Analyzing BEV Suitability and Charging Strategies Using Italian Driving Data

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***Abstract*—Battery Electric Vehicles (BEVs) are rapidly evolving from a niche alternative to a mainstream transportation option, often replacing Internal Combustion Engine (ICE) vehicles. Despite growing interest, significant barriers remain, including range anxiety, the inconvenience associated with public charging stations, and higher costs. This study analyzes extensive telemetry data collected from 10,441 ICE vehicle users in the Italian province of Asti to evaluate the potential for transitioning to BEVs without modifying current travel behaviors. We assess each user's electrification potential—the extent to which current BEV models can meet their daily mobility needs—under varying charging scenarios. To do so, we replicate trips and parking events, simulating and monitoring the battery state of charge. The analysis reveals that at least 35% of the users could already adopt BEVs, assuming access to overnight charging.**

***Index Terms*—BEV, charging policy, electrification, telemetry, driving patterns.**

I. Introduction

Transportation is a leading contributor to anthropogenic greenhouse gas emissions. Widespread deployment of electric vehicles is widely viewed as an effective mitigation strategy, given their higher energy efficiency compared to gasoline vehicles. Accordingly, governments and automotive manufacturers are making substantial investments in EV technologies to achieve significant emissions reductions [1]. Pure Battery Electric Vehicles (BEVs) operate exclusively on stored electrical energy and therefore require an external power source to recharge their batteries [2]. BEVs can be charged at home, at workplaces, or at public stations, using different power levels. Although high-power DC fast chargers offer significant convenience on long trips, slower AC chargers are more common and are suitable for overnight or daytime charging at home and work [3].

Range anxiety, long recharge times, charging-station delays, and upfront and energy costs slow down BEV adoption and its associated societal benefits, as advances in battery capacity and charging speed have yet to fully mitigate these concerns [4]. The primary objective of this study is to perform a multi-scenario simulation of the transition from internal combustion engine (ICE) vehicles to BEV models, using real-world driving data from an Italian province (Asti). These data are provided by the company UnipolTech, and comprise more than 10 thousand users with a car and 10 million trips over 1 year of data. By replaying each trip across different BEV configurations, varying in battery capacity, charging power, and road-type performance, we evaluate which models best accommodate diverse user routines. We compare multiple charging scenarios, from users charging slowly at night to users charging with fast DC charger only when the battery SoC is low.

This multi-scenario approach enables a rigorous assessment of how seamlessly ICE vehicles can be replaced by BEVs under varying charging regimes and travel demands, thereby highlighting the key factors that govern a successful transition to electric mobility.

Results show that the current technology in terms of consumption, battery capacity, and charging power is suited for part of the population, but not all. Indeed, even disregarding costs and assuming availability of charging opportunities, few users can perform 100% of the trips they used to do with their ICE vehicle. With the most favorable charging policy and the largest battery vehicle, 72% of the users can satisfy all their trips.

II. Related Works

Numerous studies have studied the real-world feasibility of replacing internal-combustion vehicles with battery-electric vehicles (BEVs), each contributing valuable insights while also exhibiting limitations that our work seeks to address.

In an early empirical assessment, [5] analysed five weeks of trip and location data for 166 privately-owned vehicles under six hypothetical battery-capacity scenarios (8–36 kWh) and slow AC charging powers (2.4–7.2 kW AC) to evaluate daily driving feasibility. While results showed that even small-battery BEVs could meet most trip demands, the small number of users limits their statistical validity. [6] leveraged one month of GPS traces in two Italian cities to simulate fourteen distinct recharging strategies across six BEV categories. Their algorithm checked the state of charge sufficiency on a trip-by-trip basis. Both these works overlooked model-specific consumption profiles and temporal variability in driving patterns.

[7] advanced the scale and temporal span of such analyses by exploiting one year of telematics data for over 52,000 vehicles. They introduced the Daily Vehicle Kilometers Traveled (DVKT) metric and flagged Critical Days when DVKT exceeded a fixed 200 km BEV range. However, this approach assumed a uniform 200 km range available each morning and did not update the state of charge on a per-trip basis.

More recently, [8] examined 200 vehicles using trip records to investigate three charging powers and three BEV models. Although their work highlighted the potential effects of private-parking availability, it lacked variation in charging policies and employed a single consumption value. Finally, [9] utilises a year of data for 226,000 vehicles in three cities to compute a functional compatibility index under a single 300 km-range BEV and single charging speed. By applying density-based clustering to infer home-charging locations, they achieve a mobility-index assessment, yet fail to diversify BEV ranges and charging rates.

In summary, prior work has moved from short-duration, small-sample investigations to large-scale, year-long telematics studies, yet most still rely on average consumption rates, static state-of-charge assumptions, or limited temporal scopes. Our research advances this field by implementing a multi-scenario simulation framework that: (1) applies vehicle- and road-type-specific energy profiles, (2) updates state-of-charge on a per-trip basis, and (3) captures seasonal and spatial variations in charging behavior. This approach enables a more granular and realistic assessment of the transition from ICE vehicles to BEVs under diverse charging regimes.

III. Dataset Details and Characterization

We use real data from telematics supplied by the UnipolTech company, which covers the period from 1 October 2023 to 30 September 2024 for 10,441 private users with a car registered in the province of Asti, Italy. All records were fully anonymised, without providing any personal details of vehicle owners and geolocalization, in accordance with Italian privacy regulations.

Telematic black boxes permanently installed on each car recorded every ignition-on to ignition-off event. Raw data contains for each trip corresponding to a cycle ignition-on to ignition-off, the vehicle anonymised ID, the start and end timestamps, and the distance covered across road categories (urban, extra-urban, highway). In total, 13,064,904 trips within an ignition cycle were captured.

From the trip sequence, we can easily obtain the Parking-events, as the inter-time between the end of a trip and the start of its successor. To clean the dataset, we discard parking events with durations shorter than 2 min, merging the surrounding trips. Additionally, we discarded any trips lasting under 1 minute or exceeding 12 hours, those covering less than 5 meters or over 800 kilometers, and trips with average speeds below 5 km/h or above 130 km/h. After cleaning, the dataset comprises 10,141,809 trips and more than 98,889,757 km driven distance.

To characterize the behaviour of users, we report in Fig.1 the distribution of the average number of daily trips on active days (i.e., days with at least a trip) and in Fig.2 the distribution of the average daily distance (on active days). Half of the users perform fewer than 5 trips per active day. Still, 10% of the users have more than 8 daily trips. In median, users drive an average of 40 km per active day, with only 4.5% exceeding 100 km. These findings confirm that routine daily distances

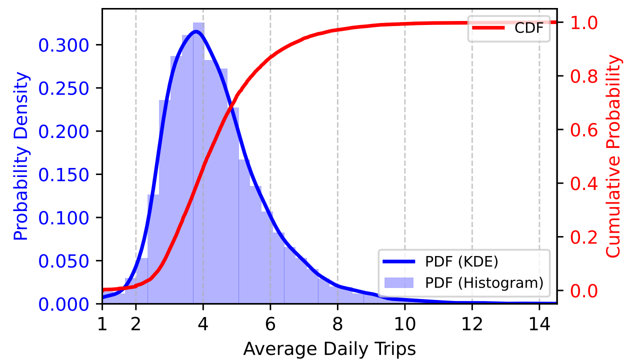

Fig. 1: PDF and CDF of average number of daily trips per user (active days). X-axis is limited to 99.9% of the users.

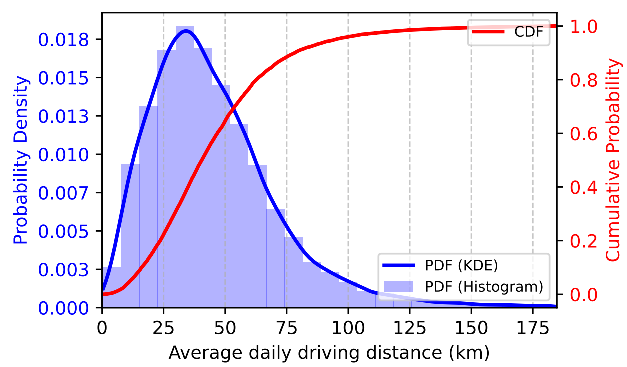

Fig. 2: PDF and CDF of Average daily driving distance (km) per user (active days). X-axis is limited to 99.9% of the users.

are easily covered by the autonomy of contemporary BEVs, including lower-capacity models (see Table I).

IV. Simulating BEVs charge and discharge

We replicate exactly the trips recorded by the ICE vehicles, without modifying their itineraries or schedules to accommodate battery constraints. We consider multiple BEV model types, and then simulate their State of Charge (SoC), by updating it given the consumption on the road type. According to multiple charging policies, the SoC is increased when the car is parked and charged.

We consider four charging policies, inspired by the literature [10]–[13]:

1) **Scenario 1 (Workplace AC charging).** From 08:00 h to 20:00 h on Monday through Friday, any continuous parking period of six hours or longer enables 7.4 kW AC charging when $\mathrm{SoC} < 75\%$.
2) **Scenario 2 ([Unrestricted AC charging] OR Low SoC slow charging).** Whenever $\mathrm{SoC} < 25\%$, regardless of day or hour, AC charging at 7.4 kW is applied during any parking period of six hours or more.
3) **Scenario 3 (Overnight home charging).** The vehicle is charged via a 7.4 kW AC connection when it is parked

TABLE I: Technical specifications of the four BEV models used in our trip-replication simulations [14].

Vehicle model	Usable net capacity (kWh)	Estimated autonomy range (km)	Consumption urban/highway/comb. (Wh/km)
Fiat 500e	21.3	135	101 / 170 / 133
Renault Megane E-Tech	40.0	260	103 / 167 / 133
Tesla Model 3	57.5	420	93 / 142 / 116
Audi A6 e-tron	94.9	610	109 / 161 / 134

for at least six hours between 20:00 h and 08:00 h and its state of charge falls below 75% (SoC $<$ 75%).

4) **Scenario 4 (Opportunistic fast charging OR Low SoC fast charging).** If SoC $<$ 25%, at any time, a parking event of 20 min or more triggers a 50 kW DC fast-charge session.

The scenarios encompass both slow AC charging, reflective of residential and workplace setups, and fast DC charging, as typically deployed along highways. Moreover, to limit the number of charges, we used two SoC thresholds (25% and 75%).

The study focuses on four commercially available BEV car models chosen to represent a spectrum of battery capacities and driving ranges. Specifications for the four BEV models are summarized in Table I. Vehicle specifications and consumption figures were sourced from the EV Database website [14], where values correspond to mild ambient conditions (23 °C, no air-conditioning) and, for highway figures, a constant speed of 110 km/h. A key innovation of our work lies in the segmentation-based energy-use calculation: by decomposing each journey into road-type segments and applying the corresponding Wh/km rates, we achieve a more precise estimate of trip energy consumption than methods that rely on single, averaged efficiency values. This granular approach, enabled by our uniquely detailed telematics dataset, constitutes the principal novelty of this study.

When simulating the charge and discharge process, we count the number of charges performed and, when the SoC reaches 0, we mark the corresponding trip as not feasible. The SoC then remains 0 until a charging event is initiated. Notice that any trip in between will still be marked as not feasible. Here, we focus on two metrics: the percentage of feasible trips and the monthly number of charges. We compute these metrics for each user in the dataset and report statistics on the obtained distributions. Other metrics will be reported in the extended version of this digest.

V. Main results

The preliminary results presented in this digest highlight the suitability of the four proposed charging policies and the four vehicle models under evaluation.

Figure 3 shows the average percentage of feasible trips across different scenarios. Scenario 1 yields the lowest performance. This means that charging during the day, typical for users with access to workplace charging infrastructure, is not feasible for the pattern of most users. On average, users

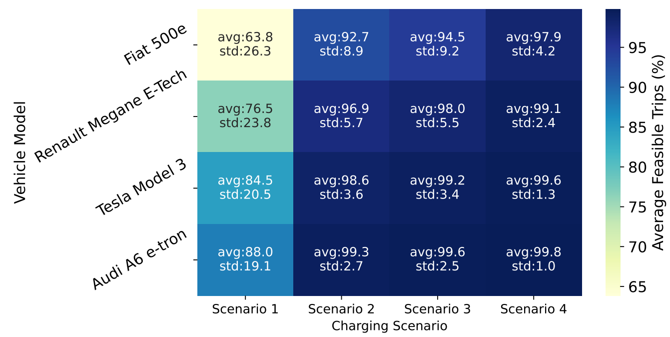

Fig. 3: Feasible trip percentage by charging scenario and vehicle model. Color represents the average among users, with average and standard deviation also reported.

are able to complete only 63% to 88% of their trips under this scenario.

The distribution of feasible trip percentages for Scenario 1 is shown in Figure 4 using violin plots. The Fiat 500e proves to be unsuitable for most users, whereas performance improves with vehicles offering greater range. For the Audi A6 e-tron, which has the highest autonomy among the tested models, this policy is potentially viable for many users: 43% of them can complete more than 99% of their trips. Nonetheless, for the majority of users, this charging policy still entails substantial compromises.

For the remaining charging policies, differences in the feasible trip percentage are less pronounced. Scenario 2 already allows many users to complete nearly all of their trips, while both Scenario 3 and Scenario 4 further improve the results. Scenario 4 performs best overall, with average feasible trip percentages exceeding 98% for all vehicle models except the Fiat 500e.

If we define suitable users as those able to complete at least 99% of their trips, our analysis identifies the worst-case scenario as the combination of the smallest battery vehicle (Fiat 500e) and Scenario 1, where only 7% of users meet this threshold. Conversely, the best-case scenario is achieved with the largest battery vehicle (Audi A6 e-tron) under Scenario 4, where 95% of users are classified as suitable.

These findings indicate that, with the current capabilities of BEV technology, full electrification remains inadequate to accommodate the mobility needs of all users in the studied Italian province. Still, many users are instead suited for a BEV car, given that they have a convenient charging station at home, at the workplace, or a fast one.

Finally, we also evaluate the number of charging sessions required under each policy. This is a critical metric, as users generally prefer to meet their mobility needs with minimal inconvenience related to locating charging stations and repeatedly plugging and unplugging the vehicle.

To illustrate this, we focus on the Audi A6 e-tron, the vehicle with the highest overall performance, achieving more than 99% of feasible trips in Scenarios 2, 3, and 4. Figure 5 shows the distribution of monthly charging sessions for this

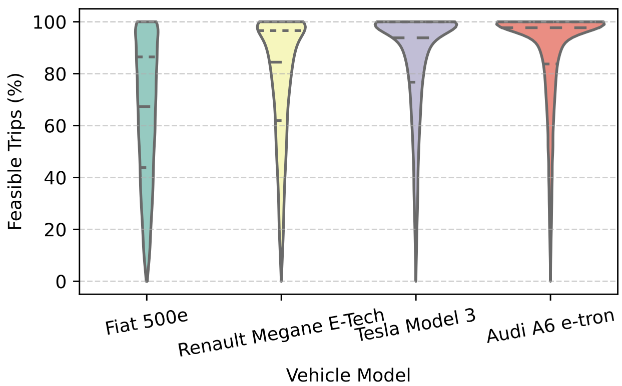

Fig. 4: Feasible trip percentage for charging scenario 1. Distribution among users is represented through violin plots, with marked quartiles.

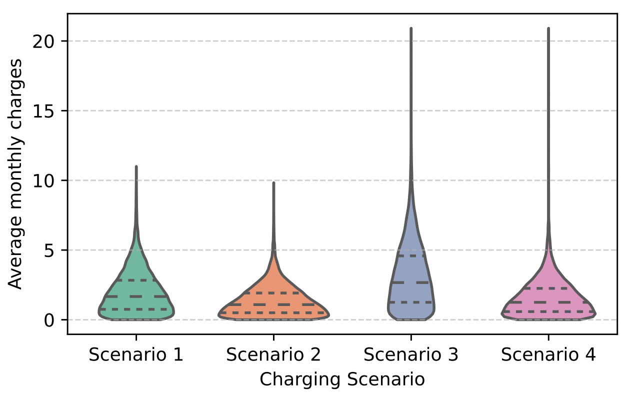

Fig. 5: Average monthly number of charging events with Audi A6 e-tron vehicle, changing charging scenario. Distribution among users is represented through violin plots, with marked quartiles.

model. Although Scenarios 2, 3, and 4 provide similarly high feasibility, the number of charging sessions varies significantly. Notably, Scenarios 2 and 4 reduce the required number of charges by nearly half compared to Scenario 3. In Scenario 2, the median number of monthly fast DC charges is just 1.1, increasing to as many as 9.8 for users with long-distance driving demands.

VI. Limitations and Conclusions

We evaluated the transition feasibility from a population of an Italian province, under varying charging regimes, travel demands, and vehicle models available on the market. We showed how the travel patterns of part of the population are compatible with the current BEV models. Indeed, at least 40% of the users could already adopt BEVs, assuming access to overnight charging. Still, even the most promising charging scenario and largest battery vehicle are not enough for a non-negligible fraction of the population.

Several simplifying assumptions may affect our simulation. First, we treated energy consumption as invariant to external factors such as ambient temperature and assumed constant charging power throughout a session, despite evidence that charge rates typically decline once a battery's state of charge exceeds about 80% [15]. Second, we presumed that charging infrastructure was accessible at every parking event, since precise charger locations were unavailable. Finally, we did not conduct a full cost–benefit analysis, omitting considerations of long-term operational and maintenance expenses, as well as fluctuations in electricity prices, which would be necessary to evaluate the economics of different charging strategies. Finally, applying the methodology to other regions would validate generalizability and inform localized policy and infrastructure planning.

VII. Acknowledgment

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