Mapping Heavy-Duty Truck Alternatives

Comparing the future impacts of different fuels

HIGHLIGHTS

Diesel trucks are the dominant powertrain in the heavy-duty vehicle sector today, but new alternatives are available. This analysis compares the greenhouse gas emissions and health impacts for different truck types and different fuels over the lifetime of the vehicle. The impact of the different fuels is different based on regional differences, including both social characteristics like population and demography and technological differences like the make-up of the electric grid. However, across the country an electric truck fueled by a clean grid remains the cleanest alternative in all applications studied.

Appendix: Methodology

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1 Introduction

Trucks powered by fossil fuel combustion directly emit pollution from the tailpipe. However, in thinking through the total impact of these vehicles on the public, it is important to also consider the impacts of the fossil fuel infrastructure supporting these vehicles—there are emissions associated with the refining of petroleum into gasoline or diesel fuels, and there are emissions also associated with the obtaining that petroleum feedstock in the first place.

Electric trucks do not directly emit any tailpipe pollution, but there are emissions associated with the production of electricity needed to power these trucks. There are also emissions associated with the provision of fuel for the electricity grid.

In order to provide the most apples-to-apples comparison for the usage phase of these vehicles (i.e. well-to-wheels),[1] emissions and impacts from all three phases of the lifecycle are considered, in total: 1) feedstock; 2) fuel; and 3) use. For upstream emissions from fuel and feedstock (i.e. tank-to-wheels), this data is generally obtained from the latest version of Argonne National Lab's (ANL's) "Greenhouse gases, Regulated Emissions, and Energy use in Technologies" (GREET) Model (2022) (Wang et al. 2022). Direct emissions from use are further discussed below and were taken based on modeling largely consistent with EPA's MOVES model (US EPA 2021), though with additional considerations. In assessing the impact of these technologies, we consider emissions produced over the expected lifetime usage of the vehicle, which includes degradation of the emissions controls over time.

The Heavy-duty Truck Market Is Diverse

Heavy-duty trucks come in a range of vehicle sizes and weights and undergo a wide range of operation. To capture typical behaviors of interest, we consider a representative list of vehicle classes and duty cycles (Table 1).

Duty Cycles Cover a Range of Capability and Usage

To best match real-world performance, we relied almost entirely on representative duty cycles from the National Renewable Energy Lab (NREL), primarily that collected as part of its FleetDNA program, which uses real-world data to generate a representative test cycle (NREL 2022). There are two exceptions, one for school buses and another for refuse trucks. While FleetDNA data is available for these cycles, there is not a single representative duty cycle published, so we designed our own to best match the available test data by combining the representative cycles in ratios that matched the duty cycle statistics of the Fleet DNA dataset.

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[1] *This analysis is limited to consideration of the usage of the vehicles and does not include emissions associated to manufacturing or end-of-life. Even for electric vehicles, the usage phase is the dominant source of lifetime greenhouse gas emissions (e.g., Iyer, Kelly, and Elgowainy 2023 shows usage emissions five times larger than manufacturing emissions for a long-haul truck, even when considering a battery-pack replacement). Additionally, the literature to-date has focused almost exclusively on non-greenhouse gas emissions, excluding a core part of this analysis (lifetime public health impacts).*

Table 1. This analysis covers a range of heavy-duty vehicle classes, types, and duty cycle

Vehicle Class	Vehicle Type	Duty Cycle
Class 4	Delivery Van	FleetDNA (Local Delivery, Representative)
Class 6	Delivery Truck	FleetDNA (Local Delivery, Representative)
Class 6	School Bus	Test cycle matching NREL School Bus Data
Class 8	Refuse Truck	Test cycle matching NREL FleetDNA Refuse Truck data
Class 8	Tractor (Drayage)	FleetDNA (Drayage, Representative)
Class 8	Tractor (Regional)	FleetDNA (Regional-Haul, Representative)
Class 8	Tractor (Line-Haul)	FleetDNA (Long-Haul, Representative)
Class 8	Transit Bus	FleetDNA (Transit Bus, Representative)

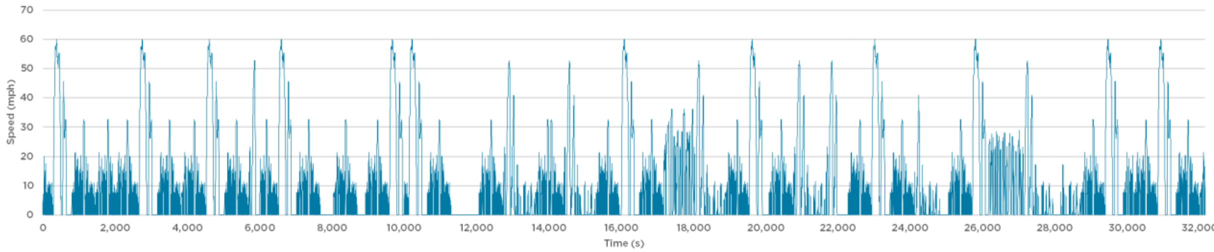
To best match real-world performance, we have relied on duty cycle data collected in the real world by NREL, primarily through its FleetDNA program.

In the case of school buses, this combined three representative cycles identified by NREL, the Orange County Transit Bus Cycle (OCTA), CARB Heavy-heavy Duty Transient Combined Cycle (HHDDT), and the Rowan University Composite School Bus Cycle (RUCSBC) (Duran and Walkowicz 2013). For the refuse truck, we combined two different refuse truck cycles for different refuse types, the NREL Miami-Dade Refuse Cycle (developed by NREL from automated side-loader refuse truck data from vehicles operated by Public Works and Waste Management in Miami-Dade County, Florida) and the NREL Neighborhood Refuse Cycle (developed with EPA as part of the Smartway program, representing automated side-loader refuse truck operation) with the Braunschweig city driving cycle, a low-speed transient driving schedule with frequent stops. Zero-velocity time at the beginning and end of the representative cycles was eliminated, and then an integer number of cycles was combined to match NREL FleetDNA speed bin data. Additional idle time between the randomly ordered cycles was added as needed to match the idle share in the FleetDNA data. Because the representative data cycles did not contain any assumed changes in grade and lacked specificity on engine on/off time, we applied the EPA grade profile used in the Phase 2 Greenhouse Gas Regulations (in whole number steps to ensure symmetric uphill/downhill profile) and assumed key-off park after 90 seconds of idle. These aggregate test cycles are shown in Figure 1 and Figure 2. A comparison of the UCS-derived cycles and the FleetDNA data is shown in Table 2 and Figure 3.

As can be seen in the data, these assembled test cycles largely match key test cycle metrics, including average speed, aerodynamic speed, characteristic acceleration, and kinetic intensity.[2] One notable disparity occurs for the stopping characteristics of the refuse cycle, where the UCS aggregate test cycle clearly shows a greater frequency of stops than the Fleet DNA dataset. However, this is limited by our use of entire test cycles rather than microtrips, and both the Miami-Dade and Neighborhood test cycles have stopping frequencies greater than the FleetDNA average (10.3/1.33 and 10.5/1.96 stops per mile/minute, respectively).

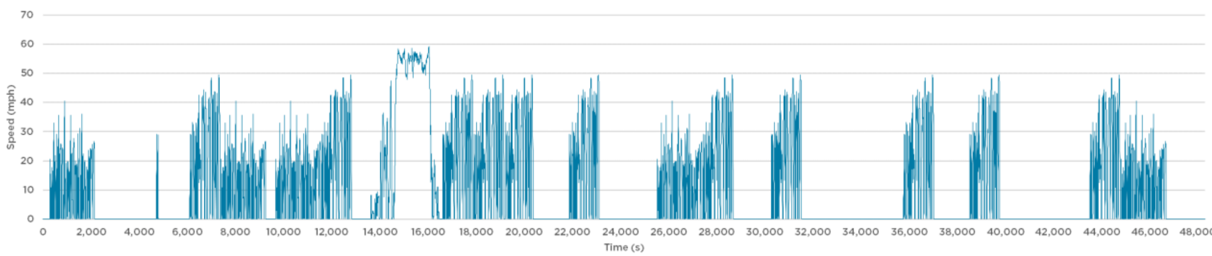
[2] *These metrics are described more fully in O'Keefe et al. 2007.*

Figure 1. UCS-generated Heavy-duty Test Cycle for a Refuse Truck



By combining established refuse truck cycles, we were able to match many of the characteristics of the NREL FleetDNA data for refuse trucks. However, because these cycles had more frequent stops than the FleetDNA dataset, the UCS test cycle shown above has more frequent stop-start behavior. SOURCE: UCS analysis.

Figure 2. UCS-generated Heavy-duty Test Cycle for a School Bus



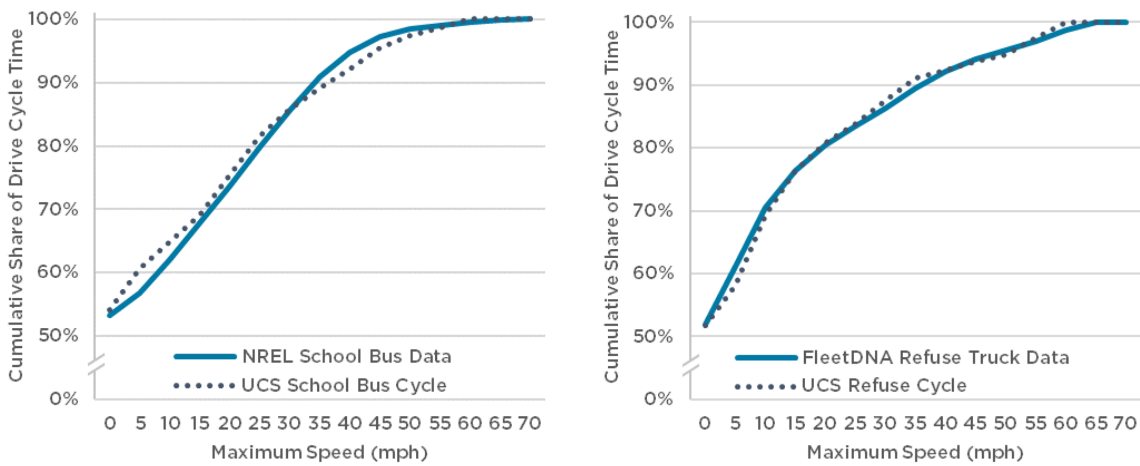
By combining established bus cycles, we were able to match many of the characteristics of the NREL FleetDNA data for school buses. However, because these cycles had more frequent stops than the FleetDNA dataset, the UCS test cycle shown above has slightly more frequent stop-start behavior. SOURCE: UCS analysis.

Table 2. UCS-generated Duty Cycles Compare Favorably to NREL FleetDNA Data

Cycle Characteristic	School Bus		Refuse Truck	
	UCS	FleetDNA	UCS	FleetDNA
Characteristic Acceleration (ft/s²)	0.69	0.63 ± 0.10	0.71	0.50 ± 0.12
Aerodynamic Speed (ft/s)	52.7	47.6 ± 8.8	55.4	48.9 ± 9.5
Kinetic Intensity (1/mile)	1.32	1.63 ± 0.66	1.22	1.11 ± 0.50
Average Driving Speed (mph)	23.1	23.3 ± 4.0	20.6	20.7 ± 6.5
Stops per Mile	2.66	1.73 ± 0.61	10.04	4.01 ± 3.18
Stops per Minute	0.47	0.34 ± 0.12	1.66	0.66 ± 0.34

Utilizing a combination of vocational duty cycles allowed us to match well NREL-collected data on school buses and refuse trucks.

Figure 3. Speed Bin Data for UCS Data Cycles Agrees with NREL-collected Real-world Data



A profile of cumulative speed bin data for school buses and refuse trucks collected by the National Renewable Energy Lab (NREL) and the duty cycle generated by UCS for use in this report affirm the representativeness of the UCS duty cycles for these vocations.

While it might be expected that more frequent stoppage results in greater kinetic intensity for the cycle, that does not appear to be the case.

Unlike the other vehicles listed in Table 1, refuse trucks spend a significant amount of fuel use through power-take-off (PTO), in this case while the vehicle is compacting trash. Real-world data shows that a significant amount of operation time is spent at idle, during which the PTO is operational, and one study showed that 30 percent of fuel energy went towards operation of the compactor (Wysocki et al. 2018). However, due to limited data and the use of GEM (detailed below) to assess fuel consumption, this analysis considers fuel consumption rates solely based on the fuel use from the drive cycle.

Vehicles are Designed with Different Usage in Mind

In order to have a systemic approach to the operational characteristics of the different vehicles, we rely on modeling supporting EPA and NHTSA's Phase 2 Greenhouse Gas Emissions and Fuel Economy Standards (US EPA 2022a). Vehicle characteristics were determined by the final stringency required under those regulations, based on a regulatory category corresponding to each vehicle type (Table 3). Because the final regulatory category is based on an average fleet mix of characteristics (i.e., in most cases stringency was not predicated on a single technology package but on an assumed mix of technology packages), a given vehicle's technology package was determined based on the mix of technology features needed to most closely match the average characteristics of the vehicle class. To the extent there are lingering errors, those differences were assessed in a way to ensure that the fuel economy of the diesel vehicle would match or exceed that required by the respective regulatory cycle.

Table 3. UCS Analysis Covers a Range of EPA Regulatory Classes and Applications

Vehicle Class	Vehicle Type	EPA Regulatory Class
Class 4	Delivery Van	LHD-Urban (Vocational)
Class 6	Delivery Truck	MHD-Urban (Vocational)
Class 6	School Bus	School Bus (Custom Chassis)
Class 8	Refuse Truck	Refuse Truck (Custom Chassis)
Class 8	Tractor (Drayage)	Class 8 High-roof Day Cab (Tractor)
Class 8	Tractor (Regional)	Class 8 High-roof Day Cab (Tractor)
Class 8	Tractor (Line-Haul)	Class 8 High-roof Sleeper Cab (Tractor)
Class 8	Transit Bus	Transit Bus (Custom Chassis)

EPA regulatory classes align well with the vehicle categories studied in this analysis, with little overlap.

Note: LHD = Light Heavy-duty; MHD = Medium Heavy-duty

Both electric trucks and combustion engine-powered trucks are likely to improve in efficiency in the coming years. New trucks are required to meet fuel economy standards through at least 2029 and greenhouse gas emissions standards through 2032.[3] When originally setting standards through the 2029 model year, NHTSA and EPA set standards predicated predominantly on the increased efficiency of combustion engine-powered vehicles. The level of ambition of those targets based on EPA's judgment was reiterated in a recent rulemaking, where EPA stressed that it had "set the existing [heavy-duty (HD) greenhouse gas (GHG)] Phase 2 standards at levels that would require *all* [emphasis added] conventional vehicles to install varying combinations of emission-control technologies.... The HD GHG Phase 2 standards were based on adoption rates for technologies in technology packages that EPA regards as appropriate under [the Clean Air Act] section 202(a) for the reasons given in the HD GHG Phase 2 rulemaking" (87 FR 17440-1).

A number of new technologies have been developed since the Phase 2 rules were finalized, including some like cylinder deactivation which could aid manufacturers in compliance with new NO_X emissions standards as well as reduce fuel use and greenhouse gas emissions.[4] One study shows as much as a one-third further reduction possible in fuel use from conventional trucks by 2035 (Buysse et al. 2021). However, a large share of these reductions come from advancements in technology that would be directly applicable to electric truck efficiency as well (tires, axle efficiency, aero, weight reduction). Because such vehicle-level improvements would affect both classes of vehicle in this study but have no known schedule of likely deployment and were not considered when setting the standards, we have not assumed any improvement beyond what the Phase 2 standards require. For trucks powered by a combustion engine, this means a combination of vehicle-level improvements outlined in the compliance modeling and a 2027-compliant heavy-duty engine.

[3] *81 FR 73478-4274 (2016); 89 FR 29440-831 (2024).*
[4] *88 FR 4296-4718 (2023).*

Electric trucks are assumed to have the same vehicle characteristics as conventional trucks,[5] with no further improvements in efficiency over time. This conservative assumption was chosen to account for the uncertainty in how future improvements to batteries and power electronics would manifest themselves in future generations of electric trucks—for example, improvements in battery cell density may be used to increase the vehicle's range rather than reduce weight, which could then be used to improve freight efficiency. In the case of long-haul electric trucks, it is likely that all such improvements would be applied to increasing the range of the vehicle—while long-haul is a shrinking slice of the truck market (Mihelic and Roeth 2019), a major reason for the lack of availability of a long-range electric truck is the impact of weight on payload using today's current battery technology, though manufacturers have already increased range on the few Class 8 electric tractors on the market and will likely continue to do so (Volvo Trucks 2022). At the same time, manufacturers are already deploying some advanced strategies in aerodynamics on the current generation of vehicle (like the Tesla semi [AirShaper 2022]) and high-volume EVs from major OEMs are being built based on post-MY2021 platforms,[6] so it is necessary to distinguish between first-generation (e.g., MY2021) and later (MY2027+) models. We have similarly assumed no post-MY2027 differences in vehicle characteristics for other alternative fuel vehicles.

[5] *The GEM model used to assess fuel consumption considers a fixed gross vehicle weight for a given vehicle class. While there may be some differences in unladen weight for some classes of vehicle, trucks with alternative powertrains are granted a 1-ton allowance that compensates for some of this. Additionally, for tractor-trailers, over two-thirds of loads "cube out", which would not yield any penalty related to weight, and our methodology for assessing the efficiency of trucks inherently considers like-for-like load.*
[6] *"The VNL platform was designed to be used in Volvo's future trucks powered by alternative power systems, and while the truck has yet to make it into the hands of owners—deliveries begin in October—Volvo has already announced the next power system to be used in the all-new VNL." (Brasher 2024).*

2 Modeling Greenhouse Gas Emissions and Fuel Usage

Greenhouse gas emissions for conventional vehicles are directly related to the fuel used throughout the duty cycle of those vehicles. Gasoline and diesel are widely distributed commodities, and the entire nation has adopted the same fuel standards (whether that be Tier 3-compliant gasoline or ultra-low sulfur diesel), so a single national average fuel energy density and upstream emissions profile was chosen. While natural gas and propane are regulated in a different manner, the extraction, refining, and distribution are similarly national in scale and are therefore assumed to lack regionality when it comes to the upstream impacts of the vehicles.

In contrast, greenhouse gas emissions for electric trucks are dependent upon the electric grid powering them, which makes them much more geographically dependent. The upstream emissions associated with the electric grid are discussed in much greater detail later in the report.

Below, the methodology to assess the efficiency of the two types of vehicles is described in greater detail.

UCS Used an EPA Model to Project Diesel-powered Truck Improvements

Given the wide range of operating conditions, it is critical to establish a consistent framework for assessing the expected fuel usage for diesel-powered trucks. In this case, we utilize the latest version (Phase 2 v4.0) of the Greenhouse gas Emissions Model (GEM) designed by EPA to assess the appropriateness of its greenhouse gas emissions program and measure compliance with that program.

Phase 2 GEM is a physics-based simulation of a heavy-duty truck, modeled in MATLAB using Simulink with Stateflow. There are four submodules governing the simulation: 1) Ambient subsystem, which establishes road grade, temperature, etc.; 2) Driver subsystem, which is a time-based controlling module that attempts to match a given duty cycle, with some look-ahead; 3) Powertrain subsystem, which includes the engine, transmission, electric accessories, and driveline; and 4) Vehicle subsystem, which consists of the chassis and relevant physical forces on the vehicle related to aerodynamic drag, rolling resistance, etc.

Rather than simulating the fuel used by the vehicles through the regulatory cycles, we used the representative duty cycles outlined above to assess fuel usage, including regulatory payload, tires, etc. The fuel economy for each vehicle based on features needed for each regulatory class to meet the 2021 and 2027 GHG standards is shown in Table 4. Table 4 includes both the GEM result for the modeled individual vehicle as well as the EPA requirements for that vehicle, which are based on fleet average requirements.

Table 4. UCS Analysis Covers a Range of EPA Regulatory Classes and Applications

Vehicle Type	Regulatory Class	Representative Fuel Economy (mpg-diesel)		GEM-modeled Regulatory Cycle Result (g CO_2/ton-mi.)		EPA Regulatory Requirement (g CO_2/ton-mi.)	
		2021	2027	2021	2027	2021	2027
Delivery Van	Light HD-Urban	10.1	10.9	422	375	422	375
Delivery Truck	Medium HD-Urban	7.1	7.6	295	265	295	265
School Bus	Custom (School Bus)	5.5	6.2	298	268	298*	271
Refuse Truck	Custom (Refuse)	3.2	3.6	323	292	323*	298
Tractor (Drayage)	C8 Day Cab – HR	4.9	5.3	85.6	75.7	85.6	75.7
Tractor (Regional)	C8 Day Cab – HR	6.4	7.3	85.6	75.7	85.6	75.7
Tractor (Line-Haul)	C8 Sleeper Cab – HR	6.9	8.1	75.7	64.3	75.7	64.3
Transit Bus	Custom (Other Bus)	4.4	4.7	302	270	302*	286

Despite matching well the greenhouse gas emissions standards on the test cycle, as simulated in GEM, the fuel economy for diesel-powered trucks remains quite low through 2027 in the identified applications, owing to intense duty cycles.

**Note: Because the simplified GEM model used for compliance utilizes a 2027-model year engine map rather than the engine map associated with the vehicle, the regulatory standards for the custom chassis vehicles for 2021 are compared to the vocational standard (e.g., MHD-U) rather than the custom chassis standard for 2021-2026.*

GEM uses an assumption of ultra-low-sulfur diesel (ULSD) certification fuel, and all fuel economies are characterized assuming the energy content of a 100-percent petroleum-based ULSD. However, in the real world, trucks operate on a range of fuels meeting the ULSD specification, including mixtures containing biodiesel and renewable diesel (RD). According to the latest projections of the Energy Information Administration's (EIA's) *Annual Energy Outlook* (AEO) (US EIA 2023), just under 10 percent of the on-road diesel energy comes from renewable sources, and that is projected to see only a modest increase through 2050.[7] Using the VMT-weighting approach described in detail elsewhere in the methodology, it is expected that 10.2 percent of the energy required for a model year 2035 HDD truck would come from biofuels, compared to 10.0 percent for a model year 2023 HDD truck. Similarly, there is only a small shift towards greater usage of RD (from 6.6 percent to 7.0 percent) for these vehicles over their respective lifetimes. Averaging fuel use projected by EIA over the 2023-2050 time period, the AEO dataset projects a value nearly identical with that of the 2035 vehicle (10.2 percent of energy coming from bio-based diesel, with just 3.2 percent coming from biodiesel), so we utilize these shares for all HDD trucks given the minimal variation.

[7] *See Table 36 (Transportation Sector Energy Use by Fuel Type Within a Mode) and Table 17 (Renewable Energy Consumption by Sector and Source).*

To assess the upstream greenhouse gas emissions impact from diesel trucks, we assume that 88.8 percent of the energy needed comes from ULSD, 3.2 percent from biodiesel, and the remainder from RD. The upstream impacts from bio-based diesel are based on the feedstock used, so we assign the respective feedstocks for biodiesel and RD according to the 2023 data from a recent analysis of 2011-2023 biodiesel and RD feedstocks (Gerveni et al. 2024).[8] The final emissions values are then weighted accordingly, as modeled by GREET. On average, total greenhouse gas emissions for the bio-based diesel considered are 74 percent lower than that of 100 percent petroleum-based ULSD, leading to a 7.4 percent overall reduction for the assumed ULSD mix.

Though most renewable diesel is used in California as a result of local state policy (the low carbon fuel standard, or LCFS) (Figure 2 in Gerveni et al. 2023), we have not assumed any regional variation in emissions from diesel trucks, consistent with our approach to other fossil fuels.

Direct emissions of CO_2 utilize the respective factors from the GREET model. However, methane (CH_4) emissions are regulated by EPA both directly and as part of the tailpipe regulations of hydrocarbons, which are vehicle-dependent, and so therefore these are incorporated into the total greenhouse gas emissions via 100-year global warming potentials found in IPCC AR6 (see footnote 17 and surrounding text). N_2O emissions were excluded for combustion vehicles, though these represent less than 1 percent of direct tailpipe GHG emissions.

Electric Vehicles Are More Energy-Efficient Than Diesel Trucks

More than half of the energy contained in diesel fuel is wasted in the combustion process of a diesel truck (figure 5 in DOE 2013). In contrast, electric motors can be 90 percent efficient or more (figure 8.E.3 in DOE 2015). Electrification thus presents a tremendous opportunity for improving the efficiency of the trucking sector.

Efficiency gains can be further improved in duty cycles where there is significant braking, since electric trucks can use regenerative braking to limit energy wasted in the form of heat. Clearly such an opportunity varies widely among applications, and previous studies on hybrid-electric trucks showed that the relative advantages could be characterized exclusively by a few parameters specific to a given duty cycle (O'Keefe et al. 2007). Below, we walk through a simple model for the advantage of fully electric trucks.

Given the relatively small (but growing!) number of electric trucks on the road today, there is scant data on real-world efficiencies. Early data from the California Air Resources Board showed that the efficiency improvement of electric trucks over their diesel counterparts could largely be considered as to the average speed of their duty cycle (CARB 2018). Additional modeling data compiled by two different national labs can help fill in some of the gaps in the CARB 2018 dataset (Liu et al. 2021, Hunter et al. 2021), which is especially important for high speed applications like long-haul trucks, for which there is limited data.

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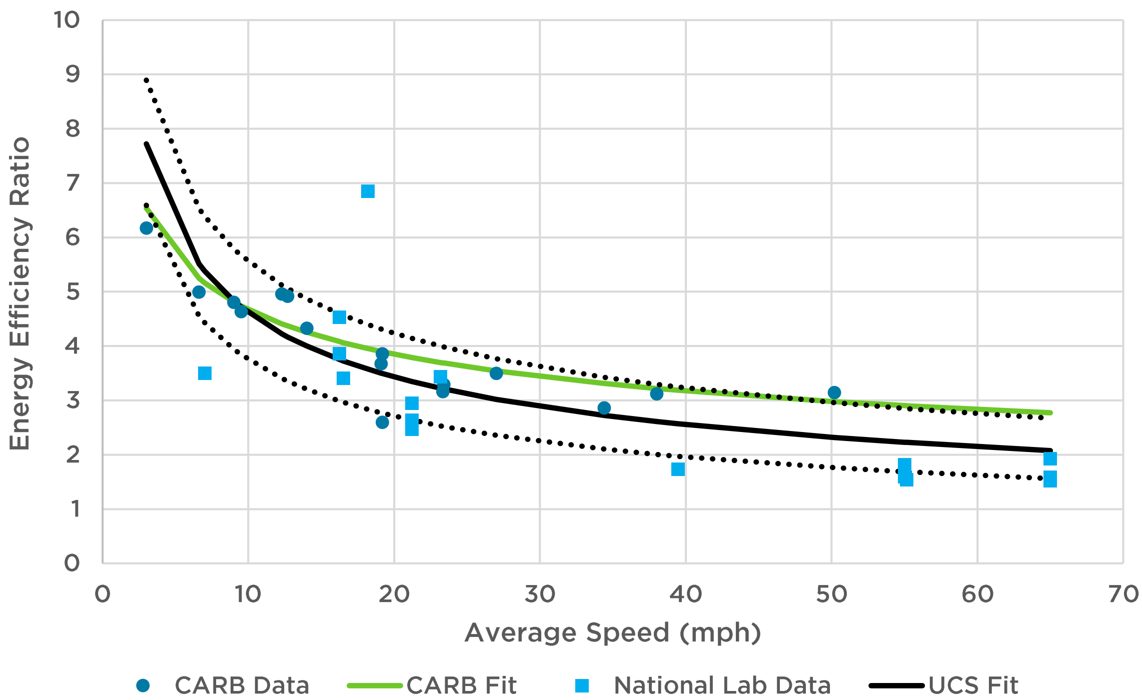
[8] *This analysis is in relative agreement with the AEO values, with RD feedstocks representing 63 percent of the bio-based diesel market, by weight, in 2023.*

Figure 4. The Efficiency Improvement for Electric Trucks Is Dependent Upon Average Speed



Real-world and test-lab data provided by CARB (dark blue circles) plus more recent simulations by national laboratories (light blue squares) show that electric trucks are significantly more efficient than their diesel equivalent, at any speed. Fitting the data on a log-log plot finds a strong correlation which can then be used to interpolate to different duty cycles (black line, with dotted lines representing 95-percent confidence intervals). CARB's original fit (green line) is shown for reference.

SOURCES: CARB 2018, Liu et al. 2021, Hunter et al. 2021, UCS Analysis

Figure 4 shows that the new simulation data is largely consistent with CARB's dataset. We fit the data to a general exponential relationship with average duty cycle speed, consistent with CARB's formulation. While at the lowest speeds, our estimate is up to 36 percent more efficient than CARB's estimate, at high speeds we see a significant reduction compared to CARB's data. CARB's original formulation lies near the maximum EER of our 95 percent confidence bars at high speed, and for the duty cycles considered in this analysis, the average speeds are in the realm where our estimate of the EER is equal to or below that of CARB, making our analysis more conservative.

To date, much of what little systematic data is available on the efficiency of electric trucks looks at the opportunity for electric trucks in the long-haul sector, which can help provide a comparative sample of our electric truck assumptions. Pulling the data from the sources cited in a recent literature review (Basma et al. 2021), we find that CARB's data is at the upper maximum in EER, with the data indicating an average EER = 1.95-2.24, quite consistent with our fit at high speeds (1.6-2.7).

Table 5. Estimates of EV Efficiency Compared to Diesel Trucks Agrees with Real-world Data

Vehicle Type	Simulated Data (MY2021 EV)			Real-world Data		
	Diesel (mpg)	Electric (kWh/mi)	EER	Diesel (mpg)	Electric (kWh/mi)	EER
Delivery Van	10.1	1.2	3.2		1.1-1.4	
Delivery Truck	7.1	1.7	3.2	7.6	1.4-1.7	3.6
School Bus	5.5	1.5	4.5	7	1.4-1.7	4.0
Refuse Truck	3.2	2.6	4.6			
Tractor (Drayage)	4.9	1.8	4.4			
Tractor (Regional)	6.4	2.4	2.5	8.0	2	2.4
Tractor (Line-Haul)	6.9	2.3	2.4			
Transit Bus	4.4	2.0	4.3	3.9-4.3*	1.9-2.2	4.1-5.3

On an energy basis, electric trucks can be more than 4 times as efficient as their diesel counterparts, particularly on the most intense duty cycles. Our modeling is consistent with the limited data on real-world applications—in fact, if anything our assumption about the energy efficiency (kWh per mile) of these trucks undersells the performance of electric trucks.

**Note: Transit bus data mpg is based on diesel equivalency of compressed natural gas buses run on the same routes. EER and energy efficiency includes an assumption of a 90-percent charger efficiency.*

SOURCES: Jeffers and Eudy 2021 (transit bus), Kelly et al. 2015 (delivery truck), Kelly and Prohaska 2017 (school bus), LeCroy and Dobbelaere 2024 (delivery van, delivery truck, regional tractor, school bus, transit bus), Mihelic et al. 2020 (regional and line-haul), and Mihelic et al. 2022 (regional and line-haul).

A comparison of the derived electric vehicle efficiencies for the vehicles of interest and available real-world data affirms this methodology (Table 5). Fleet demonstrations conducted by the North American Council for Freight Efficiency (NACFE) find that Class 8 diesel tractors can achieve at least 8.0 mpg, with a subset achieving as high as 8.7 mpg (Mihelic et al. 2020). A recent analysis of fleets running electric trucks showed an average efficiency of about 2 kWh/mi (Mihelic et al. 2022). Similarly, NREL data on efficiency from transit buses, school buses, and delivery trucks identify similar efficiencies of electric trucks in those operations.

Non-diesel Combustion Vehicles Offer a Less Efficient Alternative

While diesel engines have the largest market share among heavy-duty vehicles, there are spark-ignition (SI) gasoline, propane, and natural gas engines available. Hydrogen combustion is currently a SI technology in development and on the road in demonstration projects.[9]

[9] *For an overview of some active projects, see presentations from the Clean Truck Partnership Workshop on the Role of Hydrogen in California's Trucks held by the California Air Resources Board online, November 28, 2023 (Alger 2023, Hergart and Gerty 2023, Kreso 2023, and Bartel 2023).*

EPA has not set through Phase 2 or its Phase 3 regulations any new requirements for SI engines. Therefore, this analysis does not assume any improvements in efficiency for gasoline, propane, or natural gas engines compared to current technology. In the case of hydrogen combustion, there is ongoing work to look at in-cylinder injection of hydrogen, which is expected to yield both increases in efficiency and increases in particulate matter emissions from the engine (Thawko and Tartakovsky 2022). Because this technology is touted as a direct diesel replacement in "fuel agnostic" engines (Nebergall 2023), and because there is otherwise limited information on its efficiency, we have assumed that such engines will be comparable to diesel engine efficiency on an energy-equivalent basis. This could lead to as much as an 33% overestimate in efficiency based on modeling of other SI engines (described below).

For propane, gasoline, and natural gas engines, we have used GEM to model the performance of these vehicles, based on a modern natural gas engine (Seo et al. 2020). Using EPA's ALPHA/GEM engine resizing methods within MATLAB, the engine was resized to produce comparable power to the diesel equivalent engines. A comparison of these four representative SI engines and the torque and power characteristics of some current offerings are shown in Table 6. For an additional comparison, we also include the light heavy-duty (LHD) engine included with the GEM model as the default vocational engine, based on the Ford Triton 6.8L V10, which features a substantially different torque curve owing to it being naturally aspirated.[10]

Table 6. UCS Spark-ignition Engines Are Comparable to Those Available on the Market

Engine Description	Max Torque (@ Speed)	Max Power (@ Speed)
EPA SI Engine (300)[a]	591 N-m (3100 RPM)	224 kW (4000 RPM)
Cummins B6.7N (200)[b]	705 N-m (1600 RPM)	149 kW (2400 RPM)
Modeled LHD Engine	852 N-m (1000-1300 RPM)	149 kW (1700-2010 RPM)
Cummins L9N (280)[c]	1220 N-m (1300 RPM)	209 kW (2000 RPM)
Modeled MHD Engine	1151 N-m (1000-1300 RPM)	201 kW (1700-2010 RPM)
Cummins L9N (320)[c]	1356 N-m (1300 RPM)	239 kW (2000 RPM)
Modeled HHD Vocational Engine	1490 N-m (1000-1300 RPM)	260 kW (1700-2010 RPM)
Cummins X15N (500)[d]	2508 N-m (1000-1400 RPM)	382 kW (1600-1800 RPM)
Modeled HHD Tractor Engine	2534 N-m (1140-1400 RPM)	379 kW (1580-1825 RPM)

Spark-ignition (SI) engines simulated in GEM cover a range of operating behavior consistent with the current generation of heavy-duty SI engines on the market. UCS engines have a more similar torque and power curve than that of EPA, which is naturally aspirated.

SOURCES: a) US EPA 2022a, b) Cummins Westport 2018a, c) Cummins Westport 2018b, d) Cummins Inc. 2022.

[10] *Because the Ford Triton 6.8L V10 differs so substantially from other spark-ignition engines, it was found to be much less scaleable for the large number of applications studied and was frequently, even when resized, unable to complete a duty cycle when modeled in GEM or was found to be substantially less efficient, even for applications like school buses where the engine is known to be deployed today.*

Table 7. Compression-ignition Engines Are Significantly More Efficient Than Spark-ignition

Vehicle Type	Model Year	Compression Ignition (CI) Fuel Economy	Spark Ignition (SI) Fuel Economy	SI Energy Efficiency Penalty
Delivery Van	2021	10.1 mpg	8.4 mpg	6.9%
	2027	10.9 mpg	8.8 mpg	10.8%
Delivery Truck	2021	7.1 mpg	6.0 mpg	6.4%
	2027	7.6 mpg	6.2 mpg	9.4%
School Bus	2021	5.5 mpg	4.7 mpg	4.2%
	2027	6.2 mpg	5.1 mpg	9.0%
Refuse Truck	2021	3.2 mpg	2.6 mpg	10.9%
	2027	3.6 mpg	2.7 mpg	20.6%
Tractor (Drayage)	2021	4.9 mpg	3.6 mpg	20.0%
	2027	5.3 mpg	3.8 mpg	24.6%
Tractor (Regional)	2021	6.4 mpg	4.6 mpg	23.6%
	2027	7.3 mpg	5.0 mpg	30.5%
Tractor (Line-Haul)	2021	6.9 mpg	5.0 mpg	23.7%
	2027	8.1 mpg	5.5 mpg	33.0%
Transit Bus	2021	4.4 mpg	3.3 mpg	18.8%
	2027	4.7 mpg	3.4 mpg	22.1%

On an energy basis, the modeled spark-ignition (SI) engine-powered vehicles are between 6.4 and 33 percent less efficient than those powered by compression-ignition (CI) engines. This gap is consistent with the literature. Because SI engines are not required to improve under EPA's greenhouse gas emissions standards while CI engines are, the efficiency gap for the modeled vehicles grows between the 2021 and 2027 model year. This is consistent with EPA's greenhouse gas emissions standards for SI vehicles, where under Phase 2 SI requirements were 7.7-11.5 percent less stringent for SI vehicles in 2021 compared to CI vehicles and 9.6-15.1 percent in 2027 on the regulatory test cycles.

While there may be some small differences based on the particular characteristics of the fuel, it is assumed that all three fuels have identical combustion efficiencies on an energy basis. A comparison of the energy equivalence for the compression-ignition (diesel) and spark-ignition vehicles is shown in Table 7. The shortfall in energy efficiency falls within the expected window for natural gas trucks.[11] Additionally, for LHD and MHD vehicles, we have included energy efficiency information for the default spark-ignition engine for the Phase 2 GEM

[11] *"However, current natural gas engines are 5 to 15 percent less energy efficient than diesel engines" (81 FR 73921). "This means that you can expect a CNG vehicle will get around 15% to 20% less miles per [diesel gallon equivalent] vs. a comparable diesel equipped vehicle" (Seger et al. 2024). "This represents a 33% fuel consumption penalty for the natural gas powered tractor. … A second example from the same conference compares two Class 8 vocational trucks in the Kroger fleet. … The natural gas truck suffers from 17 to 20% higher fuel consumption" (Reinhart 2016).*

modeling, which is based on the Ford Triton 6.8L V10 engine. Propane and natural gas versions of this engine are available today, though it has since been replaced by the 7.3L "Godzilla" engine (Williams 2019). Since the Triton V10 is a prior generation engine, it is not surprising that the turbocharged engine modeled across all SI vehicles in our analysis shows an increase in efficiency beyond the default SI engine EPA assumed in its Phase 2 modeling.

For all non-diesel fuels, we use the default values in GREET for SI combustion to calculate the upstream emissions. Gasoline is assumed to be E10 gasoline and includes emissions related to ethanol; all other fuels reflect no addition of biofuels.

Electrification Shows the Lowest Carbon Intensity of All Fuels

In order to put our analysis into the context of the current lifecycle analysis literature, we've summarized the total carbon intensity (reflecting direct combustion emissions plus upstream emissions related to fuel and feedstock) in Table 8, by fuel source. Because tailpipe methane emissions are related to the tailpipe emissions of volatile organic compounds (VOCs), which are regulated under federal tailpipe regulations and are discussed in the following section, there is some variability across vehicle types for the fossil fuel sources, particularly natural gas.

Additionally, it should be emphasized that model year is distinct from calendar year—while some lifecycle analyses may specify grid from a particular calendar year, this modeling effort looks at the lifetime-averaged usage. As described elsewhere, this means that it reflects a specific projected deployment of energy sources over time rather than a single mix. Additionally, while the hydrogen is primarily sourced from natural gas via steam-methane reforming (SMR), the usage of grid electricity to compress the gas is a non-negligible component of the upstream emissions associated with its usage, which explains the model year variance. Lastly, because the table represents only the carbon intensity of the fuels, differences in the efficiency of the powertrain are not considered; this is particularly important to note for the comparison of hydrogen from electrolysis and electricity.

Table 8. Summary of Carbon Intensity of Different Fuels for Heavy-duty Trucks

Fuel Type	Grid	Model Year	Carbon Intensity	Units
Diesel	n/a	All	83.9	g CO2e/MJ
Gasoline	n/a	All	90.3-90.5	g CO2e/MJ
Natural Gas	n/a	All	78.5-78.6	g CO2e/MJ
Propane	n/a	All	75.5-79.2	g CO2e/MJ
Hydrogen (Nat. Gas SMR)	AEO	2023	314.8	g CO2e/kWh
		2027	308.4	g CO2e/kWh
		2030	305.7	g CO2e/kWh
		2035	303.9	g CO2e/kWh
	NREL	2023	304.8	g CO2e/kWh
		2027	296.2	g CO2e/kWh
		2030	291.9	g CO2e/kWh
		2035	288.9	g CO2e/kWh
Hydrogen (Grid Electrolysis)	AEO	2023	488.8	g CO2e/kWh
		2027	386.4	g CO2e/kWh
		2030	354.1	g CO2e/kWh
		2035	332.2	g CO2e/kWh
	NREL	2023	301.1	g CO2e/kWh
		2027	159.9	g CO2e/kWh
		2030	95.3	g CO2e/kWh
		2035	52.0	g CO2e/kWh
Electricity	AEO	2023	258.9	g CO2e/kWh
		2027	204.2	g CO2e/kWh
		2030	187.2	g CO2e/kWh
		2035	175.8	g CO2e/kWh
	NREL	2023	157.5	g CO2e/kWh
		2027	81.7	g CO2e/kWh
		2030	47.3	g CO2e/kWh
		2035	24.2	g CO2e/kWh

3 Modeling Smog-forming and Particulate Pollution

Despite the advent of diesel particulate filters, particulate emissions (PM) from trucks remain a critical public health issue. PM is often denoted by the size of the pollutant, either $PM_{2.5}$ or PM_{10}, for particles less than 2.5 or 10 μm in diameter, respectively.

An additional source of particulate matter (as well as ozone) is smog. Smog is formed from the reaction of nitrogen oxides (NO_X) or sulfur oxides (most commonly SO_2) with volatile organic compounds (VOCs) in the presence of sunlight. All three of these pollutants can be released directly from combustion-powered trucks.

All four pollutants mentioned above (PM, NO_X, SO_2, and VOCs) can be emitted from electric power plants as well as from the processes to obtain and refine fuel for both the transportation and power sectors. These emissions are discussed in the section on modeling of the electric grid.

The modeling of these pollutants generally is discussed below.

Emissions from Brake and Tire Wear Represent a Serious Concern

In addition to emissions related to combustion, PM from brake and tire wear represent a substantial source of PM emissions from all trucks.

There is limited available data on the tire and brake wear of electric vehicles, and what little study has been conducted is almost exclusively on light-duty passenger vehicles (see OECD 2020 for a review). Electric trucks are given a 2,000-pound allowance for gross vehicle weight rating, meaning that loaded they could weigh as much as 2,000 pounds more than their diesel equivalent (23 U.S. Code § 127(s)), which would thus increase wear associated with tires. However, 2,000 pounds represents a small share of the total weight of a heavy-duty vehicle, and tire wear should be proportional to weight. Additionally, electric trucks can recoup energy through regenerative braking, which also has the benefit of reducing brake wear, an offsetting effect. These competing effects likely mitigate much of the potential difference in PM emissions from the two types of vehicles, and with limited data available to the contrary, this analysis assumes that PM emissions from brake and tire wear is assumed to be equivalent for all types of heavy-duty truck.

While there is no difference in these emissions between the different types of trucks, the health impacts of these emissions are factored into the analysis as a share of the total health impacts from a given heavy-duty vehicle, regardless of the fuel.

Emissions from Combustion Trucks Worsen Over Time

Unlike light-duty vehicles, tailpipe emission standards have not historically been regulated at the vehicle level but rather the engine. This leads to standards that are based on lab tests of an engine on a dynamometer, rather than a tailpipe test. There are two such federal standards governing diesel vehicles considered in this study. The way in which these engine standards translate into real-world emissions is complicated by a number of factors, which are discussed below.

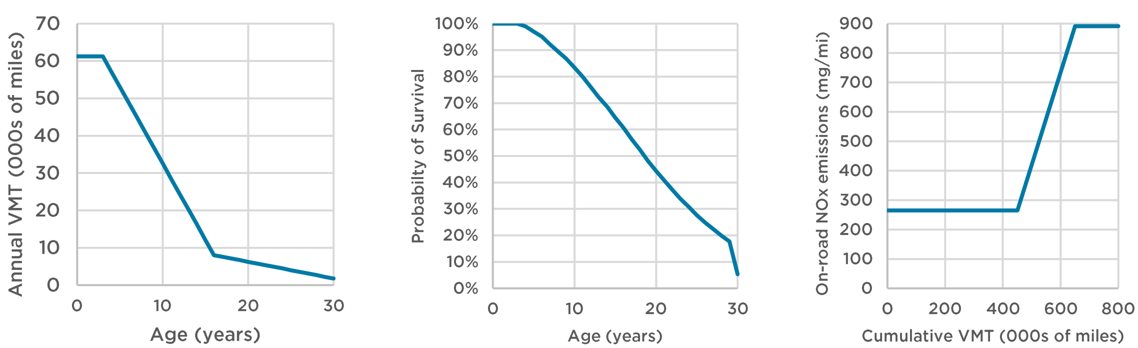
Because the emissions controls may be improperly maintained outside of the warranty period, we use a similar process as used in the EPA MOVES3 model to account for changes in emissions in $PM_{2.5}$ and NO_X over a vehicle's lifetime related to mal-maintenance and tampering. This is then used to assess an average g/mi value for the usable lifetime. In this analysis, the usable lifetime is defined by B10 data for Class 4-8 vehicles, defined as the point at which 90 percent of the fleet must be rebuilt (Lowry 2017). This is a conservative representation of the emissions impact of trucks, as the median engine (B50) can exceed this lifetime by as much as 50 percent according to that same dataset. Furthermore, it is an averaging process weighted towards the period under which a manufacturer is responsible for ensuring emissions controls are operational, though it still exceeds the full useful life and warranty periods of all standards considered.

We utilized survival and mileage data from the MOVES model for each vehicle type, along with our assumed vehicle lifetime, to establish the expected share of lifetime mileage traveled by a vehicle in a given year. This was used to develop an average emissions profile over the lifetime of a combustion-engine vehicle (Figure 5), and to weight the electric grid utilized by an electric truck over its lifetime (discussed in greater detail later in the methodology).

Current Federal Standards Hold for Model Years 2010-2026

In 2001, EPA set emissions standards for heavy-duty trucks which were anticipated to require selective catalytic reduction (SCR) of engine emissions to reduce NO_X and diesel particulate

Figure 5. Lifetime emissions for a regional tractor includes tampering and degradation



Average lifetime on-road emissions are determined using a weighting of annual miles traveled, survivability, and real-worlds emissions considering not just EPA's on-road requirements but MOVES factors related to tampering and malmaintenance over the lifetime of the vehicle. The tampering and malmaintenance factors increase linear with miles traveled between the warranty period and the full useful life, as in the EPA MOVES model.

filters (DPFs) to reduce PM. Due to flexibilities in the final rule, these standards did not fully phase in until 2010. These standards require an average achieved standards of 0.20 g NO_X/bhp-hr, as measured on the HD Federal Test Procedure (FTP) cycle, over the full useful lifetime mileage of the vehicle up to 435,000 miles for Class 8 trucks.

There is a large volume of evidence that exists on the effectiveness of this rule, which shows that in the real-world these engines emit far more NO_X than intended by the rule. This is primarily related to shortcomings in the in-use requirements on manufacturers. A number of exceptions in the in-use requirements (which fall under what is known as a "not to exceed" (NTE) limit) mean that diesel emissions controls on these trucks operate suboptimally in a wide range of behavior which are not regulated under the in-use requirements. Essentially, these engines perform relatively well on the narrow range tested, but extremely poorly on the more than 90 percent of operating conditions not covered by those test procedures. As a result, these trucks can emit more than 7 times the required NO_X standard under low-speed operation according to official data submitted by manufacturers as part of the in-use testing program (Badshah et al. 2019).

To translate that data into real-world operation, we rely upon the MOVES3 emissions rates (US EPA 2021, which are normalized to power and binned to different speed conditions.[12] This data was recently updated for the MOVES3 model to reflect the real-world operating characteristics and shortcomings based on heavy-duty in-use testing (HDIUT). To apply these data, the modeled truck data is normalized and binned in an analogous manner to determine the frequency of operating modes used to define MOVES3 emissions rates. The on-road NO_X emissions are then converted into a g/mile. The GEM model can provide engine torque, speed, and power data, allowing for easy determination of operating mode for MOVES3 categorization.

While real-world NO_X emissions fell well short of the anticipated reductions for 2010 and beyond, DPFs have proved more effective than originally anticipated. The MOVES3 model used by EPA to model real-world emissions impacts included an update to $PM_{2.5}$ emissions rates based on the same recent heavy-duty in-use testing (HDIUT) data with which the NO_X emissions were updated (Figure 2-26 in US EPA 2022b). This data was summarized for a nationally representative duty cycle for each vehicle class (Classes 2b-3, 4-5, 6-7, 8, and bus). As in the case of NO_x, the appropriate speed bins for the duration of the duty cycle are used.

Quantities of VOCs are determined as a share of the MOVES3 hydrocarbon (HC) emissions based on MOVES3 speciation data (US EPA 2022c). For diesel vehicles with aftertreatment systems, VOCs represent 59.83 percent of the total HC emissions. Additionally, there are direct methane emissions resulting from all fossil-fuel trucks, which are considered as part of the tailpipe greenhouse gas emissions of each truck. These represent just 38 percent of the total HC emissions, and generally amount to less than 1 g CO2-eq./mi.[13]

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[12] *See Section 2.1.1.3 in US EPA 2022b for a clearer description of the calculation of operating modes. Section 1.8 details data-related updates to the MOVES3 model, and Sections 2.1, 3.1, and 4.1 detail the process used for heavy-duty diesel, gasoline, and natural gas engines, respectively.*

[13] *100-year global warming potential (GWP) is used throughout the analysis, with GWP values (GWP_{100} of CH_4 is 29.8, and for N_2O is 273) obtained from the 6th Assessment Report of the International Panel on Climate Change (Calvin et al. 2023).*

While ultra-low-sulfur diesel (ULSD) fuel has substantially reduced on-road emissions of SO_2, the direct emissions are considered as a ratio of the fuel based on the relative sulfur content. This analysis uses the emissions factors from GREET, which itself is based on an average in-use percentage of 11 ppm sulfur content, by weight, consistent with EPA's analysis of the ULSD requirements (US EPA 2004).

For gasoline-fueled vehicle emissions, we similarly use MOVES emissions by operating mode, weighting emissions by the modeled operational data for each vehicle's duty cycle. For propane-fueled vehicles, we relied upon EPA emissions certification data to assess the relative performance of the small number of propane engines compared to their gasoline counterparts—like a similar industry analysis, we found that emissions of total hydrocarbons (THC) and NO_x were similar to gasoline engines, while $PM_{2.5}$ emissions were found to be approximately 60 percent of gasoline particulate emissions.[14] VOCs were then determined based on the relative share for VOC/THC for propane in MOVES. For natural gas-fueled vehicles, MOVES data was used to assess the emissions.

For all combustion vehicles, lifetime emissions increases with respect to tampering and malmaintenance reflect the assumptions from MOVES (Figure 5). For diesel vehicles, this means that through the warranty period, emissions are expected to reflect "as new" and then increase linearly to the end of the regulatory useful life, at which point emissions flatten. For SI engines, MOVES uses a single annual adjustment, reflecting an increase after 5 years' lifetime.

Federal Standards for Model Years 2027+ Are More Stringent But Complex

In December 2022, EPA finalized federal NO_X standards for model years 2027 and beyond. Nominally, these standards lead to as much as a 90 percent reduction in NO_x on the FTP test cycle. However, this does not translate to a 90 percent reduction in real-world emissions.

The real-world requirements of the 2022 NO_x rule reflect a completely redesigned in-use requirement to replace the ineffective NTE protocol. Under this new program, a truck's duty cycle is divided into overlapping, 300-second bins in what is known as a "moving average window" (MAW) approach. Depending upon the average CO_2 emissions from the engine within a bin, the NO_X emissions are compared to a given engine requirement based on different lab test cycles and an in-use factor. Here CO_2 is used as a surrogate for power in assigning the comparison, either to Bin 1 (for normalized CO_2 rate less than or equal to 6 percent), or Bin 2 (greater than 6 percent normalized CO_2).

The Bin 1 standard (10 g NO_x/hr) is based on the optional Clean Idle standard, since it corresponds to operation comparable to idling and low-power of the low-load cycle. The Bin 2 standard (58 mg NO_x/hp-hr for LHD, 73 mg NO_x/hp-hr for MHD and HHD) is based on a 25/75 percent mixture of the LLC (50 mg NO_x/hp-hr) and FTP (35 mg NO_x/hp-hr) standards, respectively, along with a conformity factor of 1.5 and, for MHD and HHD engines an additional "interim" adjustment of 15 mg NO_x/hp-hr.

[14] *UCS analysis of US EPA 2024a found that for similar engines, there was statistically no significant difference for these pollutants, though there was a wide spread in over the different displacement engines. The same could not be said for particulate matter, which showed a clear reduction. This is similar to an industry-funded review (figure 2, Ryskamp, R. 2017).*

On top of this, the Bin 1 and Bin 2 standards are further adjusted with respect to the work-day temperature of the vehicle being tested. This temperature adjustment factor enables manufacturers to scale the in-use requirement for each bin linearly within a given temperature window ($41°F < T < 77°F$), below which data is exempted and above which the factor is unity. This scalar can be as much as a 60 percent increase in emissions for MHD and HHD engines and as much as 76 percent for LHD engines (Table III-18, 88 FR 4349).

In its own analysis, EPA assumed that in virtually all operating conditions, the off-cycle standards would represent the binding constraint on engine emissions (US EPA 2022d at p. 238). However, in assessing the rule's impact, the Agency assumed a more binding idling standard (5 g NO_x/hr instead of 10 g NO_x/hr), ignored the interim adjustment for MHD engines (15 mg NO_x/hp-hr), ignored the additional allowance for measurement accuracy (5 mg NO_x/hp-hr), and ignored the temperature adjustment altogether. This means that EPA's own analysis assumes that emissions in the real-world will be much lower than what is actually required by the finalized standards.

In addition to the NO_x standard, PM standards were reduced and warranty and useful-life periods increased. For $PM_{2.5}$ emissions, the standard is meant to act as a backstop—current vehicles meet the in-use requirements for $PM_{2.5}$, and therefore it is assumed that vehicles meeting this standard will perform equivalently to today's vehicles. The same assumption is made for HCs, for which EPA did not set an additional standard.

As in the case of the 2010+ standards, malmaintenance and tampering were considered. However, because the difference between engine-out and tailpipe emissions is so much greater, so is the impact of any tampering. This analysis relies upon new MOVES3 factors for tampering developed as part of EPA's 2027 NO_X rulemaking, adjusted with respect to the

Table 9. Modeled Vehicles Correspond to Government Multiple Classifications

Vehicle Type	GVWR Vehicle Class	Federal Highway Vehicle Class
Delivery Van	Class 4	2-axle 6-tire single-unit truck (Class 5)
Delivery Truck	Class 6	2-axle 6-tire single-unit truck (Class 5)
School Bus	Class 6	Buses (Class 4)
Refuse Truck	Class 8	3-axle 6-tire single-unit truck (Class 6)
Tractor (Drayage)	Class 8	5-axle combination truck (Class 9)
Tractor (Regional)	Class 8	5-axle combination truck (Class 9)
Tractor (Line-Haul)	Class 8	5-axle combination truck (Class 9)
Transit Bus	Class 8	Buses (Class 4)

While generally throughout this report vehicles are classified by their gross vehicle weight rating (GVWR) based on the maximum weight of the loaded vehicle, as per regulatory classifications, the Federal Highway Administration classifies its observations of truck traffic based on the number of axles and other design characteristics of the vehicle. This table illustrates how this analysis translated between the two classification schemes.

finalized in-use requirements. For all other pollutants, malmaintenance and tampering emissions are the same as MOVES3, though the phase-in reflects the increased warranty, etc.

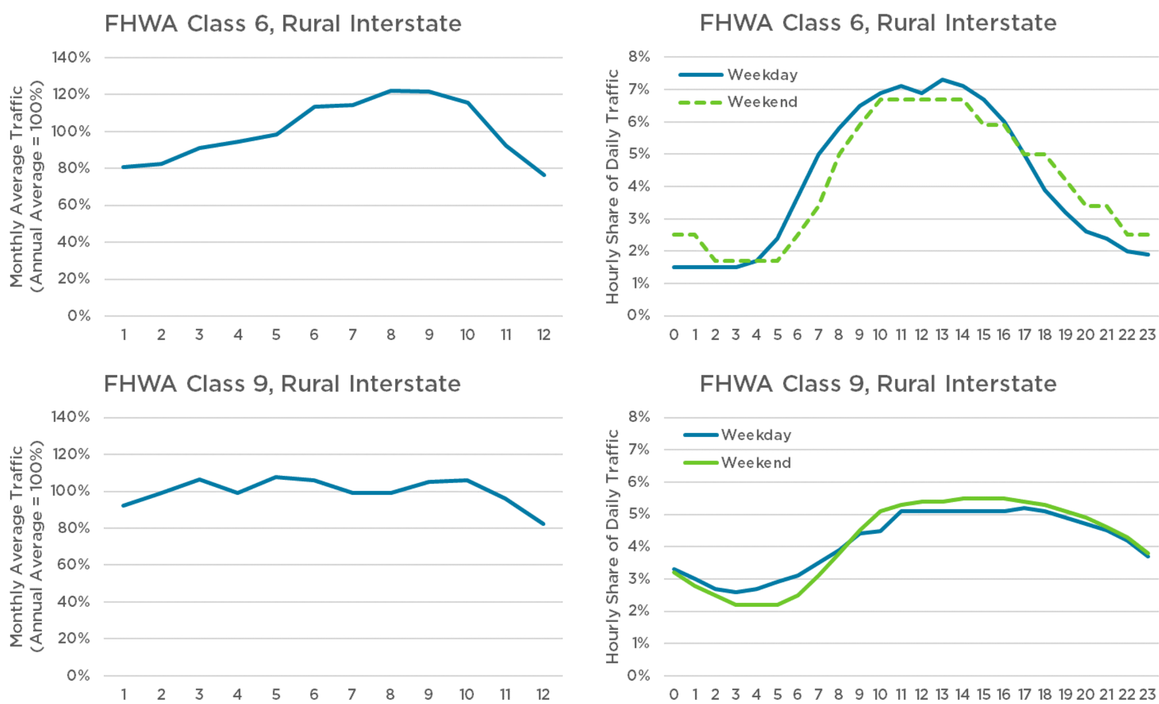
EPA's Regulations Increase Allowable Emissions Based on Temperature

To assess the average impact the temperature adjustment has on real-world NO_x emissions, it is necessary to consider the temperature profile experienced by a truck through the workday, since this determines the magnitude of the additional allowance granted to manufacturers. Below is detailed an average temperature profile experienced by freight traffic throughout the United States. First, hourly traffic flow for a given truck type is assessed. Then, this hourly traffic volume is correlated to an experienced temperature. Finally, this data is then weighted by the freight volume of a given geography to provide an expected national profile for each truck type. This is then used to assess the magnitude of the additional allowance for different vehicle types. Those vehicle types (from the Federal Highway Administration, FHWA) are then applied to those studied in this analysis (Table 9).

Data from the Federal Highway Administration Provides Hourly Truck Traffic Information

It is possible to look at average truck traffic to obtain a national profile for a given vehicle

Figure 6. Traffic Volume Data for Class 6 and Class 9 Trucks on Rural Interstates



Traffic flow data is available across a broad range of trucks and road types, illustrating different hourly and seasonal behavior. For example, FHWA Class 6 straight trucks observe a clear workday operation and more peaked seasonal behavior than FHWA Class 9 tractor-trailers, which show more homogeneity at both the hourly and monthly level.

Table 10. The Federal Highway Administration (FHWA) Classifies Vehicle by Body Type

Class	Class Definition	Class Includes	Number of Axles
1	Motorcycles	Motorcycles	2
2	Passenger cars	All cars Cars with one-axle trailers Cars with two-axle trailers	2, 3, or 4
3	Other 2-axle, 4-tire single-unit vehicles	Pick-ups and vans Pick-ups and vans with one- or two-axle trailers	2, 3, or 4
4	Buses	Two- and three-axles buses	2 or 3
5	2-axle, 6-tire single-unit trucks	Two-axle trucks	2
6	3-axle, 6-tire single-unit trucks	Three-axle trucks Three-axle tractors without trailers	3
7	4+ axle single-unit trucks	Four-, five-, six-, and seven-axle single-unit trucks	4 or more
8	4 or less axle combination trucks	Two-axle trucks pulling one- and two-axle trailers Two-axle tractors pulling one- and two-axle trailers Three-axle tractors pulling one-axle trailers	3 or 4
9	5-axle single-trailer trucks	Two-axle tractors pulling three-axle trailers Three-axle tractors pulling two-axle trailers Three-axle trucks pulling two-axle trailers	5
10	6+ axle combination trucks	Multiple configurations	6 or more
11	5-axle multi-trailer trucks	Multiple configurations	4 or 5
12	6-axle multi-trailer trucks	Multiple configurations	6
13	7+ axle multi-trailer trucks	Multiple configurations	7 or more
14	Unused	---	---
15	Unclassified Vehicle	Multiple configurations	2 or more

The Federal Highway Administration (FHWA) uses body type to define its vehicle classes rather than weight. The vehicles modeled in this study generally fall into Classes 4-13. Because Classes 7-8 and 10-13 are atypical truck configurations, they were not considered explicitly in the use of FHWA data on truck traffic.

SOURCE: Hallenbeck et al. 2014

Table 11. Roadways Are Classified By the Federal Highway Administration (FHWA)

Federal Highway Road Class	Roadway Description
Class 1	Rural Interstate
Class 2	Rural Principle Arterial
Class 6	Rural Minor Arterial
Class 7	Rural Major Collector
Class 8	Rural Minor Collector
Class 11	Urban Interstate
Class 12	Urban Other Freeways and Expressways
Class 14	Urban Principle Arterial
Class 16	Urban Minor Arterial
Class 17	Urban Collector

Traffic count data is available my functional road class. Hourly and monthly traffic flow data on local roadways was not available for this analysis but remains a small share of the total traffic flow (less than 14 percent in 2020; FHWA n.d.).

SOURCE: FHWA n.d.

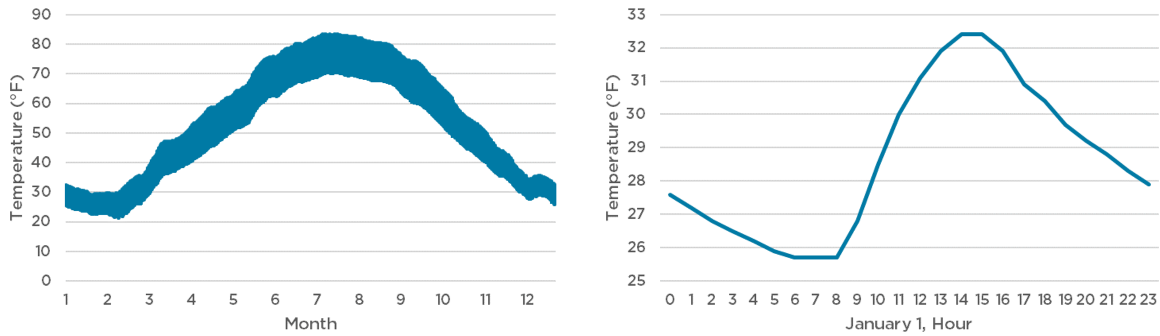
class. A report requested by FHWA details hourly truck traffic for different vehicle types by hour over the course of the day, by month compared to an annual average, and for different road types (Hallenbeck et al. 1997). The report identifies different usage profiles, noting differences in hourly travel profiles for vehicles like long-haul trucks, which include a non-trivial amount of overnight travel, as compared to local delivery vans or buses, which operate on a business hours basis (Figure 6). This travel pattern data is used to create a 365-day × 24-hour data set for each truck class defined by FWHA (Table 10), based on the traffic volumes for each road type (Table 11).

Climate Data Provides a Temperature Profile for a Truck In a Given Geography

The National Ocean and Atmospheric Administration (NOAA) has collected hourly temperature data from sites around the country for decades. This data has been used to compile "climate normal" temperature and climate information to represent the average weather a location would be expected to see, for comparison to current and future weather conditions (NOAA 2021).

This data is available on a site-by-site basis (Palecki et al. 2021). Thus, for a given region, it is possible to obtain a typical temperature profile for the year. With the hourly travel data already collected for each truck class, it is thus possible to estimate the typical temperature experienced throughout the work day (Figure 7).

Figure 7. Climate Normal Temperature at Chicago-Midway Airport



Climate normal temperature shows clear seasonal behavior over the year, but the hourly result shows even a wide range of temperatures over the course of a single day. This variance causes the wide band present in the annual data.

SOURCE: NOAA 2021

Combining Truck Traffic and Climate Data Yields a National Average Temperature Profile

Because the hourly temperature data for a region can now be applied to the hourly truck traffic profile for each type of truck over the course of the year, the question now is how to consider the different geographies around the country.

The Freight Analysis Framework (FAF) from the FHWA provides a way to weight truck traffic around the country (US DOT 2017). The FAF divides the country into 132 freight regions. Data is available on value and ton-mileage of freight by different modes between those regions, including via truck. Most of those regions are defined by cities, which correlates well to NOAA climate monitoring sites. However, for the remainder (which take the form "Rest of [State]"), a temperature monitoring site was identified by looking at the daily truck volume (Figure 8) and assigning the site with the highest volume flow not already covered by a freight area (e.g., "Rest of Virginia" was assigned to Roanoke, VA, because the Washington, DC; Richmond, VA; and Virginia Beach-Norfolk, VA metropolitan areas were already covered).

Having correlated freight areas with temperature data, now it becomes a question on how to weight those different freight areas. This analysis averaged the freight ton-mileage for which a given site is an origin and for which the freight area is a destination. The top ten freight areas represent just over one-quarter of the traffic flow and are shown in Table 12, along with the location of their representative climate monitor and freight share.

These regions of the country span a wide assortment of climate behavior, and (as is indicated in Figure 8) if anything this methodology weights typical workday operation away from the coldest regions of the United States, where one might expect the temperature adjustment to make the biggest impact given the relatively high temperature below which it affects manufacturers' obligations.

Combining this freight data with the traffic volume and NOAA temperature data allows us to calculate a representative national profile for any given truck type—an example of line-haul

Figure 8. Estimated average daily volumes for trucks on the National Highway System, 2017

According to data from the Freight Analysis Framework, freight traffic volumes largely follow the interstate system but include heavier volumes around freight hubs including ports and multimodal/rail facilities, as is highlighted in Table 12. (Figure reproduced from US DOT 2018.)

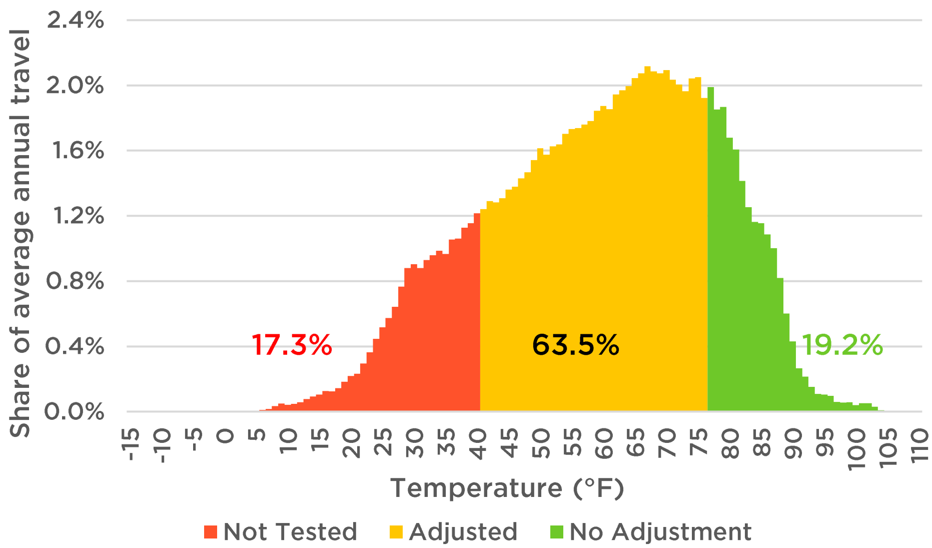
Table 12. Modeled Vehicles Correspond to Government Multiple Classifications

Freight Area	Representative City	State	Share
Rest of TX	Amarillo	TX	5.0%
Los Angeles CA	Los Angeles	CA	4.3%
Iowa	Des Moines	IA	3.0%
Dallas-Fort Worth TX-OK (TX Part)	Dallas-Ft. Worth	TX	2.8%
Houston TX	Houston	TX	2.6%
Chicago IL-IN-WI (IL Part)	Chicago	IL	2.3%
Rest of WI	Madison	WI	2.3%
Rest of IL	Springfield	IL	2.3%
San Francisco CA	San Francisco	CA	1.9%
Rest of MN	Duluth	MN	1.8%

The highest average freight ton-mileage is found at ports of entry and/or through stops on freight corridors.

SOURCE: US DOT 2017

Figure 9. Freight-weighted temperature profile for line-haul tractor-trailers (FHWA Class 9).



Nearly two-thirds of freight travel occurs at a temperature under which the in-use standard is relaxed, and more than 17 percent of freight travel occurs at a temperature for which in-use data is exempted. This leads to a substantially relaxed in-use requirement for manufacturers under the federal NO_x *standards for model years 2027 and later.*

SOURCE: UCS Analysis

tractor-trailers (FHWA Class 9) is shown in Figure 9. In this example, just over 17 percent of operation would be excluded from the in-use program, and just over 19 percent would be required to meet the in-use protocol with no temperature adjustment. This means nearly two-thirds of the expected operation of an average truck would receive an additional adjustment related to temperature.

Additional Emissions Allowances Are Allowed Under EPA's Regulations

Though much of the temperatures experienced by a truck are very moderate, the impact of this large temperature coverage leads to a rather substantial expected adjustment for trucks. Manufacturers submitted the data underpinning this adjustment factor, and as with any flexibility it should be assumed that manufacturers will take full advantage of this in designing and packaging emissions controls such that there will be increased emissions at different temperatures. Since manufacturers have flexibility on determining which vehicles are measured against the in-use requirements, it's likely this adjustment factor will even be selected for explicitly in the design phase.

To calculate the impact of the temperature adjustment, the temperature adjustment for the idle and in-use bin was applied, and temperatures below 41°F were ignored. The freight-weighted adjusted bins are shown in Table 13. It should be noted that in-use emissions will be even higher due to the exempted data below 41°F, where there is absolutely no guarantee that emissions controls are operating effectively.

Table 13. Impact of EPA's Real-world Emissions Allowances Vary by Vehicle Class

FHWA Class	Adjusted Bin 1 (g NO_x/ hr)	Adjusted Bin 2** (mg NO_x/bhp-hr)	Operation Share Not Tested	Opeartion Share Adjusted	Operation Share with No Adjustment
4	11.8	74	18.1%	62.6%	19.4%
5	11.6	72	15.4%	61.6%	22.9%
6	11.5	71	14.1%	61.3%	24.7%
7	11.4	70	11.6%	60.3%	28.1%
8	11.5	72	14.4%	61.0%	24.5%
9	11.8	73	17.3%	63.5%	19.2%
10	11.7	73	17.1%	64.0%	18.9%
11	11.9	75	19.0%	65.6%	15.4%
12	11.9	75	19.8%	64.5%	15.7%
13	11.9	75	18.7%	66.5%	14.8%

Compared to a nominal Bin 1 standard of 10 g/hr and a nominal Bin 2 standard of 58 mg/hp-hr, under EPA's flexible real-world allowances, the typical truck could emit 14-19 percent higher emissions at idle and 21-30 percent additional in-use emissions.

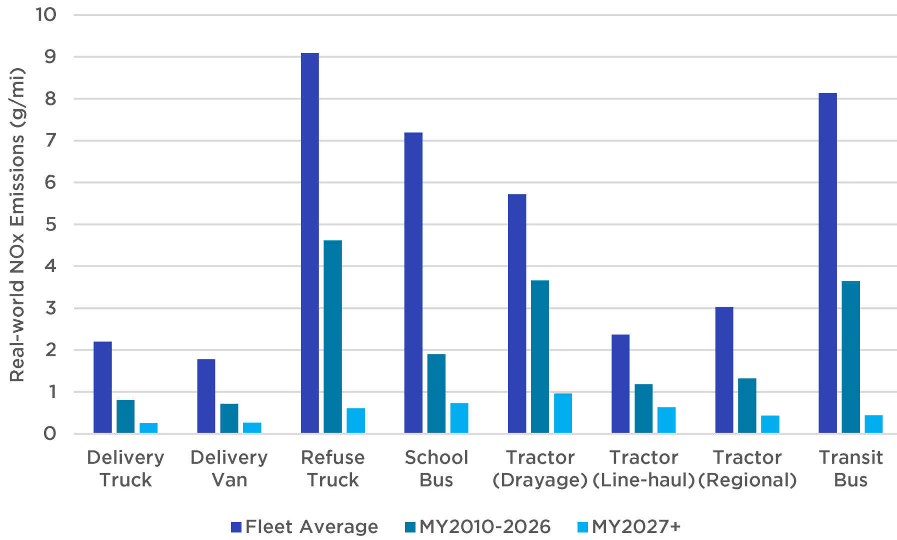
***Note: The adjusted Bin 2 values do not include the 15 mg/hp-hr interim allowance for MHD and HHD engines nor the additional 5 mg/hp-hr allowance for measurement accuracy (40 CFR § 1036.420), the latter of which our analysis excluded.*

These adjusted off-cycle bins represent a significant increase which EPA did not consider in its analysis of the emissions from engines certified to the final NO_X standards, with idle emissions in particular more than double those assumed in the regulatory impact analysis. While we have not attempted to convert these substantial increases into a fleet-wide estimate of benefits, it is clearly significant. And with manufacturers getting to preferentially select the trucks tested under this program, it could be manipulated even further to erode the efficacy of the in-use requirements.

There is no temperature adjustment for any pollutants other than NO_X. For $PM_{2.5}$ and HCs, current vehicles already achieve the required targets, so it is assumed that vehicles meeting the EPA standards will achieve the levels of performance of today's vehicles. MOVES3 data is then used to estimate the emissions for each vehicle category.

Lifetime-weighted pollution rates are calculated as in the other classes, considering a multiplicative adjustment for effectiveness as calculated by EPA in support of the rule (US EPA 2022d). The malmaintenance factors were again adjusted relative to the values used in the rulemaking to reflect differences between the modeled and finalized standards, consistent with the approach taken in assessing the malmaintenance impact on the CARB standards.

Figure 10. Lifetime Average Real-world NO_X Emissions for Different Diesel Vehicles



A comparison of the impacts of the federal NOX standards over time shows a substantial difference in emissions, with the most recent federal standards between a 73-95 percent reduction in lifetime-average on-road NOx emissions compared to the average truck on the road today.

SOURCE: UCS Analysis

Tailpipe NO_x Emissions Vary Both by Application and Regulation

To illustrate the impact of NO_X emissions standards on real-world tailpipe emissions, lifetime average emissions are compared across vehicle types in Figure 10 to reflect not just emissions when the vehicle is new but averaged over the expected lifetime to account for in-use factors, degradation related to expired warranty and malmaintenance, etc. As noted previously, this lifetime is determined by the mileage at which 90 percent of the fleet would be rebuilt.

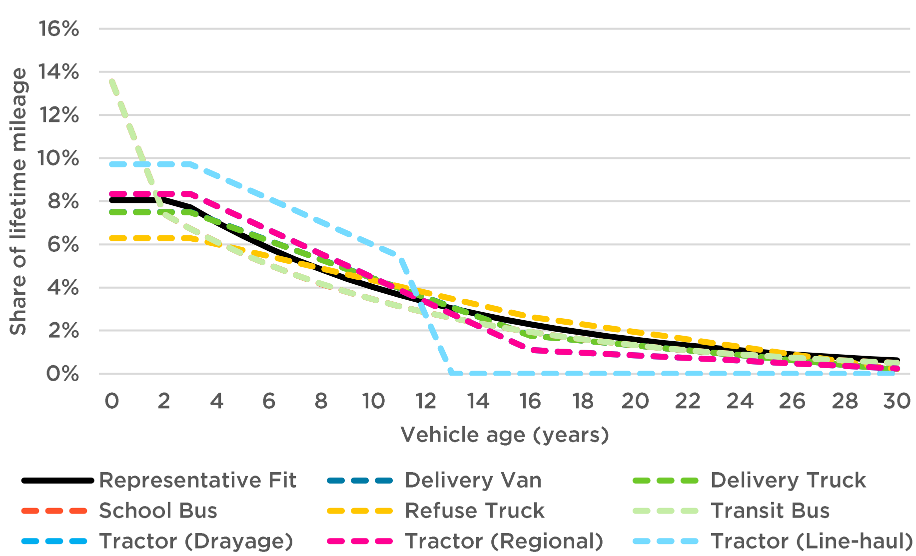
4 Modeling the Future Electric Grid

While electric trucks have zero tailpipe emissions, the electricity associated with charging the batteries powering electric trucks certainly has associated global warming, smog-forming, and particulate emissions. At the same time, these emissions have generally been declining over time, and this is expected to continue (Figure 4 in Reichmuth et al. 2022). Unlike a conventional truck, where associated emissions get worse over time through malmaintenance and tampering, an electric truck will be powered by an increasingly cleaner grid, which means decreasing emissions impacts over its lifetime.

In order to project the lifetime-average emissions associated with an electric truck, we utilize two projections, one from the Energy Information Administration representing no additional policy changes (US EIA 2023) and one from the National Renewable Energy Lab (NREL) consistent with achieving net-zero grid emissions by 2035 (Standard Scenario 2023 with high CCS costs in Gagnon et al. 2023). These scenarios are described in greater detail below.

As in the case of the combustion trucks (Figure 5), the lifetime average is weighted by expected survival rates and annual VMT by age (Figure 11). We have considered 4 different model years of electric truck, representing the first year of usage of the truck: 2023, 2027, 2030, and 2035. To simplify the number of grid scenarios modeled, the grid emissions are weighted by a representative fit to the VMT data to identify a typical lifetime weighting characteristic of all trucks broadly (solid line, Figure 11). The truck type for which the curve is least

Figure 11. Share of Lifetime Vehicle Miles Traveled for Different Truck Types, by Age



Despite having different usage, survival rates, and annual miles, the range of truck types analyzed largely have a similar profile when normalized to the total expected lifetime mileage of an application. The solid line represents the profile used to estimate the projected energy share via age for a truck.

representative is long-haul tractors; however, the difference is not sufficient to significantly impact the conclusions of this analysis.[15]

The *Annual Energy Outlook* Represents Business-As-Usual (BAU)

The Energy Information Administration's (EIA's) *Annual Energy Outlook* (AEO) is a well-documented benchmark for many analyses (US EIA 2023). Despite the longevity and widespread utilization of AEO, EIA's own analysis shows that the AEO has historically underestimated the deployment of clean energy technology, overestimated the deployment of coal power, and overestimated the emissions associated with the electric grid (US EIA 2022a). Therefore, even though we have used the latest available version of AEO (US EIA 2023), which includes accounting for recent supportive policies including the Inflation Reduction Act and Infrastructure Investment and Jobs Act (also known as the bipartisan infrastructure law), this scenario likely represents a conservative assessment of the emissions from the future grid powering electric trucks.

To assess the future emissions on an annual basis, we utilize the supplemental data tables corresponding to grid production for the energy market modules contained in NEMS, which largely correspond to the standard NERC subregions (Figure 3, US EIA 2022b). These tables have power generation by different sources for each subregion, over time. The mileage weighting is then used to calculate representative truck operation in the grid region.

Because the NEMS energy market modules do not directly correspond to state boundaries, if we want to examine grid emissions at the state levels we must translate these subregional data to state-level date. We were not able to obtain a detailed GIS map of the energy market module boundaries; however, those subgrids are based on NERC data and share a strong relationship with EPA's eGRID subregions, which are also based on NERC subregions (compare Figure 3, US EIA 2022b to EPA 2024b).[16] These data are available at sufficient level of detail to allocate subregions at the county level.

In order to translate these grid-level estimates to state-level estimates, we assign each county subdivision (identified by a 5-digit Federal Information Processing Series [FIPS]) to a subgrid based on the eGRID subregion map. Where a county falls into multiple subregions, we've assigned it based on the subregion associated with the maximum power production in the subregion according to EPA eGRID 2021. Then, the state grid is determined using county population data as a weight for the subgrids.

[15] *For example, for a 2030 long-haul tractor powered by a BAU grid, utilizing the MOVES3 weighting instead of the representative curve results in a 3.6 percent increase in lifetime CO2 emissions, a 5.6 percent increase in lifetime NOx emissions, and a 4.1 percent increase in lifetime PM2.5 emissions directly from the US national average grid. Compared these results to a 2030 diesel-powered long-haul tractor, using the MOVES3 long-haul combination truck weighting would yield a reduction in lifetime well-to-wheels greenhouse gas emissions of 73 percent and a reduction in monetized public health impacts of 31 to 44 percent, compared to 74 percent and 34 to 46 percent, respectively.*

[16] *The most notable disparity occurs in the Midcontinental ISO (MISO) region, where EIA's MISW subregion contains all of Wisconsin and the upper peninsula of Michigan and nearly all of Minnesota and Iowa while EPA's MROE subregion is limited to only part of Wisconsin and the upper peninsula of Michigan, with the western part of Wisconsin and all of Minnesota and Iowa assigned to MROW. However, the modeled grids for these two regions are largely in agreement, with deviations of around 10 percent, much more similar to each other than to the national average.*

AEO 2023 includes the total direct emissions of CO_2, NO_x, and SO_x from the electric grid. To calculate grid emissions of $PM_{2.5}$ and VOCs and the emissions associated with the upstream extraction of the fuel, the state-averaged grid data by power source is then plugged into GREET 2022. While GREET is only broken into 10 electricity regions, we have used the appropriate region for each grid in order to best match the mix of technology used. For example, the efficiency and mix of natural gas technologies in the Midwest Reliability Organization (MRO) region is different than that of SERC, and we assume that this difference would persist, on average, over time.[17]

Achieving Net-Zero Emissions by 2035 Is Possible with a Clean Grid

While AEO 2023 provides a reasonable, if conservative, assessment of business as usual, EIA did not examine any policy cases consistent with holding the impacts of climate change to 1.5 to 2°C. Therefore, to assess a "clean energy" scenario, we utilize analysis from the National Renewable Energy Laboratory (NREL), which considers a wide range of policy futures as part of its Cambium project. NREL utilizes a least-cost structural model to project future grid elements together with a tool that models hourly grid operation to assess grid characteristics under different future policy scenarios (Gagnon et al. 2023).

The NREL analysis is able to generate a long-run marginal emissions rate, which is defined as the emissions induced or avoided by a long-term change in electricity demand, such as what would be induced by an increasing share of electric vehicles. While recent analysis of the long-run marginal emissions rate shows that it can more accurately predicts emissions impacts related to operational responses to changes in electricity demand than either the short-run marginal emissions rate or the average emissions rate (Gagnon and Cole 2022), the marginal production by source is not provided with the Cambium model data, which means it is not possible to establish non-greenhouse gas long-term marginal emissions rates, either directly or in a comparable manner to the AEO 2023 data. Additionally, AEO 2023 provides average emissions data, so using average emissions rates provides a clearer "apples to apples" comparison between the two different futured sets of data. As a result, this analysis uses the average emissions rate for greenhouse gas emissions.

There are a number of potential future grid conditions based on today's policy landscape. UCS has conducted its own economywide decarbonization analysis, consistent with the science-based position to address climate change by achieving net-zero emissions by 2050 (Clemmer et al. 2023). The Cambium scenario most consistent with this UCS modeling is the 2023 Standard Scenario with a 100 percent reduction by 2035 and assumed high costs for CCS (Gagnon et al. 2023). For comparison, the Biden administration, which has also called for a net-zero emissions economy by 2050, has called for a 100-percent "carbon pollution-free" power sector

[17] *Alternatively, it could be assumed that the more polluting grid regions may rapidly conform to cleaner grid regions by preferentially shifting away from the dirtiest plants, so this represents a conservative assumption. Adopting in each region the same average U.S. grid mix profile yields a wide range of emissions (values provided in g/MMBtu): compared to the U.S. average total emissions of 136,717 (GHG), 15.1 (VOC), 98.2 (NO_x), 8.1 ($PM_{2.5}$), and 86.7 (SO_x), the GREET regions would yield 135,110-176,159 (GHG), 13.8-24.8 (VOC), 75.4-156.8 (NO_x), 4.7-12.2 ($PM_{2.5}$), and 59.0-169.1 (SO_x). The average of the GREET regions has emissions 5.5 to 12.7 percent higher for these pollutants, and generally more regions have emissions performances worse than the national average, again emphasizing how this assumption errs on attributing greater emissions to the grid than using a constant national value.*

by 2035 to help achieve these targets, so this is consistent with the latest presidential objectives, even if that has not been fully implemented yet via policy.

Like AEO 2023, the Cambium data includes direct emissions associated with its grid: the three primary greenhouse gases (CO_2, CH_4, N_2O), NO_x, and SO_x. To assess the remaining non-greenhouse gas emissions ($PM_{2.5}$ and VOCs), as well as the upstream impacts from the grid, we apply source generation from the NREL Cambium analysis to GREET in the same manner as above used for AEO 2023. Losses associated with transmission and distribution are included in this analysis, as in the case for AEO 2023.

The Cambium data is available at the balancing area level, which is even more finely refined than the AEO 2023 data. These are then aggregated to generation and emissions assessment (GEA) regions, which largely overlap with the NERC regions. There are, however, a few differences. The upstate New York (NYUP) and New York City/Westchester (NYCW) subregions are combined into a single balancing area (p127), and the Long Island (NYLI) subregion is not listed as a separate GEA region but only as its own balancing area (p128).

Other than these differences, the Cambium analysis is treated identically to the AEO 2023 data in this analysis.

Generation Outside the Contiguous United States Can Be Cleaner, Too

Both the Cambium data and AEO 2023 data is available only for the contiguous United States, so there is no data modeled for Alaska or Hawaii from either source. Instead, we have incorporated our own estimates based on available data.

Hawaii's Renewable Portfolio Standard Sets a Strong Path Forward

Hawaii has a 100 percent renewable portfolio standard (RPS) for 2045, along with interim targets. As such, Hawaiian utilities have to report on their progress in achieving those targets (Katsura 2023, Rockwell 2023). In addition to these reports, the utilities include planned projects not yet online, including projects already approved by regulators (Hawaiian Electric Company 2023a, Kaua'i Island Utility Cooperative n.d.). Most of these planned projects are utility-scale solar, though the West Kauai Energy Project includes pumped hydropower and is expected to provide over 20 percent of Kauai's power renewably in the coming years. In addition to the approved projects, there are additional planned "Stage 3" required renewable proposals that will substantially increase the renewables on the grid before 2035 beyond what is already confirmed over the next five years, including specifically for firm power (State of Hawaii PUC n.d.). These and the existing plans support the utilities' planned shutdown of fossil fuel power plants, which we anticipate will continue (Hawaii Electric Company 2023b). Some of this firm power is driven by a significant growth in battery-energy storage systems (BESS), which can also increase the available capacity of existing variable renewable resources (GE Energy Consulting 2017). Based on the amount of BESS already planned and the modeling prepared for the Hawaii Natural Energy Institute, we project an increased utilization of just under 15 percent for resources already part of Oahu's grid.

The required RPS targets represent a conservative assessment of the future grid in Hawaii, which we utilize as the BAU case. Compared to RPS targets of 40 percent in 2030 and 70 percent in 2040, it's estimated that the Hawaiian Electric Company will achieve 82 percent in 2035 (up from 32 percent today) and the Kauai Island Utility Cooperative 93 percent in 2035 (up from 69.5 percent today).

The projected grid data was then applied to GREET. To calculate direct emissions from this grid mix, we scale back as needed eGRID2021 data to accommodate the various renewable projects, with an exception for the closure of Hawaii's last coal plant in Oahu (Shao 2022). Unlike eGRID2021, which was the starting point for the Hawaii grid projection, consumer-side solar was included in our assessment of the final GREET mix for both sales and production because it represents a substantial share of both the total generation and contribution towards achieving the RPS targets, and its exclusion in eGRID is based primarily on data collection limitations at the national level. To calculate the emissions from this grid mix, we use GREET, as above.

Electricity Generation In Alaska Is Complex But Getting Cleaner

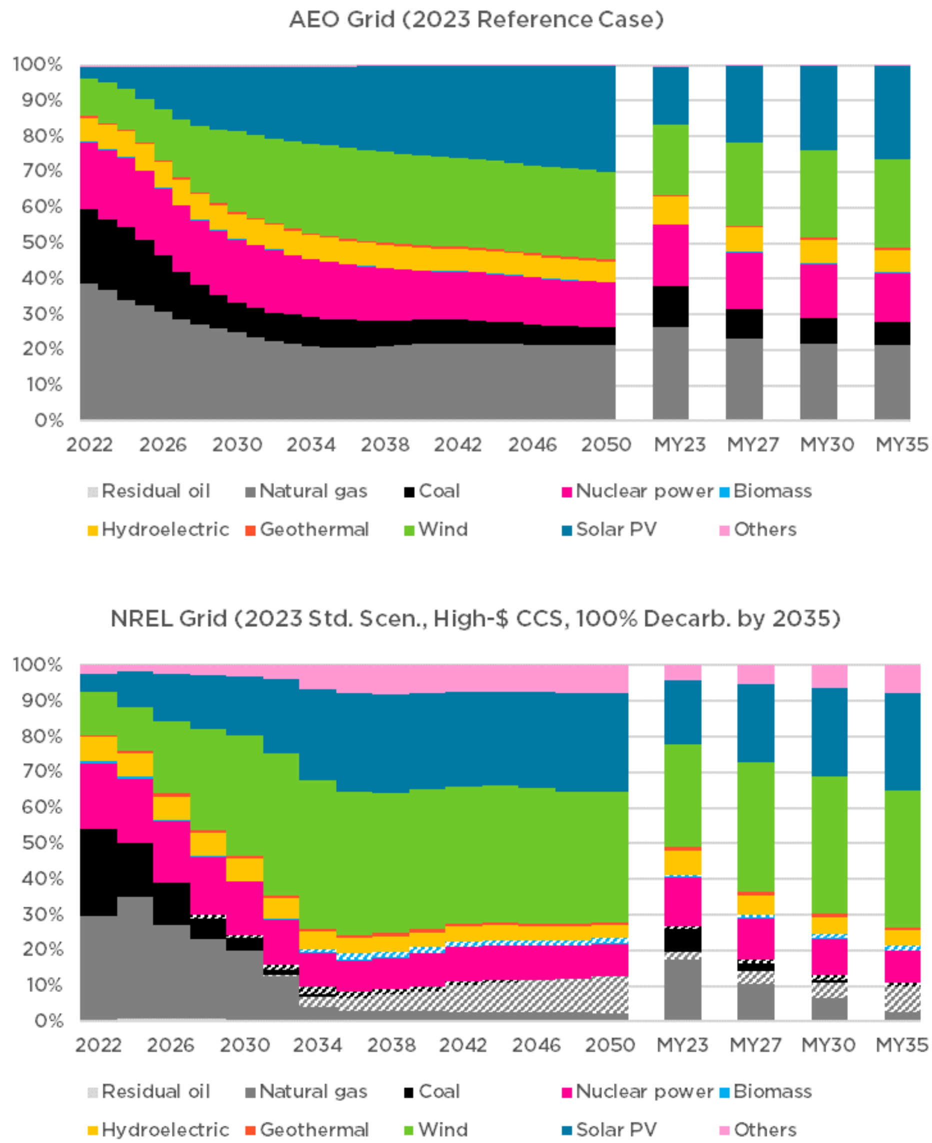
Unlike Hawaii, Alaska does not have any RPS requirements, though Alaska has put forth an RPS in back-to-back legislative sessions, and recent issues with natural gas pricing and availability may help provide the final inertia necessary (George and Stone 2024). A recent study by NREL showed how to achieve an 80 percent RPS in the state's "railbelt", which represents 75 percent of the state's electric load (Denholm et al. 2022). This essentially corresponds to the eGRID subregion labeled ASCC Alaska Grid (AKGD). As part of its analysis of the railbelt, NREL considered a number of different scenarios. Because the RPS is identical in all scenarios, there is little difference in greenhouse gas emissions in any of the individual scenarios, though the fossil source generation does differ in each scenario. Because of planned expansion of both wind and hydroelectric generation, our analysis uses Scenario 2 as a reasonable estimate of a future, cleaner railbelt grid (DeMarban 2022, Kleinschmidt Associates 2022). In addition to the railbelt, Alaska is serviced by a large number of microgrids due to the state's unique environment, size, and sparse population. Hydroelectric power currently provides nearly two-thirds of the generation needed in the rest of the state, though this is currently backed up with diesel generators in order to provide continuous power, and many areas are serviced solely by diesel generators. Battery backup and wind power have enabled some of these microgrids to substantially reduce reliance on diesel to date, and future renewable energy projects are planned in a number of areas to reduce the high electricity costs of diesel dependency (US EIA 2024). For simplicity, it was assumed that diesel fuel generation was replaced with renewable sources to achieve the same 80 percent RPS as AKGD, which leads to shares that are virtually identical to Scenario 1 in the NREL analysis for the ASCC Miscellaneous subregion (AKMS).

While the analysis for Alaska is less ambitious than the Cambium policy case, it leads to substantial levels of greenhouse gas emissions reductions achievable in the timeframe of interest for this analysis of electric trucks. However, in the interim both Alaska and Hawaii are likely to have a considerable share of remaining diesel/oil generation.

Electricity Production Will Increasingly Rely Upon Renewable Energy

The national average grid generation by source is summarized for both the business-as-usual (AEO) and "clean" (NREL) grids in Figure 12. Consistent with UCS's own energy modeling scenarios we have minimized the use of CCS, in this case by utilizing the high CCS cost from the NREL Standard Scenarios (AEO 2023 does not incorporate CCS). The sources are categorized in the same manner as GREET.

Figure 12. Share of National Average Electricity Generation by Source



Both the business-as-usual (AEO, top) and "clean" (NREL, bottom) electric grids show an increasing share of renewable and zero-carbon energy emissions over time. That means that the greenhouse gas emissions per mile associated with the use of an electric vehicle purchased in a given model year (2023, 2027, 2030, or 2035) will be reduced year-over-year. The lifetime-averaged share of generation, by source, is captured in the bars on the right.

Note: Shares of generation utilizing carbon capture and sequestration (CCS) are shown as hashed lines in the color of the respective source.

5 Characterizing Public Health Impacts from Heavy-duty Trucks

By shifting emissions from the on-road to electricity sector, not only do electric trucks change the amount of emissions of different pollutants, but they also shift the impacts of those emissions. For example, while 36 million people live within 3 miles of a power plant (US EPA 2015), 72 million people are estimated to live within 200 meters of a freight route (88 FR 4324), a larger slice of the population despite it being a much narrower radius of proximity. However, in both cases, the populations are disproportionately communities of color and lower-income, a severe environmental justice issue.

For the health impacts of VOCs, NO_X and SO_2, in particular, location can matter significantly because the largest impact (as measured in monetized impacts) is related to the secondary formation of particulate matter from these pollutants, the dependence of which is related to complex, spatially dependent air quality modeling. Additionally, the formation of ozone, which contributes to this secondary particulate formation, can also have direct health effects on neighboring populations.

Because the location of the sources of pollution and the location of the affected populations vary so significantly between the electrical grid, freight traffic, and the upstream impacts from the fossil fuels used in both, this analysis attempts to consider location in its estimates of the health impacts from these very different emissions sources using EPA's Co-benefits Risk Assessment (COBRA) tool, version 5.1 (US EPA 2024c).

EPA's COBRA Model Offers a Tool to Consider Both the Type of Source and Location of Pollution in Identifying Harm

The COBRA tool uses a matrix to model changes in total concentration of $PM_{2.5}$ and ozone (O_3), including via secondary formation from other pollutants. The impacts from these changes are then determined from health impact functions taken from the literature to estimate changes in premature mortality, heart attacks, etc. and reflect input assumptions on population. These can then further be converted into a monetary value.[18] The air quality analysis underpinning the COBRA model is solely applicable to the contiguous United States, however, so public health impacts from Alaska and Hawaii are excluded from this analysis.

To reflect the difference in source of emissions, COBRA is used to determine per tonnage impacts for four different sector categories: 1) Highway Vehicles—Diesel—Heavy-duty, for direct emissions from trucks; 2) Fuel Combustion—Electric Utility, for grid emissions; 3) Petroleum and Related Industries—Petroleum Refineries and Related Industries, for upstream refinery emissions; and 4) Petroleum and Related Industries—Oil and Gas Production, to capture upstream emissions from fossil fuels. It should be noted that feedstock emissions from

[18] *Consistent with the COBRA model, a low and high estimate were used for estimating $PM_{2.5}$-related mortality, utilizing two different epidemiological studies of the impacts of $PM_{2.5}$ on mortality in the United States (Wu et al. 2020 [low] and Pope et al. 2019 [high]). Throughout the report, the range of estimates given for health impacts trace back to this uncertainty.*

the electric grid include coal mining, which is not captured in #4; however, natural gas plants remain the larger share of feedstock emissions according to GREET's modeling, something that is especially true in the case of the future grid, and since this modeling exercise does not consider explicitly emissions from specific plants, this seems a reasonable compromise for simplicity.

In all cases, these factors are aggregated at the state level. This means that impacts are proportional to the respective sources of such emissions in the subregion. For example, if one region's freight traffic travels more distant from population centers, on average, this will be reflected in a reduced impact factor. Or, if a region's emissions are dominated by a single power plant, that region's grid impacts will largely reflect an impact factor in line with that plant's outcomes.

By considering upstream health impacts from diesel fuel use in this way, we may not be accurately reflecting the real-world market outcomes. For example, the refinery level impacts from reducing diesel fuel use may largely result in emissions reductions outside the subregion of interest. At the same time, there is regionality associated with oil and gas production and extraction, so reductions in fuel use and their associated production are not entirely diffuse, so this assumption is more reasonable than assuming a single national average impact for the refinery and oil and gas emissions, particularly since we are aggregating data at the state level, which is already substantially larger territory than point sources like refineries or even particularly heavily trafficked or dense subregions.

To assess the health impacts, the changes in emissions associated with the feedstock, fuel, and use for different categories of truck are considered and multiplied by their respective factors for all pollutants (NO_x, SO_X, $PM_{2.5}$, VOCs) to assess the relative health benefit in a given subregion. Our analysis assumes the default assumptions on population, incidence of underlying health impacts, health impact functions, and economic valuation in the COBRA model for a given year (see below). Additionally, we assume a 2 percent discount rate, now the default for COBRA and consistent with the latest A-4 Circular guidance (White House CEA 2024).

Health Impacts of Pollution Are Time-Dependent

Because we are concerned with the impact of emissions from trucks over their lifetime, it is not just important at what levels the emissions are produced or where, but also when. As populations shift and grow over time, the health impacts from emissions will increase, affecting more people. At the same time, the baseline levels of health may change over time as baseline emissions levels change.

In order to assess the health impacts for different years, EPA has made available estimates of population, incidence, and emissions for a range of years (US EPA 2024d). One can then actually calculate from these data sets the health impacts per ton of different pollutants from different sources over time.

Given the long lifetime of heavy-duty trucks, which can be on the road for 30 years or more, pollution emitted at the earliest years of operation may have a reduced impact compared to later operation. At the same time, more miles are traveled in the earliest years of operation.

While it is technically possible to create time profiles for every type of truck for each pollutant in each state for each fuel source, such an endeavor is computationally prohibitive. Moreover, the regional variations are generally small over time, since regional disparities in population growth are relatively low—aggregated at the state level, population growth from 2030-2050 varies nationwide from 0.1 to 1.4 percent, with a median growth rate of 0.6 percent and a national average growth rate of 0.7 percent.

For simplification, we have considered the time dependence of emissions at the average national level. This may result in smoothing out some differences in state-by-state population and emissions shifts over time. However, those are already largely captured in the actual truck emissions figures, and the difference here is in the second-order effect of the impact of those emissions.

To account for years in between the COBRA-modeled years of interest, we have assumed a constant rate of change in the intervening years. This set of pollutant- and source-specific data is then applied to the annual emissions from a given model year vehicle for a particular duty cycle and fuel source. For combustion trucks, the duty cycle is critical, since emissions over time will vary with annual mileage, assumed load, etc. For electric trucks, emissions are only associated with the grid fueling those trucks, and therefore only a single analysis for each pollutant is needed (see Figure 11 and surrounding discussion), for a given electric grid and model year.

When considering the economic value of health impacts for a given truck, we have socially discounted the values to the model year in question at a 2 percent discount rate, to reflect a net present value for the model year in question. This ensures a fair comparison for a given model year between trucks but means that the economic impacts for emissions from later model year trucks appear greater due to increasing population over time. For our analysis, we are interested only in comparing truck types within the same year of operation; moreover, our analysis considers the question "If you were to purchase a truck in the year…", at which point one would not be discounting the impacts to today but projecting them forward from Age 0, i.e. the model year, as we have done. Had we instead discounted to the current year, this would have undervalued all health impacts in future model years, misleading a reader into thinking that health impacts for a given tonnage for a vehicle sold in a later model year were less because of economic discounting.

Sample Data for a Model Year 2027 Line-Haul Tractor Highlights the Benefit of Electrification

To provide some additional supporting data for comparison to the literature, well-to-tank, tank-to-wheel, and well-to-wheel data on national-average greenhouse gas emissions and monetized health impacts are provided for a line-haul Class 8 tractor-trailer for every model year and fuel type considered (Table 14). Additionally, comparative maps of greenhouse gas emissions and health impacts are shown for a model year 2027 electric tractor-trailer fueled by the business-as-usual (AEO) grid, compared to a diesel tractor-trailer of the same model year (Figure 13).

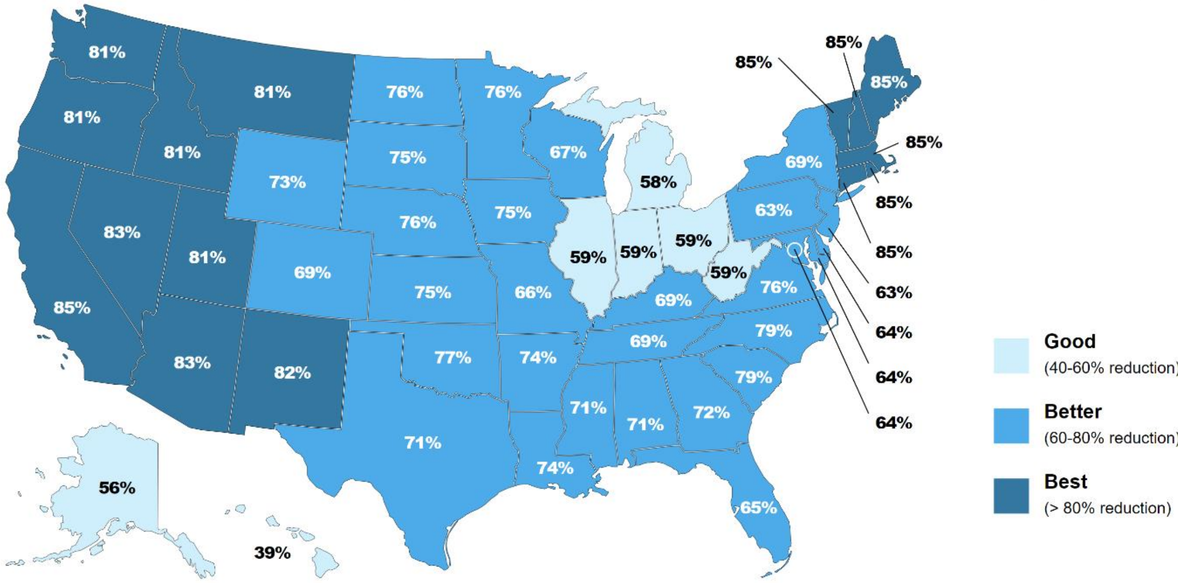
Table 14. National Average Data for Line-Haul Tractors Show the Benefits of Electric Trucks

Powertrain (Grid)	Model Year	Well-to-Tank			Tank-to-Wheels			Total (Well-to-Wheels)		
		CO_2e /mi.	Health Impact $		CO_2e /mi	Health Impact $		CO_2e /mi	Health Impact $	
			Low	High		Low	High		Low	High
Diesel	**2023**	180	$54,957	$80,194	1,471	$139,141	$182,716	1,651	$194,098	$262,910
	2027+	154	$46,993	$68,572	1,258	$77,572	$103,949	1,411	$124,565	$172,521
Gasoline	**2023**	427	$126,609	$186,365	1,781	$154,537	$201,910	2,208	$281,146	$388,274
	2027+	393	$116,382	$171,311	1,637	$84,939	$113,003	2,030	$201,322	$284,314
Natural Gas	**2023**	420	$89,271	$122,569	1,446	$151,398	$198,176	1,866	$240,669	$320,745
	2027+	386	$82,060	$112,668	1,334	$82,003	$109,469	1,720	$164,063	$222,137
Propane	**2023**	340	$83,879	$130,281	1,578	$154,773	$201,550	1,917	$238,652	$331,831
	2027+	312	$77,104	$119,757	1,450	$85,124	$112,590	1,762	$162,228	$232,347
Battery-Electric Vehicle										
AEO Grid	**2023**	594	$100,281	$165,358	-	$4,137	$8,913	594	$104,419	$174,271
	2027	401	$64,371	$105,925	-	$4,253	$9,161	401	$68,624	$115,086
	2030	368	$58,532	$96,332	-	$4,347	$9,364	368	$62,879	$105,696
	2035	345	$54,743	$90,187	-	$4,520	$9,738	345	$59,263	$99,925
NREL Grid	**2023**	361	$86,041	$138,238	-	$4,137	$8,913	361	$90,179	$147,152
	2027	160	$43,138	$68,477	-	$4,253	$9,161	160	$47,391	$77,639
	2030	93	$30,028	$47,458	-	$4,347	$9,364	93	$34,375	$56,822
	2035	48	$21,314	$33,943	-	$4,520	$9,738	48	$25,834	$43,681
Hydrogen ICE Vehicle (SMR H_2 from Natural Gas)										
AEO Grid	**2023**	1,667	$109,156	$169,121	-	$104,379	$137,602	1,667	$213,535	$320,368
	2027	1,400	$91,372	$140,518	-	$36,041	$50,398	1,400	$127,413	$199,588
	2030	1,392	$92,003	$141,025	-	$36,839	$51,514	1,392	$128,842	$200,023
	2035	1,387	$98,556	$150,284	-	$38,312	$53,573	1,387	$136,868	$210,502
NREL Grid	**2023**	1,612	$105,795	$162,721	-	$104,379	$137,602	1,612	$210,174	$313,968
	2027	1,343	$86,367	$131,691	-	$36,041	$50,398	1,343	$122,408	$190,761
	2030	1,327	$85,284	$129,504	-	$36,839	$51,514	1,327	$122,123	$188,502
	2035	1,317	$90,676	$137,025	-	$38,312	$53,573	1,317	$128,987	$197,244
Hydrogen ICE Vehicle (Electrolytic H_2 from Grid)										
AEO Grid	**2023**	2,617	$441,670	$728,288	-	$104,379	$137,602	2,617	$546,049	$879,535
	2027	1,765	$283,180	$465,978	-	$36,041	$50,398	1,765	$319,221	$525,048
	2030	1,618	$257,490	$423,778	-	$36,839	$51,514	1,618	$294,329	$482,776
	2035	1,519	$240,822	$396,745	-	$38,312	$53,573	1,519	$279,133	$456,963
NREL Grid	**2023**	1,592	$378,953	$608,845	-	$104,379	$137,602	1,592	$483,332	$760,091
	2027	706	$189,771	$301,242	-	$36,041	$50,398	706	$225,812	$360,312
	2030	409	$132,097	$208,774	-	$36,839	$51,514	409	$168,936	$267,772
	2035	209	$93,761	$149,320	-	$38,312	$53,573	209	$132,073	$209,539
Hydrogen Fuel-Cell Electric Vehicle (SMR H_2 from Natural Gas)										
AEO Grid	**2023**	1,291	$84,536	$130,976	-	$4,137	$8,913	1,291	$88,673	$150,457
	2027	1,078	$70,369	$108,218	-	$4,253	$9,161	1,078	$74,621	$124,058
	2030	1,072	$70,855	$108,608	-	$4,347	$9,364	1,072	$75,202	$123,736
	2035	1,068	$75,901	$115,739	-	$4,520	$9,738	1,068	$80,422	$130,595
NREL Grid	**2023**	1,248	$81,933	$126,019	-	$4,137	$8,913	1,248	$86,071	$145,500
	2027	1,034	$66,514	$101,420	-	$4,253	$9,161	1,034	$70,767	$117,260
	2030	1,022	$65,680	$99,735	-	$4,347	$9,364	1,022	$70,027	$114,864
	2035	1,014	$69,833	$105,528	-	$4,520	$9,738	1,014	$74,353	$120,385
Hydrogen Fuel-Cell Electric Vehicle (Electrolytic H_2 from Grid)										
AEO Grid	**2023**	2,027	$342,052	$564,023	-	$4,137	$8,913	2,027	$346,189	$583,504
	2027	1,359	$218,087	$358,866	-	$4,253	$9,161	1,359	$222,339	$374,706
	2030	1,246	$198,302	$326,366	-	$4,347	$9,364	1,246	$202,649	$341,495
	2035	1,170	$185,465	$305,547	-	$4,520	$9,738	1,170	$189,986	$320,404
NREL Grid	**2023**	1,233	$293,481	$471,520	-	$4,137	$8,913	1,233	$297,618	$491,001
	2027	544	$146,150	$231,997	-	$4,253	$9,161	544	$150,402	$247,837
	2030	315	$101,732	$160,784	-	$4,347	$9,364	315	$106,079	$175,913
	2035	161	$72,209	$114,997	-	$4,520	$9,738	161	$76,730	$129,853

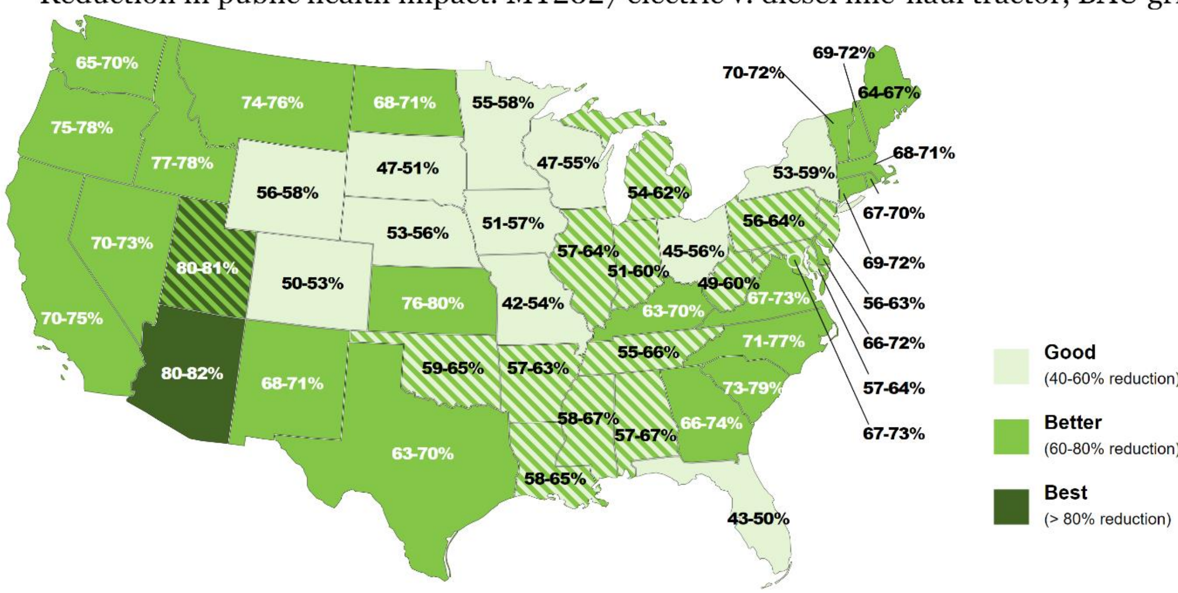
Data on the largest trucks on the road highlights the importance of moving to a zero-emission future.

Figure 13. Impacts of 2027 Electric Line-Haul Tractor-Trailer Compared to Diesel Equivalent

Reduction in greenhouse gases: MY2027 electric v. diesel line-haul tractor, BAU grid



Reduction in public health impact: MY2027 electric v. diesel line-haul tractor, BAU grid



Even under the projected business-as-usual electric grid, a brand new model year 2027 electric line-haul tractor-trailer will significantly reduce greenhouse gas emissions and public health impacts around the country compared to a MY2027 diesel tractor-trailer.

Note: Health impacts are estimated under both low and high estimates of $PM_{2.5}$ mortality, which is why the data is shown as a range. Hashed coloring means that the range of estimates spans multiple color ranges.

SOURCE: UCS Analysis

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