EVS38
Göteborg, Sweden, June 15-18, 2025

Factors Influencing Propulsion Energy Consumption in Battery Electric Heavy-Duty Trucks on Urban and Rural Routes

Parivash Pirasteh[1], Carlos Camacho[1], Sławomir Nowaczyk[2].

[1]*Volvo Group Trucks Technology, Gothenburg, Sweden*
[2]*Center for Applied Intelligent Systems Research, Halmstad University, Sweden*

Executive Summary

The heavy-duty truck industry is undergoing a significant transition from diesel-powered vehicles to electric trucks, driven by environmental concerns and advancements in battery technology. This shift necessitates a comprehensive understanding of the factors influencing propulsion energy consumption, as these insights are crucial for optimizing the performance and range of electric trucks. Using data from a fleet of 19 trucks monitored over a period of 11 months, we investigate key variables affecting energy consumption including gross combination weight (GCW), road inclination, acceleration, speed and ambient temperature in heavy-duty trucks, comparing their impact on urban and rural routes. Our findings revealed that rural route showed 6% higher energy consumption per kilometer compared to urban route. All algorithms consistently perform better in rural environments compared to urban ones, likely due to more complex traffic patterns, intersections, and variability. The results also indicate that acceleration and road inclination are the most significant factors affecting energy consumption, regardless of the type of trip (urban or rural). These results have important implications for fleet management, route optimization, and the development of more energy-efficient heavy-duty vehicles.

---

1 Introduction

Globally, governments are intensifying their focus on the transportation sector due to its substantial role in environmental pollution, greenhouse gas emissions, and energy consumption. This heightened concern for environmental and energy issues has catalyzed significant advancements in electric vehicle (EV) technology[6]. Battery Electric Vehicles (BEVs) have been extensively researched since their introduction. Various studies have focused on key factors influencing BEV performance, such as driver behavior, speed and external conditions like topography, and the impact of ambient temperature [1, 2, 3, 4]. While BEV cars have been the center of attention, there is a growing need to extend this research to BEV trucks. Unlike cars, BEV trucks are subject to unique factors such as GCW and more pronounced effects of ambient temperature. These differences justify the importance of targeted investigations specific to trucks.

In particular, BEV trucks vary by emission standards and other performance characteristics. For this study, we focus on a heavy-duty BEV variant, aiming to examine energy consumption across both rural and urban environments. Urban routes are often characterized by stop-and-go traffic, frequent accelerations, and short travel distances, leading to increased energy consumption due to constant braking and acceleration. In contrast, rural routes typically involve longer stretches of consistent speed with fewer stops, but may also include varying terrain and higher average velocities, which can further affect fuel efficiency. Understanding how these factors interact is essential for optimizing BEV truck design, improving route planning, and accurately predicting range and energy requirements in diverse operating conditions.

Energy consumption in vehicles is influenced by a variety of factors that must be considered holistically. it is essential to account for all aspects from vehicle characteristics i.e.weight, route characteristics i.e. urban vs rural area, driving behavior, speed and acceleration and environmental conditions i.e. topography and ambient temperature [5]. This paper aims to provide a comprehensive analysis of the factors affecting propulsion energy consumption in BEV trucks, contrasting the unique challenges presented by urban and rural environments. In the following

sections, we present our research methodology and findings.
Recent research by [8] demonstrates the value of incorporating detailed route information—such as road topography, traffic signals, and speed limits—from sources like OpenStreetMap (OSM) and Shuttle Radar Topography Mission (SRTM) to improve the accuracy of BEV energy consumption predictions. Unlike conventional strategies that assume static driving conditions, model introduced in [9] incorporates a dynamic speed trajectory reflecting both acceleration and deceleration behavior, which is further used in a detailed powertrain model. This modeling framework results in a marked improvement in prediction accuracy—achieving a mean absolute prediction error of approximately 4.1% across diverse test cycles—highlighting the importance of factoring in driver behavior, route topology, and real-time traffic conditions.
Section 2 provides a comprehensive overview of the data collection and preparation processes and how different trips have been defines. In Section 3, we present the results and analysis, which are structured into three main components: input features, model performance, and feature importance. Section 3.1 introduces and explains the input features selected for the modeling process, highlighting their relevance and expected impact on predictive performance. Section 3.2 discusses the development and evaluation of multiple machine learning models, including training procedures, and performance metrics. In Section 3.3, we conduct a SHAP (SHapley Additive exPlanations) analysis to interpret model outputs and rank feature importance, with a specific focus on comparing rural and urban trip characteristics. Finally, Section 4 summarizes our findings, discusses key insights, and outlines potential directions for future work.

2 Data Collection and Preparation

2.1 Truck Specification

The dataset is derived from 19 heavy-duty Volvo electric trucks monitored over a period of 11 months. We collect data from the CAN bus in trucks to collect data. The model of the heavy-duty trucks features a 4x2 axle configuration and a tractor type design, equipped with a total battery capacity of 540 kWh (6 battery packs) using Lithium Nickel-Cobalt-Aluminum Oxide (NCA) technology. The truck's body weight ranges between 10 to 13 tons, depending on the configuration. For propulsion, it is powered by three electric motors delivering a combined total of 500 kW of power and 800 Nm of torque.

2.2 Trip Classification

The data was sampled at a rate of 1 Hz, capturing detailed and high-frequency measurements. The data is from the periods when the truck was driving, and it covers 935 trips. To classify the trips as either urban or rural, a speed-based categorization method was employed. A trip was designated as urban if at least 80% of the time the truck was operating at speeds between 0 to 60 km/h. Conversely, trips were categorized as rural if at least 80% of the trip was driven at speeds between 60 to 90 km/h.
To ensure a consistent and meaningful analysis, only trips with a minimum distance of 19 kilometers were included. This filtering step helped maintain a balance between rural and urban trips while avoiding skewed results from shorter trips, which might introduce bias due to incomplete or unrepresentative driving patterns.
Furthermore, trips that involved stops longer than 6 minutes were excluded from the analysis to minimize the impact of extended non-driving events, which could distort the energy consumption data. However, trips with shorter stop durations were retained, particularly because brief stops—such as those at traffic lights—are common in urban areas. These shorter stops are critical to accurately reflect urban driving conditions and energy consumption patterns. After applying the filtering criteria, The dataset was refined to include 95 rural trips and 136 urban trips, totaling 13,371 kilometers driven. Of this, 2,992 kilometers were driven in urban trips and 10,379 kilometers in rural trips.

3 Result and Analysis

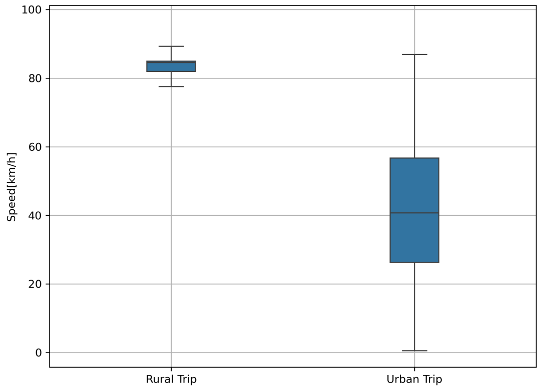
3.1 Input Features

For predicting energy consumption, it is important to consider both environmental and vehicular features. Ambient air temperature, vehicle speed, acceleration, gross combination weight, and road inclination are features that we took into account. Vehicle speed and acceleration are important since they reflect the dynamic behavior of the vehicle and directly influence energy demand due to changes in kinetic energy. At the same time, road inclination and gross combination weight contribute more toward the potential energy component and and resistance forces acting on the vehicle. The reason for considering temperature is that it influences both the efficiency of the vehicle's powertrain and the performance of auxiliary systems like heating or cooling. Although this study focuses solely on propulsion energy, auxiliary energy consumption is not included as a target feature.

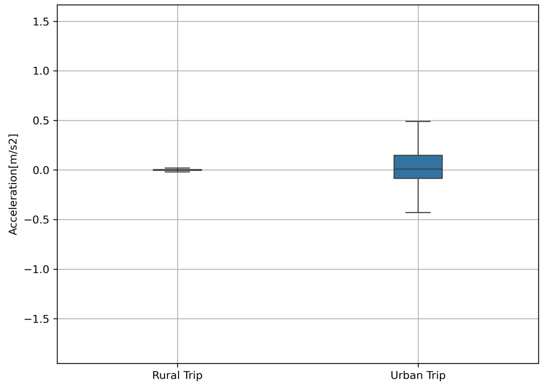
Figure 1 compares the distribution of different features between rural and urban trips. For speed (1a), rural trips show consistently higher speeds with less variation (mostly between 75-85 km/h), while urban trips display much greater variability (ranging from near 0 to 85 km/h) with a lower median around 40 km/h, reflecting the stop-and-go nature of urban driving. For acceleration (1b), urban trips show more variability (ranging from about -0.5 to 0.5 degree) compared to rural trips which maintain more consistent acceleration values near zero, indicating steadier driving conditions on rural routes. The ambient air temperature distributions (1c) are indeed similar between both environments as expected, with rural areas showing slightly higher median temperatures and marginally greater variability. The gross combination weight distribution (1d) demonstrates a clear distinction, with rural trips associated with significantly heavier loads (median around 18,000 kg) compared to urban trips (median around 11,000 kg). This supports the observation that trucks typically carry heavier loads for between-city missions in rural settings, while urban deliveries involve lighter cargo loads.

Alongside road inclination we also define four topography states per kilometer based on road inclination: flat, predominantly flat, hilly, and very hilly. A kilometer is classified as flat if 98% of it has a road slope less than 3%. It is classified as predominantly flat if 98% of the kilometer has a slope less than 6%. If 98% of the kilometer has a slope less than 9%, it is considered hilly. If these conditions are not met, the kilometer is classified as very hilly. For this particular feature, we did not separate trips into urban and rural categories due to insufficient data points for certain topographies across different trip types.

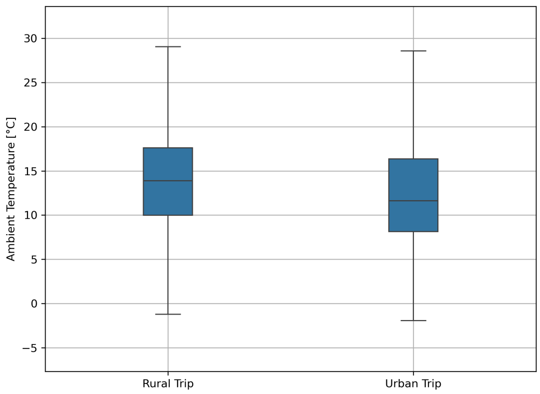
The stacked bar chart (1f) presents a comparison of kilometers driven on rural trips versus urban trips across different terrain types. Rural trips clearly dominate in terms of total distance covered. The terrain composition shows that rural driving primarily occurs on flat terrain, which constitutes roughly 8,500 kilometers of the total rural distance, with the remaining 1,500 kilometers taking place on ”P-Flat” terrain. Urban trips display a more balanced distribution between terrain types, with approximately equal portions driven on flat and P-Flat terrain. Notably absent from both trip categories is any significant distance covered on ”P-Hilly” or ”Very Hilly” terrain types, suggesting that most driving, whether rural or urban, occurs on relatively flat ground.



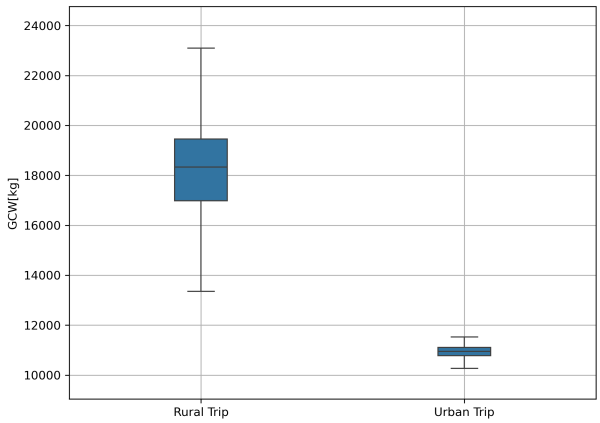
(a) Speed Distribution Comparison Between Rural and Urban Trips.



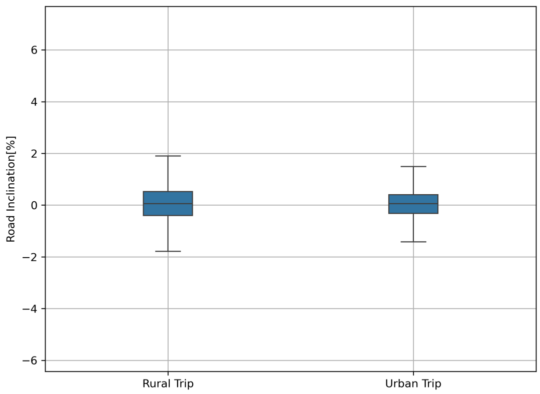
(b) Acceleration Distribution Comparison Between Rural and Urban Trips.



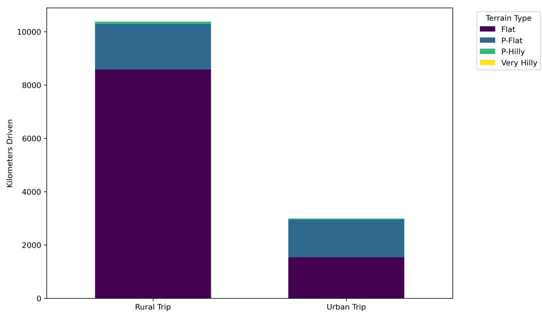
(c) Ambient Air Temperature Distribution Comparison Between Rural and Urban Trips.



(d) GCW Distribution Comparison Between Rural and Urban Trips.



(e) Road Inclination Distribution Comparison Between Rural and Urban Trips.



(f) Comparison of Kilometers Driven on Rural Trips vs. Urban Trips.

Figure 1: Distribution of Input Features across Rural and Urban Trip.

3.2 Model Performance and Evaluation

When implementing machine learning models for energy consumption prediction, we select 20% of the data for testing while using the remaining 80% for training. This train-test split is a standard practice that allows us to evaluate how well our models generalize to unseen data. By reserving a portion of the dataset that the model hasn't

encountered during training, we can assess its real-world performance and detect issues like overfitting, where a model performs well on training data but poorly on new data.
Before applying our models, we standardize the data by transforming features to have zero mean and unit variance. Standardization is crucial for several reasons: it ensures all features contribute equally to the model regardless of their original scales, prevents features with larger magnitudes from dominating the learning process, improves the convergence speed of gradient-based algorithms. This preprocessing step is particularly important when dealing with energy consumption data where input features (such as speed, distance, vehicle characteristics) might have widely different scales and units, which could otherwise bias the model training process and negatively impact prediction accuracy.
Assessing the precision of machine learning models is essential for choosing the most suitable model. In this research, we utilized two evaluation metrics, R^2 and $RMSE$, to measure the effectiveness of the proposed machine learning models in forecasting the energy consumption of BEV trucks. By leveraging these metrics, the most suitable model can be pinpointed, supporting the examination of critical factors driving energy use. The formulas for these metrics are provided below:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{1}$$

Where y_i is the actual observed value for the i-th observation. $\hat{y}_i$ is the predicted value for the i-th observation. $\bar{y}$ is the mean of all observed values.n is the total number of observations. $\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$ represents the sum of squared residuals (SSR) and $\sum_{i=1}^{n}(y_i - \bar{y})^2$ represents the total sum of squares (TSS).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{2}$$

Where y_i is the actual observed value for the i-th observation. $\hat{y}_i$ is the predicted value for the i-th observation. n is the total number of observations and $\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$ is the sum of squared differences between predicted and actual values. The square root of the mean square error gives us the $RMSE$, which has the same units as the response variable.
Our goal is to predict the energy consumption per kilometer. Focusing on energy consumption per kilometer provides a clear and standardized metric for evaluating the efficiency of vehicles, particularly BEV trucks. This metric allows for straightforward comparisons across different vehicles and driving conditions.
This study utilized four widely used and effective machine learning algorithms—Extreme Gradient Boosting (XGB), Random Forest (RF), Multilayer Perceptron (MLP), and Support Vector Regression (SVR)—for modeling. Based on the performance metrics shown in the table 1, there's a clear difference between how machine learning algorithms perform in rural versus urban route modes for energy consumption prediction. The rural route models demonstrate substantially higher R^2 values (ranging from 0.410785 for SVR to 0.929184 for RF) compared to their urban counterparts, indicating that the algorithms explain a much larger proportion of the variance in energy consumption data for rural routes. This is further supported by the lower $RMSE$ values for rural routes across all algorithms, with RF performing the best with an $RMSE$ of 142.691815. For urban routes, the models show moderate predictive power with XGB, RF, and MLP achieving R^2 values around 0.66-0.69, while SVR performs notably poorly with an R^2 of only 0.174276 and the highest $RMSE$ of 399.486913. This significant disparity in performance between rural and urban environments suggests that energy consumption patterns are more predictable and consistent in rural settings, while urban environments likely introduce more variables and complexities that make accurate prediction more challenging. The Random Forest algorithm appears to be the most effective overall, showing the highest R^2 and lowest $RMSE$ values in both route modes.

ML Algorithm	Route Mode	R^2	$RMSE$
XGB	Urban	0.661465	255.792062
	Rural	0.928756	143.122584
RF	Urban	0.694978	242.800918
	Rural	0.929184	142.691815
MLP	Urban	0.698011	241.590943
	Rural	0.922675	149.105346
SVR	Urban	0.174276	399.486913
	Rural	0.410785	411.595533

Table 1: Performance Metrics of the Considered ML Algorithms.

3.3 Feature Importance

Understanding feature importance is essential when analyzing factors influencing propulsion energy consumption in electric trucks, as it helps identify which variables contribute most significantly to energy usage. This process not only facilitates better insight into the underlying relationships within the data but also assists stakeholders and engineers in prioritizing areas for improvement and optimization.

In our study, we employed a Random Forest model due to its robustness, interpretability, and capability to capture complex, nonlinear relationships between input variables and propulsion energy consumption. To accurately interpret the feature importance derived from our Random Forest model, we utilized SHAP [7]. SHAP is a game-theoretic approach designed to explain individual predictions and provide a global interpretation of feature importance. By calculating Shapley values, SHAP assigns each feature an importance score based on its contribution to the prediction, thereby offering a transparent and intuitive explanation of the model's behavior.

For visualization purposes, we generated a beeswarm plot, which effectively illustrates the distribution and impact of each feature on the model's predictions. Additionally, we created scatter plots to explore the correlation between individual feature values and their corresponding SHAP values, providing a clearer understanding of how each feature influences propulsion energy consumption.

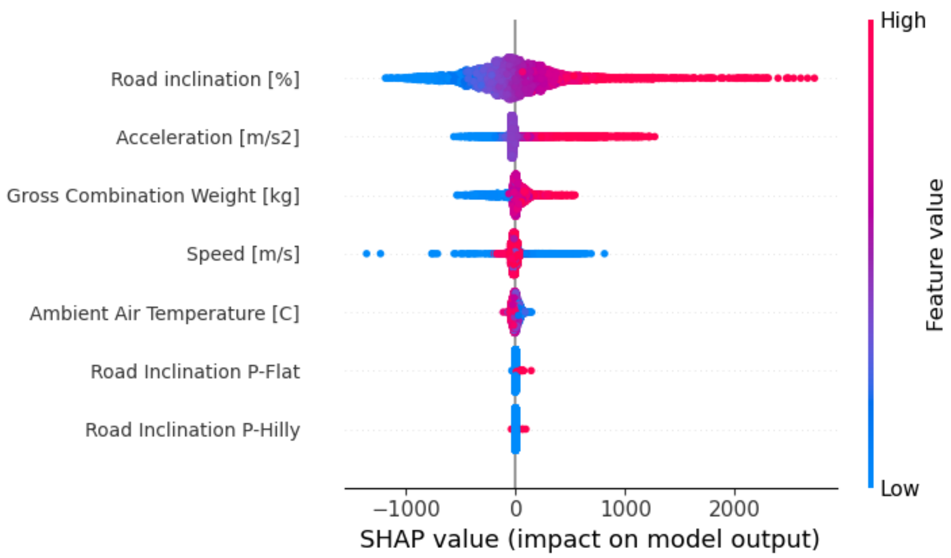


Figure 2: SHAP Beeswarm Plot of Feature Importance for Energy Consumption in Rural Trip.

Figure 2 indicates that road inclination and acceleration have the most substantial impact on propulsion energy consumption during rural driving. Higher road inclination and acceleration generally increase energy consumption, as indicated by the high SHAP values associated with these features. Gross combination weight and speed also show notable but comparatively smaller effects. Ambient temperature and road inclination profile categories

(P-Flat and P-Hilly) exhibit lower overall influence, suggesting their impact on energy consumption is context-dependent and less pronounced.

An explanation to this result is that in rural areas, characterized by highway driving conditions, features like road inclination and acceleration have a more pronounced impact on propulsion energy consumption due to the higher speeds and steadier driving conditions typically experienced. At higher speeds, the resistance from gravity (related to road inclination) and inertial forces (related to acceleration) become more significant, thus greatly influencing energy consumption. These conditions make it easier to clearly identify and measure the direct impacts of road inclination and acceleration on energy usage.

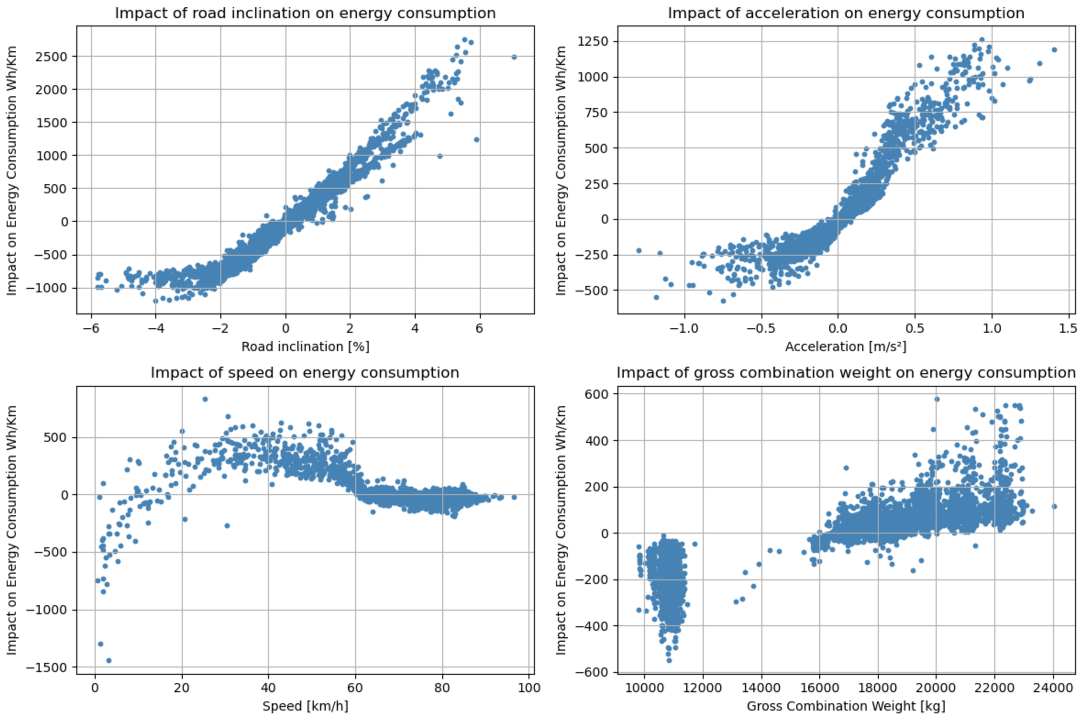


Figure 3: Impact of Four most Important Features on Energy Consumption for Rural Trips.

Figure 3 further clarify these relationships. Road inclination displays a strong positive correlation with propulsion energy consumption, clearly indicating increased energy usage on steeper inclines. Acceleration similarly shows a positive nonlinear relationship, highlighting the considerable energy demand associated with higher acceleration levels. The scatter plot for speed reveals a more complex relationship, indicating peak energy consumption at intermediate speeds, after which consumption stabilizes or even slightly decreases at higher speeds. Finally, gross combination weight shows a moderate positive correlation when the trucks are load, though the impact is less pronounced compared to road inclination and acceleration.

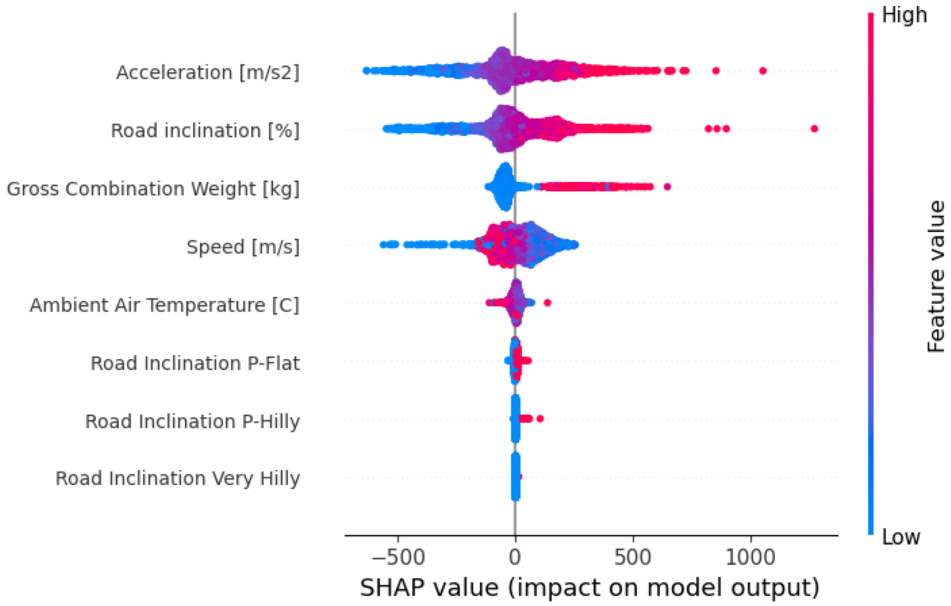


Figure 4: SHAP Beeswarm Plot of Feature Importance for Energy Consumption in Urban Trips.

In contrast, the SHAP beeswarm plot for urban driving indicates that acceleration has the greatest impact on propulsion energy consumption, surpassing road inclination. This shift in feature importance can be attributed to frequent acceleration and deceleration events commonly experienced in urban driving scenarios, significantly increasing energy consumption. Road inclination remains influential but is relatively less impactful compared to rural driving. Gross combination weight and speed continue to show moderate but clear impacts, while ambient air temperature and road inclination profile categories (P-Flat, P-Hilly, and Very Hilly) display smaller, less pronounced effects.

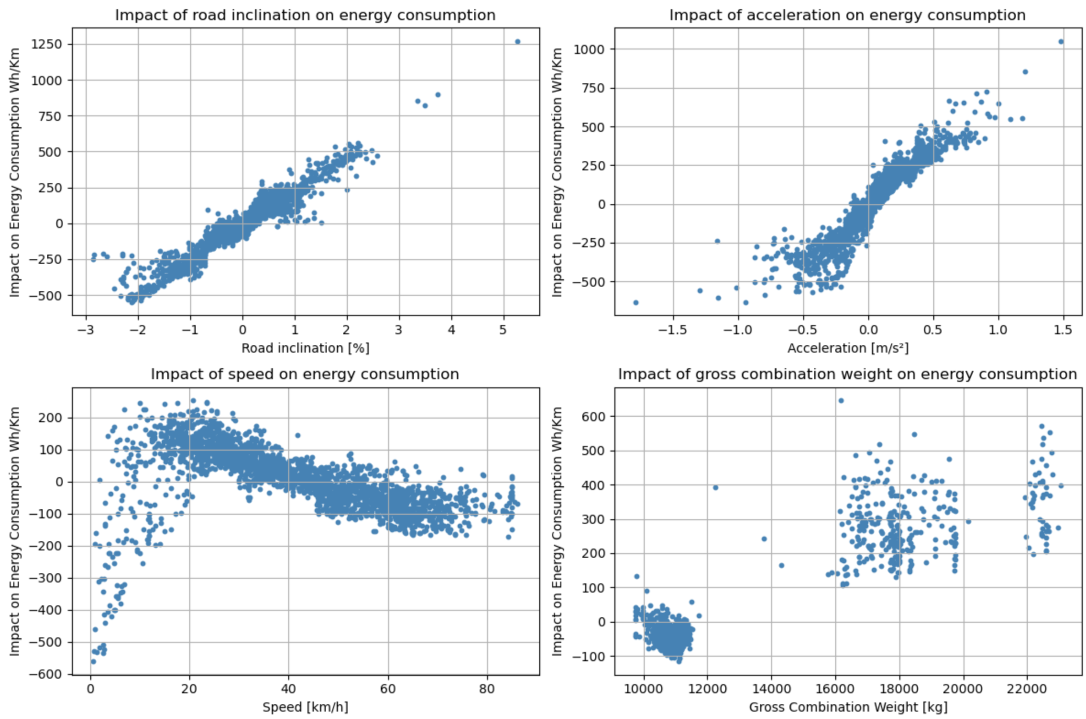


Figure 5: Impact of Four most Important Features on Energy Consumption for Urban Trips.

Figure 5 reinforces these findings. Acceleration demonstrates a pronounced positive correlation with energy consumption, reflecting the frequent stop-and-go nature of urban driving. Road inclination remains positively correlated, although with slightly less variability and lower overall SHAP values compared to rural contexts. Speed displays a complex relationship, highlighting increased energy consumption at lower speeds due to frequent acceleration and deceleration, followed by stabilization or slight reduction in energy consumption at higher speeds. Gross combination weight continues to show a moderate positive relationship, indicating consistently higher energy consumption for heavier loads, although less markedly than acceleration or road inclination.

4 Conclusion

Real-world driving tests were conducted to examine the energy consumption patterns of commercial BEV trucks across both urban and rural driving conditions. The research employed machine learning techniques to process and analyze the extensive dataset collected during these tests. This analytical approach facilitated accurate energy consumption predictions and highlighted the critical variables that impact how BEV trucks utilize energy. The following are the key findings from this research:

- Energy consumption behaviors are easier to forecast and more regular in rural areas. In contrast, urban settings appear to contain more complexities that interfere the prediction process, resulting in less accurate modeling outcomes.
- The Random Forest algorithm outperforms others, achieving the highest R^2 and lowest $RMSE$ values across both route modes.
- The factors that have an impact on the energy consumption, in descending order for rural trips were found to be road inclination, acceleration and gross combination weight and for urban trip were found to be acceleration and road inclination.
- The average energy consumption of BEVs was found to be 6% higher on rural trips compared to urban trips. This is primarily due to higher speeds, which increase aerodynamic drag exponentially with velocity, resulting in greater energy consumption.

Acknowledgments

The work was carried out with support from Vinnova (Sweden's innovation agency) through the Vehicle Strategic Research and Innovation Programme, FFI.

References

[1] W. Achariyaviriya, W. Wongsapai, K. Janpoom, T. Katongtung, Y. Mona, N. Tippayawong, and P. Suttakul, "Estimating energy consumption of battery electric vehicles using vehicle sensor data and machine learning approaches," *Energies*, vol. 16, no. 17, p. 6351, 2023.

[2] K. Janpoom, P. Suttakul, W. Achariyaviriya, T. Fongsamootr, T. Katongtung, and N. Tippayawong, "Investigating the influential factors in real-world energy consumption of battery electric vehicles," *Energy Reports*, vol. 9, pp. 316–320, 2023.

[3] Y. Al-Wreikat, C. Serrano, and J. R. Sodré, "Effects of ambient temperature and trip characteristics on the energy consumption of an electric vehicle," *Energy*, vol. 238, p. 122028, 2022.

[4] Y. L. Murphey, R. Milton, and L. Kiliaris, "Driver's style classification using jerk analysis," in *2009 IEEE Workshop on Computational Intelligence in Vehicles and Vehicular Systems*, pp. 23–28, 2009.

[5] G. M. Fetene, S. Kaplan, S. L. Mabit, A. F. Jensen, and C. G. Prato, "Harnessing big data for estimating the energy consumption and driving range of electric vehicles," *Transportation Research Part D: Transport and Environment*, vol. 54, pp. 1–11, 2017.

[6] X. Zhang, Y. Zou, J. Fan, and H. Guo, "Usage pattern analysis of Beijing private electric vehicles based on real-world data," *Energy*, vol. 167, pp. 1074–1085, 2019.

[7] S. Lundberg and S.-I. Lee, ”A unified approach to interpreting model predictions,” *arXiv preprint arXiv:1705.07874*, 2017.

[8] T. Wicaksono, F. Mahardhika, A. F. Wijaya, and L. Susilawaty, ”Machine Learning-Driven Feature Prioritization for Bev Charging Infrastructure in Polluted Areas of a Developing Country,” *Available at SSRN 5019598*, 2023.

[9] F. Morlock, B. Rolle, M. Bauer, and O. Sawodny, ”Forecasts of electric vehicle energy consumption based on characteristic speed profiles and real-time traffic data,” *IEEE Transactions on Vehicular Technology*, vol. 69, no. 2, pp. 1404–1418, 2019.