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# Real-world Energy Efficiency Analysis and Implications: Medium- and Heavy-Duty EV Deployments Across the U.S.

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**Executive Summary**

While the market for medium- and heavy-duty battery-electric vehicles (MHD EVs) is still nascent, a growing number of these vehicles are being deployed across the U.S. This study used over 1.5 million miles of operational data from multiple types of MHD EVs across various regions and operating conditions to address knowledge gaps in total cost of ownership and operational range. First, real-world energy cost savings were determined: MHD fleets should experience energy cost savings regardless of vehicle platform, with the most savings seen in transit buses and HD trucks. Second, operational range was modeled given duty cycle, vehicle configuration, use case, climate, and terrain, to help fleets across various geographies throughout the U.S. assess the suitability of EVs for their operating needs. Finally, this paper suggested considerations for MHD fleets to optimize their efficiencies and range based on the model findings.

*Keywords: BEV (battery electric vehicle), heavy-duty, cost, range, efficiency*

## 1. Context

In recent years, the number of medium- and heavy-duty (MHD) electric vehicle (EV) options available on the market has significantly increased, up 36% globally since 2021 [1]. However, adoption of MHD EVs has not occurred at the same pace due to barriers like high up-front costs and general uncertainty of the ability of EVs to meet duty cycle requirements [2]. Research regarding MHD EVs' performance in real-world deployment settings has been scarce [3], and industry stakeholders struggle with a lack of information and data to understand MHD EVs' actual duty cycle suitability, total cost of ownership, and performance in the face of variables like climate, terrain, and driving speed. Understanding the in-use energy efficiency of MHD EVs will help fill these knowledge gaps and advise on the two major concerns in EV adoption: total cost of ownership and range.

A preliminary model-based comparison [4] showed that MHD EVs were 2–4 times more energy efficient than diesel vehicles, while a 2018 California Air Resources Board (CARB) meta-analysis using data from real deployments found that battery-electric trucks and buses were 3–6 times as efficient as diesel counterparts, with a vehicle's precise estimated energy efficiency ratio (EER)[1] depending on its vehicle platform and duty cycle,

[1] Energy efficiency ratio (EER) is defined as the efficiency of an EV divided by the efficiency of its baseline diesel counterpart.

with greater efficiency at lower average speeds [5]. Given that electricity is consistently cheaper than diesel per unit of energy [6] and that heavier vehicles tend to consume more energy per mile than light vehicles [7], fleets switching from diesel to electric MHD vehicles should experience energy cost savings, which helps reduce total cost of ownership. This study not only supported these previous model- and data-based findings but also estimated the energy cost savings associated with improved efficiency.

To address users' uncertainty about real-world EV performance, predictive models have been widely used to project EV energy consumption, efficiency, and range and to understand their determinants and trade-offs (Table 1). Previous research successfully adopted simulation-based models, machine learning models, and neural networks for light-duty EVs and identified features that most strongly impacted vehicle efficiency to guide fleets' actions. These methodologies can be applied to MHD EVs to better understand the key determinants of vehicle efficiency under real-world physical conditions. Findings can help ease fleet uncertainty on EV adoption before procurement and improve MHD EV efficiency in operation.

Table 1: Previous research modeling energy efficiency of light-duty EVs

| **Literature** | **Model** | **Features that significantly impacted light-duty energy efficiency** |
|---|---|---|
| Qi et al. 2017 [8] | PCA, decision tree, ANN | Negative kinetic energy, positive kinetic energy, speed, traffic |
| Fetene et al. 2017 [9] | Regression | Speed, acceleration, trip distance, season, rush hour, battery level when trip starts, temperature, precipitation, wind speed, visibility |
| Modi et al. 2019 [10] | CNN | Significant features not specified, but the selected model used features: speed, road elevation, tractive effort |
| Weiss et al. 2020 [11] | Regression | Vehicle weight |
| Xu et al. 2020 [12] | Simulation based inference model | Speed, road type |
| Ahmed et al. 2022 [13] | Regression | Speed, acceleration, vehicle weight |

The Medium- and Heavy-Duty Electric Vehicle Data Collection project, funded by the U.S. Department of Energy (DOE), collected data from a variety of MHD vehicles and made it publicly available for researchers. Using this diversified and robust vehicle performance dataset from 107 vehicles across six vehicle platforms and eight U.S. states, this study (1) compared the energy costs of MHD EVs and their conventional diesel internal combustion engine (ICE) counterparts; (2) generated a machine learning model to predict energy efficiency and highlight significantly impactful features; and (3) applied the model to predict operational range for transit bus in four cities and HD truck in local and regional duty cycles.

## 2. Data Collection and Preparation

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. Data was aggregated by day or by trip, depending on the data logger's frequency of reporting. Table 2 and Fig. 1 summarize the makeup, status, and geographic distribution of the on-road vehicle dataset.

Data needed for the energy cost savings analysis was gathered from external sources. Baseline diesel average fuel economy values were sourced by taking the average of all fuel economy values corresponding to each vehicle platform from (1) CALSTART's TCO tool [4] and (2) the U.S. DOE Alternative Fuels Data Center's average fuel economy dataset [14], where available. The price of diesel ($/gallon) was gathered from the U.S. Energy Information Administration's (EIA) diesel price forecast dataset [15]. The price of electricity ($/kilowatt-hour(kWh)) was gathered from (1) the EIA's electricity price forecast dataset [15] and (2) levelized costs of delivered electricity of $0.17–$0.38 per kWh estimated by the National Renewal Energy Laboratory (NREL) given a set of 20 scenarios, ranging from kilowatt- to megawatt-scale charging and accounting for variations in location type, utilization rate, cost of Electric Vehicle Supply Equipment (EVSE) installation and upgrades, and various utility rates [16].

Table 2: Vehicles included in the following analysis

| Vehicle Platform | Gross Vehicle Weight Rating (lbs) | Number of Vehicles in Analysis | Number of Vehicle-Days in Analysis |
|---|---|---|---|
| Transit Bus | > 33,000 | 56 | 19,799 |
| Type C School Bus | > 33,000 | 16 | 1,681 |
| Class 8 Day Cab Tractor | > 33,000 | 14 | 1,269 |
| Class 7 Box Truck | 26,001–33,000 | 5 | 652 |
| Class 6 Box Truck | 19,501–26,000 | 6 | 2,025 |
| Class 4 Step Van | 14,001–16,000 | 10 | 1,298 |
| **Total** | | **107** | **26,724** |


Figure 1: Map of MHD EV deployments included in this study; marker radius indicates vehicle count

Some data parameters corresponding to input features for the efficiency model in Section 3.2 were not directly collected by onboard data loggers; in these cases, data was downloaded from external sources (Table 3).

Table 3: Features as inputs to the energy efficiency predictive model

<table>
<tr><th colspan="2">Feature Groups</th><th>Features</th><th>Sources</th></tr>
<tr><td colspan="2">Duty Cycle</td><td>Average Driving Speed, Total Distance, Total Run Time, Driving Time, Idling Time Percentage</td><td>MHD EV Data Collection (CALSTART, 2023)</td></tr>
<tr><td colspan="2">Vehicle Configuration</td><td>Manufacturer, Model Name, Model Year, Weight Class, Vehicle Platform, Body Style, Rated Energy, Nominal Range, Estimated Payload</td><td>MHD EV Data Collection (CALSTART, 2023); ZETI Database (CALSTART, 2023) [25]</td></tr>
<tr><td colspan="2">Use Case</td><td>Vocation, Sector</td><td>MHD EV Data Collection (CALSTART, 2023)</td></tr>
<tr><td colspan="2">Geography</td><td>Region, State</td><td>MHD EV Data Collection (CALSTART, 2023)</td></tr>
<tr><td rowspan="3">City Profile</td><td>Climate</td><td>Average Ambient Temperature, Average Precipitation</td><td>ERA-5-Land hourly dataset [19]; NLDAS-2 hourly dataset [18]; NOAA daily average temperatures [17]</td></tr>
<tr><td>Road</td><td>Average Road Grade</td><td>R package slopes [23] applied on OpenStreetMap network [21]</td></tr>
<tr><td>Congestion</td><td>Annual Hours of Delay (general, highway)</td><td>Urban Mobility Report Congestion Data (Texas A&M Transportation Institute, 2021) [20]</td></tr>
</table>

For each vehicle in the dataset, a climate profile consisting of temperature and precipitation data was gathered. When not collected by onboard data loggers, daily average ambient temperatures were downloaded from the National Oceanic and Atmospheric Administration (NOAA) [17]. Trip-level temperatures were downloaded from the National Aeronautics and Space Administration’s (NASA) NLDAS-2 dataset [18] at the midpoint location and time of the trip. Hourly precipitation was downloaded per city for 2018–2022 from the ERA-5-Land hourly dataset [19] and summed by day or trip, depending on the granularity of the corresponding vehicle’s data.

Annual congestion data from 2019 was used to avoid the impact of the COVID-19 pandemic [20]. The metric *annual hours of delay* was used for buses while *annual truck hours of delay* was used for trucks. For cities not covered by the dataset, metrics were collected for the city’s nearest neighbor by physical distance.

City road slope was computed using road network data from Open Street Map [21], 1 arc-second Digital Elevation Model from the U.S. Geological Survey (USGS) TNM database [22], and the R package *slopes* [23]. Road grade for each road segment in each city was computed as an aggregated mean.

Since actual payload data was not available, maximum payload per vehicle model was obtained from CALSTART's Zero-Emission Technology Inventory (ZETI) database [24], which contains vehicle specification data for 839 models of MHD trucks and buses [25]. When payload was measured in units other than weight (e.g., passengers or volume), they were converted to weight [26].

# 3. Real-world Energy Efficiency Analysis and Implications

## 3.1. Energy efficiency advantages indicate energy cost savings

In this study, energy cost was defined as the cost of fuel in U.S. dollars needed to drive a vehicle one mile. Maintenance costs were not included due to a lack of sufficient historical maintenance data to accurately assess EVs' longer-term maintenance needs. Fig. 2 below shows the analysis procedure.

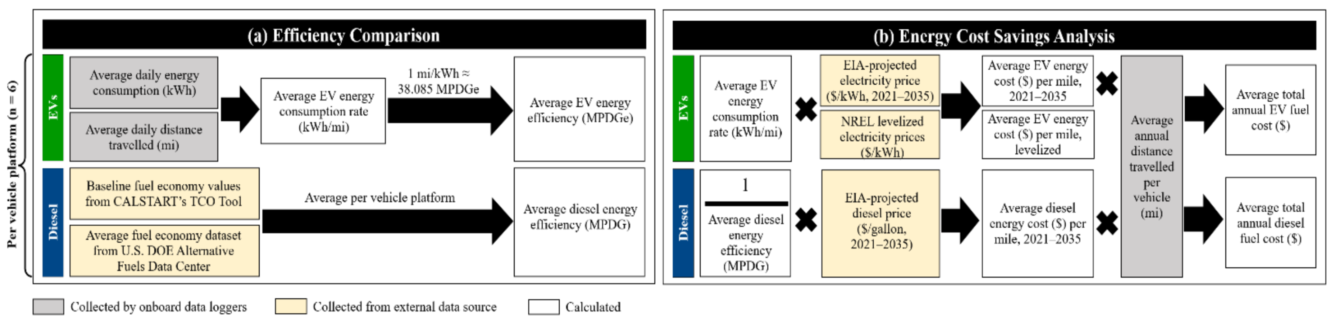


Figure 2: (a) Efficiency comparison analysis procedure and (b) energy cost savings analysis procedure

### 3.1.1. Efficiency comparison

First, a comparison of energy efficiency between each EV platform and its diesel counterpart was conducted (Fig. 2a). MHD EVs performed an average of 3.4–5.7 times as well as their conventional counterparts, mirroring CARB's estimated EER results [5] (Table 4). HD trucks and transit buses had the highest estimated EERs, while MD trucks and school buses—the most efficient vehicle platforms for both fuel types—had lower EERs. Vehicle platforms maintained similar efficiency rankings relative to each other regardless of fuel type, aside from Class 8 trucks, which were the least efficient diesel vehicles but second least efficient EVs.

Table 4: Average and 95% confidence interval of energy efficiency by vehicle platform

| Vehicle Type | Vehicle Platform | Average EV Energy Efficiency (MPDGe) | Average Baseline Fuel Economy (MPDG) | Energy Efficiency Ratio (EER) |
|---|---|---|---|---|
| Medium-Duty Truck | Class 4 Step Van | **34.2** (± 0.023) | 9.04 | 3.8 |
| | Class 6 Truck | **28.2** (± 0.005) | 8.21 | 3.4 |
| Heavy-Duty Truck | Class 7 Truck | **18.6** (± 0.050) | 4.40 | 4.2 |
| | Class 8 Truck | **20.1** (± 0.013) | 3.56 | 5.7 |
| Bus | Type C School Bus | **27.4** (± 0.034) | 7.06 | 3.9 |
| | 35–40 ft Transit Bus | **20.1** (± 0.009) | 3.83 | 5.2 |

### 3.1.2. Energy cost savings comparison

For each vehicle platform, average energy cost savings per mile were (1) projected from 2021–2035 using EIA price projections [15] and (2) calculated using the average levelized electricity costs estimated by NREL [16] with 2022 diesel price projections [15] (Fig. 2b). Together, these complementary sources of electricity prices presented a more nuanced understanding of EVs' energy costs: while the EIA source provided price projections on a per-year basis over a broad time period, NREL's estimates, despite their lack of temporal granularity, accounted for the real-world variability of charging costs associated with 20 diverse charging infrastructure scenarios.

In 2022, EV buses and trucks had an average cost savings of $0.365 per mile and $0.343 per mile, respectively; by 2035, projected bus and truck per-mile cost savings increase slightly to $0.413 per mile and $0.387 per mile, respectively (Fig. 3a).

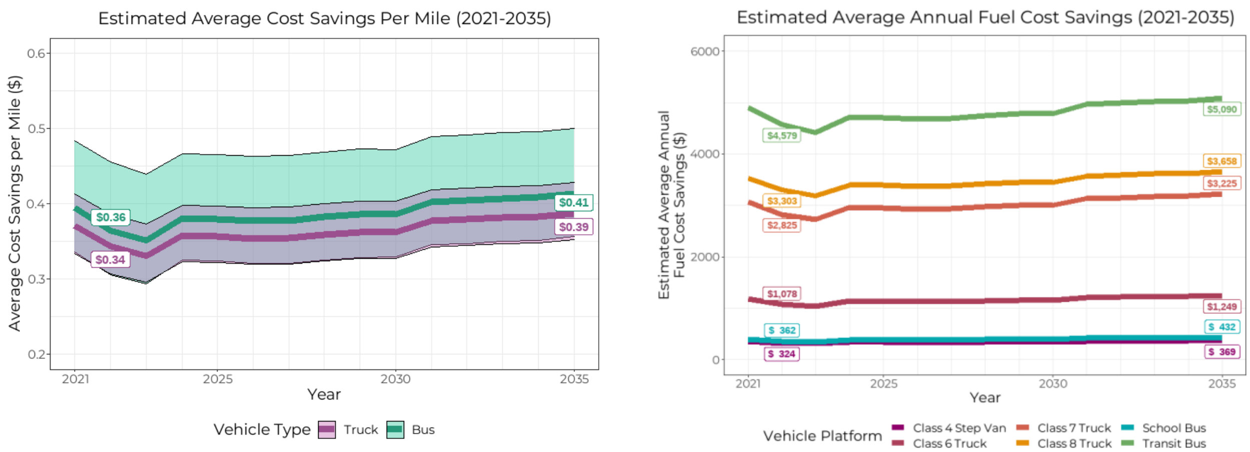


Figure 3: Estimated fuel cost savings over time (a) per mile by truck and bus and (b) annual total by vehicle platform. Annotations indicate 2022 and 2035 cost savings estimates.

In a single-year cross-section of these results, energy cost savings were smaller when using electricity prices based on NREL's breakeven costs relative to the EIA's national average electricity price projections. However, for both estimates, the average cost per mile was consistently lower for EVs than for baseline vehicles. Thus, even when accounting for the installation and upkeep of EVSE infrastructure, fueling MHD EVs is still less expensive per mile on average than fueling their diesel counterparts.

Finally, for each vehicle platform in the real-world dataset, estimated total annual cost savings were determined using EIA-projected average cost per mile and average annual distance traveled per vehicle in each vehicle platform (Fig. 2b). Because of the combination of their high per-mile fuel cost savings and high annual distance traveled, transit buses and HD trucks have high estimated annual fuel cost savings (Fig. 3b). Transit buses, which had the highest per-vehicle average annual mileage (8,717 miles per year), experienced the greatest fuel cost savings, followed by Class 8 and Class 7 trucks, which had local/regional duty cycles and traveled an average of 5,817 and 7,412 miles per year, respectively. These results support previous DOE findings that a vehicle's duty cycle strongly impacts total cost of ownership [27]: although school buses were much more efficient than transit buses, their lower annual average distance (1,693 miles) resulted in much lower average annual fuel cost savings. Thus, switching from diesel to electric is more cost-effective for higher-mileage than lower-mileage vehicle platforms.

## 3.2. Energy efficiency prediction based on known real-world factors

Many factors affect actual EV efficiency, including ambient temperature, driving speed, topography, and manufacturing configurations. However, studies determining these variables' relative impacts are lacking. This paper incorporated real-world data from these factors and developed machine learning models on in-use performance data to estimate energy consumption rate (kWh/mi).

### 3.2.1. Model selection and feature engineering

Knowing the mechanisms that affect vehicle efficiency can inform fleets' operations by predicting efficiency performance and ultimately range. When selecting from a wide array of machine learning algorithms, we considered the tradeoff between interpretability and performance. On one end of the spectrum, linear models are the most interpretable but are generally weak in predictive performance, especially when dealing with high-dimensional data and non-linear relationships. On the other end, neural networks can achieve higher predictive performance at the expense of high computation costs and low interpretability, as they are essentially "black box" models. Tree-based algorithms stood out to best fit our use case, as they offer a balance between interpretability and predictive performance.

Before training the machine learning models, exploratory data analysis and feature engineering were conducted to select and transform 22 features as inputs to the models (Table 3). Fig. 4 illustrates the feature engineering procedure. Since vehicle types and regions were imbalanced in the data, we applied stratified sampling when splitting train and test data and SMOGN resampling [28] on the training data to ensure model performance.

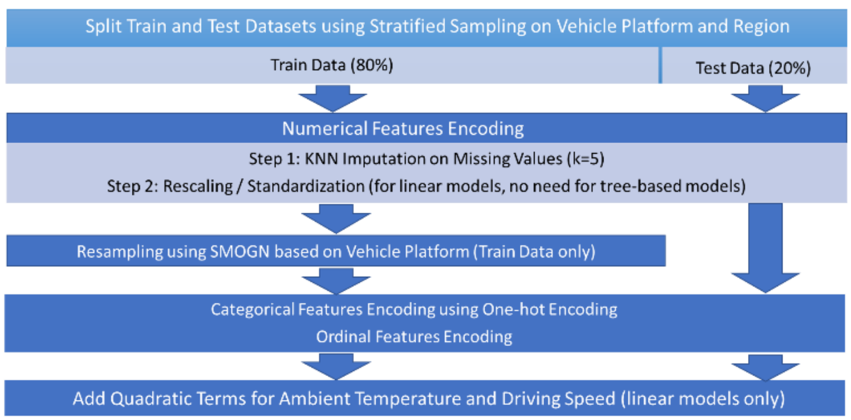


Figure 4: Feature engineering procedure on train and test datasets

### 3.2.2. Model training and performance

The study applied five algorithms to predict vehicle efficiency, calculated as total energy consumption divided by driving distance and measured by energy consumption rate (kWh/mi). Using Scikit-Learn [29] and other Python packages to train, tune, perform k-fold cross-validation on the model. Mean Absolute Error (MAE) was the key evaluation metric in training, while other common metrics are also provided in Table 5. Among the five models, tree models (XGBoost, Random Forest, and Gradient Boosted Trees (GBR)) had better performance than linear models (Lasso and Ridge Regression). The GBR model had the highest $R^2$ value (77%) and was selected as the best model to predict operational range.

Table 5: Model performance metrics

| Regression Models | $R^2$ | Mean Absolute Error (MAE) | Mean Squared Error (MSE) | Root Mean Squared Error (RMSE) |
|---|---|---|---|---|
| Lasso (L1 Regularization) | 0.486414 | 0.426722 | 0.413611 | 0.643126 |
| Ridge (L2 Regularization) | 0.519174 | 0.403068 | 0.387229 | 0.622277 |
| XGBoost (XGB) | 0.751825 | 0.249201 | 0.199865 | 0.447063 |
| Random Forest (RFR) | 0.761570 | 0.242875 | 0.192017 | 0.438198 |
| Gradient Boosted Trees/Gradient Boosting (GBR) | **0.772317** | **0.226611** | **0.183362** | **0.428208** |

### 3.2.3. Model result analysis

Preliminary analysis indicated that MHD EVs were most efficient when operated at daily average speeds between 20–40 mph compared to lower speeds. At speeds below 20 mph, a higher percentage of idling time versus drive time was observed, which likely contributed to worse efficiency. This analysis also indicated that MHD EVs driving more than 100 miles per day achieved a higher average efficiency than those traveling less. Again, a higher percentage of idling time was observed in shorter trips resulting in worse efficiency. The ideal operating environment included minimal traffic, mild to warm ambient temperatures (50–80 °F) [30], and relatively flat terrain. Lastly, decreases in the vehicle size and weight significantly increased vehicle efficiency.

While these results were not unexpected, further analysis revealed the most important factors in the GBR model by using the SHAP (Shapley Addictive exPlanations) value [31], which shows the effect each feature has on predicting efficiency (Fig. 5). Clear horizontal separation (red dots on one side and blue on the other) shows the direction and magnitude of the impact each feature has on the output. For example, high driving speed values had a negative effect on the output (kWh/mi) and thus are associated with improved efficiency. Among the top features, average driving speed, congestion hour delay, ambient temperature, total distance, driving time, and idling time percentage had clear patterns. In contrast, features like model year, precipitation, total run time, road grade, and nominal range were in the top 20 features but did not show a clear pattern.


Figure 5: Gradient Boosted Trees Model top features ordered by feature importance (left: beeswarm plot; right: bar plot)

All tree models achieved similar $R^2$ scores (75–77%). Each model's feature importance ranking was slightly different, but all three models included average driving speed, average ambient temperature, and total distance in their respective top five (Table 6).

Table 6: SHAP identified top features impacting the prediction on energy efficiency

| Top Features | Gradient Boosted Trees | Random Forest | XGBoost |
|---|---|---|---|
| Average driving speed | #1 | #1 | #1 |
| Congestion hour delay | #2 | #4 | #5 |
| Average ambient temperature | #3 | #2 | #2 |
| Total distance | #4 | #3 | #3 |

Average driving speed was consistently the most important feature across all models, meaning it had the biggest effect on efficiency. Energy efficiency of transit buses became less optimized with high variations when average driving speed is lower than 10 mph. (Fig. 6). Heavy-duty trucks were more likely to have energy efficiency as high as 4 kWh/mile when average driving speed was less than 15 mph. However, for both vehicle types, when average speed reached 20–40 mph, the efficiency converged to a narrow range of values and stabilized around 1.5–2 kWh/mi.

The average driving speed feature was aggregated by day, which must be understood within the context of fleet operations. Real-world driving over a day involved a variety of speeds. Lower average speed may indicate a larger share of driving in urban congested areas with frequent or longer stops. From the results, a daily average speed of 20–40 mph may imply a duty cycle with fewer stops and less traffic or loading time, and MHD trucks operating were observed to achieve higher energy efficiency. Future studies on MHD EVs may tailor efforts to further understand mechanisms behind their energy efficiencies at different speeds.

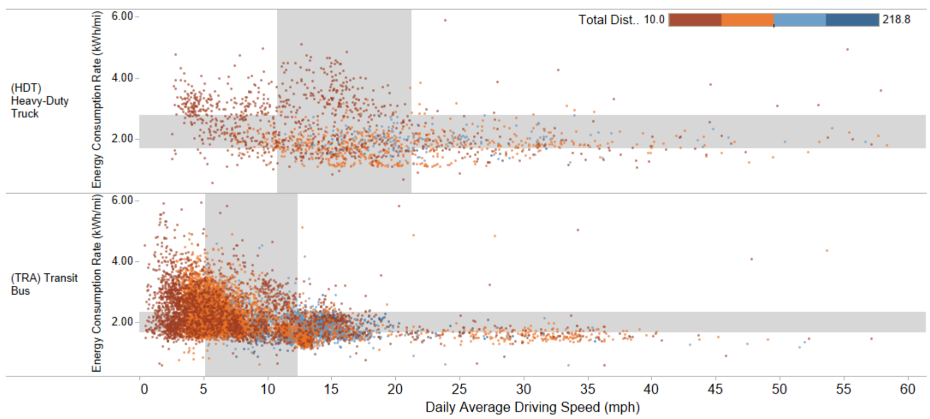


Figure 6: Scatter plot of energy efficiency and daily average driving speed for HD Truck and transit bus

## 3.3. From efficiency prediction to operational range

It is critical for fleets to assess how MHD EVs will accommodate their operations and duty cycle needs when planning procurement. The efficiency model was used to address this issue by predicting and visualizing the operational range of MHD EVs based on hypothetical operating conditions, manufacturer-rated battery capacities, and an assumed 90% SOC battery buffer (Equations 1 and 2). Vehicles were assumed to be brand new and operating at full State of Health. Predicted operational range values can help gauge the maximum range a vehicle might achieve in the real world versus manufacturer specification.

*Operational range (mi) = Usable battery capacity (kWh) / Energy efficiency (kWh/mi)* *(1)*

*Usable battery capacity (kWh) = Nominal battery capacity (kWh) * Battery State of Health (%) * State of Charge buffer (%)* *(2)*

We used the model developed in Section 3.2 to predict operational range for three different vehicle types (i.e., transit bus, local HD truck, regional HD truck) in four different cities (i.e., Los Angeles, Louisville, Missoula, Chicago). BYD K9M 2022 was used for transit buses while Freightliner eCascadia 2021 was chosen for local and regional HD trucks. One year of operation was simulated (Table 7) to predict the energy efficiency. Using our real-world data as a benchmark, we summarized monthly and weekly averages of daily total distance, total run time, and driving time for these vehicle types. For each pair of month and day of week, 200 data points were simulated using the averages and standard deviations of residuals, assuming a normal distribution. For each day in 365 days, one data point was randomly sampled from the pool of 200 data points based on day of week and month. Forecasting was used if data was missing or underrepresented. Daily average driving speed and idling time percentage were calculated from the simulated features. All duty cycle features were engineered and validated to have similar ranges and distributions as the real-world data.

Table 7: Averages and 95% confidence intervals of simulated duty cycle features

| Vehicle Type | Total distance (miles) | Driving time (hours) | Total run time (hours) | Average driving speed (mph) | Idling time percentage (%) |
|---|---|---|---|---|---|
| Transit bus | 83.5 (±3.8) | 5.6 (±0.2) | 8.4 (±0.4) | 15.6 (±0.7) | 25.2 (±2.6) |
| Local HD truck | 45.3 (±1.4) | 2.8 (±0.1) | 4.1 (±0.2) | 18.0 (±0.9) | 28.5 (±2.0) |
| Regional HD truck | 71.3 (±4.0) | 3.2 (±0.2) | 4.3 (±0.2) | 22.7 (±1.3) | 23.3 (±1.5) |

In simulated duty cycles, transit buses traveled the farthest with the longest run time and driving time but the lowest daily average driving speed due to frequent stops or residential speed limits. Local HD trucks traveled the shortest distance with the shortest driving time and highest idling time percentage. Regional HD trucks traveled long distances with the highest speed and lowest idling time percentage. Regional HD trucks spent a greater fraction of time driving, indicating that they travel on highways and have fewer stops.

Table 8: Profiles of four U.S. cities

| City | Average ambient temperature (℉) | Precipitation (inches) | Congestion hour delay (hours) | Average road grade (%) |
|---|---|---|---|---|
| **Los Angeles, CA** | 65.7 (±1.0; 46-86) | 0.002 (±0.0004) | 952,183,000 | 2.1 |
| **Louisville, KY** | 59.6 (±1.7; 22-86) | 0.006 (±0.0005) | 30,610,000 | 1.7 |
| **Missoula, MT** | 41.8 (±1.6; 6-74) | 0.003 (±0.0002) | 2,263,000 | 1.4 |
| **Chicago, IL** | 53.2 (±2.0; 10-85) | 0.005 (±0.0005) | 331,657,000 | 0.5 |

For transit buses, operational range was modeled across cities with different climates, congestion levels, and hilliness (Table 8, Fig. 7). Congestion and hilliness were constant throughout the year while climate variables changed seasonally. Average ambient temperature had the strongest impact on operational range. The transit bus in Los Angeles, with the warmest winters, showed the most consistent operational range throughout the year, despite a high congestion hour delay that was 30 times that of Louisville. The operational range of the transit bus in Missoula dropped significantly in cold winter months, during which average ambient temperature fell as low as 6 ℉. In summer, when ambient temperature was no longer the limiting factor, transit buses in Missoula had a longer average operating range than in the other regions, likely due to Missoula’s light traffic.

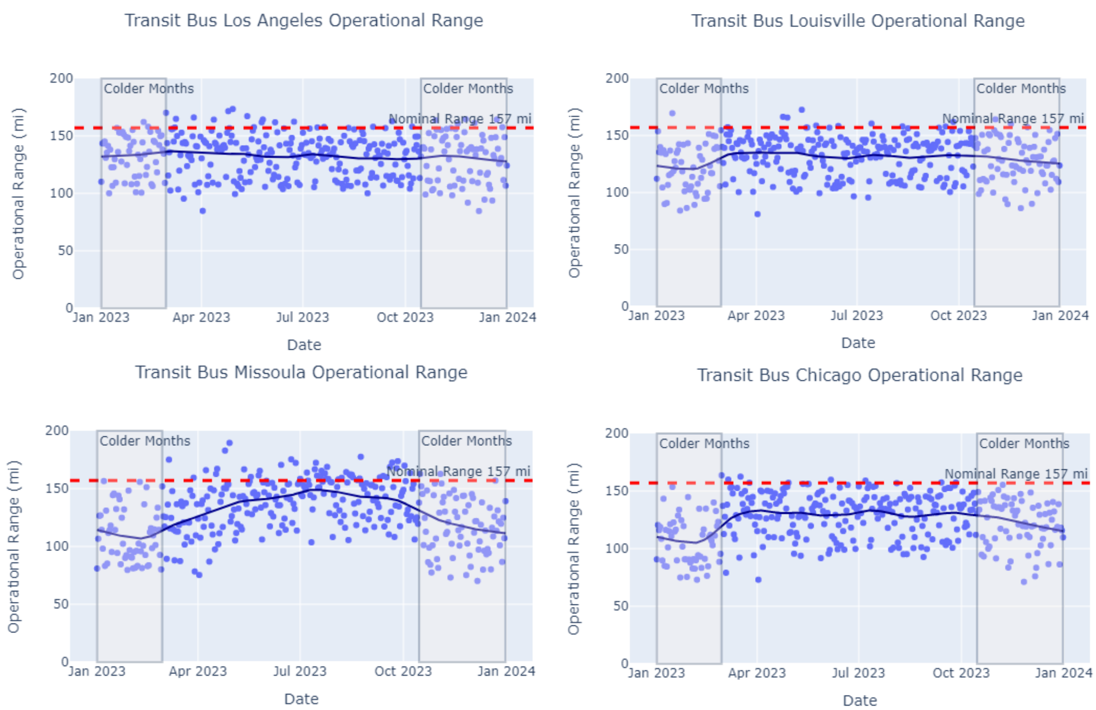


Figure 7: Transit Bus year-round operational range estimations in four U.S. Cities (Vehicle model: BYD K9M 2022; top left: Los Angeles, CA; top right: Louisville, KY; bottom left: Missoula, MT; bottom right: Chicago, IL)

The comparison between the local HD truck and the regional HD truck highlighted the impact of duty cycle on operational range. Due to lower daily average driving speed, shorter total distance, and higher percentage of idling time, local HD trucks consistently had a lower operational range throughout the year. This could be a result of local HD trucks operating in urban areas and thus spending more time idling or in traffic. From the model estimates, local HD truck fleets might even need to deploy trucks with a nominal range nearly double the expected daily range to meet duty cycles in colder months. While the same truck model had better range as a regional HD truck overall, there were still days when range dropped to about 60% of the nominal range. In summary, fleets need to be prepared for these rare occasions when transitioning to a fully electric fleet.

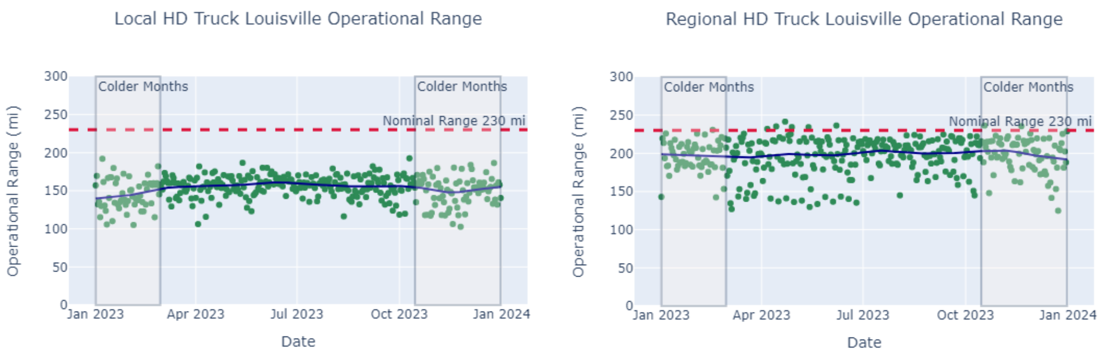


Figure 8: HD Truck Year-round operational range estimations in Louisville, KY
(Vehicle model: Freightliner eCascadia 2021; left: local duty cycle; right: regional duty cycle)

# 4. Conclusion

As EV adoption grows, the value of a publicly accessible operational dataset from early MHD EV deployments will only increase. This study made use of such a dataset to provide a high-level understanding of energy cost savings across various types of MHD EVs. A novel approach employing the predictive power of machine learning to model MHD EVs' energy efficiency was also executed. The outcome of this analysis could help fleets across various geographies throughout the U.S. assess the suitability of EVs for their operational needs.

MHD EVs were found to perform an average of 3–6 times as efficiently as their diesel ICE counterparts, demonstrating that theoretical efficiency advantages associated with EVs hold true in practice. By using EVs instead of diesel vehicles, fleets should experience energy cost savings, regardless of vehicle platform, with the greatest savings seen in transit and HD truck fleets, especially those with high-mileage duty cycles.

This study found that a vehicle's operational range could be substantially lower than its nominal range in conditions with low temperatures, high congestion, hilly terrain, and local duty cycles, so it highlighted the importance to estimate operational range when choosing a MHD EV. Using the efficiency model presented in Section 3.2, fleets can evaluate a vehicle's real-world operational range to determine whether it meets their duty cycle needs. Based on these results, there are two notable considerations that fleets should take into account before purchasing MHD EVs.

1. Because temperature can significantly impact vehicle efficiency and range, fleets should account for reduced operational range in colder months. In Missoula, operational range for transit buses decreased by 30% in winter relative to summer.
2. Due to variations in duty cycle characteristics, local haul operations (less than 100 miles daily) can have 25% lower operational range than regional haul (100-300 miles daily) despite using the same vehicle model in the example city. Accordingly, local HD truck fleets might need to deploy trucks with a nominal range nearly double the expected daily range to meet more extreme duty cycle conditions.

While this study addressed several critical issues for fleets, it also had limitations. The energy cost savings analyses were based on average efficiency values, average miles driven for vehicle platforms, and average price estimates, and EIA fuel prices did not account for EVSE installation or maintenance costs. As a result, an individual vehicle may experience a different real-world efficiency and different cost savings. Additionally, demand charges for electricity and vehicle efficiency improvement rates can be incorporated into scenario analyses in the future. When modeling energy efficiency, predictions for trucks were limited to local and regional haul (less than 300 miles per day) and were not generalized to long-haul duty cycles. Compared to route-based energy consumption modeling, our model required less granular inputs, both in terms of time (i.e., duty cycle at vehicle-day level) and geography (i.e., city served as the geographic area of operation for all climate inputs). The energy efficiency model is therefore best used to quickly estimate a vehicle's efficiency in a given city or compare a vehicle's performance across cities or duty cycles. However, the model can still be improved with additional computational resources and data. Incorporating more features and more detailed features would enable better predictions. For example, using actual cargo weight, rather than a maximum payload constant for each vehicle model, would improve the payload feature's explanatory power, especially for trucks. Similarly, incorporating a targeted route as an input would provide details about actual road grade and traffic level that are not decipherable from city-level approximations (i.e., average road slope and congestion level).

Future work can use the output of the efficiency model to understand energy costs for fleets given their selected vehicle model, use case, and city profile. Finally, we plan to build a user-friendly, web-based tool making use of the model to help fleets predict operational capabilities of MHD EVs operating in their regions, thus boosting fleets' confidence in the EV transition. This tool will be a resource for accelerated MHD EV deployment: by addressing EV performance knowledge gaps in an intuitive, accessible manner, it will enable a better understanding of real-world MHD EV efficiency and range among fleet managers, policymakers, and the public.

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