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Supplementary material for this article is available [online](#)

Abstract

The urgent need to decarbonize the transportation sector combined with falling battery prices has spurred industry and policy interest in long-haul truck electrification. The charging behavior and resulting loads from electrified long-haul freight trucks are crucial for the smooth operation of the electric grid and have far-reaching environmental impacts (e.g., greenhouse gas and other air pollutant emissions). However, the aggregate energy impact of a fleetwide shift to electrified long-haul freight trucking has not been explored. This study combines electric truck design scenarios, bottom-up truck weight modeling, vehicle energy modeling, large-scale truck traffic data, and simulation of likely operation and charging behaviors to estimate end-use energy consumption and location-specific hourly charging loads for a national fleet of long-haul electric trucks. Relative to a fleet of future diesel trucks, electrification would reduce direct end-use energy consumption by 0.9×10^{18} J (0.9 quadrillion BTU), but electrification might increase life cycle energy consumption depending on the electricity source. The electricity required to charge long-haul electric trucks is equivalent to five percent of annual electricity consumption in the United States (US). The simulated truck charging loads peak during the day across the US grid regions, but the charging peaks' exact timing is sensitive to when trucks are dispatched for operation. The load shapes suggest that electric trucks' charging loads can coincide with peaks in solar power generation, and planning could enable on- or off-site integration between truck charging stations and renewable electricity generation.

1. Introduction

Countries around the world have set up ambitious policy targets to attain carbon neutrality by mid-century (United Nations Environment Programme (UNEP) 2020). The electricity sector has been the focus for decarbonization efforts due to the relatively low cost of decarbonization, which is mainly due to a recent drop in the price of natural gas and the growing economic competitiveness of renewable electricity generation technologies, including wind and solar. The next step is the electrification of important end uses, which makes the transportation sector a prime target due to its large size and reliance on petroleum-derived fuels (International Energy Agency (IEA) 2020a, 2020b). Within the transportation sector, long-haul trucking is recognized as being particularly difficult to decarbonize (Davis *et al* 2018). With about two million drivers employed and 2.9 million heavy-duty trucks registered, the US trucking sector hauls 71% of total freight by payload, 73% by value, and 42% by payload weight-distance (Davis and Boundy 2019, US Bureau of Labor Statistics 2020). Furthermore, heavy-duty trucks (class 7 and 8) consume more than four times the energy used to operate

smaller and lighter trucks (class 3–6 trucks, including those used for the last-mile delivery) (Davis and Boundy 2019). As the most important freight transportation mode, the trucking sector's reliable operation is essential across the supply chain. Meanwhile, trucking is projected to play a more significant role in the economy, which arises from accommodating the rapid growth of e-commerce. Studies project a 70%–100% increase in trucking demand—as measured in terms of payload weight-distance—between the 2010s and 2040s (US Federal Highway Administration (FHWA) 2017, Liu *et al* 2015). Thus, given the growth in this energy-intensive sector, it is crucial to investigate effective and feasible decarbonization strategies.

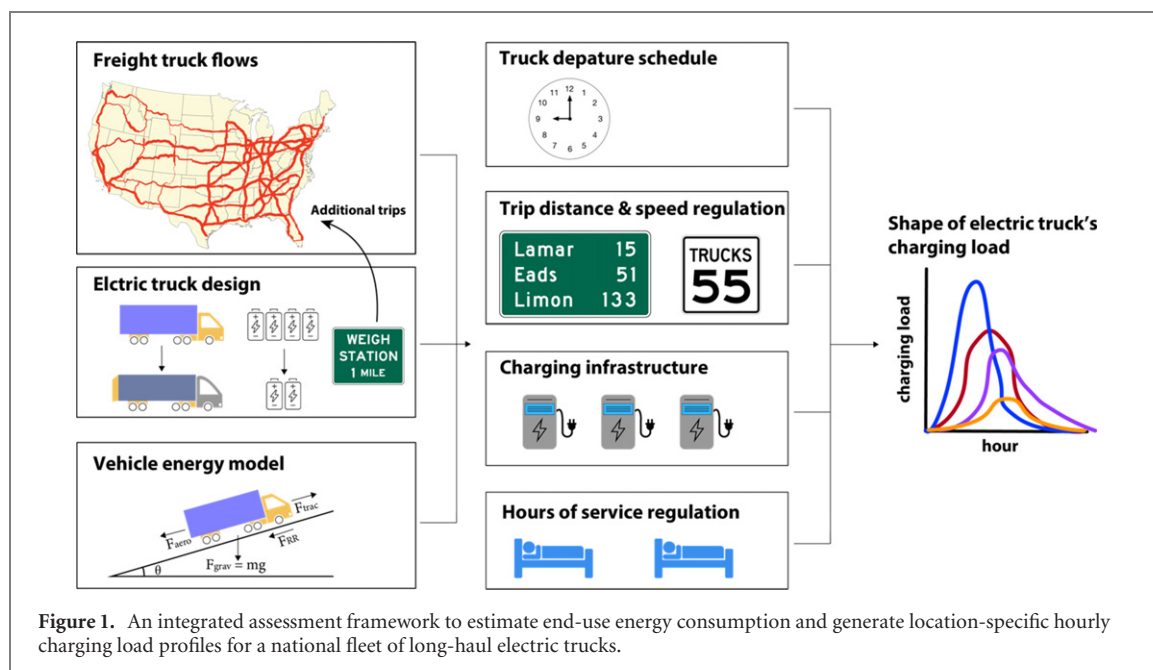
Historically, the trucking industry has not voluntarily adopted new fuels and vehicle technologies (Engineering 2020, Tong *et al* 2019). Incremental improvements to trucking energy use and emissions, such as diesel hybrid-electric technologies and natural gas trucks, which were pursued in periods of high oil prices and low natural gas prices, have limited greenhouse gas (GHG) emissions reduction potential (Tong *et al* 2015). Advanced biofuels, which could reduce the life-cycle carbon footprint by 80% or more (Baral *et al* 2019), face scale-up challenges ranging from long lead times to gain approval for new fuel blends to limited investments in fuel production infrastructure and feedstock crops (Richard 2010, Taptich *et al* 2018). Mode-shifting from truck to rail could decrease GHG emissions as rail is less energy and emissions-intensive than trucking for long-distance bulk freight transport (Zhou *et al* 2017, Kaack *et al* 2018, Taptich and Horvath 2015). However, the role of rail transport has diminished over time in the United States (US) due to congestion along major railroad corridors, and the limited access to the specialized and costly infrastructure required for railroads (e.g., direct-access terminals, railways, and intermodal depots for truck delivery), which play against the speed and flexibility advantages of long-haul trucking (Davis and Boundy 2019).

A promising pathway for freight truck decarbonization is electrification, which includes battery-electric vehicles as well as fuel cell electric vehicles (California Air Resources Board (CARB) 2015, Moultaq *et al* 2017). If electricity or hydrogen are produced using renewable energy (such as wind or solar), vehicle electrification could speed up decarbonization in the transportation sector. Battery-electric vehicles have already become a mainstream technology for light-duty vehicles in Norway; they are the fastest-growing transportation technology in China and the US (Stephens *et al* 2018). While previously considered impractical, heavy-duty vehicle electrification is becoming an increasingly viable approach due to rapidly-falling battery prices and the continued build-out of charging infrastructure—which is still mostly targeted at light-duty electric vehicles (EVs) (ICF 2019, Sharpe *et al* 2020). Some of the largest fleet operators, such as Walmart and Amazon, have ordered battery-electric trucks of all sizes from truck manufacturers (e.g., Tesla, Rivian, Volvo, and Cummins) (Hall and Lutsey 2019). In the meantime, policymakers are attempting to accelerate this electrification trend. The US federal government has recently announced a plan to shift its vehicle fleet to fully battery-electric vehicles (Kaplan 2021). California enacted Advanced Clean Truck regulation, which requires significant sales of zero-emissions trucks starting in 2024 (California Air Resources Board (CARB) 2020).

Recent research has shown that battery-electric trucks could soon reach performance that would make them viable for mass adoption (in terms of payload and driving range) based on projected battery technology improvements (i.e., higher battery specific energy) and aerodynamic truck design (Sripad and Viswanathan 2017, Guttenberg *et al* 2017, Sripad and Viswanathan 2019, Phadke *et al* 2019, Hovi *et al* 2020). Furthermore, vehicle automation technologies (such as truck platooning) could further reduce electric trucks' energy consumption and improve battery lifetime (Guttenberg *et al* 2017). Electric trucks' economic competitiveness depends on the trade-off between the higher upfront purchasing cost and reduced operating cost (ICF 2019, Burke and Miller 2020). Sripad and Viswanathan (2019) quantified the likely ranges for prices of electricity and batteries, battery lifetimes, as well as vehicle drag coefficients so that electric trucks have a 5 years payback period relative to the purchase of new diesel trucks (Sripad and Viswanathan 2019). As electricity rate structures are crucial drivers of electric trucks' operating costs, Phadke *et al* proposed reforms of electricity rate structures in order to incentivize further adoption of electric trucks (Phadke *et al* 2019).

Shifting from diesel trucks to battery-electric trucks adds significant energy demand to the electricity sector. Yet, little is known about how truck flows and driving schedules impact this demand and hence the grid via charging loads. As highlighted by prior research, the shape of EVs' charging loads not only characterizes the energy needs of vehicle electrification for the electric power grid but also influences the economic and environmental impacts of vehicle electrification (Muratori *et al* 2019, Tong and Azevedo 2020, Muratori and Mai 2020, Coignard *et al* 2018, Tong *et al* 2021).

In contrast to the rich literature on light-duty EVs, the potential load shapes of electric trucks charging in aggregates remain unexplored, in part because detailed data on commercial truck trips are notoriously difficult to obtain. As a result, prior truck electrification studies have used total charging load from an assumed simple use case of electric trucks instead of a detailed hourly load profile (Sripad and Viswanathan 2017, Guttenberg *et al* 2017, Sripad and Viswanathan 2019, Phadke *et al* 2019). The coarse temporal resolution of electric trucks' charging load limits the economic and environmental analysis on truck electrification since the dispatch of the electric power grid occurs on a much shorter timescale (i.e., minutes). Furthermore, the studies mentioned



above did not account for real-world factors (e.g., truck speed, payload, road grade) in truck operation, which could have a significant effect on energy consumption, charging needs, and engineering designs for electric trucks (Reyna *et al* 2015, Smith *et al* 2019). A more recent study by Tong *et al* did account for some of these real-world complexities, but its focus was on the estimation of local human health impacts and monetized climate damages rather than the energy impacts and the electricity load shapes (Tong *et al* 2021).

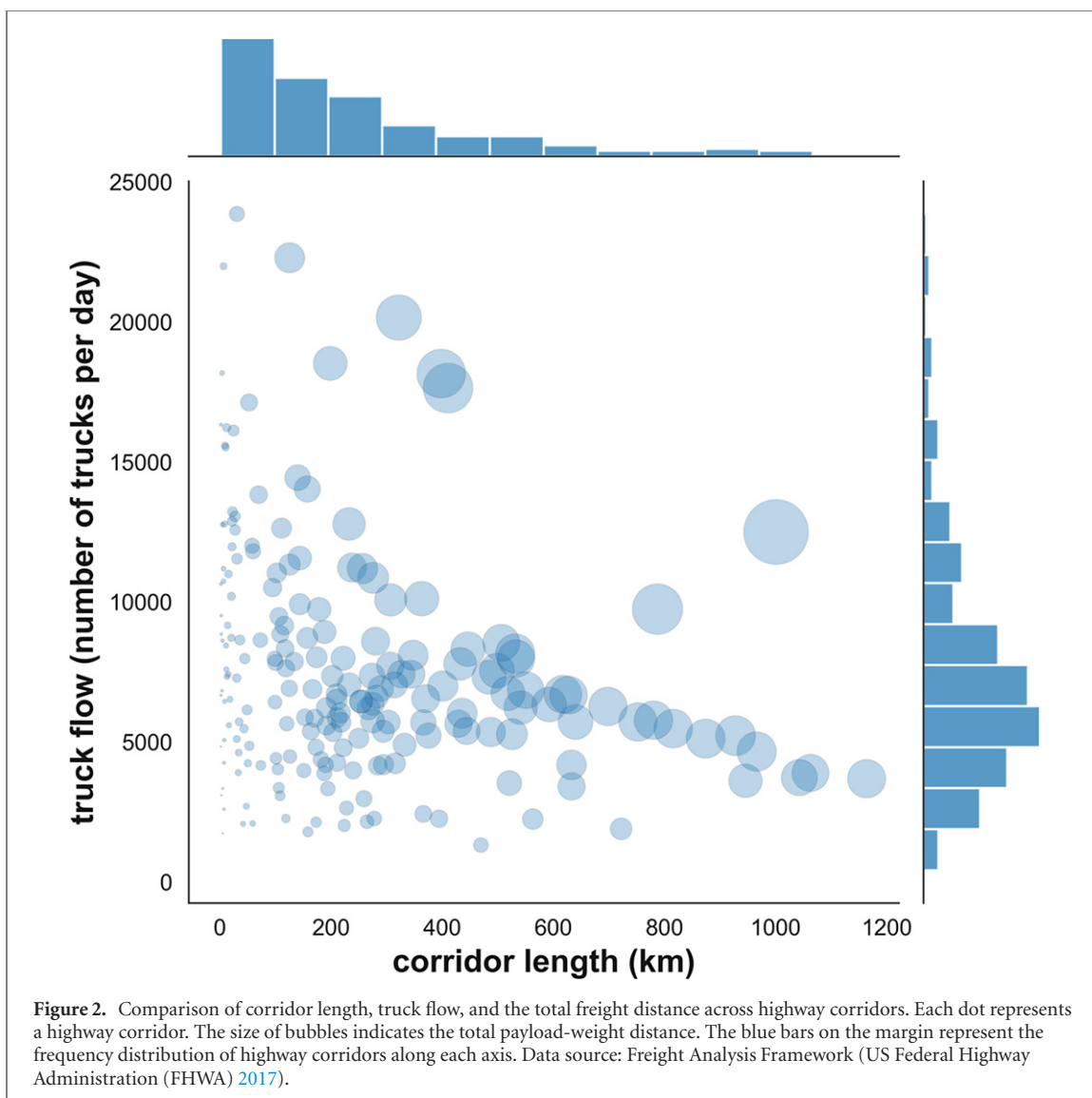
To fill this knowledge gap, we combine electric truck design, bottom-up truck weight modeling, vehicle energy modeling, large-scale truck traffic data, and simulation of electric truck operation as well as charging behavior to estimate energy consumption and location-specific hourly charging loads for a national fleet of long-haul electric trucks. Our modeling framework is based on the assumption that electric trucks must deliver the same level of freight service as current diesel trucks despite technological disadvantages such as shorter range, longer charging time, and lower payload-carrying capacity. The modeling framework presented here is open-source, flexible, and scalable, allowing quick updates to simulate the rapidly-changing reality given the profound uncertainty of technology development and technology adoption (Tong *et al* 2021).

2. Methods

We developed an integrated assessment framework to estimate the end-use energy consumption and location-specific hourly charging load profiles for a national fleet of long-haul electric trucks. The modeling of charging behavior and quantification of the resulting charging loads is critical for the planning and operation of the electric grid and associated charging infrastructure, both of which are essential for the successful transition to electrified trucking at scale. In this work, long-haul freight trucks refer to heavy-duty freight trucks that operate on the national highway network (figure 1 top-left panel) and serve locations at least 50 miles apart, yet excluding trucks that are part of a multi-mode system (e.g., freight-rail-freight) (US Federal Highway Administration (FHWA) 2017). As shown in figure 1, the framework considers long-haul truck flows (in 2012, the most recent year) (US Federal Highway Administration (FHWA) 2017), electric truck design, a vehicle energy model, the truck departure schedule, truck speed regulation, charging infrastructure, as well as hours of service regulation. The truck flow data have a spatial resolution of 1 km. We simulated truck activities (including driving, charging, and idling) at a temporal resolution of 1 min to derive hourly charging load profiles at pre-determined charging stations. Although we present and discuss load profiles for a 100% electrification scenario across the US, our framework can generate load profiles for any adoption level of electric trucks on some or all highways in the US.

2.1. Freight demand model

We used the highway assignment database in the Freight Analysis Framework (FAF; v4.3) to model freight demand (US Federal Highway Administration (FHWA) 2017). The FAF database estimates freight flows between 137 zones in the US based on the commodity flow survey as well as trade and shipping data. It then allocates freight flows to (diesel) long-haul trucks using a traffic assignment model accounting for dead-head



miles (when the trailer is empty). The FAF database presents a snapshot of daily-average long-haul truck operation (such as truck flow, payload) as well as road infrastructure (such as speed limit, road grade) for 2012 (the most recent data year). The FAF database projects freight trucking demand in 2045 based on the 2012 estimates by extrapolation of economic growth. On average, trucking demand in 2045 is projected to be 70% higher than that in 2012 (figure S2 in the supporting information (<https://stacks.iop.org/ERIS/1/025007/mmedia>)). The increase in freight trucking demand is consistent across all highways studied. We chose to use the actual trucking demand in 2012 to avoid additional uncertainty, but our estimates can be easily updated to reflect the projected trucking demand in 2045.

We transformed the FAF database into an origin-and-destination database following (Tong *et al* 2019). We assumed that freight is carried by long-haul trucks in a series of connecting corridors. In each corridor, long-haul trucks operate in a hub-and-spoke manner (i.e., move cargo from one end of a corridor to another end). We assumed that each freight shipment originates and ends at an endpoint of these corridors, so we do not have to model shipments that are moved partially in any corridor. Long-haul trucks operating in different corridors were assumed to be temporally independent. Thus, trucks in one corridor do not wait for trucks from a connecting corridor, even if they carry the same cargo. This is a simplification, but we do not believe it would lead to substantial bias in our first-order estimates. However, the future availability of container-level freight data will allow for more detailed modeling of infrastructure prioritization for truck electrification.

We use a subset of the national highway network, shown in the top-left panel of figure 1. The selection criteria include (1) national coverage, (2) connection to major cities and freight centers, and (3) ranking of highways by truck traffic. The selected highway network consists of 131 intersections (usually cities) and 200 corridors covering a total road distance of 48 192 km. Of the 200 corridors, 154 corridors are long-distance corridors that connect two different cities or townships, and the remaining 46 are urban corridors, whose lengths

Table 1. Electric truck design scenarios and parameters.

Technology scenario		Pessimistic	Base-case	Optimistic
Long-haul trucks				
Equivalent frontal area (m ²)		5.95	5.4	4.9
Rolling resistance		6.4725/1000	5.5725/1000	4.8575/1000
Empty vehicle weight ^a (kg [lb])	Diesel tractor	8618 [19 000]	7756 [17 100]	6895 [15 200]
	Trailer	6123 [13 500]	5511 [12 150]	4899 [10 800]
Battery technology^b				
Specific energy (W h kg ⁻¹)	Cell	250	343	400
	Pack	160	240	320
Pack factor		64%	70%	80%

^aValues in US conventional units are listed after the SI unit values and are in the bracket.

^bPack-level specific energy is used in the analysis. The set of cell-level specific energy and pack factor illustrates a possibility to realize the assumed values.

Table 2. Diesel truck design scenarios and parameters.

Technology scenario		Current design	Incremental design	Advanced design
Long-haul trucks				
Equivalent frontal area (m ²)		5.95	5.4	4.9
Rolling resistance		6.4725/1000	5.5725/1000	4.8575/1000
Empty vehicle weight ^a (kg [lb])	Diesel tractor	8618 [19 000]	7756 [17 100]	6895 [15 200]
	Trailer	6123 [13 500]	5511 [12 150]	4899 [10 800]

^aValues in US conventional units are listed after the SI unit values and are in the bracket.

are less than 20 miles and part of urban highway. We find substantial heterogeneity in corridor length and truck traffic due to divergent social-economic factors, geographic conditions, and build-out of road infrastructure (figure 2).

2.2. Vehicle energy model

We estimated the specific energy consumption of diesel trucks (as the benchmark) and electric trucks based on a standard vehicle powertrain model (Sripad and Viswanathan 2017). Modeling detail is available in the supporting information (S.I.). The vehicle energy model calculates the tractive energy needed to overcome the aerodynamic drag and rolling frictional forces as well as gravity. Road-level energy consumption is computed using the modeled truck speed (determined by the truck speed limit and road grade), truck weight, and road grade from the FAF database. We assumed a standard drive cycle, CARB HHDDT cycle's 'cruise and composite' segment (National Renewable Energy Laboratory (NREL) 2019), due to the lack of availability of real-world second-by-second drive cycle data. We did not consider regenerative braking in our model, which may result in underestimates of energy efficiency for electric trucks and should be explored in future work. This choice was made as the impact of regenerative braking depends on the design strategy and control algorithm implemented by individual truck manufacturers. However, since long-haul trucks operate mainly in high-speed cruise mode, the modeling choice of excluding regenerative braking likely has limited impact on the estimated aggregate energy impact of electrifying long-haul trucks. It is notable that our model does not include the effect of congestion on truck energy use which, if included, would exacerbate the impact of excluding regenerative braking. Finally, we assumed typical weather and excluded the impacts of extreme weather, which is known to adversely affect the performance and lifetime of EVs (Yuksel and Michalek 2015).

2.3. Electric truck design

The baseline long-haul truck in our model is a high-roof tractor with a box trailer, which is the current prevalent configuration on the road (US Environmental Protection Agency (EPA) 2016). The truck design parameters include the equivalent frontal area, rolling resistance coefficient, and gross vehicle weight. As shown in table 1, we modeled three vehicle design scenarios: base-case, pessimistic, and optimistic, derived from the regulatory impact assessment for trucks' fuel efficiency standards (US Environmental Protection Agency (EPA) 2016).

Electric trucks are assumed to have a 1 or 2 MW h battery. The pessimistic pack-level specific energy is 160 W h kg⁻¹, the same as Tesla model 3 (Field 2019). We assumed the base-case pack-level specific energy increases by 50%, from 160 W h kg⁻¹ to 240 W h kg⁻¹ (USDRIIVE 2017). Finally, the optimistic pack-level specific energy doubles to 320 W h kg⁻¹, assuming a battery technology breakthrough (beyond lithium-ion technologies) (Sripad and Viswanathan 2017). The purpose of these scenarios is to illustrate the potential

outcomes of battery technology developments such as new materials, manufacturing advances, and increased packing efficiency, and further discussed in (Tong *et al* 2021).

2.4. Diesel truck design

We also modeled one type of current and two types of future diesel trucks (incremental-design and advanced-design) to provide a fairer counterfactual comparison relative to future electric trucks. The design parameters of diesel trucks include the equivalent frontal area, rolling resistance, and empty vehicle weight (table 2). To ease comparison, diesel trucks' design parameters are aligned with those of electric trucks.

2.5. Bottom-up truck weight model

An empty electric truck's weight is calculated as the weight of an empty diesel truck plus the weight of components unique to electric trucks (i.e., battery and electric motors) minus the weight of components unique to diesel trucks (i.e., diesel engine, fuel tank, and pollution control devices) (refer to S.I. for detailed assumptions). A long-haul truck's empty weight is the sum of a tractor's weight and an empty trailer's weight. The maximum payload is the difference between the federal gross vehicle weight (GVW) limit (80 000 short tons in the US) and an empty tractor-trailer's weight.

2.6. Electric truck flow and payload by highway corridor

To estimate truck flows and payloads for electric trucks across the highway network, we first calculated diesel trucks' payload on each highway corridor from the transformed FAF database. Then, for any corridor, if diesel trucks' payload is no greater than the maximum payload of electric trucks, the number of electric trucks is assumed to be the same as diesel trucks. Otherwise, we calculated the number of electric trucks loaded to the federal GVW limit to carry the same freight as diesel trucks. This calculation allows for additional truck trips to compensate for electric trucks' lower payload-carrying capacity. We assumed that extra electric trucks are readily available to meet this demand for additional trips.

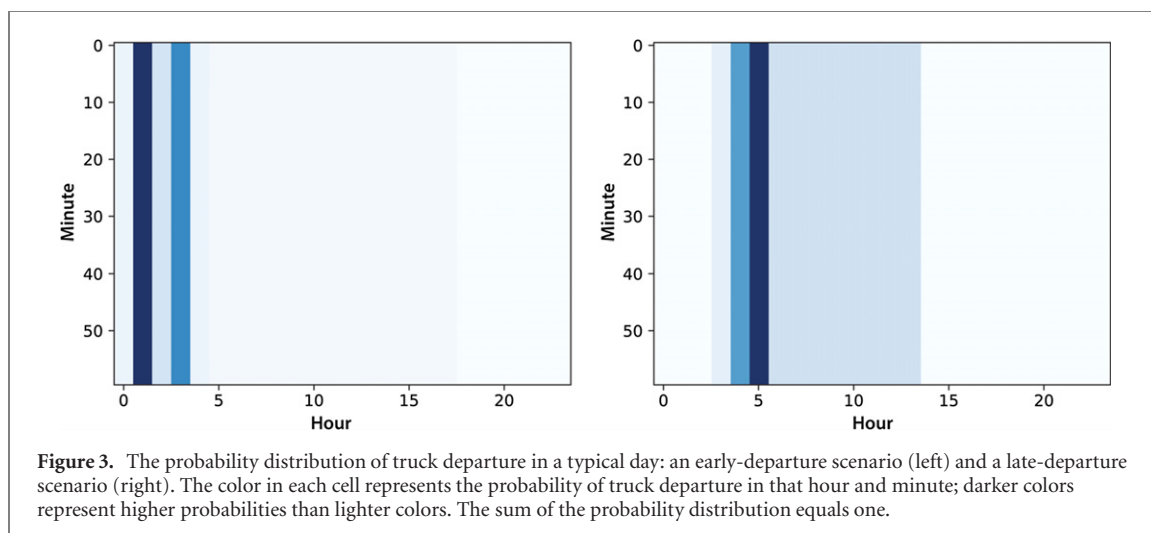
2.7. Electric truck charging infrastructure

The goal of the truck charging simulation was not to predict optimal charging station locations along key corridors but rather to develop a simplified model of charging behavior that would result in realistic hourly load curves in each grid region. We modeled vehicle charging behavior such that no detours or waiting are required to charge trucks. Ensuring adequate infrastructure to support this idealized assumption has an economic impact, but these costs are beyond the scope of this study. Electric trucks stop and charge at charging stations that they encounter from the trip origin to the destination. In terms of charging station locations, we considered a heuristics-based planning strategy for charging infrastructure, which simulates the real-world distribution of refueling stations driven by market competition (Tong *et al* 2019). Charging stations are always located at highway intersections (endpoints of highway corridors) and, when necessary, are installed along highway corridors to cover electric trucks' trips. The number and locations of charging stops within any highway corridor are determined using the trip energy consumption (outputs from the freight demand model and the vehicle energy model) and allowable battery capacity (85% of battery's state of charge (SOC)). For simplicity, charging stations are sized to meet the peak charging need (meaning charging station sizing is never the limiting factor for truck charging power in our model). Finally, we assumed that charging infrastructure planning is optimized for either 1 MW h or 2 MW h electric trucks. We did not run any blended scenarios in which both 1 MW h and 2 MW h electric trucks coexist.

As an example of our approach, consider a hypothetical scenario in which a fleet of 1 MW h electric trucks moves freight across a 1000 km highway corridor. The vehicle energy model first calculates the specific energy consumption using truck characteristics as well as the road grade and speed limit; the result for this hypothetical corridor is 1.7 kW h per km. The model then calculates the range of the 1 MW h and 2 MW h electric trucks as 500 km and 1000 km (assuming 85% battery SOC). For 1 MW h electric trucks, the charging infrastructure model 'builds' two charging stations at the trip origin and the trip destination (i.e., highway intersections) and one charging station in the middle of the highway corridor, or 500 km away from the trip origin. However, for 2 MW h electric trucks, the charging infrastructure model 'builds' only two charging stations at the trip origin and the trip destination. In reality, more charging stations would be built than this idealized scenario, but this is assumed to have a minimal impact on the total load curves for each grid region, as the spatial distribution of overall energy demand does not change significantly.

2.8. Electric truck charging behavior

We assumed that electric trucks are fully charged (as a result of off-duty charging) after drivers' off-duty rest (≥ 8 h). Once dispatched, electric trucks are driven to the trip destination, and the trip time is determined by the local speed limits as well as road conditions and characteristics. We assumed that when electric trucks



encounter charging stations, they will always make a stop to charge, regardless of their estimated state of charge. Because the planning of the charging infrastructure considers the trip energy consumption of electric trucks with perfect foresight, electric trucks make charging stops only when needed in interstate corridors. However, in our simplified model, electric trucks would make additional non-essential charging stops in urban highway corridors. This modeling assumption does not substantially impact total load curves but does slow truck trips in urban areas and may serve as a proxy for congestion, which is not otherwise built into our model. The charging session at the trip destination was assumed to start immediately after arrival. Demand response, load flexibility, or smart charging are not considered but worthy of future investigation.

We explored scenarios with varying charging power, ranging from 0.5 MW to 4 MW for charging en route trips. During the off-duty time, we assume a lower charging power of 150 kW to minimize cost. The charging efficiency is 97% assuming solid-state transformer-based medium-voltage extreme fast charging technology (Srdic and Lukic 2019). This charging technology is more energy-efficient than existing technologies and is expected to be widely available soon (Srdic and Lukic 2019).

2.9. Electric truck travel diary

We generated temporal-spatial profiles (i.e., travel diaries) for long-haul trucks. The travel diary records an electric trucks' activities (e.g., driving, charging, and idling) by time and location. Driving duration is calculated using the distance to the next stop (i.e., charging stops or trip destination) and the truck speed profile. A time zone adjustment is applied when trucks drive across time zones. Charging duration is the ratio between the amount of charged energy and charging power plus a 10 min set-up time (Meintz *et al* 2017). We further constrained long-haul trucks' temporal profile to obey hour-of-service regulations. In any 24 consecutive hours, a driver can only drive up to 11 h and can be on duty for a maximum of 14 h. Furthermore, a mandatory 30 min break is required after 8 h of consecutive driving (US Federal Motor Carrier Safety Administration (FMCSA) 2011).

2.10. Electric truck departure scenario

The starting time in the travel diary is when an electric truck departs from the off-duty location. We assume that off-duty locations are always at highway intersections. We model the temporal distribution of truck departures using a probability distribution over a discrete time grid on a given day (noted as 'truck departure scenario') (figure 3). The first truck departure scenario, based on long-haul (diesel) trucks that operated between Northern California and nearby states in 2015 (July to November, at least three months of data for each truck), has two probability peaks of departure at 1 AM and 3 AM (Boriboonsomsin *et al* 2017). The second scenario has one 5 AM probability peak, based on long-haul (diesel) trucks headquartered in Southern California and operated within California in 2016 (July to August).

2.11. Location-specific load curve

We generated charging load profiles for electric trucks according to their travel diaries. Charging loads from different electric trucks at the same charging stations (determined by a unique set of latitude and longitude) were combined to create location-specific charging load profiles, which can be further aggregated for electric power grid analysis.

Table 3. Annual vehicle distance traveled, annual energy consumption, and fleet-average specific energy consumption of long-haul diesel and electric trucks (that meet the long-haul freight demand in the US in 2012). This table is used to compare the end-use energy consumption between diesel trucks and electric trucks. Life cycle energy consumption needs to account for the energy loss and transport of diesel and electricity, which depends on the electricity generation mix.

Metric	Unit	Diesel truck			Electric truck					
		(Truck design)			(Truck design)					
		Current design	Incremental design	Advanced design	Pessimistic		Base-case		Optimistic	
		N/A			(Battery capacity)					
				1 MW h	2 MW h	1 MW h	2 MW h	1 MW h	2 MW h	
Vehicle distance	billion km		114		121	188	114	126	114	114
End-use energy consumption	TW h		N/A		223 ^b	347 ^b	184 ^b	210 ^b	161 ^b	170 ^b
	billion liters of diesel	49	44	40			N/A			
	EJ (10 ¹⁸ J)	1.9 ^a	1.7 ^a	1.5 ^a	0.8 ^b	1.3 ^b	0.6 ^b	0.7 ^b	0.5 ^b	0.6 ^b
	Quads ^c	1.8 ^a	1.6 ^a	1.4 ^a	0.8 ^b	1.2 ^b	0.6 ^b	0.7 ^b	0.5 ^b	0.6 ^b
Specific energy consumption	kW h km ⁻¹		N/A		1.9	1.9	1.6	1.7	1.4	1.5
	liter/100 km	43	39	35			N/A			
	MJ km ⁻¹	16.6	14.8	13.4	6.7	6.7	5.8	6.0	5.1	5.4

^aThe higher heating value is used to calculate the equivalent energy content for diesel fuel. Energy loss in the refining and transport of diesel is not considered.

^bEnergy loss in the process of electricity generation is not considered. The average energy efficiency of operating coal-fired power plants and natural gas combined cycle power plants in the US is 34.1% and 44.7%, respectively (US Energy Information Administration (EIA) 2021).

^c1 Quad equals 1 quadrillion (10¹⁵) BTU or 1.055 × 10¹⁸ J.

3. Results

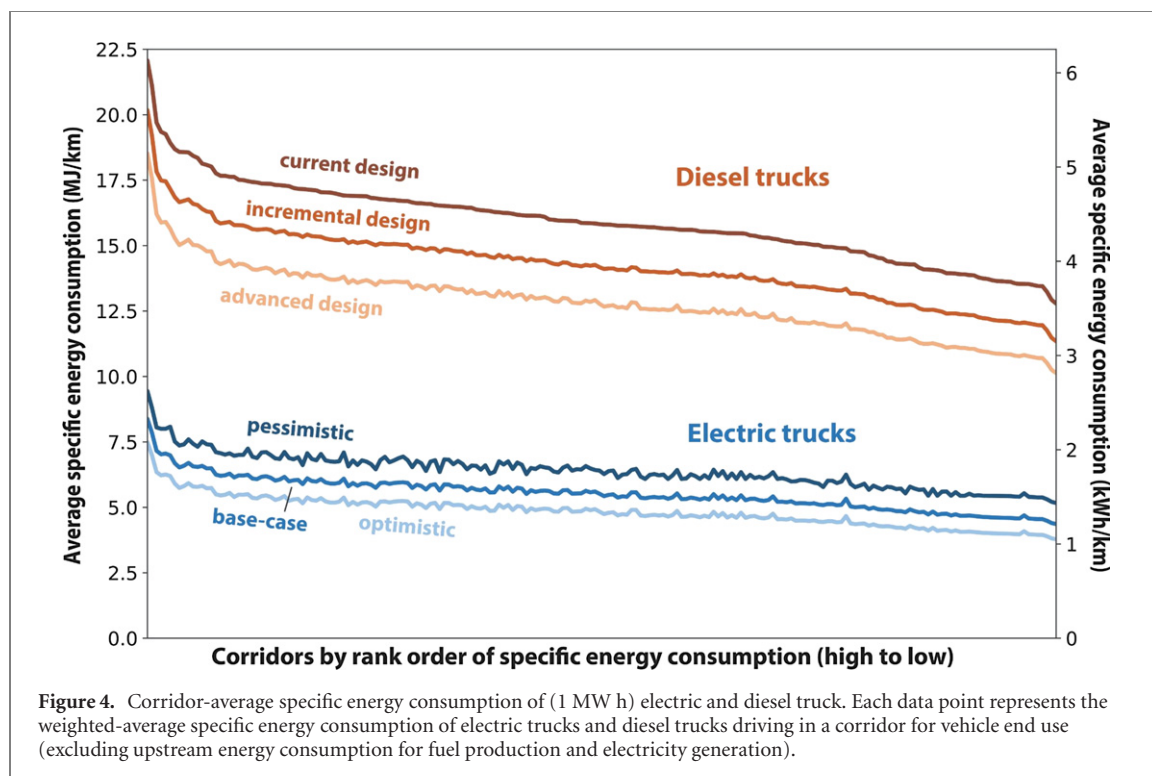
3.1. Varied performance of electric trucks

The weighted-average specific end-use energy consumption for the national fleet of 1 MW h base-case electric trucks is 5.8 MJ km⁻¹ (1.6 kW h km⁻¹), which is 55% lower than future diesel trucks (table 3 and figure 4). We note that the higher energy efficiency of electric trucks needs to be balanced by energy loss at fossil fuel power plants when considering the well-to-wheels energy efficiency. However, if electric trucks are charged solely with renewable electricity, the vehicle-level fuel efficiency has more practical relevance as there are no combustion-related losses from electricity generation. The highly-spatially-resolved model uncovers the varying impacts of real-world factors included in this study (e.g., truck speed, truck weight, and road grade) on electric trucks' energy consumption. For example, a 1 MW h base-case electric truck would consume 4.8–8.3 MJ (1.2–2.3 kW h) per km of vehicle distance traveled when driving in various operating conditions (figure 4). We note that some real-world factors have a larger impact on electric truck's specific energy consumption than battery technology improvements.

The varied profiles of specific energy consumption in different highway corridors translate into a variable driving range for long-haul electric trucks. The 1 MW h and 2 MW h electric trucks, assuming the base-case scenario, could drive 365–702 km and 687–1297 km for a single charge (85% battery SOC) (table S4 and figure S4 in the S.I.). For comparison, the vehicle range of a single-tank future diesel truck is 939–1706 km. This comparison indicates that charging infrastructure planning may need to incorporate real-world driving conditions, such as road grade and speed limits, in order to accommodate varying charging needs across the nation.

Battery technology advancement is essential to close the performance gap between electric trucks and diesel trucks. The fleet-average specific energy consumption for optimistic-case 1 MW h electric trucks is 5.0 MJ km⁻¹ (1.4 kW h km⁻¹), or 13% lower than base-case electric trucks due to reduced battery weight. For the same battery capacity, the optimistic-case electric trucks could drive 73 km further, on a single charge, than base-case electric trucks. With lighter freight, electric trucks could have a higher driving range, more likely to achieve the same driving range as diesel trucks.

We note that our estimates for the fleet-average specific energy consumption are higher than those reported in the literature (Davis and Boundy 2019, Tong *et al* 2015, Sripad and Viswanathan 2017). This was due to three factors related to the 'definition' of long-haul trucks (Davis and Boundy 2019, Tong *et al* 2015, Sripad and Viswanathan 2017). First, the high-roof tractor modeled in this study has a greater frontal area, resulting in larger aerodynamic drag than those assumed in the literature (e.g., low-roof tractor) (Sripad and Viswanathan



2017). Second, long-haul trucks modeled in this work are heavier than those in the literature, which assumed a predetermined, yet simplified, payload (Sripad and Viswanathan 2017). Finally, we included ‘real-world’ auxiliary loads (for heating, cooling, and electronic devices), which were excluded in existing studies (Sripad and Viswanathan 2017).

3.2. The weight penalty of long-haul electric trucks

A crucial trade-off in electric truck design is between range and maximum payload. Compared to diesel trucks, the battery capacity required to achieve a comparable range for electric trucks adds substantial weight. For the base-case scenario (at 240 W h kg^{-1} battery specific energy), a 1 MW h battery weighs 4.2 tonnes or 50% of the weight of a currently operating diesel tractor (S.I. table S4). Given federal regulation on GVW (maximum weight of 36.3 tonnes), electric trucks’ increased weight will reduce the allowable payload. Hence a fleet of electric trucks may require additional truck trips to haul the same cargo as a fleet of conventional trucks.

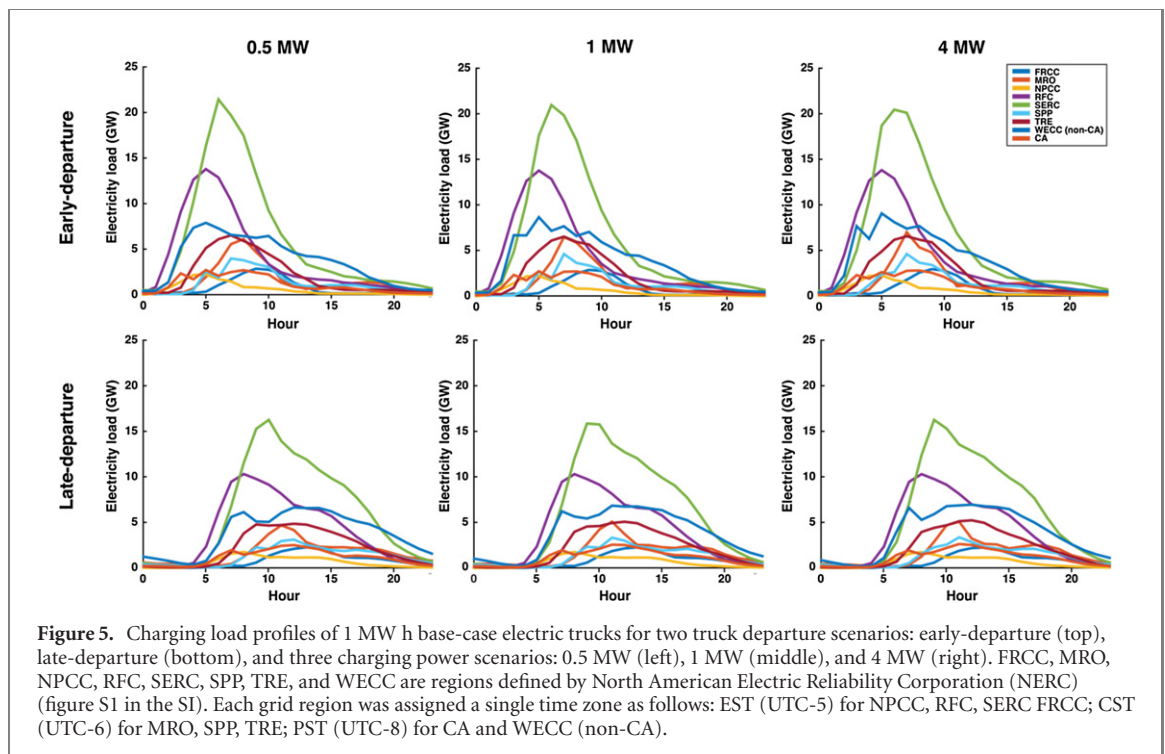
We show that a national fleet of 1 MW h base-case electric trucks could provide the same freight service level as diesel trucks without increasing fleet-wide vehicle distance traveled (table 3). However, 2 MW h base-case electric trucks would lead to a 10% increase in total vehicle distance traveled to compensate for reduced payload capacity. In our pessimistic case, which relies on battery and truck technologies available today, 2 MW h electric trucks would require a 65% increase in total vehicle distance relative to diesel trucks, whereas 1 MW h trucks would only increase the total vehicle distance by 6% (table 3). However, with faster-than-expected battery technology improvements (optimistic scenario), 2 MW h electric trucks could carry a reasonable payload (20.3 tonnes) for a much greater range (1154 km). In this case, electric trucks’ technical performance is closer to future diesel trucks, which could carry a maximum payload of 24.5 tonnes for 1301 km.

3.3. Energy consumption of a national fleet of electric trucks

A shift from diesel trucks to electric trucks substantially reduces the fleet’s end-use energy consumption. A national fleet of 1 MW h base-case electric trucks consumes 0.5 Quads ($6 \times 10^{17} \text{ J}$) of electricity (table 3). For comparison, a nationwide fleet of more efficient future diesel trucks consumes 1.4 Quads ($1.5 \times 10^{18} \text{ J}$) of diesel fuel. The savings in end-use energy consumption is owed to the fundamental thermodynamic constraints of compression-ignited internal combustion engines. In contrast, electric motors’ efficiency can be as high as 90% (although additional energy losses may occur at power generation facilities) (Sripad and Viswanathan 2017).

3.4. The shape of the electric truck charging load curve

Truck electrification impacts the dispatch of power plants in the electric power grid. The total annual charging load for a 1 MW h base-case electric truck fleet is 184 TW h (table 3), the equivalent of 5% of the US electricity



load in 2018. Because the additional load will not be constant throughout the day, there will be hours when electric trucks add more than 5% to system-wide load.

Based on our modeled driving and charging behaviors, the charging load profile for electric trucks is likely to peak in the middle of the day (figure 5), but the exact timing of the daily peaks varies slightly across electric grid regions. This results from the region-specific truck flow patterns and highway network topology as well as the scope of the regional electricity grid regions (as determined by North American Electric Reliability Corporation (NERC), see figure S1 in the SI for detail). In the early-departure scenario, the charging profiles for electric trucks in SERC, RFC, and California have a narrow peak that spans 5–6 h, while the shapes of the charging load in other regions are flatter. In the late-departure scenario, the distribution of electric trucks' departure is less concentrated in time. As a result, the shape of the charging load becomes less peaky in most electric grid regions. In both truck departure scenarios, there is a period of very low charging load (2 PM to 1 AM in the early-departure scenario and 0–5 AM in the late-departure scenario), which is partly due to the 8 h off-duty time required by regulation.

The daily peak of truck charging load is solely driven by long-haul truck operation. Electric trucks are likely to charge during the trip because the energy stored in the battery might not meet the energy need for long trips. As long-haul trucks provide a time-sensitive service, we assume trucks follow a sequence of driving, charging, and idling activities after being dispatched from the trip origin. As a result, unlike passenger vehicles which are usually charged before or after a trip, long-haul trucks are more likely to re-charge during a trip. Furthermore, heavy-duty trucks (including long-haul trucks) are not used evenly across time. A recent study of >3.5 billion records from weigh-in-motion traffic sensors shows that about twice the number of trucks operate during the day (6 AM–7 PM) than during the night (0 AM–4 AM) (Nehiba 2020), implying that truck driving and charging are more likely to happen during daylight hours. The results show an absence of large peaks in the evening when drivers are expected to complete their trips because we assume 150 kW off-duty charging to preserve battery health and minimize charging costs.

The shape of electric trucks' charging load is sensitive to the truck departure scenario but is robust to charging power, battery capacity, and battery technology development. Charging power determines the rate of charging but does not change the energy to be charged. The higher the charging power, the peakier the shape of the charging load. 2 MW h electric trucks lead to slightly flatter charging loads than 1 MW h electric trucks. This is because 2 MW h electric trucks require less en-route charging and need more time in each charge session, which is farther from each other in time, than 1 MW h electric trucks. Finally, battery technology development does not have a noticeable impact on the shape of the charging load since the driving and charging assumptions remain the same. However, battery technology development substantially impacts the magnitude of charging loads, as advanced batteries reduce electric trucks' energy consumption by alleviating the payload penalty.

4. Discussion

4.1. The shape of the electric truck charging load

The load curve from a fully electrified fleet of long-haul freight trucks is distinctly different from that of privately-owned EVs, whose charging peaks are likely to be in the evening hours when vehicles are parked at home. We find that the single most important determinant of the temporal pattern of the load curve is the dispatch of the trucking fleet, which is controlled by firms across the supply chain. Peak charging loads from truck electrification may occur midday when the curtailment of renewable sources is most likely (figure 5). This is promising as the rollout of renewables has resulted in a well-known ‘duck curve’ pattern when excess electricity is generated from wind and solar power in the middle of the day (Coignard *et al* 2018). As characterized by the ‘duck curve’, the integration of a large quantity of wind and solar energy in the current electric power grid has caused negative electricity prices during the day and led to the need for a sizable ramping capacity in the early evening (Coignard *et al* 2018). The temporal coincidence of truck electrification load and solar irradiance suggests a potential synergy in powering truck electrification with solar photovoltaics installed in the bulk electric grid or rooftop of charging stations. Thus, a transition to electric trucks could help mitigate the ‘duck curve’ and facilitate a transition to a high-renewable electric power grid—especially when combined with appropriate electricity pricing structures.

This paper further investigates the sensitivity of electric trucks’ charging profiles to non-truck-dispatch-related factors ranging from truck battery capacity and battery technology to charging power. We find that the daily peak shape is robust to these non-dispatch-related factors. However, there is significant residual uncertainty because electric trucks are still in the development and pilot phases, and their exact roles in the long-haul trucking sector are yet to be defined. More detailed, yet still confidential, data collected via electronic logging devices, cellphones, and traffic sensors might shed new light on the long-haul operation and improve the characterization of electric trucks’ charging loads (US Department of Transportation (DOT) 2015, Xu *et al* 2018, Nehiba 2020).

Further, this paper assumed a single-driver long-haul operation, the prevalent form in the long-haul trucking sector (Tong *et al* 2019). However, long-haul operations could also take other forms. For instance, sleeper-cab long-haul trucks with a team of two drivers could drive day and night continuously, only stopping to re-charge or load and unload cargo. In this case, the charging decisions are not subject to mandatory drivers’ rest times but are still constrained by the operating hours for warehouses, ports, and charging stations.

Finally, smart charging (VIG) reflects an increased level of coupling and integration between electric trucks and the electric power grid. Smart charging may reduce charging expenses for the fleet owners, operating costs for the electric power grid, or the total system costs, depending on the objective. In the case of smart charging, different objectives may lead to distinct operating and charging decisions and various shapes of charging loads. Smart charging is outside the scope of this study because of a substantial amount of data and assumptions involved but is worthy of future research.

4.2. Uncertainty in end-use energy consumption from long-haul trucks

In this study, we strive to provide a first-order estimation of the end-use energy consumption from a nationwide fleet of future diesel and electric long-haul trucks. Furthermore, we aim to investigate the impacts of some truck design and operation decisions, including driving speed, vehicle weight, road grade, on long-haul truck end-use energy consumption. While we show that these factors have direct effects on the end-use energy consumption of long-haul trucks and lead to far-reaching implications for the planning of charging infrastructure and electric grids through the estimated charging load, we note here that our consideration of the ‘real-world’ factors is far from complete. Fundamentally, we face the challenge of balancing the fine-resolution modeling of truck operation (so that the results are accurate) and the need to ensure broad coverage of the national long-haul fleet (so that the results are relevant). Furthermore, long-haul electric trucks are still being designed and tested, and the actual operation data is proprietary, both of which add to uncertainty in how they will be designed and operated.

In the context of this study, a few important limitations exist due to data availability that prevent the complete modeling of long-haul truck operations. First, we used the most recent long-haul truck flow data, which was dated in 2012. As truck electrification would take decades to substantially penetrate into the existing fleet, it is very likely that truck flow patterns may change over time. Second, we did not model traffic congestion and chose to use a single drive cycle in the estimation of the specific energy consumption of long-haul trucks. Regarding electric trucks, we did not model the impact of extreme temperatures and excluded regenerative braking. While we believe they do not affect the order-of-magnitude estimation of the total end-use energy consumption, they may substantially impact the energy consumption of long-haul trucks in certain regions. Thus, studies investigating the adoption of electric trucks or planning of charging infrastructure in specific

regions should consider these ‘real-world’ factors more carefully and use the actual truck operation data where possible.

Finally, we want to highlight here that the energy consumption estimated in this study is the end-use energy that is used to power long-haul trucks directly. In the context of energy systems, end-use energy (such as diesel or electricity) needs to be produced by primary energy (such as crude oil, coal, natural gas, or renewable energy sources, wind or solar), which involves large energy losses from the combustion process or transportation. We chose to focus on end-use energy because it is most relevant for vehicle operation and has direct impacts on the estimation of charging load from electric trucks. However, a complete assessment of the energy impact should account for the upstream energy consumption. Regarding electric trucks, it is challenging to estimate the upstream primary energy demand for electricity generation as it would vary dramatically across grid mixes and change over time as the grid evolves.

4.3. Challenges and opportunities for grid integration

It is challenging to build a national network of charging stations to power long-haul trucks from the perspective of electric power grid integration. Each 1 MW h base-case long-haul electric truck consumes about 850 kW h (assuming 85% battery SOC) for a driving range of 530 km. This amount of electricity is enough to power 29 US households for one day (US Energy Information Administration (EIA) 2020). Meanwhile, a four-lane charging station’s peak power would be above 4 MW, much higher than an extreme fast-charging station for passenger vehicles. Furthermore, charging stations for long-haul trucks are likely to locate in rural areas with poor infrastructure. Thus, the substantial energy and power needs of charging stations require upgrading existing infrastructure or building new infrastructure (such as transformer, distribution lines, and even transmission lines). Although the study of technical solutions for grid integration is outside the scope of this paper, we note that charging stations represent a unique opportunity to integrate renewable energy and onsite energy storage technologies. These onsite distributed energy resources (DER) will reduce the grid integration cost and increase charging stations’ resiliency. The charging load profiles should be leveraged in the technical design and economic analysis of charging stations equipped with onsite DER technologies.

4.4. Broad society-relevant implications of truck electrification

It is expected that a shift from diesel trucks to electric trucks in the long-haul trucking sector will bring broad social benefits, including decarbonization, elimination of tailpipe emissions of local air pollutants, and noise reduction. However, this transition will take time, as vehicle turnover is a key limiting factor in the pace at which any fleet can be electrified (Scown *et al* 2013). This study provides only a hypothetical snapshot of what a fully electrified fleet would mean for the grid as opposed to a multi-year scenario where adoption and infrastructure roll-out may vary by region. Truck electrification’s environmental impacts are sensitive to the source and composition of electricity that electric trucks are charged to (Tong and Azevedo 2020, Tong *et al* 2021). The location-specific charging loads generated by the innovative modeling framework in this study will support truck electrification’s design and implementation so that the future long-haul trucking sector will deliver the expected social goods.

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Data availability statement

The full datasets that are too large to be included in their original form in the SI are available upon reasonable request to the authors.

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