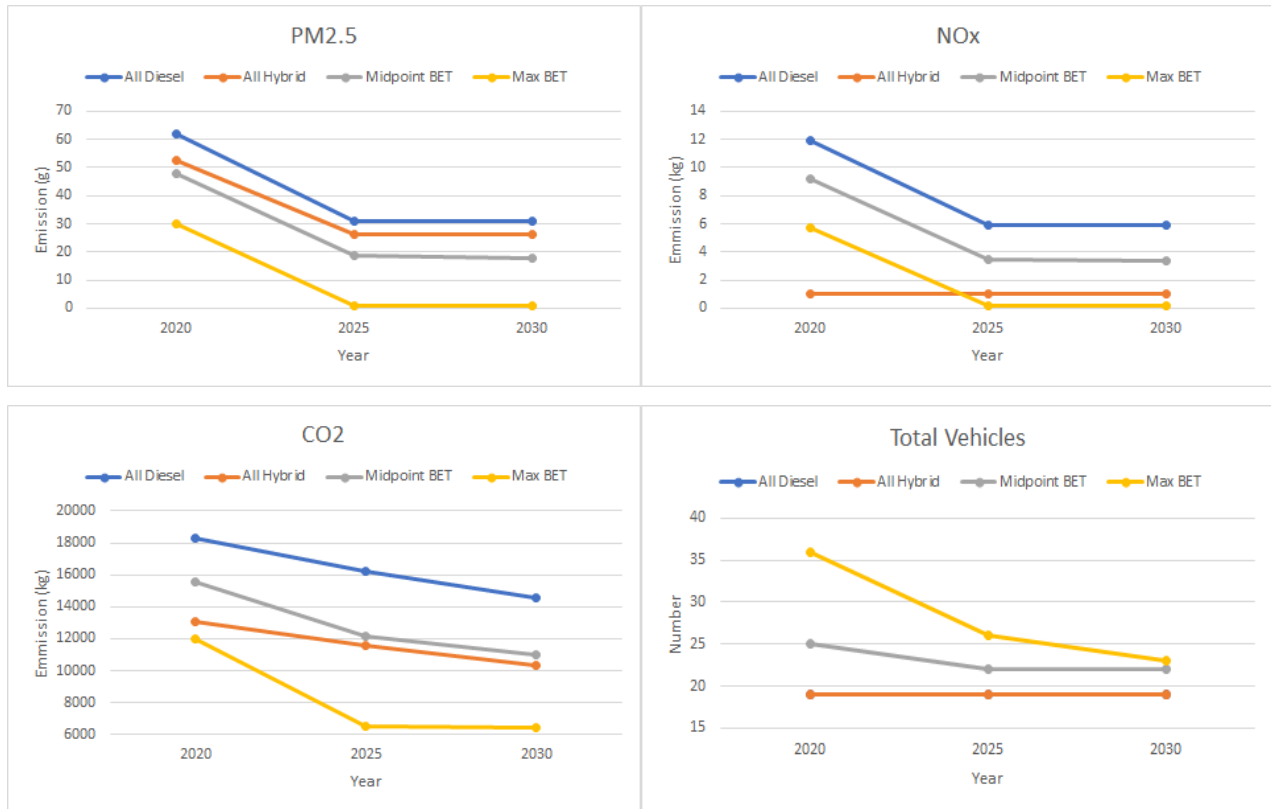
5.3   Simulation model results: costs

To simplify the analysis, we treat each scenario in each target year as a new service, meaning that we use purchase cost as capital costs for the vehicles. We do not consider life cycle costing but rather only the direct costs of purchase and operating the vehicles.

5.3.1   Capital costs

Vehicle cost is calculated by considering the total cost as a sum of component costs. The components for vehicles include: glider, engine, transmission, engine after treatment system (EATS), fuel storage, battery, and motor/controller. All costs are in 2020 dollars.

Diesel capital costs for 2020 are based on commercial sales data. For 2025 and 2030, we take into account the expected added costs required to meet EPA GHG emissions standards, to meet the California NO_X standard, and the anticipated shift to automatic transmissions (NRC, 2010; EPA, 2016). For hybrid and BET, we start with the glider cost and build up with the various components. The exception is 2020 BET, for which we use the average price paid for vehicles currently in demonstration. Hybrid capital costs are based on Zhu (2014), but we use our battery costs of $180/kwh, $109/kwh, and $80/kwh for 2020, 2025, and 2030 respectively.

For BEHDTs, the critical factor is the battery. We use the same battery pack size as in the simulations. Battery pack costs have decreased significantly in recent years, and expectations

are that costs will dramatically decline by 2030. Battery price estimates vary greatly, and this estimate is the most reasonable based on two different forecasts (Goldie-Scot, 2019; Moultak et al., 2017). Capital costs for diesel, hybrid and BEHDT are given in Table 3. The increased cost for hybrid is due to addition of automated transmissions. The price of BEHDT is forecast to decline by almost one half within this decade.

Table 3: Capital costs for diesel, hybrid and BET, $2020

	Diesel	NG Hybrid	Battery electric
2020	$118,800	$144,800	$300,000
2025	$124,800	$139,700	$164,900
2030	$129,900	$144,406	$157,300

5.3.2   Operating costs

Operating costs include fuel, maintenance and driver costs. Fuel and maintenance costs are based on the estimates in the CAAP (San Pedro Bay Ports, 2019). We assume fuel cost per diesel gallon equivalent (DGE) and maintenance cost per mile are constant across the target years. See Table 4 below. For more details, see Giuliano et al, 2020. If our scenarios consisted of exactly the same number of vehicles, drivers and shifts, we could omit driver costs without affecting results. However, the BEHDT scenarios require more vehicles, and hence more drivers.   We use a flat rate of $27/hour, including wages and fringe benefits, the national average as reported by the American Transportation Research Institute (ATRI) for 2016 (Hooper and Murray, 2017).

Table 4: Operating cost assumptions (2020 dollars)

	Diesel	NG Hybrid	Battery electric
Fuel economy	mi/DGE	mi/DGE	kWh/mi
2020	5.0	5.53	2.94
2025	5.65	6.24	2.75
2030	6.3	6.96	2.58
Fuel cost	$3.88/DGE	$2.92/DGE	$0.151/kWh
Maintenance cost	$0.16/mi	$0.16/me	$0.08/mi

5.3.3   Annualized costs

We compute annualized capital costs in order to spread the costs over the expected life of the vehicle. As noted above, we consider each target year as a new scenario: the fleet operator purchases a new fleet, and the service life of each vehicle is seven years. We know that diesel trucks have a much longer service life, but we assume that increasingly stringent emissions requirements will force their early retirement. We do not have enough information on hybrids or BETs to know their service life. Batteries are expected to last 5-7 years, but lose capacity over time. Presumably technology improvements will rather quickly make older hybrids and BEHDTs outdated, so we cannot predict whether there will be any resale market for them beyond 5 or 7 years. We assume no residual value for any of the vehicles, which therefore gives advantage to hybrids and BEHDTs. We use the purchase prices in Table 3 and the number and type of

required vehicles to generate the annualized capital cost.   Annualized operating costs are based on 5 days/week, 50 weeks/year operation, and one 8-hour shift per day.

Annualized costs are given in Table 5. The first set of rows gives vehicle capital costs, the second set gives vehicle operating costs, the third gives driver costs, and the last set gives total annualized costs. The lowest cost scenario is highlighted in each set of rows. Capital costs are lowest for diesel and highest for the Maximum BET due to the higher capital costs of BEHDTs. The big difference between 2020 and 2025 is due to the assumed cost reduction in BEHDTs. With regard to vehicle operating costs, all diesel is the highest across all target years. This is due to greater fuel efficiency of hybrids and much lower fuel and maintenance costs for BEHDTs. If we were considering vehicle operating costs only, any scenario would be preferable to diesel.

The third panel gives driver costs. The driver costs across the scenarios reflect the required size of the vehicle fleet. Diesel and hybrid are the same for all scenarios, as there are the same number of vehicles in every scenario. Either diesel or hybrid give the least cost for driver costs. Driver costs are higher for the BEHDT alternatives, but decline over time as the additional number of required vehicles declines. When we combine all costs, the hybrid alternatives become lowest cost, with Max BET a very close second in 2025 and 2030. The Midpoint BET is never the lowest cost option because of the additional vehicles required and the presence of large numbers of diesels.

Table 5: Annualized costs for each scenario

Capital costs	All diesel	All hybrid	Midpoint BET	Maximum BET
2020	$ 358,891	$ 437,437	$ 789,135	$ 1,457,874
2025	$ 377,017	$ 421,838	$ 506,682	$ 675,318
2030	$ 392,426	$ 436,221	$ 502,304	$ 570,874
Vehicle operating costs	**All diesel**	**All hybrid**	**Midpoint BET**	**Maximum BET**
2020	$1,456,182	$1,070,401	$1,310,931	$1,123,265
2025	$1,317,293	$976,931	$1,094,283	$786,000
2030	$1,207,064	$901,620	$1,004,675	$741,824
Driver operating costs	**All diesel**	**All hybrid**	**Midpoint BET**	**Maximum BET**
2020	$ 1,026,000	$ 1,026,000	$1,350,000	$1,944,000
2025	$ 1,026,000	$ 1,026,000	$1,188,000	$1,404,000
2030	$ 1,026,000	$ 1,026,000	$1,188,000	$1,242,000
Total annualized costs	**All diesel**	**All hybrid**	**Midpoint BET**	**Maximum BET**
2020	$2,482,182	$2,096,401	$2,660,931	$3,067,265
2025	$2,343,293	$2,002,931	$2,282,283	$2,190,000
2030	$2,233,004	$1,927,620	$2,192,675	$1,983,824

5.4   Comparison of benefits and costs

We compare the three alternative fuel scenarios relative to diesel as the base case. Table 6 gives emissions reduction savings. In all but one case (2020 NO_X), the Max BET scenario generates the most emissions reduction savings. The Midpoint BET is never the best option for emissions reductions.

Table 6: Net emissions savings, relative to diesel

Net emissions savings		All Hybrid	Midpoint BET	Max BET
PM 2.5 (g)				
	2020	2350	3525	8075
	2025	1175	3150	7525
	2030	1175	3275	7525
NOX (kg)				
	2020	2725	675	1550
	2025	1225	600	1425
	2030	1225	625	1425
CO2 (kg)				
	2020	1311500	687750	1576500
	2025	1160500	1019750	2429500
	2030	1040500	880500	2024000

Table 7 provides a measure of cost-effectiveness; the cost per unit of emissions removed. Because of the lower total costs of hybrid relative to diesel, emissions savings come with cost savings for each pollutant and for every target year. Even for $PM_{2.5}$, all hybrid is the most cost effective alternative. In 2030 costs turn positive for all BET, but notably below the savings for hybrid. The midpoint BET scenario has the worst of both worlds because of the large number of vehicles required and the number of diesels in the fleet. These results suggest that if cost effectiveness is the criterion for selection, a shift to a hybrid fleet would be preferred through 2030. Emissions would be reduced while annualized costs would decline. However, if maximizing $PM_{2.5}$ or CO_2 reductions is the criterion, our results show what the incremental cost of doing so would be.

Table 7: Cost (savings) per unit of emissions removed, relative to all diesel

cost per emissions reduced		All Hybrid		Midpoint BET		Max BET	
PM$_{2.5}$ (per gram)							
	2020	$	(130.74)	$	172.76	$	208.55
	2025	$	(251.52)	$	21.79	$	19.27
	2030	$	(222.68)	$	21.22	$	(9.41)
NO$_X$ (per kg)							
	2020	$	(112.75)	$	902.21	$	1,086.49
	2025	$	(241.26)	$	114.42	$	101.76
	2030	$	(213.59)	$	111.18	$	(49.68)
CO$_2$ (per kg)							
	2020	$	(0.23)	$	0.89	$	1.07
	2025	$	(0.25)	$	0.07	$	0.06
	2030	$	(0.25)	$	0.08	$	(0.03)

5.5   Simulation model results: Summary

Our results should be interpreted with caution. The simulation scenarios include daily tours that are much simpler than actual tours. We assume just one shift per day, and assume all truck types can carry the same cargo load. If we accounted for multiple shifts or potential differing cargo load capacities between the truck types, costs for the BET alternatives would increase, because the number of vehicles required would have to increase. Similarly, if vehicles operate more than one shift per day, the time available for charging is greatly reduced. Therefore, these estimates are likely optimistic for the BET alternatives.

There are additional issues not taken into account. First, we have not considered infrastructure costs. Large numbers of BETs would require an extensive infrastructure of charging stations. If firms are expected to provide their own charging stations, they would need both the space and the funds to do it. NG hybrids pose a similar problem, as home-based fuel facilities would also require substantial investment.

Second, we have not considered the organizational costs of incorporating a new technology into a firm's operations. A mixed fleet requires vehicle type specific maintenance practices. In the case of BETs, operations would have to be restructured to accommodate shorter range vehicles. By definition the new route structure would be less efficient, leading to higher overall costs for the firm in an industry with narrow profit margins. All of these issues add to the costs of using hybrids or BETs.

Finally, our results do not consider market response. Even if hybrids or BETs dominate in 2025 or 2030 based on annualized costs, fleet owners would not necessarily switch. The results for hybrids are a case in point. If hybrids lead to cost savings to the firm, why are we not seeing an expanding market for them? Possible explanations include the slow turnover of truck fleets, uncertainty regarding regulation, or uncertainty regarding the performance of the technology.

5.6   Case studies

The simulations allow us to generate general information on the trade-offs between using diesel or hybrid electric trucks vs BETs, but the demand portrayed does not capture all of the possible complexities in practice. We conduct two case studies of drayage firms to better understand the actual patterns of short-haul operations. We use actual operations to estimate what share of current demand could be provided by BETs.

Two Los Angeles based trucking firms provided daily truck movement data for detailed analysis. We obtained 2 months of data from Firm 1 and 1 month of data from Firm 2. We use the following definitions: a *trip* is one move from an origin to a destination; a *tour* is a sequence of trips that starts and ends at the home base; *total daily distance* is the total mileage over a 24-hour period.

The two firms have very different patterns of operation, which results in different challenges and barriers they would face in an electrification process. Firm 1 is a drayage and delivery service company. Their trucks are operated only during the daytime, sometimes with multiple tours in a day. Trucks return to their yard at night, which makes overnight charging possible. Firm 2 is also a drayage firm, but the bulk of Firm 2's business is direct store delivery; they operate nearly 24

hours per day. Trucks are used across multiple driver shifts each day. Charging could only be conducted between two tours, which is not always at night.

After cleaning the data, trip, tours and daily distance were constructed for each truck. We have weight data for each load. We assume that trucks can only be charged at the firm home base. Therefore, the distance and loads of a single tour determines whether diesel trucks can be replaced by battery electric trucks. If the single tour distance can be covered by the range of a BEHDT, then electrification would be possible, provided there is enough time between tours for charging.

Table 8 gives information on tours and daily distance. About two thirds of all daily tours are well within the BET range (less than 80 miles). Daily distance is much longer; between 26% and 49% for Firm 1 and just 22% for Firm 2 are within 80 miles. However, expected battery improvements would put much of these services within BET range.

Table 8: Tour and Daily Distance

Firm 1				
Single tour	< 40 mi	40 – 80 mi	80 – 120 mi	>120 mi
Month 1	54%	15%	8%	23%
Month 2	59%	14%	6%	21%
Daily distance	<40 mi	40 – 80 mi	80 -120 mi	>120 mi
Month 1	4%	22%	18%	56%
Month 2	13%	27%	13%	47%
Firm 2				
	<40 mi	40 - 80 mi	80 – 120 mi	>120 mi
Single tour	20%	44%	17%	19%
Daily distance	10%	12%	12%	66%

We use the firm data to estimate what share of operations can be served by BEHDTs in 2020, 2025, and 2030. As in the simulation analysis, we assume the same set of daily tours for each target year. We calculate the electricity consumption for each tour based on distance and weight. For days with multiple tours, there must be a break of at least 4 hours in order to be able to recharge the vehicle.[3] Table 9 gives results without and with considering the gross vehicle weight (GVW) limit. We estimate the BEV battery weighs approximately 5,000 pounds.[4] If the load including battery weight for any trip in the tour exceeds the GVW of 80,000 lbs, the tour cannot be performed by the BEHDT. For Firm 1, about 30% of all tours could be operated

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[3] Availability of quick charging could reduce the time window somewhat, but time is still needed to move the vehicle to the charger, add or remove trailer, etc.

[4] BEV battery weight is not available from manufacturers, but estimates exist depending on range and load. Fulton and Burke from UC Davis estimate a 500-mile Tesla Semi with current battery efficiency and 1134 KWh capacity would weigh 13,400 pounds while Tanktwo estimates a 300-mile version of the Semi to weigh 9,400 pounds (Burke & Fulton, 2018; Tanktwo, 2020). More in line with the 2020 battery capacity kWh in our study, Oak Ridge National Laboratory (ORNL) and National Renewable Energy Laboratory (NREL) calculate a battery weight at 4,680 pounds for a 235 kWh battery (Smith et al., 2019). Over time it is expected that batteries will become more efficient providing for longer distances at a lower battery weight.

by BEHDT today, and over 80% by 2030. If we take the GVW limit into account, the share drops by about one third. For Firm 2, intensive utilization of the vehicles limits the share in 2020, but with better battery technology about two thirds of operations could be served. However, when we impose the weight limit very little of the operations could be performed by BEHDTs, even in 2030.

Table 9: Share of truck days that can be served with BETs, without and with weight limits

Firm 1	Target Year:	2020	2025	2030
Battery Capacity (kwh)		240	525	650
Average % of truck days that can be operated by ZEVs	Without Weight Limits	30%	61%	82%
	With Weight Limits	18%	43%	58%
Firm 2				
% of truck days that can be operated by ZEVs	Without weight limits	8%	38%	64%
	With weight limits	2%	12%	22%

The short-haul heavy-duty market for BET trucks is limited at the present time mostly due to range limitations, but other factors, like the GVW limit also play a role. In general, firms with low weight cargo, operating 1 or 2 shifts, and travelling very short daily distances (less than 80 miles) are good candidates for this technology. The case studies demonstrate that specific operational characteristics of the firm must be clearly understood to gauge the extent of how BEHDTs can be deployed without causing severe disruptions. The picture changes dramatically in 2025 and 2030. With better performing BEHDTs, the potential market, from a purely operational perspective, greatly increases.

6. Discussion and conclusions

Our analysis leads to the following conclusions.

6.1 BEHDTs are not a practical substitute at this time

First, BEHDTs are not yet practical substitutes for conventional diesel due to limited range, required charging time, and the impacts these limitations have on freight operations. Our simulation results show that in order to use a significant number of BEHDTs, the total number of vehicles required increases. More vehicles add to total costs, generating a high price per ton for CO_2 emissions removed.

Our simulation results are optimistic, in that they assume one shift per day and equal load capacity of BEHDTs. Our case studies and interviews revealed that many drayage firms use vehicles for multiple shifts per day, making it difficult to use trucks that must remain out of service for hours in order to refuel. Also, most loads are close to the maximum allowable. At about 5,000 pounds, battery weight would cause widespread overweight trips, or would require breaking up loads to meet the limit. Our case studies showed the effect of taking multiple shifts and weight restrictions into account.

Our analysis did not consider infrastructure costs, but we did incorporate infrastructure constraints by assuming charging at a single location. Lack of charging facilities restricts the routes that can be assigned to those that assure arrival back to the home location within the

range limit. By taking the lack of charging infrastructure into account, our results differ from those of technical studies such as Cabucoglu et al. (2018), Burke and Sinha (2020), and Liimatainen, et al. (2019), where charging infrastructure is assumed to be widely available.

For all these reasons hybrid-electric trucks appear to be a more attractive option in the near term. Using hybrids does not impact freight operations. The substitution of vehicles is one to one, substantially reducing capital costs relative to BEHDT.

6.2   The medium-term market for BEHDTs depends on many factors

Potential market penetration for BEHDTs is much greater in 2025 and 2030 due to the assumed improvements in battery technology and reduction in the price of BEHTDs. The difference in our results between 2020 and 2025 is particularly dramatic, because we used actual performance data for 2020, which reflects the effects of grades, driver behaviors, and load factors. If the out-year projections do not take these factors into account, they are likely to be optimistic.

Potential market penetration also depends on availability of charging infrastructure. The cost of construction of charging stations is substantial: about $50,000 for the charger and $55,000 for infrastructure upgrade. How the infrastructure will be funded and deployed remains unclear.[5] If firms are expected to build their own charging stations, this would be an additional upfront cost for investing in BEHDTs. A network of charging stations would be required in order to reduce the range problem.

Another key factor will be the availability and magnitude of subsidies. At present a market for BEHDTs without subsidies does not exist, because they are not competitive with conventional diesel or hybrid. While the capital cost differential is expected to shrink considerably in the coming years, the range and other limits will remain. In theory, if operators are fully compensated for all the additional costs of BEHDTs, they would restructure their businesses to accommodate them. The question is whether subsidizing BEHDTs is the best policy course for reducing GHGs.

6.3   The short-haul market is very diverse

Our research revealed the diversity of the short haul market. Small firms (those with fewer than 20 trucks) represent a sizable share of all operations. For example, data from the Los Angeles and Long Beach ports truck registry shows that two thirds of all firms serving the ports are small, and they account for about 28% of all gate moves (Port of Los Angeles, 2020). Some firms have their own vehicles and employees; others lease vehicles and use employee drivers, some use owner operators exclusively, and still others use a mix. Introducing BEHDTs has different implications for different business models. Owner operators are unlikely to consider them, because such a vehicle would severely restrict job opportunities. Those who lease vehicles may be more inclined to use BEHDTs as long as the price is right and the vehicle is able to do the job.

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[5] There are many efforts taking place in California, mostly focused on infrastructure for passenger vehicles. A newly established West Coast Clean Corridor Coalition has identified a plan for truck chargers along the I-5 corridor. The major utilities have plans within their jurisdictions. CEC and CARB offer funding under various programs. However, there is not yet a funded plan in place. For more information, see https://www.hdrinc.com/portfolio/west-coast-clean-transit-corridor-initiative; https://www.energy.ca.gov/programs-and-topics/programs/clean-transportation-program/clean-transportation-funding-areas-0.

Those who own their own fleets may consider BEHDTs when a vehicle is due for replacement but we expect would be averse to shedding vehicles otherwise unless sufficient subsidies were available.

Although we were able to conduct only two case studies, our firms could not have been more different. They illustrate the great variation in products hauled, delivery patterns, and operational constraints that exist even within a small submarket. Any comprehensive zero emission or near zero emission program would need to take this variation into account.

Finally, larger firms are more likely to be able to successfully integrate BEHDTs into their operations. This is a matter of proportions: one BEHDT in a fleet of 100 vehicles will not greatly impact operations; one BET truck in a fleet of 10 would be critical. Larger firms have more options for routing and trip assignments, all else being equal.

6.4   Policy implications

Our conclusions suggest the following policy implications. First, solving the emissions problems of heavy-duty trucks may best be accomplished by flexible policies that support multiple new technologies, both zero and near zero. At this time, the only type of ZEV on the market is the BEHDT, which is not expected to be economically competitive with diesel until around 2030 for short haul applications. This limits feasible market penetration, and hence takes few diesel trucks off the road. In contrast, hybrid trucks are near zero and could be regulated to use battery power in sensitive areas. Hydrogen fuel cell trucks are in early testing. They do not have the range or charge time problems of BEHDTs and thus may become a viable option post 2025-2030.

Second, whether battery electric, natural gas hybrid, hydrogen fuel cell, or something else, the next fuel system will require new production and distribution infrastructure. While the present gasoline/diesel system evolved with the emergence of the auto and truck, current efforts to promote alternative fuel trucks are technology forcing. It is therefore unlikely that infrastructure investments will come exclusively from industry. Rather, there will be a need for a comprehensive infrastructure plan and a source of funding to carry it out.

6.5   Limitations and future research

Our research contributes to the literature by 1) starting with a base case that is informed by experience using BEHDTs and hybrids in drayage service; 2) accounting for the limited availability of recharging facilities; 3) accounting for the effect of differences in performance on operations, 4) developing a two stage solution approach for the vehicle routing problem that solves the distance minimization problem as a minimum cost flow problem, and then solves the minimum fleet size problem as a bin packing problem, and 5) conducting case studies to extend the simulation model results.

There are several limitations to the research. First, our simulation model routes are constructed such that only trucks with containers either empty or full travel from/to the port, or a truck without a container can make another pick up on its return trip to the port. A firm might restructure their routes to allow for pick-up of containers between locations outside the port as well as from/to the port generating possibly more efficient routes. Second, our simulation model did not consider multiple shifts or differences in cargo load capacities between the

different truck types. The simulation model could be extended to consider more complex scenarios. Third, we have not considered infrastructure costs or the costs of stranded assets to trucking firms. For firms, the question is what vehicle to purchase or lease, given that the fleet must be expanded, or a vehicle must be retired. More research on the willingness of firms to replace vehicles would help inform the subsidies required to move to near zero and zero emission trucks in advance of current market demand. Finally, a full assessment would require a life cycle approach, considering all upstream and downstream costs of each technology alternative.

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Appendix A: Simulation model parameters

1. Speed
   a. Short distance average speed – 20 miles/h
   b. Long distance average speed – 45 miles/h
   c. Long distance criteria – > 5 miles of radius (10 miles of round trip)
2. Diesel trucks
   a. Estimated refueling time – 0.25 h
   b. Tank capacity – 226 gallons (FEV North America Inc., 2015)
   c. MPG under different states (no container, empty container, fully loaded container) – 8 | 7 | 5 mpg
3. Battery electric trucks.
   a. Charging time – 3 hours for 0-80% and another 2 hours for 80-100% (based on demonstration interview results). This is the same for all years which reflects the development of the charging technology. That is, the battery efficiency is expected to increase in future years but the charging time is assumed to remain the same due to improved charging technology.
   b. Charging pattern – 0-20% should be left unused in order to keep the battery from degrading too much (interview results).
   c. Battery capacity and consumption:

Year	Consumption Rate with Fully Loaded Container (kwh/mile)	Consumption Rate with Empty Container (kwh/mile)	Consumption Rate with No Container (kwh/mile)	Battery Capacity (kwh)
Present*	4	2.82	2.4	240
2025	3.37	2.1	1.6	525
2030	3.18	2.01	1.5	650

   b. Vehicle range:

Year	Fully Loaded Container (mile)	Empty Container (mile)	No Container (mile)
Present*	60	85	100
2025	156	250	328
2030	204	323	433

4. Other Parameters.
   a. Truck daily operation time limit – 8 hours. (Including traveling and refueling times).
   b. Truck refueling detours – None. Detours for diesel trucks are omitted due to the pervasiveness of diesel gas stations, and detours for BE trucks are omitted since we assume charging only occurs at the truck depots located near the Port.
   c. Distance increase factor – 1.25, based on prior research on network distance vs straight line distance.