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Research Article

The Impact of Road Types on the Energy Consumption of Electric Vehicles

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The widespread adoption of battery electric vehicles (BEVs) is hindered by their limited ranges and long charging times. Optimizing eco-driving strategies and BEV-specific routing through a thorough understanding of the BEV discharge behavior is vital to overcome these barriers in the short term. Therefore, this study investigates the impact of road types on the BEV discharge behavior while accounting for explanatory variables (i.e., ambient temperature, the initial state of charge, and driver). Thirty participants drove a 2017 Volkswagen eGolf along two predefined routes in Rhode Island. The results illustrate that BEVs are the most efficient on-road types with medium speed and low variation (i.e., "major collectors," "minor arterials," and "other principal arterials"). Meanwhile, findings confirmed a significantly higher average energy consumption rate on roads with higher average speeds ("interstates" and "other freeways/expressways"). Moreover, "local roads," associated with a low average travel speed and a high variation in speed, showed a negative effect on BEV efficiency. The study further supported previous findings that BEVs are less efficient in colder temperatures. Thus, adapting eco-driving strategies, including the alteration of route choice to avoid "local roads" and "interstates," can offer BEV drivers the potential for energy savings and range extensions. We propose a consideration of these findings to mitigate the effects of BEV range limitations and ease BEV adoption and ownership.

1. Introduction

Today, scarcity of nonrenewable energy resources and increasing ecological awareness have intensified efforts to transition to more environmentally friendly technologies. In transportation, the electrification of vehicles is a promising technology for greener, low-emission transportation systems. The global electric vehicle (EV) stock has significantly increased over the last decade. In 2020, more than 10 million EVs were registered worldwide, 20% of which were in the United States (U.S.), making it one of the biggest EV markets in the world [1]. Among EVs, battery electric vehicles (BEVs) have become increasingly popular and currently represent more than 75% of U.S. EV sales, and the growing demand for BEVs is expected to continue well into the future [1].

Nevertheless, range limitations and an insufficient charging infrastructure feed range anxiety (i.e., drivers' fear of running out of charge before reaching their destination) and impede BEV adoption [2]. In addition to equipping EV models with larger batteries, one way of mitigating these limitations is adjusting driving behavior and optimizing BEV-specific routing. In other words, the range of BEVs can be extended by minimizing energy consumption through eco-driving and route choices. Understanding how operating characteristics on different road types impact energy consumption can be a practical and beneficial consideration in optimizing the energy-based routing of EVs. Knowing how much energy the BEVs consume in different driving situations is a prerequisite for range optimization. Findings of economical driving behavior can be directly implemented by drivers and further be used in vehicle navigation to identify the most economical route ("eco-routing") [3]. Table 1 summarizes key findings of studies relevant to this paper.

To date, most of the literature investigating the impact of traffic planning and road types on fuel consumption and

Table 1: Studies relevant for this paper by author, year, location, type of vehicle analyzed, and relevant key findings of the publications.

Author (s)	Year	Study location	Methods	Vehicles studied	Relevant key findings
Bingham et al.	2012	United Kingdom	Multimethod analysis of driving data	BEVs	Nonaggressive driving reduces BEV energy consumption; less acceleration and deceleration increase efficiency
Brundell-Freij & Ericsson	2005	Sweden	Linear regression analysis	ICEVs	Traffic environment, driver, and car mass affect performance
Ericsson	2000	Sweden	ANOVA	ICEVs	Street type has the highest impact on driving patterns; driving patterns vary with time of the day
Ericsson et al.	2006	Sweden	Network analysis using Dijkstra algorithm	ICEVs	Route choice impacts efficiency due to differences in traffic patterns
Faria et al.	2013	Portugal	Life-cycle assessment	ICEVs, PHEVs, & BEVs	Aggressive driving and climate control decrease vehicle efficiency
Faria et al.	2019	Portugal	Multimethods approach; nonparametric testing	ICEVs	Road characteristics and driving behavior impact vehicle efficiency
Fetene et al.	2017	Denmark	Regression analysis, parametric and nonparametric testing	BEVs	Road type does not affect BEV efficiency; BEV performance varies with weather conditions and driving behavior
Fiori et al.	2019	Italy	Simulation analysis using different vehicle simulators	ICEVs, EVs	ICEVs and EVs consumption behavior differ with speed; EV energy consumption increases with speed
Franke et al.	2015	Germany	Statistical sample comparison	BEVs	Eco-driving from ICEVs applicable to BEVs for increase in efficiency; experience increases eco-driving potential
Galvin	2017	Germany	Simulation modeling and regression analysis	BEVs	BEV efficiency is lower in modest to high acceleration; BEV energy-optimal speed at approx. 37 mph
Hallmark et al.	2002	U.S.	Linear regression analysis and regression tree analysis		Various traffic characteristics and volume impact emission rates
Jensen	1995	Denmark & Sweden	Regression analysis	ICEVs	Emission levels are impacted by ambient temperature and speed rather than road type
Kurien et al.	2020	India	Simulation modeling	BEVs	The range potential of BEVs decreases with speed and slope
Liu et al.	2021	China	Path modeling	BEVs	Avoidance of traffic can decrease BEV efficiency; BEVs are less efficient in lower temperatures and higher speeds
Sivak & Schoettle	2012	—	Literature review	ICEVs	Efficiency differs with route choice and ultimately the type of road
Wu et al.	2015	U.S.	Energy consumption modeling	BEVs	BEVs more efficient during in-city driving than freeway driving
Yao et al.	2013	China	Analysis of vehicle-specific power distribution	BEVs	BEV efficiency depends on the road type and speed; consumption on arterial roads is notably different

driving behavior has focused on conventional internal combustion engine vehicles (ICEVs) [4, 5]. Ericsson et al. [3], and Brundell-Freij and Ericsson [4] discovered that the road and traffic environment, the driver demographics (e.g., age and gender), and the car mass affect driving behavior. However, the studies lack a quantification of the road and traffic impacts on fuel consumption. Hallmark et al. [6] identified different on-road geometric and operational variables at signalized intersections and explored their effect on the time an ICEV spends in a specific operating mode. The findings aimed to improve emission estimates for passenger vehicles but lack the quantification of fuel consumption. In Faria et al. [7], the fuel-saving potentials of ICEVs based on driving behavior, road types, and road grade were assessed. The research was conducted under natural conditions and monitored 47 drivers in Lisbon, Portugal over six months. The highest fuel-saving potential was observed on minor arterial roads and collector roads with a speed limit of 50 km/h (31 mph). However, the study did not include BEV consumption models. Ericsson [8] investigated the variability in urban driving patterns and concluded that the street type has the most significant influence on the driving pattern for ICEVs. Furthermore, the study discovered that the average speed and deviation of speed are significantly different between different road types. However, specific consumption factors were not considered nor quantified. Jensen [9] evaluated different driving patterns and the resulting emissions of ICEVs on different road types.

The author concluded that speed is the most critical factor, while the speed deviation in traffic did not explain fuel consumption. Slightly higher emissions were discovered on express roads compared to motorways.

Meanwhile, findings regarding ICEV consumption do not necessarily apply to BEVs. More specifically, BEVs' speed-related energy consumption is fundamentally different compared to ICEVs. According to Galvin's model, the minimum energy consumption of BEVs is at approximately 37 mph before increasing exponentially [10]. These findings were later supported by Fiori et al. [11] and Liu et al. [12], showing that BEVs reach their highest efficiency at lower speeds than ICEVs. Speed and its variation differ significantly between road types. Therefore, road types are expected to be a significant factor in the analysis of assessing the depletion rate of BEVs [13]. In conventional vehicles, frequent braking and accelerating significantly increase fuel consumption compared to trips with a steady speed, such as driving on highways or the interstate [7]. This effect could be different in electric vehicles because of the ability to recharge while decelerating [14]. Additionally, BEV efficiency is more sensitive to ambient temperatures than ICEV fuel consumption. At low temperatures, BEVs are significantly less efficient than in warm temperatures due to higher battery storage losses [15, 16] and internal resistance [17]. Therefore, different factors possibly impacting the energy consumption of EVs should be understood carefully.

Various studies have started this process using different approaches (see Table 1). For example, in Faria et al. [18], the energy consumption of three BEV models (i.e., Nissan Leaf, Smart ED, and Peugeot iOn) was investigated on a defined test track. In this study, the influence of the air conditioning system (i.e., off, on-cooling, on-heating), the driving style (i.e., aggressive, moderate), and the degree of urbanicity (i.e., urban, rural) were examined as influencing factors of energy consumption. An aggressive driving style increased the power consumption of the Nissan Leaf by 48% (25.01 kWh/100 mi to 16.85 kWh/100 mi). With a regular driving style and the air conditioning switched off, the Nissan Leaf consumed 21.1 kWh/100 mi on the combined route. However, cabin heating increased the energy consumption to 29.5 kWh/100 mi. Faria et al. [18] demonstrated the negative effect of aggressive driving behavior and quantified its influence on energy consumption in a naturalistic driving setting. Franke et al. [19] supported these findings by investigating the effects of the application of eco-driving strategies on BEV efficiency. The authors stated that driving economically has significantly reduced BEV energy consumption [19]. Kurien et al. [20] modeled BEV energy consumption using acceleration and slope as input parameters in MATLAB Simulink. The results show that BEV efficiency decreases with speed and an increasing slope. In other words, high slope angles and traveling at high speeds were found to substantially limit the achievable ranges of EVs.

However, few studies have investigated the impact of road types specifically on BEV energy consumption. Applied road classifications often differ between these studies due to differences in the underlying definitions by municipalities, states, or countries. Yao et al. [14] collected data from road networks in Beijing to estimate EV energy consumption and emission factors using vehicle-specific power based on speed and acceleration. The authors discovered that energy consumption on principal arterial roadways was significantly higher than on other road types. In Wu et al. [21], data were collected through a BEV conversion driven by a single university faculty member over a total period of five months in California. The authors posited that in-city driving requires more energy than freeway driving. However, Wu et al. [21] differentiated all trips by these urban categories and did not account for driver behavior. Another study by Bingham et al. [22] investigated data collected from different drivers in a test vehicle on urban and country roads in the United Kingdom. The authors discovered that aggressive driving could increase the average energy consumption by 30% or more. They further stated that traffic management and reducing quick acceleration and deceleration offer additional energy savings and range extension potential. Bingham et al. [22] did not specifically address a correlation between road types and energy consumption in their work. One study that directly explored the impact of road types was conducted by Fetene et al. [23]. The authors collected data from 741 BEV drivers over two years in Denmark to understand BEV efficiency behavior. No evidence was found that highway and non-highway driving were related to significantly different consumption rates. While road types were categorized in general terms, the study did not include a detailed definition and differentiation.

Consequently, current literature is associated with limitations when analyzing the impact of road types on EBV efficiency. While previous studies on the consumption characteristics of EVs suggested significant differences in energy consumption behavior over road types, they lack a clear definition of road types. The energy efficiency parameters for distinct sections in road networks are necessary for modeling and planning an energy-optimal route. EV drivers already tend to choose certain road types associated with lower consumption levels [24], yet this behavior is based on assumptions and is not proven scientifically in a naturalistic setting. Furthermore, most of the literature findings were based on simulations. Manufacturer statements regarding energy consumption and range are measured under laboratory conditions for specified driving cycles and, thus, scientifically deviate from real-world consumption [25, 26]. Hence, there is currently a gap in the literature regarding identifying and understanding the energy consumption of EVs and BEVs in a naturalistic setting with human drivers. This study aims to close this gap by contributing towards a better understanding of BEV energy consumption on carefully differentiated road types. Through various regression models, this study investigates the impact of road types on the energy consumption of BEVs while accounting for other explanatory variables (i.e., ambient temperature, the initial state of charge (SOC), and driver). The remainder of the paper will explore answers to the following research questions: Does the road type impact BEV energy consumption? If so, how do road types affect the efficiency of BEVs? With answers to these questions, vehicle operators can estimate the total cost of ownership associated with energy consumption based on vehicle usage. This is an essential element in the purchase decision of EVs and all future infrastructure decisions [2].

2. Materials and Methods

For this study, driving data were collected in a field study with a sample of human drivers. This section outlines the experimental design before describing data processing procedures. The section ends with a structured approach to the statistical analysis.

2.1. Experimental Design. For a substantial enough sample size to detect the consumption behavior over different road types, a total of 30 study participants were recruited, following previous research that investigated driving behavior and energy consumption rates [27, 28]. The driver characteristics were intentionally held as homogeneous as possible to mitigate the effect of individual differences in driving style on the average energy consumption of the vehicle. All participants were students at the university without prior experience in driving a BEV to exclude differences in driving behavior through different levels of BEV adaptation [19]. The participants were 40% female and 60% male, between the ages of 19 and 30, with a mean age of 23.73 years and a standard deviation of 2.56 years. All participants drove the test vehicle on two test routes that collectively covered all road types. Differentiation of the road types was undertaken accordingly to the U.S. Highway Functional Classification System of the Division of Statewide Planning, which defines the roads' purpose along with specific road characteristics, such as the material of a street, road width, traffic volume, location, and its function [29]. The Division of Statewide Planning distinguishes between two primary functions of a roadway: (a) access to the property and (b) travel mobility [29]. "Mobility refers to the actual ability of the road to move traffic, while accessibility refers to the ease of entering or exiting a roadway to or from adjacent priorities" [29]. Accordingly, the U.S. road network is divided into three major road classes: arterials, collectors, and local roads. The division defines these as follows: "arterials have high mobility but low land access and are typically used for longer trips whereas local roads have low mobility (travel at slower speeds) but provide the highest level of land access. These are used for shorter trips around town. Collectors are in the middle and often act as the transitional roads from arterials to local roads" [29]. Furthermore, each road class is subdivided into multiple road types. Table 2 lists the three road classes and the respective road types.

The road type "interstate" serves high-speed travel and long-distance freight transport by motor vehicle (high mobility) and connects the main urban areas of the U.S. By definition, "other freeways and expressways" include multiple lanes in both directions that are typically separated by a physical barrier (e.g., traffic barrier, a strip of grass, or a boulder) [29]. The main function of a "principal arterial," also known as a traffic artery, is to direct traffic between "collectors" and "other freeways and expressways" and ensure a high level of service between major urban and metropolitan areas [29]. Therefore, access to arterial roads is often limited and only possible through designated roads. "Minor arterial" roads serve trips of moderate length and at lower speeds. In rural areas, their purpose is to link cities and larger towns while also providing land access to the surrounding areas. Collector roads serve shorter distances at lower speeds than arterial roads. Typically, "minor collectors" are shorter, with a higher density of local driveways and lower speed limits. "Major collectors" might have multiple travel lanes and serve a higher annual traffic volume. "Local roads" offer direct access to abutting land and are often designed to hinder traffic. These roads make up the most significant proportion of all roads within the U.S. but are not intended to serve long-distance travel. Therefore, "local roads" are usually traveled at the beginning and end of a trip.

Table 2: Road classes and types.

Road class [29]	Road type
Principal arterial	Interstate Other freeway & expressway Other principal arterial
Minor arterial	Minor arterial
Collector	Major collector Minor collector
Local roads	Local

Two test routes were differentiated to obtain driving data from all road types: (i) Route A and (ii) Route B. The road types covered by Route A were "other freeways and expressways," "other principal arterial," "minor arterial," "major collector," "minor collector," and "local roads." To include the road type "interstate" and avoid the risk of entering a critical SOC through excessive distances, the research was extended by Route B, which included the road type "interstate." Due to unforeseen construction on a road section on Route A, the road type "minor collector" had to be excluded from the analysis. Table 3 shows the distances covered on each test route and road type.

Based on EV driver travel patterns [30, 31] and research on air pollution [32, 33], peak hours for travel were assumed between 7 : 00 AM and 9 : 00 AM and after 4 : 00 PM. These times were avoided to mitigate the impact of commuter traffic on the data. Accordingly, weekends and holidays were excluded due to possible differences in traffic density. Street surface conditions, bad visibility, and darkness significantly influence the vehicle's energy consumption [34, 35]. Darkness was avoided, and trials with wet roads or low visibility were rescheduled. Data were collected in April and May of 2019. This short trial period was chosen to minimize the outside temperature range and avoid seasonal temperature effects [23]. Air conditioning settings were held constant. The windows remained closed to keep the aerodynamic drag the same throughout each test drive. The test vehicle, a 2017 Volkswagen eGolf, is equipped with a 35.8 kWh battery pack and offers multiple driving modes (i.e., Normal, Eco, and Eco+) and recuperation intensities (i.e., B, D, D1, D2, and D3) [36, 37], which in turn have a

Table 3: Distance covered on each road type.

Test route	Route A (miles)	Route B (miles)	Total (miles)
Total distance	24.7	34.4	59.1
Interstate	—	13.6	13.6
Freeways/ expressways	5.6	—	5.6
Other principal arterial	6.1	19.0	25.1
Minor arterial	1.8	—	1.8
Major collector	6.2	1.8	8.0
Minor collector	(2.3)	—	4.1
Local road	2.6	—	2.6

significant influence on the driving and energy consumption behavior of the vehicle [38, 39]. In this research, the driving mode "normal" was used since it uses the full power of the electric engine and, therefore, makes the best use of the vehicle's performance. Additionally, the recuperation mode "D" was used, which recuperated energy only while applying the brakes. Since the participants in this study were first-time EV drivers, they were given a brief introduction to the car before the test drive. They were provided with the opportunity to adjust the seat to their comfort for safety reasons. The same playlist was played during the test drives to exclude differences in behavior due to the music being played [40].

2.2. Methods of Data Collection and Data Processing. The test vehicle was equipped with a controller area network (CAN) bus gateway with a data logger to collect energy consumption data. The CAN bus gateway is a device offered by the company FleetCarma which allows for the extraction of the corresponding data from the vehicle's onboard diagnostics-II system and links it to the corresponding GPS location and time [41]. The resulting data included information on the vehicle's geographic location, battery current, battery voltage, and speed at a rate of 1 Hz. The raw data were processed in Python through project-specific code using the Pandas [42] and Matplotlib [43] packages. Before data processing, the raw data were cleaned to ensure comparability and uniformity of each trial. The start and endpoint of each test route and the coordinates of each new road type were defined. Additionally, data before the starting point and ending point were deleted. A perfect match of the GPS location and the location of the drives was rarely achieved due to minor deviations of every drive and the GPS tracking method. Due to the previously mentioned construction on Route A, this 1.9-mile stretch was removed from the data. The total energy consumption for each road type of every trial could be calculated based on the battery current and voltage. The formula of uniform motion relates information about distance, time, velocity, and initial distance to each other and led to the total distance driven for every trial.

2.3. Methods of Data Analysis. The dependent variable in this study was the average energy consumption per mile. This continuous variable could be expressed as the difference in the state of charge per distance (ΔSOC/distance) and was measured in kilowatt-hours per mile (kWh/mile). The explanatory variables considered consisted of continuous variables (i.e., "initial SOC" and "ambient temperature") and categorical variables ("driver" and "road type"). Linear regression models allow for analyzing the effect of categorical and continuous variables on a continuous dependent variable and have been used for analyzing EV efficiency in the past [37]. Therefore, the linear regression analysis was chosen to examine the impact of the considered explanatory variables on the average energy consumption per mile. The necessary variables for the analysis and the computation method are summarized in Table 4.

To determine whether different road types impact the energy consumption of EVs, all six road types (see Table 3) were evaluated on their distinct influence on BEV energy consumption. After the datasets for all drives on both test routes were separated into the different road types, a sample size of $n = 390$ data points was achieved. The continuous variables "temperature" and "initial SOC" were considered in the model. To analyze the impact of categorical variables "road type" and "driver," dummy variables were used in the regression models. Since differences in driver behavior significantly influence the energy consumption rate of vehicles, the characteristics of the participants were chosen to be as homogeneous as possible to minimize the effects of individual driver behavior. The factor "driver" was still included in the models as an independent categorical control variable. Drivers were numbered randomly from 1 through 30. The driver with the average consumption closest to the sample average on both test routes was chosen as a reference for the driver dummy variable. As the most consistent road type in lane and shoulder width, median separation, and entrance/exit ramps, the road type "interstate" served as reference [44]. A stepwise selection was then applied to find a potentially better fitting model. In addition to considering all variables separately, additional regression models accounting for interaction effects between particular variables and "road type" were analyzed and compared. These models accounted for an interaction effect between "driver" and "road type," "temperature," and "road type," and "speed" and "road type," respectively. The impact of speed has been shown in various studies [10–12, 20] and was, therefore, included in the analysis.

All regression models were tested for the observance of the different prerequisites of linear regressions (i.e., no outliers, independence of residuals, homoscedasticity, and normality of residuals). An analysis of variance (ANOVA) table and a detailed explanation of the results are only given for regression models that fulfilled all the mentioned prerequisites. The detection of potential outliers was carried out through the Grubbs' test [45]. Normality testing was performed through histograms and scatterplots of the quantiles of the data. Under consideration of the sample size, the Jarque-Bera test statistic was calculated to support normality testing mathematically. To analyze real-world data, a similar study by Bartels et al. [36] chose a significance level of $\alpha = 0.1$. To reduce the risk of a Type I error, we decided to use a significance level of $\alpha = 0.05$ for all statistical tests. The

Table 4: Variables and explanation of computation.

Measure	Unit	Methodology of calculation
Total energy consumption	kWh	Transform wattage and voltage information provided at 1 Hz intervals to kWh using power-law and energy equation.
Total distance	Miles	Sum of speed information (mph) provided at 1 Hz intervals is divided by the total duration of the run.
Average consumption per mile	kWh/mile	Total energy consumption of the drive is divided by the total distance.
Speed	Mph	Average speed for the run.
Driver	Categorical	Drivers were differentiated by unique IDs and then numbered.
Road type	Categorical	Road types were differentiated according to the definitions of the division of Statewide Planning [29].
Temperature	°F	Average ambient temperature information at 1 Hz.

coefficient of determination (R^2-adj.) was calculated and interpreted for all models according to the guidelines of Cohen [46] to assess all regression models. R^2 values for models with endogenous latent variables can be divided into a weak explanation of variance ($0.02 \leq R^2 < 0.13$), moderate explanation of variance ($0.13 \leq R^2 < 0.26$), and strong explanation of variance ($R^2 \geq 0.26$).

3. Results

Before carrying out the regression models, the prerequisites listed in the previous section were checked. Although one data point for the road type "local road" appeared to be significantly higher with an average consumption of 0.39 kWh/mile, the Grubbs' test for outliers did not support the appearance of an outlier ($p = 0.671$). Therefore, no data points were removed from the data set. According to both the histogram of the data (Figure 1(a)) and the scatter plot of sample quantiles versus theoretical quantiles (Figure 1(b)), the data appeared to be approximately normally distributed. In addition, the Jarque-Bera test statistic supported evidence for normally distributed data ($p = 0.068$).

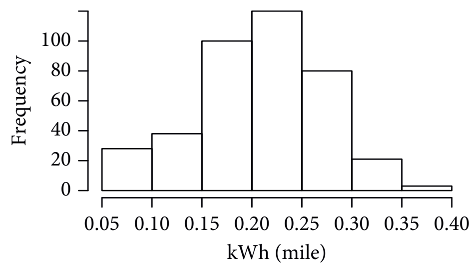
Table 5 summarizes the descriptive statistics for the average energy consumption per mile, the speed in miles per hour (mph), and the variation in speed in mph for all considered road types. The results match presumed speeds on some road types considering their definition. The highest average and median speed were found on "interstate," followed by "other freeways and expressways" and "other principal arterial." In contrast, "local road" and "major collector" showed average and median speeds than "minor arterial," which was related to the second-highest variation in speed. A comparatively high variation in speed was discovered on "interstate" and "other freeways and expressways," which are typically related to steady speeds. The results further indicated that mean, median, and maximum average energy consumption were comparatively higher on "interstate" and "local road." Meanwhile, the road type "major collector" had the lowest minimum, median, and mean energy consumption with 0.0616 kWh/mile, 0.1486 kWh/mile, and 0.1608 kWh/mile, respectively. The highest minimum average consumption per mile was on the "interstate" with 0.1987 kWh/mile. Data from the road types "major collector" and "local road" showed higher variation than other road types with a standard deviation of 0.0685 kWh/mile and 0.0683 kWh/mile, respectively. This is also shown in Figure 2. The plot further shows that the road types "other freeways and expressways" and "other principal arterial" have more minor variations than some other road types.

The results for the first regression model that considered all factors separately without any interaction effects are summarized in Table 6.

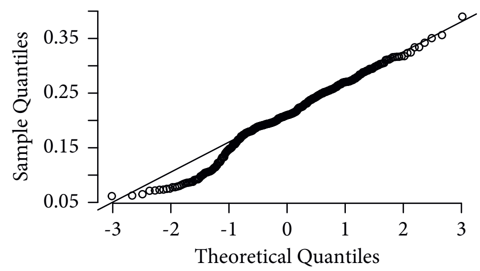
While the factors "driver" ($p = 0.774$) and "initial SOC" ($p = 0.065$) did not show any significance under the chosen significance level, "temperature" ($p = 0.040$) and "road type" ($p \leq 0.001$) impacted the energy consumption of the vehicle significantly. Additionally, all different road types showed statistical significance. This model had a coefficient of determination of 35.95%. According to the Jarque-Bera test for normality, there was evidence that the residuals were following a normal distribution ($p = 0.088$). The plot of the residuals versus fitted values is displayed in Figure 3. It provides further evidence of a linear relationship between the dependent and the independent variables. Furthermore, the residuals are randomly distributed along the zero line, which supports the assumption of homoscedasticity.

An extended ANOVA table is summarized in Table 7. All road types are significant for the model when considered separately. Negative coefficients of all road-type dummy variables provide evidence that driving on the road type "interstate" is related to the highest consumption with a coefficient of 0.374 kWh/mile compared to driving on any other considered road type. For example, driving on "local roads" would reduce the average consumption per mile by 0.0284 kWh/mile, and driving on the road type "major collector" by 0.1093 kWh/mile. The road types "minor arterial" and "other principal arterial" have a 0.0647 kWh/mile and 0.0654 kWh/mile lower consumption than "interstate."

The factors "initial SOC" and "driver" were removed from the initial model through a stepwise regression process. The significant factors "temperature" and "road type" remained explanatory variables. The results provided evidence of the significance of the factor "road type" for the dependent variable ($p \leq 0.001$). Although remaining in the model, "temperature" did not show the significance for BEV energy consumption ($p = 0.136$). This model had an R^2-adj. of 37.06%. However, the residuals did not follow a normal distribution ($p = 0.024$). Due to the violation of this



(a)



(b)

Figure 1: (a) Histogram and (b) Q-Q plot of average energy consumption per mile for the entire sample.

Table 5: Descriptive statistics of consumption data per mile by road type.

Variable	N	Mean	St. Dev.	Minimum	Q_{25}	Median	Q_{75}	Maximum
Interstate								
Energy	60	0.2662	0.0301	0.1987	0.2477	0.2663	0.2885	0.3176
Speed	60	61.4583	5.4816	31.8297	58.6115	62.2175	65.3182	70.0913
Speed variation	60	14.6438	2.984	8.2689	12.6918	14.5925	15.7563	30.3741
Other freeways and expressways								
Energy	30	0.2329	0.0178	0.1873	0.2242	0.2373	0.2414	0.2701
Speed	30	55.7797	3.1491	49.3646	54.4795	55.0529	58.0075	62.8758
Speed variation	30	14.3000	2.3692	9.5429	12.4092	14.3427	15.9368	20.4052
Other principal arterial								
Energy	90	0.2028	0.0170	0.1739	0.1901	0.1990	0.2103	0.2566
Speed	90	39.0169	3.4641	31.5417	36.933	38.9302	41.2102	49.7854
Speed variation	90	11.588	2.8368	4.822	9.4748	11.4359	13.5615	18.2315
Minor arterial								
Energy	30	0.2092	0.0247	0.1654	0.1941	0.2120	0.2172	0.2706
Speed	30	22.1247	2.5702	16.686	20.0286	22.8377	23.685	27.3325
Speed variation	30	12.1563	1.1815	10.1625	11.3649	12.1708	13.1329	14.3568
Major collector								
Energy	120	0.1608	0.0685	0.0616	0.1033	0.1486	0.2152	0.2886
Speed	120	29.9445	4.9478	17.9305	26.3254	29.5199	34.0545	40.9641
Speed variation	120	11.2858	1.9104	6.9983	9.8735	11.2197	12.3264	16.844
Local road								
Energy	60	0.2438	0.0683	0.1262	0.1773	0.2591	0.2952	0.3900
Speed	60	31.4344	4.3612	17.3194	28.6242	32.3901	34.4652	38.1414
Speed variation	60	9.285	2.4479	5.2914	7.4655	8.809	10.201	16.1907

criterium of linear regression, the results for this model will not be further explained.

Three more regressions were modeled, which accounted for possible interactions between particular variables and "road type." All of these models included the continuous variables "temperature" and "initial SOC." A model that included the interaction between "driver" and "road type" adds one dummy variable for each driver and road type combination, leading to a total of 180 [30 ∗ 6] combinations. However, the coefficient of determination of this model was R^2-adj. = 1.169%. The residuals did not follow a normal distribution based on the Jarque-Bera test ($p = 0.010$). The model will, therefore, not be considered further.

Table 8 summarizes the ANOVA results for the regression model that accounted for interaction between "temperature" and "road type." The results showed that the interaction effect "temperature" and "road type" is significant for the vehicle's mean energy consumption ($p \leq 0.001$). The factors "driver" ($p = 0.815$) and "initial SOC" ($p = 0.085$) did not show the significance for the dependent variable. This regression model explained 35.33% of the variance. The Jarque-Bera test statistic indicated that the residuals followed a normal distribution ($p = 0.1652$).

Figure 4 plots the model's residuals versus fitted values that account for an interaction effect between "temperature" and "road type." The residuals occurred randomly along the zero line, which supports the assumption of a linear relationship. There is also no indication for heteroscedasticity of the residuals.

An extended ANOVA table for this model can be found in Table 9, displaying p-values for all "road type" dummies and their coefficients. The respective interaction effects of "temperature" with the road types "major collector" ($p = 0.021$), "minor arterial" ($p = 0.040$), and "other principal arterial" ($p = 0.029$) were significant. The highest effect on the dependent variable was caused by an interaction

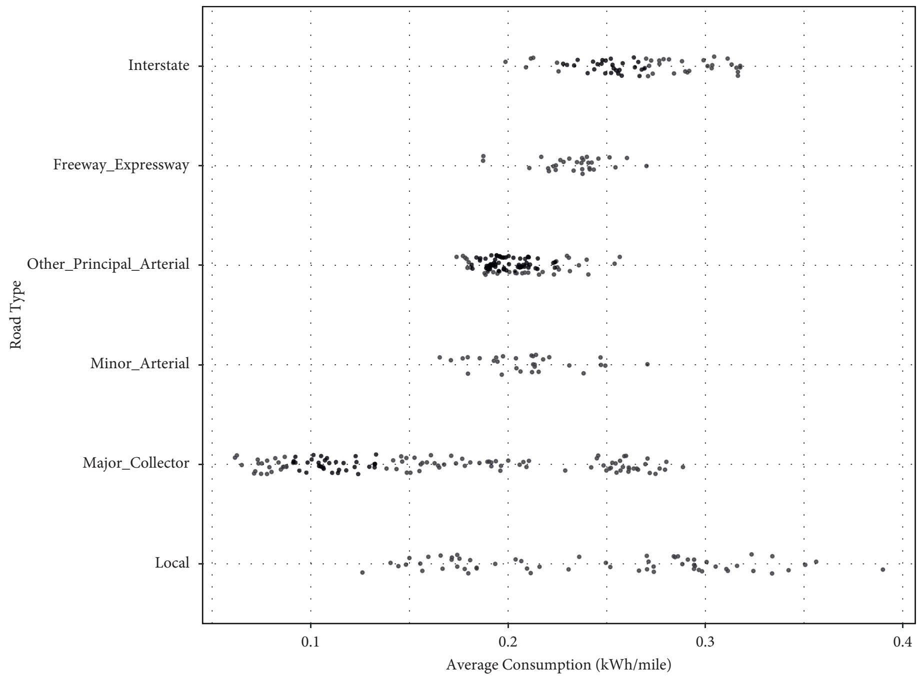


Figure 2: Jitter plot of mean energy consumptions for all road types.

Table 6: ANOVA of the road type analysis.

Source	Df	SS	F value	Pr ($>F$)
(Intercept)	1	0.1535	61.8465	0.0000***
Initial SOC	1	0.0085	3.4323	0.0648·
Temperature	1	0.0106	4.2549	0.0399*
Driver	29	0.0569	0.7909	0.7737
Road type	5	0.5645	45.4916	0.0000***
Residuals	353	0.0876		

Note. $^{\cdot} p \leq 0.1$, $^{*} p \leq 0.05$, $^{**} p \leq 0.01$, $^{***} p \leq 0.001$.

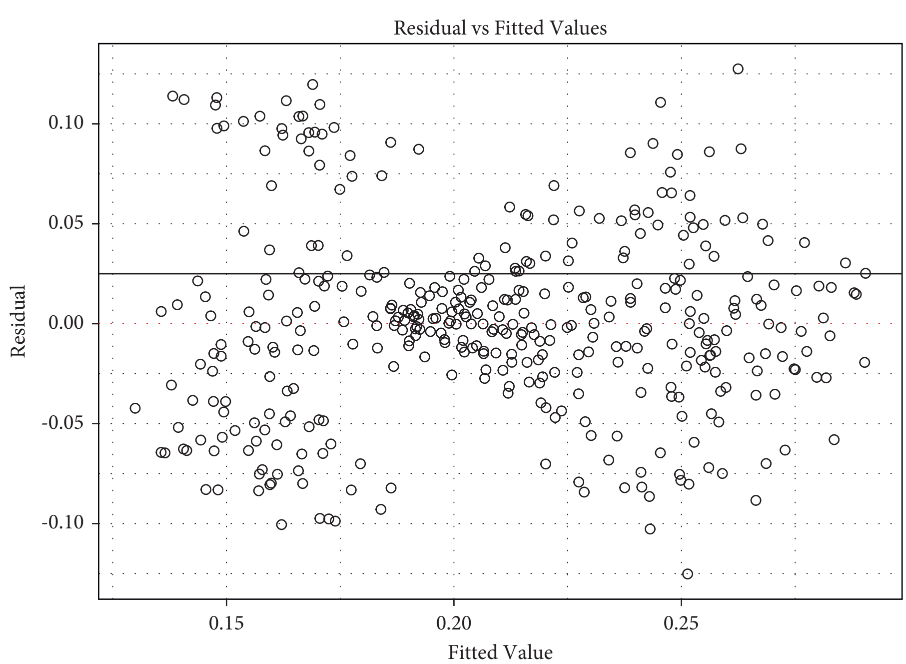


Figure 3: Residuals versus fitted values plot for initial model.

Table 7: Extended ANOVA table of the road type analysis.

Source	Df	SS	F value	Pr (>F)
(Intercept)	1	0.0476	61.8465	0.0000***
Initial SOC	1	0.0002	3.4323	0.0648.
Temperature	1	0.0008	4.2549	0.0399*
Driver 1	1	0.0217	0.0324	0.8574
Driver 2	1	0.0197	0.2440	0.6220
Driver 3	1	0.0196	0.0888	0.7659
⋮	⋮	⋮	⋮	⋮
Driver 30	1	0.0231	1.2769	0.2590
Freeway/expressway	1	0.0115	12.2220	0.0005**
Local	1	0.0094	9.1264	0.0027**
Major collector	1	0.0081	180.3918	0.0000***
Minor arterial	1	0.0115	31.4945	0.0000***
Other principal arterial	1	0.0084	60.7776	0.0000***
Residuals	353			

Note. $^{*}p \le 0.1, ^{*}p \le 0.05, ^{**}p \le 0.01, ^{***}p \le 0.001$.

Table 8: ANOVA of the road type analysis with interaction effect of road type and temperature.

Source	Df	SS	F value	Pr (>F)
(Intercept)	1	0.1158	46.2141	0.0000***
Initial SOC	1	0.0075	2.9865	0.0848·
Driver	29	0.0551	0.7578	0.8150
Temperature × road type	6	0.5561	36.9845	0.0000***
Residuals	353	0.8846		

Note. $^{*}p \le 0.1, ^{*}p \le 0.05, ^{**}p \le 0.01, ^{***}p \le 0.001$.

between "temperature" and "major collector." Accordingly, an increase in "temperature" by 1°F would decrease the energy consumption by 0.0024 kWh/mile. In contrast, "temperature" and "road type" have the lowest effect when driving on an "interstate" with a decrease in consumption of 0.006 kWh/mile for an increase in "temperature" by 1°F. The model led to equal coefficients of −0.0024 for "temperature" interactions with "minor arterial" and "other principal arterial." The coefficients of "temperature" and "local road," and "temperature" and "other freeways and expressways" were given as −0010 and −0012, respectively. This shows that the effect of temperature is lower on road types related to a higher general consumption compared to the first model.

A final regression model was analyzed accounting for an interaction effect between "speed." Although leading to the highest coefficient of determination with an R^2-adj. of 0.4976, the residuals of this model did not follow a normal distribution ($p \le 0.001$). Therefore, the condition of normally distributed residuals was not met, and the model could not be considered for the analysis.

4. Discussion

Different regression models were used to investigate the impact of road type on electric vehicle efficiency. All explanatory variables (i.e., "initial SOC," "driver," "temperature," and "road type") were initially considered separately. This first model showed the highest explanation of variance with a coefficient of determination of 35.95%. Furthermore, there was evidence for homoscedasticity of the data. The model discovered that both the factor "temperature" and the factor "road type" are significant for the energy consumption of electric vehicles. Road types, in general, appear to impact BEV efficiency significantly. Accordingly, a fully charged battery operating at a battery service life optimal ambient temperature of 68°F [16, 17] driving on an "interstate" would lead to the highest energy consumption. Figure 5 visualizes the consumption behavior under the given circumstances for all drivers on different road types.

The black line displays the mean of the fitted values for all drivers. Driving on an "interstate" would lead to an average consumption of 0.2367 kWh/mile in the applied setting. The negative regression coefficients have shown that driving on any other considered road type would increase the vehicle's efficiency. For example, driving on a "local road" as the second-largest energy-consuming road type would lead to an average consumption of 0.2082 kWh/mile. Ceteris paribus, the lowest average consumption, was related to driving on a "major collector," which was associated with a consumption of 0.1273 kWh/mile on average among all drivers. The remaining considered road types, "other freeways and expressways," "other principal arterial," and "Minor Arterial," show similarity in terms of means of the fitted values. Table 10 summarizes the relative change in mean energy consumption from one road type based on the fitted values of the first model. BEVs operate most efficiently on "major collectors" with a savings potential of 46% when choosing this road type over an "interstate." Avoiding the "interstate" in all cases leads to a reduction in consumption per mile of at least 12%. Avoiding "local roads" can save between 5% and 38% if choosing an alternate road type that is not an "interstate." The difference in efficiency between "minor arterial" and "other principal arterial" is only marginal and does not appear to be significant when choosing one over the other.

While this study differentiated between road types more carefully than previous studies, the results align with findings in [21], which found that in-city driving is related to higher consumption levels than freeway driving, assuming that in-city driving means a high ratio of "local roads." The relatively high average consumption level on "local roads" might be caused by the high variation in speed on these roads, which are often interrupted by intersections. In Bingham et al. [22], it was stated previously that less acceleration and deceleration could reduce the average consumption of BEVs. Since one of the road type classification criteria is the ability of a road to move traffic [29], the relatively high consumption on "local roads" is consistent with Bingham et al.'s findings. In other words, "local roads" are not designed to move high traffic volumes while ensuring uninterrupted flow.

This study could not confirm previous findings by Yao et al. [14], who found in their study that BEVs perform the least efficiently on principal arterial roadways. While their underlying definition of this type of road might differ, "other principal arterials" were not related to the highest consumption in this study. The results provided evidence that "interstates" in particular lead to high consumption, which contradicts the results of [23]. The authors posited that a

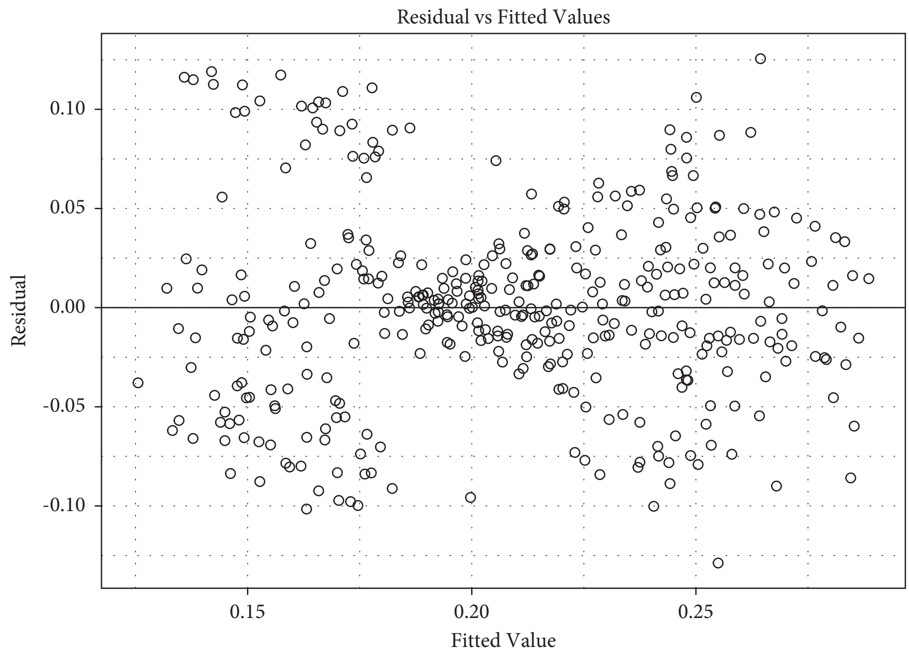


FIGURE 4: Residuals versus fitted values plot for the model with interaction effect of road type and temperature.

TABLE 9: Extended ANOVA table of the road type analysis with interaction effect of road type and temperature.

Source	df	SS	F value	Pr ($>F$)
(Intercept)	1	0.0460	46.2141	0.0000***
Initial SOC	1	0.0002	2.9865	0.0848
Driver 1	1	0.0218	0.0471	0.8287
Driver 2	1	0.0198	0.2323	0.6301
Driver 3	1	0.0197	0.1063	0.7448
⋮	⋮	⋮	⋮	⋮
Driver 30	1	0.0233	1.450	0.2293
Temperature × interstate	1	0.0008	0.6972	0.4041
Temperature × freeway/expressway	1	0.0008	2.375	0.1242
Temperature × local	1	0.0008	1.748	0.1869
Temperature × major collector	1	0.0008	9.591	0.0021**
Temperature × minor arterial	1	0.0008	4.231	0.0404*
Temperature × other principal arterial	1	0.0008	4.818	0.0288*
Residuals	353			

Note. $^{*}p \leq 0.1$, $^{*}p \leq 0.05$, $^{**}p \leq 0.01$, $^{***}p \leq 0.001$.

significant difference between highway and nonhighway driving could not be found. Again, the underlying definitions used in [23] and this study might differ and could be caused by general differences in classification criteria between the U.S. and Denmark. Furthermore, the study showed that BEV discharge behavior could be fundamentally different from ICEV fuel consumption behavior. Notably, while ICEVs perform more efficiently on road types with steady speeds (e.g., highways and interstates) [7], BEVs appear to behave more efficiently on different road types (i.e., "principal arterials" and "minor arterials"). The only road type where ICEVs and BEVs are relatively efficient is on "major collectors" [7].

While the results of this study have provided evidence that BEVs' discharge behavior depends on the used type of road, other factors impact BEV efficiency. More specifically, with an increase in ambient temperature, BEVs operate more efficiently. This behavior aligns with studies on battery performance in different temperatures [15–17]. Batteries are, in general, less efficient in extreme temperatures [47]. The factor, "initial SOC," was insignificant as previously also shown in [37]. The control variable "driver" was not found to significantly impact the energy consumption of electric vehicles. This variable was used as a control variable. Its insignificance was likely due to the homogeneous driver demographics of the sample (all participants were students under the age of 30 and had no previous experience in BEV driving). This result aimed to mitigate the effect of variation in driving styles. It should be stated that previous studies demonstrated the impact of driver behavior (e.g., aggressive versus nonaggressive) on BEV efficiency [18, 19, 48]. Furthermore, the impact of traffic congestion on BEV consumption behavior was minimized to the extent possible by controlling for the

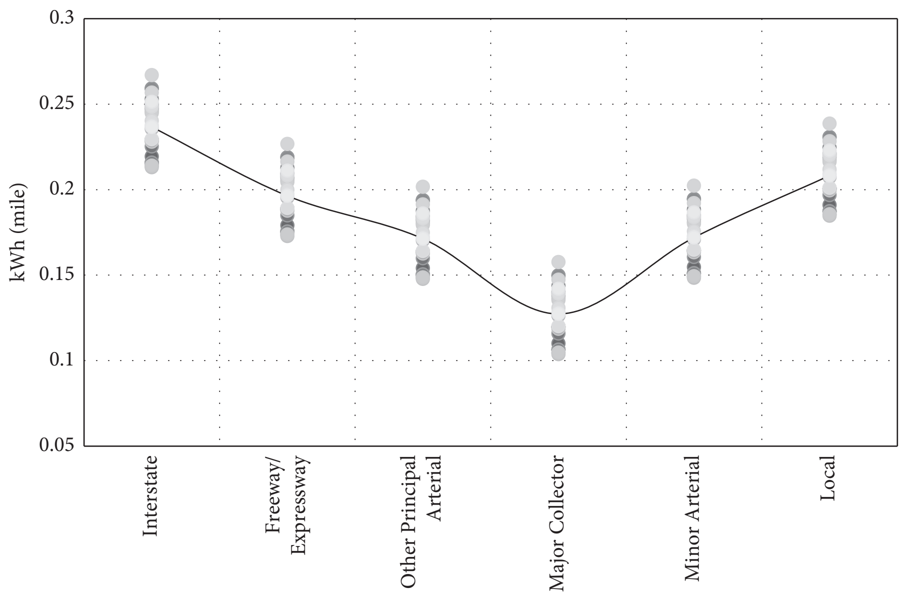


Figure 5: Fitted values for drivers and different road types.

Table 10: Energy consumption comparison matrix.

Road type	Interstate (%)	Freeway/expressway	Principal arterial	Major collector	Minor arterial	Local
Interstate		−17.02%	−27.62%	−46.20%	−27.32%	−12.01%
Freeway/expressway	20.51		−12.77%	−35.17%	−12.41%	6.03%
Principal arterial	38.15	14.64%		−25.68%	0.41%	21.55%
Major collector	85.89	54.25%	34.56%		35.11%	63.56%
Minor arterial	37.59	14.17%	−0.41%	−25.98%		21.06%
Local	13.66	−5.69%	−17.73%	−38.86%	−17.39%	

time of the runs and, therefore, not accounted for. However, it should be mentioned that the negative effect of traffic on BEV performance was previously discovered in Jonas et al. [49].

A stepwise selection did not lead to a better model because the residuals for the model without the factors “driver” and “initial SOC” did not follow a normal distribution. This was also found in the model accounting for the interaction between “road type” and “driver.” In contrast, the model including the interaction between “temperature” and “road type” led to residuals following a normal distribution. Thus, the model could explain almost the same percentage of variance as the first model. The model demonstrates that individual interactions between the road types “minor arterial,” “major collector,” and “other principal arterial” with the factor “temperature” are individually significant for BEV discharge behavior. More specifically, the effect of temperature varies with the road type. Accordingly, the lowest energy savings potential per 1°F increase in ambient temperature can be observed on “interstates” (−0.006 kWh/mile), followed by “local roads” (−0.0010 kWh/mile), “other freeways and expressways,” and “other principal arterials,” and “minor arterials” (both −0.0017 kWh/mile). Finally, the highest savings potential was found for “major collectors” with a reduction in average energy consumption of 0.0024 kWh/mile per 1°F increase in ambient temperature.

Both models demonstrated the importance of road type for the efficiency of BEVs and contributed to a deeper understanding of BEV consumption behavior. Future studies aiming to improve BEV-specific routing and establish consumption estimation models should consider road types as an essential variable. Drivers can consider these results in improving their eco-driving behavior and, hence, extending achievable ranges significantly by adjusting their route choices accordingly. Furthermore, the results of this study can be implemented into smart routing applications to increase the eco-driving potential. Adjustments to routing made by drivers and service providers can reduce the impeding effect of range anxiety and contribute to BEV adoption.

5. Conclusion

Understanding the consumption behavior of BEVs and driving factors is essential to reducing the barriers to widespread adoption. This study is the first to implement an analysis that captures the effect of carefully differentiated road types on the energy consumption of BEVs while using real-world driving data by a sample of BEV-inexperienced drivers. Multiple models have been analyzed and compared. We discovered that the type of road is crucial for the BEV consumption of BEVs. Considering the type of road in driver’s route choices and BEV-specific smart routing applications offers significant energy savings potential of up to 46%. We discovered that the highest consumption levels are related to driving on "interstates" and "local roads." The performance of BEVs was found to be significantly less efficient on roads that allow for high-speed traveling (i.e., "interstates") and roads with deficient mobility that interrupt traffic regularly (i.e., "local roads"). The results provide strong evidence of the importance of route choice on BEV efficiency.

However, there are limitations to the study. The road type "minor collector" could not be considered in this study due to unforeseen construction. Further research is needed to determine the effect of this specific road type on energy consumption. There was no slope data available for the test drives, meaning the effect of elevation differences was not considered as a factor that may have affected the results. Future work should consider slope or elevation data since the interaction between the type of road and the slope is presumed but not currently quantified. Traffic data were not available for the test routes during data collection. Traffic volume and environment often correlate with the type of road. Therefore, considering traffic and intersection measures in future studies would be a beneficial extension of this study. Additionally, test runs were undertaken by a small and homogeneous sample of drivers. Testing with a broader and more diverse sample of drivers would account for differences in driving behavior.

The findings of this study can be used by service providers, academics, and BEV users to improve energy-optimal route planning and range forecasts. In addition, the practical consideration of these findings can help BEV drivers to successfully apply and optimize eco-driving strategies that extend achievable ranges. The results thereby contribute to a better understanding of BEV efficiency factors and facilitate the transition to low-emission transportation systems.

Abbreviations

ANOVA: Analysis of variance
B: Braking energy recuperation: very high
BEV: Battery electric vehicle
D: Conventional braking setting
D1: Braking energy recuperation: light
D2: Braking energy recuperation: medium
D3: Braking energy recuperation: high
EV: Electric vehicle
GPS: Global positioning system
ICEV: Internal combustion engine vehicle
Mph: Miles per hour
OBD-II: On-board diagnostics port-II
PHEV: Plug-in hybrid electric vehicle
SOC: State of charge
U.S: United States.

Data Availability

Based on the URI Institutional Review Board certification (HU#1627–055), the driving data collected for this study cannot be shared.

Conflicts of Interest

The authors declare no conflicts of interest.

Authors' Contributions

Taris Wilde and Gretchen Macht contributed to conceptualization; Tim Jonas and Taris Wilde contributed to data curation; Tim Jonas and Taris Wilde contributed to formal analysis; Taris Wilde, Christopher Hunter, and Gretchen Macht contributed to methodology; Tim Jonas created the software; Gretchen Macht supervised the study; Tim Jonas, Taris Wilde, Christopher Hunter, and Gretchen Macht did validation; Tim Jonas, Taris Wilde, and Gretchen Macht contributed to writing–original draft; Tim Jonas, Christopher Hunter, and Gretchen Macht contributed to writing–review and editing. All authors have read and agreed to the published version of the manuscript.

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