35th International Electric Vehicle Symposium and Exhibition (EVS35)
Oslo, Norway, June 11-15, 2022

A Cross-Country Analysis of Medium-Duty and Heavy-Duty Electric Vehicle Deployments

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Summary

Data on medium- and heavy-duty electric vehicles (MHD EVs) is lacking but essential as transportation electrification accelerates. This paper addresses knowledge gaps in duty cycle performance and energy efficiency using real-world data gathered from over 200 MHD EVs - one of the largest and most diverse datasets of its kind. Analysis revealed that MHD EVs covered similar duty cycles to diesel vehicles provided they were below 200 miles per day. While EVs showed energy savings, their efficiency was found to be impacted by cold climates. These learnings enhance the industry's understanding of MHD electrification and inform future EV deployment strategies.

Keywords: heavy-duty, EV (electric vehicle), efficiency, telematics, data acquisition

1 Introduction

In recent years, the number of electric vehicle (EV) options available in the medium-duty and heavy-duty (MHD) category has significantly increased. Along with CALSTART, the California Air Resources Board (CARB) created the Beachhead Strategy to aid the development of MHD EVs by recognizing first-success applications where zero-emission (ZE) technologies are viable in order to develop future ZE applications [1]. The visualization illustrated in Figure 1 shows vehicles in waves of electrification, with advancements in early categories used by subsequent technologies [2].

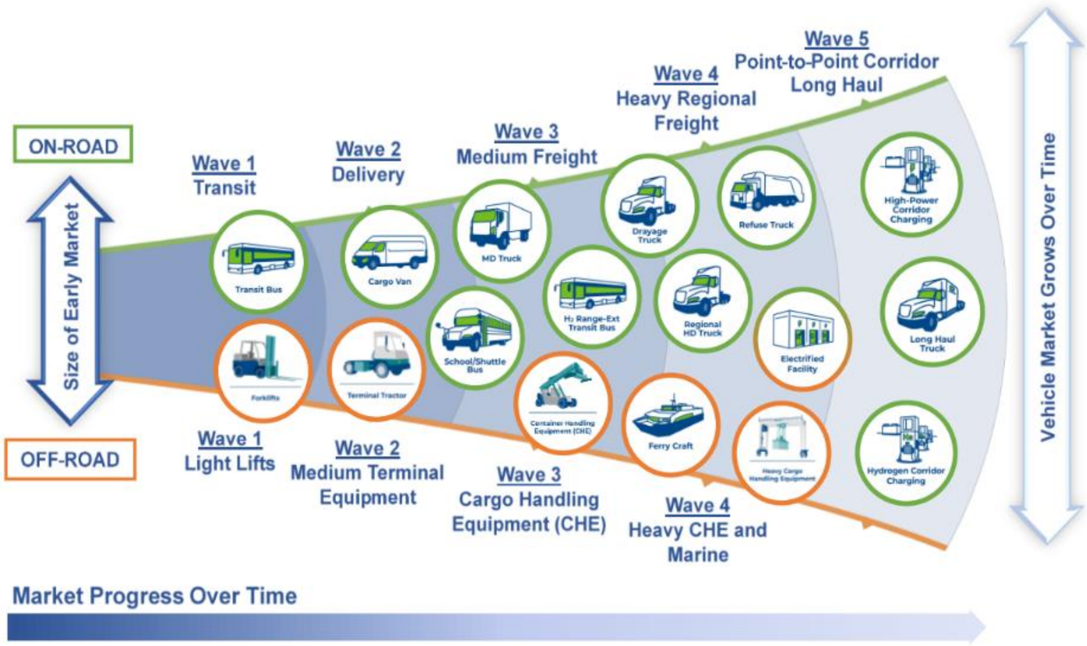


Figure 1: CARB's Beachhead Model as of April 2022 [2]

However, several barriers to adoption exist across different MHD applications, such as range and performance in different climates and uncertainty of their ability to meet the same duty cycle requirements as conventional vehicles [3]. Research regarding these vehicles' deployment in real-world settings has been scarce [4]. Industry stakeholders struggle with a lack of data that could help answer questions like duty cycle suitability, effects of terrain, weather, and traffic flow. Funded by the U.S. Department of Energy (DOE), Office of Energy Efficiency and Renewable Energy (EERE), the Medium- and Heavy-Duty Electric Vehicle Data Collection project goals are to gather, aggregate, classify, publish, and visualize anonymized operational data from over 200 battery electric (BE) MHD vehicles to stimulate research in this area.

The dataset gathered for this study provides a robust and diverse cross-section of EV platforms and models, encompassing a wide range of applications, duty cycles, geographies, and climates. Supplemental data include information on charging sessions, maintenance and repair records, and energy consumption of fleet facilities being gathered and reported when available. The project required a significant amount of outreach, coordination with partners, and relationship-building in order to gather datasets with the appropriate metrics and timespan of observations, secure a diverse range of vehicles and geographies, interpret and condense datasets into the required structures and levels of aggregation, and troubleshoot and resolve issues within the data. Regional Clean Cities Coalitions—DOE-sponsored organizations that bring together public and private stakeholders—were leveraged to recruit additional fleets, and their networks were utilized to communicate project results. Overall, this project aims to improve the public understanding of current deployments of MHD EVs and detect trends in MHD EV performance while providing a robust and publicly accessible dataset to facilitate further research and insights.

2 Data Sources

Onboard data loggers, either from third party suppliers or pre-installed by vehicle manufacturers, were used to collect data directly from vehicles' Controller Area Network (CAN bus). Data collected include battery state of charge (SOC), mileage traveled, vehicle key-on/runtime, vehicle idle time, and number of trips in a day. Data were aggregated according to either per-trip statistics or per-day statistics, depending on the system's reporting characteristics. Ambient temperature data were manually appended when onboard loggers did not collect this data to provide an estimation of each day's weather conditions. To date, 13 states are represented within the data with the hope of further increasing geographic diversity as the project continues. Table 1 and Figure 2 below summarize the makeup, status, and geographic distribution of the various datasets.

Table 1: Confirmed vehicles for the project and included in the following analysis

	Vehicle Types	Number of Vehicles Confirmed	Number of Vehicles in Analysis	Number of Vehicle Days Data in Analysis
HD	Transit Buses	124	34	3,791
	Class 7 Box Trucks	5	5	478
	Class 8 Day Cab Tractor	14	14	1,057
MD	Class 6 Trucks	54	10	220
Off-Road	Yard Tractors	45	28	6,695
Total		242	91	12,241

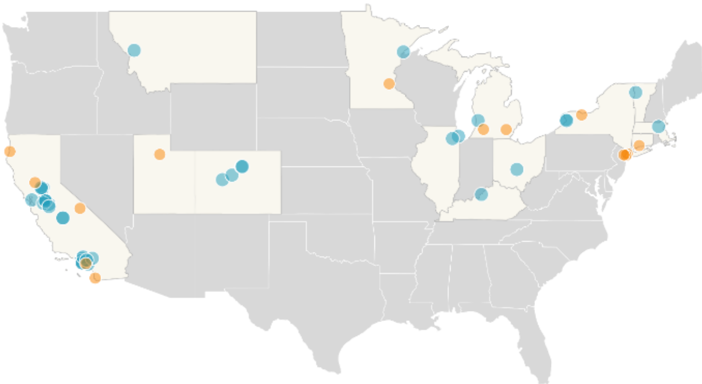


Figure 2: Map of active ZE vehicle deployments that have agreed to be included in this dataset and analysis (blue) and fleets currently pending inclusion (orange)

Confirmed vehicles represent the datasets that will be included once the project is completed. The data collection effort is still ongoing, so not all confirmed vehicles were included in the analysis.

2.1 Data Preprocessing

The data format and granularity were not uniform across deployments and therefore were preprocessed via a series of steps programmed in Python to eliminate erroneous entries and accurately characterize vehicle performance. Data were anonymized and assigned Vehicle IDs to protect the identity of the fleets. In addition to vehicle performance parameters, vehicle attributes were collected from fleets, manufacturer websites, or other sources to provide adequate context (e.g., vehicle model configurations, fleet type, etc.). "Nominal" means that the attribute was provided by the manufacturer as vehicle specification rather than measured in use. Table 2 lists the vehicle performance parameters and attributes included.

Table 2: Vehicle performance parameters and vehicle attributes

Vehicle Performance Parameters		Vehicle Attributes	
Mileage traveled	Driving speed	Weight class	Nominal range
Vehicle energy efficiency	Energy consumption	Nominal efficiency	Battery capacity
Driving time	Idling time	Towing capacity	Region
Ambient temperature		Vocation	Vehicle platform
		Body style	

3 Duty Cycle Suitability Analysis

An enhanced understanding of current MHD EV deployments, including the duty cycles they can meet, is important for developing EV deployment strategies. While EV technology is rapidly improving, there are still performance limitations that need to be considered. This duty cycle analysis uses data collected for this project together with operational findings from several earlier demonstrations and pilot studies [5]–[12]. Table 3 shows the duty cycles of MHD EVs.

Table 3: Duty Cycle of MD/HD EVs in DOE Database

Vehicle Type	Daily Distance (mi)	Daily Key-on Time (hr)	Daily Average Driving Speed (mph)	Description and Use Case
Transit Bus 	92	14	18	City routes, returning to bus depot each day. Buses rely on overnight depot charging.
MD Step Van 	44	14	23	Return to base, urban delivery of mail or packages, variable routes
HD Day Cab Tractor 	58	4	20	Return to base, port drayage or regional duty cycle, fixed routes
HD Box Truck 	48	4	16	Return to base, regional duty cycle, fixed routes
Yard Tractor 	32	10	3	Single to multiple shifts, fixed routes

Since the parameters are not normally distributed, median was used rather than mean to represent the central tendencies of the distributions. The daily key-on time includes both idle time and driving time. The daily average driving speed, which is also represented by median in the table, is computed as daily distance divided by daily driving time (not including idle time) for every vehicle-day. The following section provides additional insights on some of the specific operations and use cases of these MHD EV deployments, further enhancing understanding of EV performance in real-world operating environments.

EV transit bus deployments in the Midwest and West Coast regions showed that buses typically drove 50–140 miles per day, with 200 miles seen in some extreme cases. Daily operation spanned 8–18 hours. The usual transit fleet duty cycle in urban areas includes frequent service stops, mixed stop-and-go driving, and acceleration, with some fleets stopping more than 80 times within a single route. Buses had daily average driving speeds of 12–20 mph overall. BE transit buses operating in regions with colder climates sometimes were equipped with auxiliary fuel fired heaters to provide supplementary heat to the cabin while also reducing energy draw on the battery [13]. This was due to the significant impact ambient temperature conditions can have on an EV’s performance, specifically its range. A more comprehensive analysis on temperature and efficiency is covered in Section 4.2.

Yard tractor deployments in the Midwest, Northeast, and West Coast regions were in operation about 6–13 hours per day, and in some cases up to 21 hours per day. Daily driving distance was between 19–48 miles and average speed was around 2–7 mph. On a typical day, roughly equal time was spent idling and driving.

MD step vans operating in California picked up and delivered packages from distribution centers. Data showed that they drove 22–48 miles over 13–15 hours; the maximum distance logged was 88 miles while maximum runtime was over 22 hours. Average speed was around 20–25 mph but could reach up to 55 mph.

HD box trucks, equipped with a 150-mile range and 264 kilowatt-hour (kWh) battery, were used for freight hauling in regional routes. They mostly drove 35–80 miles a day for 3–7 hours; the maximum driving distance was logged around 133 miles a day and maximum runtime was close to 11 hours. Average speed was around 11–25 mph but could reach 60–70 mph.

The HD day cab tractors were used for regional freight hauling and drayage by various fleets in California. They mostly drove 35–91 miles a day for 2–6 hours; maximum distance was logged at 200 miles a day, including a midday opportunity charge, and maximum runtime was close to 14 hours. Most of the daily average speed was 14–25 mph but could reach highway speeds of 60–70 mph. Data showed that HD trucks were capable of meeting duty cycles that have a single shift and travel less than 200 miles (322 km) per day. A recent study reported results of a demonstration of 13 commercial EV trucks operating under real-world conditions in eight states [6] and concluded similarly that EV trucks were capable of replacing all vehicle segments except long-haul or regional-haul operations with the longest routes. Challenges for these segments included unpredictable routing, longer idle times, and trucks not returning daily to base to charge.[14]

4 Real-World Energy Efficiency

This study sought to quantify energy efficiency across different operating environments and use cases. Many important factors can impact a vehicle's energy efficiency, including payload, number of passengers, driving speed, idling time, terrain, congestion, and number of stops, but not all of these can be recorded via data loggers or are not broadcast by all vehicles. Our study focuses on the metrics we were able to quantify and record with the goal of gaining insights on performance by aggregating a large dataset.

4.1 Energy Efficiency by Vehicle Platform

Figure 3 shows the MHD EV energy efficiency across vehicle platforms and body styles, using box plots to show the distribution of efficiency performance.

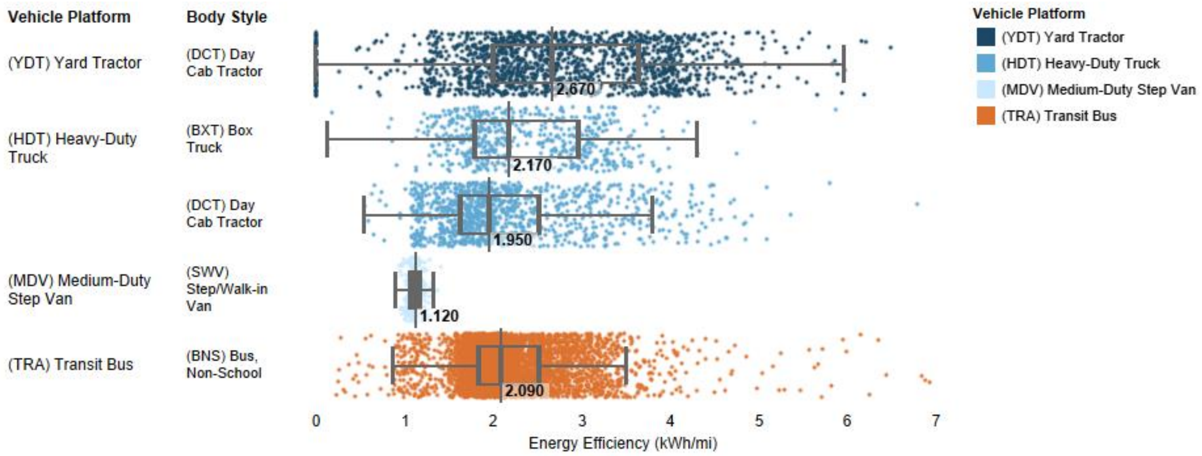


Figure 3: Daily energy efficiency values for MHD EVs grouped by vehicle platform

In the figure, each dot represents a vehicle's aggregated operation for an entire day. All vehicles with data collected were grouped by vehicle platform and, in the case of heavy-duty trucks, by body style as well. The edges of each box show the first and third quartile of the distribution, and the middle line represents the median. The low and high outliers likely represent anomalous days (e.g., if the vehicle did not operate in service but was moved from one end of the lot to another or it was turned on and idled in place for a moment).

Yard tractors used significantly more energy than on-road HD trucks, possibly due to their duty cycles, which included a high percentage of idle time and very low driving speeds. The distribution of the data is quite broad, with many data points around both 2 kWh/mi and 4 kWh/mi and less efficient than the nominal values cited by manufacturers (2.3–2.5 kWh/mi). The median efficiency of the electric yard tractors is equivalent to

14.1 miles per diesel gallon equivalent (MPDGe[1]) and still twice as efficient as fossil-fueled units (6.5 MPDG on average).

The HD box truck nominal efficiency was listed at 1.76 kWh/mi, and slightly lower than the first quartile of the measured values (1.79 kWh/mi), meaning that over 75% of the operating days measured were less than the nominal value. The median efficiency at 2.17 kWh/mi (or 17.6 MPDGe) was over twice that of similar diesel trucks (8 MPDG).

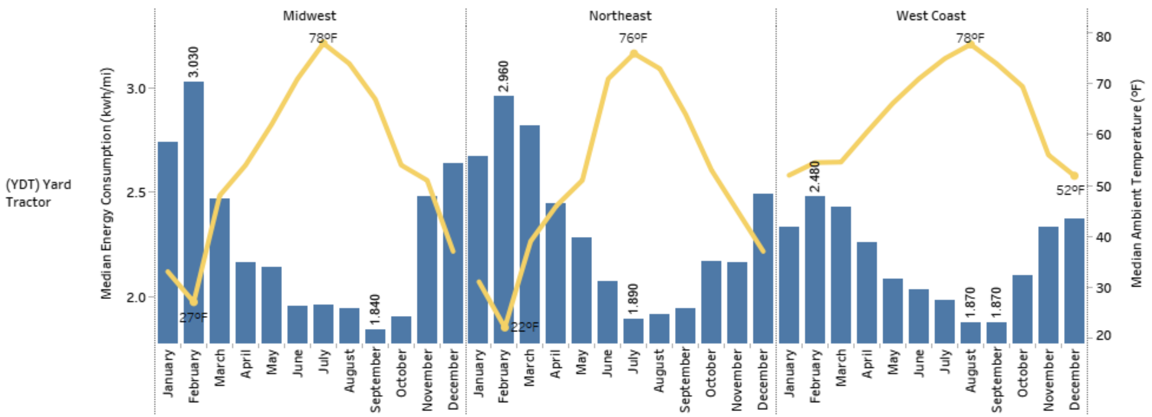
The HD day cab tractors were marginally more efficient than the HD box truck EVs and significantly more efficient than diesel units, using nearly one-third of the energy that diesel units used. Based on the operations of 14 HD day cab tractors for about eight months, we observed that more than half of the real-world operations are more efficient than the nominal efficiency. It is possible that these data are somewhat skewed given that all the units were studied in warmer months and in a mild climate region (California). As more data are collected across more diverse deployments, further investigation will help understand these factors.

The MD EVs required 40-60% less energy to travel a mile than their HD EV counterparts. There were five vehicles, with a battery capacity of 85 kWh, tested for approximately nine months from May 2019 to January 2020. Energy efficiency had a median of 1.12 kWh/mi. Previous studies estimated the efficiency of Class 6 electric delivery trucks at 24.09 MPDGe (about 1.58 kWh/mi) [15] and 1.53 kWh/mi [16]. As these studies were from several years ago it is expected to see modern vehicles with improved efficiency.

There are five different vehicle models for the 34 buses, with a wide range of battery capacities from 79 kWh to 440 kWh. Most of the measured energy efficiencies were between 1.8–2.5 kWh/mi, with a median of 2.09 kWh/mi (18.23 MPDGe). Compared to similar diesel buses that might average 4 MPDG, EVs are over four times more efficient. A recent study reported similar values of 1.86 kWh/mi [17].

4.2 Seasonal Energy Efficiency Across Regions

Hot and cold conditions are known anecdotally to impact the performance of EV batteries and ultimately vehicle range, but the relationship is not well defined. We observed seasonal patterns in vehicle efficiency across different regions, focusing on yard tractors and transit buses where the most data were available. In Figure 4, one can observe distinct trends in energy efficiency across three different regions—Midwest, Northeast, and West Coast.



[1] MPDGe is miles per gallon diesel equivalent, assuming 38.1 kWh of electricity is equivalent to the energy powered by 1 gallon of diesel fuel

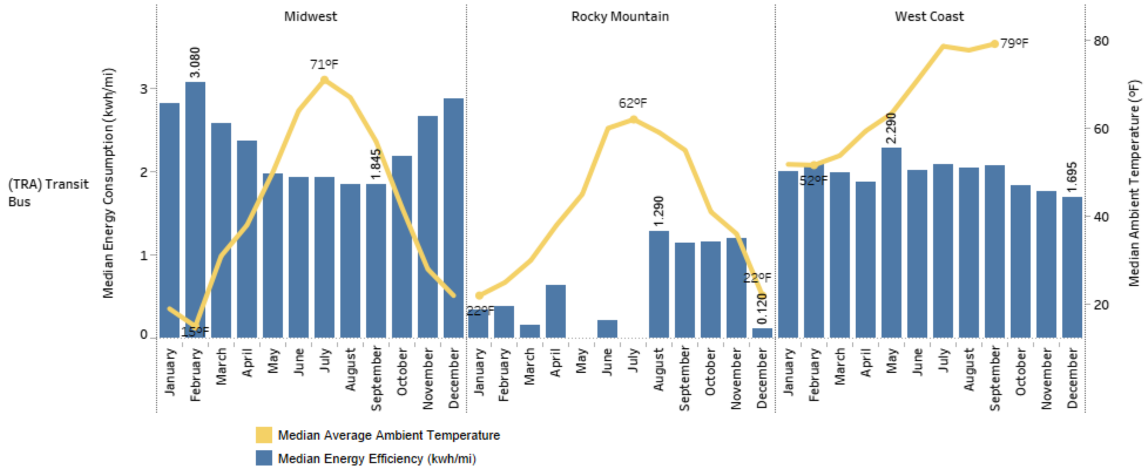


Figure 4: EV yard tractor and transit bus energy efficiency and ambient temperature in three U.S. regions

The yellow lines show the median of daily average ambient temperature while the bars in blue show the median daily energy efficiency by month. In colder months (November to February), yard tractors have substantially reduced efficiency. In the Midwest and Northeast regions, where annual temperature fluctuations are more extreme, the corresponding efficiencies show a greater range. Yard tractors in these regions consume around 1.5 times more energy in the coldest versus warmest months, while in the West Coast region, the difference is closer to 1.3. Interestingly, the most efficient months across all regions have very similar values for kWh/mi, seeming to confirm that cold weather has more of a negative effect on efficiency than warm. The negative correlation between efficiency and temperature seems well established, but a regression analysis was conducted to understand whether it is statistically significant and to quantify the impact.

4.2.1 Regression Analysis of Transit Bus Efficiency and Ambient Temperature

Knowing to what degree ambient operating temperatures affect range is an important consideration for fleets when choosing the right battery configurations for their vehicles. To assess the correlation between energy efficiency and ambient temperature, we fitted a multivariate Ordinary Least Squares (OLS) regression using 3,791 vehicle-days of data sampled from 34 transit buses operating in three regions across the country between 2016 and 2021. Transit buses were selected for focus because they had the best data availability, including the widest coverage by time (2016-2021) and by region (Midwest, Rocky Mountain, and West Coast. Table 4 provides an overview of the transit buses included in the analysis.

Table 4: Transit bus configurations and data collection timeline

Region	Manufacturer/ Model	Range (mi)	Battery Capacity (kWh)	Bus Length (ft)	Fuel-fired Auxiliary Heater	Model Year	Timeline
West Coast	Proterra/ZX5	40	79	40	No	2018	2018 Q1 – 2018 Q3
	BYD/K9S	145	266	40	No	2017/ 2018	2018 Q3 – 2019 Q2
	CCW/repowered New Flyer GE40LF	130	308	40	No	2016/ 2017	2016 Q4 – 2018 Q3
Midwest	Proterra	200	440	40	Yes	2018	2018 Q2 – 2021 Q2
Rocky Mountain	New Flyer/XE40	225	440	40	Yes	2019	2020 Q4 – 2021 Q4

The model was developed to test whether ambient temperature impacts transit bus energy efficiency, while holding other variables constant (i.e., average driving speed, idling time percentage, and region of operation). The region variable serves as a proxy to control for unobserved variables (e.g., geography, driving conditions, ridership, etc.) that differ across regions. The model specification is shown in Equation (1).

$$Energy\ Efficiency = \beta_0 + \beta_1 Average\ Ambient\ Temperature + \beta_2 \\ (Average\ Ambient\ Temperature)^2 + \sum \beta_i Region_i + \sum \theta_j Control_j + \varepsilon \quad (1)$$

A quadratic curve is fitted to the data with temperature both as linear and second-order terms. This reflects the fact that an optimal temperature exists for battery performance. Regression results are shown in Table 5.

Table 5: Regression result of transit bus energy efficiency vs. ambient temperature

	Coefficient	**Standard Error**	**P-value**	**[0.025**	**0.975]**
Average Ambient Temperature	-0.0325	0.001	0.000	-0.034	-0.031
Average Ambient Temperature Squared	0.0002	9.81e-06	0.000	0.000	0.000
Average Driving Speed	-0.0396	0.002	0.000	-0.045	-0.035
Idling Time Percentage	0.0270	0.066	0.680	-0.101	0.155
Rocky Mountain	-1.1440	0.038	0.000	-1.218	-1.070
West Coast	0.0786	0.011	0.000	0.056	0.101
Constant	3.9734	0.058	0.000	3.860	4.087

Number of Observations 3,791	Adjusted R-Squared 0.622

Based on these results, a 1°F change in temperature has a stronger effect on efficiency between 30°F and 55°F (0.01–0.02 kWh/mi increase) than between 56°F and 78°F (0.001–0.01 kWh/mi change). In other words, a bus consumes an additional 1–2 kWh for every 100 miles in cold temperatures versus 0.1–1 kWh more in warmer temperatures when temperature drops 1°F. The results are statistically significant at the 99% confidence level. The coefficients indicate that the optimal ambient temperature for transit buses to operate is around 81°F (27°C) when the other variables are controlled. When ambient temperature is above or below this level, energy demand starts to increase at an accelerating rate for each marginal change in average temperature. It is important to note the unbalanced sampling across regions that could be a source of bias in the model. The Midwest and West Coast regions have comprehensive data across seasons while the Rocky Mountain region covers less than a full year, limiting the temperature variations observed[2].Figure 5 below shows the observed data and fitted values from the model; there appear to be three separate trends likely driven by the controlled variables.

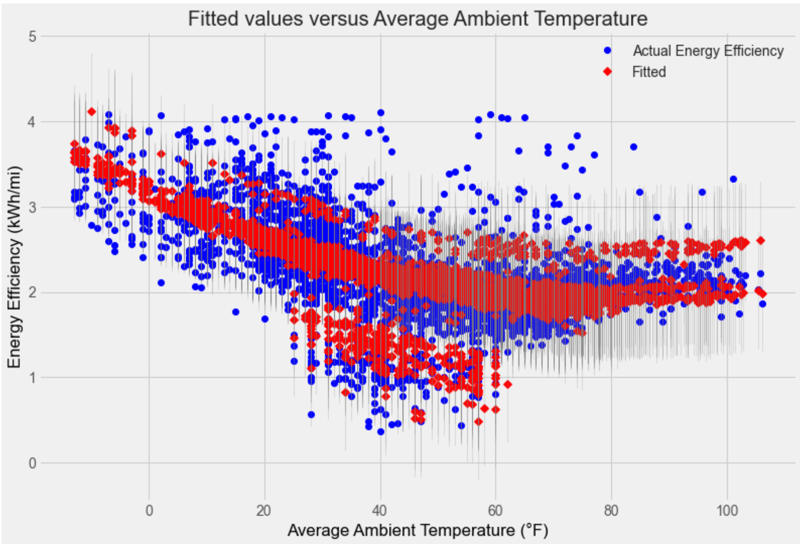


Figure 5: Transit bus energy efficiency (kWh/mi) vs ambient temperature (°F):
fitted values (red) with 95% prediction confidence intervals (grey) and actual values (blue)

Based on manufacturer provided operating manuals, it appears that EV buses' fuel-fired auxiliary heaters are programmed to operate when temperature goes below 40°F and to stop when temperature is above 45°F. This

[2] Data captured during 2020 Q4 and 2021 Q1 included much noise when the data loggers were initially installed, so this period of data were not included in the analysis.

can help explain the energy efficiency performance in the Midwest and Rocky Mountain regions, shown in Figure 6, where temperatures can be very low in winter and early spring.

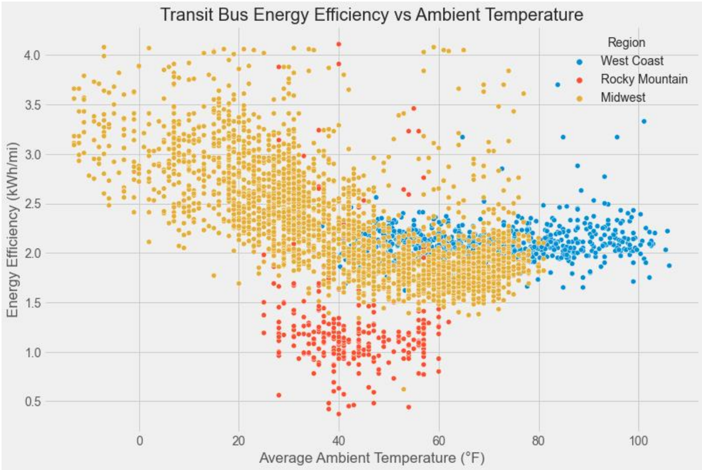


Figure 6: Transit bus energy efficiency (kWh/mi) vs ambient temperature (°F), colored by geographic regions (blue for West Coast, red for Rocky Mountain and yellow for Midwest)

When ambient temperatures drop below 40°F, there is a strong increase in energy demand, reaching as high as 3–4 kWh/mi. Above 45°F, energy efficiency becomes much more stable at around 1.5–2.5 kWh/mi.

4.2.2 Regression Analysis of Yard Tractor Efficiency and Ambient Temperature

A similar regression analysis was performed on the other vehicle platform with extensive data: EV yard tractors. There were 5,356 vehicle-day observations of EV yard tractors operating in three regions in the U.S. (Midwest, Northeast, and West Coast). Table 6 provides an overview of the vehicles included in the analysis.

Table 6: EV yard tractor configurations and data collection timeline

Region	Manufacturer/ Model	Towing Capacity (lbs)	Battery Capacity (kWh)	Model Year	Timeline
West Coast	Kalmar/Ottawa T2E Terminal Tractor	80,000	220/176	2019/2020	2020 Q1 – 2021 Q3
	BYD/Q1M	-	218	2020	2020 Q3 – 2021 Q3
	Orange EV/EV T-series	81,000	80	2020	2020 Q1 – 2020 Q4
	Orange EV/EV T-series	81,000	160	2019/2020	2020 Q2 – 2021 Q2
Midwest	Orange EV/EV T-series	81,000	160	2016/2017/2019	2020 Q3 – 2021 Q3
Northeast	Orange EV/EV T-series	81,000	160	2017	2020 Q3 – 2021 Q3

The model specification is shown in Equation (2) and the results are shown in Table 7 below.

$$Energy\ Efficiency = \beta_0 + \beta_1 Average\ Ambient\ Temperature + \beta_2 (Average\ Ambient\ Temperature)^2 + \sum \beta_i Region_i + \sum \theta_j Control_j + \varepsilon \quad (2)$$

Table 7: Regression result of EV yard tractor energy efficiency (kWh/mi) vs. ambient temperature (°F)

	Coefficient	Standard Error	P-value	[0.025	0.975]
Average Ambient Temperature	-0.0446	0.005	0.000	-0.054	-0.035
Average Ambient Temperature Squared	0.0002	4.12e-05	0.000	0.000	0.000
Average Driving Speed	-0.1101	0.003	0.000	-0.116	-0.104
Northeast	0.1338	0.032	0.000	0.071	0.197
West Coast	0.1272	0.019	0.000	0.090	0.164
Constant	4.4755	0.149	0.000	4.184	4.767

Number of Observations 5,356	Adjusted R-Squared 0.276

Controlling for the other variables listed, the coefficients indicate that the optimal ambient temperature is around 111.15°F (44°C), which is out of range for existing data (~25-95°F). This is likely not an actual optimum and more observations into colder temperature performance could shift this optimum lower and steepen the curve's shape. The existing data only observed a down-sloping curve, substantiating the impact of a colder climate on vehicle efficiency. The relatively flat curve means that each 1°F lower in ambient temperature between 30-61°F is associated with a similar increase in energy demand (0.02–0.03 kWh/mi increase) compared with the effect of each 1°F between 62-86°F (0.01–0.02 kWh/mi increase). In other words, a marginal decrease in average temperature would consume an additional 2–3 kWh for every 100 miles in cold temperatures versus 1-2 additional kWh in warm temperatures. This is a larger difference than for transit buses, which indicated a greater sensitivity to temperature in the current model. The results are statistically significant at the 99% confidence level, but the model currently underfits the data with an adjusted R-squared of 27.6%. The inclusion of other independent variables, such as actual payload and idling time, could help further explain the wide variation observed in efficiency and improve its predictive ability. These results should be interpreted as a first step and will hopefully be improved as deployments increase and more data are collected. Figure 7 below displays the fitted and observed values versus temperature.

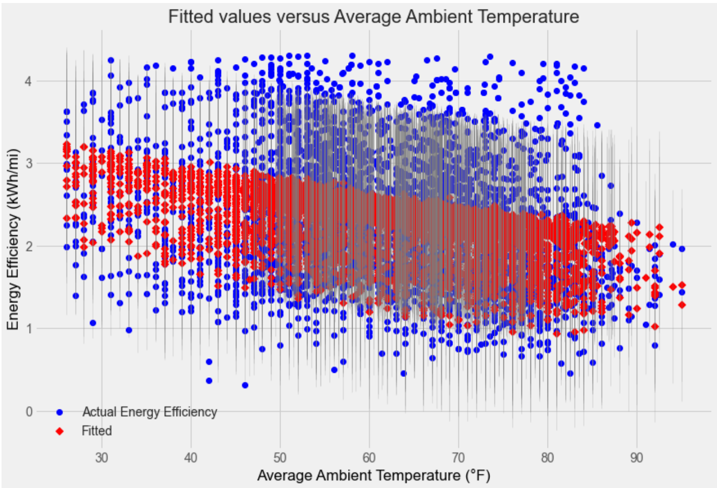


Figure 7: Tractor energy efficiency (kWh/mi) vs. ambient temperature (°F): fitted values (red) with 95% confidence intervals (grey) and actual values (blue)

5 Conclusion

At the current stage of EV market adoption, research into MHD EV deployments is lacking and therefore our understanding of real-world performance is limited. While still relatively scarce, MHD EV deployments are now steadily growing. Collecting and analyzing operational performance data from early deployments and building a publicly accessible national dataset will provide critical learnings to better inform industry stakeholders while accelerating the adoption of cleaner transportation technologies.

EV yard tractors, MD trucks, and delivery vans were found to perform comparably to the conventional baseline vehicles used on similar duty cycles. However, EV models in the HD truck segment proved capable of meeting duty cycles limited to one shift and less than 200 miles (322 km) per day. Although real-world efficiency is typically worse than nominal efficiency regardless of vehicle segment, MHD EVs were found to be 2–4 times more efficient compared to comparable diesel vehicles, which presents a significant advantage in fuel savings.

Seasonal patterns in vehicle efficiency were observed across regions. By conducting regression analyses on transit buses and yard tractors, we were able to better quantify the impacts that colder temperatures had on vehicle efficiency.

- For transit buses operating between 30°F and 55°F, 1°F lower in ambient temperature is associated with 1–2 kWh additional energy consumption for every 100 miles traveled; when between 56°F-78°F, the impact diminishes to 0.1–1 kWh additional consumption. The optimal ambient temperature is around 81°F (27°C), holding other variables constant. Below 40°F, we observed a sharp increase in energy consumption, up to 3–4 kWh/mi. Above 45°F, energy efficiency was much more stable in the range of 1.5–2.5 kWh/mi.
- For yard tractors operating between 30°F and 61°F, 1°F lower in ambient temperature was associated with 2-3 kWh of additional energy consumption for every 100 miles; when between 62-86°F, the impact diminishes to 1-2 kWh additional consumption. As more data becomes available, adding other important independent variables such as payload and idling time can improve the fitness of the model and allow for better understanding of how external factors affect efficiency.

Further analysis should be conducted to understand the relationship between vehicle efficiency and driving speed, urban congestion, and other factors. Analysis on SOC of electric trucks and buses on different routes at different times of day can inform the MHD EV industry and fleet owners about vehicle charging patterns in relation to their duty cycles.

Having insight into the current use patterns of MHD vehicles across sectors, climates, regions, and geographies will help establish regional benchmarks to help fleets understand how electrified vehicles are likely to perform in their operations. Using this data, the industry can better understand factors that impact battery efficiency and range (e.g., climate and the presence of fuel-fired heaters); expected vehicle behavior metrics for a wide range of platforms, duty cycles, and climates; differences in performance between geographic regions; and how MHD EVs can fit into a fleet's operations.

A public-facing dashboard to facilitate consumption and interpretation of this data is in progress. The project will also generate customized fleet-facing reports quantifying observations from the data for each participating fleet. To increase its comprehensiveness, the project will continue recruiting additional EV fleets with differing body styles and duty cycles and in underrepresented locations to help inform additional aspects of MHD EV adoption by fleets.

Acknowledgements

This project was made possible through the funding and support of the Office of Energy Efficiency and Renewable Energy ("EERE"), an office within the United States Department of Energy.

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Presenter Biographies

Kevin Leong is a Deputy Director overseeing CALSTART's Data Validation and Assessment Team. He has been with CALSTART for six years and manages several zero-emission medium- and heavy-duty truck and bus demonstrations along with guiding the strategic oversight over the data team. Kevin is a graduate of the University of California, Irvine with a Bachelor's degree in Mechanical Engineering and a Master's degree in Engineering Management.

Yin Qiu is a Data Scientist on the Validation & Assessment team. She focuses on leveraging the power of data analytics and visualization to convey the stories and insights from CALSTART's collected data to promote clean transport. Yin graduated from UC Berkeley with a Master of Information Management and Systems and a Certificate of Applied Data Science. She also holds a Master of Public Policy from Georgetown University and a Bachelor of Management from Sun Yat-sen University.

Chase LeCroy is a Technical Program Manager responsible for leading data collection and analytics strategy on CALSTART's Validation & Assessment Team, overseeing a team working on several large-scale data synthesis projects including the one described above. He has worked on various medium- and heavy-duty clean transportation projects across many sectors. Chase has a Bachelor of Science in Earth Science from Rice University and a Master of Environmental Science and Management from UC Santa Barbara.