Operational and Economic Drivers of Long-Haul Freight Electrification

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SUMMARY

Electric alternatives for heavy-duty vehicles have reached technical readiness, but deployment remains limited. Here, we investigate when fleet electrification becomes economically optimal for operators and how fleet operations change under different scenarios. In the baseline case, with current technology costs and no policy interventions, we observe partial fleet electrification when companies evaluate operations over four or more years. With projected future reduced costs, this threshold decreases to approximately one year. In many cases, the optimal solution is a mixed fleet configuration, where electric trucks serve high-demand routes surrounding ports and manufacturing hubs, while diesel trucks are retained for lower-demand and longer-distance routes. We further examine the effects of several policy interventions, including subsidies for co-located solar installations, relaxation of federal truck weight limits, implementation of a carbon penalty, and combinations of these policies. Among the individual policies, relaxing the federal weight limit has the most significant impact on fleet electrification. Combining solar subsidies with either a carbon penalty or weight-limit relaxation results in substantially higher levels of installed solar capacity.

KEYWORDS

Decarbonization, Electrification, Long-haul Freight, Heavy-duty Vehicles, Policy Interventions, Transportation

INTRODUCTION

Electrification is a potential avenue to reduce transportation emissions – which currently contribute 16% of global emissions[1], and 29% in the United States[2]. Fully electric passenger vehicles have been commercially available since 2010[3], and as of March 2026 approximately 8 million plug-in EVs have been sold worldwide[4]. The cost of running an electric sedan is on average $0.06 to $0.12 per mile cheaper than equivalent internal combustion engines[5]. This means that many passenger EVs can now recover cost differences within their lifetime – dependent on local electric rates and availability of home charging[6].

Medium- and heavy-duty trucks contribute a large fraction of transportation emissions (23% in the U.S.[2]) and still rely almost exclusively on fossil fuels. The heavy weight and long mileage requirements of freight trucks make electrification more technically challenging[7,8]. Early research focused on hydrogen as a fuel source for heavy-duty trucks[9]; however more recent work has demonstrated that electric heavy goods vehicles may be cheaper[10–12] and benefit from an already developed electricity distribution system.

Lee et. al.[13] compares the total cost of ownership between diesel and electric freight vehicles, highlighting that while electric vehicles often require higher initial investment, their lower operating costs can offset this over time, leading to potential long-term cost advantages. In this paper, we aim to answer the question: *at what point do electric heavy duty vehicles become more cost-effective than diesel trucks?*. Previous works have investigated the payback period[14], life-cycle costs[15], and environmental costs[16] of electric heavy-duty vehicles. These studies all suggest electric alternatives should have lower operational and environmental costs than diesel alternatives. Sripad et. al concludes that battery cost and vehicle utilization will strongly influence whether the vehicles can recover costs within their lifetimes[17]. However, these early works are limited by their implicit assumptions that vehicle usage will not change significantly with electrification, while recent work shows that electrification will significantly alter routing and dispatch due to charging needs and payload constraints[18].

Electric trucks are inherently heavier than diesel trucks due to the weight of their batteries. Since trucks are limited to an 80,000-pound gross vehicle weight in the U.S., this reduces the payload capacity of electric trucks, meaning that, unlike with passenger vehicles, it is inappropriate to compare vehicle-to-vehicle. There are also many decisions to be made with a heavy-duty delivery fleet that affect fueling cost and vehicle utilization – including whether to install private chargers or rely on public infrastructure, whether to implement battery swapping[19], and/or co-locate solar power[20]. Therefore, for fair comparison the total capital and operational costs of the required fleet, personnel, and infrastructure should be compared. Various previous work has addressed the joint charging and routing of electric delivery vehicles[21–23], but none considers how this affects the economics of diesel vs. electric trucks.

Given the trade-off between capital and operational costs, in this paper, we examine how the cost-optimal long-haul delivery fleet changes for given payback periods. The payback period is important, because fleet operators need confidence that they will have continuous business for this period; if it takes many years to see a return-on-investment, then there is more financial risk, given uncertainty around future product demand and fuel/labor costs. Our novel optimization formulation includes a wide variety of possible fleets – including mixed diesel/electric, battery swapping, public or private charging, and distributed renewable energy. Our proposed model extends the classical vehicle routing problem[24] to include sizing of the system, including trucks (electric or diesel), chargers, and possible batteries or distributed energy. We consider a large fleet transporting goods within an 800-mile radius, as previous research has shown the economics of electric heavy duty vehicles improves with larger fleet sizes[25,26]. Given the importance of local costs and routing, we consider three case studies at different locations in the United States, summarized in Figure 1.

RESULTS

Our case study focuses on the long-haul delivery of goods from a port to surrounding cities. This was selected due to the regularity of routes around ports, given that electric trucks will be most competitive when their utilization is high. To assess the geographic impact on the payback period, we defined three distinct geographic networks composed of 7 cities, each centered on a major port city: Savannah, GA; Long Beach, CA; and Houston, TX. In each case, we consider the distribution of goods arriving at the port to a number of surrounding cities. The rationale for selecting the three geographic networks is based on differences in fuel prices, electricity rate structures, observed traffic patterns, and charging infrastructure costs. For the costs of electrified heavy-duty vehicles, we consider two scenarios: a higher cost representative of early adopters, such as the current Tesla or Nikola semi-trucks, and a lower cost based on Tesla estimates for what an optimized mass-produced truck would cost. More details of the costs and formulation are described in the Methods section.

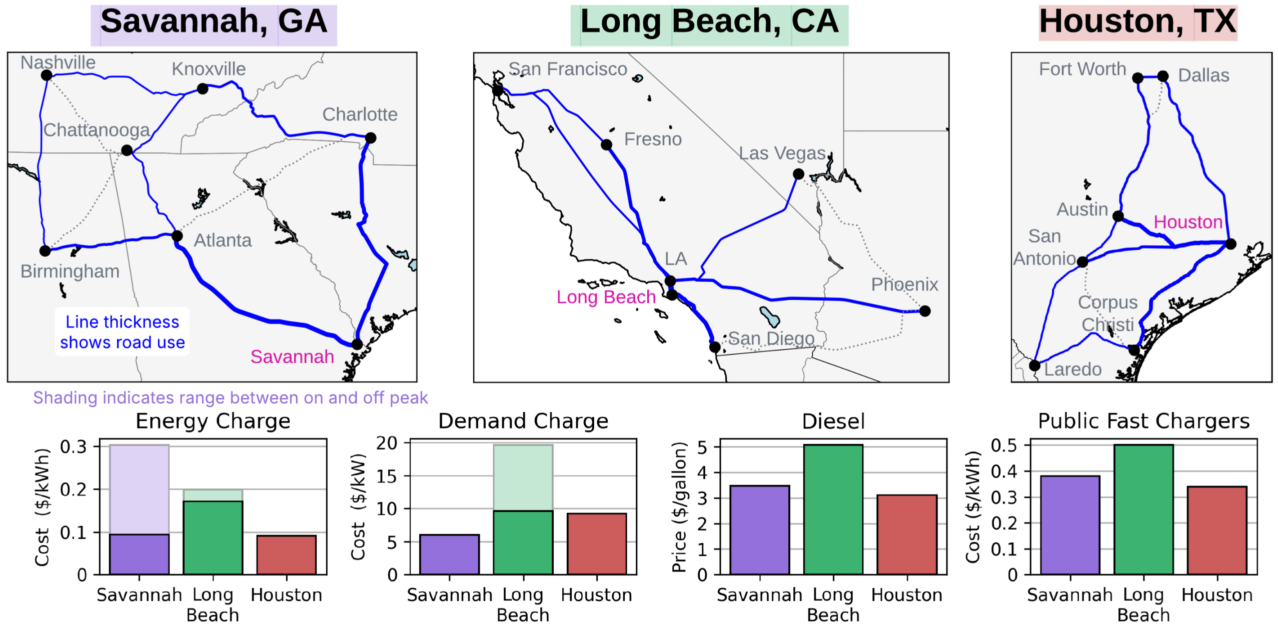

Figure 1: A summary of the three considered operating regions and their major differences.

Fleet differences associated with electrification

Electric alternatives are heavier and therefore require a larger number of vehicles to move the same volume of goods (due to weight limits on heavy-duty vehicles). The need for charging stops also means that the same driving schedule can not be met, so a deeper analysis is needed to understand the differences. Figure 2 breaks down the differences in both capital and operational costs between a fully electric and a fully diesel fleet in each of the areas using the low-cost scenario. In both cases we fix the fleet to be fully electric or diesel, but optimize over all other operational and capital expenses.

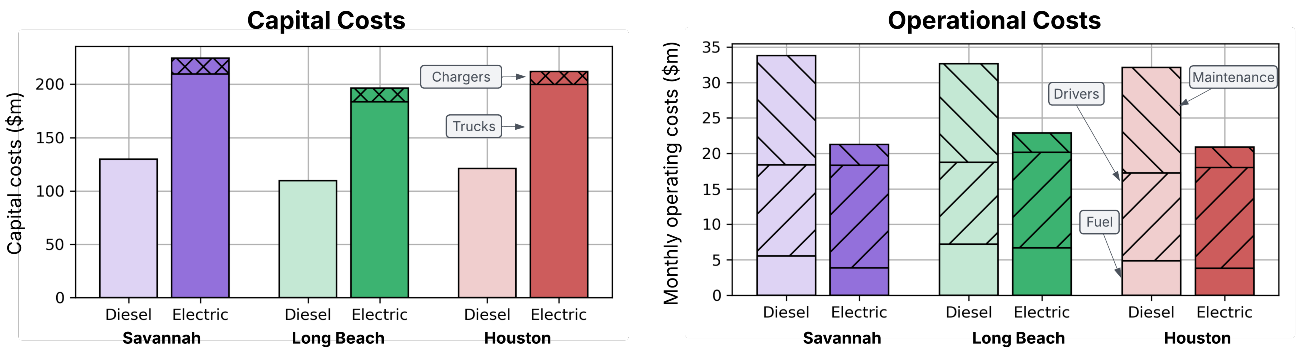

Figure 2: A comparison of the capital and operational costs with optimal operation between a fully electric and a fully diesel fleet (using the low or “mass-produced” costs for electric trucks).

The capital costs associated with EVs are significantly higher, due to: higher vehicle price, need for more vehicles, and the installation of chargers. Our model allowed for either private chargers to be installed or public fast chargers to be used, but in all fully electric cases, it was optimal to exclusively use private charging. The operational costs are lower in all areas, primarily driven by the lower maintenance costs associated with EVs. Overall fuel costs were lower in all scenarios, although the reduced price per mile is offset by 17–25% of additional mileage. The higher driver costs associated with the extra distance largely cancel out the fuel savings.

Tipping points for electrification

Given the lower operational costs, whether electric vehicles compete with diesel equivalents depends on the amount of time they are expected to be in regular service. The longer the expected return-on-investment, the more challenging it is for investors to commit to making the switch, given uncertainty in future profits and costs. Our framework poses the problem the other way around: "given a fixed payback period over which costs must be recovered, what is the most profitable HGV fleet?".

Fig.3 visualizes the optimal mix of vehicles for a range of payback periods in each operating region and for both high-cost (early adopters) and low-cost (mass produced) scenarios. In the futuristic low-cost scenario, we see the fleets in all three locations switching to fully electric between a two and three-year payback period. Whereas in the high-cost scenario, which reflects the current prices and efficiencies of electric trucks, the fleet is fully electric until at least three years of continued operation is considered. In the high-cost scenario we see a much larger window where mixed fleets are optimal, which we explore further in the next section.

The results also vary to a lesser extent by location. We see that in Long Beach, where both the diesel and electric costs are higher, it takes more years before electric vehicles are installed. This make sense because we assume the revenue per product is the same in all areas, and so this network is the least profitable. Savannah and Houston have similar diesel and fast charging prices but slightly differing utility rates – Houston has a higher demand charge and Savannah has a higher and more variable energy charge. We do not see a significant difference in these areas, likely because the truck cost outweighs the energy cost, meaning the dispatch is not very sensitive to time-varying tariffs. While Fig. 3 only shows the composition of the vehicles, below we discuss the extent to which other capital and operational decisions vary across the considered scenarios.

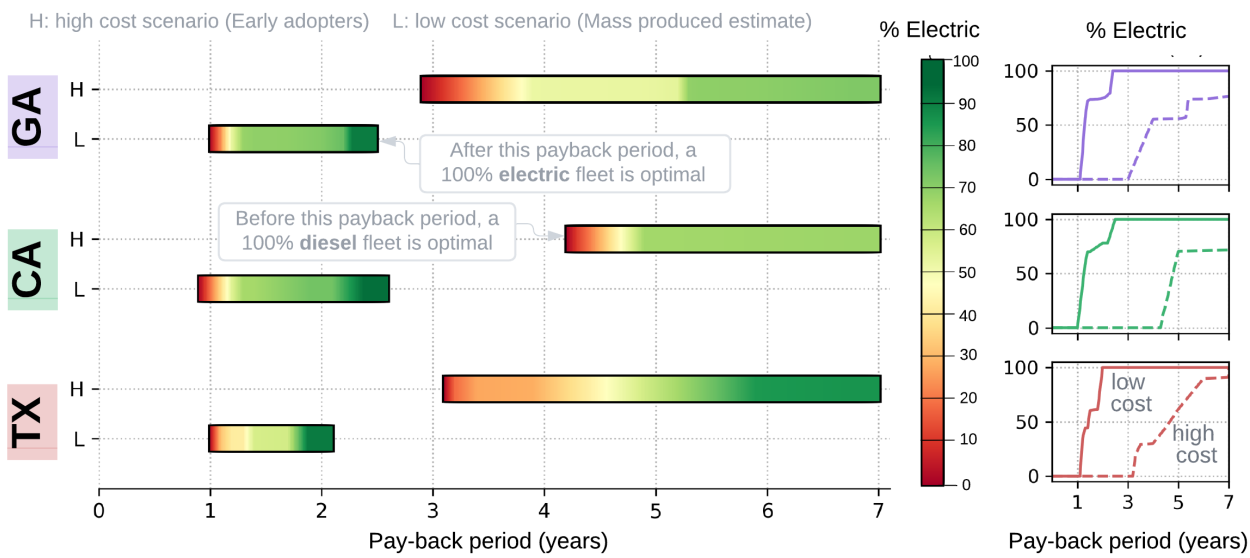

Figure 3: The range of payback periods for which a mixed fleet was optimal in each of the scenarios. Below the range, a fully diesel fleet is optimal, and above the fleet is fully electric.

Charging infrastructure: Our model allowed freight operators to use a mix of public charging infrastructure at the going rate, or to install their own chargers and be billed by the utility. The latter adds capital cost, but results in lower operational costs. We found that in all cases where the fleet was fully electric, the freight operator relied only on privately installed chargers. However, in cases where mixed fleets were optimal, we find some (small) use of the public infrastructure. We discuss this further in our mixed fleet operation discussion below. It is worth noting that here we have assumed that public chargers will always be available with no wait time. Freight operators may prefer building their own charging infrastructure due to certainty around availability.

Un-met product demand: We assumed that all the products supplied resulted in a fixed revenue of $0.1 per kg. Freight operators, can therefore choose not to deliver specific products if the required system costs outweigh the payment associated with delivery. However, in all the scenarios considered, we saw that all product demand was satisfied. This means that at the assumed price, it was worth the capital investment to deliver all goods, even with relatively short payback periods.

Co-located solar: Where private chargers were installed, we allowed co-located solar to be installed. This further increases capital costs, but then the generated energy can be utilized at zero cost if it aligns with vehicle charging, and sold back to the utility otherwise. For the payback periods we considered, no solar was installed in any location or scenario. This is consistent with public research suggesting that solar systems usually recover their costs in eight to eleven years without carbon incentives[27]. In other words, solar is likely to be profitable if fleet operators consider operating for decades, but not over the lifetime of a single fleet.

Battery swapping: Our model also permitted the purchase of additional batteries at the charging stations, thus allowing battery swapping – where a vehicle can swap its empty battery for a full one. Battery swapping avoids delays from charging, and reduces the number of fast chargers needed. However, for the considered scenarios, we did not see any additional batteries purchased. It's worth noting that here we consider only the costs from the perspective of the fleet operator. In practice, other work has demonstrated that battery swapping has other benefits from the perspective of power system operation. In the future, more complex pricing mechanisms may be developed to more accurately capture these costs. However, with today's utility rates we do not see additional batteries present in the cost-optimal fleet. This is consistent with our previous research, which demonstrated that using a flat electricity price, battery swap only becomes competitive when additional batteries cost less than 40% of a vehicle[28].

Mixed fleet operation

We observe that for many payback periods, mixed fleets with some diesel and some electric trucks were cost-optimal. Considering the low-cost Savannah case with a payback period of 1.5 years, we examined how the system dispatched electric vs. diesel trucks. Figure 4 highlights the differences. We find that the electric fleet outnumbers the diesel fleet, but is used for only a subset of the trips – between the most popular cities. The diesel fleet, around 25% of total vehicles, carries goods to the most distant cities, whose routes are less trafficked. The diesel fleet has a higher utilization and mileage, due to not needing to stop to charge. We see that charging infrastructure is installed in four out of seven of the cities, those most frequented by electric vehicles. The public charging infrastructure, which is more expensive is used primarily in Chattanooga, where no private chargers are installed, and occasionally in Atlanta. This demonstrates that, in some cases, a low-utilized private charger is more costly than public charging.

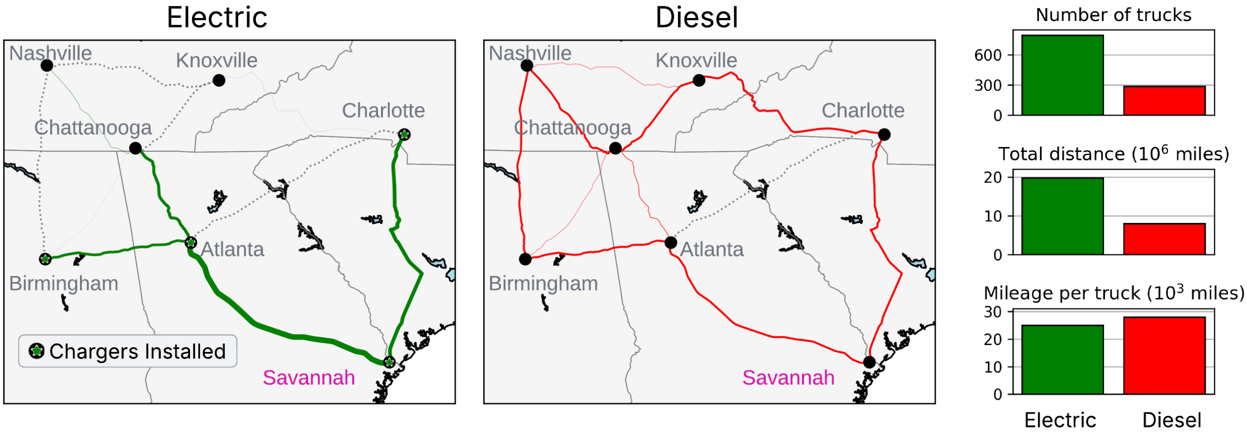

Figure 4: From a case where a mix of electric and diesel trucks were optimal, this figure illustrates the differences in their usage considering four weeks of operation.

Policy mechanisms to ease the transition

In this section, we consider how regulators could decrease the required payback period for electric alternatives. Federal subsidies or tax breaks can directly reduce or eliminate the capital cost difference between electric and diesel HGVs. However, these policy mechanisms are expensive and have limited social benefits beyond reducing transportation emissions. Here, we instead investigate more nuanced mechanisms that may accelerate the switch to electric HGVs and have other benefits. Figure 5 summarizes how each of the considered subsidies affects the repayment period, and each are discussed individually below.

Subsidies on solar co-located with vehicle charging

The federal government has previously provided incentives for installing large-scale solar, offering subsidy levels of up to 60% for the projects constructed in the eligible year[29]. In some cases, this makes it more economically attractive to install solar alongside the vehicle chargers, allowing the system to benefit from zero marginal cost solar-generated energy and cheaper installation costs. Our above analysis showed that the solar subsidy rarely improved the payback period at which electric trucks became competitive. This is because, even with the solar subsidy, the payback period is longer than the three years at which we see electric alternatives becoming profitable. The main exception is for the Long Beach high cost scenario, which we believe to be driven by the relatively high electricity prices in California. This results in the solar starting to payback around the four-year mark, which is around when electrification becomes competitive in the high vehicle cost case.

Relaxation of the HGV weight limit for electric alternatives

There is U.S. legislation, the Natural Gas Vehicle (NGV) and Electric Vehicle (EV) Weight Exemption, which relaxes the weight of electric trucks by 2,000 pounds[30]. In other words, allowing trucks to exceed the standard 80,000-pound limit, increasing their payload capacity to be closer to that of diesel trucks. This additional weight does not achieve parity in the payload of electric and diesel trucks, but does reduce the number of additional trips needed to transport the same load. We see that this regulation change results in a reduction in payback period across all considered scenarios – most significantly in the high vehicle cost case where the payback is reduced by over a year in some cases. This is by far the most impactful policy considered, likely

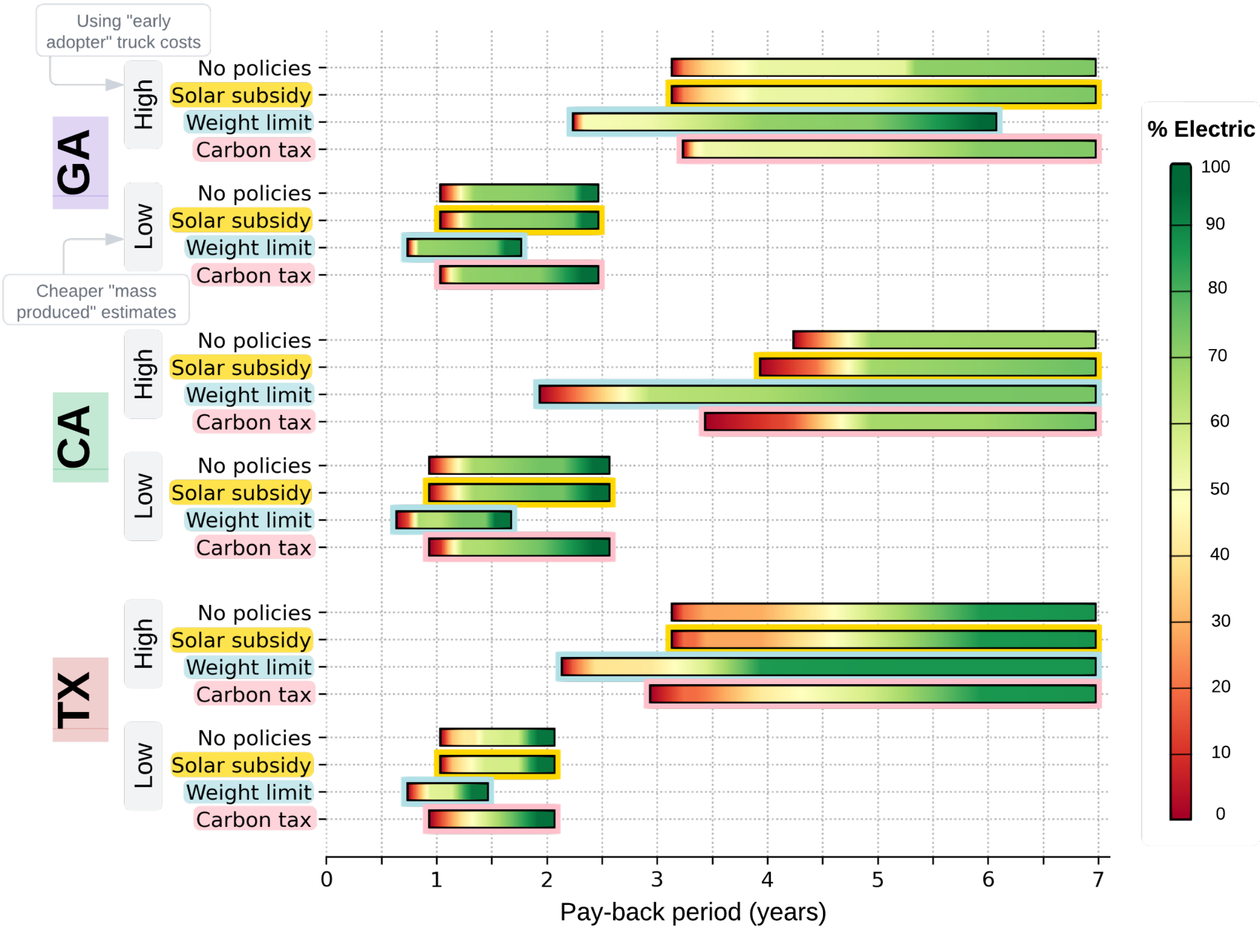

Figure 5: We evaluate how the payback period of an electric fleet varies with three possible policy mechanisms: a solar subsidy, relaxation of the truck weight limit, and a carbon tax. In each case we visualize the region of payback periods where a mixed fleet is optimal, for each of the locations and both vehicle models.

because it reduces the capital costs of electric alternatives (due to fewer trucks being required), while the other policies focus on operational costs.

Implementation of a carbon penalty

One mechanism commonly considered for incentivizing the transition to low-carbon alternatives is a carbon tax[31]. Such a tax would penalize the carbon dioxide emitted by diesel trucks, but also, to a lesser extent, the electricity consumed from electric trucks. We tested the effect of a $50 per ton of CO_2 tax, using the average grid emission rates from the operating area (e.g. California for Long Beach)[32]. We assumed that all grid electricity was charged using this average rate, but that locally generated solar was exempt. Figure 5 shows that the carbon penalty has a limited effect in the low cost scenario, but a noticeable impact in the high cost scenario, although the effect varies significantly by region. In Georgia the grid emissions factor is relatively high, so, given that the number of electric miles driven is higher, there is little difference between the penalty paid by fully electric and fully diesel trucks. The California grid has a much lower carbon intensity, so in Long Beach, we see the greatest shortening of the payback period at which a mixed fleet becomes optimal. However, it should be noted that the carbon penalty reduces the profit per delivered good compared to with no incentives (assuming a constant product price). Given that the return-on-investment for electric trucks relies on higher profits due to lower operational costs, the penalty can have the converse effect. While we see the window of mixed fleet operation may move earlier, the fully electric point is not significantly affected.

Combination of policy mechanisms

The policy mechanisms mentioned have very different effects, and given their (relatively) low cost, it is plausible that multiple could be implemented. Here, we explore the effect of combining any two policies. Figure 6 visualizes the impact of two policies on the Long Beach (CA) case with the high cost scenario and a fixed payback period of 4.5 years. This case was selected as one of the most reactive to policies, and the payback period was chosen to be within the mixed- fleet range without subsidies. We show the change in both the percentage of the fleet that is electric and the quantity of solar installed (other variables such as battery swapping are not shown as there was no change observed).

Regarding fleet composition, we do not see further effect from combining policies – as seen previously, the weight limit has the strongest effect, followed by a carbon tax. However, we see that combining the policies does exhibit change in the charging infrastructure decisions regarding co-locating solar. With only singular policies, we only see a relatively small amount solar installed with a solar subsidy, and none with other policies. Whereas the addition of either the carbon tax or the weight limit significantly increases the amount of solar installed. The carbon tax is the most dominant additional policy – increasing the solar installed by a factor of ten compared to only a solar subsidy.

Overall, carbon pricing and relaxed truck weight limits act as the primary drivers for fleet transition, while solar deployment is a secondary effect that depends on the presence of a solar subsidy. We see a multiplicative rather than additive effect for policies on solar deployment: adoption only scales significantly when combined with policies that first grow the electric fleet and, consequently, the energy demand available for solar to serve.

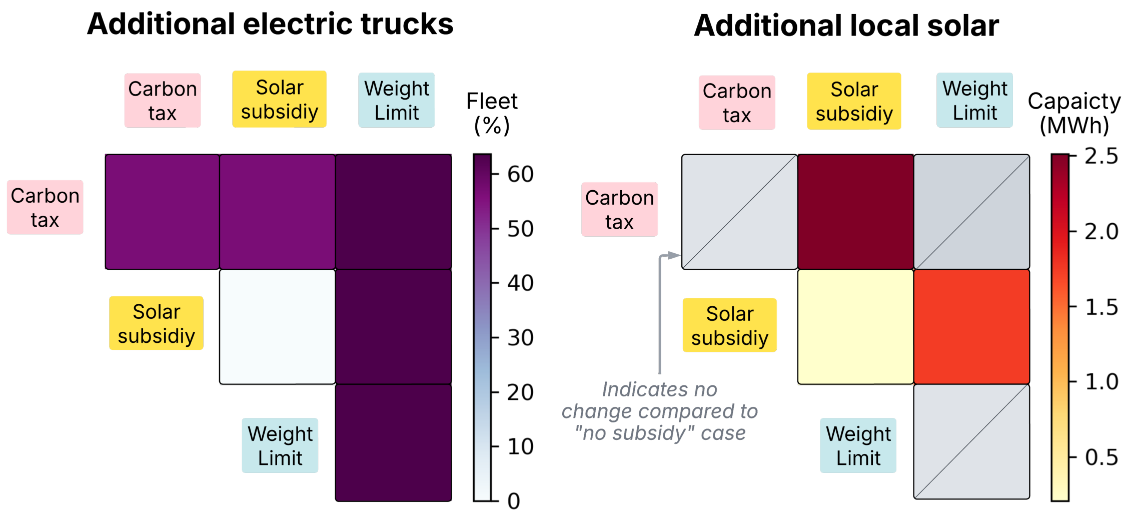

Figure 6: The effect of combining two policy mechanisms for the Long Beach (CA) case study with a 4.5-year payback and the early adopters' costs. The left shows the change in electrified trucks, and the right shows the change in installed solar, both compared to a baseline without any subsidies.

DISCUSSION

Our analysis shows that electric alternatives to heavy-duty vehicles *can* recover their higher up-front costs over between one and four years of high utilization, due to lower fuel and maintenance costs. The capital costs of the electric trucks have the largest impact on this payback period – with current costs around four years, but future estimates dropping to one year or less. Although fuel costs can vary significantly between states, diesel and electric prices tend to correlate, so we did not see a substantial difference between operating areas.

There exists a distinct "in-between" scenario in which the most optimal fleet contains a mix of electric and diesel vehicles. In these cases the electric trucks are tasked with the most popular routes close to hubs, and diesel trucks do the less common, further out routes. Especially with today's higher truck costs, there is a large window of payback periods where the mixed fleet is the most profitable. Additionally, a mixed fleet may have other benefits that we did not explicitly consider – such as reduced financial risk and redundancy in fuel sources. A mixed diesel and electric fleet may therefore be a medium-term preferred solution for fleet operators.

The federal weight limit on heavy-duty trucks results in electric alternatives having a reduced payload compared to diesel. We find that a relaxation in this limit, as implemented in the State of California, has a significant effect on the break-even point in all cost and location scenarios. A carbon tax can also reduce the payback period, but only if the grid electric mix is relatively low-carbon.

In most cases, installing solar power at chargers will take over seven years to recover costs – which may be prohibitively long for fleet operators. A subsidy for installed solar can make co-located solar more profitable, particularly when combined with a relaxation of weight limits or a carbon tax. A solar subsidy may be preferred over a direct subsidy on electric trucks, since the generated energy will have more direct societal benefits.

Limitations of the study

Our model makes some simplifying assumptions about freight dispatch, which we believe do not significantly degrade the conclusions of this study. Most significantly, we do not consider drivers' specific schedules, but rather assume that there will always be a driver available to complete the truck route. We also do not consider power system constraints regarding the use of electricity or installation of chargers, but rather use average costs. Both of these could increase costs in the electrified scenario, although these costs are presently non-dominant, suggesting the effect would be small.

Another limitation of the case study relates to the implementation of the payback period, as we do not consider a discount rate or an interest rate corresponding to inflation, which could slightly affect the economics of the problem. We chose to consider this simplified problem as inflation and financing costs counteract to some extent, and add additional parameters to the analysis, which can confuse the findings. These assumptions should not significantly affect the comparison between diesel and electric trucks, but can affect the absolute values of costs.

Finally, our analysis is purely economic and entirely from the perspective of the fleet operator. The model presented in this paper does not address environmental factors or include environmental objectives, such as minimizing carbon emissions, in the formulation. There are other factors which must be considered, including grid operating costs[33,34] and human health related to air pollution[35].

METHODS

The proposed model consists of three main components: transportation and supply chains, covering the movement of goods, fleet operations, including both diesel and electric trucks, and logistics planning; energy systems, integrating renewable and non-renewable generation with associated infrastructure components such as solar installations, battery storage, and charging facilities which account for electricity pricing structure and system costs; and battery swapping, which represents an alternative to conventional charging for electric fleets.

Nomenclature

Symbol	**Description**	**Unit**
Indices and Sets		
i, j	Locations in the supply chain network	–
$h \in \{\text{private}, \text{public}\}$	Charging infrastructure type	–
$k \in \{\text{elec}, \text{diesel}\}$	Truck type (electric or diesel)	–
N_t	Total number of time steps	–
t	Time index	–
Parameters and Decision Variables		
c^{batt}	Battery cost	\$/battery
c_k^{cap}	Truck capital cost	\$/truck
c^{charger}	Charger cost	\$/charger
c_k^{carbon}	Carbon penalty	\$/gallon or \$/kWh
c_i^{demand}	Demand charge at location i	\$/kW
c^{diesel}	Diesel fuel cost	\$/gallon
c^{driver}	Driver cost	\$/mile
c_k^{m}	Maintenance cost per mile	\$/mile
c^{space}	Warehouse space cost	\$/unit
c^{solar}	Solar installation cost	\$/kW
$c_{\text{elec}}^{\text{sub}}$	Electric truck subsidy	\$/truck

Symbol	Description	Unit
$c_{\text{solar}}^{\text{sub}}$	Solar subsidy	\$/kW
c^{unmet}	Unmet demand penalty	\$/kg
$d_{i,j}$	Distance between locations i and j	miles
$E_{i,j}$	Energy consumption between locations i and j	kWh
$L_{i,j,k}^{(t)}$	Load transported from i to j by truck type k at time t	kg
h_i	Peak nonrenewable demand at location i	kW
p_c^{max}	Maximum charging rate per charger	kW
$p_i^{(t)}, p_{i,h}^{(t)}$	Power purchased at location i by infrastructure type h	kW
$p_{i,\text{curt}}^{(t)}$	Curtailed power at location i, t	kW
$P_{i,\text{private}}^{(t)}$	Time-of-use electricity price for private charging infrastructure	\$/kWh
$P_{i,\text{public}}$	Constant electricity price for public charging infrastructure	\$/kWh
P_i^{fic}	Feed-in compensation rate	\$/kWh
q_i	Unmet demand at location i	kg
$r_i^{(t)}$	Solar capacity factor at location i, t	–
$x_i^{(t)}$	Inventory at location i, t	kg
$y_{i,j,k}^{(t)}$	Trucks traveling from i to j of type k	trucks
$z_{i,h}^{(t)}$	Non-renewable power at location i by infrastructure type h	kW
$C_i^{(t)}$	Cumulative battery charge at location i, t	kWh
N_i^{batt}	Number of batteries at location i	units
N_i^{charger}	Number of chargers at location i	units
S_i	Solar capacity installed at location i	kW
T^{batt}	Battery capacity per electric truck	kWh
$T_{\text{load},k}$	Truck load capacity	kg
W_i	Warehouse capacity at location i	kg
$Y_{i,k}^{(t)}$	Stationary trucks at location i, t	trucks
$\hat{Y}_k$	Total fleet of truck type k	trucks
γ	Fuel consumption rate for diesel trucks	gallons/mile
Δ_t	Time step duration	hours
η_c	Charging efficiency	–
$\tau_{i,j}$	Travel time from location i to j	time steps
θ_k	Empty-weight fraction for truck type k	–
μ	Time to fully charge a battery	hours

Assumptions

Transportation and Supply Chains: The model considers a mixed fleet of electric and diesel freight, with fleet sizes denoted by $\hat{Y}_{\text{diesel}}$ and $\hat{Y}_{\text{electric}}$. A set of operational and economic parameters, including capital costs, maintenance costs, and payload capacity, characterizes each type of truck. Diesel trucks additionally incorporate diesel consumption per mile, whereas electric trucks account for energy consumption in kWh per mile and battery capacity. Trucks are allowed to traverse a set of feasible paths, denoted by ij, which are drawn from a set of all possible routes. At any location i, the number of stationary trucks of each type is represented by $Y_{i,\text{diesel}}^{(t)}$ and $Y_{i,\text{electric}}^{(t)}$. The number of trucks moving of each type along the paths a path ij is denoted by

$y_{i,j,\text{electric}}^{(t)}$ for electric trucks and $y_{i,j,\text{diesel}}^{(t)}$ for diesel trucks. The load transported along each path by each truck type is captured using the variables $L_{i,j,\text{electric}}$ and $L_{i,j,\text{diesel}}$.

Energy Systems: The model accounts for both non-renewable and renewable energy generation. Non-renewable power is sourced from the grid and represented in the model as $z_i^{(t)}$, denoting the amount of non-renewable grid-supplied power at location i and time t in kW. This power can be delivered through either public charging infrastructure, represented by z_{public}, or newly installed infrastructure, z_{private}. In the latter case, the model incorporates the corresponding capital cost for each additional charger installed, N_i^{charger}. Energy obtained from the public and the installed chargers is subject to different energy rates, which vary by location and time-of-use (TOU). Renewable energy from solar generation is also incorporated into the model. In any location i and time t, the renewable energy available depends on the factor of local solar capacity and the installed capacity S_i (in kW). The installation cost of solar capacity is included in the model, but once installed, solar energy is assumed to be free of charge. Furthermore, any excess solar power, $p_{i,\text{curt}}^{(t)}$ at location i and time t can be sold back to the grid at a feed-in-charge rate.

Battery Swapping: In addition to fast-charging infrastructure, the model incorporates an alternative charging mechanism through battery swapping. The approach allows for the installation of a specified number of batteries N_i^{batt} at each location i, allowing trucks to exchange depleted batteries for fully charged ones with minimal downtime.

Model Formulation

The model presented runs over a planning horizon of N_t time steps, each lasting Δ_t hours. The model objective is to minimize the capital and operational costs of the system.

An overview of the objective can be established as:

$$\min \quad N_t \Delta_t (c^{\text{capex}} - c^{\text{subsidy}} + c^{\text{penalty}}) + c^{\text{opex}}$$

where c^{capex} signifies the capital costs levelized over the payback time period in \$/hour, c^{subsidy} signifies the subsidy savings levelized over the payback time period in \$/hour, c^{penalty} signifies the carbon penalties levelized over the payback time period in \$/hour, and c^{opex} signifies the operational costs over the planning horizon in dollars (\$).

In the model, the capital cost considers the purchase of diesel and electric trucks, warehouses for finished products, the cost of batteries for battery swapping, the cost for newly installed charging infrastructure, and the cost for solar capacity installed. It can be expressed as:

$$c^{\text{capex}} = \sum_k c_k^{\text{cap}} \hat{Y}_k + c^{\text{space}} \sum_i W_i + c^{\text{batt}} \sum_i N_i^{\text{batt}} + c^{\text{charger}} \sum_i N_i^{\text{charger}} + c^{\text{solar}} \sum_i S_i$$

where $c_{\text{elec}}^{\text{cap}}$, $c_{\text{diesel}}^{\text{cap}}$, c^{space}, c^{batt}, c^{space}, c^{charger}, and c^{solar} is the cost per unit of electric trucks, diesel trucks, warehouse space, chargers and solar. $\hat{Y}_{\text{elec}}$ and $\hat{Y}_{\text{diesel}}$ give the total number of diesel and electric trucks in the fleet, W_i is the maximum warehouse capacity at location i, N_i^{batt} is the number of batteries at location i used for battery swapping, N_i^{charger} is the number of chargers at each location i, and S_i is the maximum solar capacity in kW.

The operational cost of the model accounts for energy consumption, vehicle operation, diesel fuel, and unmet demand penalty. It is expressed as:

$$
\begin{aligned}
c^{\text{opex}} = \Delta_t \sum_{i,t} P^{(t)}_{i,\text{private}} z^{(t)}_{i,\text{private}} + \sum_{i} c^{\text{demand}}_i h_i \\
+ \Delta_t \sum_{i,t} P_{i,\text{public}}\, z^{(t)}_{i,\text{public}} - \Delta_t \sum_{i,t} P^{\text{fic}}_i\, p^{(t)}_{i,\text{curt}} \\
+ (c^{\text{driver}} + c^{\text{m}}_{\text{elec}}) \sum_{i,j,t} d_{i,j}\, y^{(t)}_{i,j,\text{elec}} + (c^{\text{driver}} + c^{\text{m}}_{\text{diesel}}) \sum_{i,j,t} d_{i,j}\, y^{(t)}_{i,j,\text{diesel}} \\
+ c^{\text{diesel}} \sum_{i,j,t} \gamma d_{i,j} \left[\theta_{\text{diesel}}\, y^{(t)}_{i,j,\text{diesel}} + \frac{1-\theta_{\text{diesel}}}{T_{\text{load,diesel}}} L^{(t)}_{i,j,\text{diesel}} \right] \\
+ c^{\text{unmet}} \sum_{i} q_i
\end{aligned}
$$

The operational cost of the model accounts for energy consumption from either public or newly installed private charging infrastructure, vehicle operation, diesel fuel, and unmet demand penalties. Energy consumed from public infrastructure is billed at a flat rate of $P_{i,\text{public}}$ (\$/kWh), while newly installed private infrastructure is subject to a time-of-use energy price $P^{(t)}_{i,\text{private}}$ (\$/kWh). In both cases, the power drawn (kW) is multiplied by the time step duration Δ_t (hours) to convert to energy consumed (kWh). Private infrastructure additionally incurs a demand charge c^{demand}_i (\$/kW) applied to the peak nonrenewable power demand h_i (kW), where $z^{(t)}_{i,\text{private}} \leq h_i$ for all t. Any excess solar energy curtailed, $p^{(t)}_{i,\text{curt}}$ (kW), can be sold back to the grid at a feed-in compensation rate P^{fic}_i (\$/kWh), and is similarly multiplied by Δ_t to obtain the energy credited. Vehicle-related costs include a per-mile maintenance cost for electric and diesel trucks, $c^{\text{m}}_{\text{elec}}$ and $c^{\text{m}}_{\text{diesel}}$ (\$/mile), and a driver cost c^{driver} (\$/mile), each applied to the total miles traveled. Diesel fuel costs are determined by the diesel price c^{diesel} (\$/gallon). Fuel consumption between locations i and j is modeled as a linear function of distance $d_{i,j} \cdot \gamma$, where γ is the fuel consumption rate (gallons/mile). Consumption depends on truck weight via the empty-weight fraction θ_{diesel}, defined as $\frac{T_{w,\text{diesel}}}{T_{w,\text{diesel}}+T_{\text{load,diesel}}}$, where $T_{w,\text{diesel}}$ (kg) is the empty truck weight and $T_{\text{load,diesel}}$ (kg) is the full load capacity. The additional fuel consumed to carry a payload is scaled by the fraction of load carried relative to full capacity, where $L^{(t)}_{i,j,\text{diesel}}$ (kg) is the load transported along route i, j at time t. Finally, any unmet demand q_i (kg) across all locations incurs a penalty cost of c^{unmet} (\$/kg).

The policy cost structure distinguishes between two components: subsidies that reduce the operator's effective costs and carbon penalties that internalize environmental externalities. The subsidy component is expressed as:

$$
c^{\text{subsidy}} = c^{\text{sub}}_{\text{elec}} \hat{Y}_{\text{elec}} + c^{\text{sub}}_{\text{solar}} \sum_{i} S_i
$$

where $c^{\text{sub}}_{\text{elec}}$ represents the government subsidy provided to reduce the effective purchase cost of electric trucks, and $c^{\text{sub}}_{\text{solar}}$ denotes the subsidy applied to installed solar capacity. The carbon penalty component is expressed as:

$$
c^{\text{penalty}} = \Delta_t\, c^{\text{carbon}}_{\text{elec}} \sum_{i,t} z^{(t)}_{i,\text{private}} + c^{\text{carbon}}_{\text{diesel}} \sum_{i,j,t} \gamma d_{i,j} \left[\theta_{\text{diesel}}\, y^{(t)}_{i,j,\text{diesel}} + \frac{1-\theta_{\text{diesel}}}{T_{\text{load,diesel}}} L^{(t)}_{i,j,\text{diesel}} \right]
$$

where $c^{\text{carbon}}_{\text{elec}}$ captures the carbon penalty for electricity, combining the carbon intensity (kg CO_2 per kWh) with a carbon tax (\$/kg CO_2). The $c^{\text{carbon}}_{\text{diesel}}$ is the carbon penalty applied to diesel consumption, combining the carbon intensity of diesel (kg CO_2 per gallon) with the same carbon tax and applying it to total gallons consumed. Both terms enter the objective function in opposite directions: c^{subsidy} reduces the operator's total cost, while c^{penalty} increases it.

We divide the constraints into two categories: supply chain constraints, which govern fleet movement, storage, and freight flows; and energy system constraints, which is made up off battery, charging, solar, and power balance. Some of these restrictions are introduced as simplified versions in[36].

To begin with, we present the supply chain constraints. Equation

$$Y_{i,k}^{(t)} - Y_{i,k}^{(t-1)} = \sum_j y_{j,i,k}^{(t-\tau_{j,i})} - \sum_j y_{i,j,k}^{(t)}$$

is a truck balance constraint that ensures the number of stationary electric or diesel trucks of type k at location i and time t equals the number of stationary trucks at time $t-1$, plus the number of trucks arriving at location i from any location j where the travel-time lag $\tau_{j,i}$ (time steps) accounts for the time required to traverse route j, i minus the number of trucks departing from location i to any location j at time t. Equation

$$x_i^{(t)} - x_i^{(t-1)} \leq q_i^{(t)} + \sum_j L_{j,i,\text{elec}}^{(t)} - \sum_j L_{i,j,\text{elec}}^{(t)} + \sum_j L_{j,i,\text{diesel}}^{(t)} - \sum_j L_{i,j,\text{diesel}}^{(t)}$$

ensures that the quantity of finished product stored at time t and location i equals the quantity at time $t-1$ and location i, adjusted simultaneously for the net injection or removal of product (with q positive for imports and negative for demands) and the net product flows via electric and diesel trucks between locations, where L represents the load carried by trucks of type k from location i to j at time t in kg.

Equation

$$\sum_i Y_{i,k}^{(t)} + \sum_{i,j} \sum_{\tau=0}^{\tau_{i,j}} y_{i,j,k}^{(t-\tau)} \leq \hat{Y}_k \quad \forall\, t, k$$

ensures that the total number of stationary trucks of type k across all locations plus all trucks of type k currently in transit between any pair of locations i, j, accounting for every time step τ of their journey from departure up to the full travel time $\tau_{i,j}$, does not exceed the total available fleet size $\hat{Y}_k$ at any time t. This formulation correctly reflects that a truck dispatched at time $t-\tau$ and traveling a route of duration $\tau_{i,j}$ time steps remains unavailable for redeployment until it arrives at its destination. Equation $x_i^{(t)} \leq W_i$ limits the amount of finished product being stored at time t and location i to be less than the warehouse capacity, W, at location i. Equation $L_{i,j,k}^{(t)} \leq T_{\text{load},k} \cdot y_{i,j,k}^{(t)}$ for all location i, time t, and vehicle type k bounds the quantity of product transported by electric or diesel trucks from location i to location j at time t does not exceed the load-carrying capacity of each truck type multiplied by the number of trucks traveling from location i to location j at that time. When the electric truck's weight limit is relaxed, the load-carrying capacity is correspondingly increased. Equation $x_i^{(0)} = x_i^{(T)}$ is a boundary constraint that ensures the quantity of product at time 0 equals the quantity at the final time period T, guaranteeing that no additional or missing product accumulates in the system.

Now we break down the energy system constraints. Equation

$$C_i^{(t)} - C_i^{(t-1)} = \eta_c \cdot p_i^{(t)} \cdot \Delta_t - \sum_j E_{i,j} \left(\theta_{\text{elec}} y_{i,j,\text{elec}}^{(t)} + \frac{1-\theta_{\text{elec}}}{T_{\text{load,elec}}} L_{i,j,\text{elec}}^{(t)} \right)$$

ensures that the cumulative charge of electric vehicles at location i and time t equals the cumulative charge at time $t-1$, plus the energy added through charging (accounting for charging efficiency) over the duration of a single time step, Δ_t, minus the energy consumed by trucks traveling from location i to any location j. This consumption accounts for both the energy required to move the empty portion of the truck, scaled by the fraction of the truck's weight that is empty relative to its total loaded weight, and the energy required to move the truck's load, scaled by the fraction of the truck's load weight relative to the full load capacity of an electric truck and multiplied by the amount of product transported from i to j at time t.

Equation

$$C_i^{(t)} - C_i^{(t-1)} \leq \frac{\eta_c \cdot \Delta_t}{\mu} T^{\text{batt}} Y_{i,\text{electric}}^{(t-1)}$$

also ensures that the change in cumulative charge between time $t-1$ and t does not exceed the total battery capacity of the electric trucks, T^{batt}, taking into account the number of electric trucks at location i at time $t-1$, the charging efficiency, the hours required to fully charge each truck, and the duration of a single time step.

Equation $C_i^{(t)} \leq (Y_{i,\text{elec}}^{(t)} + N_i^{\text{batt}}) \cdot T^{\text{batt}}$ requires that the cumulative charge in location i and time t does not exceed the total available energy capacity, given by the count of the electric truck and the additional batteries in location i, each scaled by the battery capacity (assuming that the battery and truck capacity are identical).

Moreover, to charge the trucks, we can use either the current charging infrastructure or the chargers installed in the system. Equation $p_i^{(t)} = p_{i,\text{private}}^{(t)} + p_{i,\text{public}}^{(t)}$ shows that the purchased power at location i and time t is equal to the amount of purchased power from newly installed chargers, $p_{private}$, and from public chargers,p_{public}, at location i. Equation $z_i^{(t)} = z_{i,\text{private}}^{(t)} + z_{i,\text{public}}^{(t)}$ ensures that the total amount of non-renewable power available at location i and t is equal to the available non-renewable power from the newly installed chargers, $z_{private}$, plus that from the public infrastructure z_{public}. Equation $p_{i,\text{public}}^{(t)} \leq z_{i,\text{public}}^{(t)}$ ensures that the amount of purchased power from the public infrastructure does not exceed the total non-renewable power available from that infrastructure. Equation $p_{i,\text{private}}^{(t)} \leq r_i^{(t)} S_i + z_{i,\text{private}}^{(t)} - p_{i,\text{curt}}^{(t)}$, meanwhile, ensures that the power consumed from the private infrastructure at location i and time t equals the sum of renewable power generated from the installed solar nameplate capacity at location i in kW, S, multiplied by the solar capacity factor at location i and time t, and the non-renewable power available from newly installed chargers, minus the amount of energy curtailed, $p_{i,\text{curt}}^{(t)}$, at time i and location i. Equation $p_{i,\text{private}}^{(t)} \leq N_i^{\text{charger}} \cdot p_c^{max}$ ensures that the power consumed at location i from newly installed chargers does not exceed the total available charging capacity, given the number of installed chargers, N^{charge}, multiplied by their maximum charging rate, p_c^{max}.

Equation $S_i \leq N_i^{\text{charger}} \cdot p_c^{max}$ ensures that the installed solar capacity at location i does not exceed the number of chargers at location i multiplied by the maximum charging speed per charger. The constraint is a proxy for the interconnection limit, allowing us to avoid including a connection cost as long as the amount of solar capacity remains below the total charging capacity. Equation $p_{i,\text{curt}}^{(t)} \leq r_i^{(t)} S_i$ restricts the amount of, $p_{i,\text{curt}}^{(t)}$, curtailed power to be less than the renewable generation. Equation $C_i^{(0)} = C_i^{(T)}$ is a boundary constraint requiring that the cumulative charge at location i in time 0 is equal to the cumulative charge in the last time period T. Finally, we have non-negative constraints applied to all decision variables, such as:

$$W_i,\, x_i^{(t)},\, y_{i,j,k}^{(t)},\, L_{i,j,k}^{(t)},\, C_i^{(t)},\, p_i^{(t)},\, N_i^{\text{batt}},\, z_{i,\text{private}}^{(t)},\, z_{i,\text{public}}^{(t)},$$
$$Y_{i,k}^{(t)},\, p_{i,\text{private}}^{(t)},\, p_{i,\text{public}}^{(t)},\, N_i^{\text{charger}},\, S_i,\, p_{i,\text{curt}}^{(t)} \geq 0$$

Model Validation: To provide additional validation of the model, we examine a diesel-only scenario and assess whether the resulting truck utilization levels are realistic. Specifically, we calculate the average monthly mileage per truck by dividing the total fleet miles traveled by the number of trucks in the fleet. This value is then compared against reported utilization figures for heavy-duty Class 8 trucks. According to[37], team-driven trucks, where multiple drivers rotate so that the vehicle can operate nearly continuously, commonly travel between 5,000 and 6,000 miles per week.

For our diesel-only baseline the 782 truck fleet travels a collective 23.1 million miles over the 28 days. This corresponds to around 7,300 miles per truck per week. Our formulation does not include individual drivers' schedules, so it is unsurprising that our truck mileage is higher than the realistic range. However, given the focus of this paper is on the comparison between diesel and electric vehicles, and this assumption affects both fleets, we believe that our model is sufficiently realistic to justify our broad conclusions.

CASE STUDY

As noted previously, the analysis considers 3 distinct geographic networks. Each regional network does not have all city pairs directly connected; however, the network remains fully connected through intermediary links, ensuring feasible freight movement between all locations. The intercity distance between all the cities in the 3 distinct geographic networks were pulled from (Distance Between Cities, 2025)

Set Up and Parameters

Each distinct geographic network features unique localized electricity rate structures, diesel prices, and average vehicle speeds (miles per hour) based on local traffic conditions. Deterministic vehicle speeds were derived from Google Maps travel time estimates between cities, averaged across three time periods representative of morning, afternoon, and evening traffic (8:00 AM, 1:00 PM, and 6:00 PM), and subsequently converted to average travel speeds based on intercity distances.

We optimized to determine the optimal number of mixed-fleet trucks, composed of both electric and diesel vehicles. For diesel trucks, different fuel prices were used per network as shown in the 1st column of Table 2 .

Table 2: Electricity Carbon Intensity and Fuel Costs by City

City	Carbon Intensity (kg CO_2/kWh)	Diesel Cost ($/gallon)
Savannah	0.382	3.468
Houston	0.3329	3.106
Long Beach	0.1944	5.060

Several characteristics distinguish diesel trucks from their electric counterparts. For diesel trucks, we use the Freightliner Cascadia Evolution, which has a fuel efficiency of 10 miles per gallon (Motobiscuit, 2025).

In the case study, two distinct cost scenarios—early adopters and mass production were considered, whose heavy-duty trucks exhibit varying technical characteristics that influence the model outcomes. These differences include capital cost, battery capacity, driving range, and energy consumption per mile in kWh/mile. A detailed breakdown of these characteristics is provided in Table 3 (Motowatt, 2025; Inside EVS, 2025).

Table 3: Electric Truck Specifications by Cost Scenario

Scenario	Capital Cost ($)	Battery Capacity (kWh)	Driving Range (miles)	kWh/mile
Low Cost (Mass Produced)	180,000	900	500	1.70
High Cost (Early Adopters)	270,000	1000	400	2.25

Between electric and diesel trucks, we also accounted for differences in maintenance costs. The maintenance cost for electric trucks is 0.101 $/mile, while for diesel trucks it is 0.601 $/mile (Rizon, 2025). We also considered the differences in vehicle weight. The unloaded electric truck weights 12,000 kg, whereas the unloaded diesel truck weighs 7,938 kg (Next Big Future, 2023. For both diesel and electric trucks, we considered a driver cost of 0.5 $ per mile corresponding to roughly $30/ hr wage and assuming a 60 mph speed (Salary, 2025).

The supply chain framework in the case study considers imported goods delivered across cities within each geographic network, assuming independence between networks. Each city exhibits a monthly demand for the finished product. Details of the demand and other parameters used in this case study are presented in our previous work (Davila Severiano, 2025).

The power systems framework in this case study considers the installation of private chargers, solar panels, and battery systems, each with its own associated capital cost. Chargers also have operational characteristics, including charging efficiency and charging speed, the breakdown of which can be seen in Table 4.

Table 4: Electrification System Parameters

Parameter	Value
Charger Cost (per charger)	$100,000
Annual Charger Maintenance Cost (per charger)	$1,000
Charging Efficiency	0.9
Charging Speed	450 kW
Solar Installation Cost	$3,130 kW
Battery Cost (per battery)	$100,000

Finally, we introduce the parameters used for the policy mechanisms considered in this study. For the carbon penalty, the electricity carbon intensity for each of the geographic networks is shown in the 2nd column of Table 2 and is derived from[38], which reports emission rates for eGRID subregions across the United States. For this analysis, we selected the subregion corresponding to each geographic network: South Electric Reliability Council (SERC) for Savannah, GA; Electric Reliability Council of Texas (ERCT) for Houston, TX; and California-Mexico (CAMX) for Long Beach, CA.

Simulation Environment

The case study was implemented in Python (version 3.10.10) using the packages of CVXPY, NumPy, and Pandas. The model's optimal solution was obtained using Gurobi, a Python-based optimization solver, under an academic license. Initial computations were performed on a Dell XPS 16 Laptop containing the 13th Gen Intel Core i7 processor and 16.0 GB of RAM. To improve computational efficiency, the Phoenix cluster at the Georgia Institute of Technology was employed.

Reducing Complexity

The number of variables and constraints in our problem, as well as the size of the network and planning horizon, led to incredibly long computation time take a long time to run due to its size. To reduce its complexity and allow for more efficient solving, we relaxed all integer variables to be continuous. These variables include those related to the number of trucks, the number of chargers, and the number of batteries to be installed.

Lead contact

Requests for further information and resources should be directed to and will be fulfilled by the lead contact, Rina Davila Severiano (rseveriano3@gatech.edu).

AUTHOR CONTRIBUTIONS

Conceptualization, R.D.S. and C.C.; methodology, R.D.S. and C.C.; investigation, R.D.S. and C.C.; writing-–original draft, R.D.S. and C.C.; writing-–review & editing, R.D.S. and C.C.; funding acquisition, C.C.; resources, C.C; supervision, C.C.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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