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Master's Degree Thesis

Data-Driven Simulations for E-Mobility: Performance Across Italian Cities

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Abstract

As mobility evolves, Electric Vehicles (EVs) are becoming increasingly prevalent, offering new challenges and opportunities for understanding user behavior and optimizing charging strategies.

This thesis presents the enhancement and evaluation of a Battery Electric Vehicle (BEV) simulator, along with an analysis of the factors behind unsatisfied trips for specific EV models under predefined charging policies. The study uses real-world driving data on ICE cars provided by UnipolTech.

A previous version of the simulator developed by the research team was enhanced in terms of efficiency, scalability, realism, and flexibility, and models the behaviors of diverse charging profiles, specifying constraints based on time of the day, day of the week, charging durations, state-of-charge (SoC) thresholds, and charger preferences (AC or DC); integrating 50 EV models with different battery capacities, energy consumption rates and charging capabilities. From this catalog of EV models, five representative cars were selected for detailed analysis, ranging from small-battery EVs like the Dacia Spring to high-autonomy vehicles such as the Audi A6 Sportsback e-tron.

A central focus of the study is the categorization and analysis of unsatisfied trips; those that could not be completed due to insufficient battery charge or were inhibited from recharging due to restrictions from predefined charging policies. For this study, nine different charging policies were simulated and analyzed, ranging from highly flexible to time-restricted approaches.

Anonymized trip data were obtained from five Italian provinces: Milano, Asti, Grosseto, Sassari, and Trieste; selected to represent diverse geographical, demographic, and territorial contexts. These cities vary in population density and area, seeking to capture variations in driving behavior influenced by urban size, road networks, and typical trip patterns.

Over 90% of trips are shorter than 35 km, while seasonal trends highlight longer trips during summer vacations and specific holidays.

The results of the simulations indicate that flexible charging policies consistently achieve the highest satisfaction rates, often exceeding 93%, whereas restrictive policies lead to a greater proportion of unsatisfied trips. EV adoption and trip satisfaction depend not only on vehicle performance but also on aligning charging policies with specific user behavior conditions.

Cross-city analysis showed that, despite differences in territory and population density, average trip distances, including typical maximum distances and average parking times per user, fall within the capabilities of small-battery EVs. With a flexible charging policy, Milano could reach up to 85% of satisfied users (being

the least adaptable), while Sassari emerges as the most adaptable city, achieving 98% satisfaction, mostly with low-range EVs. However, under stricter policies, the forecast changes significantly: overall satisfaction rates drop, with Sassari still leading at 46.5%, followed by Milano at 39.3%. In this scenario, fulfilling user needs requires higher-range EVs compared to the flexible policy case.

The study suggests that, with well-designed policies and adequate infrastructure, BEVs can meet daily mobility demands efficiently and sustainably, supporting broader EV adoption in urban environments with driving patterns similar to those observed in the studied cities. For users who regularly undertake longer trips, however, selecting vehicles with greater autonomy and adopting a planned charging strategy remains essential to ensure high satisfaction levels.

Acknowledgements

I would like to thank my supervisors, Luca Vassio and Danilo Giordano, for their patience and guidance throughout the process of this research.

Above all, I am deeply grateful to my family for standing by me from afar during this journey. Their unconditional faith, love, support, and encouragement gave me the strength to continue, even in the most challenging moments.

I am also deeply grateful to the Vaira Rodríguez family, who welcomed me as one of their own and contributed in countless ways to making this journey more enjoyable and meaningful. Their kindness, care, and genuine interest in my wellbeing made me feel at home and supported during every step of the way.

To my friends, whether near or far, who brightened my days and brought joy, laughter, and encouragement throughout this journey, thank you.

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Chapter 1

Introduction

The global shift toward sustainable mobility has accelerated the adoption of Electric Vehicles (EVs) as a viable alternative to internal combustion engine (ICE) vehicles. EVs offer multiple benefits, including reduced greenhouse gas emissions, lower air pollution, and decreased dependence on fossil fuels. The European Climate Law writes into law the goal set out in the European Green Deal for Europe's economy and society to become climate-neutral by 2050. The law also sets the intermediate target of reducing net greenhouse gas (GHG) emissions by at least 55% by 2030, compared to 1990 levels. [1]

The first half of 2025 marked a significant milestone for the European battery electric vehicle (BEV) market, with new registrations up 34% compared to the same period in 2024. This substantial increase underscores the region's ongoing transition towards electrified mobility and highlights the success of supportive policies and investments in charging infrastructure. For the full year, electric car sales in the United States are expected grow almost 10% in 2025, with a slight increase in the electric car sales share.[2]

In a European context, according to the latest available data from July 2025, electric cars held a market share of 16.8% in France, 18.4% in Germany, 8.9% in Spain, and 21.3% in the United Kingdom. In the same month, Italy remained at 4.9%, while countries like Belgium and the Netherlands recorded market shares of 31.8% and 30.9%, respectively. In Italy, the market share of e-cars thus rose to 4.8%, up from 3.4% in August 2024.[3]

In Latin America, sales volumes and penetration rates doubled in many countries, with electric cars reaching a market share of 4% in 2024. Brazil towered over other countries in the region with nearly 125 000 electric car sales, more than twice the number of 2023 sales, and the electric sales share doubled to 6.5%. Costa Rica, Uruguay and Colombia also achieved impressive EV market shares of around 15%, 13% and 7.5%, respectively. These increases are in large part the result of government incentives such as tax exemptions, reduced registration fees, a relaxation of traffic restrictions for EVs, and relatively high fossil fuel prices. [4]

However, their widespread adoption also introduces new challenges related to energy management, charging infrastructure, and user behavior. Understanding how EV users interact with charging networks and how charging policies affect trip feasibility is crucial for designing strategies that maximize satisfaction and ensure efficient use of resources.

Battery Electric Vehicles rely on limited battery capacities, making trip planning and charging decisions central to daily mobility. Unlike ICE vehicles, whose refueling is fast and widely accessible, BEV users must consider the availability, location, and type of chargers, as well as vehicle-specific parameters such as battery size, energy consumption, and charging rates. These factors, combined with user habits and urban contexts, can lead to scenarios where trips may be partially or fully uncompleted if charging strategies are not appropriately aligned with mobility patterns.

1.1 Context and Motivation

Despite the rapid growth of EV markets, challenges remain in understanding how different user behaviors, vehicle characteristics, and urban environments interact with charging strategies. Many EV users face uncertainties regarding charging availability, optimal charging times, and the impact of limited battery capacities on trip feasibility. Additionally, potential users transitioning from ICE vehicles may be hesitant to adopt EVs, as they are unsure whether an EV can reliably meet their daily mobility needs.

These challenges highlight the need for data-driven tools that can simulate EV usage, evaluate charging policies, and assess trip satisfaction under realistic conditions.

Using these tools, a general assessment per city can be obtained from the provided user samples to evaluate the potential adaptability of each city to an e-mobility transition. Additionally, the same tools could be applied to individual case scenarios, allowing a single user to input their trip data and driving behavior into a simulator to analyze any unsatisfied trips and their underlying causes, providing greater confidence in deciding whether to transition to an EV.

This thesis is motivated by the need to bridge this knowledge gap by combining empirical driving data with a flexible, scalable Battery Electric Vehicle simulator. By analyzing real trips in different Italian cities and evaluating multiple charging strategies, the study aims to provide insights into how charging policies influence user satisfaction, how vehicle performance aligns with typical urban mobility patterns, and what strategies can support broader EV adoption. To achieve these goals, the following objectives are defined:

Objectives:

- Enhance an existing BEV simulator to improve realism, scalability, efficiency, and flexibility.
- Replicate and analyze user trips from five Italian cities with diverse geographical and demographic contexts to assess EV adoption feasibility.
- Categorize and analyze the causes of unsatisfied trips under specific charging policies to assess their impact on trip satisfaction and user behavior in each city.
- Compare BEV simulator results with empirical public charging data to gain insights into how closely the simulations reflect real-world behavior.
- Identify suitable vehicle models and charging strategies that support daily mobility needs and foster broader EV adoption.

1.2 Thesis Structure

The structure of this thesis is divided by chapters, following a logical progression from Related Work, Methodology, Results and finally Conclusions.

- **Chapter 1: Introduction**

  Provides the context and motivation for the study, setting the stage for the specific objectives of the thesis.

- **Chapter 2: Related Work**

  This section reviews existing research and studies relevant to the adoption and usage of Battery Electric Vehicles (BEVs), establishes the foundation and justification for enhancing the BEV simulator and evaluating charging policies in the context of Italian cities.

- **Chapter 3: Data Management**

  Details the sources of the empirical driving data and explains how the data were structured in preparation to be used as input for the simulations. Describes the collection, preprocessing, and characterization of the data used in the thesis.

- **Chapter 4: Methodology**

  Describes the predefined charging policies considered in the study, detailing the rules, constraints, and flexibility levels applied for each policy. Next, it introduces the enhanced BEV simulator, explaining its features, presents the methodology used to evaluate BEV trip feasibility. Later, outlines the methodology for categorizing unsatisfied trips, identifying cases where trips could not be completed due to insufficient battery charge or were restricted by charging policies.

- **Chapter 5: Results**

  Contains the outcomes of the BEV simulations and analyses conducted in the study. It summarizes the characteristics of the replicated trips, across the five Italian cities. The section then evaluates the performance of different charging policies, highlighting their impact on trip satisfaction and user behavior. It also includes the categorization of unsatisfied trips.

- **Chapter 6: Conclusions**

  Discusses the impact of different charging policies on trip satisfaction and the main causes of unsatisfied trips, emphasizing the importance of aligning vehicle performance and charging strategies with user behavior and city-specific conditions.

Chapter 2

Related Work

The current thesis continues the work previously conducted by Jamalof [5], who used real-world driving data from 1,000 insurance customers to assess EV adoption feasibility, focusing on user-specific trip patterns. A custom-designed simulator formed the core of that study, evaluating EV feasibility by processing inputs such as trip data, user parameters (e.g., anxiety thresholds, minimum parking durations), vehicle parameters (e.g., battery capacity, consumption per road type, maximum charging power), and grid parameters (e.g., AC and DC charging powers). The first phase of Jamalof's study adopted a more abstract approach, as input parameters were not tied to specific EV models, instead considering diverse driving conditions and vehicle energy demands. The second phase introduced nine distinct charging profiles to account for real-world variations in charging behavior, incorporating conditions such as charging during weekdays or weekends, overnight or daytime hours, and SoC thresholds. These charging policies, initially defined in Jamalof's work, were later adjusted and refined for the current research. Phase Three retained the nine user profiles from Phase Two to ensure consistency in behavioral modeling, but shifted focus from hypothetical battery capacities and consumption patterns to the real-world specifications of commercially available EVs. The current thesis builds directly upon this framework, overcoming the limitations of Jamalof's simulator by providing a deeper analysis of the causes of unsatisfied trips and incorporating the complexity of evaluating trips across different geographical contexts.

Part of the limitations observed during Jamalof's research concerned the scalability and flexibility of the simulator. The programming techniques employed were designed for a relatively small dataset of about 4 million trips from the city of Asti. Computations were performed row-by-row, which becomes infeasible for larger datasets, like those considered in the current study, due to long execution times and the increased complexity of handling large volumes of data. Regarding flexibility, the simplicity of the constraints set for each charging policy limited the simulator's responsiveness. For example, a vehicle parked even slightly outside the allowed charging window, by just one minute, would not trigger a charging session. Similarly, SoC thresholds were applied only to a few predefined policies, while for other policies the vehicle could recharge anytime it was parked, provided the minimum parking time was met. Another area for improvement was the definition of charging window hours, which were previously set based on theoretical assumptions. In the current study, these timings were adjusted using actual user data from each city, allowing the simulator to better reflect real-world charging habits.

Another studies on the field considers a latent-based segmentation framework for the investigation of charging behaviour of electric vehicle users. This paper analyses observational data from a representative sample of German BEV owners who provided information on mileage and charging activities over a timeframe of eight weeks. BEV charging patterns, related vehicles kilometres travelled (VKT) and battery charging behaviour are assessed via a multifaceted empirical framework that pairs a hazard survival-based model with a log linear regression approach. A latent class method is also employed to segment BEV owners into different charging segments. The model suggests two types of charging behaviour exist, consisting of regular and irregular chargers. Charging frequencies and patterns are found to be radically different between the two groups under study, with regular chargers estimated to charge their vehicles 1.5 times more than irregular chargers. Lastly, the framework proposed is used to explore how charging behaviour will mutate due to both technology advancements (BEV driving range improvements) and user-centric factors (VKT variations). Neither technological or user factors are predicted to substantially affect the inter-charging duration of irregular chargers, whereas both increasing BEV driving ranges and reducing VKT results in a longer elapsed time between two consecutive charges for regular chargers. [6]

Macaluso proposes a modelling approach to represent parking activities in urban areas and obtain key indicators of the electric energy required. The agent-based model reproduces the dynamics of user parking and assesses the impacts on the electricity grid during the day. Since the focus is on parking activities, no detailed data on vehicle trips are required to apply the standard demand modelling approach, which would require Origin-Destination matrices to simulate traffic flows on the road network. Preliminary results concerning the city of Turin are presented for simulated scenarios to identify zones where charging demand can be critical and peak events in electric power over the day. The model is designed to be scalable for all European cities because, as the case study shows, it uses available data. The results obtained can be used for the design of charging infrastructure (power and type) by zones. [7]

Gerboni offers a novel user-friendly methodology to assess different recharging scenarios. The methodology was applied to a real case study on an international car manufacturer based in Italy. Several scenarios were addressed regarding the recharge at home of electrified vehicles, considering meter upgrades and different recharging speeds. The Vehicle-to-Grid (V2G) case was also investigated. The results show that PHEVs are the most flexible solution where domestic slow recharging is the only or preferred choice. BEVs become viable when at least a 4.5 kW supply contract is available together with a fast-recharging infrastructure with a suitable home grid, or where daytime parking lots with recharging facilities are available. The application of the proposed methodology to a real case study suggests that this approach can usefully help decision makers to identify the type of investments to be made and where they should be carried out. [8]

Di Luca proposes a dedicated battery management system (BMS) is required to contemporaneously optimize the battery's state of charge (SoC) and to increase the battery's lifespan through tight control of its state of health (SoH). Despite the advancements in the modern onboard BMS, more detailed data-driven algorithms for SoC, SoH, and fault diagnosis cannot be implemented due to limited computing capabilities. To overcome such limitations, the conceptualization and/or implementation of BMS in-cloud applications are under investigation. The present study hence aims to produce a new and comprehensive review of the advancements in battery management solutions in terms of functionality, usability, and drawbacks, with specific attention to cloud-based BMS solutions as well as SoC and SoH prediction and estimation. Current gaps and challenges are addressed considering V2X connectivity to fully exploit the latest cloud-based solutions. [9]

Alamin proposes the structure of a battery digital twin designed to reflect battery dynamics at the run time accurately. To ensure a high degree of correctness concerning non-linear phenomena, the digital twin relies on data-driven models trained on traces of battery evolution over time: a state of health model, repeatedly executed to estimate the degradation of maximum battery capacity, and a state of charge model, retrained periodically to reflect the impact of aging. The proposed digital twin structure will be exemplified on a public dataset to motivate its adoption and prove its effectiveness, with a high degree of accuracy and inference and retraining times compatible with onboard execution. [10]

Regarding trips satisfaction, transport authorities and providers use various standardized indicators in order to evaluate the system performance. The main objective of this study is to identify the most significant variables that describe travellers' satisfaction. An original survey and stakeholder consultation were conducted across Europe. The relations between overall satisfaction and travel experience variables, subjective well-being indices, travel-related attitudes as well as individual- and trip-specific attributes were investigated for individual trip stages as well as the whole journey experience. The segmentation of the population into distinguished travellers' groups revealed distinctively different sets of main determinants of their satisfaction with various trip stages. The results of this survey will facilitate the development of a traveller satisfaction measurement tool. [11]

Chapter 3

Data Management

3.1 Data Collection

For the development of the experiments and respective simulations, it was used the data provided by *UnipolTech*. The data is collected by the Insurance Agency using a data collector developed by themselves, named *Unibox*; the black box provided by the insurance company *Unipol* for its customers, has several features, starting with its tracking system, which is installed in the vehicle and is satellite-based. This system allows constant monitoring of the user's driving style and is already installed in about 4 million vehicles in Italy. [12] The data was gathered from a sample of their customers who volunteered for data analytics.

The anonymized data was provided for five carefully selected cities, chosen to represent diverse contexts based on differences in geographical location, population density, and territorial area. The selected cities are Milan, Asti, Grosseto, Sassari, and Trieste.

Table 3.1: Resident population distribution and territorial area for each city. [13]

City	**Population** (residents)	**Area** (km^2)	**Density** (residents/km^2)
Milano	3 247 623	1 574.45	2 063
Asti	207 310	1 508.95	137
Grosseto	215 328	4 502.28	48
Sassari	471 653	7 697.80	61
Trieste	228 049	212.83	1 072

The cities were chosen to capture variations in driving behavior influenced by differing territorial sizes and population densities. As detailed in Table 3.1, Milan exemplifies a mid-size urban area with a high population density; Asti represents a smaller territory with moderate density; Grosseto encompasses a larger area with sparse population; Sassari combines extensive land coverage with low density; and Trieste is characterized by a limited area coupled with a dense population, still with a low number of residents.

3.2 Data Characterization

3.2.1 Raw Data

The data supplied by *UnipolTech* with the information of the trips made by their users contained the following structure:

	id_veicolo	id_viaggio	categoria_strada	istante_start	istante_stop	tot_km
0	1	0	E	2024-08-27 18:15:46	2024-08-27 18:18:16	0.71
1	1	0	U	2024-08-27 18:15:46	2024-08-27 18:18:16	2.02
2	1	1	U	2024-08-27 19:59:20	2024-08-27 20:24:41	8.51
3	1	1	E	2024-08-27 19:59:20	2024-08-27 20:24:41	2.02
4	1	2	U	2024-08-27 21:15:03	2024-08-27 21:16:05	0.00

Figure 3.1: Example of the raw trips dataset and its features.

- **id_veicolo:** The vehicle ID is an anonymous identifier that allows to distinguish the trips performed by that user.
- **id_viaggio:** The trip ID identifies the unique trip made by each user, it can be repeated for the same user if the trip was routed on different road types. The number can be restarted on each month.
- **categoria_strada:** The road category identifies the different kind of roads a user could take.
  - E: Extra urban
  - U: Urban
  - A: Highway
  - "-": Other type of roads
- **istante_start:** The start timestamp of the trip segment.
- **istante_stop:** The stop timestamp of the trip segment.
- **tot_km:** The distance of the trip segment in kilometers (km).

Besides the information of the trips, it was also provided some anonymous information related to the users and the kind of vehicle that is driven by them.

	id_veicolo	commerciale	eta_approx	genere	tipo_veicolo	annomese_immatricolazione	aliment_auto
0	1	N	48	M	7	2016-06	B
1	2	N	65	M	1	2018-05	D
2	3	N	70	F	1	2015-09	B
3	4	N	36	M	1	2016-06	D
4	5	N	61	M	1	2016-05	B

Figure 3.2: Example of the user information dataset and its features.

- **commerciale:** Indicates if the vehicle is used for commercial purposes or not.
  - N: Personal Vehicle
  - S: Commercial Vehicle
- **eta_approx:** Approximate age of the user.
- **genere:** The gender of the user. Commercial vehicles do not have an assigned gender.
  - M: Male
  - F: Female
- **tipo_veicolo:** The categorization of the vehicle based on its purpose, engine size and weight.
  - 1: Passenger private car
  - 2: Bus
  - 4: Truck over 3.5 tons
  - 6: Special-purpose truck over 3.5 tons (camper)
  - 7: Motorcycles ($>$ 50 cc)
  - 8: Truck up to 1.5 tons
  - 9: Truck from 1.5 to 3.5 tons
  - 10: Special-purpose truck up to 1.5 tons
  - 11: Special-purpose truck from 1.5 to 3.5 tons
  - 12: Agricultural machinery
  - 13: Mopeds ($<$ 50 cc)

- **annomese_immatricolazione:** Year and month of the subscription to Unipol services.
- **aliment_auto:** The fuel type of the vehicle.
  - B: Gasoline
  - D: Diesel
  - E: Electrical
  - G: LPG
  - H, I: Hybrid
  - M: Methane
  - "-": Unknown

3.2.2 Filtered and Curated Data

The experiments conducted in this thesis focus on the evaluation of trips and users within defined spatial and temporal boundaries. All data exceeding these boundaries were excluded. The following filters were applied to the raw data sequentially, in the order presented below:

- **Time filter:** The analysis considers a one-year period, from June 01^{st}, 2024, to May 31^{st}, 2025. Any trips falling outside this time frame were discarded accordingly.
- **Short Stop Durations:** Due to the nature of the data collection through *Unibox*, certain trips were split by brief stops lasting only a few seconds or minutes. To correct for this, a threshold was applied to define the minimum duration of a valid stop. Trips separated by pauses shorter than this threshold were merged together and treated as a single trip. The threshold was defined in 1 minute after evaluating the stopping time distribution of the cities.
- **Duration and Distance Outliers:** To ensure data reliability, trips were filtered based on their duration and distance to exclude unrealistic values. The distributions of both metrics were analyzed to establish suitable thresholds. Trips shorter than 1 minute or longer than 12 hours were removed. Similarly, trips covering less than 5 meters or more than 800 kilometers were excluded. The assumption is that extremely long trips, likely include breaks due to the driver's physiological needs; such trips are treated as separate segments after each stop, and therefore not affected by this filter.

- **Active Users:** The analysis includes only *active users*, defined as those who completed at least one trip in every month of the analysis period. Users who did not use the vehicle for an entire month were excluded from the dataset.

- **Monthly duration gaps:** Since trips may not begin or end precisely at the start or end of each month, gaps often exist between trips. These gaps are necessary to compute parking durations. To ensure monthly consistency, where the sum of driving and parking durations equals the total number of hours in the month, additional rows were inserted into the dataset to account for these intervals.

Table 3.2: Total number of trips and users before and after filtering for each city.

City	**Number of Trips**			**Number of Users**		
	Raw	Filtered	Percentage	Raw	Filtered	Percentage
Milano	167 418 918	113 213 729	67.6%	156 779	89 761	57.3%
Asti	13 810 127	9 368 413	67.8%	10 657	6 608	62.0%
Grosseto	23 919 766	16 345 873	68.4%	17 851	11 223	62.9%
Sassari	34 068 209	21 539 607	63.2%	23 841	13 624	57.1%
Trieste	6 303 595	4 211 655	66.8%	6 282	3 902	62.1%

After the filtering process (*Table 3.2*), the retained trip data exceeded 63% for all cities. Sassari and Milan experienced the highest reduction in user counts; however, both still retained over 57% of their original users. Notably, despite the lower retention percentage, these two cities maintained a higher absolute number of users compared to others with a greater retention rate.

Figure 3.3 illustrates the progression of trip and user counts after each filtering step. The values were independently normalized against their total raw value to facilitate comparison across cities. Overall, it is evident that the active user filter accounts for the most significant reduction in both trips and users.

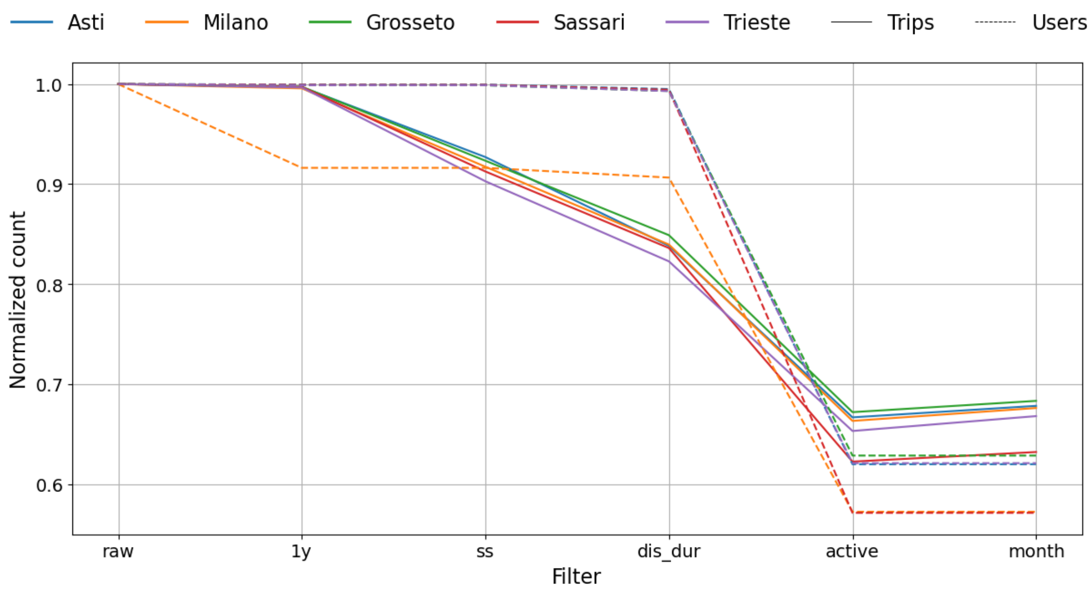


Figure 3.3: Normalized count for filtered trips and users per city.

3.2.3 Data Exploration considering only *Active Users*

After applying the *Active Users* filter described above, the users under study are distributed across cities and genders, as detailed in Table 3.3. A portion of these users corresponds to commercial usage.

Table 3.3: User counts and gender distribution by city.

City	Total	Commercial		Female		Male	
		Count	%	Count	%	Count	%
Milano	89 761	6 998	7.80	33 568	37.39	49 195	54.81
Asti	6 608	321	4.86	2 663	40.30	3 624	54.84
Grosseto	11 223	499	4.45	4 601	41.00	6 123	54.55
Sassari	13 624	548	4.02	5 492	40.31	7 584	55.67
Trieste	3 902	199	5.10	1 585	40.62	2 118	54.28

Overall, the gender distribution appears relatively homogeneous across the cities, with female users representing approximately 40%, male users around 55%, and commercial users accounting for the remaining 5%. Milano stands out as the city with the highest share of commercial users (7.8%) while also recording the lowest proportion of female users (37%). In contrast, Grosseto reports the highest share of female drivers at 41%, whereas Sassari shows the lowest proportion of commercial vehicles, with only 4% of its fleet.

For the demographic characterization, the active users were grouped also into age bins:]18–25],]25–35],]35–45],]45–55],]55–65],]65–75],]75–85], and]85–100] years. The youngest user across all cities is 18 years old, and the oldest is 100 years old. Users classified under the "unknown" category correspond to commercial vehicles.

The highest concentration of users is found in the 55–65 age group (Figure 3.4) with about the 20-25% of the users, a pattern consistent across all the studied cities. Asti represents the city with the youngest user population leading the first part of the age curve, while Trieste reports a higher percentage for older age groups compared to the other cities. It is noticeable that only Milano and Sassari have users above the 85 years old.

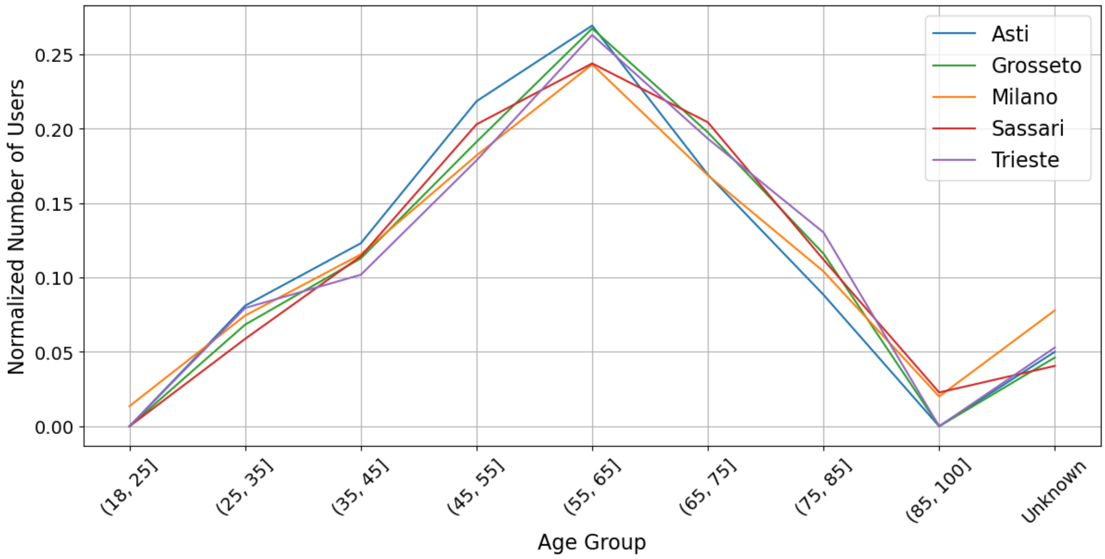


Figure 3.4: Normalized count for users per age group by city.

The user information dataset also provides the fuel type required by each user's vehicle. The distribution of users by city and fuel type is presented in Table 3.4. In general, the current fleet in each city is dominated by gasoline vehicles, followed by diesel. Although the presence of electric vehicles (EVs) is limited, these users are of particular importance for the purposes of this thesis, as they will be used for validation by representing real trips made with Battery Electric Vehicles *(BEVs)*.

Table 3.4: Number of users per fuel type and city

City	Diesel	Electrical	GPL	Gasoline	Hybrid	Methane	Unknown
Milano	22 775	374	5 805	48 948	8 791	844	2 224
Asti	2 825	18	700	2 446	387	65	167
Grosseto	5 531	18	771	3 832	566	250	255
Sassari	6 334	27	355	5 497	508	11	892
Trieste	1 214	9	38	2 268	253	5	115

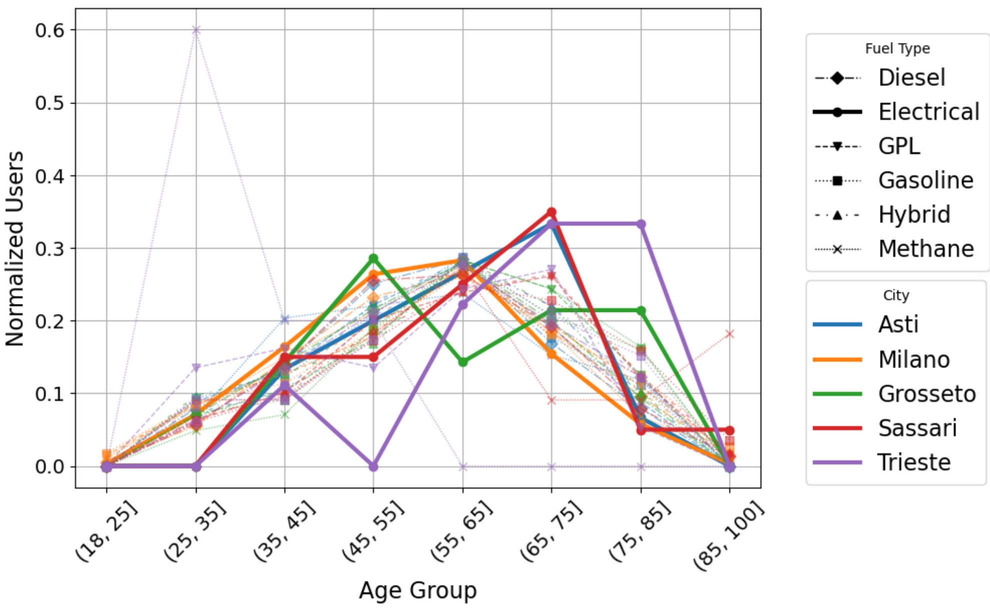
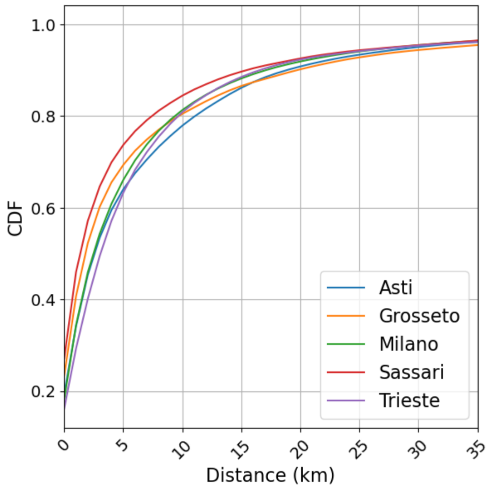


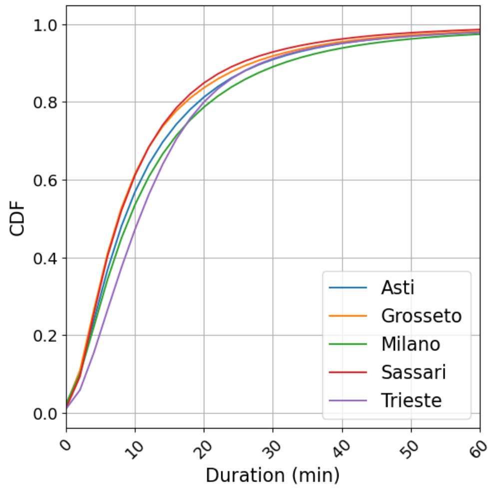
Figure 3.5: Normalized count of users by age group per fuel type.

By combining the information presented in Figure 3.4 and Table 3.4, it is possible to analyze the preferred fuel type across different age groups, as illustrated in Figure 3.5. The distributions were normalized by city and fuel type over the various age groups. A notable outlier is the relatively high adoption of methane-fueled vehicles among users aged 25–35 in Trieste. In general, the other fuel types display consistent patterns, with the largest share of users observed in the 45–75 age range. This trend primarily reflects the overall age distribution of the user, as seen in Figure 3.4, rather than a significant influence of fuel type. Focusing on electric vehicle (EV) users (represented by the thicker line), some distinctive patterns emerge. In Milano, EV users are comparatively younger, with the city being the only case where EV adoption is observed among individuals aged 18–25. Milano also reaches its peak among the 55–65 age group, which accounts for nearly 30% of its EV users. In Grosseto, the highest share of EV users is observed in the

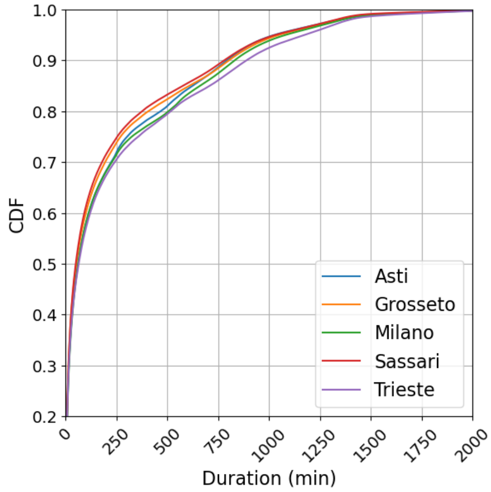
45–55 group, while in Asti, Sassari, and Trieste the peaks are shifted toward the older 65–75 age group. Trieste, in particular, shows a relatively high concentration of users also within the 65–85 range, although this distribution is less representative given the limited number of EV users in the sample.



(a) Trip distance



(b) Trip duration



(c) Stopped duration

Figure 3.6: Cumulative distribution functions for (a) trip distance, (b) trip duration, and (c) stopped duration between trips, for each city.

Digging into the trips themselves, the distributions of the distance and trip duration, as well the stopped time in between the trips per user on each of the cities were computed as a Cumulative Distribution Function as seen on Figure 3.6.

Figure 3.6a illustrates the CDF of trip distances. Across all five cities, over

90% of trips are shorter than 35 km, with more than 60% being under 5 km. Sassari records the highest frequency of short trips, while Trieste shows the lowest. However, Trieste surpasses Asti, Grosseto, and Milano in the proportion of trips longer than 6 km.

Figure 3.6b presents the CDF of trip durations. Similarly, more than 90% of trips across all cities last less than one hour. In Sassari and Grosseto, approximately 60% of trips last under 10 minutes, while in Trieste the corresponding threshold is 15 minutes; Asti and Milano fall between these values. Milano exhibits the highest share of long-duration trips, which may be associated with traffic congestion during peak hours.

Finally, Figure 3.6c shows the distribution of inter-trip stop durations per user. Considering the start and end time of the trips, the parking times can be estimated. The inter-trip parking times can be computed as follows, the start of the parking will be the end time of the last trip, and the end of the parking will be the start time of the following trip for each independent user.

These values are incorporated into the original dataset for each trip, representing the parking duration in minutes following the respective trip. The input dataset for the BEV simulator (described in Section 4) is required to contain the columns illustrated in Figure 3.7.

	vehicle_id	trip_id	start_trip	end_trip	dis_highway_Km	dis_urban_Km	dis_other_Km	dis_tot_Km	trip_duration	end_parking_time	park_dur_min
0	2	pre_trip	2024-06-01 00:00:00	2024-06-01 00:00:00	0.000	0.000	0.000	0.000	0.000000	2024-06-02 07:33:21	1893.350000
1	2	2	2024-06-02 07:33:21	2024-06-02 07:45:48	0.000	0.400	0.000	0.400	12.450000	2024-06-02 07:48:28	2.666667
2	2	3	2024-06-02 07:48:28	2024-06-02 07:58:50	0.000	3.099	2.000	5.099	10.366667	2024-06-02 11:38:46	219.933333
3	2	4	2024-06-02 11:38:46	2024-06-02 11:52:49	11.699	0.000	3.401	15.100	14.050000	2024-06-02 15:45:04	232.250000

Figure 3.7: Example of the input dataset to the BEV simulator.

These pauses can be considered as potential opportunities for EV charging, providing valuable insights for evaluating the charging policies, which will be discussed in Section 4. The results for the five cities, indicate that more than 20% of stops last longer than 6 hours (360 minutes), around 20% fall between 2 and 6 hours, and approximately 60% are shorter than 2 hours. Being Trieste the city with higher density of longer stop durations.

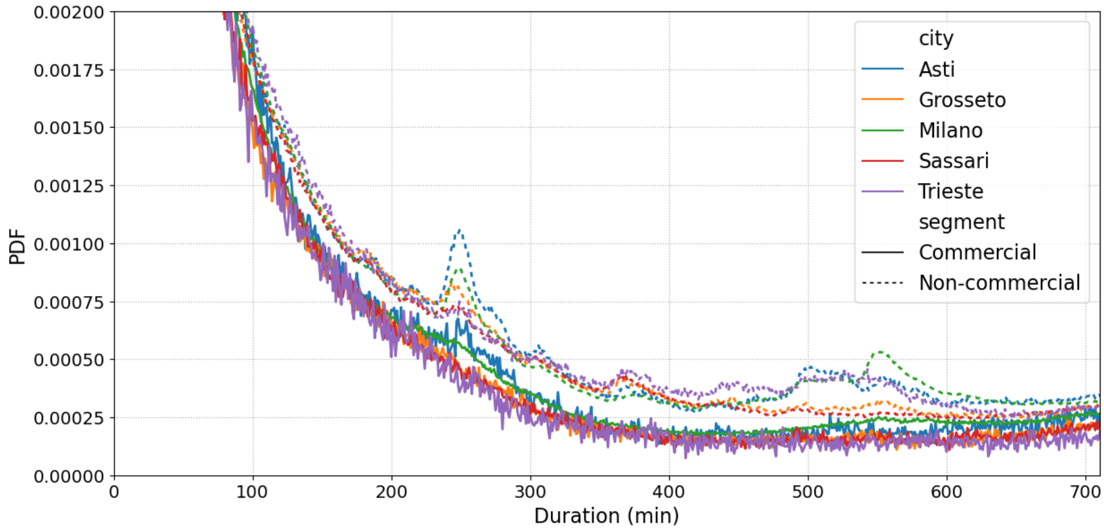


Figure 3.8: Probability density function of stopped time between trips for commercial and non-commercial vehicles, for each city.

By merging the datasets provided by *UnipolTech* using the *vehicle_id*, it is possible to characterize the trips for a specific category of users. In this case, we can evaluate the inter-trip stopping behavior of the commercial and non-commercial users.

Figure 3.8 presents the probability density function (PDF) of inter-trip stop durations per city for *Commercial* and *Non-Commercial* users. While the overall trend is similar for both categories, commercial users tend to exhibit a higher density of shorter stops. The plot has been truncated to highlight longer pauses. In this scaled view, non-commercial users show a pronounced peak at approximately 4 hours (250 minutes), reflecting a consistent stopping behavior. In Asti, commercial vehicles display a slight tendency toward a similar pattern. Additionally, a smaller increase is observed around 8 hours (500 minutes), although this pattern is not consistent in Sassari and Grosseto. These local variations in stop duration are likely influenced by typical working hours, where a standard workday of 8–9 hours may be interrupted by a midday break, or by just personal habits.

Another notable observation for commercial users is that, starting with Milano, there is an increase in the frequency of stops around 500 minutes, then at 600 minutes the other cities starts to rise the frequency as well for longer pauses, probably due to break schedules.

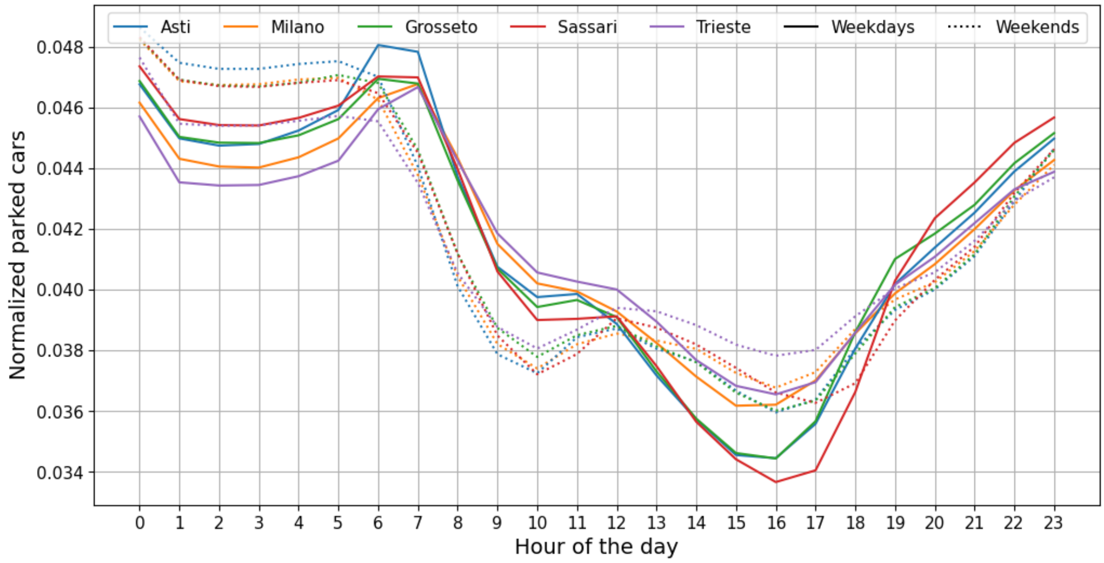


Figure 3.9: Hourly distribution of stopped vehicles per city.

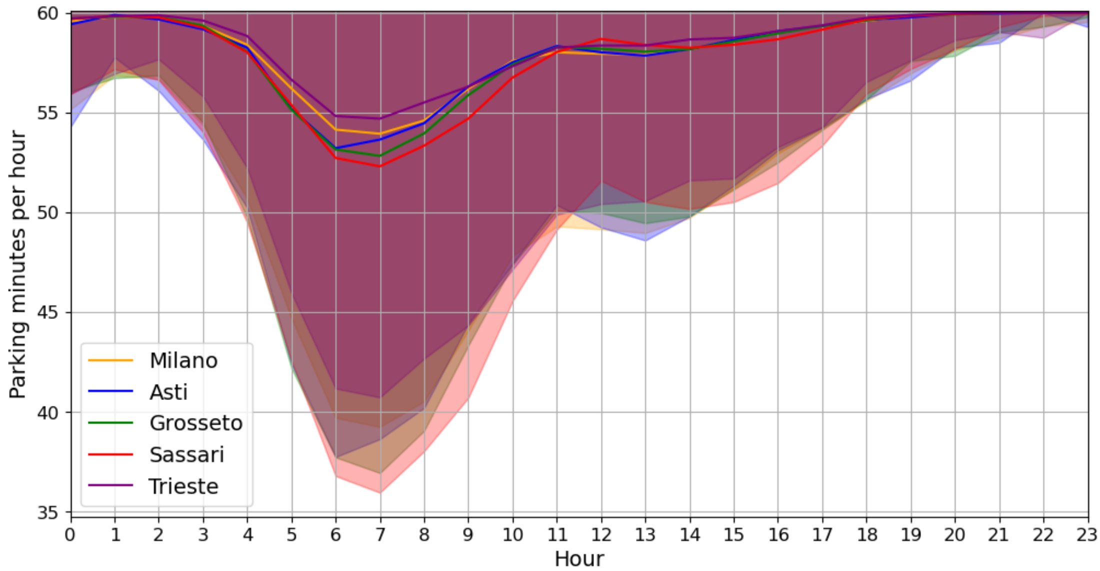


Figure 3.10: Hourly distribution of parking minutes per city.

By considering the established parking times per city, based on the start and end time of the parking, it can be estimated the number of cars that are parked on a given hour of the day. This analysis have being done also by splitting the parking in Weekdays (Monday to Friday) and Weekends (Saturday and Sunday).

Figure 3.9 illustrates the normalized distribution of users stopped at each hour of the day. The normalization was performed separately for weekends and weekdays for each city as follows:

Considering $U_{d,h}$ to be the number of users stopped in hour h on day d, where $d \in D$ (the dataset per city) and $h \in H = \{0,1,\ldots,23\}$ (the set of hours in a day). It was first computed the sum of users that where stopped per hour across all the days on the respective dataset:

$$S_h = \sum_{d \in D} U_{d,h}, \quad \forall h \in H$$

Then, it was computed the total sum across all hours:

$$S_{\text{total}} = \sum_{h \in H} S_h$$

Finally, it was normalized the hourly count to obtain the proportion of users stopped at each hour:

$$P_h = \frac{S_h}{S_{\text{total}}}, \quad \forall h \in H$$

P_h represents the normalized distribution of users stopped at hour h which at the same time are the values being displayed on Figure 3.9.

The distribution shows, as expected, that during the early morning, when users begin their journeys, the number of parked vehicles decreases. Following this initial drop, a relatively flat trend is observed on weekdays between 10:00 and 12:00, followed by a second decline around midday, indicating higher vehicle usage in the afternoon. The global minimum number of parked vehicles occurs around 16:00, after which the number of parked users gradually increases. While the general trend is similar across cities, there is a noticeable shift toward earlier vehicle usage during weekends, with a local minimum around 10:00 and a global minimum at 17:00 in Sassari and at 16:00 for the other cities. This analysis provides valuable insights for establishing charging policies, as it highlights periods during which vehicles are most frequently parked. Such periods, corresponding to high peaks or intervals with slower gradients, represent optimal opportunities for scheduling EV charging.

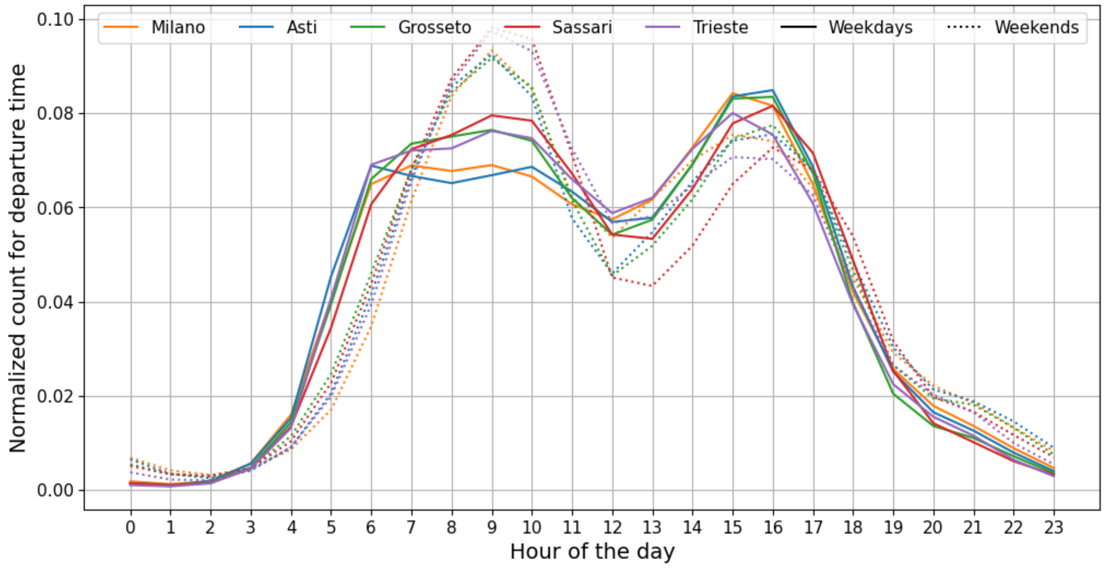
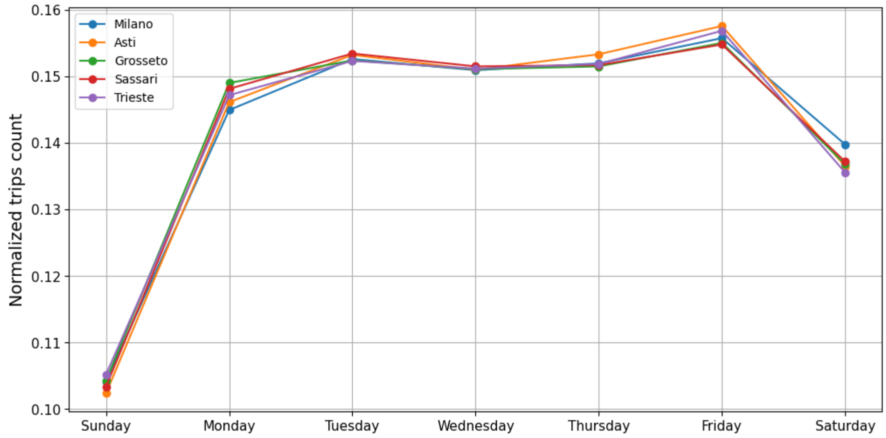


Figure 3.11: Hourly distribution for the trips start time.

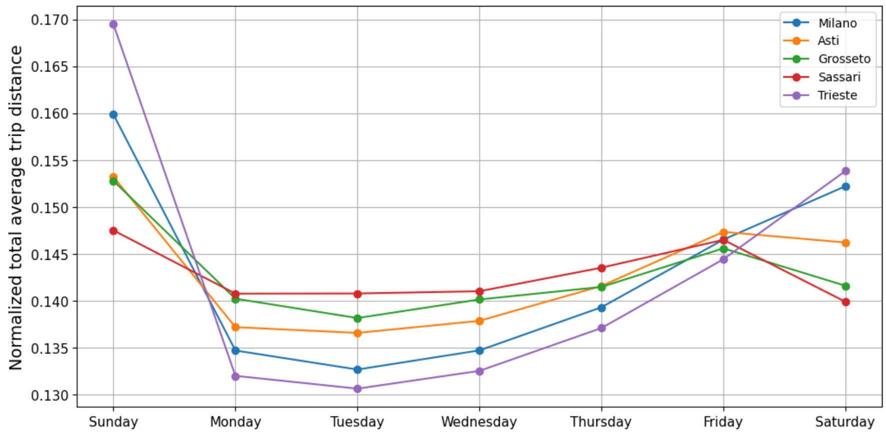
Figure 3.10 shows the distribution in minutes of the parking duration per hour. The curve represents the average time duration on each hour, while the colored area is its respective standard deviation. The highest variability is shown at 7:00, where in average the users are parked over 50 minutes, but there are still users parking only between 35 and 40 minutes.

For the Figure 3.11, the start time of the trip has being selected in order to aggregate the trips by hour, in this way it can be clearer the hours of the day where the vehicles are usually needed the most, hence, the eventual EV battery should be ready to start the trip. The Figure 3.11 indicates the total number of trips that started at a given hour normalized against the total number of trips made on the respective city during the weekdays and weekends.

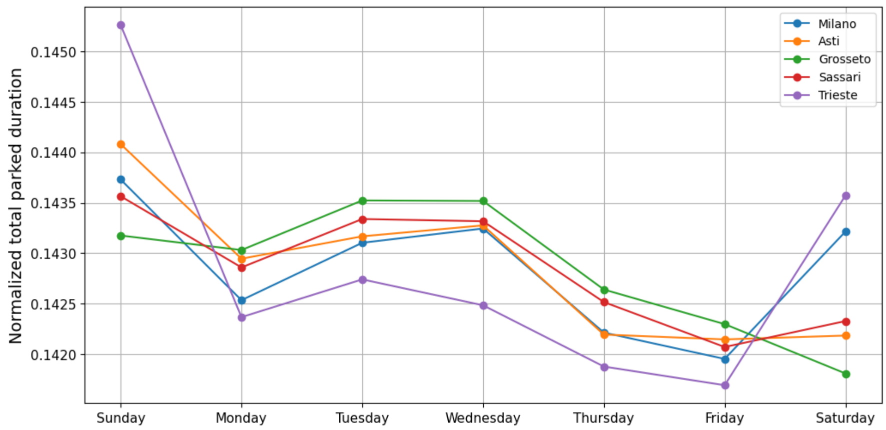
From the distribution it can be noticed that most of the trips start between 04:00 and 20:00 hours. The highest density of trips are started between 06:00 and 17:00. And the maximum peak of trips during weekdays are usually started between 15:00 and 16:00. There is a significant reduction of trips started during mid-day. In particular during the weekends, the start time of the trips are usually later in comparison to the weekday trips and its global maximum is during the morning around 09:00.



(a) Trips count



(b) Trip average distance



(c) Trip stopped duration

Figure 3.12: Weekday density distribution for (a) trips count, (b) average distance, (c) stopped duration.

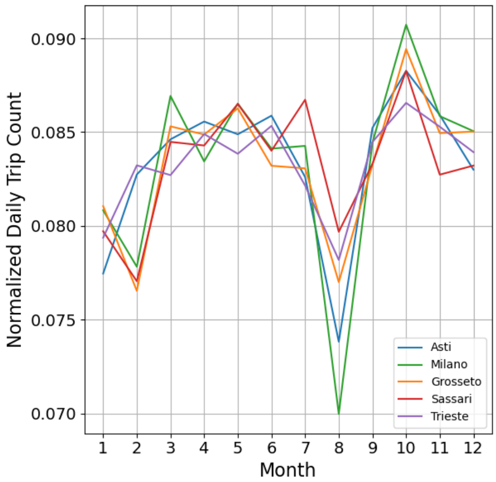
To gain a deeper understanding of travel patterns, the distribution of trips across the days of the week was analyzed (Figure 3.12a). The results indicate a consistent trend, with the majority of trips occurring from Monday to Thursday and a slight increase observed on Fridays. In contrast, weekend activity is considerably lower: trips on Saturdays account for less than 14% of the total, while those on Sundays represent fewer than 11% of all trips.

Nonetheless, as shown in Figure 3.12b, which presents the average distance traveled per user on each day of the week, it can be observed that although the number of trips during weekends is lower, the distances covered tend to be longer. In contrast, weekdays exhibit a higher frequency of trips, but these trips are generally shorter in distance.

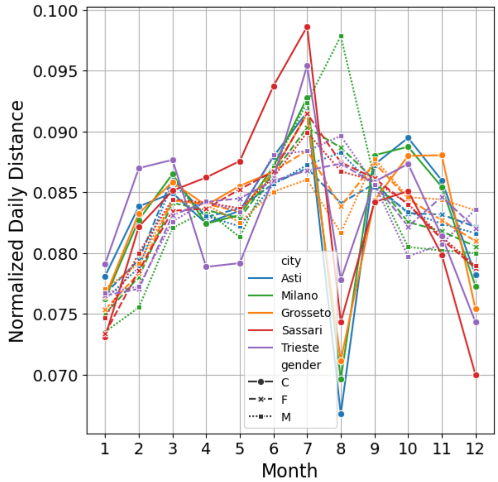
In Sassari, however, the difference between weekday and weekend distances is minimal. As noted in Figure 3.6a, Sassari has the highest density of short trips among the cities. In this case, the reduced number of trips during weekends, without a corresponding increase in distance, suggests that vehicles are simply used less frequently. While in Milano and Trieste the usage of the vehicles during the weekends is remarkable, as those are the cities with the longest distances traveled mostly during the Sundays.

Focusing on Figure 3.12c, the total number of parking hours where computed and aggregated by day of the week. It allows to understand the days of the week where the vehicles are mostly parked and eventually are available for eventually charging the battery of the EV. It can be observed that in general, Thursdays and Fridays are the busiest days, where the cars are not often parked, actually there are a lot of trips happening with average distances. During the Saturdays Milano and Trieste, seems to perform few trips of long distances, but apparently once arrived to the far destination the vehicles are parked for several time. On Sundays most of the cities reports a high percentage of vehicles parked. Despite these daily variations, the overall distribution of parking durations is relatively uniform, averaging 14.35% with a tolerance of approximately $\pm 0.15\%$.

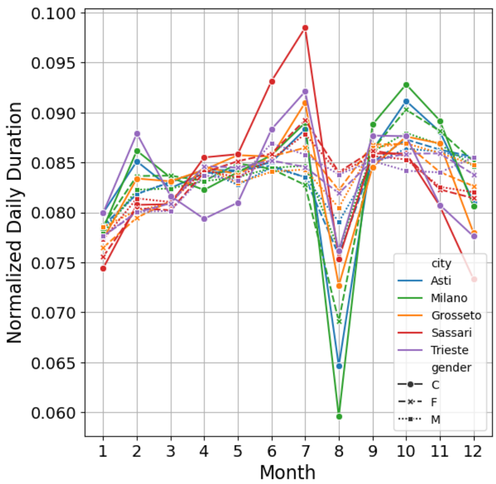
Given that the datasets encompasses an entire year of trips, analyzing the potential influence of seasonal variations on user behavior can provide valuable insights into driving patterns. Figure 3.13 presents monthly aggregated information on trip distance, duration, and inter-trip stop duration. Each subplot has been independently normalized by city and by user category (male, female, and commercial users), and further adjusted for the number of days in each month. Consequently, the final values are divided by 28, 30, or 31, depending on the respective month.



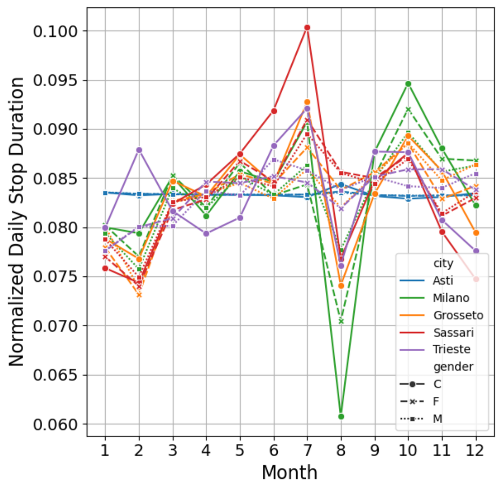
(a) Number of Trips



(b) Trip Distance



(c) Trip duration



(d) Stopped duration

Figure 3.13: Normalized number of trips per month (a) and monthly daily averages of (b) trip distance, (c) trip duration, and (d) stopped duration between trips, for each city, segmented by gender.

In general, the trends of the different parameters are similar across cities, reflecting the expected seasonal behavior, although the effect is more pronounced in some locations, like Milano. The largest variation occurs in August, corresponding to the summer vacation period in Italy. During this month, the total number of trips decreases, but the distances of individual trips tend to be longer. This pattern also impacts the daily average of inter-trip stop durations, which are reduced compared to other months. Moreover, as the overall number of trips is lower, the average trip duration is correspondingly reduced.

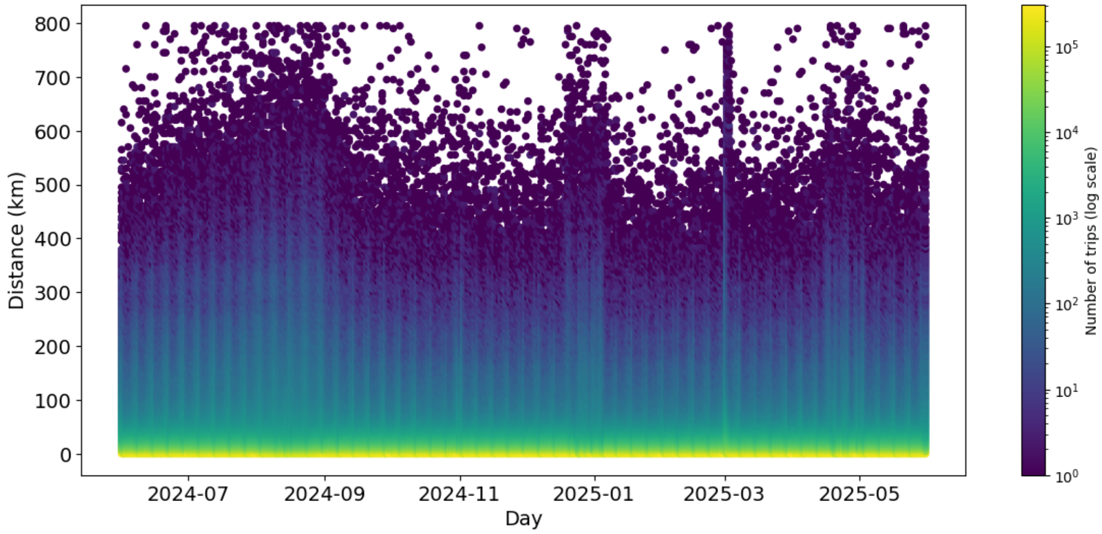


Figure 3.14: Trip durations density per date along the year for Milano.

Other seasonal events may also influence user driving behavior, but as they occur over shorter periods (e.g., long weekends or single days), their impact is partially masked in monthly averages. As shown in Figure 3.14, several clusters of trips with higher distances can be observed throughout the year represented by the vertical lines with a lighter color, meaning higher density of trips during those days for a wide range of distances, even for longer distances than usual. Weekend trips consistently contribute to increased distances, while certain dates show a more pronounced effect, often associated with holidays or special events. Specifically, from July to late September (summer vacations) there is a cluster of trips generally below 600 km. Additional clusters appear around November 1st (All Saints' Day), late December to early January (Christmas and New Year), during Easter (with even longer distances), and in May, corresponding to the long weekend around Labor Day.

3.3 Electric Vehicles Available on the Market

From the Electric Vehicle Database [14], there were chosen 50 different Electric Vehicle Models from different car manufactures and ranging different performances, costs and capabilities. These EV models are reported on Table 3.5.

The features of each EV model that were collected from EV Database consists on the *City Consumption*, *Highway Consumption* indicating the performance of the vehicle depending on the road type, and also the *Combined Consumption* for trips mixing different road types, the three consumption features indicates the Energy consumed per kilometer (Wh/km). It is also specified the the charging power (in kW) for the Fast Chargers using DC and for AC Chargers, finally it is also indicated the *Battery Capacity* installed on the car in terms of energy (in kWh). For simplicity, and due to the nature of the trips data, the *Combined Consumption* is preferred to generalize the performance of the car. The *Autonomy* (in km) was computed by calculating the ratio of the fully charged battery capacity and the Consumption, resulting in an average of the distance the car could perform with the SoC at 100% before the trip.

$$Autonomy = \frac{BatteryCapacity}{Consumption \cdot 10^3}$$

Table 3.5: Electric cars with consumption and charging data.

#	Brand	Model	City Consumption (Wh/km)	Highway Consumption (Wh/km)	Combined Consumption (Wh/km)	AC Charging (kW)	DC Charging (kW)	Battery Capacity (kWh)	Autonomy (km)	Price (Euro)
1	Audi	q4 sportback e-tron 45	121	190	154	11	175	80	519	€54,950
2	Audi	q4 sportback e-tron 45 quattro	131	203	164	11	175	77	469	€56,950
3	Audi	q4 e-tron 55 quattro	134	211	171	11	175	77	450	€61,000
4	Audi	sq8 e-tron	163	255	206	11	168	106	514	€100,350
5	Audi	q4 sportback e-tron 35	120	189	153	11	145	52	339	€47,600
6	Audi	a6 sportback e-tron performance	112	165	137	11	270	94.9	692	€75,600
7	Audi	q6 e-tron performance	134	213	171	11	260	94.9	554	€68,800
8	BMW	i4 edrive35	108	164	134	11	180	67.1	500	€57,600
9	BMW	i4 edrive40	109	166	136	11	207	81.3	597	€60,600
10	BMW	ix xdrive40	138	215	175	11	148	71	405	€77,300
11	Dacia	spring electric 45	98	172	132	6.6	34	25	189	€16,900
12	Fiat	500e hatchback 42 kwh	105	173	138	11	85	37.3	270	€34,990
13	Fiat	grande panda	112	190	148	7.4	100	43.8	295	€24,990
14	Fiat	500e hatchback 24 kwh	101	170	133	11	50	21.3	160	€30,990
15	Fiat	600e	108	178	141	11	85	50.8	360	€36,490
16	Ford	explorer extended range	122	195	156	11	135	77	493	€48,510
17	Ford	mustang mach-e er rwd	129	207	165	11	150	91	551	€78,000
18	Hyundai	inster long range	102	170	133	11	85	46	345	€25,400
19	Hyundai	kona electric 65 kwh	113	184	145	11	105	65.4	451	€47,190
20	Kia	niro ev	112	183	146	11	80	64.8	443	€45,690
21	Kia	ev6 standard range 2wd	120	193	154	11	175	54	350	€44,990
22	Kia	ev6 long range awd	127	203	162	11	263	80	493	€53,990
23	Mercedes-Benz	eqb 250+	116	183	147	11	102	70.5	479	€53,514
24	Mercedes-Benz	eqe suv amg 43 4matic	150	232	189	22	173	90.6	479	€139,438
25	Mercedes-Benz	eqt 200 standard	134	225	176	22	80	45	255	€39,623
26	Mercedes-Benz	EQB 300 4MATIC	133	211	168	11	112	66.5	395	€55,519
27	Morris-Garage	MG4 Electric 51 kWh	114	185	147	6.6	87	50.8	345	€34,990
28	Morris-Garage	MG4 Electric 77 kWh	119	191	152	6.6	144	74.4	489	€45,990
29	Morris-Garage	MG MG4 Electric XPOWER	130	213	169	6.6	142	61.7	365	€46,990
30	Peugeot	e-208 50 kWh	108	175	138	7.4	101	46.3	335	€36,525
31	Peugeot	e-208 51 kWh	103	169	134	7.4	100	48.1	358	€40,875
32	Peugeot	e-3008 73 kWh	132	212	170	11	160	73	429	€48,750
33	Peugeot	e-5008 97 kWh Long Range	137	220	176	11	160	96.9	550	€55,350
34	Peugeot	e-308	114	185	147	11	100	50.8	345	€44,765
35	Renault	Megane E-Tech EV60 220hp	105	171	136	22	129	60	441	€40,990
36	Renault	Megane E-Tech EV40 130hp	103	167	133	22	85	40	300	€42,000
37	Renault	Scenic E-Tech EV87 220hp	123	198	158	22	150	87	550	€47,900
38	Renault	5 E-Tech 52kWh 150hp	107	176	141	11	100	52	368	€32,900
39	Skoda	Enyaq 85	117	186	148	11	135	77	520	€48,900
40	Skoda	Enyaq 60	117	187	151	11	124	60	397	€44,400
41	Skoda	Skoda Enyaq Coupe RS	117	179	145	11	175	77	531	€60,850
42	Skoda	Enyaq iV 85x 4x4	120	190	152	11	175	77	506	€48,900
43	Skoda	Enyaq iV Coupe 60	112	173	140	11	124	58	414	€44,400
44	Tesla	Model Y	113	177	142	11	170	57.5	404	€45,970
45	Tesla	Model Y Long Range	118	185	149	11	250	75	503	€52,990
46	Tesla	Model Y Performance	124	195	156	11	250	75	480	€61,990
47	Tesla	Model 3	93	142	116	11	170	60	517	€40,970
48	Tesla	Model 3 Long Range Dual Motor	98	148	122	11	250	75	614	€49,990
49	Volvo	EX40 Single Motor ER	134	219	174	11	205	79	454	€55,490
50	Volvo	EX30 Single Motor	121	196	156	11	134	49	314	€44,990

By evaluating the most recent statistics from the market sells on EVs [15], and comparing the models chosen from the EV Database, five car models where chosen as reference of the further evaluations of the BEV Simulator. The *Audi A6 Sportsback e-tron Performace* (highlighted in green) represents the car with the highest autonomy, big battery and fast charging (DC), the *Dacia Spring* and *Fiat 500e Hatchback* are representing the smallest batteries and lowest autonomy; while *BMW ix* and *Tesla Model Y* are a medium range in between, these were chosen from the most popular EVs sold on Europe during the last year (2025) according to JATO, a global leader in automotive data, analysis and intelligence [16].

3.3.1 Unsatisfied Trips: Exceeding Vehicle's maximum Autonomy

Considering the Table 3.5 and the trips datasets per city, it is possible to identify the amount of trips that are exceeding the autonomy of each car model per location. The Figure 3.15 identify the percentage of users that are affected by the autonomy of each car model to fulfill their trips. While the Figure 3.16 identifies the percentage of trips that are not fully satisfied by each car model.

The coloring of the cells represents the intensity of the impact, with darker colors indicating poorer performance and lighter colors indicating better performance. The heatmap was normalized in both directions, vertically and horizontally, allowing for the identification of the city most adversely affected for each car model (horizontally), and of the car model that has the greatest negative impact on a city (vertically).

As expected, vehicles with smaller batteries rank highest in terms of user dissatisfaction and trip-related limitations. Considering the different cities, Sassari is the less affected, followed by Grosseto, Asti, Trieste and finally Milano being the one with highest unsatisfaction rate.

As an usage example, the vertical color gradient can be used to identify the car models that best match the needs of each city, by defining a threshold for the percentage of users considered acceptable to compromise. For instance, considering Trieste, if a 5% of users could be left with some unsatisfied trips, this means that EV models with an autonomy higher than 441 km are acceptable, and only the 0.01% of the trips will be affected.

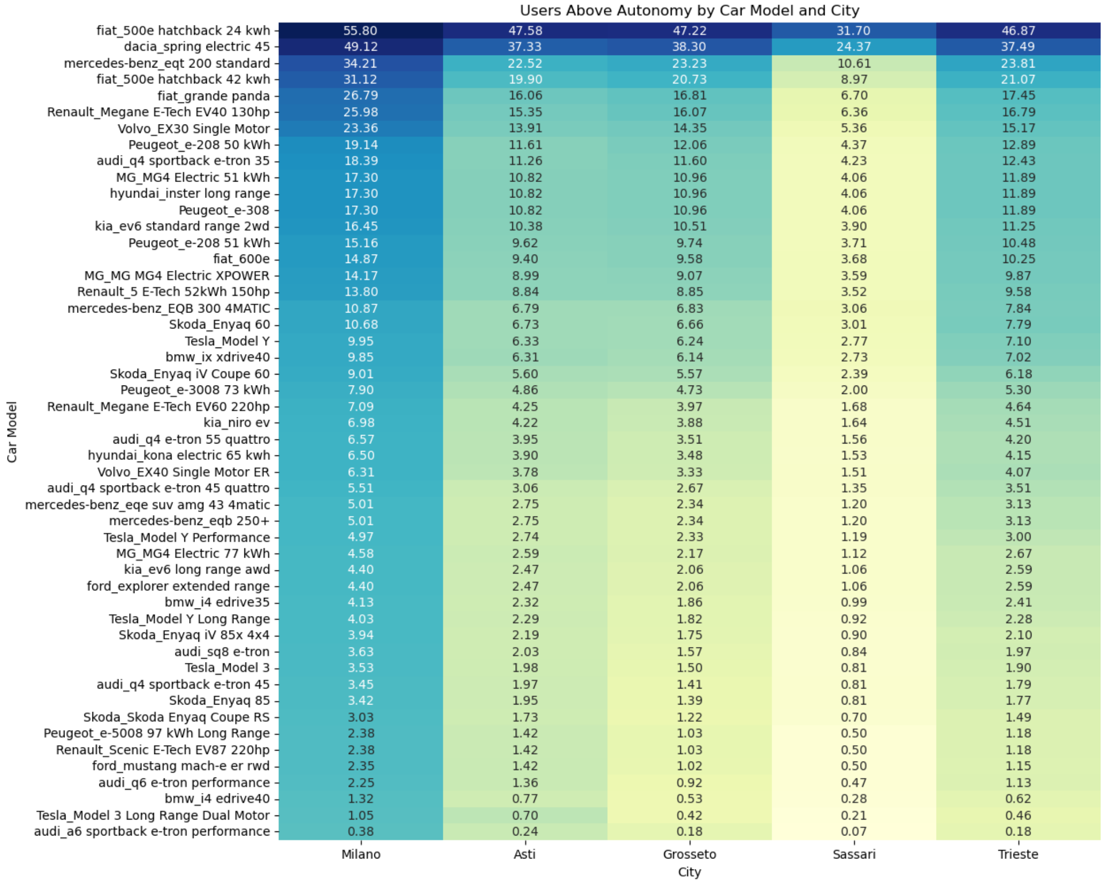


Figure 3.15: Percentage of users affected by trips above the autonomy of each EV model, per city.

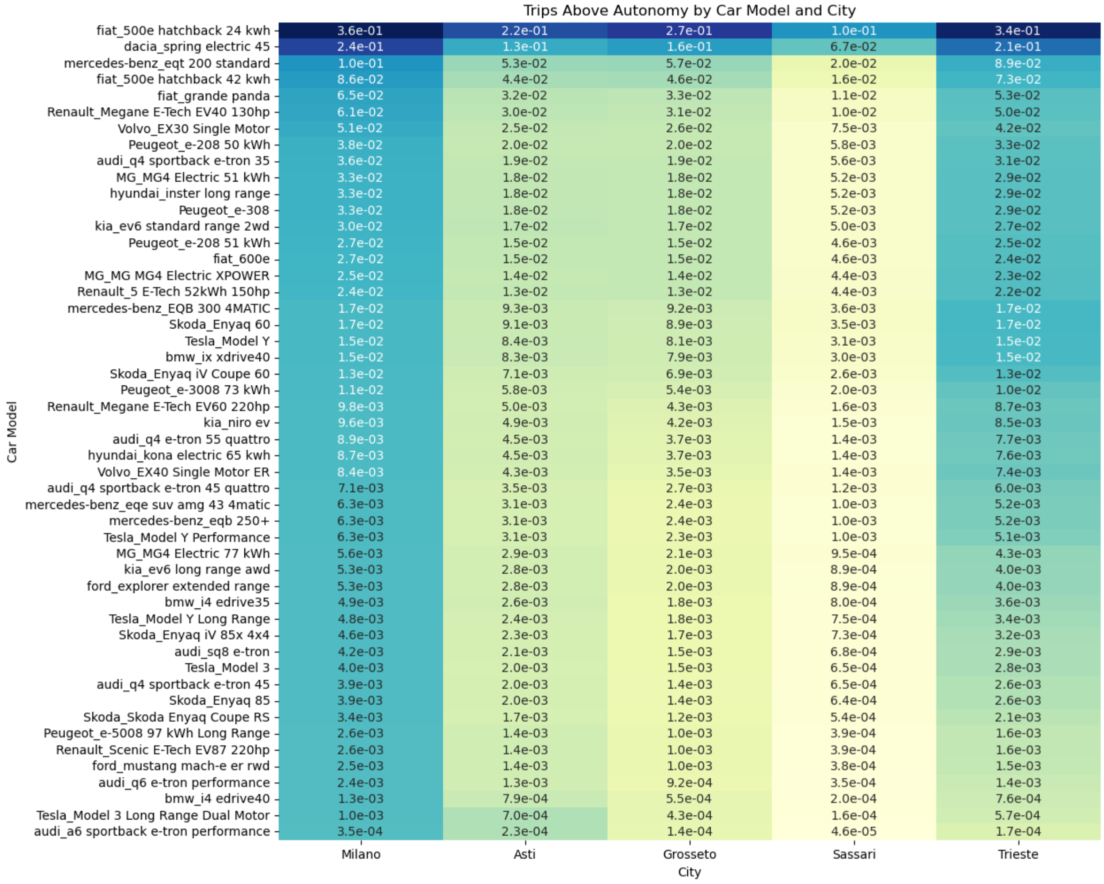


Figure 3.16: Percentage of trips above the autonomy of each EV model, per city.

Chapter 4

Methodology

Using as a reference the preprocessed and characterized data illustrated in the previous sections, this chapter focuses on describing the process undertaken to enhance the BEV simulator, building upon the foundations developed in the thesis of Jamalof [5], and the later categorization of the unsatisfied trips for the different cities and car models under study.

The BEV Simulator focuses on replicating the charging behaviors of diverse user profiles, each characterized by unique habits, time constraints, and infrastructure preferences. By incorporating these profiles into a comprehensive simulation framework, the study bridges the gap between the dataset representing real-world trips undertaken in internal combustion engine (ICE) vehicles and the algorithmic logic that governs EV charging decisions. This methodological approach enables a nuanced exploration of charging behaviors, providing insights into how various factors influence EV adoption [5].

The BEV simulator developed for this Master Thesis was further enhanced in terms of efficiency, scalability, organization, realism, and flexibility. In parallel, its performance was validated against empirical data derived from real EV trips and public charging station usage.

Naturally, as in the case of ICE trips, certain EV trips cannot be fully satisfied due to the inherent battery limitations. The scope of this work is therefore to categorize such unsatisfied trips and to analyze in detail the underlying reasons why specific BEV models may fail to accommodate them.

4.1 BEV Simulator

4.1.1 Definition of Predefined Charging Policies

An early stage of the BEV simulator was developed by Jamalof [5], where that research enabled the identification of nine charging policies defined by fixed parameters. These policies were established to replicate the charging habits of EV users. The parameters focused on describing the type of charger (slow AC or fast DC), the restricted time windows during which charging could occur, the specific weekdays when charging was allowed, as well as the minimum and maximum charging duration (if applicable). Additionally, they considered the minimum bulk State of Charge (SoC), when specified, and whether charging sessions could extend overnight across consecutive days.

The early stage of the simulator considered rigid charging conditions, such that if a stopping event did not begin exactly within the fixed pre-established time window, the charging session was not permitted. This strict approach resulted in multiple long stopping events without previous charging of the battery and eventually leading to a high percentage of unsatisfied trips, even in cases where trips were made with actual EVs. Based on this observation, the current thesis redefined the charging conditions associated with the pre-established policies to improve realism.

The first improvement was the introduction of the concept of *overlapping* with the pre-established windows. Specifically, if a stopping event began outside the allowed charging window, its duration was evaluated. If the event extended into the start of the authorized window and satisfied the minimum charging duration constraints, the charging session was permitted for the portion of time falling within the allowed window.

Another implementation done to improve the realistic behavior of the EV users, was to define a threshold for the bulk SoC, meaning the state-of-charge of the battery before a charging session, in this way, it can be replicated the necessity to recharge the battery only if it is bellow a given threshold, leading to a more realistic approach of how real EV users react and also considering a small aspect for the concept of State-of-Health (SoH) of the battery itself. Previously, only three of the nine charging policies had this threshold, mostly to limit the recharge only for cases with very low bulk SoC.

According to Jamalof [5], each user profile encapsulates specific rules governing when, where, and how often vehicles are charged. These rules account for:

- **Time of day** (e.g., overnight, afternoon charging).
- **Day of the week** (e.g., weekday, weekend charging habits).

- **Charging duration thresholds** (e.g., minimum or maximum charging times).
- **Charger preferences** (e.g., AC slow chargers, DC fast chargers).

Below is a synopsis of the nine distinct user predefined profiles and the modifications made for the current research:

1. **Frequent Users**
    - **Description:** Regularly charge their vehicles at home, typically overnight or during the weekends they may leave vehicles connected for extended periods, due to reduced usage during leisure days.
    - **Time of day:** Overnight (from 21:00 to 08:00 of next day) or for weekends (from Friday 21:00 to Monday 06:00)
    - **Day of week:** Weekdays and Weekends.
    - **Charging duration:** Minimum of 7 hours for overnight charging and more than 11 hours on weekends.
        - **Update:** Minimum of 6 hours, in general.
    - **Charger preference:** Primarily AC chargers (up to 11 kW) at home or in residential areas.
        - **Added:** Minimum bulk SoC threshold of 75% for recharge.
2. **Visitor Users**
    - **Description:** Make short, spontaneous visits to commercial or business districts, charging while running errands or attending meetings.
    - **Time of day:** Afternoon (from 12:00 to 19:00). Charge can happens only during the same day.
    - **Day of week:** Weekdays and Weekends.
    - **Charging duration:** Between 1.5 up to 7 hours.
        - **Update:** Between 2 up to 6 hours.
    - **Charger preference:** Predominantly use DC fast chargers (46 kW or higher).
        - **Added:** Minimum bulk SoC threshold of 75% for recharge.
3. **Taxi Drivers**
    - **Description:** Charge only overnight at home or in residential areas.
    - **Time of day:** Overnight (from 21:00 to 08:00 of next day).

- **Day of week:** Weekdays and Weekends.
- **Charging duration:** From 7 hours.
  - **Update:** From 6 hours.
- **Charger preference:** AC slow charging, ensuring a full battery for daily operations.
  - **Added:** Minimum bulk SoC threshold of 75% for recharge.

4. **Car Sharing Fleets**

- **Description:** Operate on a high utilization model, requiring multiple short charges throughout the day to keep vehicles available.
- **Time of day:** Anytime.
- **Day of week:** Weekdays and Weekends.
- **Charging duration:** Between 20 minutes to 1.5 hours.
  - **Update:** Between 20 minutes to 2 hours.
- **Charger preference:** Heavily rely on DC fast chargers (46-250 kW) to minimize downtime. Charging typically starts when the battery SoC drops to 20%.

5. **Conservative Drivers**

- **Description:** Overly cautious about low battery levels. They prefer AC chargers but use DC fast chargers in "emergency" cases for very low SoC.
- **Time of day:** Anytime.
- **Day of week:** Weekdays and Weekends.
- **Charging duration:** From 20 minutes.
- **Charger preference:** Primarily AC chargers (11 - 22 kW) for routine top-ups when SoC falls below 50% and with DC fast chargers (46-94 kW) as a backup for emergency use when SoC drops below 20%.
  - **Update:** AC chargers when SoC falls below 75% and with DC when it falls bellow 20%, as before.

6. **Business Travelers**

- **Description:** Require efficient, quick charging during long-distance weekday trips.
- **Time of day:** During travel breaks within typical working hours (from 08:00 to 18:00). Charge can happens only during the same day.

- **Day of week:** Monday through Friday.
- **Charging duration:** From 20 minutes.
- **Charger preference:** DC fast chargers (46 - 250 kW) along highways or business corridors.
  - **Added:** Minimum bulk SoC threshold of 75% for recharge.

7. **Weekend Travelers**
   - **Description:** Plan weekend getaways, relying on fast chargers to top up quickly during trips.
   - **Time of day:** Anytime.
   - **Day of week:** Saturday and Sunday.
   - **Charging duration:** Between 20 minutes up to 2 hours.
   - **Charger preference:** DC fast chargers (46 - 250 kW) when SoC drops bellow 30%.

8. **Workplace-Dependent Drivers**
   - **Description:** Lack access to home charging and rely solely on office chargers.
   - **Time of day:** Typical during working hours (from 08:00 to 18:00). Charge can happens only during the same day.
   - **Day of week:** Monday through Friday.
   - **Charging duration:** From 6 hours.
   - **Charger preference:** AC chargers (3.2 - 22 kW) available at the workplace.
     - **Added:** Minimum bulk SoC threshold of 75% for recharge.

9. **Casual Users**
   - **Description:** Drive infrequently, charging at irregular intervals when SoC nears 20%. They may go days or weeks without charging if the vehicle is seldom used.
   - **Time of day:** Anytime.
   - **Day of week:** Weekdays and Weekends.
   - **Charging duration:** From 8 hours.
     - **Update:** From 6 hours.

- **Charger Preference:** Prefers AC slow charging (home or public) when SoC falls bellow 20%.

To summarize the predefined charging policies described before, on Table 4.1 it can be found the main characteristics and conditions for each of the updated version of the charging policies, where the mentioned times for charging hours are considered as follows:

- **Any time:** The charging session can take place regardless the time of the day.
- **Afternoon:** The charging session could take place only if the EV is connected between the 12:00 and 19:00.
- **Daytime:** The charging session could take place only if the EV is connected between the 08:00 and 19:00.
- **Overnight:** The charging session could take place only if the EV is connected between the 21:00 and 08:00 of the following day.

Table 4.1: Summary of updated predefined charging policies conditions.

Charging Policy	Charger	Time	Days	Duration	Bulk SoC	Overnight
Frequent Users	AC	Anytime → Overnight →	Weekends Weekdays	+6 hours	≤ 75%	Yes
Visitor Users	DC	Afternoon	All days	$2\,\text{h} \leq t \leq 6\,\text{h}$	≤ 75%	No
Taxi Driver	AC	Overnight	All days	+6 hours	≤ 75%	Yes
Car Sharing	DC	Anytime	All days	$20\,\text{min} \leq t \leq 2\,\text{h}$	≤ 20%	Yes
Conservative Driver	AC & DC	Anytime	All days	+20 min	≤ 75% (AC) ≤ 20% (DC)	Yes
Business Travelers	DC	Daytime	Weekdays	+20 min	≤ 75%	No
Weekend Travelers	DC	Any time	Weekends	$20\,\text{min} \leq t \leq 2\,\text{h}$	≤ 30%	Yes
Workplace Users	AC	Daytime	Weekdays	+6 hours	≤ 75%	No
Casual Users	AC	Anytime	All days	+6 hours	≤ 20%	Yes

4.2 BEV Simulator Engine

Regarding the engine responsible for managing each trip and updating the State of Charge (SoC) according to the charging policies, this section aims to describe the underlying processes and highlight the main improvements implemented in this research compared to the earlier version of the simulator.

The original simulator was developed in a Jupyter Notebook, with execution performed cell by cell. It was based on Python functions that used iterative loops with *for* cycles to evaluate trips one at a time. Separate functions handled the classification of parking sessions (according to the temporal conditions of the charging policies), the battery update behavior (following the charging preferences), and the overall simulation execution for a given car model, culminating in the generation of output files. These functions were repeated nine times, once for each charging policy, and were executed every two or three car models, which were stored as dictionaries in a notebook cell and created independently for each charging policy with the required features. Considering the 50 car models, this setup required an average of 25 executions per function for the nine different scenarios, resulting in approximately 225 executions per function to complete the 450 individual simulations, which might not be an efficient behavior.

In the updated version of the BEV simulator engine, the primary improvements concern scalability, efficiency, and flexibility, implemented in a well-organized manner.

Initially, the 50 car models and their respective features were organized and stored in a single *JSON* file, allowing the catalog to be read only once when invoking the function responsible for executing the complete set of simulations. Each entry in the catalog contains the information presented in Table 3.5, including the car's brand and model, consumption values (in Wh/km), and charging parameters such as AC and DC power (in kW) and battery capacity (in kWh). Entries in this catalog can be added, removed, or modified, and all entries present at the time of running the simulator are used to generate a replication of trips from the selected dataset, incorporating the features of each vehicle. This structure allows for straightforward scalability of the car models considered in the study.

```
[
    {
        "consumption": [
            {"city": 121,
            "highway": 190,
            "combined": 154,
            "brand": "audi",
            "model": "q4 sportback e-tron 45"}
        ],
        "charging": [
            {"ac_charging_power_kw": 11,
            "dc_charging_power_kw": 175,
            "battery_capacity_kwh": 80}
        ]
    }
]
```

Regarding the engine code itself, it had to be rewritten following the predefined baseline to achieve greater scalability and efficiency. As shown in Table 3.2, the total number of trips considered in this research is substantial, and since the simulations require a trip-by-trip execution to update the State of Charge (SoC) after each trip and recharge accordingly, the previous approach using iterative loops became unsuitable for handling this volume of data.

Consequently, the code was migrated from individual functions per predefined charging policy in a Jupyter Notebook to a dedicated Python module. This new implementation employs parallelization techniques to accelerate simulation times and manage large datasets efficiently, while avoiding hard-coded parameters, thus allowing flexibility for defining additional charging policies in the future.

The revisited simulator follows the same structure as defined by Jamalof [5]:

1. **Reading the EV features** from the JSON catalog.

2. Reading the trips dataset and **flagging** parking events as **opportunities to recharge** the battery, if permitted, based on the allowed charging times defined by the selected charging policy parameters. Using as baseline the algorithms of the previous BEV simulator, this approach consolidates all predefined charging policy flagging functions into a single generalized function, eliminating hard-coded values and replacing them with variable parameters to allow greater flexibility and customization in defining charging policies, while incorporating the overlapping window concept.

3. Preparing of the **consumption calculations** for each trip.

4. Execution of the **simulation process**, updating the State of Charge (SoC) according to the selected charging policy and EV characteristics, while also computing additional performance indicators.

5. **Generation of the output file**, with a custom name reflecting the parameters used during the simulation.

The figure 4.1 represents the flowchart describing the inputs to the BEV simulator and its respective output, which will provide the status of the SoC before and after each trip, the energy consumption and trip feasibility as will be detailed later on this section.

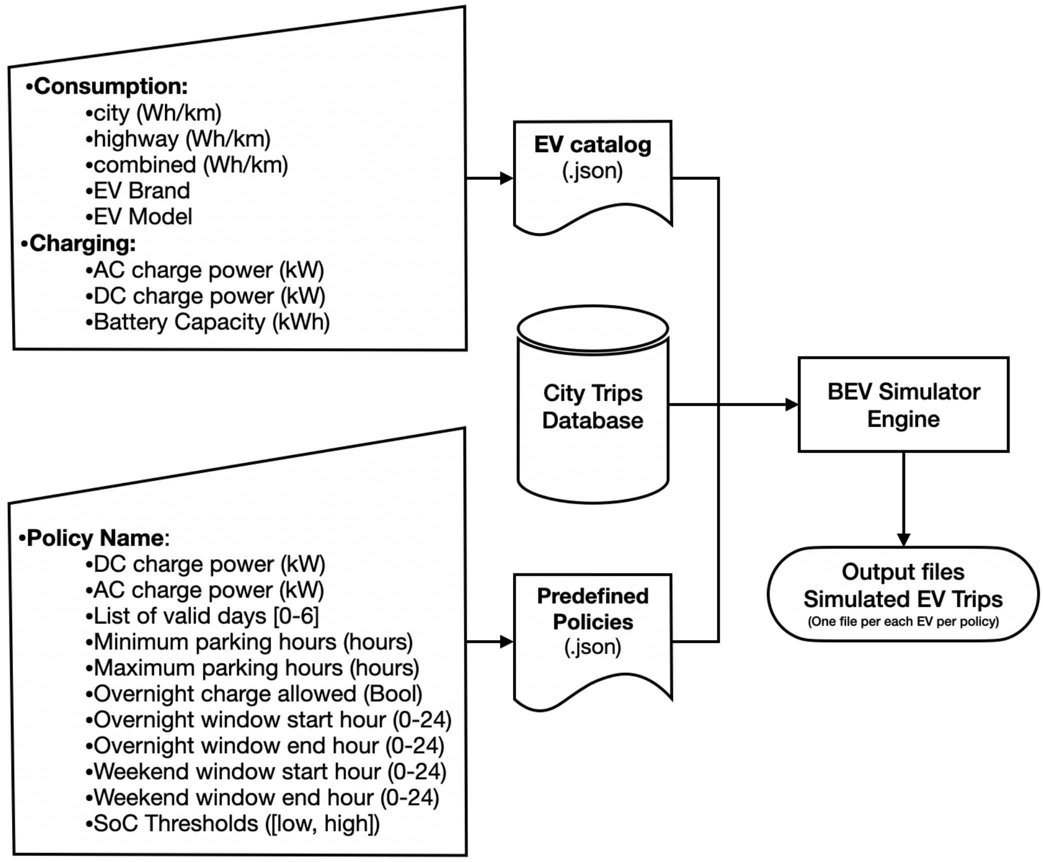


Figure 4.1: Flowchart of the BEV Simulator

The segment that follows examines each step of the process in detail.

4.2.1 Reading EV features

It is a function that takes as input the file path of the JSON catalog with the EV features. After reading the dictionary for each car model, it extracts the consumption and charging parameters. The output are two lists (consumption and charging) containing the values of these parameters for each entry in the catalog.

4.2.2 Flagging opportunities to recharge

First, a dataset containing the trips to be replicated with BEV behavior, in the format illustrated in Figure 3.7, is loaded as a Polars DataFrame. Polars is an open-source library for high-performance data manipulation, recognized as one of the fastest solutions for processing data on a single machine. It provides a well-structured, strongly typed API that is both expressive and user-friendly [17].

The flagging stage has been enhanced to accept multiple parameters, enabling the construction of a custom charging policy.

The input parameters are as follows:

- `minimum_parking_hours (float)`: Defines the lower bound in hours for the charging duration. (e.g., 20 minutes can be specified as 0.33).
- `maximum_parking_hours (float)`: Defines the upper bound in hours for charging duration.
- `overnight (bool)` Indicates whether the charging session is allowed to extend across consecutive days, spanning overnight hours. Valid values are `True` or `False`.
- `valid_days (list[int])`: A list of integers from 0 (Monday) to 6 (Sunday), representing the days of the week during which charging is permitted. The list may include specific consecutive days. If left empty, it implies that charging sessions are allowed on any day of the week (e.g., `[0,1,2,3,4]` for weekdays or `[]` for all days).
- `overnight_start_hour (int)`: Defines the starting hour of the overnight charging window, with valid values ranging from 0 to 23. This parameter is only applicable if `overnight` is set to `True`.
- `overnight_end_hour (int)`: Defines the final hour of the overnight charging window, with valid values ranging from 0 to 23. This parameter is only applicable if `overnight` is set to `True`.
- `weekend_start_charge_hour (int)`: Defines the starting hour of the charging window during weekends, with valid values from 0 to 23. This boundary applies exclusively to weekend charging sessions and is independent of the weekday configuration. In cases where the `overnight` parameter is set to `True` and the `weekend_start_charge_hour` exceeds the `weekend_end_charge_hour`, the `overnight_start_hour` will be used instead.
- `weekday_start_charge_hour (int)`: Defines the starting hour of the charging window during weekdays, with valid values from 0 to 23. This boundary applies exclusively to weekdays charging sessions and is independent of the weekend configuration. In cases where the `overnight` parameter is set to `True` and the `weekday_start_charge_hour` exceeds the `weekday_end_charge_hour`, the `overnight_start_hour` will be used instead.

- `weekend_end_charge_hour (int)`: Defines the final hour of the charging window during weekends, with valid values from 0 to 23. This boundary applies exclusively to weekends charging sessions and is independent of the weekday configuration. In cases where the `overnight` parameter is set to `True` and the `weekend_start_charge_hour` exceeds the `weekend_end_charge_hour`, the `overnight_end_hour` will be used instead.

- `weekday_end_charge_hour (int)`: Defines the final hour of the charging window during weekdays, with valid values from 0 to 23. This boundary applies exclusively to weekdays charging sessions and is independent of the weekend configuration. In cases where the `overnight` parameter is set to `True` and the `weekday_start_charge_hour` exceeds the `weekday_end_charge_hour`, the `overnight_end_hour` will be used instead.

After assigning valid values to each of the described parameters, the temporal constraints for the custom charging policy are established. Once this step is completed, the algorithm defines the corresponding window boundaries for the timestamp of each parking event and evaluates the overlapping period to compute the amount of charging hours during which the vehicle remained within the allowed charging window. Finally, a flag is assigned to each parking session, indicating whether charging is authorized based on the specified additional criteria, such as minimum and maximum parking hours, as well as the validity of the day.

The expected output corresponds to the same dataset illustrated in Figure 3.7, augmented with two additional columns: `charge_hours`, representing the total duration of the overlapping parking period, and `can_charge`, a boolean flag indicating whether all conditions are satisfied to allow battery charging for the specified `charge_hours`.

4.2.3 Consumption Calculations

At this stage, the function receives as input the trips dataset as a Polars DataFrame, along with the consumption parameters generated in Section 4.2.1.

Using the information from both inputs, the energy consumption for each trip is computed as follows:

$$trip\_Wh = d_h \cdot c_h + d_u \cdot c_u + d_o \cdot c_o$$

Considering d_h, d_u, d_o as the highway (h), urban (u), and other (o) distances in kilometers; and c_h, c_u, c_o as the corresponding highway (h), city (u), and combined (o) consumption values in Wh/km.

The output is a list of dictionaries, where each dictionary contains a list of energy consumption values for all trips, a list of corresponding `can_charge` flags, a list of indicators marking the presence of a new user within the trips, and the consumption parameters used to compute the energy consumption of the trips.

4.2.4 State-of-Charge Update

This function is responsible for updating the battery's state of charge (SoC) after each trip and applying the corresponding recharge. It is called internally on the function in charged of orchestrating the simulations, which will be described later.

It takes as input a list of energy consumption values for all trips and iterates over this list. For the first trip of each user (identified using a previously defined indicator list), the initial SoC is set to the battery's full capacity, as defined in the charging parameters. For subsequent trips, the SoC after any recharge from the previous trip is used.

After accounting for the trip's energy consumption, the SoC is updated while ensuring it remains positive and does not exceed the battery's maximum capacity, following the equation below. Here, i represents the trip, *pre_SoC* is the SoC before trip consumption, *trip_Wh* is the energy consumed during the trip, and *capacity_Wh* is the battery's maximum energy:

$$\mathrm{SoC}_i = \begin{cases} 0, & \text{if } \mathrm{pre\_SoC}_i - \mathrm{trip\_Wh}_i < 0, \\ \mathrm{pre\_SoC}_i - \mathrm{trip\_Wh}_i, & \text{if } 0 \leq \mathrm{pre\_SoC}_i - \mathrm{trip\_Wh}_i \leq \mathrm{capacity\_Wh}, \\ \mathrm{capacity\_Wh}, & \text{if } \mathrm{pre\_SoC}_i - \mathrm{trip\_Wh}_i > \mathrm{capacity\_Wh}. \end{cases}$$

The recharge procedure is subsequently executed. The algorithm evaluates whether the state of charge (SoC) after the trip falls within the allowed thresholds to initiate charging. It has been modified to allow charging at two different rates, depending on the bulk SoC prior to the recharge.

These thresholds can be used to customize the charging policy and to replicate the default behavior of EVs, which typically reduces the charging rate after reaching a high SoC to help preserve battery state of health (SoH). The SoH is generally defined as the capacity of a fully charged battery relative to that of a fresh cell [18].

If the SoC falls below the lower threshold, the battery is recharged using the fast charging rate (DC charger). If the SoC is above this threshold, the battery is charged at the slower rate (AC charger). The selected charging rate is then multiplied by the `charge_hours` allocated for the trip. If no thresholds are triggered, the recharged energy is zero. Subsequently, the SoC is updated based on the actual charged energy if at the same time it is compliant with the charge flag, ensuring it does not exceed the battery's maximum capacity.

Although the charging rates are described as AC or DC, this distinction is not strict. Both rates can be implemented using the same charger, with the lower or higher rate triggered by the respective SoC thresholds. This approach provides greater flexibility in the simulation and allows for more customizable charging policies.

The flowchart followed on this process is described on Figure 7.1.

4.2.5 Orchestration of the Simulation Process

This function is responsible for optimizing the simulations and improving their overall efficiency. It can receive the complete catalog of EV models, a list of tuples representing different charging rates (AC Power, DC Power), and a list of tuples specifying the lower and upper SoC thresholds that determine the corresponding charging speeds. Each combination of these parameters can be used to run an independent simulation for the entire list of trips in the dataset, allowing the simulations to be parallelized for increased efficiency.

The simulations have being parallelized using `concurrent.futures`, which is a Python class that allows to run functions concurrently using threads. It's useful for I/O-bound tasks like network requests, file reads/writes, or calling APIs in parallel [19]. Additionally, the Polars DataFrame is vectorized, including only the columns of interest, enhancing computational speed.

Within each thread, the battery capacity, charging speeds (AC and DC), and the bulk SoC thresholds are selected. These parameters, together with the vectorized trip columns, are passed to the previously described function to update the SoC. The function outputs are then added to the final results, including columns for the SoC before and after each trip and the amount of charged energy (if any).

At this stage, additional performance metrics are computed for each trip, such as a satisfaction indicator, which denotes whether the trip was fully completed based on the available SoC before the trip. If it is higher than the required energy to fulfill the trip, then it will be flag as satisfied.

$$\text{Trip\_Satisfied}_i = \begin{cases} \text{True}, & \text{if } \text{pre\_SoC}_i \geq \text{trip\_Wh}_i, \\ \text{False}, & \text{otherwise.} \end{cases}$$

The percentage of satisfaction is also computed, representing the portion of the trip that can be completed with the available SoC before departure. For this calculation, the available SoC (expressed in energy, [Wh]) is divided by the vehicle's specific consumption (energy per distance, [Wh/km]) to obtain the maximum feasible distance. This value is then compared to the actual trip distance (in kilometers) to determine the percentage of the trip that can be covered.

$$\text{Satisfied\_Percentage}_i = \min\left(\frac{\text{pre\_SoC}_i}{\text{consumption} \cdot \text{trip\_distance}_i} \cdot 100,\ 100\right)\%$$

Another computed metric is the instantaneous autonomy of the car for a given trip, which indicates the total distance (in kilometers) that can be traveled with the available SoC, based on the vehicle's average combined consumption.

$$\text{Instant\_Autonomy}_i = \frac{\text{pre\_SoC}_i[Wh]}{\text{consumption}[Wh/km]}$$

Finally, the output file is generated, containing the original dataset along with all the additional features described above, organized in columns. To further improve computational efficiency, the output is written in chunks.

The flowchart of the overall BEV simulator engine is described on the Figure 7.5.

4.3 Unsatisfied Trips: Categorization

One of the main objectives of this thesis is to understand the reasons behind unfeasible trips under the predefined charging policies. To this end, a categorization of trips has been created, allowing each trip to be assigned to a specific category. This enables a detailed analysis of trips that could not be completed or even started. By later aggregating the results from each category, it becomes possible to provide statistical insights per city, car model, or individual user.

An algorithm was developed to aggregate all trips for the predefined charging policies simulated for a given car model and the trips of a single city or user (if desired). This aggregation produces a single table with each category represented as a column. Each cell under a category contains a tuple composed by three values:

(unsatisfied, total, percentage)

The first value, *"unsatisfied"*, represents the number of trips under that specific category that were not fully or partially satisfied; the second value *"total"*, is the total count of trips in that category, including both satisfied and the unsatisfied trips; the third value, *"percentage"*, provides the conditional probability to obtain an unsatisfied trip under the given category.

In the following section, each of these categories will be explained in detail. Initially, there are four main categories that provide a general overview of unsatisfied trips. For trips made by a BEV, the primary reason for uncompleted trips is an insufficient battery SoC to start or complete the trip. Accordingly, unsatisfied trips can be classified as either a fully discharged battery before the trip (**Discharged**) or insufficient battery to complete the trip, meaning that the available autonomy with the current SoC is inadequate (**Exceeded Autonomy**).

Hence, to provide a general overview of user dissatisfaction under a given charging policy, the following four categories are defined:

- **Total:** This category provides an overall summary of unsatisfied trips for the given charging policy. It counts the total number of unsatisfied trips relative to the total number of trips in the dataset.
- **Ex_Aut_Charge:** This category stands out for Exceeded Autonomy *with* Charging Session before the trip. It indicates that the trip was flagged as unsatisfied even though the battery had been recharged prior to departure. In other words, despite the previous recharge, the available battery load at the start of the trip was insufficient to complete the desired distance. This results in a partially unsatisfied trip.
- **Ex_Aut_No_Charge:** Similarly, this category stands out for Exceeded Autonomy *without* Charging Session before the trip. It indicates that the trip

was flagged as unsatisfied and the battery had not been recharged prior to departure. This results in a partially unsatisfied trip.

- **Discharged:** This category includes all trips in which the battery was fully discharged before departure, i.e., the SoC was 0% at the start. In other words, trips under this category could not be started.

To gain a deeper understanding of the reasons behind the previously described categories, subcategories have been defined. These subcategories either describe the nature of parking sessions in temporal terms or characterize the SoC conditions prior to the trips.

- **Sat_Dist_(*x*)_(*y*):** Stands out for Satisfied Distance Percentage in the range between x and y. Under this category, it had been defined four ranges from]0 to 25%[, [25% to 50%[, [50% to 75%[and [75% to 100%[. This subcategory defines the satisfaction percentage of the trips under the categories with exceeded autonomy.

- **Pre_SoC_(*x*)_(*y*):** This subcategory represents the state of charge (SoC) prior to the trip, falling within the range between x and y. Five ranges have been defined:]0–25%[, [25–50%[, [50–75%[, [75–100%[, and exactly 100%. Trips in the last range correspond to trips made with a fully charged battery; if any trip in this range is unsatisfied, it indicates that the trip was unfeasible due to the limited maximum autonomy of the car model. This subcategory specifically characterizes the SoC prior to trips classified under the exceeded autonomy categories.

- **Above_SoC_th:** This subcategory represents trips for which the SoC was above the allowed upper bulk threshold, preventing a charging session. As described in the simulator section, if the battery is above this threshold, the EV cannot recharge. This subcategory indicates how many trips were unsatisfied and could not be charged prior to departure due to this condition.

- **Overlap_(*time*):** This subcategory describes the charging duration range within the allowed charging windows defined for each policy, following the overlapping concept. The *time* is expressed in ranges consistent with the predefined policies:]0–20 min],]20 min–2 h],]2–6 h], and more than 6 hours. It also includes 0 min of overlapping, representing stopping events that fall outside the predefined charging windows.

- **Next_day:** This subcategory represents stopping events that began on one day and ended on a different day. It is particularly useful for evaluating the effectiveness of charging policies that do not allow overnight recharging.

- **Weekday:** This subcategory represents stopping events that began on a weekday, from Monday to Friday, providing insight, together with the *Weekend* subcategory, into the distribution of trips throughout the week.
- **Weekend:** This subcategory represents stopping events that began during the weekend, from Saturday to Sunday, providing insight, together with the *Weekday* subcategory, into the distribution of trips throughout the week.
- **Morning:** This subcategory, complemented by the *Afternoon* and *Overnight* subcategories, represents stopping events that began during the morning period. For this study, the *Morning* period is defined as 08:00 to 12:00, in accordance with the predefined charging policies.
- **Afternoon:** This subcategory, complemented by the *Morning* and *Overnight* subcategories, represents stopping events that began during the afternoon/evening period. For this study, the *Afternoon* period is defined as 12:00 to 21:00, in accordance with the predefined charging policies.
- **Overnight:** This subcategory, complemented by the *Morning* and *Afternoon* subcategories, represents stopping events that began during the late evening/early morning period. For this study, the *Overnight* period is defined as 21:00 to 08:00 of next day, in accordance with the predefined charging policies.

4.4 User-Level Suitability of EV Models and Charging Policies per City

As a first approach to increasing the satisfaction rate in each city, the suitability of different car model and charging policy combinations was evaluated at the individual user level. Instead of generalizing all users within a city under the same car model or the same charging policy, each user was assigned the combination that maximizes their own satisfaction. This personalized selection is expected to lead to a higher overall satisfaction rate for the city. To achieve this objective, the following selection process was applied:

1. **Unsatisfied trips** – selects the combination(s) with the minimum number of unsatisfied trips.
2. **Car model price** – among the combinations with minimum unsatisfied trips, chooses the cheapest car able to achieve that minimum (As all the cars have different prices it will assign a unique car model per user).
3. **AC/DC charging power** – if several policies with that car still guarantee the minimum unsatisfied trips, AC policies are prioritized because they usually are cheaper.
4. **Charging time** – if multiple policies remain with the same AC/DC type, the one(s) with shorter charging time are preferred.
5. If, at this point, several policies are still tied in terms of AC/DC and charging time, all of them are reported as suitable for the user.

Chapter 5

Results

5.1 Simulator Validation

To validate the predefined charging policies detailed in Section 4.1.1 and summarized in Table 4.1, the updated version of the BEV simulator was employed. The following parameters were considered to describe each charging policy. For further details on these parameters, please refer to Section 4.2.2.

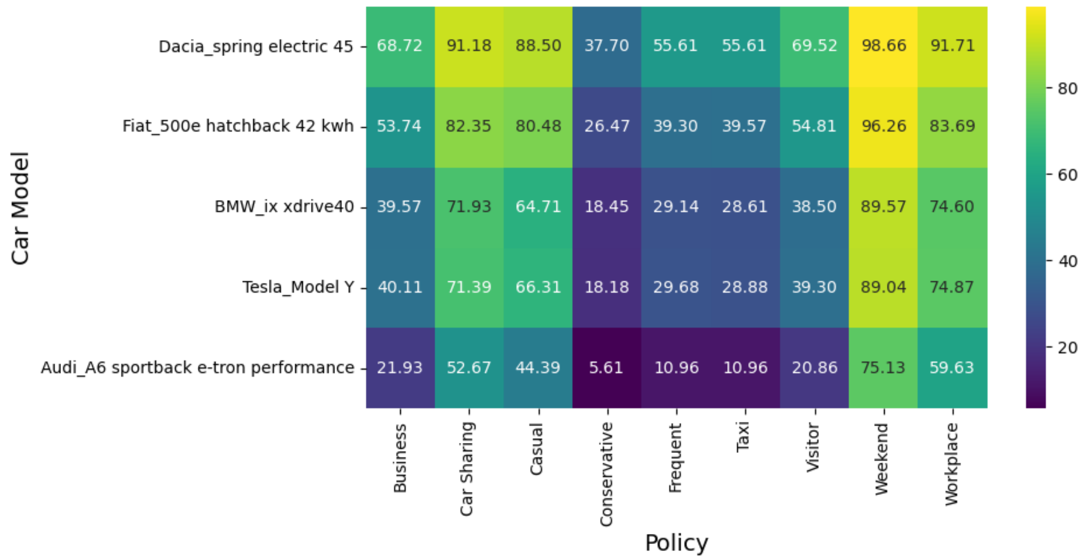
Table 5.1: Parameters definition to be use on BEV simulator for Predefined Charging Policies.

Profile	DC (kW)	AC (kW)	Valid Days	Minimum parking	Maximum parking	Overnight	Overnight (Start-End)	Weekday (Start–End)	Weekend (Start–End)
Frequent	22	22	–	6	∞	Yes	21–08	21–08	0–24
Visitor	50	50	–	2	6	No	–	12–19	12–19
Taxi	22	22	–	6	∞	Yes	21–08	21–08	21–08
Car Sharing	50	50	–	0.33	2	Yes	21–08	0–24	0–24
Conservative	50	22	–	0.33	∞	Yes	21–08	0–24	0–24
Business	50	50	0–4	0.33	∞	No	–	08–19	–
Weekend	50	50	5–6	0.33	2	Yes	21–08	–	0–24
Workplace	22	22	0–4	6	∞	No	–	08–19	–
Casual	22	22	–	6	∞	Yes	21–08	0–24	0–24

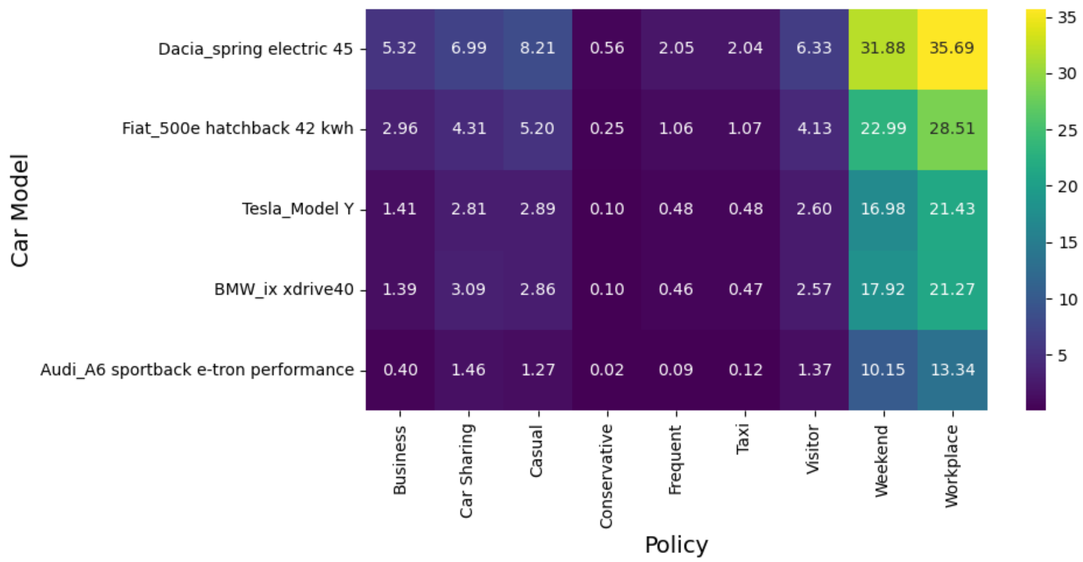
5.1.1 Replication of real EV trips

This section analyzes real trips made exclusively with electric vehicles, which are replicated using the BEV simulator to assess the behavior of the predefined charging policies. For this purpose, 374 EV users from the city of Milan were selected (Table 3.4). Ideally, if the simulator operates accurately and the charging policies are well-suited to the driving behavior observed in Milan, the results are expected to be satisfactory.

The 374 users completed a total of 479,458 trips, driving a variety of unknown car models. As a result, the feasibility of each trip depends on the specific characteristics of the individual vehicle. For the simulations, all trips were replicated using one car model at a time, considering in particular, the car models that were selected (highlighted) in Table 3.5.



(a) Unsatisfied Users Percentage



(b) Unsatisfied Trips Percentage

Figure 5.1: Percentage of unsatisfied users and trips for the replicated EV user trips from Milano.

The aggregated results from the simulator are shown in Figure 5.1, which illustrates the impact of each EV model and the selected charging policy on the trips made by EV users.

Among the tested models, the *Audi A6* exhibits the highest satisfaction rate, reflecting its superior performance compared to the other selected vehicles. Overall, the percentage of unsatisfied trips remains low, generally below 10% as shown in Figure 5.1b. In particular, for the *Audi A6*, most charging policies resulted in a satisfaction rate of around 98.5%. Nevertheless, the distribution of unsatisfied trips varies depending on the charging policy, which can be observed in the number of users affected. With this car model, on average, across the nine charging policies, approximately 35% of users experienced at least one unsatisfied trip.

It is also evident that the highest rates of unsatisfied trips, regardless of car model, occur under the *Weekend Policy* and the *Workplace Policy.* This suggests that, given the driving behavior of EV users in Milan, such policies may not be suitable. As shown in Figure 3.12c, the time vehicles remain parked during weekends is not substantially different from weekdays. However, users tend to travel longer distances on weekends, which implies that EVs should ideally be charged and ready prior to the start of weekend trips. This limitation highlights the gap in the effectiveness of the *Weekend Policy.*

Regarding the *Workplace Policy*, charging is restricted to weekdays during working hours. While this policy performs better than the *Weekend Policy*, it is still not ideal. As illustrated in Figure 3.9, only about 45% of users are parked during working hours. Consequently, reliance on this policy alone still results in a relatively high proportion of unsatisfied trips.

The most flexible policy is the *Conservative* policy, which, as shown in Table 4.1, allows charging whenever the session lasts more than 20 minutes and the SoC is below 75%. Thanks to this flexibility, it consistently achieves the highest satisfaction rates across all car models.

Even when combining the best-performing car model with the most flexible policy, there remains a small fraction of unsatisfied trips: 0.02% of trips, affecting 5.61% of users. To understand the reasons behind these cases, the categorization of trips introduced in Section 4.3 becomes particularly useful.

Note: Values contained on each cell are read as *(Number of unsatisfied trips, Total Number of Trips under that category, percentage of unsatisfied trips over the total for the category),* see section 4.3 for further details.

Policy	Total	Ex_Aut_Charge	Ex_Aut_No_Charge	Discharged
Frequent	41, 374, 10.96	0, 374, 0.0	40, 374, 10.7	35, 374, 9.36
Visitor	78, 374, 20.86	0, 374, 0.0	74, 374, 19.79	74, 374, 19.79
Taxi	41, 374, 10.96	0, 374, 0.0	39, 374, 10.43	35, 374, 9.36
Car Sharing	197, 374, 52.67	57, 374, 15.24	193, 374, 51.6	179, 374, 47.86
Conservative	21, 374, 5.61	11, 374, 2.94	13, 374, 3.48	14, 374, 3.74
Business	82, 374, 21.93	4, 374, 1.07	77, 374, 20.59	78, 374, 20.86
Weekend	281, 374, 75.13	31, 374, 8.29	280, 374, 74.87	277, 374, 74.06
Workplace	223, 374, 59.63	0, 374, 0.0	223, 374, 59.63	219, 374, 58.56
Casual	166, 374, 44.39	0, 374, 0.0	164, 374, 43.85	152, 374, 40.64

Figure 5.2: Classification of unsatisfied users made with an *Audi A6 e-tron*, for trips of EV users from Milano.

Policy	Total	Ex_Aut_Charge	Ex_Aut_No_Charge	Discharged
Frequent	432, 479458, 0.09	0, 479458, 0.0	108, 479458, 0.02	324, 479458, 0.07
Visitor	6556, 479458, 1.37	0, 479458, 0.0	253, 479458, 0.05	6303, 479458, 1.31
Taxi	555, 479458, 0.12	0, 479458, 0.0	112, 479458, 0.02	443, 479458, 0.09
Car Sharing	7006, 479458, 1.46	158, 479458, 0.03	1335, 479458, 0.28	5513, 479458, 1.15
Conservative	88, 479458, 0.02	30, 479458, 0.01	21, 479458, 0.0	37, 479458, 0.01
Business	1905, 479458, 0.4	5, 479458, 0.0	244, 479458, 0.05	1656, 479458, 0.35
Weekend	48676, 479458, 10.15	53, 479458, 0.01	2506, 479458, 0.52	46117, 479458, 9.62
Workplace	63980, 479458, 13.34	0, 479458, 0.0	1024, 479458, 0.21	62956, 479458, 13.13
Casual	6097, 479458, 1.27	0, 479458, 0.0	788, 479458, 0.16	5309, 479458, 1.11

Figure 5.3: Classification of unsatisfied trips made with an *Audi A6 e-tron*, for trips of EV users from Milano.

From Figure 5.3 it can be observed for the *Conservative* policy, there were 88 trips were unsatisfied affecting 21 different users (Figure 5.2). From those trips, 51 where partially completed (Exceeded Autonomy) and 37 trips were not able to even start, having a SoC of 0% before the trip. By splitting this unsatisfied trips in two groups, it can be analyzed the 30 trips that did charged before, but still the battery was not loaded enough, and the remaining trips that did not charged in preparation for the trip.

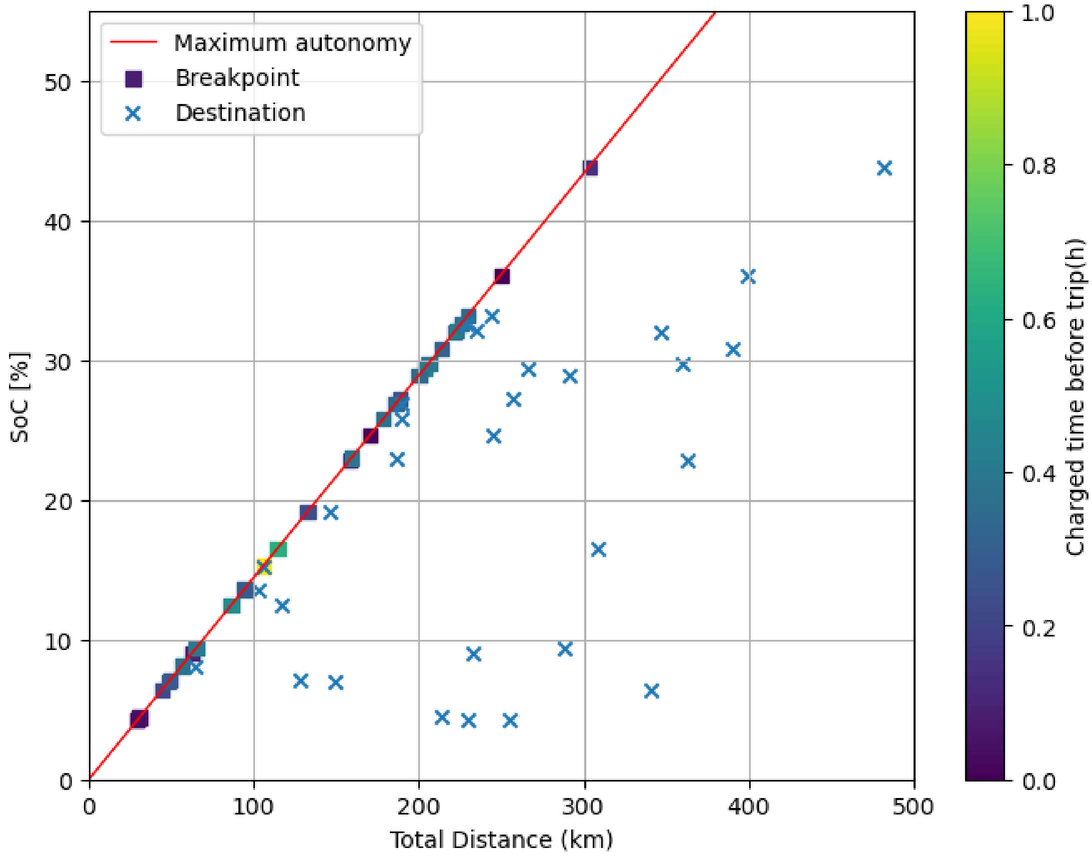


Figure 5.4: SoC of pre-charged EVs against trip distance for partially unsatisfied trips from Milano users, with an *Audi A6 e-tron* under the *Conservative Policy*.

The 30 trips in question, which were partially unsatisfied despite being charged beforehand, are shown in Figure 5.4, these trips are distributed between 11 different users. It is evident that, for most of these trips, the charging duration was too short to fully prepare the vehicle for the subsequent trip. The color bar indicates the charging time, ranging from 20 minutes to 1.5 hours, which represents the maximum charging time among these trips.

For example, one user had a battery SoC of 44% and intended to complete a 481 km trip, but only charged for half an hour beforehand. Prior to the trip, the battery was at 43%, indicating that under this charging policy, the AC slow charging rate was applied.

Another example is the user who charged for 18 minutes (green square) before attempting a 308 km trip with only 16% battery remaining. Although the vehicle used DC charging for nearly an hour prior to departure, the charging session was still insufficient to meet the trip's energy demand.

Overall, all the unsatisfied trips within this category correspond to journeys longer than 200 km, where the preceding stop allowed only a short charging duration and the average SoC before departure was below 30%. These represent very particular cases, likely influenced by the specific timing of the trips and the charging speed available, which did not align with the user's energy needs. It should also be noted that, although this car model is highly performant, the fast-charging option used by the simulator corresponds to only 20% of the vehicle's maximum charging capacity. The remaining 58 unsatisfied trips are directly associated with the fact that the EV was not recharged prior to departure. Among these, 21 trips were partially satisfied, affecting 13 users, while 37 trips could not be initiated at all, affecting 14 users. The underlying reason for the lack of recharging is the constraint set by the charging policy. In the case of the *Conservative Policy*, the only restriction is the minimum allowed charging time of 20 minutes. As illustrated in Figure 5.5, these trips were not recharged beforehand precisely because the preceding stop duration was shorter than the 20 minute threshold.

Policy	Total	Ex_Aut_No_Charge	Discharged	Overlap_0min	Overlap_20min	Overlap_less_2h
Frequent	432, 479458, 0.09	108, 479458, 0.02	324, 479458, 0.07	196, 204658, 0.1	128, 62642, 0.2	77, 67892, 0.11
Visitor	6556, 479458, 1.37	253, 479458, 0.05	6303, 479458, 1.31	3180, 183653, 1.73	2468, 73723, 3.35	695, 118326, 0.59
Taxi	555, 479458, 0.12	112, 479458, 0.02	443, 479458, 0.09	319, 256843, 0.12	140, 44186, 0.32	69, 49490, 0.14
Car Sharing	7006, 479458, 1.46	1335, 479458, 0.28	5513, 479458, 1.15	5, 4940, 0.1	2805, 133138, 2.11	217, 143110, 0.15
Conservative	88, 479458, 0.02	21, 479458, 0.0	37, 479458, 0.01	0, 4940, 0.0	58, 133138, 0.04	30, 143110, 0.02
Business	1905, 479458, 0.4	244, 479458, 0.05	1656, 479458, 0.35	1745, 234900, 0.74	155, 69520, 0.22	5, 92281, 0.01
Weekend	48676, 479458, 10.15	2506, 479458, 0.52	46117, 479458, 9.62	37776, 319199, 11.83	3961, 41619, 9.52	56, 44811, 0.12
Workplace	63980, 479458, 13.34	1024, 479458, 0.21	62956, 479458, 13.13	30446, 234900, 12.96	12864, 69520, 18.5	13119, 92281, 14.22
Casual	6097, 479458, 1.27	788, 479458, 0.16	5309, 479458, 1.11	1, 4940, 0.02	2722, 133138, 2.04	2057, 143110, 1.44

Figure 5.5: Statistics of unsatisfied trips made with an *Audi A6 e-tron*, for trips of EV users from Milano. (Overlap information between the charging policy and the stopped time).

Evaluating the 21 trips that were partially satisfied but did not charge before departure due to a stop duration of less than 20 minutes, it is observed that most of these unsatisfied trips correspond to distances below 200 km, with a pre-trip SoC of less than 30%. Figure 5.6 shows the relationship between the available SoC and the remaining distance required to complete the trip. In general, the satisfaction percentage for these trips is relatively high, with completion falling short only by a small margin of additional charge.

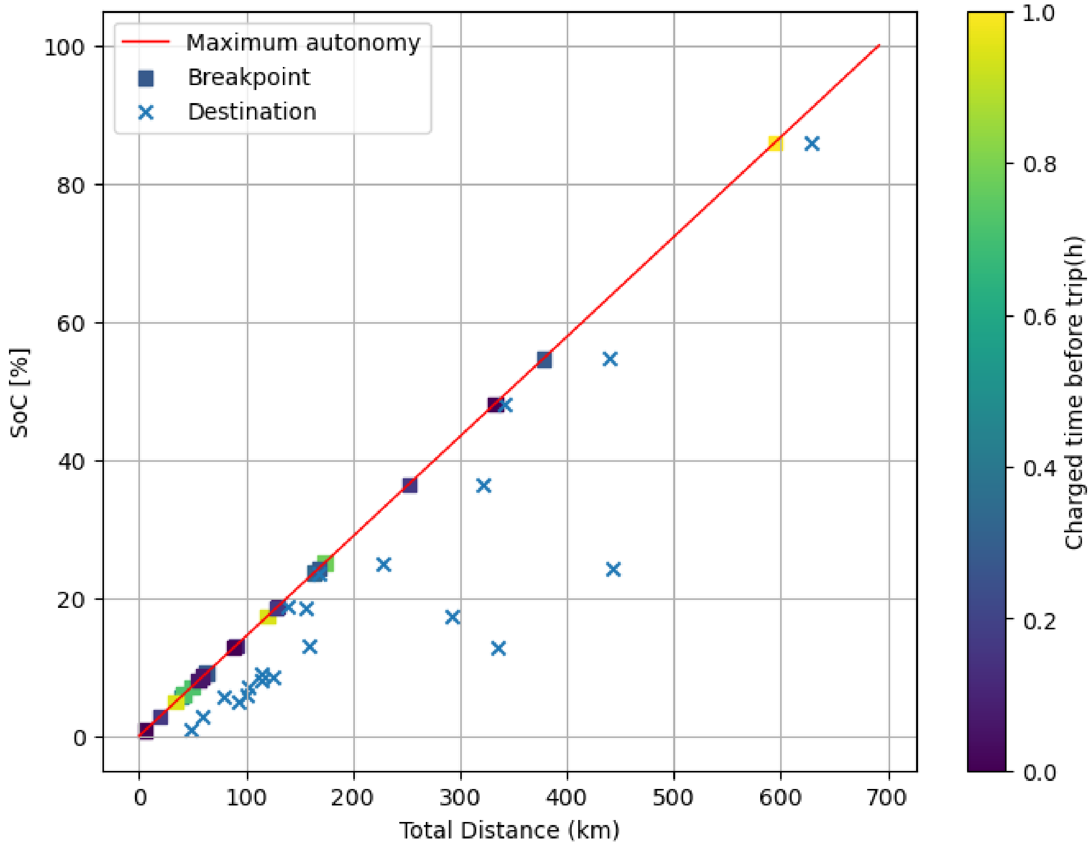


Figure 5.6: SoC of EVs against trip distance for partially unsatisfied trips without pre-charge from Milano users, with an *Audi A6 e-tron* under the *Conservative Policy*.

Considering the *Dacia Spring Electric*, which among the observed vehicles has a low autonomy of only 189 km (Table 3.5) and limited charging rates for both AC and DC (below the tested values), only 0.56% of trips were compromised under the *Conservative Policy* (Figure 5.1b). Naturally, this results in a higher percentage of affected users compared to other car models. Nevertheless, the overall outcome demonstrates that, with sufficiently flexible charging policies, the simulator can reliably replicate EV trips even for vehicles with lower capabilities, while still ensuring a high level of consistency with real-world conditions, where 100% of EV trips are assumed to be satisfied.

5.1.2 Predefined charging policies behavior against real EVSE data

For this study, access was granted to anonymized data collected from several charging stations across Milan. The dataset comprises nearly 13,000 charging sessions, including information such as charging duration, bulk SoC, and SoC at the end of the session. This dataset enables a comparison with the performance of the predefined charging policies, providing a general indication of how realistically these policies reflect actual charging behavior. It is important to note that some misalignments are expected, since the simulations are based on a single car model *(Tesla Model Y)*, while the EVSE dataset includes recharges from multiple, unspecified car models.

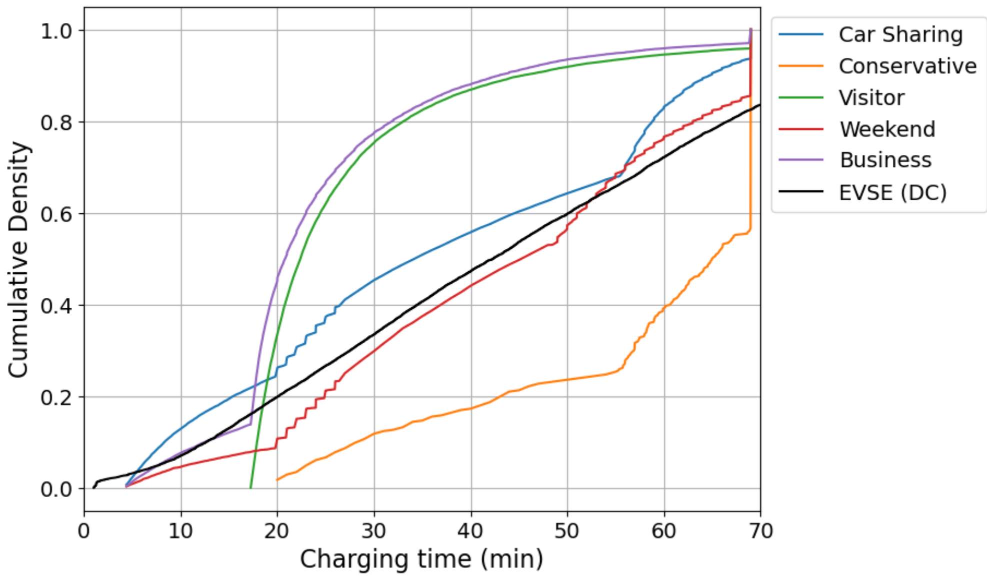


Figure 5.7: Cumulative distribution of charging durations per policy compared with EVSE (DC) charging sessions for EV users in Milano.

From Figure 5.7, it can be observed that the charging durations of EV users in the *UnipolTech* dataset for Milano resemble those of EV owners recharging at DC stations around the city when following the *Weekend* and *Car Sharing* policies. This indicates a typical behavior for DC charging sessions lasting less than 1.5 hours, while these policies, as shown in Table 4.1, set a maximum charging duration of 2 hours.

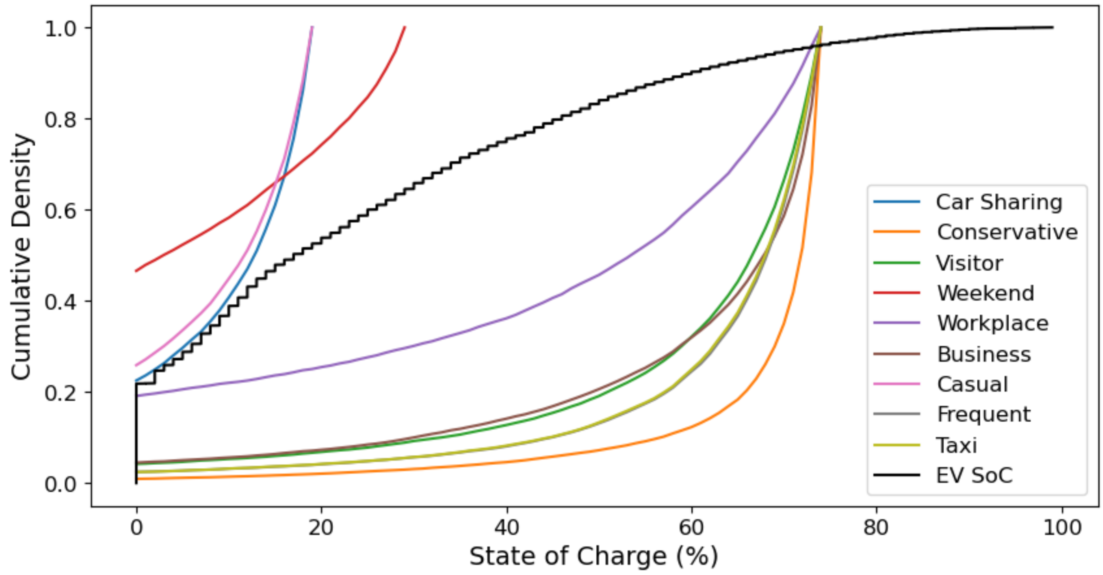


Figure 5.8: State of Charge (SoC) before the charging session for a Tesla Model Y in Milano.

Analyzing the behavior of the charging sessions under the predefined policies, it is possible to observe both the frequency at which users start recharging for a given SoC and the frequency at which charging stops.

Figure 5.8 shows the behavior of EV users in Milan charging at public stations (*EV SoC – black line*) compared with the simulated users under each predefined policy. Overall, the predefined policies exhibit a more "anxious" behavior, as a higher density of charging sessions begins at higher SoC levels. In contrast, the empirical *EV SoC* line displays a more concave growth, with a higher density of sessions starting at lower SoC values.

The policies that reflect a less anxious behavior are the *Casual*, *Car Sharing*, and *Weekend* policies, which by definition cap the maximum allowed bulk SoC threshold at 20% or 30%.

On Figure 5.9 the end of the charging session is reflected. It indicates the frequency for the SoC to which the users interrupt the charging. Again, the results from the simulations are compared against the empirical data (*EV SoC – black line*). For this case it is import to observe how the behavior is similar between certain policies and the empirical data. Both results, demonstrates the final sudden increase to 100% indicating a high density of users that recharge until the full capacity of their battery. While, the *Weekend* and *Car Sharing* again, are the policies that are closer to the model user behavior.

This is the reason, why an entire section is dedicated to categorize the unsatisfied trips for the entire collection of data for each city.

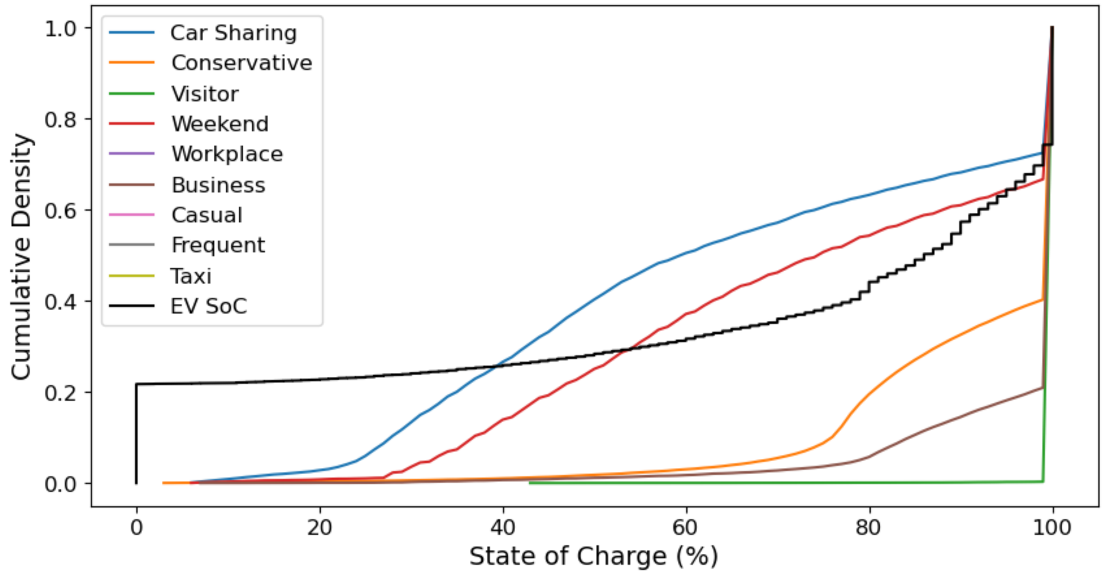


Figure 5.9: State of Charge (SoC) after the charging session for a Tesla Model Y in Milano.

In general, the BEV simulator is able to replicate trips from combustion engine vehicles with high accuracy, as verified against real EV trips. Despite the generalizations applied to users, such as the assumption of a specific car model, most trips can be reproduced with a high satisfaction rate. Under the most suitable policies, approximately 98% of trips were successfully satisfied. This indicates that these policies are particularly well-suited to the EV users in Milan, while other policies may still be more appropriate for specific users or even for different cities.

For this reason, an entire section is dedicated to categorizing the unsatisfied trips across the full dataset for each city.

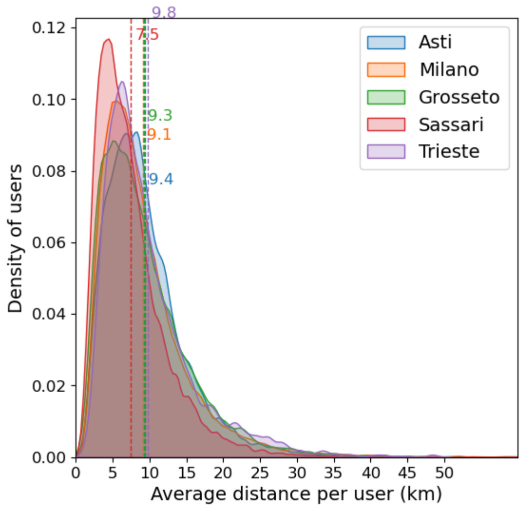
5.2 Unsatisfied Trips: Analysis per city

In order to evaluate the feasibility of adapting the users of different cities to the electrical mobility, their trips, made with different fuel types, were replicated by using different models of BEV under different charging policies. This experiment will allow to understand which city is more subseptable to increase the usage of EV on their daily basis trips, and to identify the proportion of users that might be suitable for this transition.

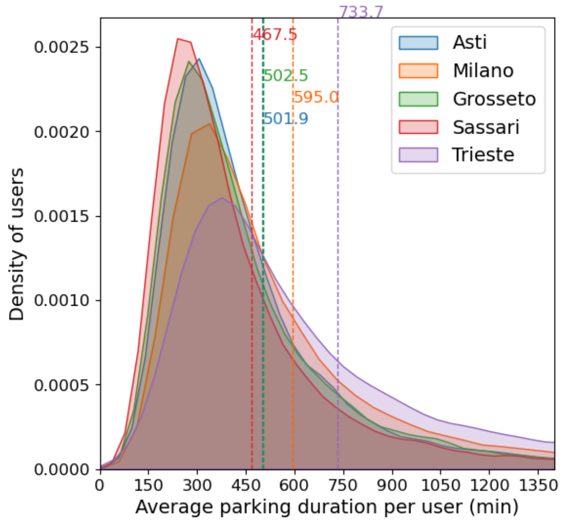
The BEV simulator detailed on section 4.2.1 was used for replicating this trips, considering a grid capacity of 22 kW for AC chargings and 50 kW for DC chargings. Consider that the simulator also takes into consideration the specific limitations of the allowed charging power for each car model, meaning that for specific cases this power might be lower.

5.2.1 User satisfaction under different charging policies

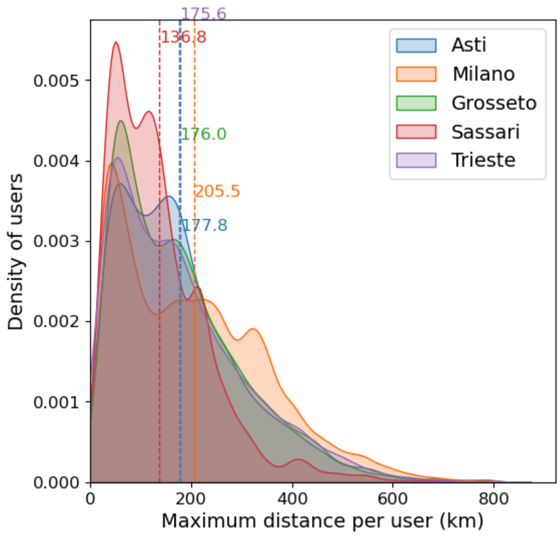
As a first step, the average behavior of each user was analyzed by evaluating trip distances and parking times.



(a) Average trip distance



(b) Average parking duration



(c) Maximum traveled distance per user

Figure 5.10: Density of users per average traveled distance, average parking duration and maximum traveled distance per city.

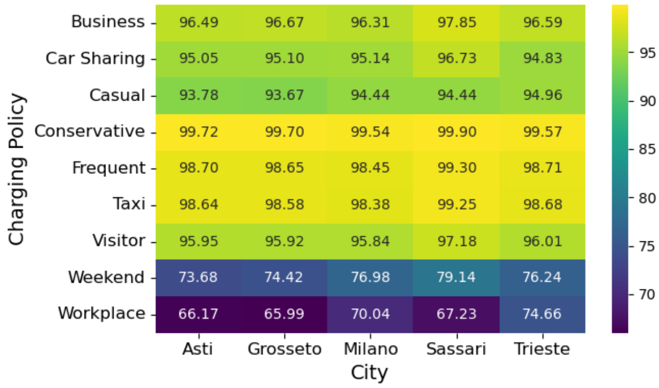
Figure 5.10 shows the distribution of average trip distance, average parking time, and maximum traveled distance per user. The data indicate that, overall, the cities under study exhibit similar patterns of user behavior: most users undertake trips of less than 50 km, and the average parking time ranges between 4 and 8 hours. Regarding maximum traveled distance per user, the city averages are close to 200 km; however, Milano shows a higher density of longer trips.

Based on this evidence, it can be concluded that the vast majority of trips in these cities could be satisfied with low-autonomy electric vehicles. Taking the *Fiat 500e*, which has a maximum range of 270 km, as a reference, it could accommodate a large proportion of user trips. However, as shown in Figure 5.10c, Sassari has the lowest average maximum distance, well within the car's range. Conversely, Milano has an average maximum distance closer to this limit, indicating that a significant percentage of users there may not be fully satisfied with this vehicle type, as some trips would exceed its range limitations.

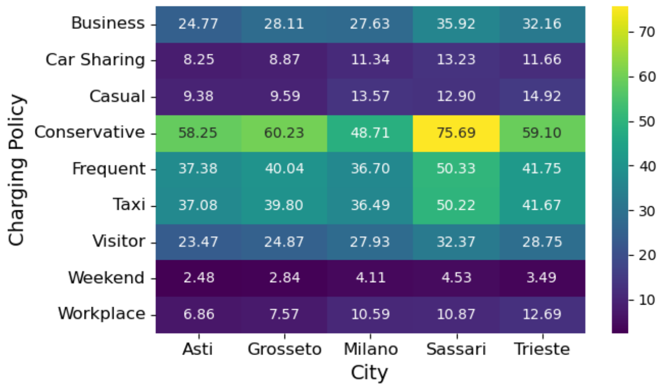
To verify this information, the percentages of satisfied trips relative to the total number of trips (Figure 5.11a), the user satisfaction rate in each city (Figure 5.11b), and the average number of unsatisfied trips per user (Figure 5.11c) were computed.

Essentially it can be observed how for all the cities, over the 93% of the trips are satisfied with most of the charging policies, however, the number of users fully satisfied is quite dramatic for more restrictive policies. Meaning that there are a few trips that were not partially or completely satisfied under a given charging policy or even due to the limitations of the chosen car model. As anticipated, Sassari shows the higher number of satisfied trips (99.90%) as well of users (75.69%) under a very flexible charging policy such as the *Conservative*, while Milano reports the lowest rate of satisfied users (48.74%). For an inverse relationship, the average number of unsatisfied trips per users during a year is minimum for Sassari (6.4), while for Trieste the average number (12.2) is above those from Asti (10.4), being Asti the second city with highest number of satisfied trips, but reaching the forth position for the satisfied users, a behavior that is also reflected on the average number of unsatisfied trips per user.

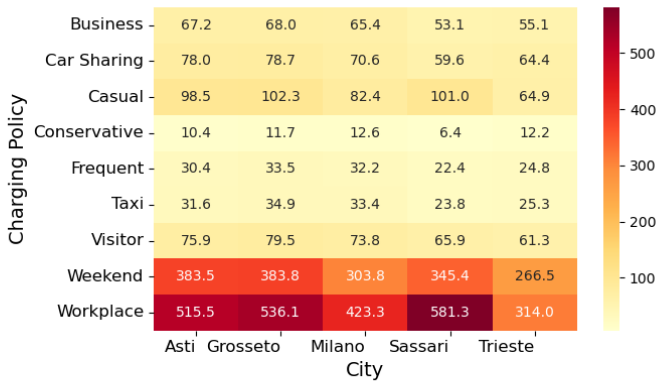
These findings suggest that a very high percentage of trips made by residents of these cities could be completed with BEVs. However, not all trips can be fully satisfied due to occasional longer trips or shorter trips that are not planned in a way that allows timely recharging in compliance with the respective charging policy constraints



(a) Trips satisfaction percentage.



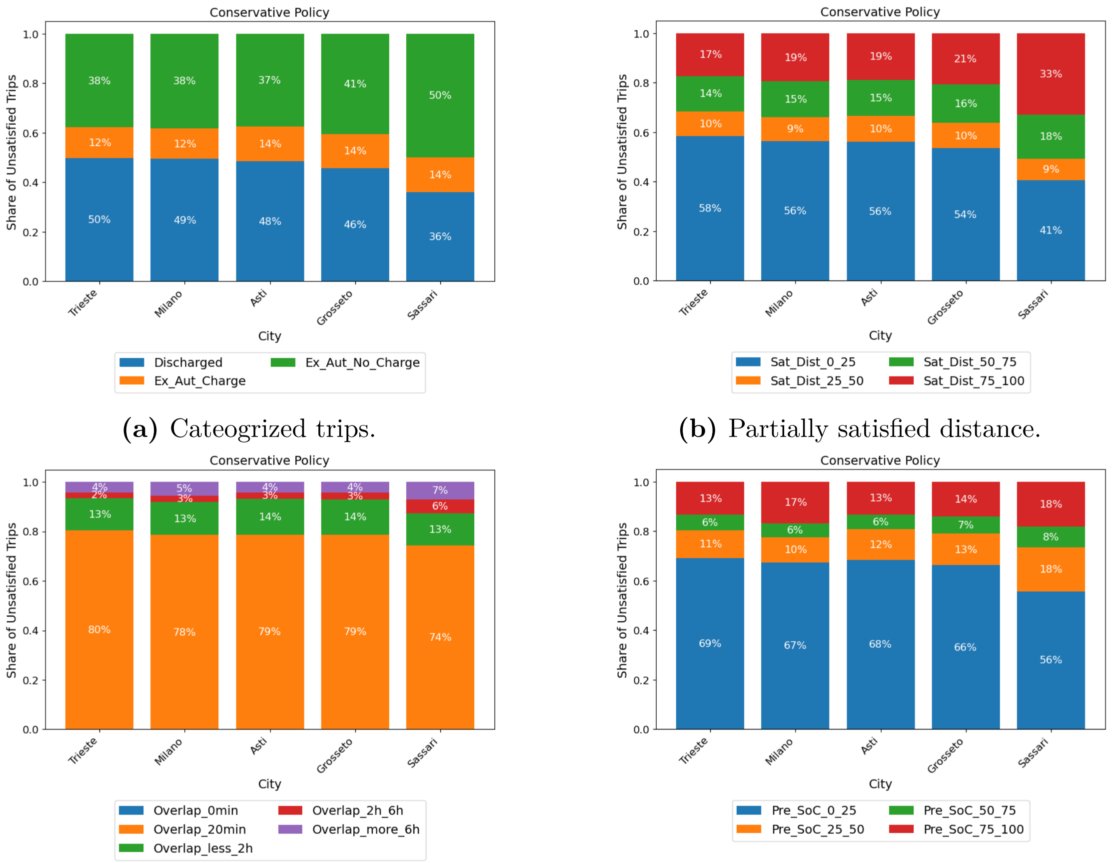
(b) User satisfaction percentage.



(c) Average number of unsatisfied trips per user.

Figure 5.11: Satisfaction percentage of (a) trips and (b) users, with the average number of unsatisfied trips per user on each city using a *Fiat 500e* with different charging policies.

To better understand the reasons behind unsatisfied trips, the procedure described in Section 4.3 was followed. For each EV model listed in Table 3.5 and for each city, a categorization table was computed. This resulted in aggregated simulated trips for each city under the 9 charging scenarios across 50 different EV models, producing a total of 450 aggregated tables per city, or 2,250 tables overall, each detailing the categorization of unsatisfied trips relative to the total number of trips per city. For example, considering only the trips replicated with a *Fiat 500e* under the *Conservative* policy, the most relevant aggregated results per city are summarized in Figure 5.15.



(a) Cateogrized trips.

(b) Partially satisfied distance.

(c) Overlapping time with policy's window.

(d) SoC before trip.

Figure 5.12: Unsatisfied trips categorization and analysis on each city, using a *Fiat 500e* and a *Conservative* charging policy.

Figure 5.15 shows the share of unsatisfied trips per category, ranging from 0.10% to 0.46% depending on the city. Figure 5.12a highlights the main categorization, revealing consistent behavior across all cities except Sassari, which reported a higher percentage (50%) of partially satisfied trips without a prior recharge. Under the *Conservative* policy, the only constraints are a minimum parking duration of 20 minutes and a minimum SoC of 75% before charging. Figure 5.12c shows that over 78% of unsatisfied trips in most cities were due to not meeting the minimum 20-minute charging requirement. In contrast, Sassari has a lower percentage under 20 minutes, due to the larger share (7%) of trips overlapping more than 6 hours, suggesting that 26% of unsatisfied trips with overlap over 20 minutes are explained by 18% of charging opportunities starting with a SoC above the allowed threshold. Figure 5.12d further shows that Sassari reports the highest SoC before unsatisfied trips, which explains why Figure 5.12b shows Sassari leading the other cities in distance traveled during the 64% of trips classified as partially satisfied.

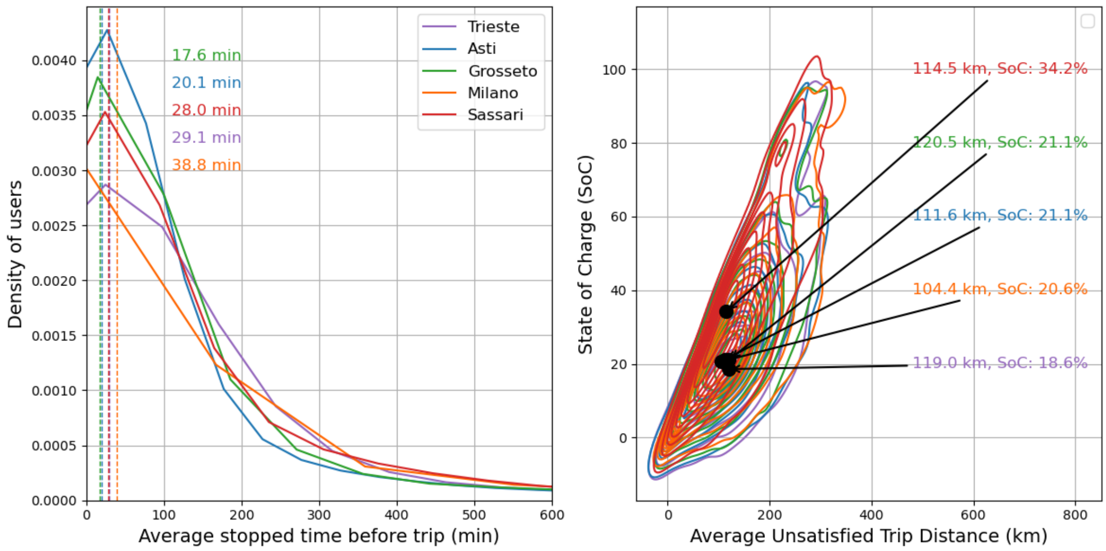


Figure 5.13: Available SoC over trip distance for unsatisfied trips under the *Conservative Policy*

By plotting the density of users based on their average unsatisfied trips, it is possible to gain visual insight into why each user was not satisfied. Figure 5.14 shows the unsatisfied trips per user for each city, representing the unfeasible trip profile of the users missing in Figure 5.11b.

Observing Figure 5.14, most cities show an average stopped time before unsatisfied trips between 17 and 39 minutes. This indicates that under the *Conservative Policy*, however a high percentage of users were parked bellow 20 minutes (minimum required by the policy) and disables the EV to recharge.

Furthermore, the level curves of trip density in terms of trip distance and available SoC show that all cities report average SoC values bellow 20%. This suggests that during available charging minutes, vehicles were in general recharged at low AC power (if it was parked longer than the 20 minutes), while the average planned trips exceeded 100 km. For a *Fiat 500e*, such trips would require at least 37% SoC, but it was only available between 10 to 20%. Under this limited scenario close to the policies boundaries, increasing user satisfaction would require adjusting its behavior: before longer trips, users should wait longer to reach the necessary SoC. For example, a trip over 100 km starting at 20% SoC could be satisfied with an additional 17% charge, which at 11 kW AC power requires 34 minutes, just 14 minutes longer than the typical available stop time.

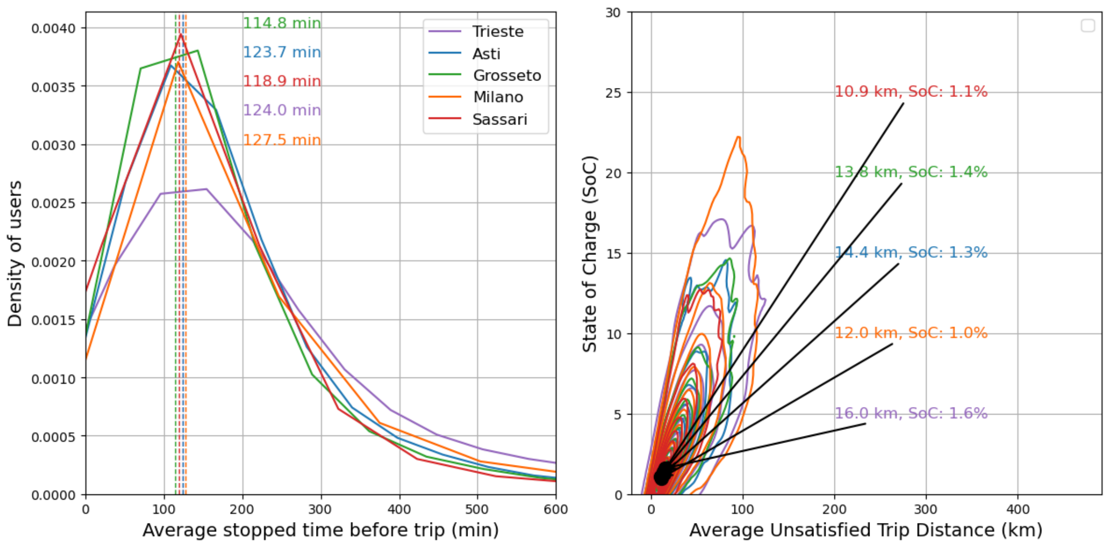


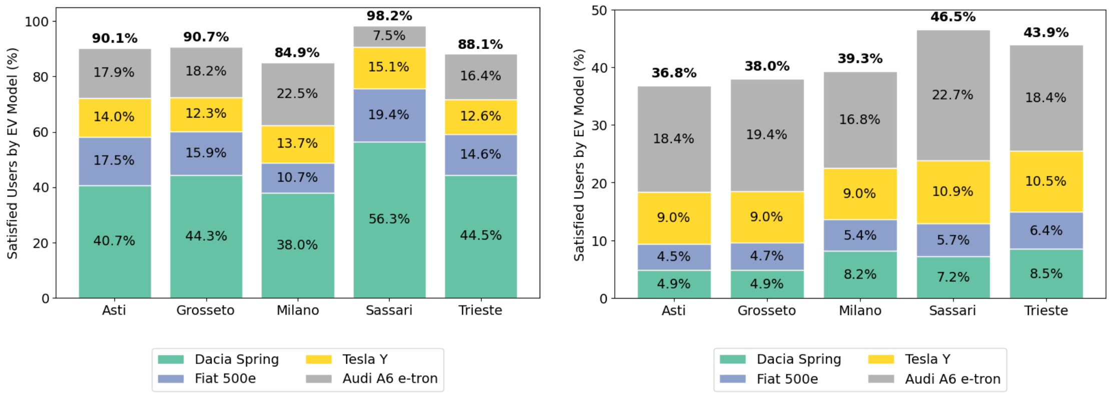
Figure 5.14: Available SoC over trip distance for unsatisfied trips under the *Casual Policy*.

A second analysis was performed using a more restrictive and realistic policy, reflecting less *"anxious"* behavior, as observed during the Validation section. The results for the *Fiat 500e* under the *Casual* policy were examined. As shown in Figure 5.11a, around 5% of trips were unsatisfied, but these affected 90% of users in Asti and Grosseto, and approximately 85% of users in the other cities.

Those 85% of users, in average are unsatisfied by non fulfilling trips of less than 16 km, but for doing them, they had available only 1% of the SoC, nonetheless having been parked in average for over 2 hours. The constraints for this charging policy are very strict, the car should be parked for over 6 hours and with a bulk SoC under 20%. Needing to match the two conditions in order to anticipate longer trips.

In both of the examples analyzed, the average user dissatisfaction is biased by those trip characteristics. Under the *Conservative* policy, which is more flexible, most of the unsatisfied trips involve longer distances where the battery was insufficient, even though it was regularly charged under an anxious pattern. In contrast, under the more restrictive *Casual* policy, the average is influenced by a higher number of shorter, more typical trips that reflect the average user behavior in each city, where the vehicle was unable to recharge sufficiently due to the SoC threshold constraints. Since the average unsatisfied distance is low and the remaining energy needed to complete these trips is minimal, the dissatisfaction occurs despite users being parked long enough to recharge; the policy restrictions prevent it. In this scenario, increasing the satisfaction rate would require relaxing the policy conditions.

In general, as observed, according to the charging policy, even with a small battery EV, most of the trips across the different cities can be satisfied, but not all the users will be equally satisfied across the cities. This is directly related with the combination of several factor such as driving behavior, the potential charging time before the trip, the available SoC before the trip and the distance of the future trip. Under the current conditions, using the *Conservative* charging policy will maximize the overall satisfaction rate, and it can be said, for the case of Milano, that at least 48% of its users will be satisfied. From Figure 7.7, the satisfaction rate of users of Milano could be increased to 85% by upgrading the car to an *Audi A6 sportback e-tron*. Meaning that if the adaptability is not limited to small battery cars, for all the cities, the user satisfaction can be increased.



(a) Satisfaction rate with *Conservative* policy.

(b) Satisfaction rate with *Casual* policy.

Figure 5.15: EV Model Distribution for Full User Satisfaction with Minimal-Range EVs per charging policy.

Figure 5.15a shows the minimum share of each EV model required per user to achieve full satisfaction under the *Conservative* charging policy. The sum of these shares represents the maximum user satisfaction rate per city given the charging constraints, without modifying user behavior and taking EV model limitations into account. On the stack bar, the upper level car models will be able to satisfy also the sum of al the percentages bellow its own stack as it has a higher autonomy than its predecessor. Overall, Sassari achieves the highest adaptability, with up to 98% of users satisfied, over 56% relying on the *Dacia Spring Electric*, the cheapest and least performant EV in Table 3.5, followed by Grosseto and Asti. In contrast, Milano is the least adaptable city, with only 84.9% of users satisfied. It shows the highest reliance on the top-range *Audi A6 e-tron*, and the lowest satisfaction when using the *Fiat 500e*.

Under the less restrictive *Casual* charging policy (Figure 5.15b), overall user satisfaction decreases. However, cities respond differently: Sassari remains the most adaptable, with 46.5% of users satisfied, while Trieste and Milano show moderate improvements, and Asti and Grosseto lag behind. Notably, the *Dacia Spring* is no longer the most suitable EV in any city; instead, the *Audi A6 e-tron* becomes the model that contributes most to increasing user satisfaction.

5.3 Analysis: User-Level Suitability of EV Models and Charging Policies per City

As described in Section 4.4, the most suitable combination of car model and charging policy was selected to increase user satisfaction while maintaining minimal cost. Following the assignment process, the overall satisfaction rate per city improved compared to the results obtained using only the *Conservative Policy* (Figure 5.15a). As shown in Figure 5.16, the satisfaction rate in Milano increased from 84.9% to 85.7%, primarily due to a higher number of users adopting the Tesla Y model. Similar improvements of approximately 1% were observed in the other cities. This indicates that, despite its flexibility and cautious nature, the *Conservative Policy* was not entirely suitable for all users.

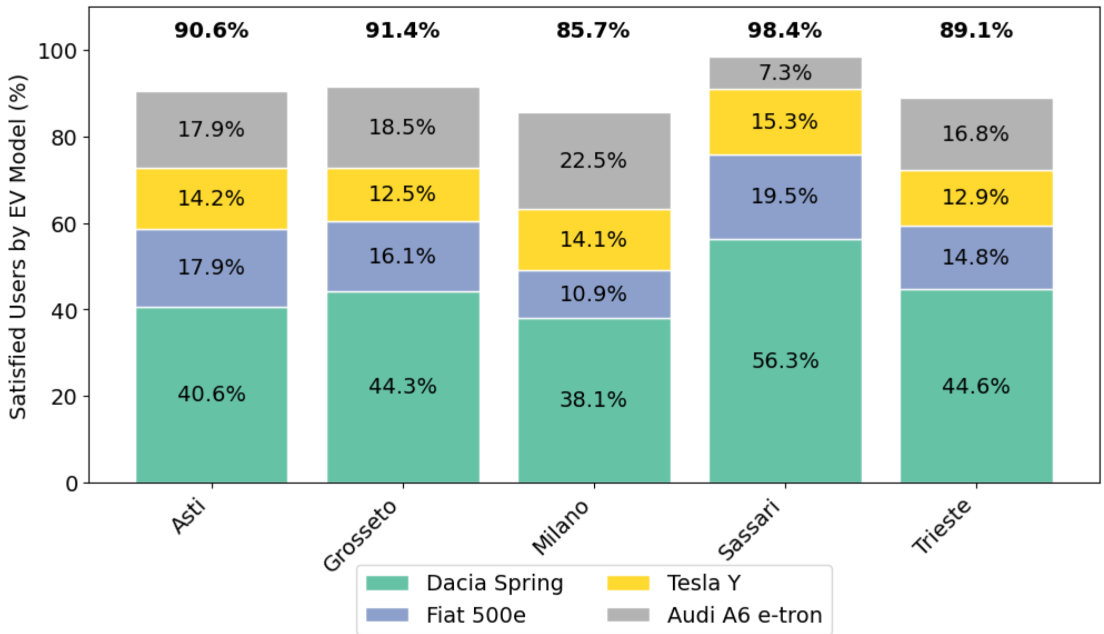


Figure 5.16: EV Model Distribution for Full User Satisfaction with Minimal-Range EVs and most suitable charging policy per user.

As described previously, the selection process assigns a single car model to each user, ensuring the minimum possible number of unsatisfied trips while selecting the most economical option. However, multiple charging policies may be considered suitable for the same user, provided that the resulting number of unsatisfied trips and the charging time remain equal to the minimum values observed across all policies. Figure 5.17 illustrates, for each city, the percentage of users with a given car model who are suitable to recharge under each charging policy.

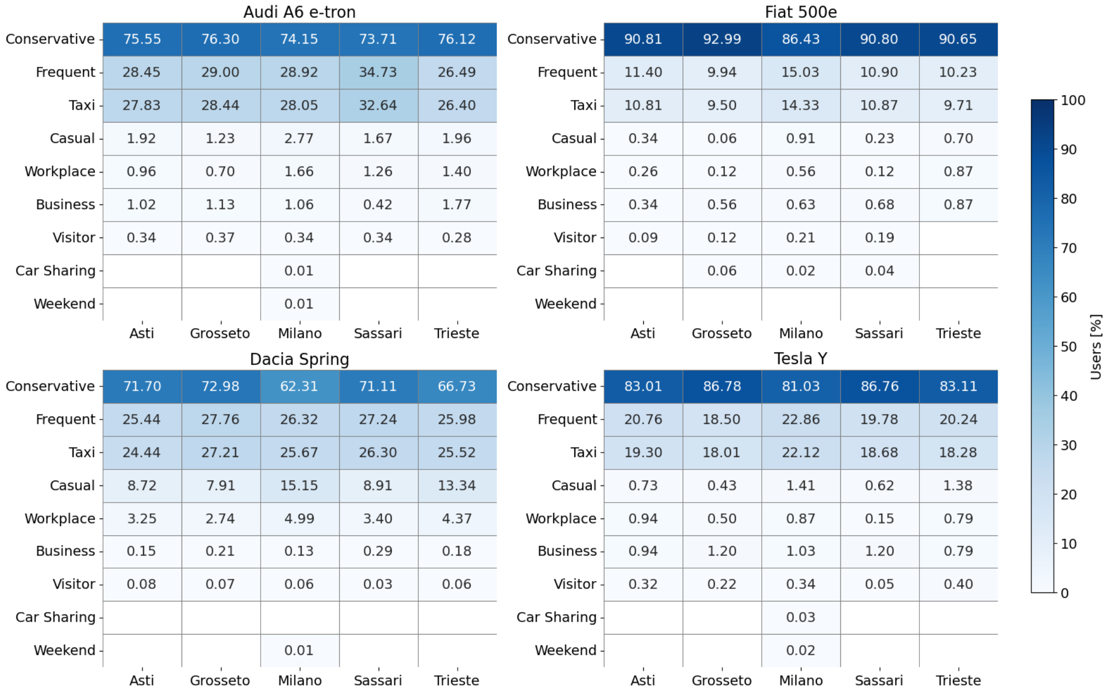


Figure 5.17: User distribution per car model and its corresponding charging policy across the cities.

The top three ranked policies are *Conservative*, *Frequent*, and *Taxi*. As expected, the *Conservative Policy* is the most commonly adopted among users across all car models. However, *Dacia Spring* users in Milano show a lower suitability rate compared to other cities, with only 62.31% of users likely to adopt this policy while owning this car model. Policies such as *Car Sharing* and *Weekend* are generally unsuitable in most cities. While *Fiat 500e* owners in Grosseto, Milano, and Sassari may find the *Car Sharing Policy* suitable, users of other car models in all cities, except Milano, do not adopt these policies at all. Milano is the only city where a small percentage of users show suitability for these policies. Nonetheless, *Fiat 500e* users in Milano are not suitable for the *Weekend Policy*, and *Dacia Spring* owners are not suited to the *Car Sharing Policy*.

The Figure 5.18 allows to profile the seasonality of the unsatisfied trips per gender on each city.

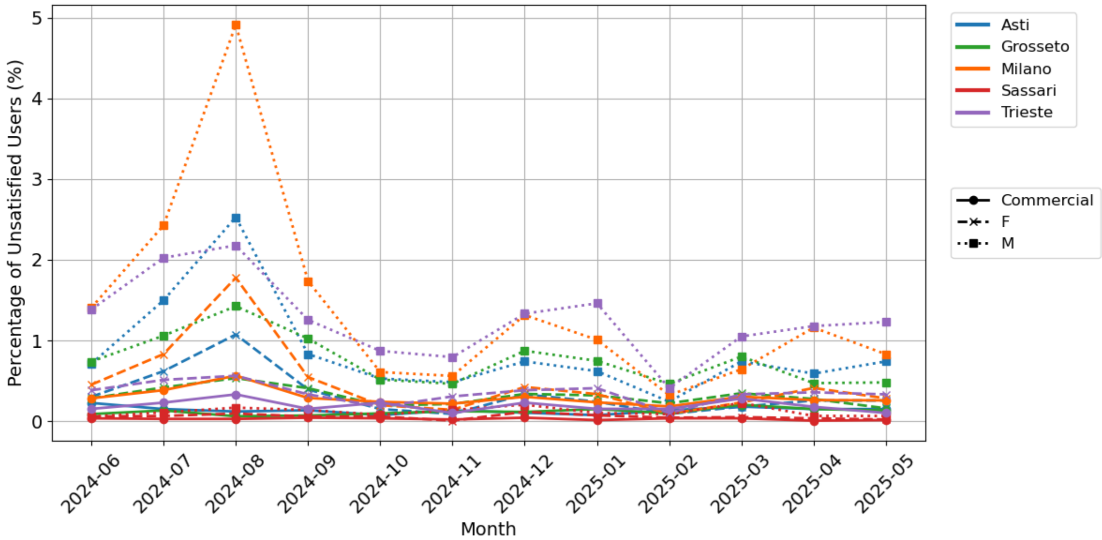


Figure 5.18: Monthly unsatisfied user percentage per city.

The plot shows that, as expected, the number of unsatisfied users increases during the holidays, particularly over the summer break. As observed previously, during these months, traveled distances are higher, and parking times before trips may not allow the car to fully recharge or provide sufficient autonomy for the trip. Single holiday trips are often not enough to meet these requirements. In August, this phenomenon affects mostly male users, with the highest percentage in Milano, followed by Asti. For the rest of the year, Trieste exhibits the highest unsatisfied user rate. From this analysis, it can be inferred that excluding these unusual holiday trips would likely increase overall satisfaction and, consequently, the city's adaptability to EV adoption. In Milano, which currently exhibits the lowest full satisfaction rate, at least 5% of unsatisfied users are due to holiday trips. If users plan these trips in advance and adjust their schedules, satisfaction could be achieved with some compromise. However, if users do not modify their habits, longer holiday trips will continue to negatively impact performance metrics. It should be noted that unsatisfied users are not necessarily consistent throughout the year; a single unsatisfied trip in any month classifies the user as unsatisfied, affecting the city's overall adaptability score. The distribution of monthly unsatisfied trip counts per unsatisfied user is shown in Figure 5.19.

During months with major festivities, the median number of unsatisfied trips per user increases. Typically, affected users experience two unsatisfied trips per month, rising to three in August. Users in Sassari are least affected, with only one unsatisfied trip on average, while Milano's users are the most susceptible to seasonal increases in unsatisfied trips with users on the 75% percentile with around four unsatisfied trips.

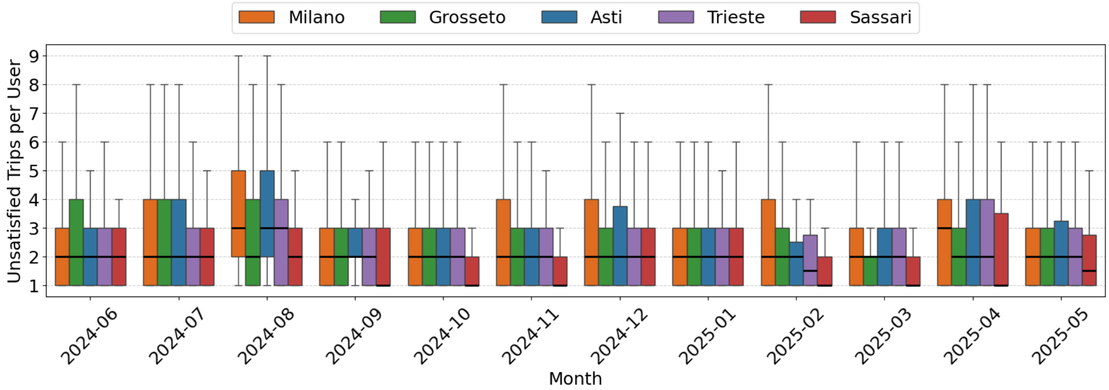


Figure 5.19: Monthly Distribution of Unsatisfied Trips per User Across Cities.

To characterize the unsatisfied users, Figure 5.20 illustrates the percentage of unsatisfied users by gender and age group, distinguishing between Commercial and Non-Commercial vehicles. For Commercial vehicles, those from Trieste and Milano are the most affected, with approximately 22% and 20% of the fleet experiencing unsatisfied trips, respectively. In contrast, Sassari is affected the least, reporting only about 4% of its Commercial fleet affected. For Non-Commercial vehicles, Trieste and Milano also rank highest in most age groups. Notably, Asti's users under 25 years old are the most affected among their age peers, with around 2% experiencing unsatisfied trips, except when compared to Sassari users. Considering gender among Non-Commercial users, males are generally more affected across all age groups and cities. However, female users in Trieste under 25 years old experience the highest percentage of unsatisfied trips, exceeding both females and males of the same age in other cities.

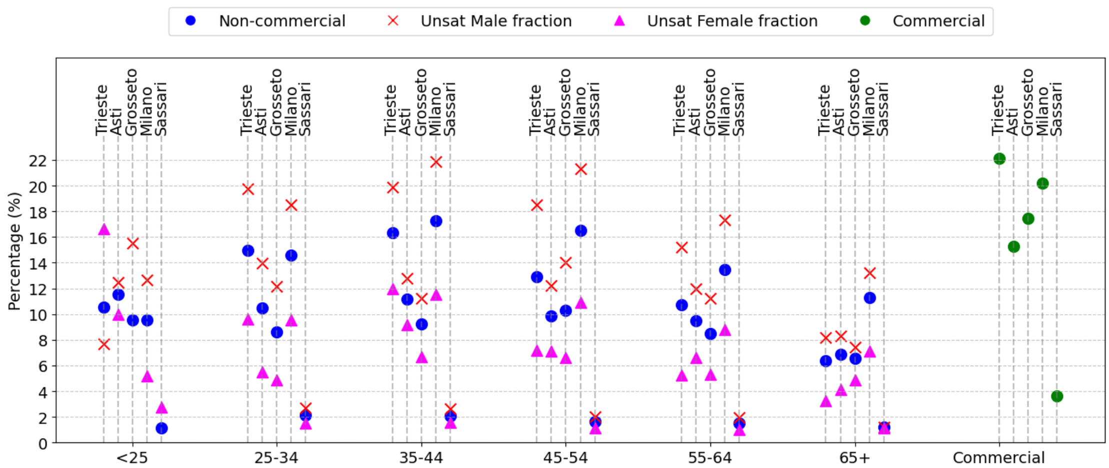


Figure 5.20: Unsatisfied user profile based on gender and age group per city

On Figure 5.21, the percentage of unsatisfied users affected based on their original fuel type is present. Showing also on top of the bar the raw number of users that are represented on the bar in question. As it can be observed, the most affected users, in proportion, are those were originally used Diesel, Hybrid or GPL.

The interesting part are the users with originally Electric Vehicles, that were actually supposed to satisfied all their trips, but are still present some on Grosseto, Milano and Trieste.

Milano shows 21 unsatisfied users, however it represents just the 5% of the EV fleet of Milano, hey were already exposed during the *Replication of real EV trips* section, and the reasons behind their dissatisfaction were explained in detail. Mostly because the charging time before the trip was not enough according to the choosen policy (mostly Conservative), or long trips out of the autonomy of the assigned car were attempted with low SoC.

In the case of Trieste and Grosseto, only a single EV user was not satisfied. The user of Trieste is a male of 44 years old that attempted to perform 3 trips of 180, 200, 380 km with only 0%, 20% and 45% of the SoC, were the 45% capacity of the battery allows only 311 km. The Grosseto user is for Commercial purpose and attempted to do 8 trips over 160 km with SoC of less than 20% which will cover only for 138 km.

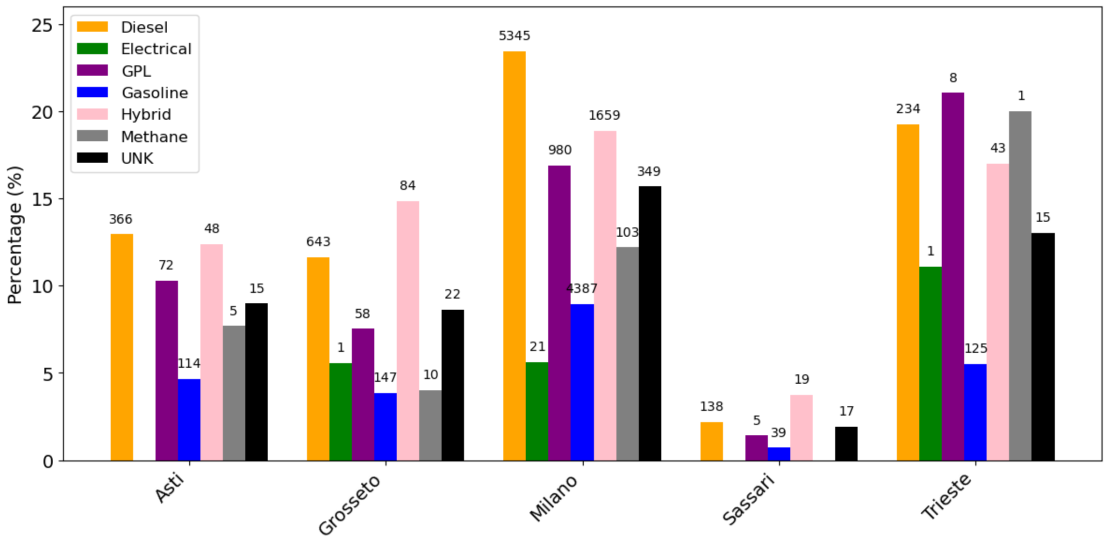


Figure 5.21: Unsatisfied user profile based on fuel per city

Chapter 6

Conclusions

This study assessed the feasibility of using battery electric vehicles (BEVs) to satisfy user trips across several Italian cities, considering diverse vehicle models and charging policies. The analysis integrated trip distances, parking durations, and vehicle state of charge (SoC) dynamics to evaluate trip-level and user-level satisfaction.

Results indicate that most urban trips can be completed using small-battery EVs, such as the Dacia Spring and Fiat 500e. In the analyzed cities, most trips are under 50 km, with average parking times between 4 and 8 hours, and users typically travel a maximum of around 200 km. However, satisfaction varies significantly by city due to differences in travel patterns and user density. Sassari achieves the highest satisfaction rates, favored by shorter trips and longer parking durations, while Milano exhibits lower satisfaction because its users frequently travel longer distances near the limits of vehicle autonomy.

Charging behavior plays a decisive role in satisfaction outcomes. The *Conservative policy*, offering greater flexibility in charging opportunities, resolves most unsatisfied trips with only minor behavioral adjustments. In contrast, the more restrictive *Casual policy* leaves a larger share of users unsatisfied, often due to insufficient charging time or unmet SoC requirements. Addressing these limitations, by relaxing policy constraints or encouraging users to plan charging before long trips, significantly could improve the satisfaction rates. Similarly, upgrading to higher-capacity EVs, such as moving from a Fiat 500e to an Audi A6 e-tron, notably enhances performance in high-demand cities like Milano, raising user satisfaction from roughly 48% to 85%.

Overall, user satisfaction depends on the interaction between technical vehicle characteristics and behavioral charging habits. Technical factors (vehicle range, SoC management) and behavioral aspects (charging discipline, trip planning) jointly define the suitability of EV adoption. Sassari stands out as the most adaptable city, achieving nearly full satisfaction under the Conservative policy and maintaining high performance even under less flexible conditions. In contrast, Milano remains the least adaptable, but still with over 85% of satisfied users, depending on long-range vehicles to meet user travel demands. Across all cities, at least 50% of users could be satisfied using low-range EVs such as the Dacia Spring or Fiat 500e.

No single charging policy suits all users. While the Conservative policy achieves the best overall results, its rigidity limits its suitability for specific user profiles. Allowing users to adopt their most compatible charging policy individually increases satisfaction by about 1% across cities, confirming the value of behavioral flexibility. Policies such as Conservative, Frequent and Taxi proved to be suitable for most users, while Car Sharing and Weekend remain largely ineffective, except for a small subset of users in Milano. These differences underscore the heterogeneous nature of urban mobility and the importance of personalized charging strategies.

Seasonal variations further influence satisfaction rates. The number of unsatisfied users peaks during the summer, especially in August, when longer leisure trips reduce charging opportunities. This effect is strongest in Milano and Asti, while Trieste consistently shows higher dissatisfaction throughout the year. Excluding these seasonal anomalies could increase Milano's satisfaction by up to 5%, highlighting how occasional behaviors can skew overall city performance. Encouraging better planning and charging before long holiday trips would mitigate these seasonal drops.

Demographic and fleet analyses reveal additional insights. Commercial fleets in Trieste and Milano experience the highest dissatisfaction, with about 20% of users affected, whereas Sassari is minimally impacted. Among non-commercial users, drivers under 25 are the most affected in Asti and Trieste. Male users are generally more prone to dissatisfaction, although young female users in Trieste exhibit the highest overall rate.

Fuel-type analysis shows that users transitioning from Diesel, Hybrid, or GPL vehicles face greater adaptation challenges, being overrepresented among the unsatisfied users. Interestingly, a few existing EV owners in Milano, Grosseto, and Trieste also reported dissatisfaction, largely due to behavioral issues like inadequate pre-trip charging or inappropriate policy selection, rather than technical vehicle constraints.

In summary, the adaptability of cities to EV adoption depends not only on vehicle performance and infrastructure but also on behavioral flexibility and charging discipline. Sassari demonstrates that successful EV integration is achievable even with modest vehicles when user behavior aligns with technical limitations. Conversely, Milano's lower satisfaction levels emphasize the need for behavioral adaptation and possibly improved charging infrastructure.

During this research, several assumptions were made to enable the analysis and to replicate trips as if they were performed with electric vehicles. Although the charging policies were designed to simulate realistic charging behavior by assigning specific time windows for charging, this does not necessarily imply that users would always charge their vehicles during those periods. Moreover, unexpected trips may require charging behaviors that differ from the usual patterns. Currently, such cases may result in unsatisfied trips, as the simulator does not allow multiple charging policies per user nor forecasts the next trip to determine the most suitable charging strategy.

Additionally, the current simulator recharges the battery whenever a parking event meets the charging policy conditions, regardless of the actual availability of a charging station at that location. Unfortunately, Origin-Destination coordinates were not available in the provided datasets, making it impossible to include spatial details that would enhance realism by considering real charging infrastructure.

For future developments, the simulator could be expanded by integrating real-world features of current EV technologies—such as automated charging parameter adjustments and scheduling based on vehicle-to-charger communication protocols. With access to location data, the simulator could be linked to public databases of charging stations, enabling it to detect when a user parks within the vicinity of an available EVSE and flag that event as an opportunity to recharge. Also, considering the thresholds on SoC to recharge set by each car, the charging speed varies continuously depending on the SoC level. The current model emulates this behavior using two discrete thresholds; however, in practice, the charging curve is more dynamic, with power gradually decreasing as the SoC increases. Incorporating additional thresholds or implementing a continuous power derating function based on the instantaneous SoC could therefore enhance the realism of the simulations.

Furthermore, given the flexibility of the BEV simulator and its easily customizable charging policy features, future work could explore optimization approaches to identify the set of charging policy parameters that maximize trip satisfaction for each user. This would allow evaluating whether the overall satisfaction rate per city improves when unsatisfied users are assigned personalized charging policies better aligned with their individual travel needs.

Chapter 7

Appendix

7.1 BEV Simulator Flowcharts

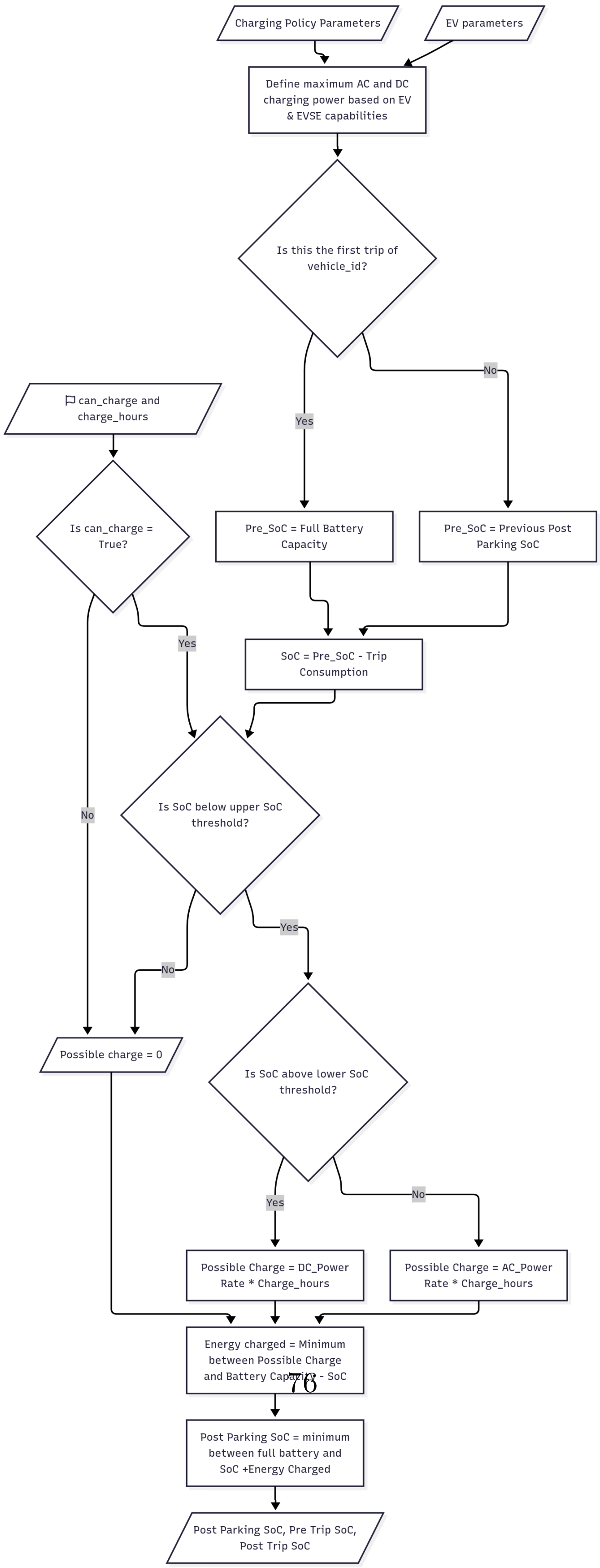


Figure 7.1: Flowchart of the update SoC process.

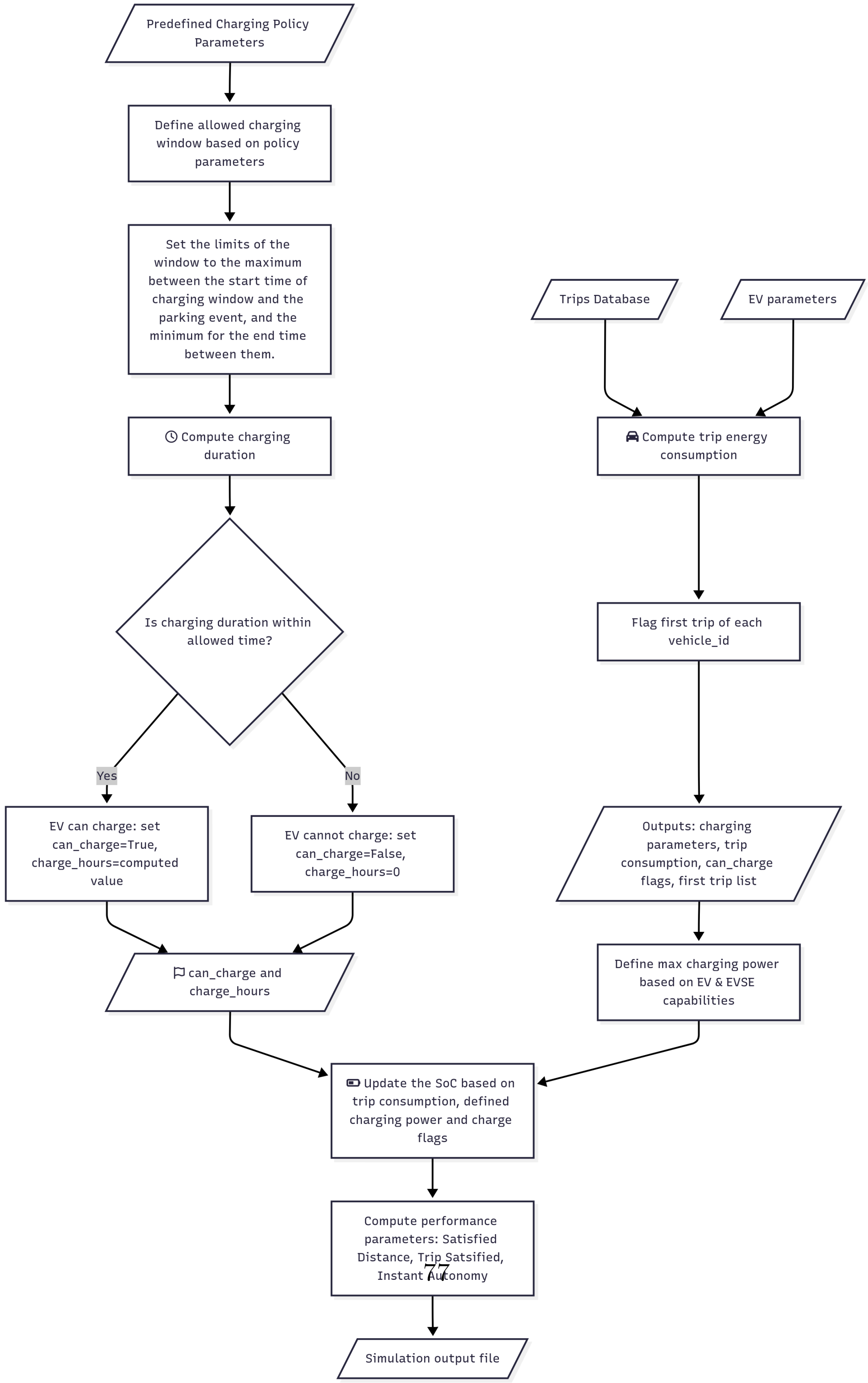


Figure 7.2: Flowchart of the overall BEV simulation process.

7.2 Unsatisfied Trips categorization shares using a Fiat 500e for all cities

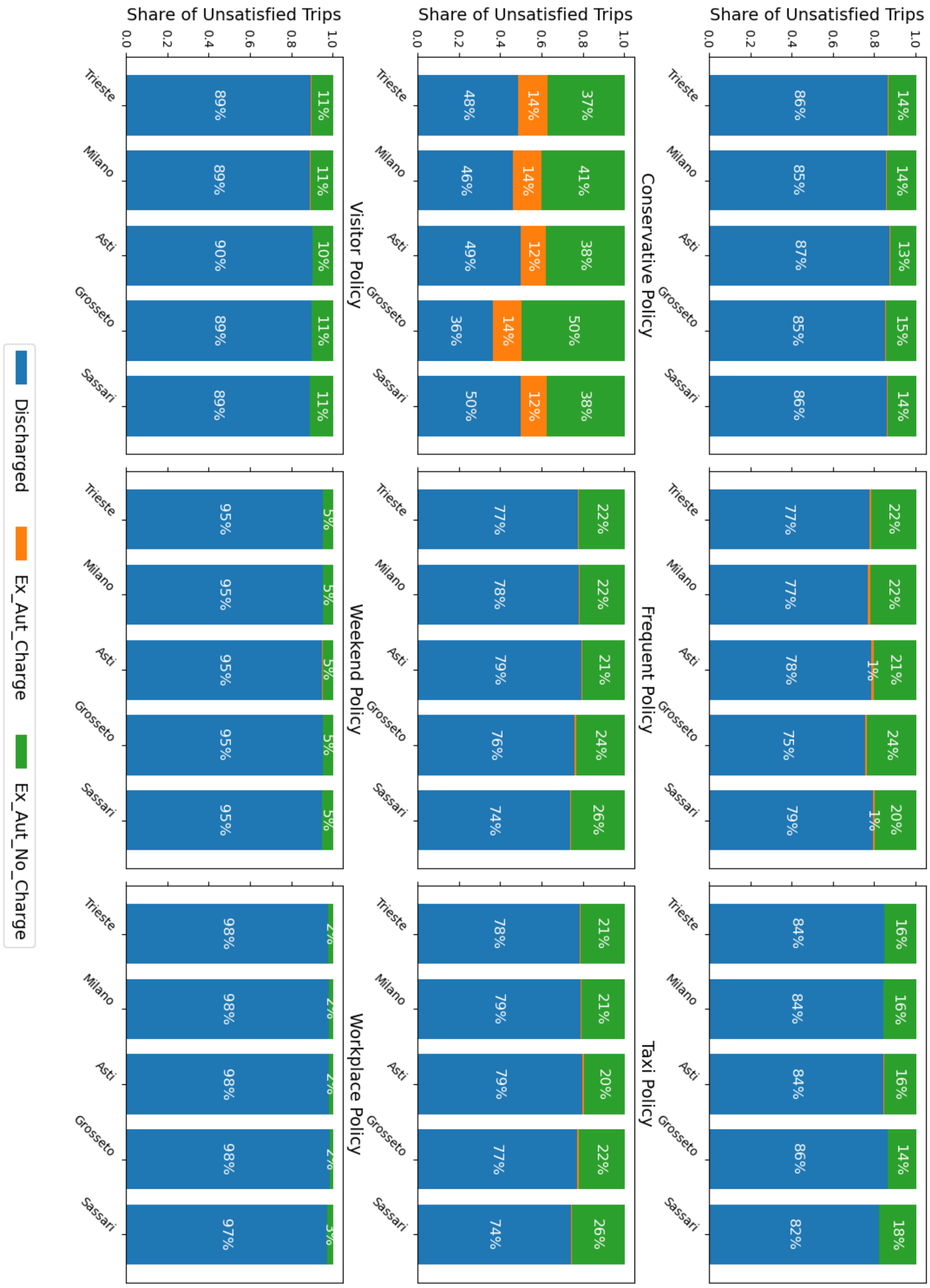


Figure 7.3: Unsatisfied trips categorization across cities.

Figure 7.4: Unsatisfied trips shares for satisfied distance across cities.

Figure 7.5: Unsatisfied trips shares for overlapped parked time with charging policy across cities.

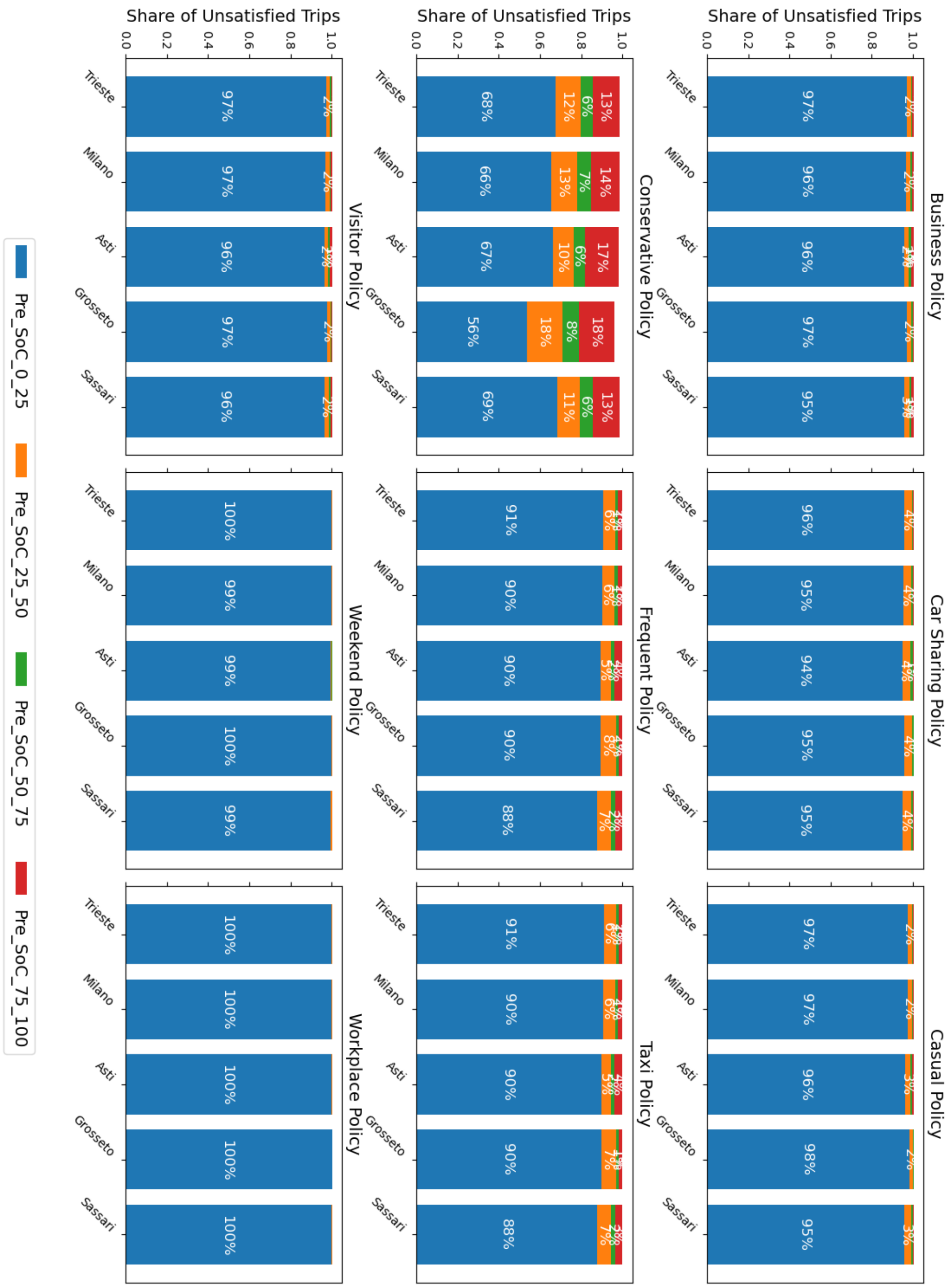


Figure 7.6: Unsatisfied trips shares for available SoC across cities.

7.3 Milano

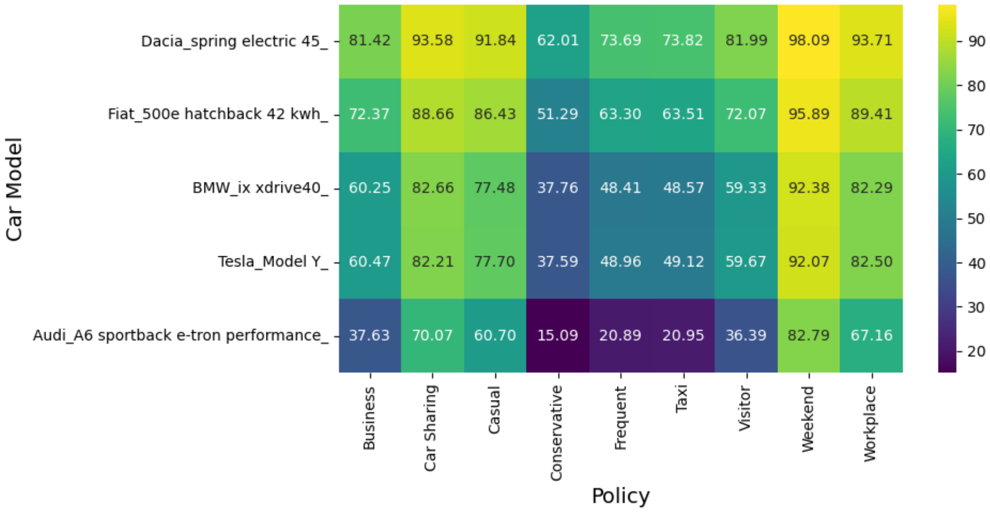


Figure 7.7: Percentage of unsatisfied users per charging policy for Milano.

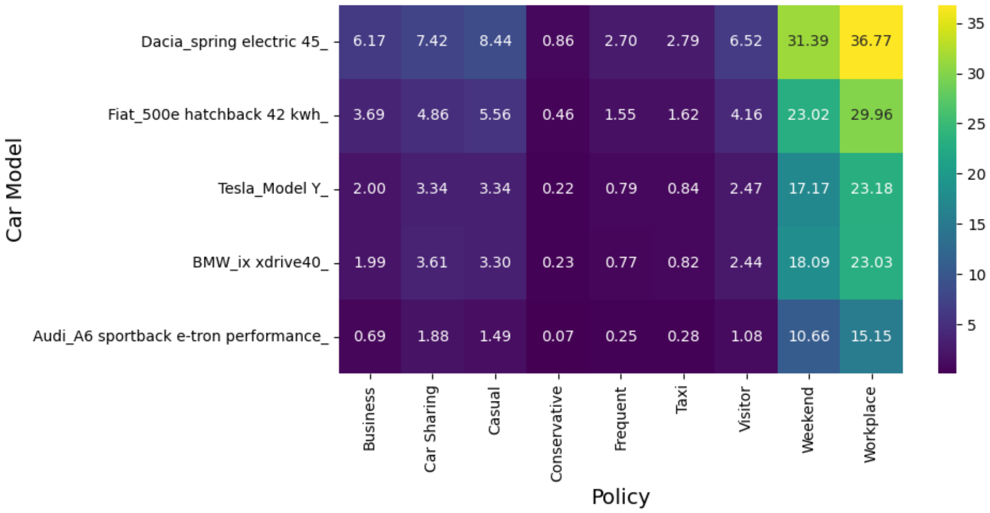


Figure 7.8: Percentage of unsatisfied trips per charging policy for Milano.

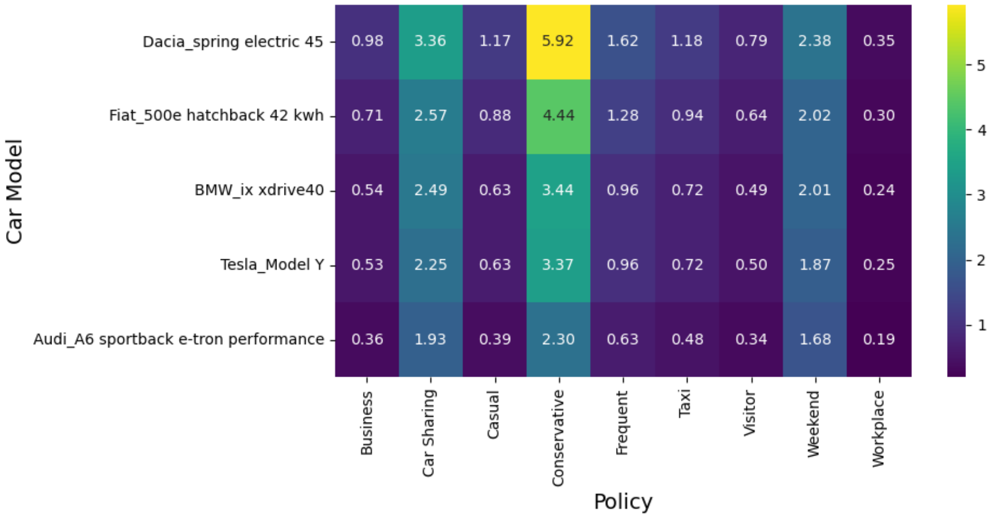


Figure 7.9: Percentage of charging time relative to total parked time per charging policy for Milano.

7.4 Asti

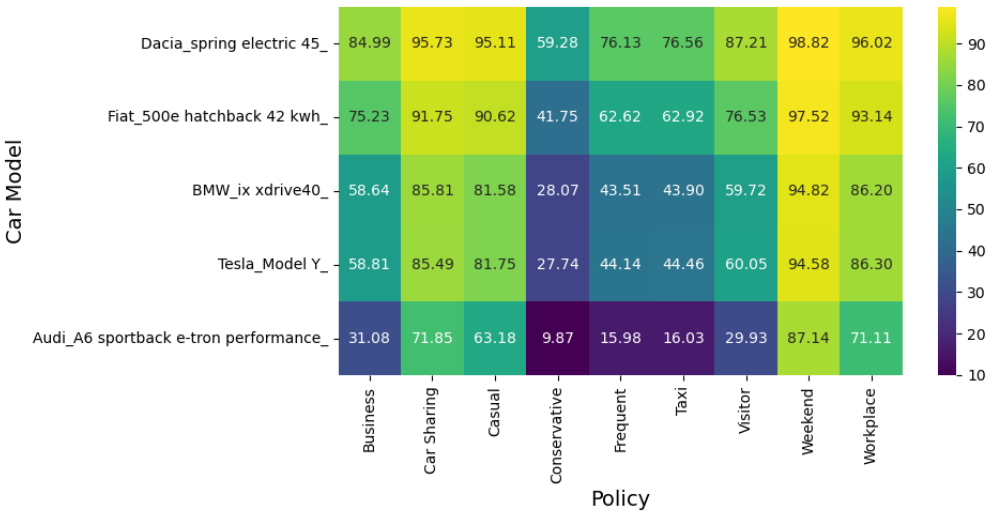


Figure 7.10: Percentage of unsatisfied users per charging policy for Asti.

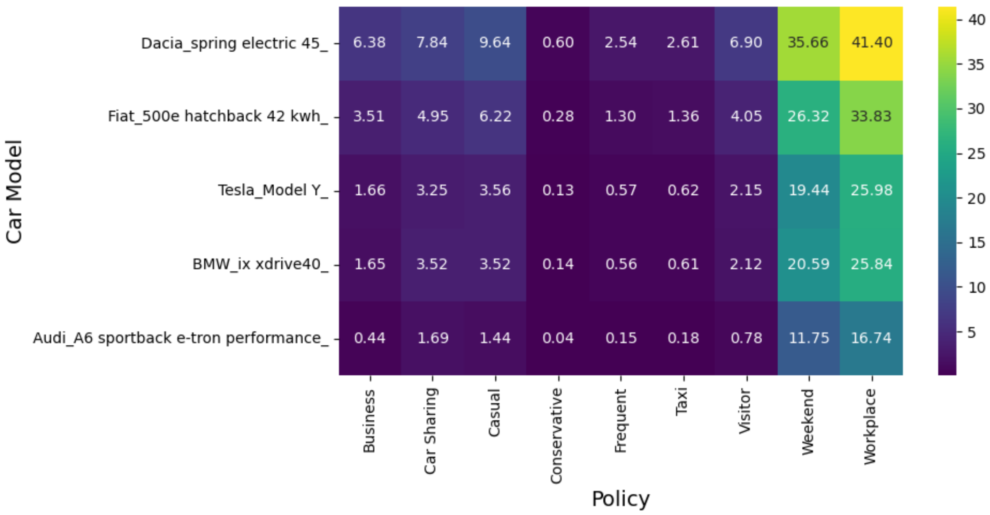


Figure 7.11: Percentage of unsatisfied trips per charging policy for Asti.

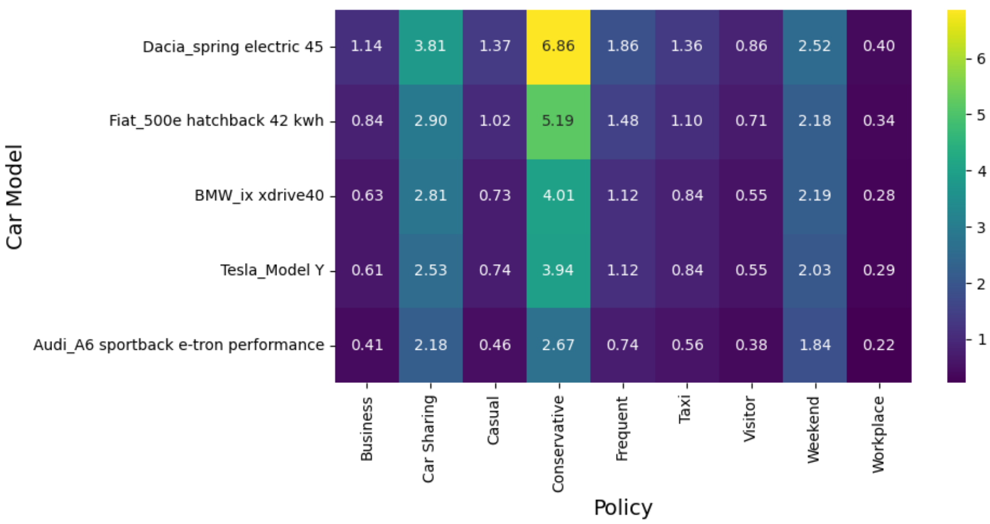


Figure 7.12: Percentage of charging time relative to total parked time per charging policy for Asti.

7.5 Grosseto

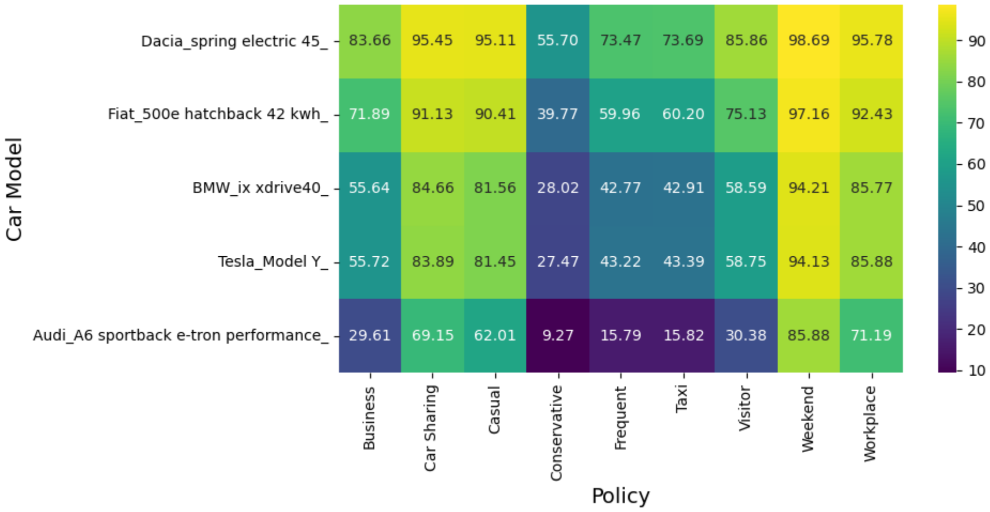


Figure 7.13: Percentage of unsatisfied users per charging policy for Grosseto.

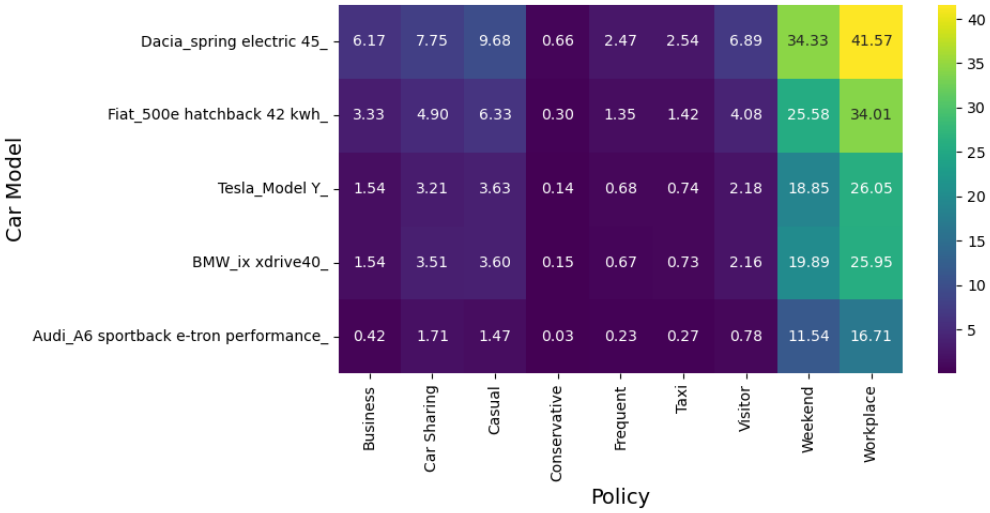


Figure 7.14: Percentage of unsatisfied trips per charging policy for Grosseto.

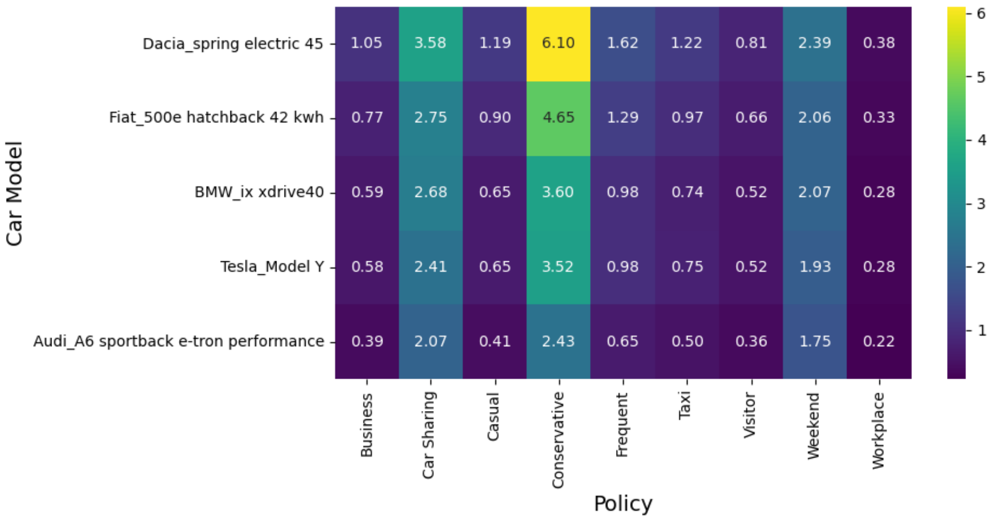


Figure 7.15: Percentage of charging time relative to total parked time per charging policy for Grosseto.

7.6 Sassari

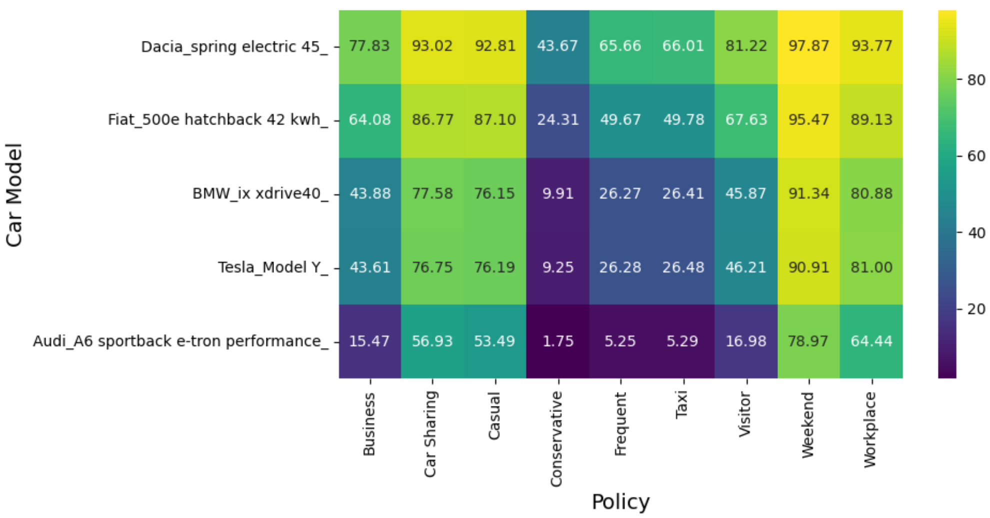


Figure 7.16: Percentage of unsatisfied users per charging policy for Sassari.

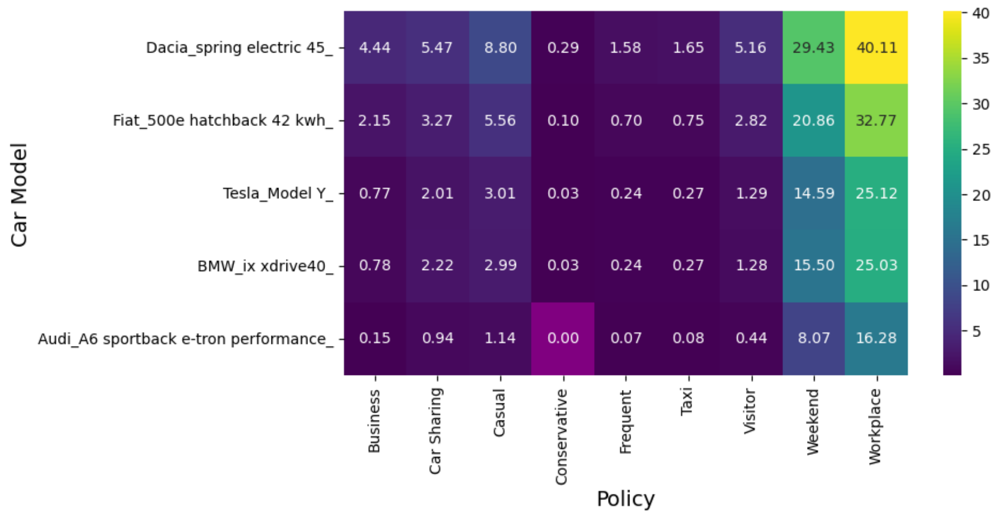


Figure 7.17: Percentage of unsatisfied trips per charging policy for Sassari.

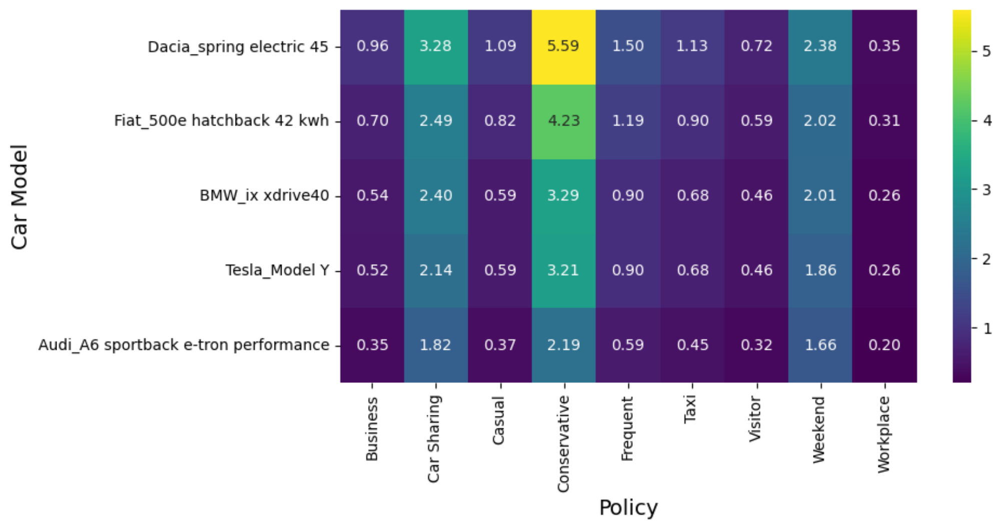


Figure 7.18: Percentage of charging time relative to total parked time per charging policy for Sassari.

7.7 Trieste

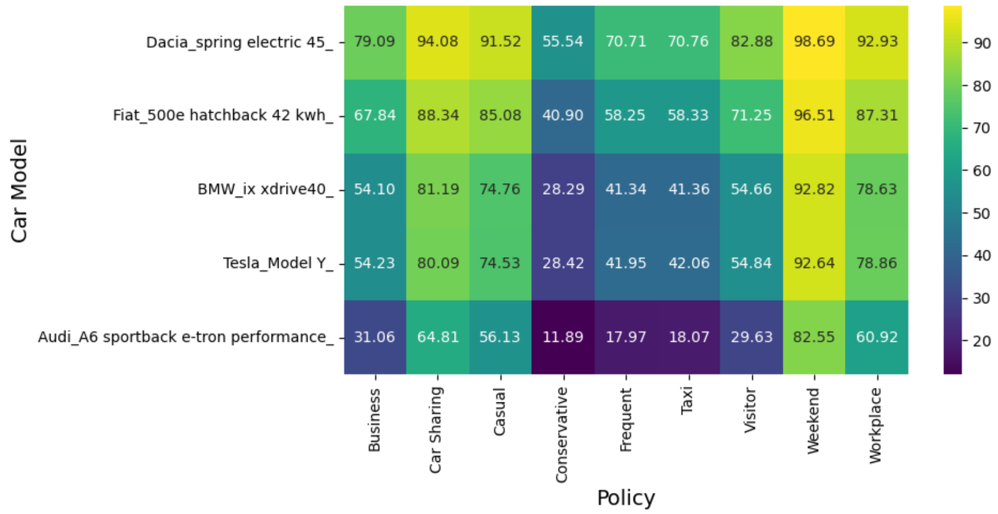


Figure 7.19: Percentage of unsatisfied users per charging policy for Trieste.

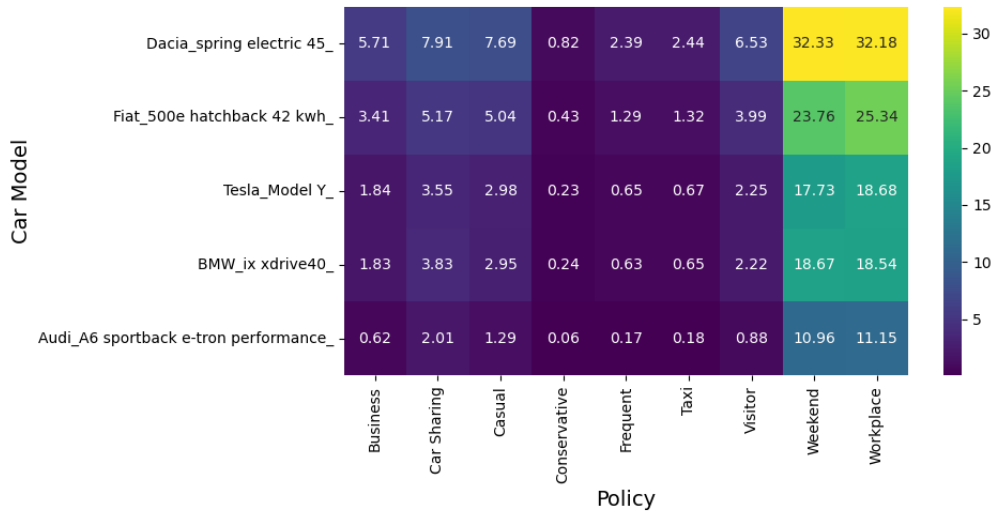


Figure 7.20: Percentage of unsatisfied trips per charging policy for Trieste.

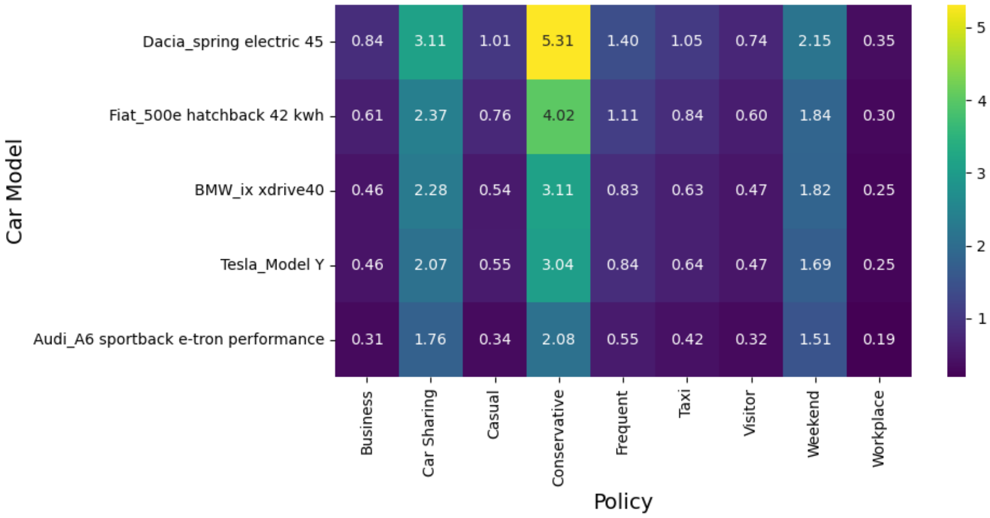


Figure 7.21: Percentage of charging time relative to total parked time per charging policy for Trieste.

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