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Article

Impact of Weather Conditions on Energy Consumption Modeling for Electric Vehicles: A Data-Driven Analysis

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Abstract: This study presents a methodology to develop an energy consumption model for electric vehicles based on dynamic vehicle and environmental data. Particular attention is given to analyzing the impact of ambient temperature on energy consumption modeling. To improve model accuracy, temperature and vehicle acceleration data were clustered using the K-Means method. As a result, four energy consumption models were created, each corresponding to a specific data cluster. This approach achieved strong validation results, with an R^2 value of 0.84 and a MAE ranging from 0.75 to 1.23 Wh, which is a satisfactory outcome given the large volume of input data. These models are designed for microscale energy consumption prediction, using vehicle speed and acceleration as input parameters.

Keywords: electric vehicle; modeling; energy consumption; machine learning

1. Introduction

With the growing problem of air pollution, which contributes both to the intensification of the greenhouse effect and the deterioration of human health, there is an urgent need to implement ecological solutions in road transport [1,2]. This sector accounts for a significant share of emissions (around 25% of global CO₂ emissions) [3,4], making technologies based on alternative fuels [5,6], modern hybrid drives [7,8], and fully electric vehicles essential [9,10]. The development of electromobility is one of the key elements of the energy transition to reduce greenhouse gas emissions and decrease dependence on fossil fuels [11,12]. Electric vehicles (EVs) are gaining popularity due to technological advancements, the growing availability of charging stations, and government initiatives that support their adoption [13,14]. However, despite numerous benefits, such as lower operating costs and reduced pollution emissions, electric vehicles still face challenges related to energy consumption optimization and the maintenance of predictable range under various operating conditions [15,16]. One of the key factors influencing the energy efficiency of electric vehicles is weather conditions, which can significantly affect the energy demand and the actual range of the vehicle on a single charge [17,18]. Ambient temperature plays a particularly important role in the operation of electric vehicles as it affects both the efficiency of the battery and the performance of vehicle thermal management systems [19,20]. High temperatures may require active cooling of the battery, leading to additional energy consumption, while low temperatures reduce the battery's ability to store and deliver energy, shortening the range [21,22]. Additionally, in winter conditions, the demand for cabin heating increases, further burdening the vehicle's energy resources [23,24]. Despite growing interest in the topic of energy consumption in electric vehicles, previous studies have focused mainly on the impact of driving style, route profile, and vehicle load [25–27]. Much less attention has been paid to the analysis of weather conditions as a factor that shapes the energy efficiency of electric vehicles. Most available energy consumption prediction models consider weather conditions, particularly temperature, in a simplified manner or rely on limited datasets, leading to inaccurate forecasts [28].

Similar studies in this field include the work by [29]. This study focuses on developing a simple, yet accurate energy consumption model for electric vehicles (EVs), using second-by-second vehicle speed, acceleration, and roadway grade data. Unlike existing models that are based on average regenerative braking efficiency, the proposed approach dynamically computes regenerative braking performance based on real-time vehicle operation. The results highlight the ability of the model to estimate EV energy consumption with an average error of 5.9%, demonstrating its effectiveness under various driving conditions. Furthermore, the study emphasizes the impact of auxiliary systems, such as heating and air conditioning, on the efficiency and range of electric vehicles. A similar work related to EV energy consumption modeling is [30]. This study focuses on improving the accuracy of EV energy consumption modeling to enhance range estimation and reduce range anxiety among drivers. A detailed EV model, based on the BMW i3, was developed using MATLAB/Simulink, incorporating the powertrain system, longitudinal vehicle dynamics, and a driver behavior model. Inclusion of a regenerative braking strategy and auxiliary systems further improves the precision of the model. Validation against real-world data showed promising accuracy levels, with simulation errors ranging from 2% to 6% compared to experimental results. There are also some studies that address aspects of energy consumption modeling in the context of temperature variations. The authors point out that temperature influences both the physical properties of the battery and the energy consumption of the air conditioning system [31]. Temperature variability affects battery performance, causing significant differences in energy delivered by the battery and its internal resistance [32]. Additionally, Vepsäläinen et al. [33] conducted an energy consumption analysis in electric buses, highlighting that temperature, rolling resistance, and vehicle mass, including passenger load, are key factors influencing energy consumption variability.

A further challenge in previous studies is the lack of unified methodologies for data clustering and modeling. Many studies rely on classical statistical methods, while machine learning techniques, such as gradient-boosting models, remain underutilized in this field. In addition, few analyses consider different temperature ranges in the context of real vehicle dynamics, which hinders a full understanding of the interactions between weather conditions and energy consumption.

This study aims to address these gaps by applying exploratory data analysis methods and modern machine learning algorithms to model the impact of weather conditions on energy consumption in electric vehicles. The real-world operational data of electric vehicles were clustered according to ambient temperature and driving dynamics, followed by the development of predictive models using the LightGBM method. As a result, the study provides new information on the impact of weather conditions on the energy efficiency of electric vehicles, contributing to the development of more accurate energy management systems and route optimization in changing environmental conditions.

The aim of this article is to fill research gaps by performing a detailed data-driven analysis of the impact of ambient temperature conditions on energy consumption in electric vehicles. The article will present energy consumption models that account for various atmospheric factors and propose methods for improving energy consumption prediction accuracy under different weather conditions. The article consists of five main sections. The first section presents an introduction and a brief review of the literature on the impact of weather conditions on energy consumption in electric vehicles. The second section describes the research methodology, including the data set and analytical techniques. The third section presents the results of the analysis, and the fourth compares them with the results of other studies. The final section contains the summary and conclusions.

2. Materials and Methods

The study involved the use of data collected from road tests to measure the operational parameters of electric vehicles. The goal of the investigation was to gather as much data as possible under varying environmental conditions, particularly with regard to ambient temperature. The data used for further analysis were obtained from a combination of our own research and a modified

version of the database [34] tailored to our needs. The general structure of the study is presented in Figure 1.

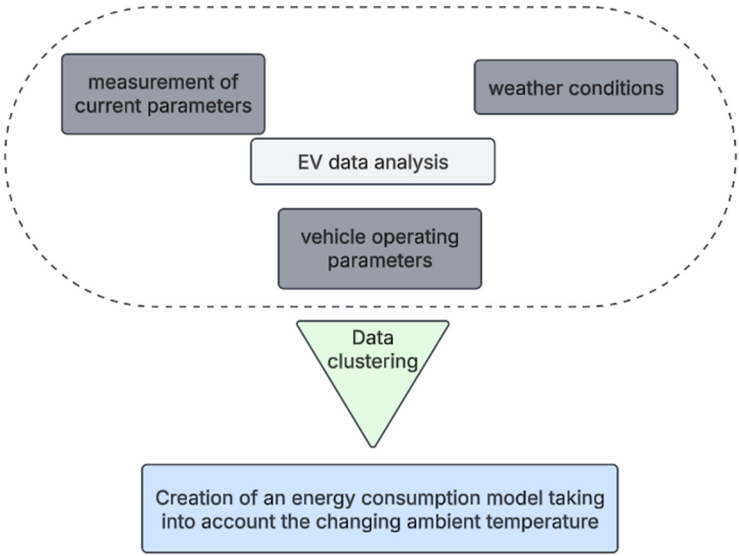


Figure 1. General scheme of work.

The study used data from a compact five-door electric vehicle designed for urban mobility. The vehicle is equipped with a single electric motor that delivers 170 hp (125 kW) and a maximum torque of 250 Nm, utilizing a permanent magnet synchronous AC motor. The rear wheel drive (RWD) configuration and the continuously variable transmission (CVT) ensure smooth driving. The vehicle’s maximum speed is 150 km/h and the acceleration time from 0 to 100 km/h is 7.2 seconds. It is equipped with a 19 kWh lithium ion battery with a voltage of 360 V, allowing for a range of up to 190 km according to the NEDC cycle. The average energy consumption is below 12.9 kWh/100 km. A full battery charge takes approximately 3 hours and 48 minutes. Data from this vehicle were processed for calculation at a rate of 1 Hz.

The data needed to create the energy consumption model include voltage, battery current, vehicle speed, acceleration, and ambient temperature measurements. The data were recorded in a CSV file and processed using Google Colab. Google Colab (Google Colaboratory) is a cloud-based platform to run and create Jupyter notebooks, enabling Python code execution without the need for additional software installation [35,36]. Users have access to free computing resources, including graphics processors (GPU) and tensor processors (TPU), which makes Colab particularly useful for machine learning and data analysis.

In the conducted study, data on the energy consumption of the electric vehicle were segmented based on two key factors: temperature conditions and vehicle dynamics. In the first stage, a clustering algorithm was applied to divide the data into groups corresponding to different temperature ranges. The optimal number of clusters was determined using the “elbow method” and the silhouette score. The elbow method analyzes the sum of squared distances between data points and their closest centroid (called WCSS - Within-Cluster Sum of Squares), selecting the point where further increases in the number of clusters no longer significantly improve the quality of the division [37,38]. The silhouette score, on the other hand, evaluates the internal cohesion of clusters and their separation, enabling a more precise determination of the optimal number of groups [39,40].

After completion of the temperature-based clustering, further data segmentation was performed, considering vehicle dynamics, represented by acceleration values. A clustering method was applied once again, based on the analysis of driving characteristics within the previously separated temperature groups. As in the first stage, the number of clusters was determined using the elbow method and the silhouette score. This two-stage approach to clustering allowed a more precise

determination of the relationship between energy consumption and both environmental conditions and driving style.

Ambient temperature data were collected over a wide range from -3.0°C to 33.5°C, covering both winter and summer conditions. Most of the measurements fell within the 3°C–6°C range for cooler days and 15°C–27°C for warmer periods. This variation in temperature allows for the analysis of the impact of atmospheric conditions on energy consumption during different seasons.

Based on the created clusters, an energy consumption model was developed for each group using the LightGBM (Light Gradient Boosting Machine) algorithm. This advanced machine learning method is based on gradient boosting, where a predictive model is built by iteratively training decision trees that correct the errors of previous iterations. LightGBM is known for its computational efficiency, ability to handle large datasets, and high prediction accuracy due to its better utilization of feature structure information [41,42]. The use of this model allowed us to identify key relationships between driving dynamics and energy consumption under various temperature conditions.

3. Results

The general procedure for generating model results is shown in Figure 2. The process of creating energy consumption models involves data segmentation to enhance their predictive capabilities. The first clustering was based on ambient temperature conditions during road tests. The data were divided into two clusters: higher temperature and lower temperature. Then, for these two clusters, additional clustering was performed on the basis of the vehicle’s acceleration. Since the goal was to develop a microscale model for applications related to vehicle traffic simulation, vehicle speed and acceleration were chosen as explanatory variables. This approach greatly enhances the potential of the model in terms of practical application. Essentially, every vehicle simulation software can easily generate these variables, and such models can also be easily applied to new real-world data from new road tests, including data from GPS systems or the vehicle’s OBD.

The creation of four clusters in total—1) higher temperature, higher acceleration; 2) higher temperature, lower acceleration; and the opposite clusters 3) and 4)—enables a high level of accuracy in modeling energy consumption conditions for electric vehicles (EVs). A total of nearly 90,000 data rows were used for model training.

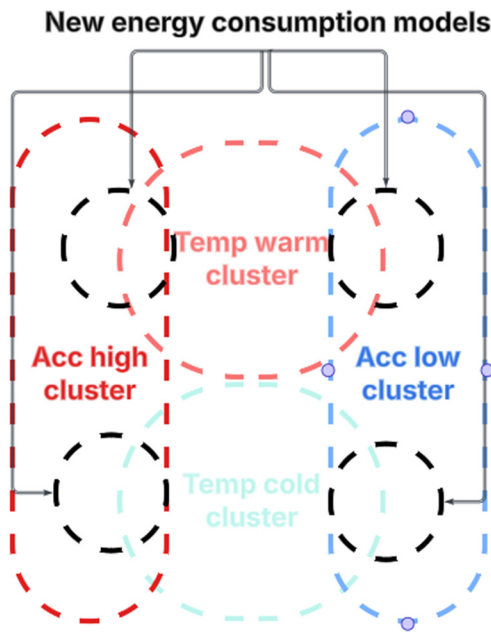


Figure 2. Simplified data clustering workflow for further model development.

3.1. Energy Consumption Versus Ambient Temperature

The relationship between energy consumption and ambient temperature plays a key role in the efficiency of electric vehicles (EV). In this section, clustering techniques are used to analyze energy use patterns in different temperature ranges. Grouping similar data points allows for the development of more accurate models that reflect the impact of external conditions on EV performance. The results provide valuable information for optimizing energy management strategies and improving range predictions.

For clustering ambient temperature conditions in relation to energy consumption, the elbow method and silhouette score were used. These methods helped determine the optimal number of clusters for the next step in model creation. The results are shown in Figure 3.

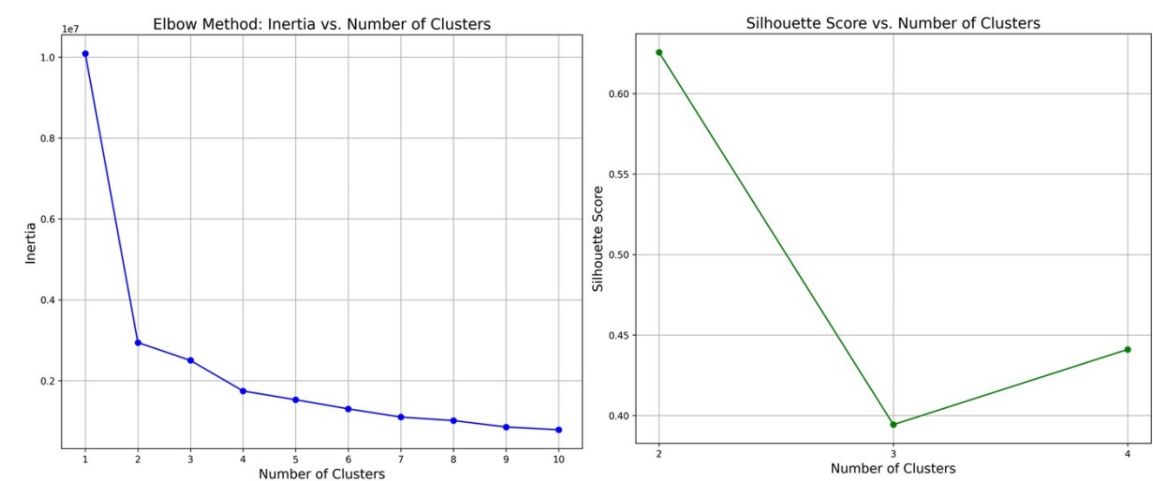


Figure 3. The plot of results for the elbow method and the silhouette score for clustering ambient temperature conditions and energy consumption of the electric vehicle.

Based on Figure 3, it can be seen that the elbow point on the graph indicates that the best predictive capabilities are associated with two clusters of data. The same conclusion can be drawn from the highest silhouette score, which also suggests that the two-cluster approach offers the best model performance. Therefore, for further processing of data related to energy consumption and temperature conditions, it was decided to use two clusters. The view of the developed data clusters is presented in Figure 4. The K-means method is a popular clustering technique aimed at dividing a dataset into k clusters, where each data point belongs to the cluster with the closest centroid [43,44]. The process begins by randomly selecting k points as initial cluster centers. Each data point is then assigned to the nearest center and the cluster centers are recalculated as the average of the points in that cluster. This process is repeated iteratively until the cluster centers no longer change, achieving stability.

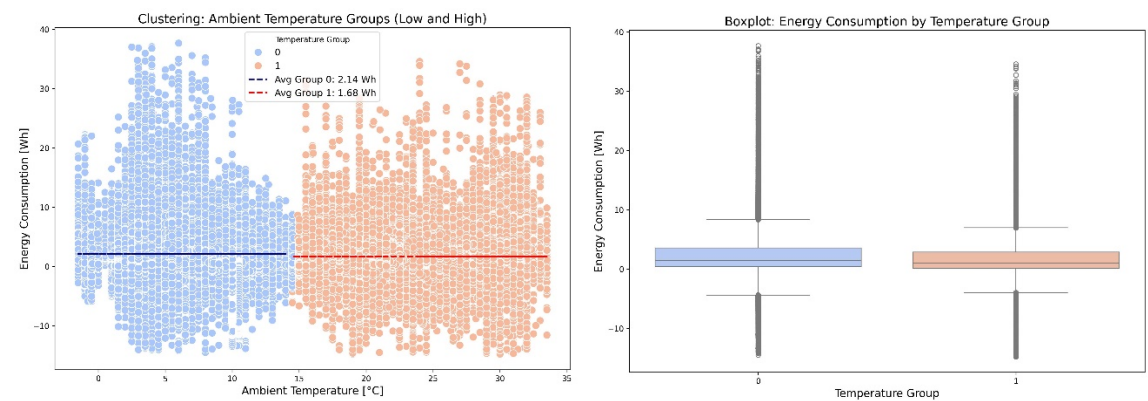


Figure 4. Data clusters of instantaneous energy consumption, categorized by ambient temperature into group 0 (low temperature) and group 1 (high temperature), along with the presentation of mean values on a boxplot.

Figure 4 illustrates the process of clustering energy consumption data for an electric vehicle based on ambient temperature. Points on the plot were divided into two temperature groups using the KMeans clustering algorithm. The blue (0) group represents lower temperatures, while the orange group (1) includes higher temperatures. The average energy consumption for each group is indicated by dashed lines—blue for group 0 (2.14 Wh) and red for group 1 (1.68 Wh). A clear difference in energy consumption based on temperature is evident: in lower temperatures, the average energy consumption is higher than in warmer conditions. This could be due to the need for additional cabin heating or the lower efficiency of the battery at low temperatures. The high density of points in both groups suggests that the data cover a broad range of measurements, and the clustering effectively separates the two distinct temperature zones.

For a better comparison of the results for the two clusters, a 3D plot (Figure 5) was prepared, presenting the relationship between speed, temperature group, and energy consumption of the studied vehicles.

Relationship between Velocity, Temperature, and Energy Consumption

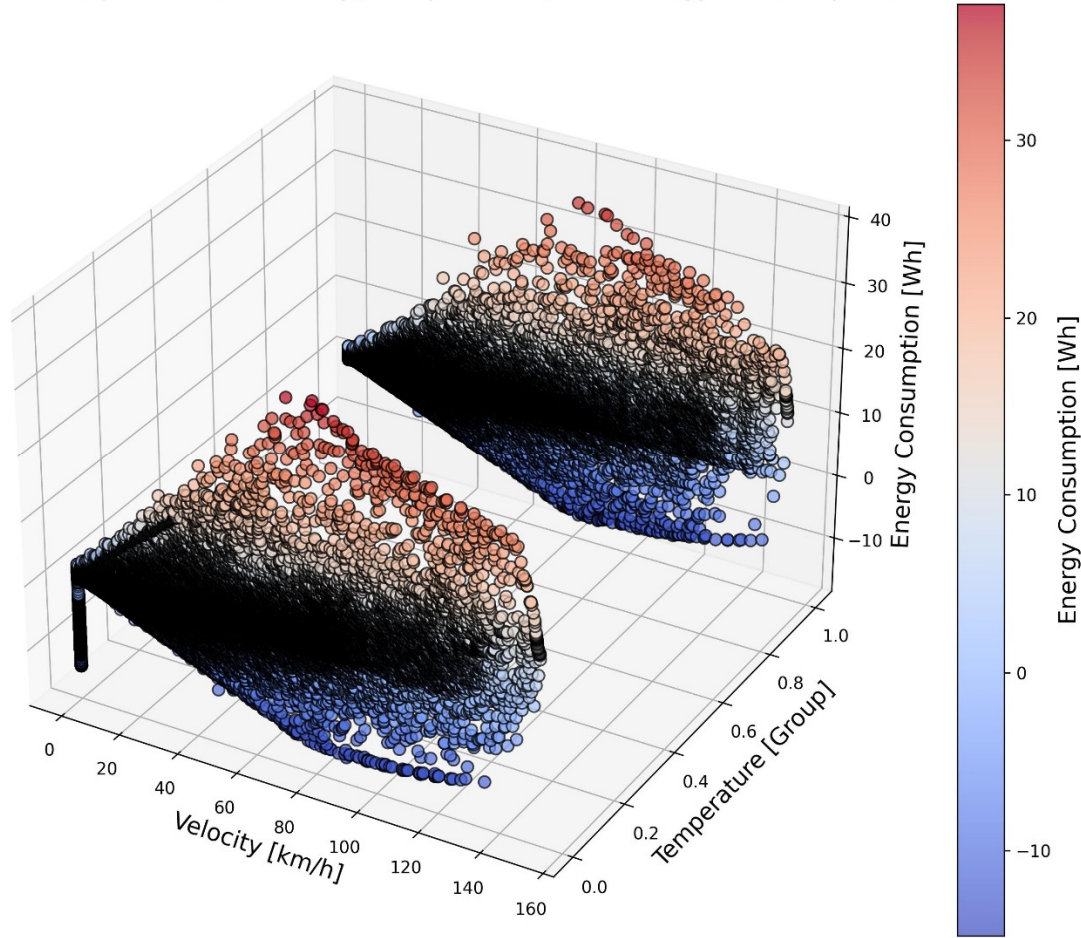


Figure 5. 3D plot showing the relationship between speed, temperature group for a given cluster, and energy consumption of the electric vehicle.

The three-dimensional plot shows the complex relationship between the speed of the electric vehicle, the ambient temperature and the energy consumption, taking into account the division into two temperature groups. The two-layer structure visible on the plot indicates the strong influence of temperature on energy consumption, with each temperature group seemingly characterized by a different energy efficiency regime. At lower temperatures, represented by the lower layer of points,

energy consumption values are more spread out, which may suggest greater variability in the efficiency of the drive system, as well as the impact of additional factors such as the need to heat the battery or cabin. In higher temperatures, where the data form a more compact structure, the energy consumption appears more predictable, indicating a more stable operation of the drive system and battery under optimal thermal conditions.

When analyzing the relationship between speed and energy consumption, the non-linear character of this relationship is evident. In both temperature groups, energy consumption tends to be minimized at moderate speeds, whereas it increases at both very low and very high speeds. This may be due to different dominant mechanisms of energy loss: At low speeds, frequent accelerations, dynamic power changes, and rolling resistance play a larger role, while at high speeds, aerodynamic drag, which increases exponentially with speed, dominates. An especially interesting aspect of the plot is the color gradient, which reflects the energy consumption values. The presence of areas in blue, indicating potential negative energy consumption values, shows the effective operation of regenerative braking under certain driving conditions, especially when decelerating at high speeds. This suggests that, in certain operational ranges, the vehicle not only minimizes energy losses but also effectively recovers part of the consumed energy, which could be significant for energy management strategies in electric vehicles.

When comparing the impact of temperature on energy consumption characteristics, it is noticeable that, in warmer conditions, energy consumption shows greater uniformity, with extreme values being less visible compared to the low-temperature group. This suggests that the impact of temperature on battery efficiency degradation is more significant in winter conditions, where both internal cell resistance and auxiliary energy demand may contribute to increased energy consumption. In practical terms, this graph highlights the importance of optimizing energy management strategies in electric vehicles, particularly in relation to ambient temperature and driving style. The clear two-stage temperature dependence and nonlinear energy consumption with respect to speed indicate the need for adaptive energy management strategies that account for dynamic changes in operational conditions to maximize the vehicle's range and efficiency.

For the created temperature groups, a density distribution plot was also created, showing the data distribution for the formed clusters (Figure 6).

Figure 6 shows the distribution of the density of energy consumption for the two temperature groups, providing a better understanding of the energy characteristics of the electric vehicle under different environmental conditions. The density curves indicate that energy consumption in both temperature groups is strongly concentrated around values close to zero, suggesting that in most cases the vehicle operates in a low energy consumption range or even recovers some energy through regeneration. However, the differences in the shape of the curves reveal important aspects: the low-temperature group (blue) shows a wider distribution, indicating greater variance in energy consumption under cooler conditions. This may be due to the additional energy demand for heating the battery and passenger cabin, as well as the less efficient operation of the drive system at low temperatures. On the other hand, the high-temperature group (orange) has a more concentrated distribution, suggesting that energy consumption in warmer climates is more predictable and less dependent on extreme operating conditions.

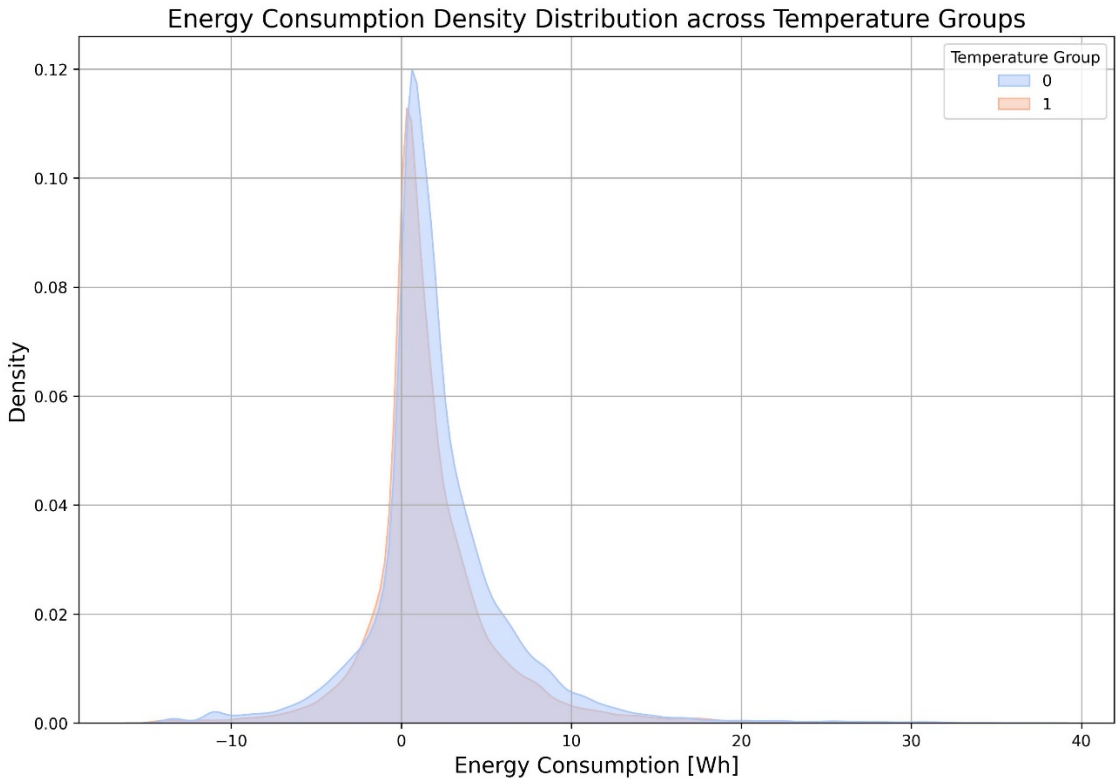


Figure 6. Density distribution of data for the created temperature clusters with respect to EV energy consumption.

3.2. Energy Consumption Versus Acceleration for Temperature Clusters

Since the feature importance analysis in the context of creating an energy consumption model using the speed and acceleration parameters showed that acceleration has significant importance and high values, it was decided to use it to create additional data clusters for the previously created ambient temperature clusters. The impact of acceleration on the energy consumption generated by the aggregated groups is presented in Figure 7.

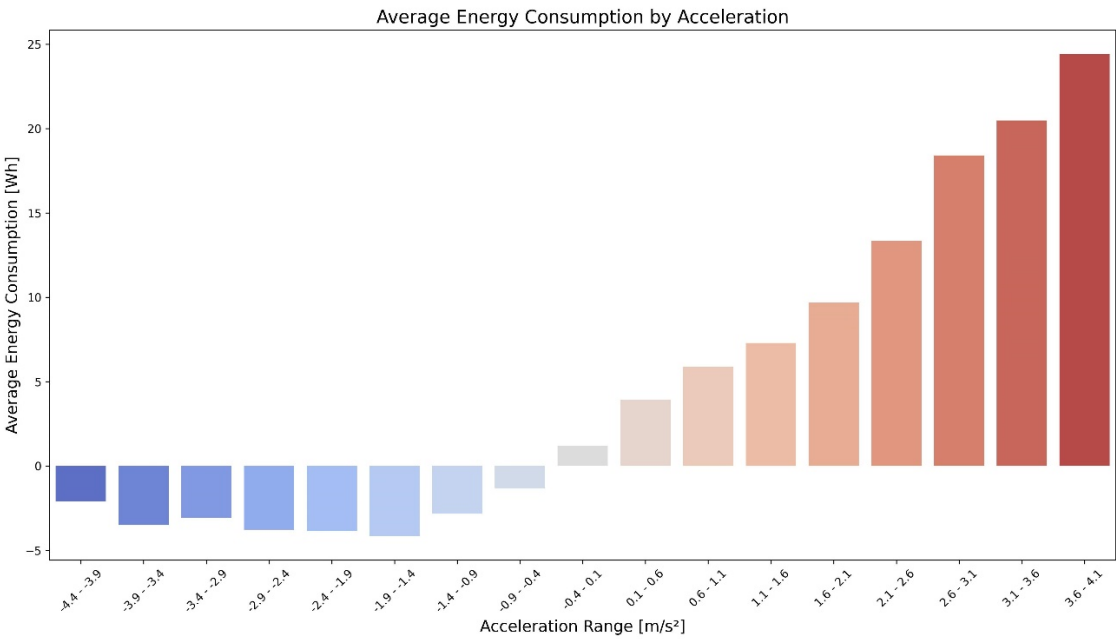


Figure 7. Aggregated acceleration groups of electric vehicles and their impact on average energy consumption.

Based on Figure 7, a trend of increasing energy consumption with increasing acceleration can be observed and this trend is linear for positive accelerations. In the braking deceleration range, i.e., for negative accelerations, a tendency to recover an average amount of instantaneous energy, around 4 Wh, can be noticed.

Similarly to the temperature parameter, for the previously developed clusters of environmental conditions, further clusters were created based on the acceleration characteristic of the vehicle. This step aims to further enhance the predictive capabilities of the energy consumption models. The results of the search for the optimal number of clusters are presented in Figure 8.

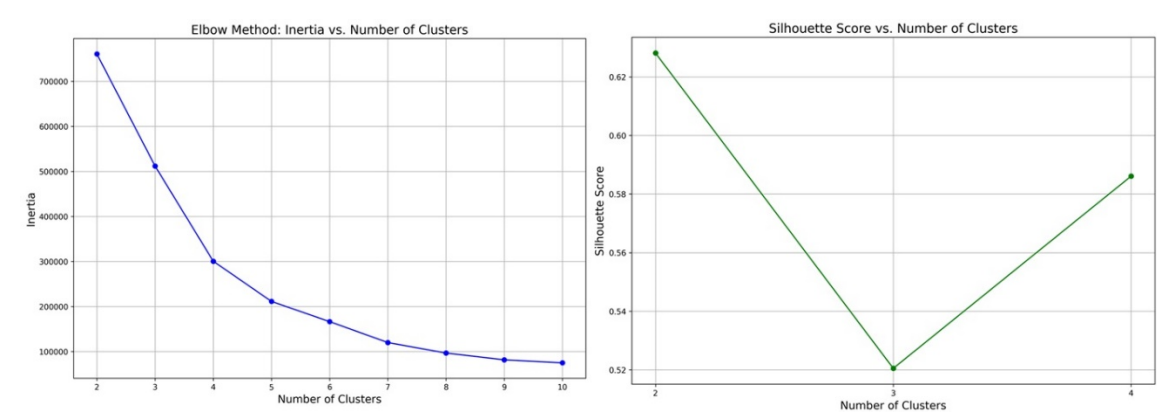


Figure 8. The plot of results for the elbow method and silhouette score to cluster the acceleration parameter data.

In the case of determining the number of clusters for acceleration, the elbow plot behaves slightly differently, as there is no typical break in the graph. This is clarified by the silhouette score, which, similar to the temperature parameter, shows the highest value for 2 clusters. Therefore, for the acceleration parameter, the same number of clusters was used (Figure 9).

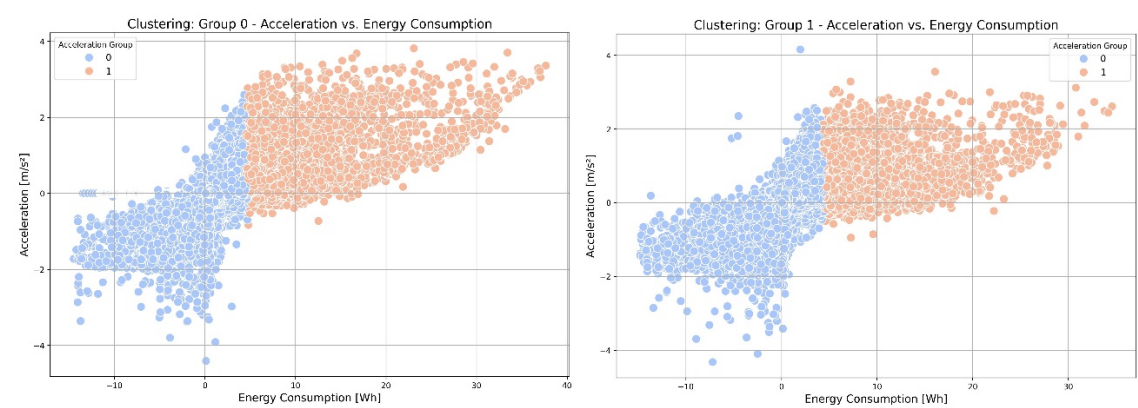


Figure 9. Clusters of instantaneous energy consumption data with division based on the acceleration parameter into low or negative acceleration (group 0) and positive and higher acceleration (group 1). The division also includes two temperature cluster groups: the left side of the plot represents the low-temperature cluster, and the right side represents the high-temperature cluster, corresponding to summer conditions.

The clusters for the two acceleration groups were divided into a group of very low or negative accelerations and a group of higher accelerations. The same division was made for the two main temperature clusters (left and right sides of the plot). From Figure 9, it can also be observed that group 0 of accelerations is characterized by a lower energy consumption or by regenerative braking.

3.3. Energy Consumption Modeling of Electric Vehicles Depending on Temperature and Acceleration Clusters

Since two explanatory variables will be considered for the energy consumption model, namely acceleration (as previously presented) and speed, a summary of instantaneous energy consumption with respect to these parameters has been prepared (Figure 10).

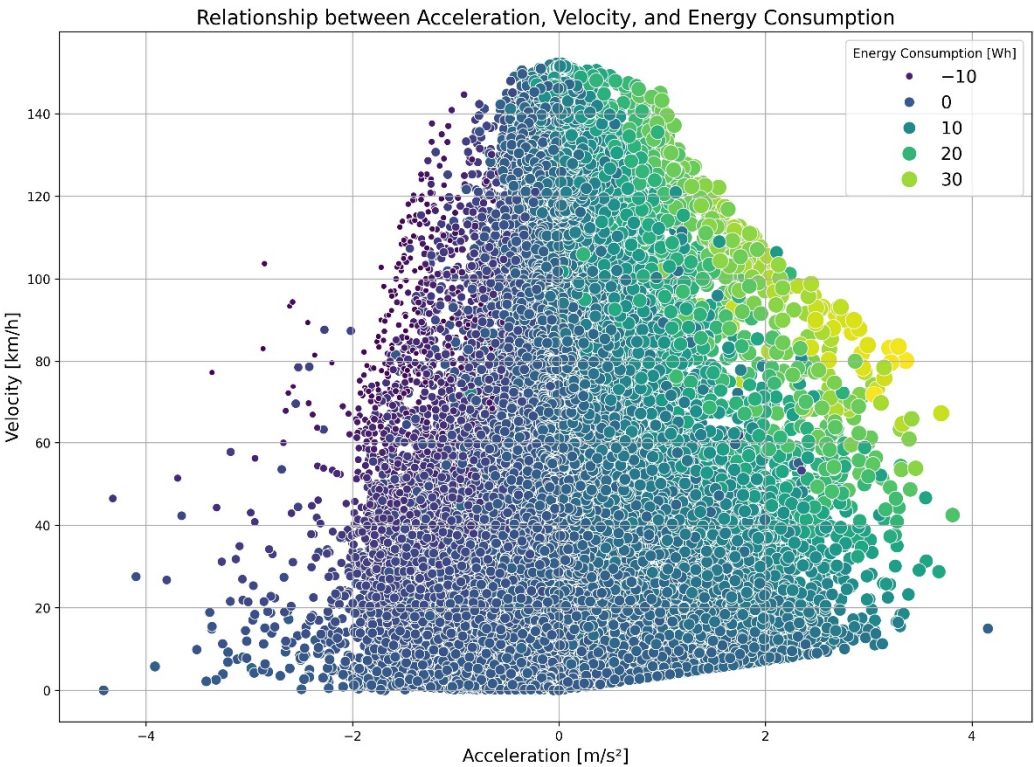


Figure 10. Energy consumption with respect to the explanatory parameters of vehicle speed and acceleration.

Based on Figure 10, it is clearly visible in which speed and acceleration ranges the highest and lowest energy consumption values for EVs occur. Sudden acceleration starting at a speed of 20 km/h leads to a significant increase in instantaneous energy consumption, reaching up to 30 kWh. The highest values are recorded in the speed range of 60-100 km/h for accelerations greater than 2 m/s². The speed and acceleration variables are good features to predict energy consumption. This set of explanatory variables, as mentioned earlier, is justified by the fact that the resulting energy consumption model is intended to be as universal as possible for microscale simulation applications.

To model energy consumption in electric vehicles, an approach based on the LightGBM algorithm was developed. This process took into account temperature and acceleration data, enabling the analysis of the impact of atmospheric conditions and driving dynamics on energy consumption. The LightGBM library was used to build regression models, with acceleration and vehicle speed as features and energy consumption as the target variable. The data was divided into groups corresponding to different temperature ranges and acceleration levels, in line with their earlier grouping, which allowed for a more detailed analysis of the impact of these factors. In each group, the data set was split into training and test sets using the train-test split method. To ensure compatibility with the LightGBM library, the column names were transformed by removing parentheses. Dataset objects for LightGBM were created, and the model was trained using optimal hyperparameters such as the number of decision tree leaves (31), learning rate (0.05), and feature fraction used for training (0.9). The training process consisted of 100 iterations. The model was built separately for the four data groups that resulted from clustering based on ambient temperature (2 groups) and acceleration (2 groups). Each group was analyzed, which allowed the inclusion of specific characteristics of the data under different operating conditions. The quality of the model was

assessed using regression metrics, including mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R^2), as well as an analysis of predictive vs. actual data plots. The results of the predictive performance in the form of 3D graphs that compare the model values to the actual values are presented in Figure 11.

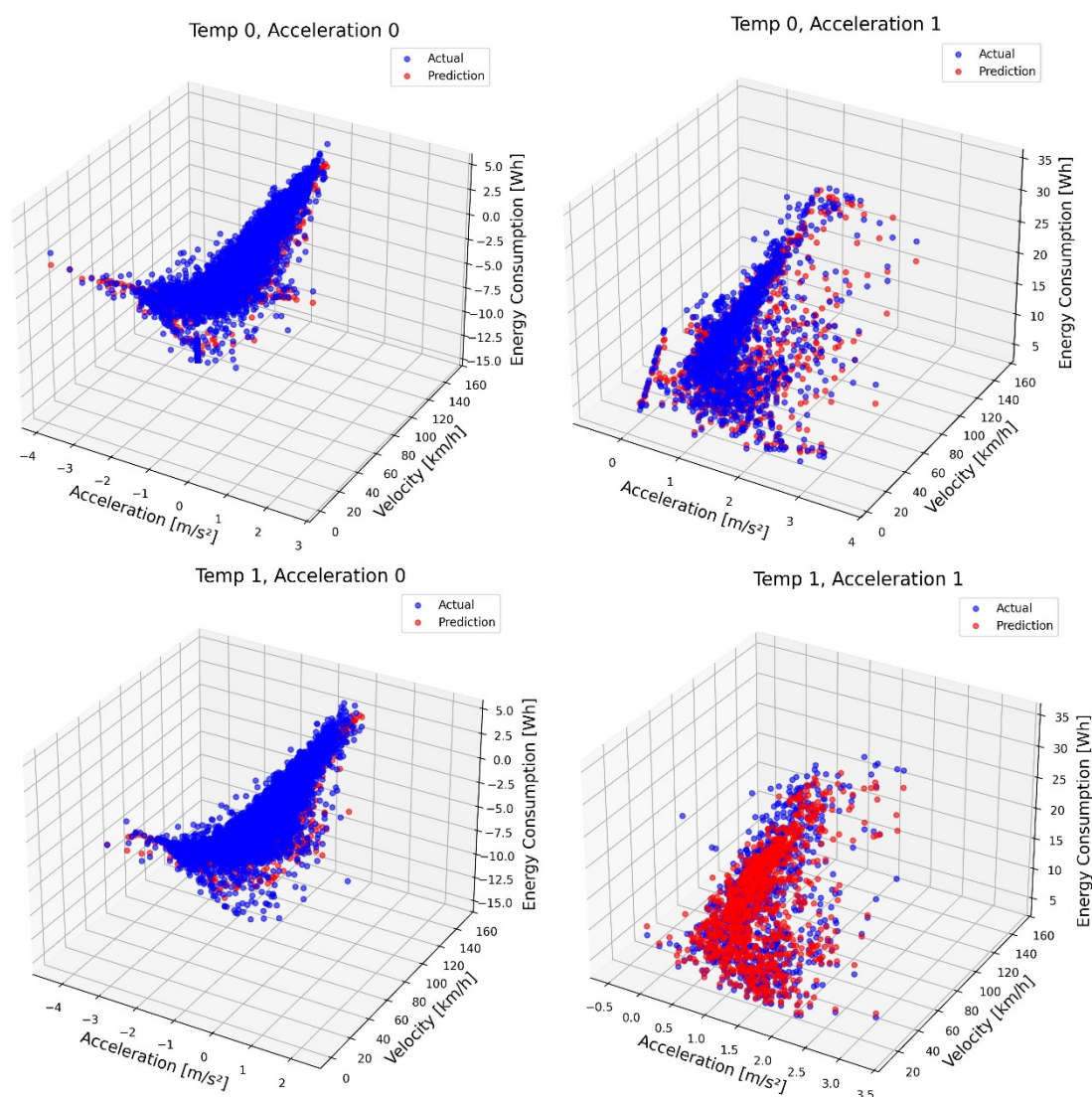


Figure 11. Comparison of predictive capabilities for the obtained models against actual energy consumption for clustered data.

The energy consumption prediction model based on LightGBM shows varying effectiveness depending on temperature and acceleration conditions. In cases where acceleration is close to zero (left column of the plots), the model achieves high accuracy, as evidenced by the close alignment of actual (blue) and predicted (red) energy consumption values. This is particularly noticeable at lower energy levels, where the predictions almost perfectly mirror the actual data.

However, with higher acceleration (right column of the plots), the model's predictions become more scattered and inconsistent, suggesting increased difficulty in modeling the relationship between energy, speed, and acceleration. It is evident that under higher acceleration conditions, the model tends to show increased error, especially at higher energy consumption values. Despite these challenges, the model still provides valuable predictions, offering a better understanding of the impact of various factors on energy consumption in electric vehicles. To further verify the models obtained, additional validation plots (Figure 12) were prepared and validation indicators calculated.

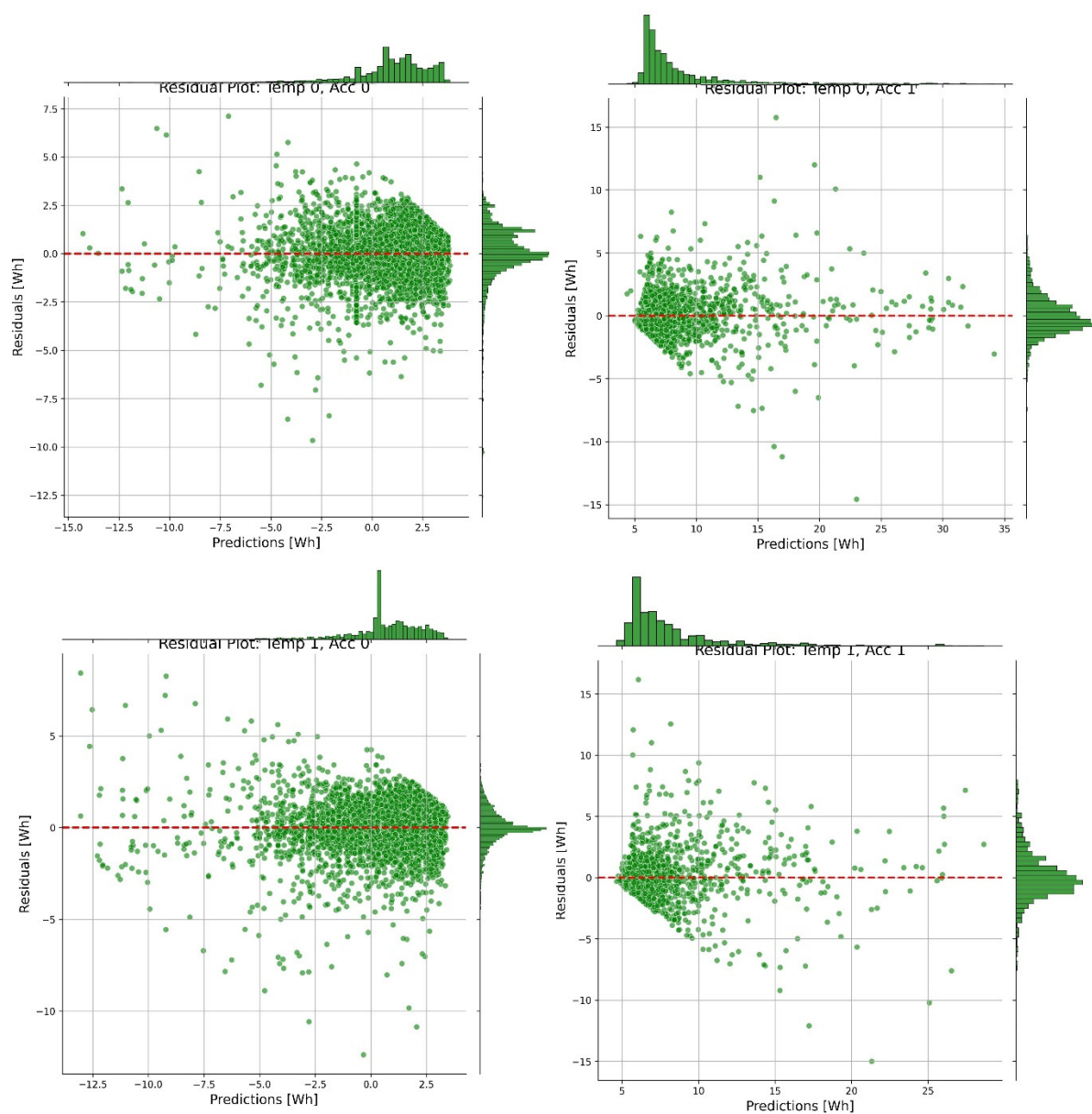


Figure 12. Residual plots for energy consumption models.

The analysis of residual plots (Figure 12) for the LightGBM model reveals its ability to predict energy consumption under various temperature and acceleration conditions. In the case of low acceleration (left column of the plots), the distribution of residuals is more concentrated around zero, indicating relatively good model accuracy, although slight tendencies toward errors can be seen in areas with very low or high predicted values. On the other hand, with higher acceleration (right column of the plots), the model shows a clearly larger spread of errors, especially for higher predicted energy consumption values. The visible heteroskedasticity, manifested by increased residual fluctuations for higher prediction values, suggests that the model may struggle to capture complex relationships under these conditions. The residual histograms placed alongside the plots show that, although most errors are concentrated around zero, there are cases of significant deviations, especially under higher acceleration conditions.

Table 1. Results of the validation metrics for the energy consumption models obtained.

Temperature Group	Acceleration group	MAE	RMSE	R ²
0 (low)	0 (low)	1.23	1.81	0.84
0 (low)	1 (high)	1.02	1.64	0.72
1 (high)	0 (low)	0.75	1.18	0.74
1 (high)	1 (high)	1.28	1.89	0.74

The results obtained from the evaluation of the LightGBM model indicate its good predictive ability to predict energy consumption under various temperatures and acceleration conditions. The high coefficient of determination (R^2), especially for the Temp 0, Acc 0 group ($R^2 = 0.84$), suggests that the model effectively explains the variability of the data in this configuration, while achieving the lowest RMSE value of 1.81 Wh, indicating minimal deviations between predictions and actual values. The model also shows a very good accuracy for Temp 1, Acc 0, where the lowest MAE value (0.75 Wh) was achieved, meaning the smallest average prediction errors. Slightly higher error values for the Temp 1, Acc 1 group (MAE = 1.28 Wh, RMSE = 1.89 Wh) may suggest greater variability of the data under these conditions; however, the results still indicate solid predictive capabilities of the model with values above 0.72. Overall, the results confirm that the LightGBM model successfully predicts energy consumption, especially under more stable conditions with lower acceleration values.

4. Discussion

The analyses carried out provide valuable information on the impact of ambient temperature and driving dynamics on energy consumption in electric vehicles (EV). The use of the LightGBM algorithm for energy consumption modeling allowed for the incorporation of these factors and an assessment of their significance under different operating conditions. Analysis of the distribution of energy consumption density for different temperature groups showed that, at lower temperatures, energy consumption is more varied. The wider distribution in the low-temperature group suggests greater variability in energy consumption, which may result from additional energy requirements to heat the battery and the passenger cabin, as well as from less efficient operation of the drive system in colder conditions. On the other hand, at higher temperatures, the distribution of energy consumption is more concentrated, indicating more predictable energy consumption in warmer climates. These findings align with previous studies suggesting that low temperatures can lead to increased energy consumption in electric vehicles. Furthermore, at cooler temperatures, electric batteries can lose up to 20% of their capacity, affecting vehicle range. Analysis of the impact of acceleration on energy consumption revealed a linear relationship within positive acceleration values. As acceleration increases, energy consumption increases proportionally. In the range of negative acceleration (regenerative braking), an average energy recovery of about 4 Wh was observed, indicating the effectiveness of the energy recovery system in electric vehicles. Similar results have been presented in the literature, where it was shown that dynamic driving, characterized by frequent and rapid acceleration, leads to increased energy consumption. However, moderate acceleration and braking promote more efficient energy management and can increase vehicle range. The application of the LightGBM algorithm for energy consumption modeling allowed the inclusion of both ambient temperature and driving dynamics on energy consumption in electric vehicles. Models trained for different temperature and acceleration groups showed varying predictive performance. Under low acceleration conditions, the model achieved high accuracy, as evidenced by the low mean absolute error (MAE) and the high coefficient of determination (R^2). In the case of higher acceleration values, the model's accuracy was slightly lower, which may result from greater data variability under these conditions. It should also be noted that the only explanatory variables for the model were speed and acceleration, which was intended to increase the universality of the models.

A similar work on the analyzed topic is [45]. The article discusses the use of electric vehicles (EVs) as a means to reduce dependence on oil, improve transportation efficiency, and reduce carbon emissions. The research focuses on evaluating the energy consumption of electric vehicles, including the analysis of data collected from a test electric vehicle. The results show that electric vehicles are more efficient on urban routes than on highways, and users tend to balance travel time and energy consumption. Additionally, a model is proposed to estimate energy consumption, which successfully predicts the power and energy consumption of electric vehicles in real time. The results presented in this work, in terms of the efficiency of electric drive at lower urban speeds, are consistent with the study developed. Another interesting similar work is [46]. The article addresses the variability of energy consumption of electric vehicles (EVs) according to external factors, such as road topology, traffic, and driving style. The goal is to analyze the correlation between vehicle kinematic parameters and energy consumption and to develop models that estimate this consumption based on real world data. Three models were proposed, using different levels of aggregation of input data, from basic travel parameters to detailed acceleration data. The results show that the first two models achieve similar results, while the third, despite a poorer fit, has potential for further development. However, the model developed in this work is somewhat limited in terms of the larger number of input data variables.

There are also numerous studies focusing specifically on the impact of temperature on energy consumption by electric vehicles (EVs). Liu et al. [47] analyzed the effect of ambient temperature on energy consumption per kilometer, taking into account the interaction with the air conditioning system. They proposed a model based on least squares regression and linear regression with mixed effects. Omitting this interaction could lead to overestimating energy consumption for heating and underestimating energy consumption for cooling. Eliminating unjustified auxiliary loads saves an average of 9.66% of energy per kilometer. Ji et al. [48] developed a model for estimating trip energy consumption (TEC) based on real data, showing that ambient temperature is a key factor affecting increased TEC and decreased battery range and efficiency. They introduced multiple regression, in which traction energy and battery thermal management were analyzed together, while energy consumption by the air conditioning system was analyzed separately. This allowed for more accurate predictions of energy consumption under different conditions. Many studies emphasize the significant impact of ambient temperature on energy consumption by electric vehicles (EVs) [49–52]. Wang et al. [53] developed a model that incorporates weather conditions and rolling resistance, while Abdelaty et al. [54] created an energy consumption estimation model based on low-resolution data, achieving 90% explanatory power for the variability in consumption. Gao et al. [55] used Grey Relational Analysis (GRA), showing that travel time, weather, and air conditioning affect the energy consumption of electric buses. Due to the long-term influence of meteorological conditions, temperature and humidity are often included in models that estimate energy consumption, for example, by estimating temperature based on the position of the vehicle. Another study in this area is [56]. This work presents new methods for optimizing energy consumption in electric vehicles, taking thermal comfort into account, and proposing three control strategies. To more accurately estimate the remaining range of electric vehicles, a method that incorporates average air conditioning power was proposed, helping to avoid errors from treating air conditioning energy as part of propulsion energy. The simulation and experimental results confirm the effectiveness of this approach, showing that the range estimation error is below 3%, which helps to better balance energy savings and the comfort of EV users.

There is also a growing number of studies using various machine learning techniques to model the operational parameters of vehicles, including electric [57,58], hybrid [59,60], and combustion [61–64] vehicles. It is important to note that it is not only crucial to develop models analyzing energy consumption by electric vehicles, but also to integrate them with traffic simulation tools such as Vissim or SUMO. To obtain realistic and reliable results, it is necessary to use basic dynamic vehicle parameters as input data for such models. This need is addressed, among other ways, by this work, which focuses on analyzing variables related to vehicle speed and acceleration. This allows for quick

and efficient collection of key data from both new road cycles and simulations, which can significantly improve traffic modeling and energy consumption forecasting in road transport.

5. Conclusions

The study highlights the significant impact of ambient temperature and acceleration on the energy consumption of electric vehicles (EVs), providing valuable information to optimize energy efficiency and range prediction. The clustering approach applied to temperature and acceleration data allowed for a more granular analysis of these factors, leading to several key conclusions.

- Energy consumption varies significantly across different temperature clusters. Lower temperatures contribute to increased and more variable energy use due to factors such as battery heating requirements and reduced drivetrain efficiency.
- The wider distribution of energy consumption in colder conditions suggests that additional energy management strategies are necessary to maintain efficiency, particularly in winter conditions.
- On the contrary, higher temperatures result in a more stable and predictable energy consumption pattern, indicating improved overall efficiency in warmer climates.
- A strong correlation between acceleration and energy consumption was observed, with energy usage increasing linearly with positive acceleration values.
- Negative acceleration (deceleration or braking) demonstrates the effectiveness of regenerative braking, with an average energy recovery of approximately 4 Wh.
- The LightGBM model proved to be an effective tool for predicting energy consumption, particularly under stable conditions with lower acceleration values.
- The highest prediction accuracy was observed in scenarios with low acceleration and moderate speeds, with an R^2 value of 0.84 and the lowest RMSE of 1.81 Wh.

Despite the high effectiveness of the LightGBM model in forecasting energy consumption in electric vehicles, an increase in prediction errors was observed at higher acceleration values. This suggests the need to include additional variables, such as road gradient, air resistance, or individual driver habits, which can significantly affect energy consumption. The results of the analyses are of practical importance for electric vehicle manufacturers, fleet managers, and policymakers shaping transportation policies, all of whom aim to increase energy efficiency and extend battery life. Particularly important appears to be the consideration of the impact of temperature and acceleration in real-time energy management systems, which could improve range forecasting and optimize charging strategies. Future research should focus on expanding the model with additional environmental factors, such as road surface conditions or wind speed, which would increase its resilience to variable operational conditions. Moreover, verification of the effectiveness of the model in real driving conditions for different types of electric vehicle is necessary to assess its universality and adaptability. A key development direction is also the creation of intelligent energy management systems that would dynamically adjust power consumption to predicted road conditions and driving styles.

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Abbreviations

The following abbreviations are used in this manuscript:

EV	Electric Vehicle
LightGBM	Light Gradient Boosting Machine
hp	Horsepower
RWD	Rear-Wheel Drive
CVT	Continuously Variable Transmission
PGU	Power Generation Unit
TPU	Tensor Processing Unit
WCSS	Within-Cluster Sum of Squares
OBD	On-Board Diagnostics
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error
R ²	Coefficient of Determination

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