ICT for Smart Mobility

01DSABH

Laboratory 3 Report

Group:

12

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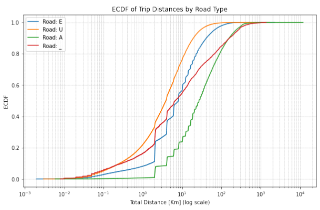
Preliminary Analysis

Road Type	**U**	**E**	**A**	**-**
Description	Urban	Extra-Urban	Highway	Unknown

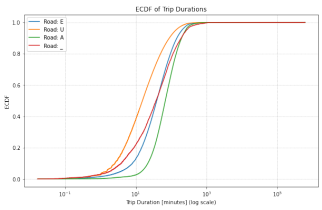
Table 1: Dataset Road Types.

1 Distribution of Trip Distance

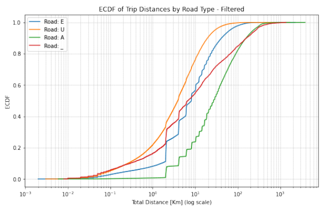
Based on the road types presented in Table 1, it is observed that highways are associated with the longest trip distances. Conversely, urban trips exhibit a distribution skewed toward shorter distances, as illustrated in Figure 1a.



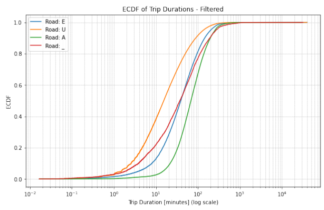
(a) Distance (Unfiltered)



(b) Duration (Unfiltered)



(c) Distance (filtered)



(d) Duration (filtered)

Figure 1: ECDF of Distance and Duration.

2 Distribution of Trip Duration

Similar to the previous section, a comparable distribution of trip durations is observed based on the road type, as depicted in Figure 1b.

3 Relationship Between Trip Duration and Distance

First, the outliers are filtered out to obtain the scatter plot of the filtered data. As shown in Figure 4b, for road type A (Highway), longer distances are covered in shorter durations. Conversely, for road type U (Urban), similar distances require longer durations. This result aligns with the expected characteristics of different road types in real-world conditions.

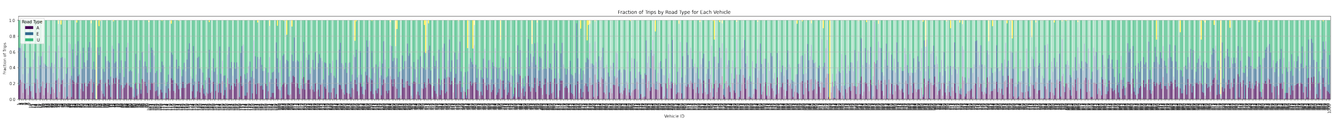


Figure 2: Road Type for each Vehicle.

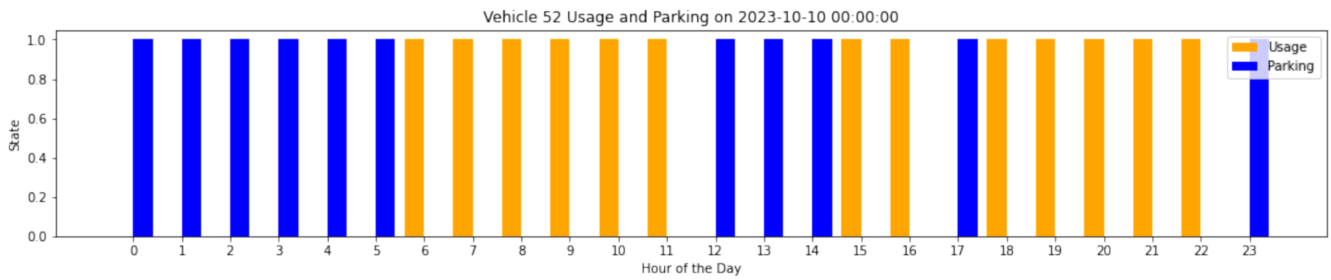
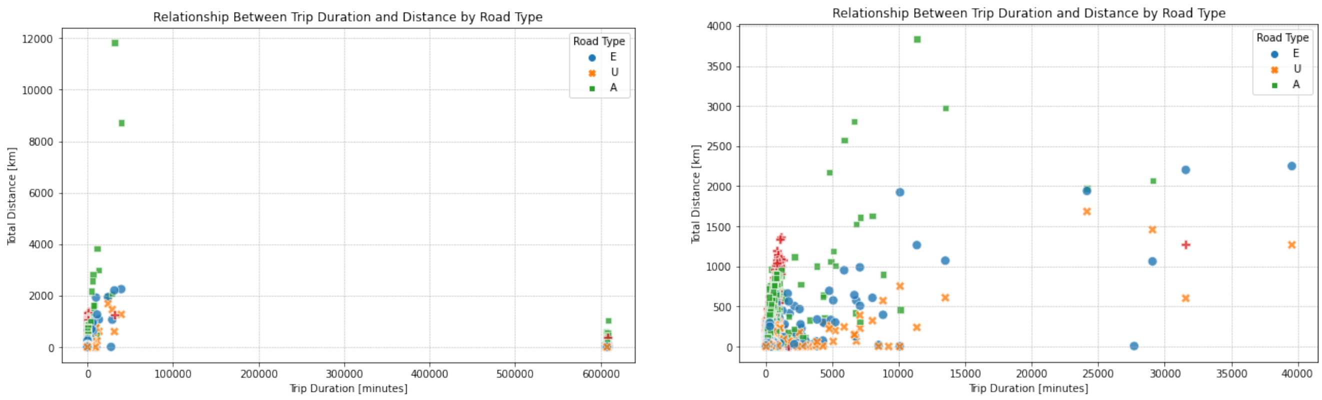


Figure 3: A vehicle simulated for a day.



(a) Unfiltered

(b) filtered

Figure 4: Duration-Distance Relations.

4 Outlier Removal and Filter Criteria

The scatter plot illustrating the relationship between trip durations and distances (Figure 4a) reveals the presence of outlier regions alongside a region representing non-outlier data. To isolate the non-outlier data, trips with **durations exceeding 50,000 minutes** and **distances above 4,000 kilometers** are filtered out. This filtering process results in a cleaner dataset, as shown in the updated scatter plot in Figure 4b, which provides a clearer representation of the relationship, particularly in relation to the road types.

Additionally, changes can be observed in the distributions of distance (Figure 1c) and duration (Figure 1d).

Tasks

Task 1: Analyzing Vehicle Behavior

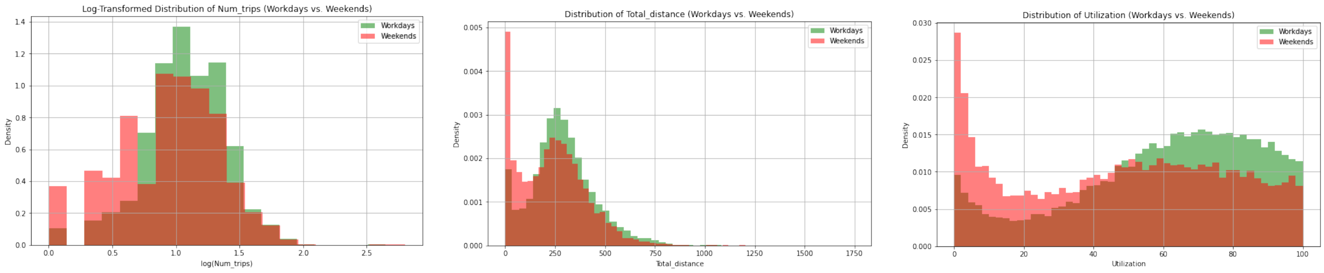
a. Statistics and Distribution

Analyzing the initial statistics of the vehicle data revealed the need for an additional filtering step, as some vehicles recorded total driving times exceeding 24 hours in a single day. After applying this filter, the statistics presented in Table 2 suggest that vehicle utilization is higher on workdays compared to weekends. Consequently, the total distance traveled by vehicles is also greater on workdays than on weekends.

Figure 11 confirms the hypothesis that workdays exhibit higher utilization compared to weekends, as shown in Figure 5c. However, the distances traveled do not display a significant difference between weekends and workdays, as illustrated in Figure 5b.

	(a) Workdays Statistics			(b) Weekends Statistics		
	Num Trips	**Total Distance**	**Utilization**	**Num Trips**	**Total Distance**	**Utilization**
Mean	16.47	290.63	60.55	13.18	235.37	47.92
STD	18.78	163.81	26.01	20.97	167.92	30.05
Min	1.00	0.01	0.003	1 1.00	0.01	0.012
Max	611.00	1745.53	99.99	631.00	1397.30	100.00

Table 2: Comparison of Workdays and Weekends Statistics



(a) Number of Trips (Log values) (b) Total Distance (c) Utilization

Figure 5: Metrics distribution.

To identify consistent behavior patterns for vehicles on weekends and workdays, Euclidean similarity was used to compare the data for these periods. Three vehicles exhibiting highly consistent behavior were identified, with their respective values reported in Table 3.

Vehicle ID	**Trips Diff**	**Distance Diff**	**Driving Time Diff**	**Utilization Diff**
87	2.22	9.01	5.56	0.39
411	1.41	4.20	1.34	0.09
882	6.18	3.30	7.10	0.49

Table 3: Comparison of Vehicle Metrics on Workdays and Weekends

b. Road Type Analysis

Figure 6 presents a visualization of the fraction of road types utilized by each vehicle. A more detailed visualization is provided in Figure 2; however, due to the dataset's size of 1,000 vehicles, the information is not entirely clear. The results indicate that most vehicles are predominantly used on urban roads, with extra-urban roads being the second most utilized category.

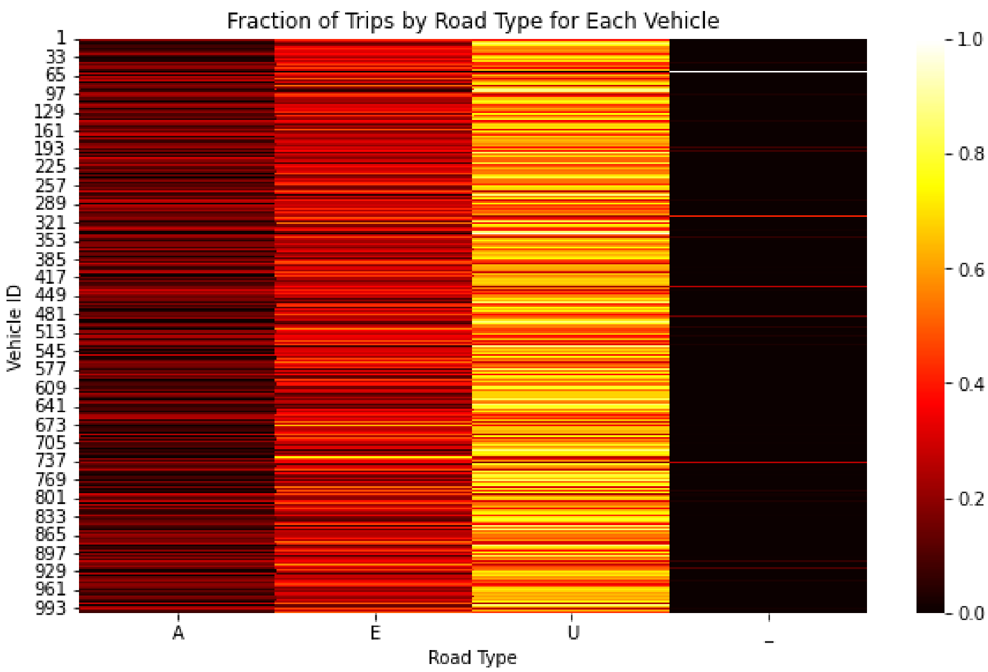
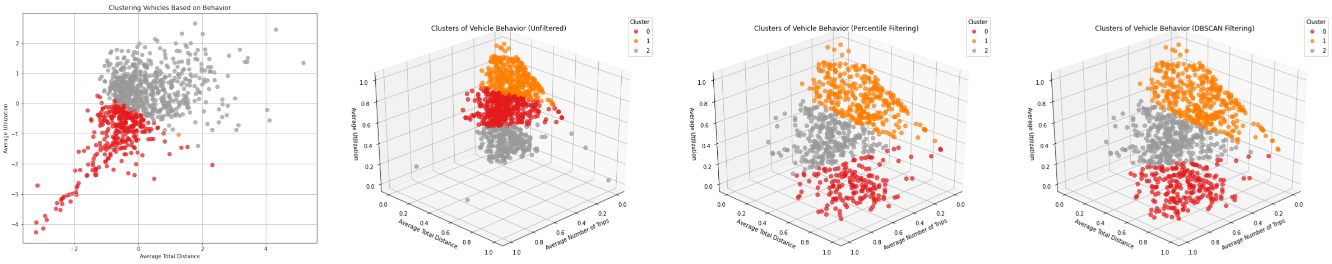


Figure 6: Road Type for each Vehicle shown in Heatmap.

c. Vehicle Categorization and Clustering



(a) 2-D (unfiltered) (b) 3-D (unfiltered) (c) 3-D (Percentile Filtered) (d) 3D (DBSCAN Filtered)

Figure 7: Vehicle Clusters

Applying K-means clustering with three clusters to the vehicle metrics from the previous section (number of trips, total distance, and utilization) resulted in the formation of distinct clusters, as shown in Figure 7a. When visualizing the data and clusters in three dimensions (Figure 7b), some outliers became apparent, which were not evident in the 2D representation. To address this, two outlier mitigation techniques were applied: percentiles (Figure 7c) and DBSCAN (Figure 7d). These methods yielded more consistent clustering results.

Task 2: EV Models and Metrics

Three models were selected for the simulation, with their specifications reported in Table 4.

Table 4: Comparison of EV Models and Their Parameters

Parameter	Alfa Romeo Junior Elettrica	Fiat Grande Panda	Tesla Model 3
Vehicle Consumption (Mild Weather)			
City (km)	475	390	615
Highway (km)	290	230	405
Combined (km)	365	295	495
Usable Battery Capacity (kWh)	50.8	43.8	57.5
Charging Power (AC)	11 kW	7.4 kW	11 kW
Fast Charging Power (DC)	100 kW	100 kW	170 kW
Cost (in Germany)	€ 39500	€ 24000	€ 40970

We then define two performance metrics as follows:

Unfeasible Trips

- **Definition:** A trip is marked as unfeasible when the vehicle's State of Charge (SoC) before starting the trip is less than the energy required for the trip.
- **Total Unfeasible Trips:** The total number of trips marked as unfeasible.
- **Percentage of Unfeasible Trips:** The fraction of unfeasible trips compared to all trips for the vehicle.

$$\text{Unfeasible Trips (\%)} = \frac{\text{Total Unfeasible Trips}}{\text{Total Trips}} \times 100 \tag{1}$$

Average SoC

- **Definition:** The average State of Charge (SoC) of the battery at the start of all trips for the simulation period.

- **Percentage Battery SoC:** SoC expressed as a percentage of the battery capacity.

$$\text{Battery Average SoC (\%)} = \frac{\sum \text{SoC at Start of Trips}}{\text{Total Trips}} \times 100 \qquad (2)$$

Task 3: Trip Replicator and EV Simulator

The general pseudocode used to simulate the EV vehicles and obtain the performance metrics defined in Task 2 is reported in Algorithm 1. Following this, we implement and execute the simulation.

Algorithm 1 Simulation of EV Charging and Performance

Input: EV models with parameters (consumption data, battery capacity, charging power)
Input: Trip data grouped by vehicle ID
Input: Charging type (AC or DC), battery parameters, parking duration threshold
Output: Total unfeasible trips, unfeasible percentage, average SoC, charging type impact
Step 1: Initialize Simulation Parameters
Load EV models (vehicle consumption, battery capacity, charging power reported in table 4)
Prepare trip data grouped by vehicle ID
Step 2: Setup the Simulation
for each vehicle in trip data **do**
    Assign EV model randomly from available models
    Initialize each vehicle's battery with full SoC (100
end for
Step 3: Simulate Trips for Each Vehicle
for each vehicle in trip data **do**
    for each trip for the vehicle **do**
        Calculate energy consumption based on road type and distance using the vehicle's consumption data
        If energy required for trip exceeds current SoC:
        Mark the trip as unfeasible
        Set SoC to 0 after the trip
        Deduct the consumed energy from the current SoC
    end for
end for
Step 4: Handle Parking and Charging
for each vehicle in trip data **do**
    for each parking event for the vehicle **do**
        If parking duration exceeds threshold (30 minutes):
        Charge the battery using the assigned charging power (AC or DC)
    end for
end for
Step 5: Record and Evaluate Metrics
Compute total unfeasible trips for each vehicle.
Compute percentage of unfeasible trips for each vehicle (equation 1).
Compute average SoC across all trips for each vehicle (equation 2)
Output: Total unfeasible trips, unfeasible percentage, average SoC, charging type impact

Task 4: Simulation Analysis

Unfeasibility of Trips, Distribution of Performance Metrics, and cluster analysis

Running the simulator outlined in the previous section allows us to obtain the performance metrics defined in Task 2. Figure 11 shows the average unfeasibility and state-of-charge (SoC) percentages for the three

EV models. The distribution of these metrics is also depicted in the figure. It is observed that the Tesla Model 3 performs more consistently, demonstrating higher reliability with a low rate of unfeasibility and a high rate of SoC. The distribution of metrics remains consistent when considering both AC and DC charging.

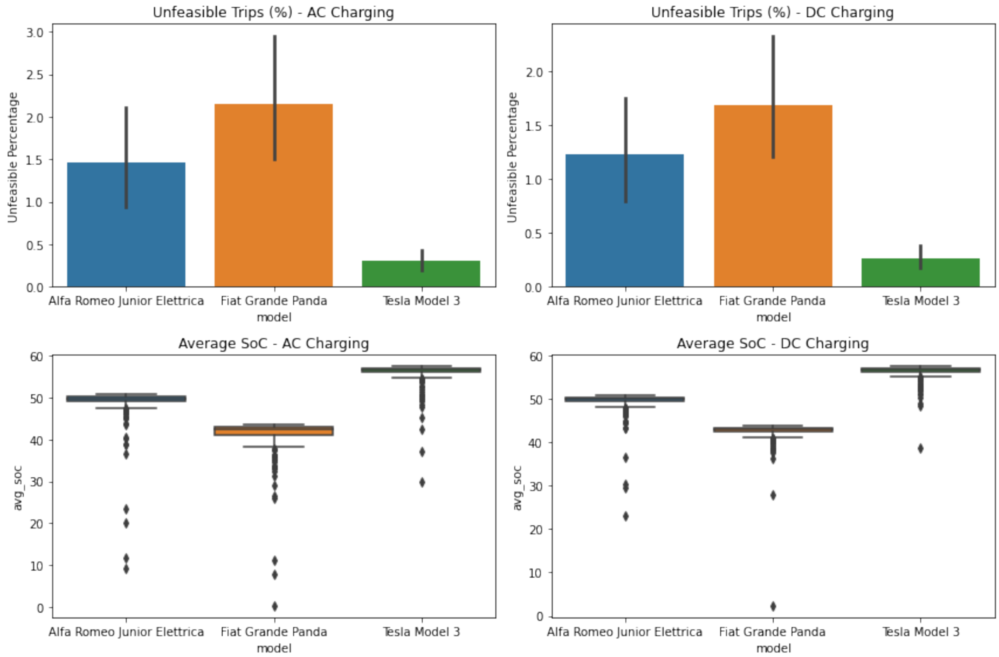
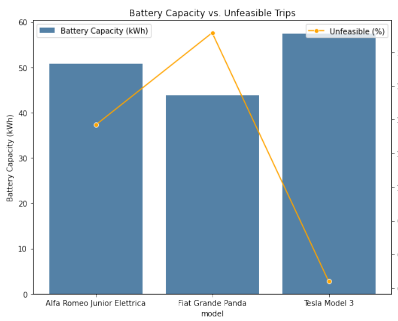


Figure 8: Distribution of Performance Metrics for EVs.

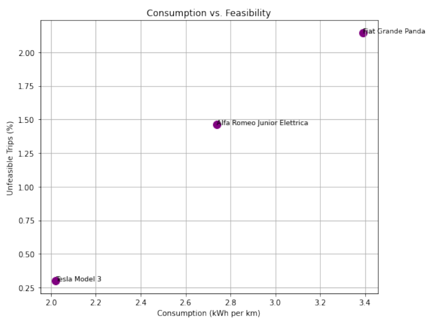
The raw metrics, without considering the specifications of the models, may not provide a comprehensive analysis. Therefore, we analyze the performance metrics in relation to their specifications, as reported in Table 4. Figure 9a demonstrates that the Tesla Model 3 exhibits a low rate of unfeasible trips, while its battery capacity is not significantly different from the other models, suggesting that the performance of this EV model is superior. In contrast, the Fiat model shows a higher rate of unfeasible trips, which can be attributed to its lower battery capacity.

We can extend the analysis by considering the consumption rate of the models, as shown in Figure 9b. This figure reveals that the relatively low unfeasibility rate of the Tesla Model 3, despite its battery capacity not being significantly higher, may be attributed to its lower consumption rate.

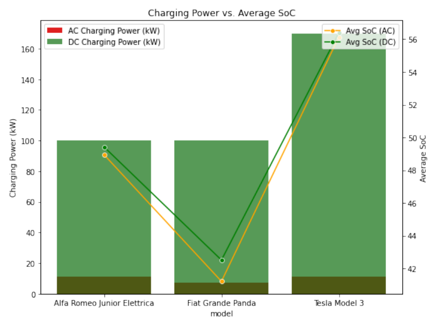
Figure 9c shows that the average state-of-charge (SoC) for the Fiat model is much lower compared to the Alfa Romeo, despite their similar charging power. However, it is consistently observed that the Tesla Model 3 outperforms the other models in terms of SoC.



(a) Battery Capacity vs. Unfeasible



(b) Consumption vs Unfeasible



(c) Charging Power vs Average SoC

Figure 9: EVs Parameters vs Metrics

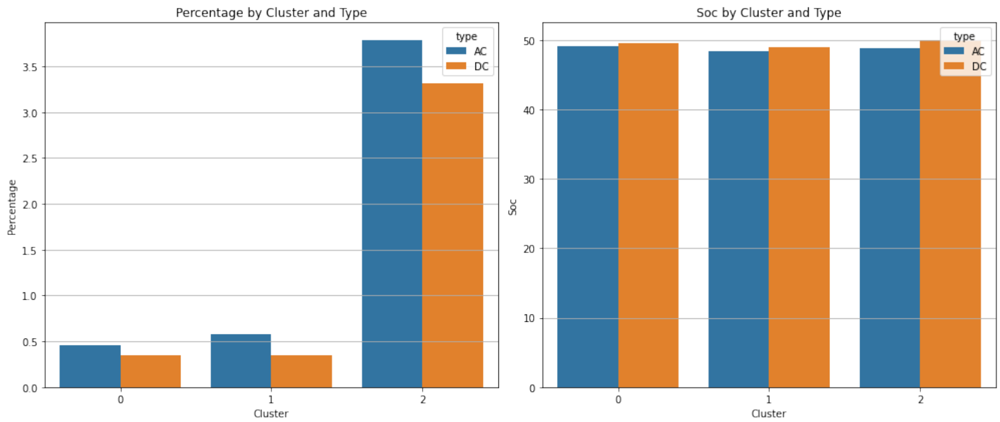
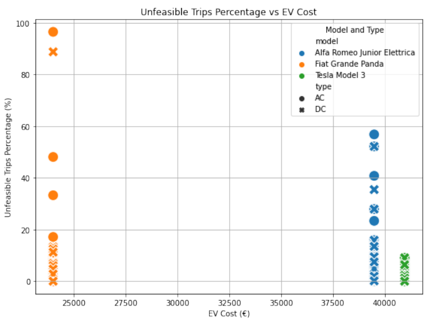


Figure 10: Performance Metrics for different Clusters

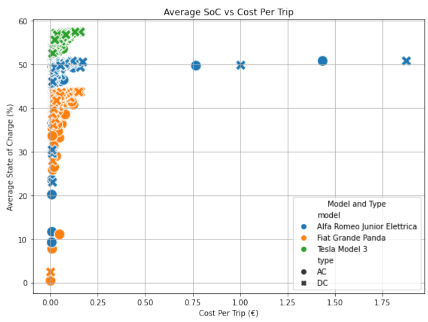
Taking into account the clusters obtained in section 4, Figure 10 reveals that cluster 2 performs significantly worse in terms of unfeasible trips. However, the different clusters exhibit similar performance when it comes to the SoC metric.

Task 5: Cost Analysis

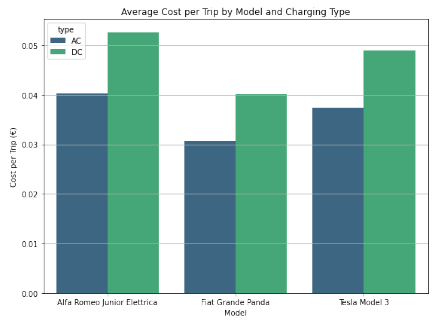
The cost of charging EVs in Italy is €0.65 per kWh for AC and €0.85 per kWh for DC [1]. Figure 11a suggests that higher-priced EVs tend to have better feasibility of trips. Similarly, Figure 11b shows that the SoC performance is generally better for higher-cost EVs. Finally, the trip cost for EVs is reported in Figure 11c, which indicates that, despite the higher upfront cost, the per-trip cost is almost identical across different EV models.



(a) EV Cost vs Unfeasiblity



(b) Trip Cost vs SoC



(c) Trip Cost for EVs

Figure 11: Cost for EVs (AC & DC)

References

[1] Plenitude. Cost of charging evs in italy, 2024.