Politecnico di Torino

Department of Electronics and Telecommunications

DEPARTMENT OF TELECOMMUNICATIONS, ELECTRONICS AND PHYSICS

ICT FOR SMART MOBILITY

Laboratory Report

Laboratory 3

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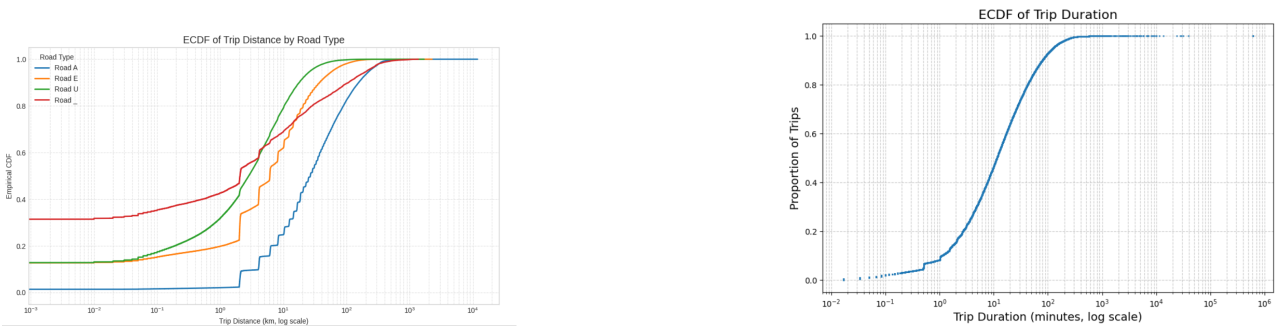
1 Preliminary Analysis

This first section regards the analysis of the dataset by analyzing key features, such as trip distance, trip duration, and their relationships. The goal is to identify any patterns or trends in the data, as well as to detect and remove any outliers that may skew subsequent analysis. This initial exploration will help ensure the dataset is clean and ready for further detailed investigation.

1.1 Distribution of Trip Distance and Duration

Figure 1 presents the Empirical Cumulative Distribution Functions (ECDF) for both metrics.



(a) Distance by Road Type

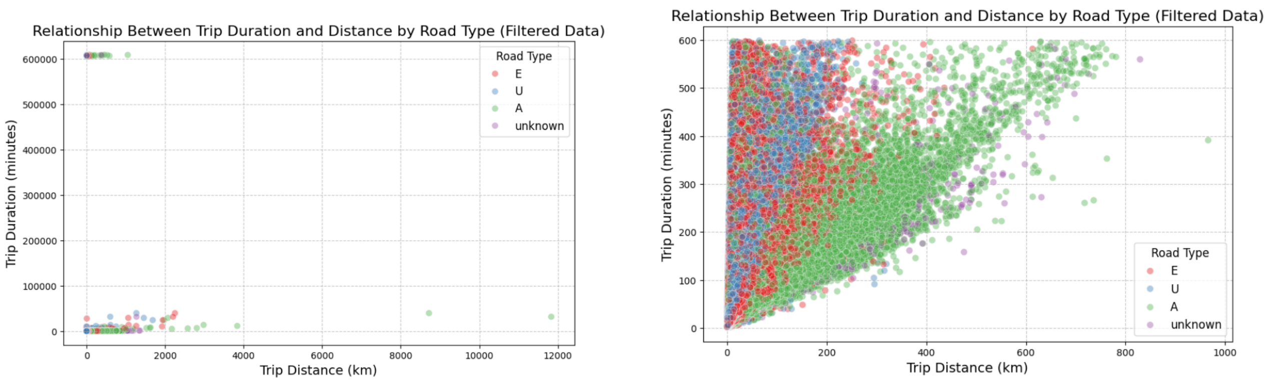
(b) Duration Distribution

Figure 1: ECDF Analysis of (a) Trip Distance across road types and (b) Trip Duration.

The distance analysis (Figure 1a) confirms that Urban roads (U) are dominated by short trips, evidenced by the steep rise in cumulative probability at low distances. In contrast, Expressways (E) and Highways (A) display smoother curves, indicating a spread toward longer trips. Regarding duration (Figure 1b), the data, aggregated at the trip level reveals a right-skewed distribution. Approximately 50% of trips last under 20 minutes, with the vast majority falling between 5 and 60 minutes. The long tail highlights distinct extended driving events, best observed via the log scale.

1.2 Duration-Distance Relationship and Data Filtering

Figure 2 illustrates the relationship between travel duration and distance before and after data cleaning.



(a) Raw Data

(b) Filtered Data

Figure 2: Travel Duration vs. Distance by Road Type (a) Raw and (b) Filtered.

The initial visualization (Fig. 2a) is heavily obscured by outliers, making distinct road dynamics difficult to interpret. Consequently, the dataset was filtered to exclude physical impossibilities, retaining only trips with distance $0.1 < d \leq 1000$ km, duration $2 < t \leq 600$ min, and average speed $1 < v < 200$ km/h. This process yielded $\mathbf{1,149,664}$ valid trips.

With outliers removed, Figure 2b reveals clear behavioral patterns. Highways (A) display a strong linear relationship, confirming they facilitate consistent long-distance travel. In contrast, Urban roads (U) show longer durations for short distances and a weaker correlation, reflecting the impact of traffic and frequent stops.

Expressways (E) bridge these extremes, showing moderate correlation consistent with mixed short-to-medium usage.

2 Task 1: Analyzing Behaviors of Vehicles

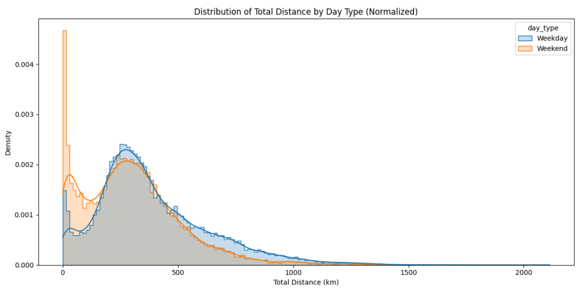
2.1 Task 1.a: Statistics and Distribution Analysis on Workdays vs. Weekends

For each vehicle, trip data was aggregated on a daily basis, computing the number of trips per day, total distance traveled, total trip duration, and daily utilization percentage. Days were classified as Weekday (Monday-Friday) or Weekend (Saturday-Sunday) to identify behavioral differences between working days and leisure periods. Table 1 demonstrates that vehicles activity is higher and more consistent on weekdays, with an average daily distance of 391.02 km compared to 300.63 km on weekends (23% reduction) and drive $\approx$90 minutes longer. The number of trips also decreases slightly from 13.83 trips per day on weekdays to 12.06 on weekends.

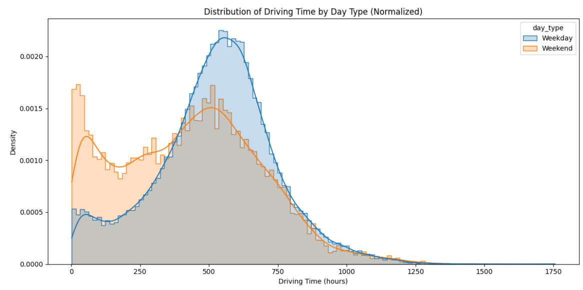
Table 1: Statistical Summary: Weekday vs Weekend Behavior

Metric	Weekday Mean	Weekday Std	Weekend Mean	Weekend Std
Total Distance (km)	391.02	248.2	300.63	220.71
Trip Duration (min)	522.48	218.75	429.42	259.79
Number of Trips	13.83	10.04	12.06	10.44

Figure 3 and the observed standard deviations confirm that weekdays follow more predictable patterns, characterized by lower variability and pronounced peaks around longer trips, typical of regular work-related commuting. In contrast, weekends exhibit significantly higher inconsistency (duration std: 259.79 vs. 218.75) and a broader dispersion toward shorter distances, reflecting reduced and less structured fleet usage.



(a) Daily distance distribution

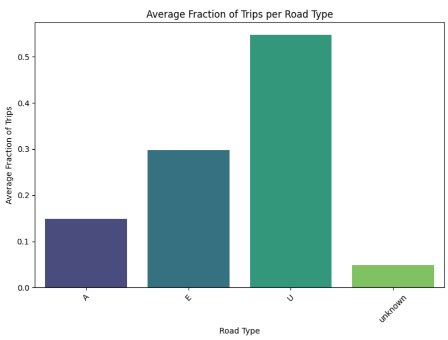


(b) Daily duration distribution

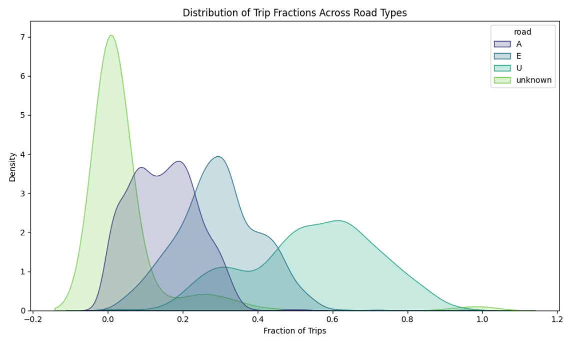
Figure 3: Distribution comparisons between weekdays and weekends.

2.2 Task 1.b: Fraction of Trips by Road Type

To characterize route preferences, we calculated the usage fraction of each road type per vehicle. Since trips often span multiple categories (e.g., Urban, Expressway), a single trip contributes to the fraction of *every* road type it traverses. Consequently, the sum of fractions per vehicle may exceed 100%, accurately reflecting the multi-segment nature of real-world driving.



(a) Average fraction per road type



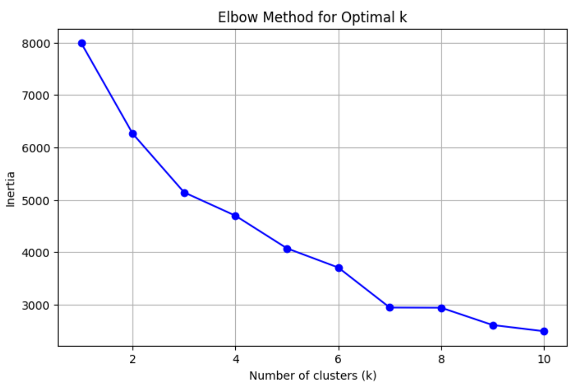
(b) Fraction distribution across vehicles

Figure 4: Road type usage analysis.

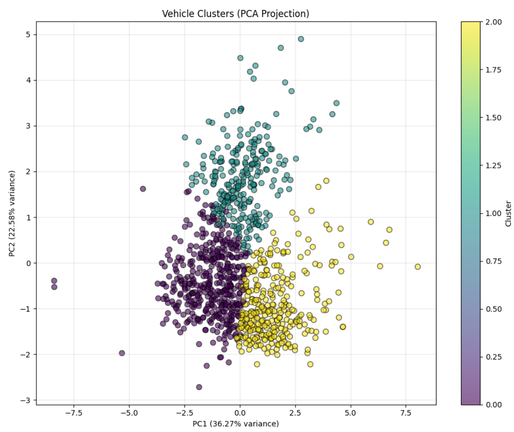
Analysis of Figures 4a and 4b reveals a fleet that is primarily urban-centric but possesses significant operational heterogeneity. Urban roads (U) exhibit the highest average usage, confirming that most operations revolve around activities like city deliveries or local commuting. Conversely, Highways (A) and Expressways (E) show lower averages, reinforcing a limited regional scope. While many vehicles show near-zero highway fractions (indicating dedicated urban roles), a distinct subset displays moderate usage consistent with suburban or inter-urban routes. This heterogeneity suggests diverse operational roles within the fleet, ranging from exclusively urban to regional vehicles, which will be further explored through clustering analysis in Task 1.c.

2.3 Task 1.c: Vehicle Clustering Based on Behavior

To categorize vehicles into distinct behavioral groups, K-means clustering was applied using features capturing both road usage patterns and operational intensity. The selected features included total distance traveled per road type (urban, expressway, highway, unknown) and average daily utilization per road type. All features were standardized using z-score normalization to ensure equal weighting across different scales.



(a) Elbow method analysis



(b) PCA projection of clusters

Figure 5: Cluster determination and visualization.

The optimal cluster count was set to 3 based on the elbow method (Figure 5a), where the inertia plateau indicates diminishing returns for additional groups. This selection is validated by the PCA visualization in Figure 5b, which reveals clear spatial separation and minimal overlap among the clusters, confirming that the algorithm successfully isolated distinct behavioral patterns.

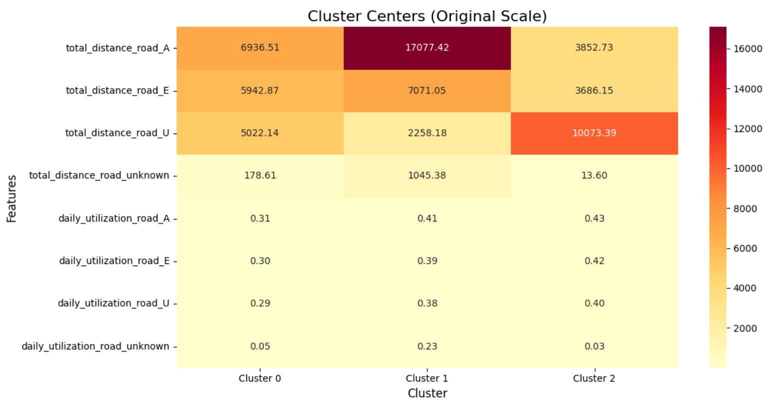


Figure 6: Cluster center analysis

Figure 6 shows the cluster center analysis, demonstrating the presence of three distinct operational roles. **Cluster 2** is strictly urban-centric, likely used for city deliveries and local services, while **Cluster 1** represents long-distance travelers heavily utilizing expressways and highways for regional operations. In between, **Cluster 0** appears as a mixed use group with balanced activity across all road types.

3 Task 2: EV Models & Evaluation Metrics

Table 2 lists the eight diverse EV models analyzed. Performance is assessed via feasibility, battery health, and efficiency. The simulation defaults to Slow Charging (AC) but triggers Fast Charging (DC) if SoC drops below 20% or during short stops (<2h) when SoC <80%.

Table 2: Selected Electric Vehicle Models with Road-Specific Consumption

			Consumption (Wh/km)		
Model	**Category**	**Battery (kWh)**	**Urban**	**Expr.**	**Hwy**
Renault Twingo E-Tech	Mini	27.5	96	128	162
Fiat 500e Hatchback	Compact	37.3	105	138	173
CUPRA Born 170 kW	Medium	77.0	118	150	186
BYD SEAL RWD	Large	82.5	121	149	181
BMW iX xDrive40	Executive	71.0	138	175	215
Lotus Eletre S	Luxury	109.0	156	196	242
Volkswagen ID. Buzz Pro	Passenger Van	77.0	154	200	252
Audi e-tron GT RS	Sport	85.0	150	185	227

4 Pseudocode of EV Trip Simulator

Algorithm 1 EV Battery Simulation Logic

Require: $Trips$, C_{bat} (Capacity), P (Power), R_{cons} (Cons. Rate)
$SoC \leftarrow C_{bat}$
for each trip $i \in Trips$ **do**
  $E_{req} \leftarrow dist_i \times R_{cons}(road\_type)$ {Compute energy required for the trip}
  if $SoC \geq E_{req}$ **then**
    $SoC \leftarrow SoC - E_{req}$; **Record** Feasible
  else
    Record Unfeasible {Skip if energy too low}
  end if
  $\Delta t_{park} \leftarrow start_{i+1} - end_i$ {Calc parking time}
  if $\Delta t_{park} > 0$ **then**
    if $SoC < 0.2C_{bat}$ **or** $(\Delta t_{park} < 2h \textbf{and} SoC < 0.8C_{bat})$ **then**
      $P \leftarrow P_{DC}$ {Fast Charge Condition}
    else
      $P \leftarrow P_{AC}$ {Slow Charge Condition}
    end if
    $SoC \leftarrow \min(C_{bat},\ SoC + P \cdot \Delta t_{park})$
  end if
end for

5 Task 4: EV Trip Simulator Implementation

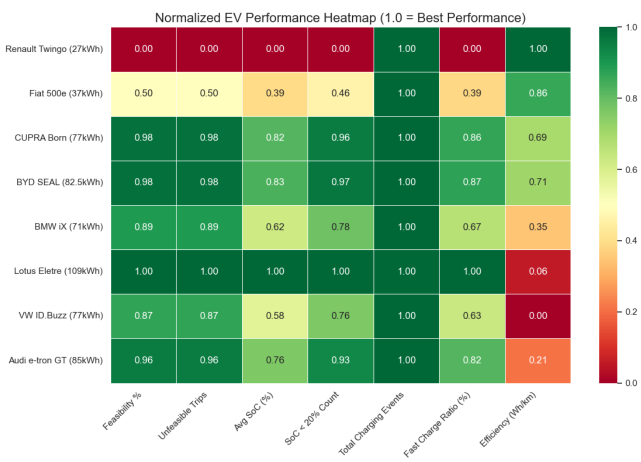


Figure 7: Normalized EV performance heatmap

To evaluate EV performance under real driving patterns, a simulation was conducted considering trip feasibility, State of Charge (SoC), charging behavior, and energy efficiency. Figure 7 shows a normalized heatmap comparing these metrics across EV models. All models achieve high feasibility, confirming their suitability for the observed trips, while clear trade-offs emerge. Larger-battery vehicles maintain higher SoC buffers and rely less on fast charging, offering greater robustness, whereas smaller EVs are more energy-efficient but less resilient.

5.1 4.a: Analysis of Unfeasible Trips

Figure 8 shows the number of unfeasible trips per EV model, defined as trips ending with zero State of Charge. Smaller-battery vehicles experience significantly more unfeasible trips due to limited energy buffers, while larger-battery EVs exhibit greater robustness under intensive driving. Overall, unfeasibility is mainly driven by the interaction between battery capacity and usage intensity.

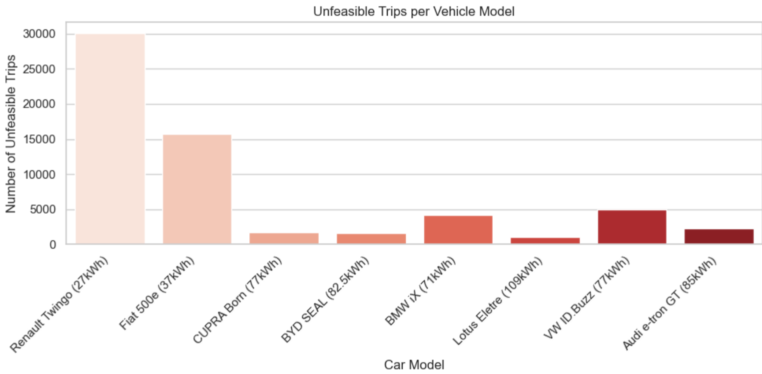
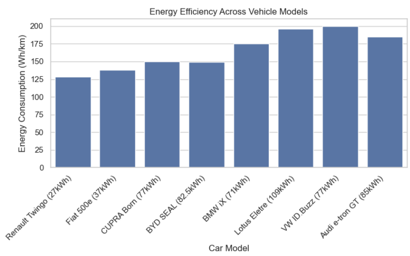


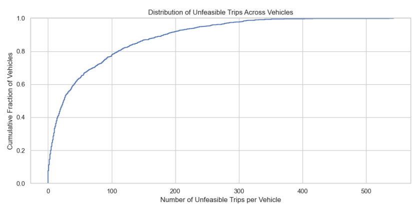
Figure 8: number of unfeasible trips per EV

5.2 4.b: Distribution of Performance Metrics Across Vehicles

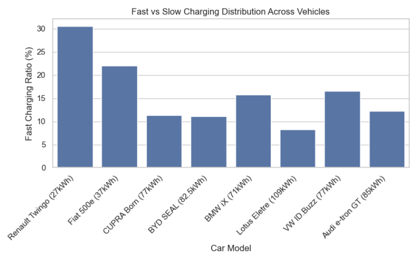
Figure 9 summarizes the distribution of key performance metrics across vehicles, highlighting significant heterogeneity in EV behavior. The energy efficiency plot 9a shows that smaller vehicles achieve lower energy consumption per kilometer, while larger vehicles exhibit higher consumption due to increased mass and power requirements. The fast versus slow charging distribution 9c reveals varying reliance on DC fast charging, with smaller battery vehicles depending more heavily on fast charging to maintain feasibility, whereas larger battery vehicles benefit from greater flexibility and reduced charging stress. Finally, the ECDF of unfeasible trips per vehicle 9b highlights a strongly skewed distribution: most vehicles experience few or no unfeasible trips, while a small subset accumulates a disproportionately large number of failures. Together, these results indicate that EV performance is not uniform across the fleet and is strongly influenced by both vehicle characteristics and usage intensity.



(a) Energy efficiency across EV models



(b) ECDF of unfeasible trips per vehicle

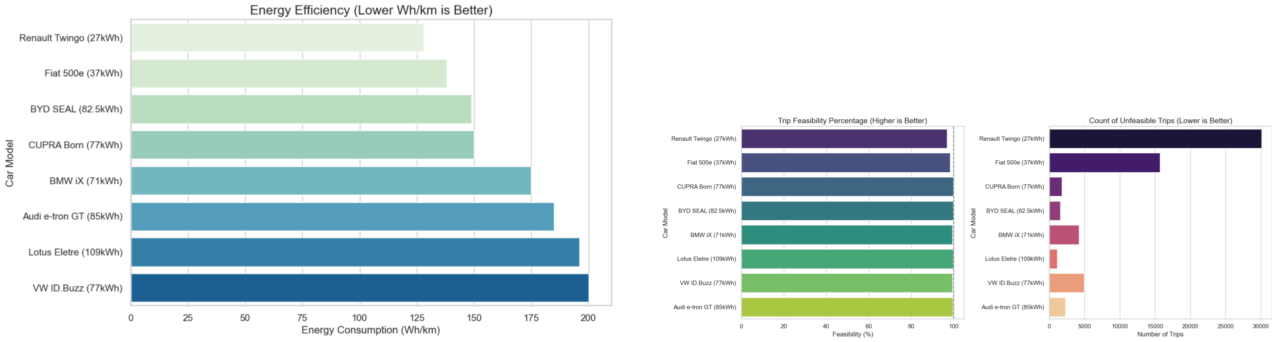


(c) Fast vs. slow charging ratio

Figure 9: Distribution of EV performance metrics across vehicles: energy efficiency, charging behavior, and feasibility.

5.3 4.c: Comparison Across EV Models

Figure10 compares EV models in terms of energy consumption, trip feasibility, and battery buffer(Appendix Figure 14). The results highlight clear differences driven by vehicle characteristics. Smaller EVs, such as the Renault Twingo and Fiat 500e, exhibit lower energy consumption per kilometer, reflecting higher efficiency, but also show reduced trip feasibility and lower average ending State of Charge. This indicates limited energy buffering capacity, which increases vulnerability to unfeasible trips under intensive driving patterns. In contrast, EVs with larger batteries achieve higher feasibility and maintain higher end-of-trip SoC levels, despite higher energy consumption. These vehicles benefit from greater battery reserves, which enhance robustness and reduce the likelihood of critical battery depletion. Overall, the results demonstrate a trade-off between energy efficiency and operational robustness: while smaller EVs are more efficient, larger EVs compensate higher consumption with increased battery capacity, resulting in improved feasibility and reliability.



(a) Energy consumption per EV model

(b) Trip feasibility percentage per EV model

Figure 10: Comparison across EV models in terms of energy consumption, trip feasibility, and battery buffer.

5.4 4.d: Impact of Slow AC Charging Only

Figure 11 compares the baseline charging strategy, which allows both AC and DC charging, with a scenario where only slow AC charging is available. The results show a substantial degradation in performance when fast charging is removed. As shown in the left plot, the number of unfeasible trips increases significantly across all EV models, with small-battery vehicles being particularly affected due to their limited energy buffer. Larger-battery EVs exhibit greater resilience, but still experience a noticeable rise in infeasibilities. In addition, right plot shows that total charging time increases dramatically under the slow AC-only scenario, leading to higher downtime for all vehicles. These results demonstrate that fast DC charging plays a crucial role in maintaining both trip feasibility and operational efficiency, and that relying exclusively on slow AC charging is insufficient for supporting intensive mobility demand.

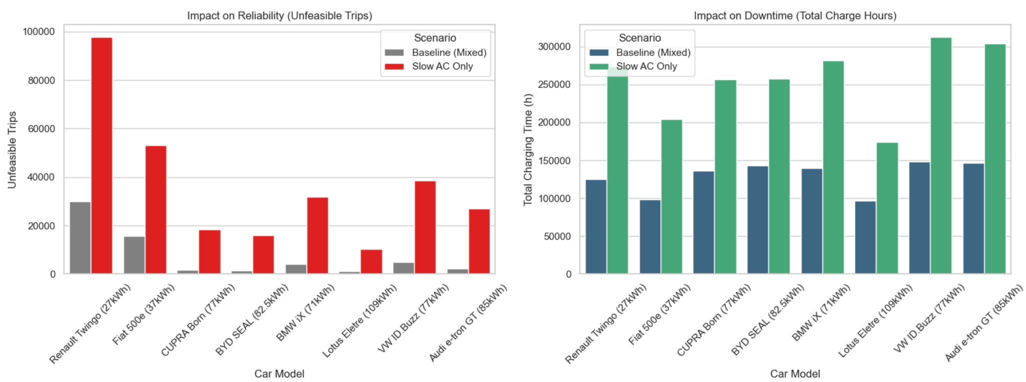
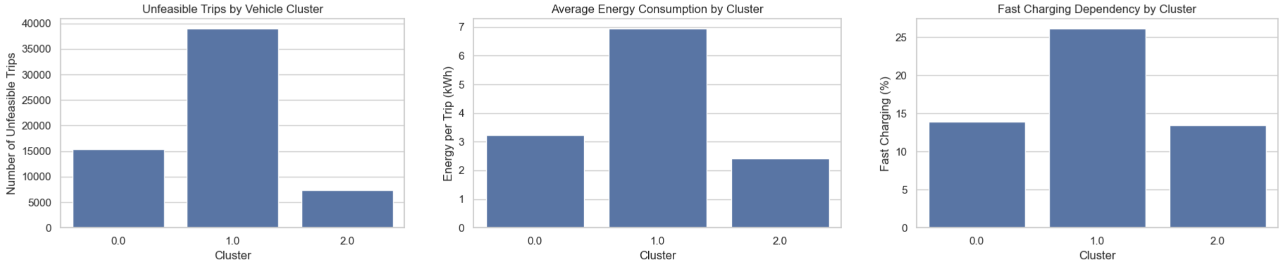


Figure 11: Impact of slow AC-only charging on reliability and charging downtime.

5.5 4.e: Cluster-Based Analysis of Vehicle Performance

The cluster-based analysis reveals clear performance differences among vehicles with distinct usage patterns. As shown in Figure 12, Cluster 1 exhibits the highest number of unfeasible trips, indicating that high-intensity vehicle usage significantly increases the risk of battery depletion. This cluster also shows the highest average energy consumption per trip and the strongest dependence on fast charging, confirming that intensive mobility demand places greater stress on both battery capacity and charging infrastructure. In contrast, Cluster 2 demonstrates the lowest energy consumption and the fewest unfeasible trips, reflecting efficient and low-intensity usage patterns that maintain higher operational reliability. Cluster 0 represents an intermediate behavior, with moderate energy demand and feasibility performance. Overall, these results confirm that clustering effectively captures heterogeneous vehicle behaviors and that usage intensity, rather than EV model alone, is a key driver of infeasibility and charging stress.



(a) Unfeasible trips by cluster (b) Avg energy consumption by cluster (c) Fast charging dependency by cluster

Figure 12: Performance comparison across vehicle clusters identified in Part 1.c.

6 Task5: Tradeoff between performance and cost

The Total Cost of Ownership (TCO) is evaluated under real-world operating conditions by combining capital and operational costs, normalized to /100 km. Operational expenditure (OpEx) is computed from simulated energy consumption and observed charging behavior, using the real fast charging percentage to weight AC and DC charging costs. Capital expenditure (CapEx) is obtained by amortizing the vehicle purchase price over its expected lifetime mileage and expressing it per 100 km. The total TCO is then calculated as:

$$\mathrm{TCO}_{100\,\mathrm{km}} = \mathrm{CapEx}_{100\,\mathrm{km}} + \mathrm{OpEx}_{100\,\mathrm{km}}. \tag{1}$$

This metric provides a comprehensive indicator of both long-term investment and operational costs.

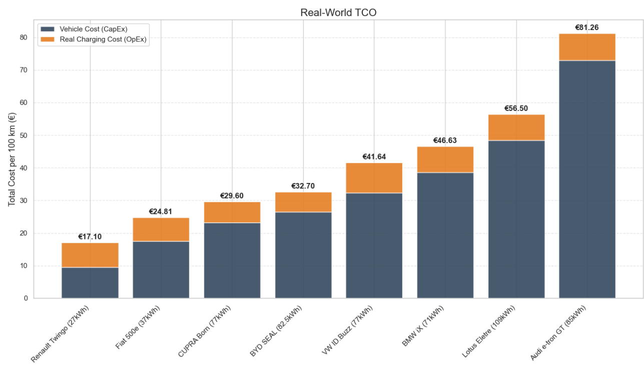


Figure 13: Total Cost of Ownership per each vehicle

The results (Table 3) reveal a clear differentiation in TCO across EV models. Small and affordable vehicles achieve the lowest cost per 100,km, mainly due to low capital expenditure despite high reliance on fast charging. Mid-range vehicles exhibit a balanced TCO resulting from moderate purchase prices and efficient charging costs. In contrast, premium EVs show substantially higher TCO values, driven primarily by elevated capital costs. Overall, CapEx dominates total ownership cost, while OpEx variations play a secondary role, indicating that vehicle affordability has a stronger impact on economic viability than charging behavior under real-world conditions.

Car Model	Fast Charge (%)	OpEx (€/100 km)	CapEx (€/100 km)	TCO (€/100 km)
Renault Twingo (27 kWh)	73.75	7.60	9.50	17.10
Fiat 500e (37 kWh)	67.60	7.32	17.50	24.81
CUPRA Born (77 kWh)	54.49	6.38	23.23	29.60
BYD SEAL (82.5 kWh)	52.10	6.21	26.50	32.70
VW ID.Buzz (77 kWh)	63.27	9.35	32.29	41.64
BMW iX (71 kWh)	60.84	7.98	38.65	46.63
Lotus Eletre (109 kWh)	49.95	8.00	48.50	56.50
Audi e-tron GT (85 kWh)	59.74	8.23	73.03	81.26

Table 3: Real-world Total Cost of Ownership (TCO) per 100 km for different EV models.

7 Task6: More Realistic Simulation

Methodology This analysis compares a baseline charging strategy with a more realistic, behavior-driven charging policy. Both scenarios use the same trip-level dataset and simulation framework, ensuring that observed differences arise exclusively from the charging logic.

In the baseline scenario, charging decisions follow a simplified heuristic that allows both AC and DC charging without strong behavioral constraints. In contrast, the realistic policy introduces decision rules that reflect real-world driver behavior and infrastructure limitations. Specifically, AC charging is prioritized during long parking periods, while DC fast charging is used only in critical situations, such as low state-of-charge or short stops, and is capped at 80% state-of-charge to reflect typical fast-charging practices.

The simulation is executed independently for each EV model by iterating over vehicles and trips, updating battery state-of-charge after each trip, and applying the corresponding charging decision during parking intervals. For each scenario, identical performance metrics are computed, including trip feasibility and fast charging ratio. Finally, results from the two scenarios are merged at the vehicle-model level to enable a direct and fair comparison between baseline and realistic charging strategies.

Car Model	Feas. Baseline (%)	Feas. Realistic (%)	Fast Ch. Baseline (%)	Fast Ch. Realistic (%)
Renault Twingo (27 kWh)	96.88	95.73	30.57	80.71
Fiat 500e (37 kWh)	98.37	97.32	21.98	75.08
CUPRA Born (77 kWh)	99.82	99.48	11.33	53.13
BYD SEAL (82.5 kWh)	99.84	99.55	11.12	51.44
BMW iX (71 kWh)	99.56	98.91	15.74	64.04
Lotus Eletre (109 kWh)	99.88	99.63	8.29	46.23
VW ID.Buzz (77 kWh)	99.49	98.78	16.55	65.22
Audi e-tron GT (85 kWh)	99.76	99.32	12.20	55.60

Table 4: Comparison between baseline and realistic charging policies in terms of feasibility and fast charging usage.

Discussion The comparison highlights the impact of adopting a more realistic charging policy. Across all EV models, trip feasibility remains high, with only a marginal decrease compared to the baseline scenario, indicating that the realistic policy does not significantly compromise operational reliability. However, a substantial increase in the fast charging ratio is observed for all vehicles, especially for small- and mid-range EVs. This reflects the policy's emphasis on reserving DC charging for critical or short-stop situations while limiting its use through an 80% SoC cap. Overall, the results demonstrate that a behaviorally realistic charging strategy preserves feasibility while shifting charging demand toward fast chargers when necessary, thereby providing a more accurate representation of real-world charging behavior.

8 Appendix

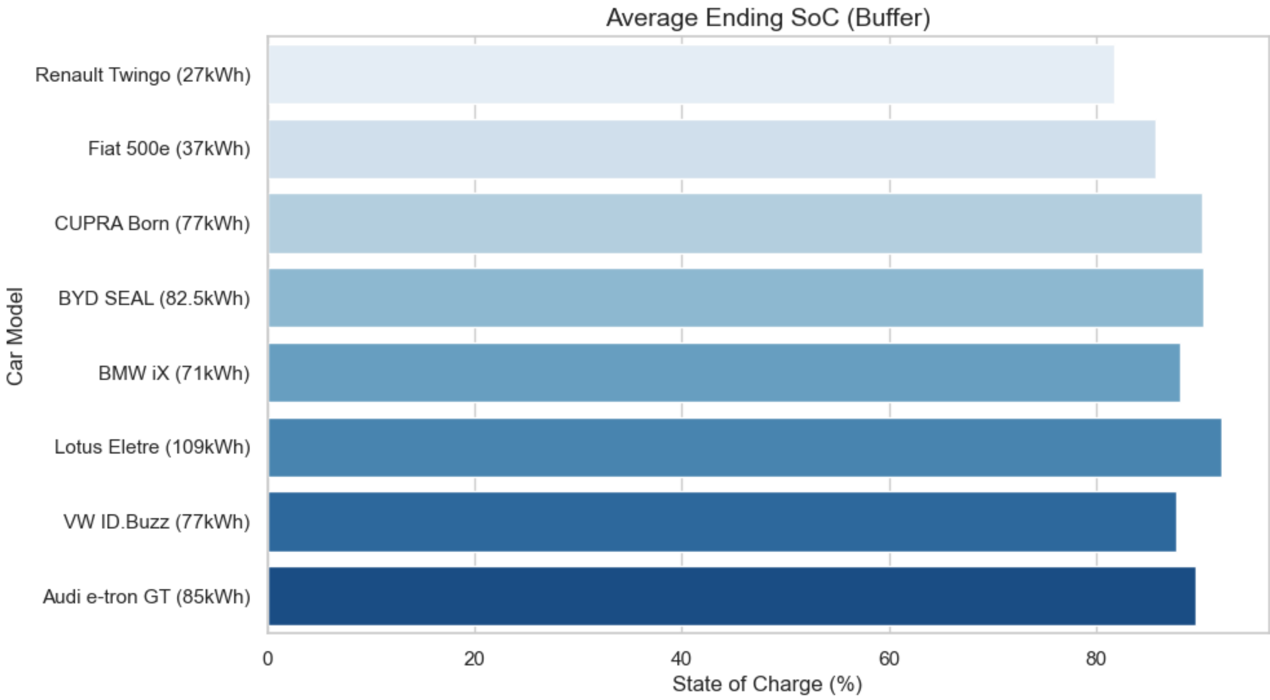


Figure 14: Average ending State of Charge per EV model