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IMPACT OF BATTERY ELECTRIC TRUCKS ON INTERMODAL FREIGHT TRANSPORTATION - AN AGENT-BASED SIMULATION STUDY

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ABSTRACT

This paper applies an agent-based simulation model to examine the feasibility of battery electric trucks (BETs) in intermodal freight transportation, focusing on the Memphis hub network. Two infrastructure deployment stages, depot charging only and depot plus destination charging, are modeled and simulated using AnyLogic platform to study truck utilization patterns. Real-world manufacturing sites are chosen, and the trucks are routed along roadways using a Geographic Information System (GIS) map. Battery charge levels and charging infrastructure are modeled under both scenarios. Four electric truck models from various manufacturers including Tesla Semi, Nikola Tre, Volvo VNR, and Freightliner eCascadia are compared in terms of performance and utilization. Results showed that battery electric trucks are a feasible solution for intermodal trucking operations and transporting goods from manufacturers to destinations. This comparison also highlights effects of changing shifts and adding opportunity charging at destinations on truck utilization under different battery efficiencies and capacities.

1 INTRODUCTION

More than 25% of total greenhouse gas (GHG) emissions in the United States (U.S.) originate from the transportation sector, particularly from seven million medium- and heavy-duty freight trucks (Breiter et al. 2023). The U.S. has committed to transitioning all new truck sales to zero-emission vehicles by 2040 (Breiter et al. 2023). Battery electric trucks (BETs) have emerged as a viable alternative to traditional internal combustion engine (ICE) trucks for heavy-duty (class 8) vehicles (Ventoniemi and Vornfeld 2023). However, several factors currently inhibit the widespread adoption of BETs for freight transportation, including limited range, lack of charging infrastructure, and the impact of cold weather conditions (Alonso-Villar et al. 2023). The shift to BET will come in phases as allowed by the availability of chargers, first at depots, then destinations (i.e., nodes served by trucks in an intermodal network such as manufacturers, warehouses, and distribution centers), and finally at public nodes. It is estimated that by 2040, 4.7 million BETs will be operating in the US, requiring 2.3 million chargers (Bernard et al. 2022). Other technology, such as wireless in-road charging and overhead charging, while very costly to implement, would significantly improve the efficiency and feasibility of BETs.

These trucks can be also applied in intermodal networks which are served to transport loads from origin to destination in the same transportation unit without handling of the goods themselves when changing modes (Crainic and Kim 2007). Based on the latest report of Environmental Protection Agency SmartWay program, intermodal transportation are critical elements of sustainable logistics and can reduce carbon emissions by up to 65% compared to regular truck transportation (Scott et al. 2023). In intermodal freight transportation, cargo is moved in large containers via multiple modes (ship, rail, truck, etc.). For domestic (as opposed to overseas) transportation, intermodal offers improved efficiency over strictly trucking through the economy of scale of locomotives and ships. In intermodal networks, trucks are usually used for drayage, which refers to the first and last stages. In the first stage, cargo is loaded into a container and delivered by truck to a rail or ship dock for long-distance transport. In the last stage, the container is again loaded onto a truck for delivery to the final destination. Drayage is usually limited to a radius of 250 miles from the rail or shipping port (DrayNow 2025).

One thing not addressed in the current literature is the impacts of charging strategies on transshipment efficiency of these intermodal networks. In these locations, in addition to delays and queues at charging stations, trucks may be required to take longer routes to use public chargers and will have to plan routes around the range between charges. This will necessarily introduce inefficiencies into the freight transportation system, increasing operator costs and reducing some GHG reductions associated with BETs. The best option for intermodal network freight is heavy-duty, tractor-trailer type trucks known as Class 8 (USDOE 2012). Currently available class 8 BETs can complete round-trip short drayage routes on a single charge; however, for longer distances routes, the truck will need to recharge at its destination to complete the trip.

This research aims to model a drayage network and assess the feasibility and efficiency of using BETs, with and without destination charging in four currently available trucks. To achieve this goal, the proposed agent-based simulation is applied for analyzing and comparing BETs in an intermodal network. Different scenarios are compared in terms of the time that trucks spend charging and their service and utilization times. This information is essential to assess the suitability of current battery-electric technology to replace traditional ICE trucks in intermodal transportation. The main contributions of this paper include:

- Proposing an agent-based simulation for analyzing and comparing BETs in an intermodal network.
- Implementing and comparing operational range and utilization of BETs under different scenarios with and without destination charging.
- Developing a model of a drayage network to explore the feasibility and efficiency of BETs.

The rest of the paper is organized as follows: Section 2 provides an overview of current research related to BETs. Section 3 describes the overall approach, case study, and assumptions. Section 4 goes into more detail on the AnyLogic agent-based simulation. Section 5 describes how each of the various trucks performed in the simulation scenarios. The last section summarizes our conclusions (see Section 6).

2 LITERATURE REVIEW

Current literature related to BETs in intermodal freight transportation focuses on environmental impacts and implementation. Environmental factors research includes comparative analyses of intermodal versus truck-only domestic transportation and life cycle analysis comparisons of BETs with traditional diesel trucks in various operational scenarios (Bhardwaj and Mostofi 2022). As an example, Iyer et al. (2023) examine the greenhouse gas (GHG) emissions of the complete cycle of trucks, from manufacturing through useful life to disposal, comparing the traditional diesel engines with alternatives, including electric, hybrid, and fuel cells. By including the manufacturing process, the authors captured the impacts of battery and carbon fiber production that offset some of the operational gains of alternative fuels over traditional diesel. The authors compiled an inventory analysis of each type of truck (ICE, BET, and fuel cell electric trucks) to determine the types and quantities of materials used in construction. Karmali et al. (2024) also investigate the integration of production planning and transportation with and without using electric trucks. This article also investigated the effects of various electric pricing policies including on utilization and costs of these trucks and showed that time of use seems the best pricing strategies adopted for integrated planning and under the presence of renewable power generation sources for their charging.

Lee et al. (2013) include life cycle analysis (LCA), GHG reduction, and total cost of ownership (TCO) for urban delivery trucks (class 4-6) in a setting such as New York City, comparing diesel with electric. This study finds that electric trucks outperform their diesel counterparts in terms of GHG emissions, energy consumption, and TCO, but the degree to which they do so depends on the drive cycle. Factors that favor the urban delivery application for the adoption of electric trucks include a large portion of time idling, low average speed, frequent accelerating, and decelerating, which favors generative braking, and local routes that make regular recharging feasible. Samet et al. (2023) consider the factors that would make BETs a viable alternative in Finland and Switzerland. The authors find that two conditions currently limit the GHG reduction potential of BETs: limited operational range and emission intensity of the electric power generation and distribution network. Improvements in these two areas could notably increase the GHG reduction potential from limited to significant. The LCA in this study includes both the use phase of BETs and various electrification scenarios.

Researchers have also examined the challenges facing large scale implementation of BETs in freight transportation and have offered recommendations and road maps for future growth. Implementation studies include feasibility analyses and estimation of future infrastructure needs and deployment. Alonso-Villar et al. (2023) examine the negative impacts of cold weather, winds, cargo weight, and liftgate use on the feasibility of adopting electric power for heavy-duty trucks. The study is based on a case study fleet in Iceland and finds that such adverse conditions could reduce the operational range of electric trucks by as much as 47%. Proposed strategies for addressing these factors include on-route charging. Bernard et al. (2022) describe the charging infrastructure that will be needed to support the BET market along with costs and implementation timeline. Whereas current technology relies on wired charging, the authors mention new approaches currently being studied, including overhead catenary charging, wireless charging (embedded in the roadway), and battery swapping. In the near future, wired, stationary charging is described in three categories: depot charging, destination charging, and public charging. Authors assume that most operators will rely on overnight depot charging as the lowest-cost option.

Further, Borlaug et al. (2021) investigate the impact of adding depot charging for BETs to existing electricity distribution grids and find that at least 75% of substations studied can support up to 100 BETs charging at 100kW each. This capacity will support projected near-term growth in Class 7-8 BETs being used for short-haul (<200 miles) operations. This range accounts for the majority of heavy-duty trucking, with 70% operating within 100 miles. Bernard et al. (2022) predict that long-haul trucks will rely on overnight public charging, an extensive expansion of infrastructure. For other charging needs during daily operation, trucks will use what authors describe as “opportunity charging," using fast and ultra-fast chargers during breaks, loading/unloading time, etc.

Current research indicates that BETs will play a vital role in achieving zero-emission targets in transportation, including for heavy-duty class 8 trucks. Furthermore, short-haul operations, into which intermodal drayage falls, is poised for electrification in the near-term. Life cycle analyses that account for manufacturing, truck operation, and the power generation grid consistently show that BET produces lower GHG emissions than existing ICE technology and often outperforms hydrogen fuel cell technology. Areas not included in these studies are operational efficiency and truck utilization due to charging times and locations. This study shows how simulation can be used to use better understand these impacts.

3 PROBLEM FORMULATION

Intermodal freight transportation refers to the movement of goods from origin to destination using multiple modes of transportation in the same transportation unit (such as a container), without handling the goods themselves when transferring between modes. Intermodal trucking is primarily associated with the first and last stages of transportation (referred to as drayage), usually within 250 miles of the rail or shipping port (DrayNow 2025). Trucks typically make a round trip from the terminal to the destination (either bringing an empty container to be filled with goods or delivering the full container and returning it empty). For the case study, we will examine intermodal drayage jobs in Memphis, TN. Recognized as one of the top five intermodal transit hubs in the U.S. and the only non-coastal city listed, Memphis hosts significant infrastructure, including Memphis International Airport, the Mississippi River, five major railroads, and key interstates (Wadlow 2021). Given its pivotal role in intermodal transport, Memphis provides extensive data for modeling, making this case study particularly impactful.

Current BET models have ranges from 150 to 500 miles (see Figure 1). These ranges refer to the maximum distances that different current BET models can travel on a single charge, depending on their design and battery capacity. This model compares the four truck models with the largest advertised range:

Tesla Semi (500 miles, fully loaded), Nikola Tre (330 miles, typical load profile), Volvo VNR (275 miles, fully loaded), and Daimler's Freightliner eCascadia (230 miles, typical load profile). Currently Tesla has the largest range and it also advertises the lowest charge time, charging from 0 to 70% in 30 minutes (Tesla 2025). The other manufacturers advertise a standard charge time from 0 to 80% in 90 minutes.

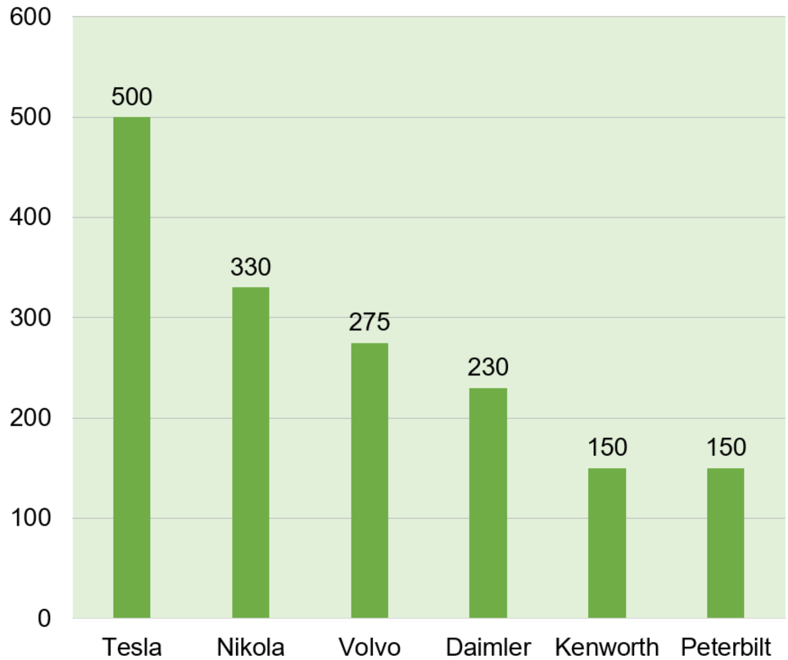

Figure 1: Advertised range (miles) of Class 8 BETs by brand.

Two phases of infrastructure deployment will be considered. In Phase I, charging is defined as depot charging and is only available at the terminal. Depot charging is expected to be the primary means of charging BETs in the US for the foreseeable future. Bernard et al. (2022) estimate that by 2040, 2.3 million charging stations will be required to support the anticipated 4.7 million BETs on the road and that 91% of these will be depot chargers. Borlaug et al. (2021) analyzed data from three fleets of short-haul trucks (those covering less than 200 miles) and found that BETs, set to be introduced soon, can fully meet the needs of these fleets with depot charging alone. Moreover, the required charging power aligns with the capabilities of existing light-duty charging systems. Phase II considers a scenario with charging available at the destination and terminal. In this case, BETs will have an additional option of charging at the manufacturer/warehouse location before returning to the terminal. Bernard et al. (2022) predict chargers at destination locations will be fast (150-350 kW DC) or ultra-fast (750kW - 3 MW DC) chargers, requiring no more than 30 minutes for sufficient charging. In this scenario, it is assumed that charging will occur during either loading/unloading or driver rest break with no significant effect on extending truck's dwell time. The actual implementation of destination chargers (type, location, and number) will determine the impact, if any, on dwell time at a particular destination. The one-way distance range for Phase I is determined by taking half of the total range of the lowest-range truck, the Freightliner, which is 250 miles. This advertised range is reduced by 20% based on the assumption that the trucks are only charged to 80% during opportunity charging (Cole 2023). The range is further reduced assuming that 10% of the range should be held in reserve during route planning. These reductions result in a one-way range of 80 miles for Phase I analysis. For Phase II, charging is available at the destination (manufacturers), effectively doubling the range to 160 miles. For the model, ten manufacturing locations are selected based on the data collected from actual firms. Seven of these are within the range of Phase I, and three are located outside of Phase I range but within Phase II range (see Figure 2).

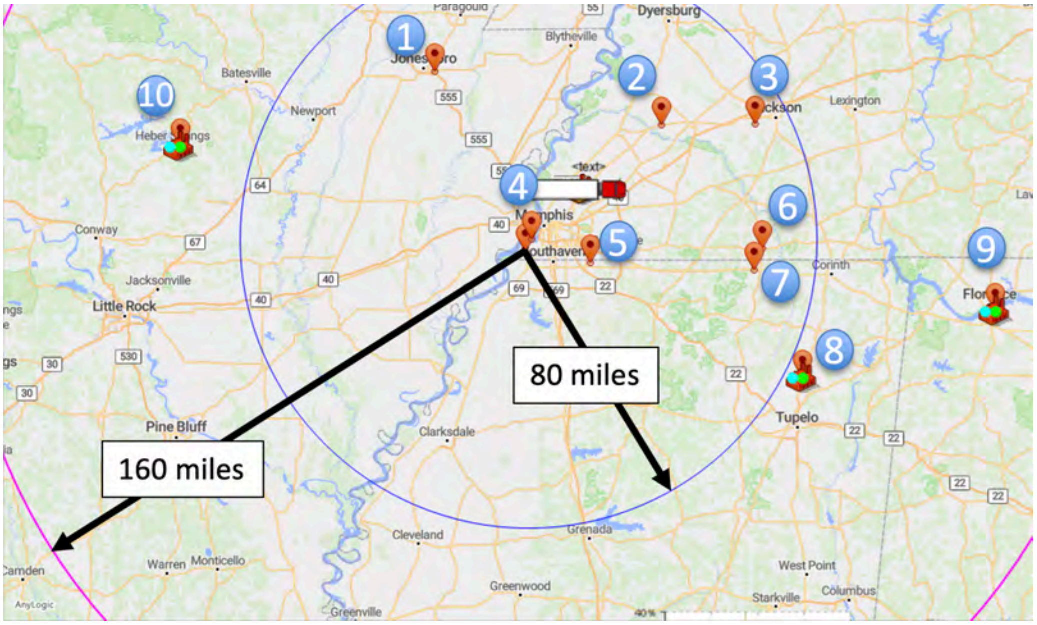

Figure 2: An illustration of the Memphis drayage area depicting the manufacturing locations (numbered) and BET ranges of Phase I (terminal charging only) and Phase II (terminal and destination charging).

The system is modeled under the following assumptions, which are grounded in relevant literature, professional experience, and input from industry contacts:

- Trucks operating a single shift per day are assumed to have greater scheduling flexibility and are fully recharged overnight at the depot.
- Trucks operating continuously (24/7) are recharged as needed, up to a maximum of 80% of their battery capacity.
- Charging time increases approximately linearly until the battery reaches 80% capacity, after which the rate of charging slows significantly.
- A minimum charge threshold of 10% is maintained to provide a safety buffer in case of unforeseen delays or disruptions.
- The depot is assumed to be located at or very near the train terminal, making the travel distance negligible.
- All trucks have access to fast chargers at the depot. In the Phase II analysis, each destination beyond the Phase I operational range is also equipped with fast-charging infrastructure.
- Trucks only accept delivery jobs that fall within their predefined operational range.
- Variations in terrain (e.g., hills) and traffic conditions are considered negligible and do not significantly impact vehicle range.
- Each driver is assumed to start the day with a maximum of 10 hours of available driving time, consistent with regulatory limits.
- Charging at the terminal is assumed to require additional dedicated time, whereas destination charging can occur concurrently with loading and unloading operations.
- All routes are modeled with a consistent average speed parameter across all four types of BETs.
- Trucks respond to delivery orders in the sequence in which the orders are received (first-come, first-served).

4 AGENT-BASED SIMULATION MODEL

The Memphis drayage network and BETs are modeled with AnyLogic (version 8.8.4) Personal Learning Edition using an agent-based method.

4.1 Main

The main agent of the model includes a Geographic Information System (GIS) map of the Memphis, TN, drayage area and three other agents: manufacturers, trucks, and the terminal. Two parameters are also defined at this level: the number of trucks and their average speed. Although the model can simulate a fleet of trucks, this study focuses on the operation of a single truck to simply compare between truck models. All distances in the model are computed using the GIS map, based on routes along existing roadways between nodes. The GIS data does not incorporate traffic conditions.

4.2 Truck

The truck agent of the model defines the characteristics and behavior of the BET (see Figure 3). Parameters are used to define the maximum range and charging rate, which are specified by the truck manufacturer's data (see Table 1). The minimum charge is also defined and is assumed to be ten%. A variable charge represent State-of-Charge (SOC) and it is defined in terms of percentage (0 to 100), representing the current battery level. Its linked state chart defines whether the truck is idle or driving. If it is driving, the charge variable is decremented every minute at a rate listed in the table.

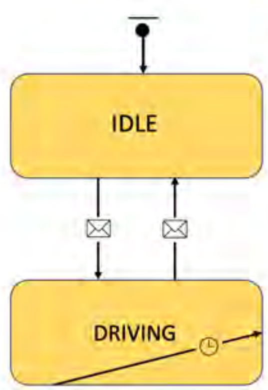

Figure 3: State transition diagram for truck agent.

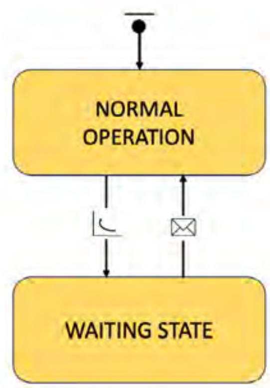

Figure 4: State transition diagram for manufacturer agent.

Table 1: Charging data for modeled BETs.

Parameters	Tesla Semi	Nikola Tre	Volvo VNR	Freightliner eCascadia
Charge rate (kW)	750	350	250	270
Traveling per charging (miles)	500	330	275	230
Energy Consumption per Mile (kWh/mile)	2	2.25	2.5	2.6
Charging efficiency (%)	95	90	88	85

4.3 Manufacturer

The manufacturer agent of the model (see Figure 4) represents the sites to which the truck must deliver intermodal containers. Each manufacturer generates a demand for a delivery by sending a message to the terminal. The timing of these messages is determined by a state chart. The messages are sent according to a Poisson process with a rate of 14 per week. After sending the request message, the manufacturer transitions to the waiting details state until the container is delivered, at which point it returns to the normal work state.

4.4 Terminal

The terminal agent (Figure 5) acts as a dispatcher, receiving delivery requests from the manufacturers and directing trucks to and from their destinations. The packing and unpacking processes are represented as delays. In the trucking industry, these delays are referred to as dwell times, and the current average is one hour and 54 minutes (Leslie and Murray 2022). These delays are modeled using a normal distribution with a mean of two hours and a standard deviation of 30 minutes (assumed).

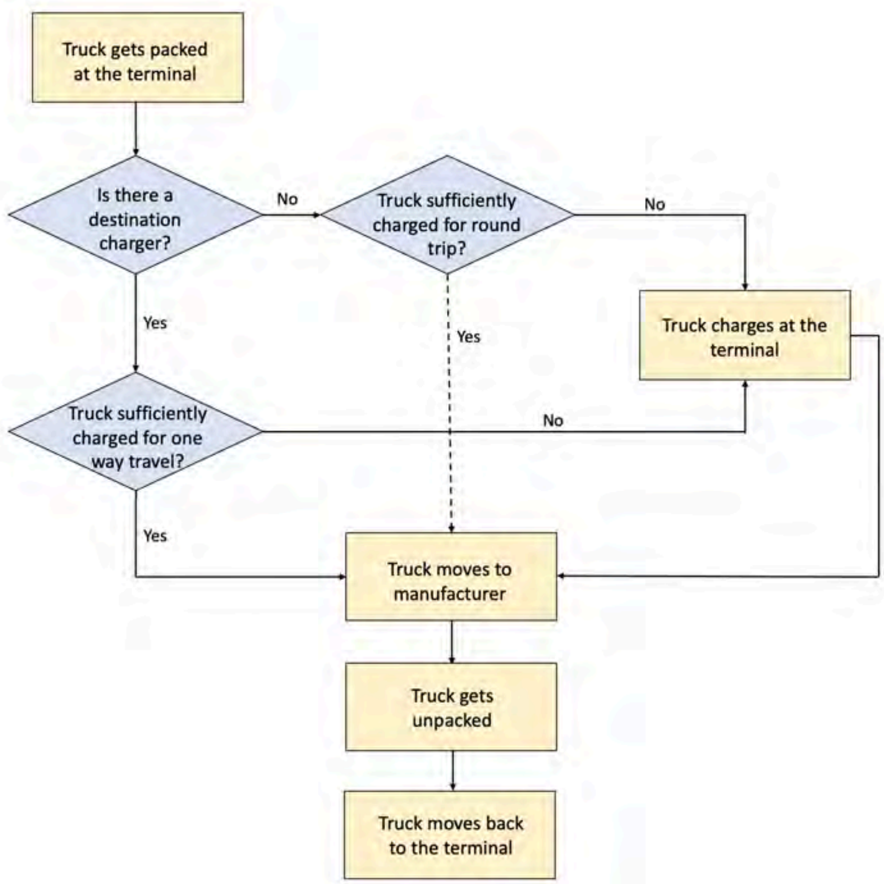

Figure 5: The flowchart for the terminal agent.

After the truck is packed, the model checks for sufficient charge to make the trip. If there is a destination charger (Phase II), it checks if the charge is sufficient for a one-way distance (since it will recharge before returning). Otherwise, it checks if the charge is sufficient for the round-trip distance. In either case, if the charge is insufficient, the truck charges at the terminal, which is modeled as a delay. The length of the delay for charging is a function of the amount of charge needed to reach 80% (the defined charge level) and the charge rate (specified in the truck agent, as defined by the truck's specifications). The terminal agent also collects data on the truck's daily charge time and daily miles driven. These are the two results by which the various truck models are compared.

5 RESULTS

All four truck models (Tesla, Nikola, Volvo, and Freightliner) were run in three scenarios: 1) Phase I on a single shift per day, 2) Phase I on a 24/7 basis (assuming multiple drives keep the truck running non-stop), and 3) Phase II on a 24/7 basis. Each simulation was run for 1500 hours to allow output data to stabilize.

5.1 Phase I with Single Shifts

To verify the simulation model, it is initially tested for a simple scenario with a single shift. This scenario is for Phase I infrastructure, where charging is only done at the depot/terminal. For this setting of the simulation, it is assumed that the truck is scheduled to operate on a single, 10-hour shift (8:00 am to 6:00 pm). The trucks start their trip with 80% SOC and receive additional charging in the terminal if needed. The resulting average daily delays spent for charging delay time and average daily miles driven are shown in Figures 6 and 7, respectively.

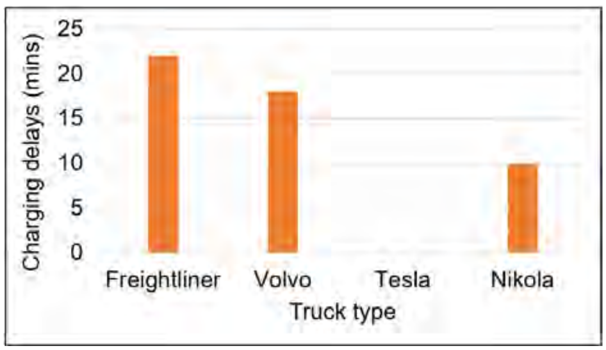

Figure 6: Average daily charge time by truck model for phase I infrastructure and single shift operation.

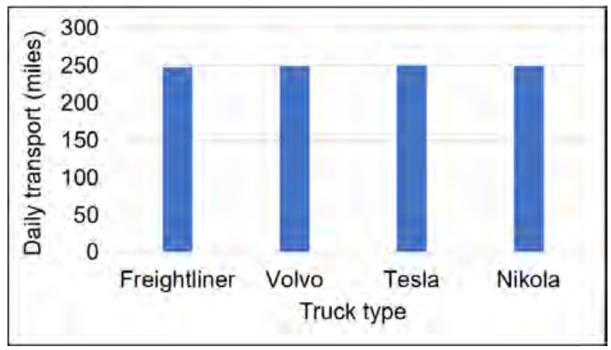

Figure 7: Average daily miles by truck model for phase I infrastructure and single shift operation.

As expected, the Tesla truck has an average of zero hours of charging delay time. This is because Tesla's range of 500 miles is sufficient to complete single-shift deliveries without stopping to recharge. The result also showed that the average daily miles for each truck is within one percent of the defined distance. This means that the single-shift scenario includes sufficient time for opportunity charging without costing the trucks an additional run before the shift ends. The results also verify that the model correctly reflects the relations between the charging efficiency and the charging rate of the trucks and their charging delays in this single shift delivery setup.

5.2 Phase I with 24-Hour, 7-Day Shifts

The second simulation scenario is for Phase I comparison infrastructure and 24/7 operation. This would require multiple drivers to use the same truck in different shifts to maximize utilization. The resulting average daily charge time and daily miles are shown in Figures 8 and 9, respectively.

In this simulation, all truck models required opportunity charging at the terminal. The greater range of Tesla and faster charging resulted in the lowest average charge time (52 min). The next lowest is Nikola, with 139 minutes/day. A larger difference in average daily miles is also seen, with Tesla leading with 439 miles/day. However, all trucks are within 10%, with the lowest, Freightliner, driving 398 miles/day.

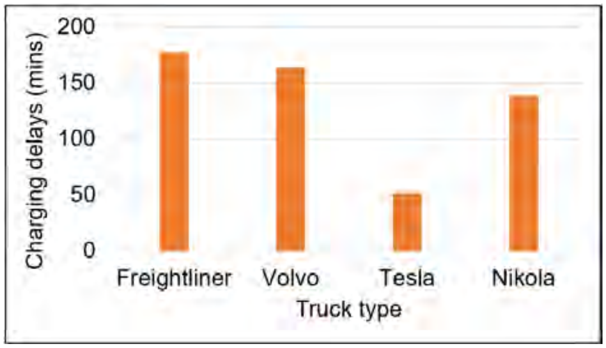

Figure 8: Average daily charge time by truck model for phase I infrastructure and 24/7 operation.

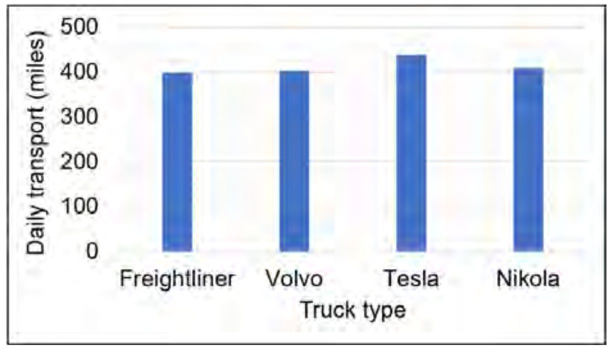

Figure 9: Average daily miles by truck model for phase I infrastructure and 24/7 operation.

5.3 Phase II with 24-Hour, 7-Day Shifts

The third simulation scenario is for Phase II infrastructure and 24/7 operation. In this scenario, manufacturers at distances greater than 100 miles (a model parameter) have a charger available. This effectively doubles the operating range of the trucks. The resulting average daily charge time and daily miles are presented in Figures 10 and 11, respectively.

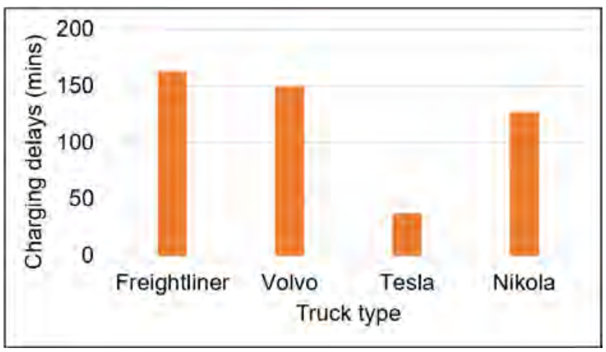

Figure 10: Average daily charge time by truck model for phase II infrastructure and and 24/7 operation.

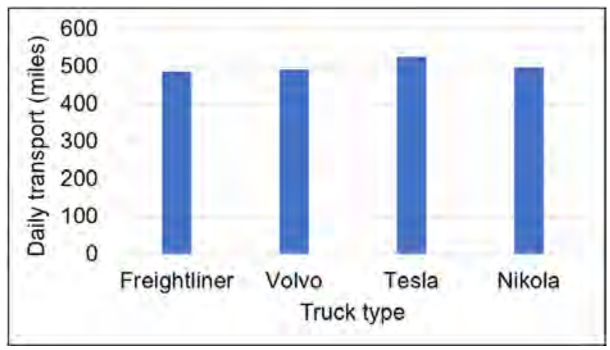

Figure 11: Average daily miles by truck model for phase II infrastructure and and 24/7 operation.

This simulation introduces three new manufacturing sites located beyond the Phase I range. Tesla demonstrates an average daily charge time of 38 minutes, which is shorter than the second scenario above. This reduction can be attributed to the assumption that destination charging occurs during loading and unloading (dwell time), thereby not contributing to the daily charge time total. This assumption stems from operational differences between loading/unloading processes at a manufacturer and at an intermodal terminal. At a manufacturer, trucks are typically backed into loading docks, where destination charging is presumed to take place via connections in the trailer while the truck remains docked. In contrast, at an intermodal terminal, containers are lifted on and off truck trailers using large cranes. Charging stations are assumed to be situated elsewhere within the terminal facility, resulting in extended overall dwell time when charging is necessary. Despite these variations, the total average daily mileage across models remains within 10%. Tesla leads the group with a daily average of 527 miles. The results for comparing three different scenarios are also summarized in Table 2.

Table 2 reflects improvements in truck utilizations when increasing shifts from single shift to 24/7. It also computes effects of adding charging possibility to destinations in 24/7 shifts settings. The results show that increasing shifts has considerable effects on trucks utilization and can increase trucks involvement up to 76%. Adding opportunity charging also offers additional 20 or 22% improvements on all four trucks.

Table 2: Scenario comparison for mileage increase.

Change Source	Freightliner	Volvo	Tesla	Nikola
More Shifts	60%	62%	76%	64%
Opportunity Charging	22%	22%	20%	22%

This comparison reveals that effects of shifts increment are highly correlated with trucks' battery efficiency and travel per charging while adding charging stations to destinations has a robust effect on all trucks regardless of their types and features.

6 CONCLUSION

As the freight industry undergoes a pivotal transition from conventional heavy-duty trucking to BETs, this study develops a simulation-based model to evaluate the feasibility and operational efficiency of BET deployment in drayage networks. Using the Memphis, TN, intermodal transportation system as a case study, we present a detailed analysis comparing the performance of four commercially available Class 8 BETs within a realistic drayage context. Our simulation approach provides a comprehensive framework for assessing the practical adoption of BETs under various operational scenarios, including both the presence and absence of destination charging infrastructure. The results demonstrate that Class 8 BETs show promise for being viably integrated into drayage operations. Notably, introducing destination charging infrastructure (Phase II) significantly extends the operational range from 88 to 175 miles and improves overall vehicle utilization, as reflected in increased average daily mileage.

While the industry often assumes that larger battery capacities and faster charging capabilities are key to improving electric truck performance, our findings challenge this notion. In scenarios constrained by specific requirements imposed by transportation agencies (such as depot-only charging and single-shift operation), such enhancements have a negligible (less than one percent) impact on utilization as measured by average daily miles driven. This underscores the importance of detailed modeling and simulation in identifying optimal combinations of vehicle configuration and charging strategy, tailored to specific operational constraints.

This study offers valuable insights for researchers, policymakers, and logistics practitioners seeking to understand and support the integration of BETs into existing freight systems. Our findings advocate for targeted infrastructure investments and highlight the need for flexible, data-driven planning approaches. Future research will continue to refine this modeling framework, integrating real-world freight data and expanding its applicability to broader logistical challenges, including diverse regional infrastructures, weather conditions, traffic, and fleet compositions. Extensions of this work could also incorporate additional decision-making layers such as partial charging strategies, dynamic routing, and destination selection to further optimize system performance and resilience. In particular, incorporating more flexible agent logic such as allowing trucks to determine charging levels based on trip needs and cost tradeoffs could enhance our models realism and adaptability.

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