POLITECNICO DI TORINO

Master Degree course in Digital Skills for Sustainable Societal Transitions

Master Degree Thesis

Adopting EVs: A Data-Driven Simulation of Real-World User Mobility

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Abstract

The transition to electric vehicles (EVs) is a critical step in sustainable urban mobility, addressing environmental concerns such as carbon emissions and air pollution. Despite rapid EV market growth, challenges like costs, range limitations, and insufficient charging infrastructure persist. This thesis uses real-world driving data from 1,000 insurance customers to assess EV adoption feasibility, focusing on user-specific trip patterns.

A custom-designed simulator forms the core of the study, evaluating EV feasibility by processing inputs: 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 simulator replicates trips through two main steps:

1. **Simulating the Trip:** Calculates energy consumption, checks SoC sufficiency, and flags trips with low or insufficient SoC.

2. **Charging Process:** Manages charging events during parking intervals to replenish energy.

Key outputs include SoC before and after trips, trip energy consumption, energy gained during parking, and metrics like feasible trip percentages, distances under anxiety, and days with anxiety or unsatisfied trips, offering detailed insights into EV adoption for varying user behaviors and vehicle specifications.

The study applies the simulator in three phases, each increasing in complexity:

1. **Abstract Scenarios:** Establishes baseline feasibility using generalized EV characteristics.

2. **Behavioral Variations:** Models nine user profiles with diverse charging preferences such as time-of-day effects, weekday variations, and state-of-charge thresholds.

3. **Real Market Vehicles:** Incorporates specifications of 50 EV models, including vehicle prices, to deliver realistic, user-focused results and cost analysis.

A two-level cost analysis enriches the findings:

1. **Aggregated Cost Analysis:** Evaluates daily charging costs and costs per kilometer under different scenarios, considering both home and public street charging with price bounds to reflect variations.

2. **Monthly Cost Tracking:** Examines how costs evolve over time, comparing them with other performance metrics to identify user behaviors.

Key findings show that larger battery capacities and faster charging reduce range anxiety and improve trip satisfaction. However, among slow AC charging options, higher power rates (e.g., 11 kW vs. 22 kW) have little impact during overnight charging, as extended charging times compensate for lower power output. Notably, based on the sample analyzed in this study, even with slow AC charging, a casual driver with 28% utilization can achieve over 70% feasibility using the most affordable EV (Dacia Spring Electric 45). Drivers dependent on public charging or with irregular travel patterns require targeted infrastructure enhancements. While home charging remains the most cost-effective, public DC fast charging offers flexibility for long-distance travel. Behavioral trends and performance metrics tracked over time further highlight adoption challenges and opportunities.

In conclusion, tailored charging strategies are vital for diverse user needs and optimal EV adoption. EV feasibility heavily depends on user travel patterns; in some cases, behavioral adjustments are necessary for effective transitions. By offering actionable insights, this study supports sustainable urban mobility and provides guidance for policymakers, EV manufacturers, and infrastructure developers.

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Chapter 1

Introduction

1.1 Context and Motivation

Combustion engine vehicles significantly contribute to carbon emissions, air pollution, and climate change. Electric vehicles (EVs), especially those powered by renewable energy, offer an eco-friendly alternative by producing almost zero operational emissions. This shift benefits both the environment and public health through reduced urban pollution [20].

In recent years, the global EV market has expanded considerably, propelled by technological advancements and increasing environmental awareness. Car manufacturers regularly introduce new EV models, driving adoption worldwide. For instance, the number of EVs in operation rose from around 100,000 in 2012 to over 1 million in 2016, exceeding 10 million by 2020. Notably, more than 3 million EVs were sold globally in 2020 alone [22].

Despite this rapid growth, EVs still face challenges such as higher purchase costs, limited driving range, and insufficient charging infrastructure. Among these issues, the fear of depleting the battery before reaching a charging station often termed "range anxiety" remains a notable psychological barrier. Overcoming these hurdles is critical to broadening EV adoption and achieving more substantial environmental and public health benefits.

Charging infrastructure development is essential to address range anxiety. Governments and private companies are increasingly promoting the establishment of public charging networks. For example, China has seen a substantial rise in public charging facilities, and the United Kingdom has observed an almost fivefold increase since 2015. Globally, the EV charging station market is projected to reach $29.7 billion by 2027. Nonetheless, accurate forecasting of charging demand and proper infrastructure planning pose significant challenges [32].

Beyond issues of infrastructure, charging times can also deter potential users. These charging durations vary based on the charger type and battery technology, ranging from minutes to hours. Although ongoing technological breakthroughs are reducing these durations, battery costs remain high and continue to influence EV pricing. However, growing governmental incentives and innovations in battery design are helping to lower these costs, making models such as the Tesla Model 3 more attainable [31].

Modeling and predicting charging behavior is vital for resolving these challenges. External influences such as the structure of the charging network and individual travel needs combine with socio-economic and psychological factors to affect user decisions. Considerations like power demand, charging duration, and the spatial and temporal clustering of charging events all inform how charging stations are used, how they impact overall grid stability, and how they shape emissions from electricity generation [1].

Nonetheless, modern EVs now rival their combustion engine counterparts in terms of comfort, range, and performance. This progress makes EVs particularly attractive for those seeking to reduce their environmental impact without drastically altering their transportation habits, a shift especially pertinent in heavily car-dependent urban environments [17].

1.2 Problem Definition

This thesis is part of a collaborative effort between UnipolTech and the Polytechnic University of Turin. Its main objective is to utilize real-world travel data from combustion engine vehicles to simulate these same trips using various electric vehicle (EV) models. By examining the results of these simulations, the research aims to identify which EV models best suit different users' driving routines and requirements.

Put simply, the core problem is determining how seamlessly electric vehicles can replace traditional internal combustion engine vehicles. This entails assessing whether EVs can manage the typical journeys of diverse user groups, considering factors like range, charging behavior, and daily travel demands. Achieving this goal requires accurately simulating EV use cases, carefully accounting for battery capacities, roadway environments (e.g., highway vs. urban), charging power, and real-world charging patterns.

1.2.1 Research Questions

To address the core problem, this thesis seeks to answer the following research questions:

1. **What are the key factors influencing the feasibility of EV adoption among diverse user groups based on real-world trip data?**

2. **How do different EV models perform in replicating the driving routines of traditional combustion engine vehicles?**

3. **What is the impact of battery capacity and charging power on range anxiety and trip satisfaction?**

4. **How do various charging strategies (e.g., home charging, public DC fast charging) affect the economic viability and operational efficiency of EVs?**

Question 1 aims to identify and analyze the primary determinants that affect whether different user segments are likely to adopt EVs. This includes examining trip patterns, user preferences, and behavioral factors that influence EV feasibility.

Question 2 focuses on evaluating the performance of various EV models in meeting the driving needs that are currently satisfied by combustion engine vehicles. This comparison will help in understanding which EV models are most suitable for specific user profiles.

Question 3 investigates how variations in battery capacity and charging power influence users' experiences, particularly concerning range anxiety and overall trip satisfaction. Understanding these impacts is crucial for optimizing EV specifications and user support mechanisms.

Question 4 explores the economic aspects of different charging strategies, assessing how they contribute to the cost-effectiveness and operational sustainability of EVs. This includes analyzing the costs associated with home charging versus public fast charging options.

This thesis aims to answer these research questions and provide a clear assessment of how feasible EV adoption is. The findings will help policymakers, EV manufacturers, and infrastructure developers make informed decisions to support sustainable urban mobility.

1.3 Approach and Thesis Overview

To achieve the research objectives, this thesis employs a comprehensive multi-level simulation strategy designed to analyze diverse electric vehicle (EV) charging behaviors and vehicle specifications. This approach integrates real-world trip data with advanced simulation models to accurately assess EV adoption feasibility. The key components of the methodology are outlined below:

- **Data Collection and Preparation:** The foundation of the simulation is built upon real trip records from traditional combustion engine vehicles. Each trip entry includes detailed information such as trip start and end times, distance traveled, and road categories (e.g., urban, highway). This real-world data ensures that the simulation accurately reflects actual driving patterns and usage scenarios, providing a realistic basis for evaluating EV performance and charging needs.

- **Simulation Parameters and Assumptions:** Critical parameters such as battery capacities, energy consumption rates, and charging power ratings are integrated into the simulation model. Additionally, behavioral models are developed to represent how users interact with the charging infrastructure, including factors like minimum parking durations, time-of-day charging preferences, and state-of-charge (SoC) thresholds that trigger charging events. A core assumption of this study is that charging is accessible anywhere a user parks, compensating for the absence of exact location data. These parameters and assumptions are essential for creating a realistic simulation environment that mirrors real-world conditions.

- **Progressive Simulation Levels:** The methodology is divided into multiple simulation levels, each increasing in complexity to model real EV charging behaviors using the provided dataset. This progressive approach allows for a nuanced understanding of different factors influencing EV feasibility.

  - ***Level One*** establishes a foundational charging model by assuming that vehicles charge during any parking event longer than a preset minimum duration. This level does not consider the time of day, battery state, or weekday/weekend effects. Simulations span ten different battery capacities and ten charging power outputs (both AC and DC). Additionally, eight energy consumption rates covering urban, highway, and mixed driving scenarios are used to represent varying levels of efficiency. At this initial level, the simulation replicates trips by sequentially processing each recorded trip, calculating energy consumption based on predefined vehicle parameters, and determining whether the EV can complete the trip without recharging. This helps identify baseline feasibility and fundamental trends in EV usage. This level can be considered as an upper bound of measured performance metrics.
  - ***Level Two*** builds upon the first approach by introducing nine distinct charging behaviors. These behaviors incorporate variables such as SoC triggers, day-of-week differences, and time-of-day effects. The same ten battery capacities and ten power outputs from Level One remain, along with the eight consumption patterns, enabling a more detailed understanding of user-specific charging patterns. In this level, the simulation not only replicates the sequence of trips but also dynamically adjusts charging events based on real-time SoC data and temporal factors, providing deeper insights into how different factors influence charging needs and vehicle availability.
  - ***Level Three*** integrates real-world data from 50 top-selling EV models in Europe as of 2024. The analysis uses each vehicle's actual battery capacity, charging rates (AC/DC), and energy consumption for different driving environments (urban, highway, mixed). This realism allows the simulation to replicate trips with specific vehicle characteristics, enabling direct comparisons of performance across diverse EV models under realistic charging scenarios defined in Level Two. This detailed replication ensures that the simulation outcomes are highly representative of real-world EV performance.

- **Cost Analysis:** The study conducts a thorough two-part cost analysis to evaluate the economic viability of EV adoption:

  1. **Aggregated Cost Analysis:** This phase assesses daily charging expenses and costs per kilometer under various scenarios, considering both home and public street charging with different pricing tiers. It provides a macro-level view of the financial implications associated with different charging strategies.
  2. **Monthly Cost Tracking:** This phase examines how charging costs evolve

over time, correlating them with user behaviors and vehicle performance metrics. It offers a micro-level perspective, highlighting trends and patterns in charging expenses that can inform long-term economic assessments.

- **Interactive Dashboard:** An online dashboard is developed to dynamically visualize the simulation outcomes. This tool displays key performance metrics, including range feasibility, the percentage of feasible trips, and estimated costs across different scenarios. The interactive nature of the dashboard allows stakeholders to explore and interpret results in real-time, facilitating informed decision-making.

Simulating and Replicating Trips: Central to this methodology is the process of simulating and replicating trips based on the collected real-world data. **Simulating trips** involves recreating each recorded trip within the simulation environment by sequentially processing trip data, calculating energy consumption based on specific vehicle parameters, and determining the resulting state of charge (SoC) after each trip. This simulation accounts for various factors such as driving speed, road type, and vehicle efficiency to accurately model energy usage.

Replicating trips ensures that the sequence, timing, and conditions of the simulated trips closely mirror those observed in the actual trip data. This replication involves maintaining the integrity of trip start and end times, distances traveled, and usage patterns to create a realistic and reliable simulation environment. By faithfully replicating these trips, the simulation can provide accurate assessments of EV feasibility, identify potential issues like range anxiety, and evaluate the effectiveness of different charging strategies under conditions that reflect real-world usage.

Pre-simulation steps emphasize thorough dataset characterization. This involves meticulous preprocessing and cleaning to transform raw trip data into a structured format, eliminating errors and inconsistencies. By ensuring high data quality, the simulations can accurately replicate real world driving conditions and user behaviors, thereby enhancing the reliability and validity of the study's findings.

1.4 Thesis Organization

The structure of this thesis is divided into five chapters, offering a logical progression from background theory to methodology and results:

- **Chapter 1: Introduction**
  Provides the context, motivation, and overarching research questions. It also details the problem statement and introduces the simulation-based methodology.

- **Chapter 2: Background**
  Explores foundational concepts and key literature that support the current research, including EV technologies, charging standards, and relevant studies in charging behavior.

- **Chapter 3: Dataset Management**
  Presents the dataset used in this research, outlines its characteristics, and describes the cleaning and preprocessing steps that prepare the data for simulation.

- **Chapter 4: Methodology**
  Delves into the multi-level simulation strategy and the parameters that shape each scenario. It also explains the metrics used to evaluate outcomes and concludes with a financial analysis of various EV adoption cases.

- **Chapter 5: Results**
  Shows the findings from the simulations, featuring detailed data visualizations that compare multiple EV models and highlight how each configuration meets user demands.

- **Chapter 6: Conclusions**
  Summarizes key insights drawn from the research, discusses practical implications, and suggests future research directions.

Chapter 2

Background

2.1 Overview of Electric Vehicles (EVs):

Electric vehicles (EVs) represent a broad category of transportation technologies designed to address various mobility needs while supporting the transition to sustainable transportation. These vehicles use different methods of propulsion, each suited to specific driving requirements and environmental goals.

Battery Electric Vehicles (BEVs) are fully electric, relying entirely on batteries as their power source. These vehicles produce zero emissions during operation, making them highly environmentally friendly. However, their driving range is limited by the capacity of the battery, which can vary depending on the model.

On the other hand, **Hybrid Electric Vehicles (HEVs)** combine an internal combustion engine (ICE) with an electric motor. The electric motor helps enhance fuel efficiency and reduce emissions, particularly during low-speed driving, allowing for a more sustainable driving experience without the need for frequent charging.

Plug-in Hybrid Electric Vehicles (PHEVs) take the hybrid concept a step further by incorporating larger batteries that can be recharged directly from the grid. This enables PHEVs to drive longer distances on electric power alone, offering more flexibility for users who want to rely on electric driving for short trips while still having the option of using the internal combustion engine for longer journeys.

Finally, **Fuel Cell Electric Vehicles (FCEVs)** use hydrogen to generate electricity through a chemical reaction in a fuel cell. These vehicles offer the advantage of quick refueling and produce zero emissions, with water being the only byproduct of the reaction, making them an attractive option for long-distance travel.

These various types of electric vehicles cater to a wide range of driving needs, from short urban commutes to longer trips, playing a crucial role in the ongoing shift toward more sustainable transportation solutions.

[28]

In this thesis, the focus is exclusively on the first category, **Battery Electric Vehicles (BEVs)**, due to their potential for zero-emission operation and their growing prominence in urban and long-distance travel.

2.2 EV Charging Technologies

2.2.1 Modes and Levels

Electric vehicles (EVs) can be charged at different locations and speeds, with costs varying accordingly. EV supply equipment (EVSE) consists of one or more charging points (CPs) that connect the power grid to EVs. These points draw AC power and convert it to DC power to charge the EV battery. Depending on the charging setup, the power conversion can occur either onboard or offboard. Charging systems are categorized based on two frameworks: "level" and "mode."

- **Charging levels** are defined by the Society of Automotive Engineers (SAE) and specify the power and voltage of the charging system.
- **Charging modes** are established by the International Electro technical Commission (IEC) and focus on the electronic communication between the EV and the power supply, which is crucial for safety and proper charge management.

The IEC outlines four charging modes:

- **Mode 1:** Involves charging directly from a standard household outlet with a simple extension cord. However, it lacks DC current shock protection and is prohibited in many countries.
- **Mode 2:** Utilizes a special cable, typically provided with the EV, which includes integrated shock protection.
- **Mode 3:** Involves the use of a dedicated charging station or a wall-mounted home charger, both of which offer AC and DC shock protection. The cable is included with the charging station.
- **Mode 4:** Designed for DC fast charging, where AC is converted to DC externally in a fast charger, which then charges the EV battery. Unlike the other modes, this mode does not rely on onboard AC-to-DC conversion.

Charging levels are distinguished by voltage and power output:

- **Level 1:** Provides 120 V AC power with a capacity of 2 kW, suitable for residential use without requiring special equipment. It is not permitted in the EU.
- **Level 2:** Uses a standard European 230/240 V AC plug, delivering power from 3 kW to 20 kW. This level supports both residential and public charging setups.
- **Level 3:** Utilizes high-voltage DC power (400 V DC), typically delivering between 50 kW and 130 kW. This level is intended for fast charging.
- **Level 4:** Operates at 400-800 V DC and can provide up to 500 kW of power. It is primarily designed for long-distance travel and heavy vehicles.

These classifications ensure EV charging is both efficient and safe while catering to diverse charging needs. [1]

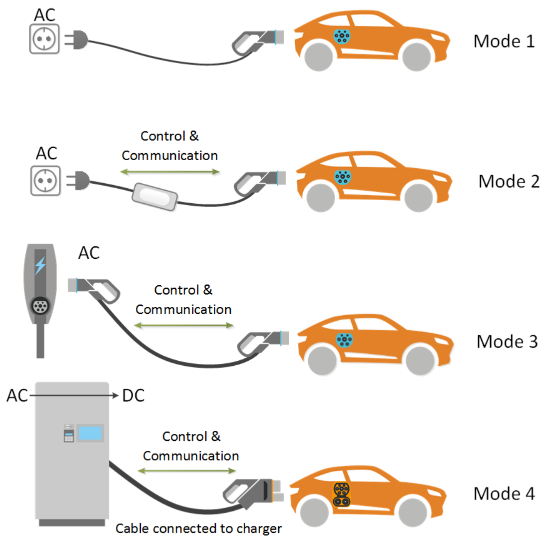

Figure 2.1: Different Charging Modes
Reproduced from [9]

2.2.2 AC and DC Charging Standards

Countries around the world have adopted different EV charging standards, and in some cases, more than one standard is used. For AC charging, the United States and Canada use the IEC 62196 Type 1 (single-phase), while the European Union uses Type 2 (three-phase). For DC charging, both regions use the Combined Charging System (CCS), which works with their respective AC standards (Type 1 in North America and Type 2 in Europe). Japan mainly uses the CHAdeMO standard for DC charging, while China relies on the GB/T standard. France and Italy initially preferred Type 3 connectors but later switched to Type 2 to match the rest of Europe. Tesla has its own brand-specific charging stations, which dominate DC charging networks in some countries like Australia, China, Pakistan, Serbia, and Hong Kong. The use of different charging standards worldwide shows the challenges of developing EV infrastructure that is consistent and compatible across regions. [20]

2.2.3 Charging Efficiency and Battery Condition

Electric vehicles (EVs) can be charged using either alternating current (AC) or direct current (DC) systems, with DC charging providing much faster speeds. The most common DC fast charging (DCFC) stations typically offer 50 kW using connectors like CHAdeMO, Combined Charging System (CCS), or GB/T standards. Tesla was the first to introduce 120 kW Superchargers with proprietary connectors, followed by CCS developing 150 kW chargers. In 2017, Porsche advanced DC charging by unveiling 350 kW CCS charging posts at their Berlin office. However, EVs capable of utilizing the full 350 kW power, such as the Porsche Taycan and the Audi e-tron GT concept, were designed with 800

V lithium-ion battery packs to handle the higher power efficiently, avoiding excessive charging currents and heat generation typical of standard 400 V systems. Additionally, a prototype 450 kW CCS charger was tested in Bavaria, Germany, in December 2018 as part of the ’FastCharge’ research project led by BMW, Porsche, and Siemens. Despite these advancements in charger power, actual charging speeds can vary based on EV specifications, environmental conditions, and the state of charge (SOC). For example, charging rates drop significantly at low temperatures; according to the Nissan LEAF Owner’s Manual, charging up to 80% SOC with a 50 kW charger can take between 30 to over 90 minutes depending on the temperature. Moreover, fast charging is generally only effective up to around 80% SOC due to safety reasons. Beyond this point, the charging current must be reduced to prevent exceeding battery voltage limits, resulting in longer times to reach full capacity. The maximum charging power is also restricted by the vehicle’s Battery Management System (BMS). EVs with smaller battery packs, such as the Nissan LEAF (40 - 62 kWh) or BMW i3 (22 - 42 kWh), are typically limited to 50 kW charging power, while vehicles with larger battery packs can accept higher power levels. This limitation is because most EV batteries can safely handle charging rates of about 1 - 1.5C. However, the Porsche Taycan is expected to exceed this with a maximum charging rate of around 3C. As interest in fast-charging technology grows within the industry, it is crucial to understand the processes that limit charging rates and the effects different charging methods have on battery lifespan. [27]

2.3 Related Work

According to a study investigating the factors influencing Battery Electric Vehicle (BEV) users’ choices regarding charging modes and locations in Japan, which uses a mixed logit model and real world data from private and commercial BEVs, key findings reveal that private BEVs with longer driving ranges prefer public charging over home charging, while commercial BEVs favor normal charging at company locations, reflecting differing operational needs. Charging behavior varies by time of day, with private users preferring overnight home charging due to lower electricity tariffs and commercial users opting for efficiency based charging. The regional density of public charging stations significantly influences preferences, with urban users favoring public charging due to accessibility and limited home charging options. Initial State of Charge (SOC), travel patterns, and familiarity with fast charging also shape choices, highlighting risk averse behavior and demand driven decisions. These findings underscore the importance of strategic infrastructure planning, including robust public charging networks and targeted incentive programs, to address diverse user needs and promote BEV adoption. [30]

Another study analyzes BEV charging behaviors using a framework that combines a rule-based algorithm with a Hybrid Choice Model (HCM) based on Mixed Logit (ML). Key findings reveal that charging decisions are significantly influenced by factors such as risk aversion, vehicle state of charge (SOC), trip type, charging infrastructure coverage, parking duration, and pricing. For trip chain decisions, gender and infrastructure coverage play critical roles, while location choices are driven by destination, charging price, and next travel distance. The results highlight that service quality, parking location functionality, and charging facility accessibility strongly impact the spatial-temporal distribution of charging demand. [33]

Expanding on insights into BEV charging behaviors and infrastructure requirements, further research has explored how driver preferences and decision-making processes influence the adoption of smart charging systems. One such study examines EV driver preferences for smart charging versus immediate charging, using a two-wave online experiment with 222 UK participants in 2020. Results show a general preference for smart charging (67.28%), influenced significantly by battery state of charge (SoC), time of day, and price concerns. Drivers often overemphasize SoC, particularly for short commutes, reflecting habits from conventional vehicle refueling. Reframing SoC information into more tangible metrics, such as travel miles or days covered based on driving patterns, increased smart charging adoption, with personalized metrics being particularly effective. Cost savings and renewable energy usage also motivated smart charging, though sensitivity plateaued after modest incentives. The study highlights the importance of presenting clear, user-friendly charging information, including personalized range and cost-saving calculations, to improve decision-making. These findings emphasize the need for behaviorally informed smart charging systems that integrate human decision-making processes to optimize user adoption and energy system efficiency. [18] Charging opportunities for plug-in electric vehicles (PEVs) are influenced by owners' travel behaviors. Charging primarily occurs at four key locations: (1) at or near home, typically overnight, (2) at workplaces or commuting hubs like transit stations, (3) at public places such as shopping centers, and (4) along travel corridors during long-distance trips. [14]

A study based on Austrian demographic data and behavioral decision rules reveals that the majority of battery electric vehicle (BEV) charging (approximately 88%) occurs at home, aligning with previous findings in the literature. [2]

Research indicates that more than 95% of trips can be managed with home charging alone. However, in developing economies like India and China, high population density and a lack of dedicated parking spaces mean that many vehicle owners park on streets and lack access to home charging facilities . In such cases, public charging infrastructure becomes essential for supporting the broader adoption of electric vehicles . Furthermore, public charging stations play a key role in enhancing the visibility of charging networks and alleviating range anxiety among potential EV buyers, even if these facilities are not always efficiently utilized. [3]

According to another study conducted in Ireland, EV users predominantly charge their vehicles at home during evening hours, coinciding with peak electricity demand. This suggests a need for incentives to encourage charging during off-peak periods to reduce grid strain. Among public charging options, car park locations were the most commonly used, and fast chargers showed the highest usage frequencies. [21]

The study [26] analyzed electric vehicle (EV) charging behaviors over a period of 1,519 days, uncovering significant trends and variations in usage. On average, EVs were charged every three to four days, with noticeably less frequent charging on weekends. The average daily charging frequency per vehicle was 0.2857, and a decline in charging frequency over time suggested that users charged their vehicles less often as their ownership period increased. Peaks in charging initiation were observed in the morning (7 - 8 AM), late morning (10 - 11 AM), and evening (5 - 6 PM). Charging primarily occurred at private parking locations, especially during nighttime (about 60%), followed by workplace parking during working hours. Public charging was less commonly used but still accounted for over 15% of the total charging sessions. Regarding parking and charging durations, charging sessions initiated in the evening were typically longer compared to those in the morning, and most vehicles were fully recharged by the end of parking.

[33] studies how people charge their electric vehicles (EVs) and what factors affect their choices. People are more likely to charge during long trips, in areas with many charging stations, or if they are more worried about running out of battery. Women and younger people are more likely to charge because they feel more nervous about the battery running out. Charging happens more often at workplaces and during long parking times, but high charging costs make people charge less. The battery charge level is also important. If the battery is already charged enough, people are less likely to charge. Charging is more common at workplaces and entertainment places, especially when parking is busy. This shows that charging stations should be placed where people park for a long time and in locations that help reduce battery worries and make charging easier.

A comparison of the total cost of ownership (TCO) between EVs and ICEVs in Sweden showed that electricity costs for EVs are significantly lower than fuel costs for conventional vehicles. Over three years, with an annual mileage of 15,000 km, fueling a BMW i3 EV costs approximately 633 euros, whereas a comparable Volvo V40d ICEV incurs 4,132 euros in fuel expenses. This cost difference suggests that lower running costs might lead to increased car use. In Germany, EVs remain economically unfeasible for most consumers due to higher electricity prices. Additionally, vehicle class and annual driving distance play a major role in determining TCO. In contrast, in the UK, California, and Texas, battery EVs and conventional vehicles have reached cost parity, largely due to government subsidies that reduce EV ownership costs. [19]

2.4 Research Group Contributions

This thesis was conducted as part of the **SmartData@PoliTo** research group,[1] based at Politecnico di Torino. SmartData@PoliTo is an interdisciplinary research center dedicated to exploring innovative approaches to data science, artificial intelligence, and big data analytics. The group brings together researchers and professionals from various domains to address complex societal and industrial challenges through cutting-edge technological solutions.

[4] examines the design factors of electric vehicle free-floating car sharing systems using rental data from three cities to model demand and supply. The study evaluates the

[1] https://smartdata.polito.it/

number and placement of chargers and fleet size under both stable and increasing demand scenarios. Findings reveal that expanding charging infrastructure is more effective than increasing the fleet to meet rising demand. Additionally, the current system is not profitable due to high vehicle and operational costs, with profitability only achievable if demand increases significantly. The existing fleet can support up to a 300% demand increase but would still leave some unmet needs.

Another study [13] investigates free-floating car sharing usage in 23 cities across Europe and North America over a 14-month period, revealing that growth has plateaued in most locations. The study identifies consistent demand patterns within continents and varying spatial usage across different urban areas. It also compares electric vehicle fleets with traditional combustion engine fleets, highlighting differences in refueling requirements. Findings show high per-car utilization in cities like Madrid, while many other cities experience stable or declining usage due to reduced service appeal or operational inefficiencies. These insights help system managers evaluate the profitability and sustainability of car sharing services.

[8] explores the optimal design of electric vehicle-based free-floating car sharing systems by addressing the placement of charging stations and the development of intelligent car return policies. Utilizing real-world rental data from Car2Go in Turin, the study conducts trace-driven simulations to assess battery usage and charging needs. Various charging station layouts are evaluated using optimization algorithms, and the effects of collaborative versus selfish car return behaviors are analyzed. Remarkably, the findings indicate that only 13 charging stations (52 poles) are sufficient to maintain a fleet of 377 vehicles in a city with one million residents, ensuring smooth operations with minimal inconvenience to customers.

Leveraging extensive rental data from four cities, another study explores the design of electric vehicle-based free-floating car sharing systems. It identifies the highly dynamic and non-stationary nature of car sharing usage patterns and develops a discrete-event trace-driven simulator to evaluate various factors such as charging station placement, smart return policies, battery management, and customer behavior regarding charging. The simulations reveal that strategically placing charging stations in approximately 8% of city zones, especially in popular short-term parking areas, ensures that all trips are feasible without battery depletion. Additionally, implementing a policy that requires customers to return cars to charging stations when battery levels are low results in rerouting for less than 10% of trips. [7]

The comparison between electric and internal combustion engine-based free-floating car sharing systems reveals that electric fleets can match the demand satisfaction of traditional systems while achieving lower emissions. Through simulations conducted in Turin using real trip data and existing infrastructure, the study assesses factors such as fleet operations, refueling strategies, and profitability. Despite the environmental benefits, the higher costs associated with electric vehicles currently make EV-based FFCS less profitable than their ICEV counterparts. Additionally, the research identifies that deploying affordable low-power chargers is the most effective strategy for electric FFCS, as it also reduces maintenance costs. The provided simulator serves as a tool for further exploration of engine type impacts on shared mobility systems. [12]

[6] Examines various strategies for designing electric free-floating car sharing systems in smart cities, emphasizing the importance of charging station availability for system sustainability. Utilizing real trip data from an operational provider in Turin, the study employs a trace-driven simulator to model battery consumption under different design scenarios, including the number and placement of charging stations and policies for mandating car returns for charging. The results indicate that deploying as few as 15 charging stations (covering 6% of city areas) can enable the system to function almost autonomously, allowing users to freely pick up and drop off cars with minimal rerouting. This demonstrates the feasibility of electric free-floating car sharing with a strategically limited charging infrastructure.

[5] Focuses on optimizing the design of electric free-floating car sharing systems by determining the minimal number and strategic placement of charging stations. Utilizing approximately 450,000 rental records from traditional combustion engine FFCS in two cities, the study develops a user behavior model and charging policies. Through trace-driven simulations, it evaluates various charging station placement strategies using both greedy algorithms and a meta-heuristic local optimization approach. The results demonstrate that installing charging stations in just 6% of city areas ensures continuous service by preventing battery depletion, while expanding to 15% of zones further minimizes user inconvenience. This research provides a data-driven framework for efficiently deploying charging infrastructure in electric FFCS.

Chapter 3

Dataset Management

3.1 Dataset Characterization

The dataset utilized in this thesis was provided by UnipolTech and contains information about user trips made using combustion engine vehicles. The data was gathered from a sample of their customers who volunteer for data analytics and have the following attributes and structure:

Column Name	Description	Example Value
id veicolo	A unique identifier assigned to each user.	1
id viaggio	A unique identifier for each trip recorded per user.	0
istante start	The date and time when the trip started.	2023-09-29 13:55:35
istante stop	The date and time when the trip ended.	2023-09-29 14:11:42
categoria strada	The category of road traveled during each segment of the trip	E
tot km categoria strada	The distance traveled on each road type (in kilometers).	1.47

Table 3.1: Datasets description

There are four distinct values for road categories in the dataset, defined as follows:

- **E**: Extra Urban
- **U**: Urban
- **A**: Highway
- **"-"**: Other road types.

The initial dataset 3.1 contained 1,415,305 rows. Since the dataset includes different categories of roads, each row represents a segment of a trip and indicates the distance traveled on a specific road type. As a result, individual rows do not represent entire trips. To make the dataset usable for analysis, preliminary processing was required, such as consolidating rows so that each represents a complete trip. The detailed steps of this pre-processing are explained in the next chapter.

	vehicle_id	trip_id	start_ts	stop_ts	road_type	Distance per Road
1	1	0	2023-09-29 13:55:35	2023-09-29 14:11:42	EstraUrban	14.31
2	1	0	2023-09-29 13:55:35	2023-09-29 14:11:42	Urban	1.47
3	1	1	2023-09-29 14:32:24	2023-09-29 14:34:31	Urban	0.03
4	1	2	2023-09-29 15:12:03	2023-09-29 15:26:55	EstraUrban	2.6
5	1	2	2023-09-29 15:12:03	2023-09-29 15:26:55	Urban	2.0
6	1	3	2023-09-29 15:37:38	2023-09-29 15:57:26	EstraUrban	2.24
7	1	3	2023-09-29 15:37:38	2023-09-29 15:57:26	Urban	2.01
8	1	4	2023-09-29 16:13:55	2023-09-29 16:13:58	EstraUrban	0.0
9	1	5	2023-09-29 16:16:28	2023-09-29 16:16:30	EstraUrban	0.0
10	1	6	2023-09-30 05:05:39	2023-09-30 05:28:37	EstraUrban	0.0
11	1	6	2023-09-30 05:05:39	2023-09-30 05:28:37	Urban	1.21

Figure 3.1: Raw Dataset

3.2 Data Pre-processing

The pre-processing phase involved organizing and consolidating the raw dataset to make it suitable for further analysis. The steps are outlined below:

1. **Removing Duplicates**

    - **Issue:** The dataset contained duplicate rows, with each segment of a trip recorded as a separate entry.
    - **Solution:** Removed duplicate rows and consolidated all information related to a trip into a single row, including start time, end time, and distance traveled on each road type (in Kilometers).
    - **Outcome:** Each row now represents one complete trip.

2. **Calculating Trip Duration**

    - **Input:** Start and end timestamps for each trip.
    - **Action:** Calculated trip duration by finding the difference between the start and end times.
    - **Outcome:** Added trip duration (in minutes) as a new attribute to the dataset.

3. **Including Total Distance**

    - **Action:** Summed up the distance covered across different road types for each trip.
    - **Outcome:** Added total distance (in Kilometers) as a useful attribute for future analysis.

4. **Sorting Trips by Timestamp**

    - **Issue:** Trips for individual users were not in chronological order.

- **Action:** Sorted trips based on timestamps for each user.
- **Outcome:** Ensured trips are sequential, reflecting the actual trip order.

5. **Adding Parking Attributes**

- **Definitions:**
  - **Start of parking:** Timestamp at the end of a trip.
  - **End of parking:** Timestamp at the start of the next trip for the same user.
- **Action:** Added "start of parking" and "end of parking" as new attributes.
- **Outcome:** Captured additional insights into user behavior between trips.

6. **Calculating Parking Duration**

- **Input:** Start of parking and end of parking timestamps.
- **Action:** Calculated parking duration by finding the difference between the two timestamps.
- **Outcome:** Added parking duration (in minutes) as a new attribute, providing further insight into user behavior.

Final Dataset

By consolidating and enriching the dataset, it became ready for further analysis. This preparation enables more meaningful insights and downstream modeling. Below is an example of the preprocessed dataset 3.2 structure.

	vehicle_id	trip_id	start_trip	end_trip	trip_duration	dis_highway_Km	dis_urban_Km	dis_other_Km	dis_tot_Km	park_dur_min
1	1	0	2023-09-29 13:55:35	2023-09-29 14:11:42	16.1166666...	0.0	1.47	14.31	15.7800...	20.7
2	1	1	2023-09-29 14:32:24	2023-09-29 14:34:...	2.11666666...	0.0	0.03	0.0	0.03	37.5333333...
3	1	2	2023-09-29 15:12:03	2023-09-29 15:26:...	14.866666...	0.0	2.0	2.6	4.6	10.7166666...
4	1	3	2023-09-29 15:37:38	2023-09-29 15:57:...	19.8	0.0	2.01	2.24	4.25	788.216666...
5	1	6	2023-09-30 05:05:39	2023-09-30 05:28:...	22.966666...	0.0	1.21	0.0	1.21	38.5
6	1	8	2023-09-30 06:07:07	2023-09-30 06:33:...	26.766666...	0.0	1.1	3.98	5.08	92.0666666...
7	1	10	2023-09-30 08:05:57	2023-09-30 08:15:...	9.7166666...	0.0	0.0	0.14	0.14	36.6666666...
8	1	11	2023-09-30 08:52:20	2023-09-30 09:03:...	11.1833333...	0.0	0.0	0.16	0.16	30.2333333...
9	1	12	2023-09-30 09:33:45	2023-09-30 09:44:...	10.45	0.0	2.43	2.01	4.43999...	64.65
10	1	14	2023-09-30 10:48:51	2023-09-30 10:51:...	2.6666666...	0.0	0.16	0.0	0.16	2.53333333...

Figure 3.2: Preprocessed Dataset

3.3 Data Exploration

Following the preliminary analysis, it is beneficial to conduct an exploratory examination of the dataset to gain a general understanding of the observed behaviors and trip characteristics. This step helps identify patterns, trends, and potential anomalies that

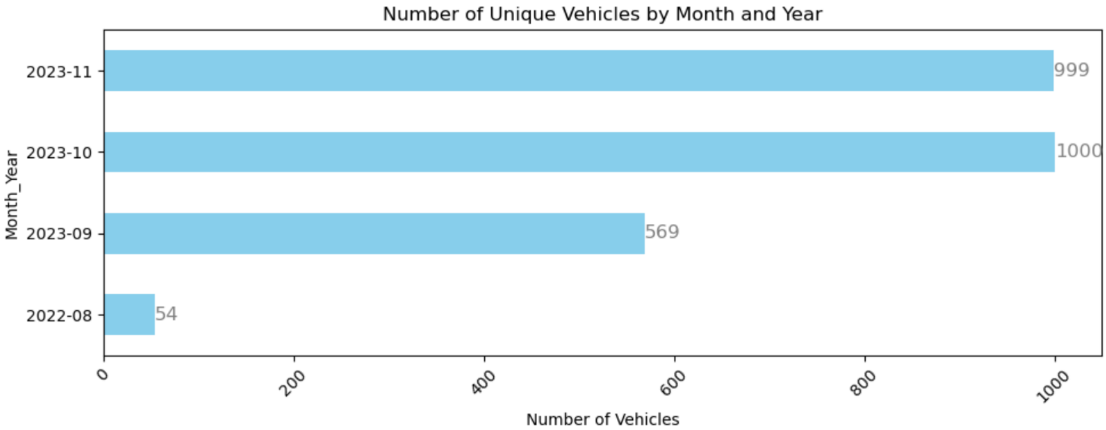

Figure 3.3: Number of Vehicles by Month and Year

could influence subsequent analyses. The following section presents several plots along with descriptions of the key insights derived from each visualization.

As depicted in the bar chart 3.3, the dataset used in this thesis includes trips recorded over a span of four months. The chart illustrates the number of vehicles active in each month. To ensure clarity and avoid potential misinterpretations, it is assumed that each vehicle represents a single user. Consequently, the dataset comprises 1,000 users, although their activity is not consistent across the provided months.

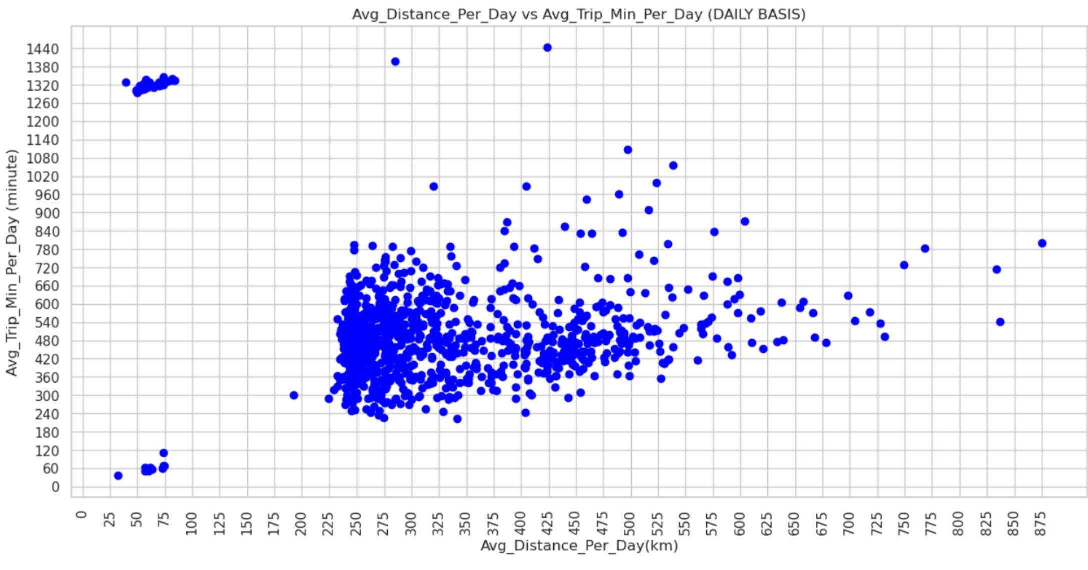

Figure 3.4: Scatter plot showing the relationship between Average Distance Per Day (km) and Average Trip Duration Per Day (minutes) on a daily basis.

The scatter plot 3.4 illustrates the relationship between the average distance traveled per trip (in kilometers) and the average trip duration (in minutes) for the dataset analyzed in this thesis. Each point in the plot represents a single trip, with the x-axis showing the average distance covered per trip and the y-axis displaying the corresponding average duration.

The data reveals a dense concentration of trips with distances between 200 and 500 kilometers and durations between 200 and 600 minutes, indicating the typical range for most trips in the dataset. However, a few outliers are evident, with trips that have exceptionally high durations (exceeding 1,200 minutes) or distances (beyond 700 kilometers). These could represent anomalies or unique trips under specific circumstances.

Although the dataset lacks detailed information on the exact types of vehicles used (e.g., bus, communal transport, or private vehicles), the high average distances and durations suggest that these vehicles are heavily utilized. This observation makes it unlikely that the trips are performed using typical home-owned family cars, which would typically exhibit lower average usage. Instead, the data likely reflects trips performed by fleet vehicles, public transportation, or other high-utilization systems.

This plot highlights important usage patterns and provides insight into the characteristics of the trips in the dataset, suggesting the vehicles analyzed serve purposes that go beyond typical personal or household use.

The cumulative distribution function (CDF) plot 3.5 illustrates the distribution of the average number of trips per day within the dataset analyzed in this thesis. The x-axis represents the average number of trips per day, while the y-axis represents the cumulative probability, which shows the proportion of data points below a given number of trips.

The CDF indicates that most vehicles or systems in the dataset perform fewer than 80 trips per day, as the curve reaches a cumulative probability of nearly 1 around this point. This suggests that the vast majority of trips fall within a moderate range of daily usage. A steep initial rise in the CDF highlights that a significant proportion of vehicles or systems average fewer than 30 trips per day, which might correspond to lower-utilization cases or smaller-scale operations.

Interestingly, a small number of outliers are observed on the far right of the plot, with average daily trip counts exceeding 200 trips per day, and one extreme case nearing 390 trips. These outliers likely represent highly utilized vehicles or systems, such as shared fleet vehicles, public transportation, or other high-frequency services.

This distribution reinforces the idea that the dataset reflects a mix of vehicle or system types, ranging from those used moderately to those subjected to heavy, frequent use. The presence of outliers highlights operational patterns that could be driven by specific fleet or transport use cases.

3.4 Data Cleaning

After completing the preprocessing step, the next crucial task is cleaning the dataset. Since this research focuses on analyzing trips, it is essential to remove rows where trip-related data, such as durations or distances, are unreasonable or inconsistent. As the

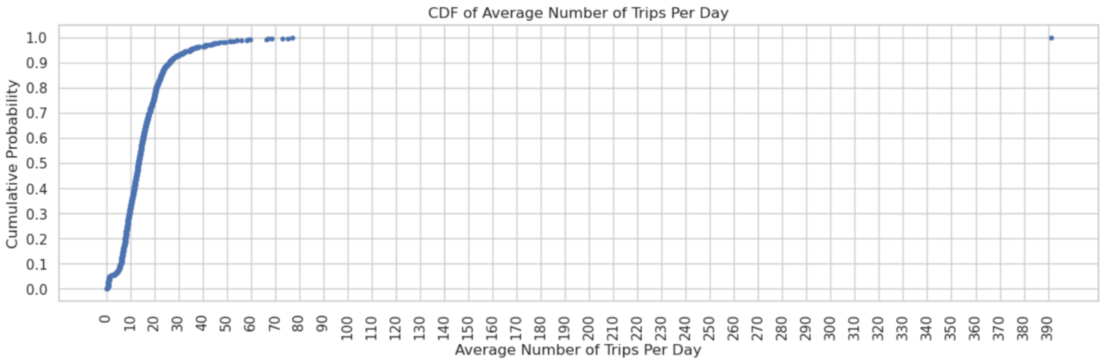

Figure 3.5: CDF of Average Number of Trips Per Day, illustrating the cumulative probability distribution of daily trips.

data for these trips was collected from devices installed in users' vehicles, potential technical issues might have introduced errors or inconsistencies. The following outlines the various situations identified during the cleaning process and the corresponding actions taken to address them:

1. **Trips with a Duration of Zero but a Positive Distance**

   These entries suggest possible recording errors, as a trip cannot cover a distance without a measurable duration. Such records were removed from the dataset.

2. **Trips with a Distance of Zero but a Positive Duration**

   This situation can occur in specific scenarios, such as:

   - **Immobility with the Engine Running**: Instances where the vehicle was stationary due to waiting, traffic delays, or stopping at lights in congested areas.
   - **Poor GPS Signal**: Situations where the vehicle was in locations with weak GPS reception, such as underground parking lots, tunnels, or densely built-up areas.

     These cases were retained unless other inconsistencies were detected.

3. **Trips with Extremely Short Durations**

   Trips with durations less than 15 seconds were excluded, as such records are unlikely to represent meaningful trips and may indicate errors.

4. **Trips with Extremely Short Distances**

   Trips covering distances below 5 meters were excluded, as these are likely to be noise or artifacts in the data.

5. **Trips with Unreasonably Long Durations**

   Trips with durations exceeding 15 hours were considered implausible and removed.

6. **Trips with Unreasonably Long Distances**

   Trips covering distances greater than 900 kilometers were deemed unrealistic and excluded.

7. **Logical Inconsistencies**

   Records with logical inconsistencies, such as a trip duration of zero paired with a non-negative distance, were identified and removed as they do not align with physical realities.

By addressing these inconsistencies and removing outliers, the dataset was refined to ensure the accuracy and reliability of the subsequent analyses.

3.5 Tools

Various tools were utilized for the development and analysis conducted in this thesis. This section provides a brief discussion of each tool, highlighting its role in supporting the researcher and its contributions to achieving the objectives of the study. The purpose of documenting these tools is to provide a comprehensive reference for potential future researchers who may seek to build upon or replicate this work.

Python

Python [25], an open-source, high-level programming language, was the primary tool used for data processing, analysis, and simulation in this thesis. Its versatility and vast ecosystem of libraries made it particularly suitable for handling complex tasks, such as data manipulation, simulation modeling, and result visualization. Python's simplicity and readability further facilitated rapid development and testing.

Pandas

Pandas [23], a Python library designed for data manipulation and analysis, was integral to processing the dataset used in this study. It provided robust tools for cleaning, transforming, and aggregating data, enabling the researcher to handle large and complex datasets efficiently. Pandas' functionality was critical for extracting insights and preparing the data for further analysis.

Streamlit

Streamlit [11], an open-source Python framework, was utilized for building interactive applications to visualize and share the results of the analysis. Its simplicity allowed the researcher to create user-friendly interfaces quickly, enabling dynamic exploration of data and simulation outputs. Streamlit played a key role in presenting findings in an accessible and engaging format.

Plotly

Plotly [24], a Python library for interactive visualization, was employed to create dynamic charts and graphs to represent the data and simulation results. Its ability to produce highly customizable and interactive plots helped the researcher convey complex patterns and trends effectively. This made Plotly an essential tool for both exploratory data analysis and final result presentation.

Jupyter Notebook

Jupyter Notebook [10], an open-source interactive development environment, was used for coding, visualization, and documentation in a single environment. Its flexibility in combining code execution with narrative explanations made it a key tool for iterative development and analysis.

PyCharm

PyCharm [16], a professional integrated development environment (IDE) for Python, supported the coding workflow by providing features such as intelligent code completion, debugging tools, and version control integration. It streamlined the development process and enhanced productivity.

Seaborn

Seaborn [29], built on top of Matplotlib, was used for statistical data visualization. Its high-level interface simplified the creation of informative and aesthetically appealing visualizations, particularly for exploring relationships within the dataset.

Matplotlib

Matplotlib [15], a widely used Python plotting library, provided static and publication-quality visualizations. It was employed for generating detailed plots that required high levels of customization, contributing to a clearer presentation of results.

Chapter 4

Methodology

Building upon the foundational data preprocessing steps and problem definition outlined in the preceding chapters, this chapter delves into the methodology employed to model real world electric vehicle (EV) charging patterns. The research 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 and infrastructure demands.

The methodology adopted for this research is divided into **three simulation phases**, each introducing additional layers of complexity to better approximate real-world electric vehicle (EV) charging behavior. Since exact location data was unavailable, a **core assumption** is made that charging is accessible anywhere a user parks, provided certain conditions (e.g., minimum parking duration) are met.

4.1 Simulation Phases

4.1.1 Phase One: Abstract Scenario Development

The first phase of the study adopts a more abstract approach, as the input parameters are not tied to a specific electric vehicle (EV). Instead, they are sourced from the **EV Database** (https://ev-database.org/), a comprehensive platform that provides detailed specifications for various EV models, including their prices, battery capacities, consumption rates, compatible charging powers, and other technical features.

To cover a broad spectrum of EV characteristics, this phase utilizes:

- **10 different values for charging power**,
- **10 different values for battery capacity**, and

- **8 different consumption rate combinations**.

These values were selected to represent a wide range of EV configurations, ensuring inclusivity across the varying specifications of existing vehicles. The primary objective of this phase is to establish baseline scenarios by simulating diverse hypothetical EV profiles.

A **basic charging model** is applied, where **any parking event longer than a predefined minimum duration automatically initiates a charging session**. This approach assumes that charging occurs whenever the parking duration exceeds a specified threshold.

Key simplifying assumptions in this phase include:

- No consideration of **time-of-day constraints** or **day-of-week variations**.
- The **State of Charge (SoC)** at the start of parking is not factored into the analysis.

By focusing solely on the minimum parking duration as the determining factor for charging, this phase provides an initial exploration of EV charging behavior under broad and generalized conditions, laying the groundwork for more specific and detailed analyses in subsequent phases.

Battery Capacities:

Ten different capacities were examined **(21.3, 37, 46, 51, 68, 84, 95, 100, 107, and 118 kWh)** to cover a broad range of values representative of various car models.

Charging Power:

Charging power is a critical parameter in assessing electric vehicle (EV) charging behavior, as it directly influences charging duration and infrastructure requirements. This study considers both **AC (Alternating Current)** and **DC (Direct Current)** charging levels to reflect the variety of charging options available in real-world settings.

AC Levels: The following **AC charging levels** are included in the analysis: **3.2 kW, 6.6 kW, 7.2 kW, 11 kW, and 22 kW.**

- **3.2 kW**: Represents basic home charging setups using standard power outlets. This option is widely accessible but provides slow charging, primarily suitable for overnight charging scenarios.
- **6.6 kW and 7.2 kW**: Reflect intermediate AC chargers commonly used in residential or small public charging stations. These levels strike a balance between charging speed and power requirements, making them suitable for vehicles parked for extended periods (e.g., at home or work).

- **11 kW**: A standard power level for modern public and workplace chargers. It delivers significantly faster charging than basic AC setups while remaining compatible with existing electrical infrastructure.
- **22 kW**: A higher-end AC charging option, typically found in public or commercial charging spaces. It is advantageous for vehicles capable of utilizing higher AC power and is effective for reducing charging durations during shorter parking events.

DC Levels: The following **DC fast-charging levels** are considered: **46 kW, 77 kW, 94 kW, 200 kW, and 250 kW.**

- **46 kW and 77 kW**: Represent entry-level DC fast chargers. These chargers are efficient for most EVs that do not support ultra-fast charging, making them ideal for urban public charging stations.
- **94 kW**: A mid-level DC fast-charging option that balances charging speed and energy efficiency, commonly seen in suburban and highway charging stations.
- **200 kW and 250 kW**: High-power DC fast chargers designed for ultra-fast charging. These chargers cater to advanced EV models with large battery capacities, enabling substantial charge levels in minutes. They are primarily installed at highway service stations to support long-distance travel.

Why Both AC and DC Levels?

The inclusion of both AC and DC levels in this study ensures a comprehensive analysis of real-world charging scenarios.

- **AC charging**: Reflects slower, routine charging situations such as overnight home charging or workplace charging, where vehicles are stationary for extended periods.
- **DC charging**: Focuses on fast-charging scenarios, where users prioritize minimizing downtime during long trips or short stops.

By simulating various combinations of charging power and battery capacities, this study aims to capture the full spectrum of potential charging behaviors and vehicle capabilities. This comprehensive approach highlights the implications for designing efficient and effective EV charging infrastructure.

Minimum Parking Durations

Two thresholds are adopted:

1. **8 hours** (480 minutes) for overnight or full-shift scenarios.
2. **20 minutes** for short stops or brief windows.

This approach evaluates how the **availability of longer or shorter parking slots** influences charging feasibility.

Consumption Profiles

Scenario	City (Wh/km)	Highway (Wh/km)	Combined (Wh/km)
1	98	172	132
2	114	187	150
3	120	200	154
4	131	201	163
5	141	244	189
6	156	234	192
7	167	264	217
8	171	265	215

Table 4.1: Consumption combinations for different driving conditions.

To account for diverse driving conditions and vehicle energy demands, eight different consumption scenarios were tested. These scenarios consider energy usage across **city, highway, and combined driving conditions**, ensuring a realistic representation of EV performance. The table 4.1 summarizes the specific consumption combinations used.

In total, 1,200 simulations were conducted during Phase 1. These simulations were divided as follows:

1. A combination of all **consumption profiles**, **battery capacities**, and **charging power levels** (both AC and DC), using a **20-minute threshold** for charging, resulted in **800 simulations**.

2. A separate analysis focused on **all battery capacities**, **only AC charging powers**, and **all consumption combinations**, contributing an additional **400 simulations**.

Together, these scenarios provide a comprehensive exploration of different configurations, covering a broad spectrum of electric vehicle characteristics and charging behaviors. The approach ensures that both **short charging events** (20 minutes) and **routine AC charging scenarios** are thoroughly represented.

By including a diverse range of parameters and configurations, this phase establishes a robust foundation for evaluating the impact of charging thresholds, vehicle specifications, and charging infrastructure on overall charging feasibility and performance. This broad coverage helps to address potential variances across real-world EV charging situations, providing valuable insights for subsequent phases of the study.

4.1.2 Phase Two: Integrating Behavioral Variability in Charging

This phase introduces **nine distinct charging profiles** that account for real-world variations in charging behavior. These profiles incorporate:

- **Day-of-week differences**: Charging patterns vary between weekdays and weekends, reflecting differences in travel and parking behavior.
- **Time-of-day effects**: Charging scenarios consider the impact of overnight versus daytime charging, capturing the variability in energy demand and grid load.
- **Driver-specific State of Charge (SoC) thresholds**: User-specific preferences for when to initiate charging based on the remaining battery percentage.

While retaining the same sets of **battery capacities**, **charging powers**, and **consumption rates** from Phase 1, this phase applies them in a **more behaviorally nuanced context**, reflecting real-world conditions more accurately.

As the analysis progresses, the level of complexity increases, introducing more realistic elements into the simulations. In this phase, the focus shifts to understanding how individual differences in charging behavior influence overall system performance. **Charging behaviors of different users** have been considered, with some profiles drawn from established studies in the literature and others based on the researchers' own ideas, designed to highlight distinctions between various user groups.

This approach allows the study to move beyond abstract assumptions and provides insights into the interplay between technical specifications and behavioral patterns. By adding these layers of detail, Phase 2 lays the groundwork for exploring the impact of user diversity on charging infrastructure design and energy system efficiency.

Behavioral Diversity in EV Charging: User Profiles

A primary challenge in EV adoption is the inherent diversity in driver behavior. While some individuals maintain regular schedules and have access to home charging, others depend exclusively on public chargers or fast-charging facilities along highways. To capture these nuances, this research simulates a spectrum of user profiles, each representing distinct charging motivations, time windows, and typical State of Charge (SoC) thresholds. By simulating a wide variety of user behaviors, the study avoids relying on a simplistic "one-size-fits-all" charging model, ensuring a realistic representation of real-world conditions.

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 vs. afternoon charging).
- **Day of the week** (e.g., weekday vs. weekend charging habits).
- **Charging duration thresholds** (e.g., minimum or maximum charging times).

- **Charger preferences** (e.g., AC slow chargers vs. DC fast chargers).

Below is a synopsis of the nine distinct user profiles analyzed in this study:

1. **Frequent Users**
    - **Description**: Regularly charge their vehicles at home, typically overnight overnight (9 PM - 8 AM) . On weekends, they may leave vehicles connected for extended periods (Starts Friday 9 PM, ends Monday 6 AM) due to reduced usage during leisure days.
    - **Charger Preference**: Primarily Level 2 AC chargers (up to 11 kW) at home or in residential areas.
2. **Visitor Users**
    - **Description**: Make short, spontaneous visits to commercial or business districts, charging for durations between 1.5 to 7 hours while running errands or attending meeting.
    - **Charger Preference**: Predominantly use DC fast chargers (46 kW or higher) in the afternoon starting from 12 PM to 7 PM.
3. **Taxi Drivers**
    - **Description**: Charge only overnight (9 PM - 8 AM) at home or in residential areas
    - **Charger Preference**: AC slow charging for 7 or more hours, ensuring a full battery for daily operations.
4. **Car Sharing Fleets**
    - **Description**: Operate on a high-utilization model, requiring multiple short charges (20 minutes to 1.5 hours) throughout the day to keep vehicles available.
    - **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 (Anxious) Drivers**
    - **Description**: Overly cautious about low battery levels, charging whenever SoC falls below 50%. They prefer AC chargers but use DC fast chargers in "emergency" cases (SoC <= 20%).
    - **Charger Preference**: Primarily AC chargers (11 - 22 kW) for routine top-ups, with DC fast chargers (46-94 kW) as a backup.

6. **Business Travelers**
   - **Description**: Require efficient, quick charging during long-distance weekday trips, ensuring SoC stays above 20% to minimize disruptions.
   - **Charger Preference**: DC fast chargers (46 - 250 kW) along highways or business corridors, typically charging for 20 minutes to 1-2 hours.
   - **Time of Day:** Charging occurs during travel breaks within typical working hours (8 AM to 6 PM).
   - **Days of the Week:** Monday through Friday

7. **Weekend Travelers**
   - **Description**: Plan weekend getaways, relying on fast chargers to top up quickly during trips. They typically charge when SoC drops to 30%.
   - **Charger Preference**: DC fast chargers (46 - 250 kW)
   - Charging occurs on **weekends**.
   - Typically requires **from 20 minutes to 2 hours for fast charging** during trips.

8. **Workplace-Dependent Drivers**
   - **Description**: Lack access to home charging and rely solely on office chargers, typically between **8:00 AM and 6:00 PM**. They often charge for a minimum of 6 hours during the working days **from Monday to Friday.**
   - **Charger Preference**: AC chargers (3.2 - 22 kW) available at the workplace.

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.
   - **Charger Preference**: Prefer AC slow charging (home or public), with sessions lasting 8 hours or more.

Profile	Charger Preference	Time of Charging	SoC Threshold	Charging Duration
Frequent Users	AC slow charging.	Overnight	None specified	Up to 24+ hours.
Visitor Users	DC fast chargers.	Daytime	None specified	1.5 to 7 hours.
Taxi Drivers	AC slow charging.	Overnight	None specified	7+ hours.
Car Sharing Fleets	DC fast chargers.	Daytime	20%	20 minutes to 1.5 hours.
Conservative Drivers	AC and DC as a backup.	Variable	50%; DC: 20%	Routine top-ups or emergency charges.
Business Travelers	DC fast chargers.	Daytime	>20%	20 minutes to 1-2 hours.
Weekend Travelers	DC fast chargers.	Daytime (weekends)	30%	20 minutes to 2 hours.
Workplace-Dependent Drivers	AC slow charging.	8:00 AM - 6:00 PM (work hours)	None specified	Minimum of 6 hours.
Casual Users	AC slow chargers.	Variable	20%	8 hours or more.

Table 4.2: Overview of the Nine User Profiles.

4.1.3 Phase 3: Incorporating Real Market Vehicle Specifications

Phase Three builds directly upon the framework established in Phase Two by retaining the same nine user profiles to ensure consistency in behavioral modeling. However, this phase shifts focus from hypothetical combinations of battery capacities and consumption patterns to the **real-world specifications** of commercially available electric vehicles (EVs). This transition allows for a more grounded and practical analysis of EV charging behaviors.

In this phase:

1. **Integration of Real Vehicle Data**: The study incorporates detailed specifications of the **50 top-selling EV models in Europe (as of 2024)**. These models were selected to represent the diversity of vehicles on the market, capturing:
   - **Battery capacities**: Real-world storage capacities, reflecting the wide range of vehicle classes .
   - **AC/DC charging powers**: Manufacturer-specified nominal values for both AC and DC charging speeds.
   - **Consumption rates**: Actual energy usage patterns across **urban**, **highway**, and **mixed driving conditions**.
2. **Enhanced Realism**: By using real vehicle data, the simulations provide:
   - More **concrete and actionable results** that align closely with the performance of actual EV models.
   - Insights that are directly applicable to manufacturers, policymakers, and potential customers evaluating the feasibility of EV adoption.
3. **Practical Relevance**: This phase stands out as the most practical and commercially relevant stage of the study. By grounding the analysis in real-world specifications, it becomes easier to:
   - Perform **cost analysis** for both users and businesses, enabling assessments of charging expenses and operational efficiency.
   - Address the concerns of **companies or potential customers** who are uncertain about transitioning to EVs, offering them a clear, data-driven perspective on real-world EV performance.
4. **Opportunities for Further Analysis**: The inclusion of real-world data opens avenues for additional investigations, such as:
   - **Cost analysis**: Estimating total charging costs under varying conditions (e.g., home vs. public charging, AC vs. DC power).
   - **Infrastructure planning**: Assessing the adequacy of current charging networks for the most popular EV models.

- **Consumer insights**: Offering potential EV adopters an understanding of the practical benefits and limitations of specific models.

By anchoring the study in real-world vehicle data, Phase Three bridges the gap between theoretical modeling and practical application. This phase is designed to resonate with industry stakeholders, offering insights that can guide decision-making for both infrastructure development and consumer adoption of EVs. Its structured and practical approach makes it the most relevant phase for addressing the challenges and opportunities in the transition to electric mobility.

4.2 How the Simulator Works

The simulation framework (figure 4.1) is designed to replicate real-world electric vehicle (EV) usage by incorporating user-specific charging behaviors and trip patterns. Below are the key steps in the simulation process:

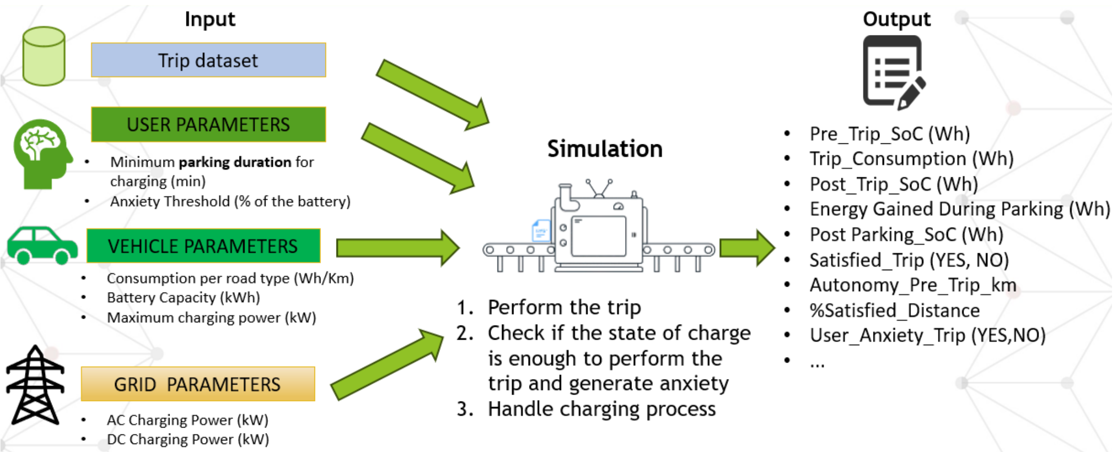

Figure 4.1: Simulation workflow showing inputs, the simulation process, and outputs.

1. **Identifying Charging Opportunities**

   Each trip in the dataset is analyzed row by row to determine if the subsequent parking interval qualifies as a charging event, based on the assumptions and parameters of the respective simulation phase.

   In **Phase One**, only the **minimum parking duration** is considered. Parking intervals exceeding a predefined threshold (e.g., 20 minutes or 8 hours) are flagged as charging events, with no regard for other factors like time of day or day of the week.

   In **Phase Two and Three**, the criteria are expanded to include **day of the week** and **time of day**, in addition to the minimum parking duration. For instance, weekday parking may be flagged for workplace chargers, while weekend events may apply to Weekend Travelers.

Across all phases, the primary goal of the first step is to evaluate whether a parking event can be flagged as a charging event, with the complexity increasing as the study progresses.

2. **Calculate Energy Consumption**
   The simulation calculates the energy consumption for each trip based on the driving conditions (e.g., urban, highway, or mixed). This is achieved using the vehicle's specified efficiency values for each road type and the distance traveled on those roads, as provided in the dataset.

   For each trip:

   (a) The energy consumption for each road type is computed individually by multiplying the road-specific consumption rate by the distance covered.

   (b) These individual energy consumption values are then summed to determine the total energy consumption for the entire trip.

   This approach ensures accurate calculation of total trip consumption by accounting for variations in energy efficiency across different road types.

3. **Calculating State of Charge (SoC) After Each Trip**
   The next step in the simulation involves determining the battery's remaining State of Charge (SoC) at the end of each trip. This is calculated as the difference between the SoC at the beginning of the trip and the energy consumed during the trip. The ground assumption is that the first trip for each vehicle in the dataset starts with a fully charged battery (100% SoC).

   For each trip:

   The energy consumed during the trip is subtracted from the SoC at the start of the trip to calculate the remaining SoC.

4. **Calculating Energy Gained During Parking Events**

   The next step in the simulation involves determining the energy gained during parking events. If, according to the first step, the "Charge Needed" flag is set to **True**, it indicates that the **day/time**, **weekday**, and **parking duration** are suitable for charging. At this stage, additional conditions defined by the charging profile are evaluated to confirm whether charging occurs and to calculate the energy gained.

   Key Considerations:

   (a). **State of Charge (SoC) Thresholds**:

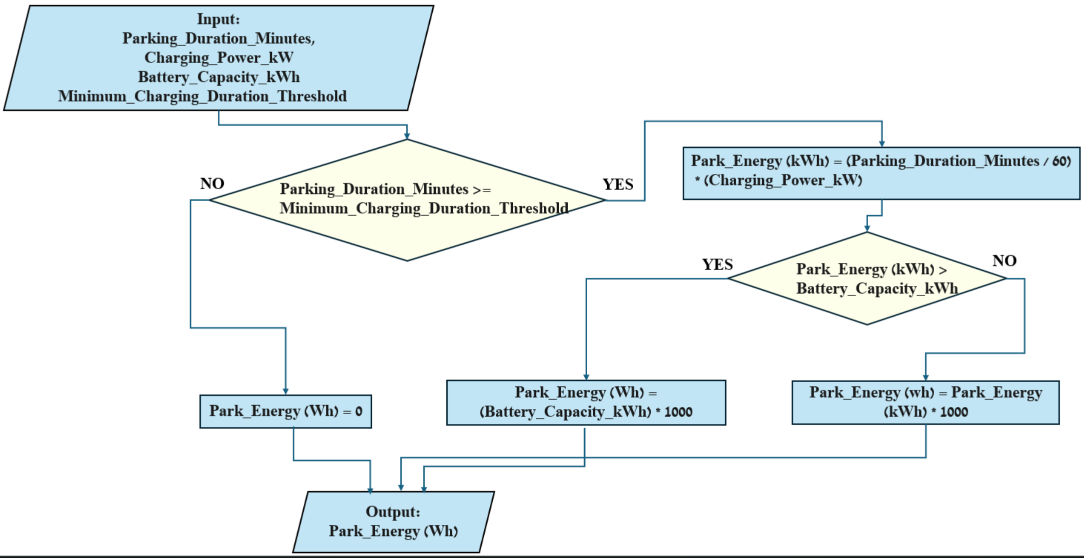

Figure 4.2: Flowchart illustrating the Calculation of Energy Gained During Parking Events

Each charging profile specifies conditions under which charging is triggered. For instance:

- In the **Casual User** profile, charging is initiated only if the SoC falls to 20%.
- The current SoC of the battery is checked against these predefined thresholds to determine if charging begins.

(b). **Charging Parameters**:

Once the conditions for charging are met:

- The energy gained is calculated by multiplying the **parking duration (in hours)** by the **output power of the charger**.
- The charger type and power are determined based on the user profile. For example:
  - Car Sharing Fleets: Always use DC fast charging.
  - Frequent Users: Prefer slower AC chargers.

(c). **Energy Calculation Function**:

A function is used to automate this process, taking the following inputs:

- `park_duration`: The parking interval in hours.
- `charging_estimation`: The estimated energy input from the charger.
- `post_trip_soc`: The battery's SoC after the previous trip.

- `Battery_Capacity_wh`: The vehicle's total battery capacity in watt-hours.
- `charge_flag`: Indicates whether charging should occur based on initial checks.

The function ensures that the energy gained during the parking event is accurately calculated, while also verifying that it does **not exceed the maximum battery capacity**. This step guarantees precise tracking of battery replenishment and avoids unrealistic energy estimates.

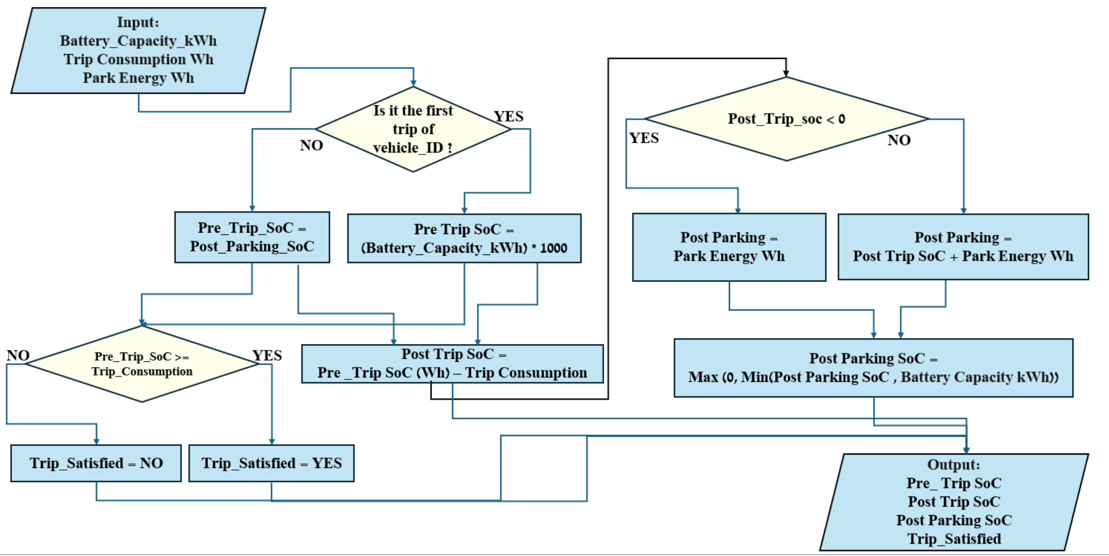

Figure 4.3: Flowchart representing the calculation of pre-trip, post-trip, and post-parking State of Charge (SoC) based on battery capacity, trip energy consumption, and parking energy gained. It evaluates whether the trip requirements are satisfied under defined conditions.

5. **Calculating the Post-Parking State of Charge (SoC)** The next step in the simulation involves determining the battery's State of Charge (SoC) at the end of the parking event. This calculation combines the results from the previous steps:

   - The **remaining energy** at the end of the trip, calculated in **Step 3**, represents the SoC after the energy consumed during the trip has been subtracted.
   - The **energy gained during the parking session**, calculated in **Step 4**, represents the energy replenished during the charging event.

   The resulting value represents the SoC at the beginning of the next trip. In essence, the battery energy carried over from the previous trip, combined with the energy replenished during the parking session, determines the starting SoC for the upcoming trip.

   This step ensures continuity in the simulation, accurately tracking how the battery's charge level evolves across successive trips and charging events. By dynamically updating the SoC, the simulation provides a realistic representation of energy utilization and replenishment in electric vehicle operations.

6. **Iterative Simulation Process for the Entire Dataset** Steps 1 through 5 are iteratively applied for every trip in the dataset, creating a comprehensive timeline of State of Charge (SoC) changes, charging events, and flagged scenarios. This iterative process ensures that the simulation accurately reflects the evolving energy dynamics of each vehicle across its daily operations.

   This repetition continues until all trips and parking events for each vehicle have been processed, ensuring that the simulation captures the cumulative impact of energy consumption and replenishment over time.

   The implementation of the simulation framework, including the iterative steps and all calculations, is provided in the code repository included in the **Appendix**[1].

Handling Battery Capacity Limits and Consumption Overruns

In developing the simulation, special care was taken to ensure that the energy calculations remained realistic and physically plausible. For instance, during the charging computation, the algorithm explicitly checks that the energy added to the battery during a charging event never exceeds the battery's maximum capacity. This safeguard is implemented by comparing the calculated charge against the battery's total storage limit and taking the minimum of the two. Such a precaution ensures that the simulation honors the physical constraints of electric vehicle batteries and prevents any overestimation of available energy.

Additionally, the simulation accounts for scenarios where the energy consumption of a trip might exceed the battery's initial state of charge. In such cases, the calculated state of charge (SoC) after the trip could mathematically become negative. Recognizing that a negative SoC is not physically meaningful, the simulation resets any negative SoC values to zero. This situation flags the corresponding trip as 'unfeasible', meaning the vehicle could not complete the trip without running out of energy. Consequently, if a trip is flagged unfeasible, the SoC at the beginning of the next trip is set to zero, indicating that the vehicle would start with an empty battery until it can charge again. This worst-case scenario, where an empty battery leads to a sequence of uncompleted trips, emphasizes the importance of timely charging events to break the cycle and restore the battery's energy, thereby allowing subsequent trips to proceed.

[1] The Appendix contains detailed documentation and scripts that support the methodologies described in this chapter, ensuring reproducibility and transparency of the results.

Improving Efficiency in Large-Scale Data Processing

When processing data, particularly when filtering to analyze the behavior of specific users, efficiency becomes a critical factor. The time it takes to complete such tasks largely depends on the size of the dataset relevant to the user, which typically represents only a subset of the entire dataset. For moderately sized datasets, operations generally complete within seconds to minutes. However, when working with very large datasets such as those containing over a million rows, it's essential to implement strategies that maintain efficient performance.

To address this challenge, several parallelization strategies can be applied to take advantage of modern multi-core processors.

One approach involves using Pandas Multiprocessing Frameworks, such as **Dask DataFrame** [2] or **Modin.pandas** [3]. These tools allow for distributing computations across multiple CPU cores, which is particularly beneficial when working with large datasets. By parallelizing tasks like data filtering and transformation, these frameworks can dramatically reduce processing times.

Another performance optimization comes from **vectorization with NumPy**[4]. If the computations involve looping through rows, these loops can be replaced with NumPy's vectorized operations. Vectorization leverages fast, low level C implementations, which can significantly improve performance by eliminating the need for slower, explicit loops.

When working with **small datasets** (fewer than 100,000 rows), the script should run efficiently even without parallelization. The overhead associated with setting up parallel tasks may not be necessary, as the data volume is manageable. However, for **large datasets** (over 1 million rows), parallel computing becomes more important. In these cases, optimized libraries like Dask and Modin, combined with techniques such as vectorization, can significantly improve performance. This is especially true when filtering data for specific users although the overall dataset may be massive, the relevant subset can be processed efficiently in parallel.

In conclusion, using parallel processing frameworks and vectorized operations allows for effective management of both small and large datasets. While smaller datasets may not need complex optimizations, large scale data processing particularly when filtering user specific behavior greatly benefits from these techniques. Distributing the workload across multiple processing units or handling data in chunks improves efficiency and ensures timely completion of complex tasks.

[2] https://docs.dask.org/en/stable/dataframe.html

[3] https://modin.readthedocs.io/en/stable/

[4] https://numpy.org/doc/stable/reference/generated/numpy.vectorize.html

4.3 Performance Metrics from the Simulation

The simulator produces several key attributes that provide insights into the performance of the electric vehicle (EV) charging model. These outputs can be divided into two groups:

- **Unaggregated Metrics**: Detailed trip-level performance indicators that capture results for each individual trip.
- **Aggregated Metrics**: Overall performance summaries that compile and analyze results across multiple trips or simulation scenarios.

The following sections describe these two groups of outputs in detail.

4.3.1 Individual Trip Performance Analysis

- **Satisfied Trips**: Counts the number of trips that were successfully completed without energy-related issues. A "Satisfied Trip" indicates that the vehicle had sufficient charge throughout the trip, as determined by comparing the pre-trip State of Charge (SoC) with the energy required for the trip.
- **Trips with Anxiety**: Tracks the number of trips during which range anxiety occurred. This happens when the battery's SoC falls below a critical threshold (e.g., 10% of capacity) at any point during the trip, as flagged in the simulation.
- **Kilometers with Anxiety**: Measures the total distance traveled under conditions of range anxiety. This metric provides a more detailed view of how far the vehicle was driven while the SoC was critically low, highlighting potential risk areas.
- **Autonomy (Km)**: Represents the estimated maximum distance (in kilometers) the vehicle could travel based on the available SoC at the beginning of a trip and the vehicle's energy consumption rate. This value is derived by dividing the pre-trip SoC by the combined consumption rate.
- **Percentage of Satisfied Distance (% Satisfied Distance)**: Calculates the percentage of the total trip distance that could be covered without encountering empty battery. This metric assesses the reliability of the charging strategy and overall energy management for each trip.

Together, these metrics provide a comprehensive assessment of the EV's performance under various charging scenarios, highlighting the effectiveness of the charging model and the feasibility of completing trips across different user profiles and assumptions.

4.3.2 Aggregated Results and Performance Indicators

After computing performance metrics for each trip, the simulation proceeds to aggregate these results into overall metrics for each simulation scenario.

- **user_tot_trips**: The total number of trips simulated for a given vehicle profile within the file.
- **user_tot_kilometers**: The total distance (in kilometers) covered across all simulated trips for the profile.
- **cnt_satisfied_trip**: The count of trips that were completed successfully without energy-related issues.
- **cnt_trips_with_anxiety**: The count of trips during which range anxiety was experienced, according to the simulation criteria.
- **Satisfied_Trip_Percent**: The percentage of trips that were fully satisfied, computed as
$$\left(\frac{\text{cnt\_satisfied\_trip}}{\text{user\_tot\_trips}}\right) \times 100.$$
- **Trips_with_Anxiety_Percent**: The percentage of trips where range anxiety occurred, computed as
$$\left(\frac{\text{cnt\_trips\_with\_anxiety}}{\text{user\_tot\_trips}}\right) \times 100.$$
- **avg_satisfied_distance_percent**: The average percentage of each trip's distance that was completed without range anxiety, averaged over all trips.
- **total_kilometers_with_anxiety**: The sum of kilometers driven under range anxiety conditions across all trips.
- **Kilometers_with_Anxiety_Percent**: The percentage of the total distance driven under range anxiety, computed as
$$\left(\frac{\text{total\_kilometers\_with\_anxiety}}{\text{user\_tot\_kilometers}}\right) \times 100.$$
- **total_days**: The total number of days on which trips were simulated, derived from the trip start times.
- **days_with_anxiety**: The number of days on which at least one trip experienced range anxiety.
- **days_with_dissatisfaction**: The number of days on which at least one trip was not fully satisfied due to insufficient charge.

- **Percentage_Anxiety_Days**: The percentage of total days that had at least one instance of range anxiety, calculated as

$$\left(\frac{\text{days\_with\_anxiety}}{\text{total\_days}}\right) \times 100.$$

- **Percentage_Dissatisfaction_Days**: The percentage of days with at least one dissatisfied trip, calculated as

$$\left(\frac{\text{days\_with\_dissatisfaction}}{\text{total\_days}}\right) \times 100.$$

Chapter 5

Results

This chapter is divided into two main sections. The first section provides a detailed explanation of the interactive dashboard, designed by the researcher to visualize the outcomes of the simulations. It explores the dashboard's functionalities, key features, and how it facilitates the interpretation of results. The second section presents the numerical findings derived from the dashboard, summarizing the insights gained from the simulation process. These results reflect the three-phase simulation approach, followed by a cost analysis. The findings are structured in alignment with the methodology, moving from simplified models to more complex and near real-world scenarios.

5.1 Interactive Dashboard Navigation

Given the large number of simulations conducted in this research, which exceed thousands of scenarios, traditional static plots created using libraries like Matplotlib would be both time-consuming and impractical for visualizing and analyzing the results. To address this challenge, **Streamlit** [1], an open-source Python framework, was employed to create an interactive web application for the visualizations. Streamlit enables the development of dynamic, data-driven applications without requiring front-end development expertise. It allows for the easy addition of interactive components, such as widgets, which are similar to defining variables in Python. Furthermore, it eliminates the need for backend coding, route definitions, HTTP request handling, or integration with HTML, CSS, and JavaScript.

This framework facilitated the creation of a comprehensive platform where all visualizations are consolidated in one place, making it more efficient for analysis. The interactive dashboard developed with Streamlit allows users to explore the results by adjusting settings and instantly observing how these changes affect the outcomes. It supports various plot types, including heatmaps, violin plots, box plots, and scatter plots, and enables users to generate visualizations either for specific users or for all users

[1] https://streamlit.io/

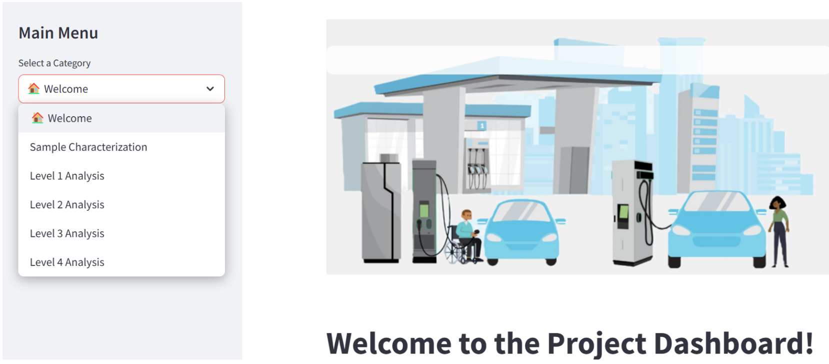

Figure 5.1: Interactive Dashboard Home Page

collectively, based on their needs. All the plots presented in this chapter are derived from this interactive dashboard, providing an intuitive and accessible way to analyze the simulation results. In the figure 5.1, the home page of the dashboard is displayed.

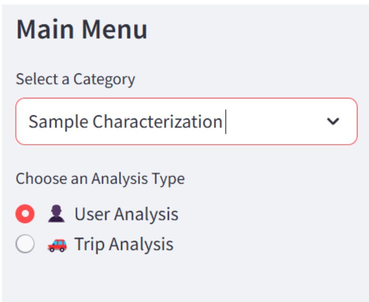

Figure 5.2: Dashboard View : Sample Characterization

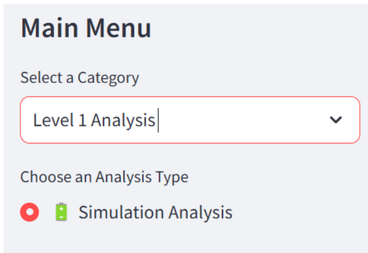

Figure 5.3: Dashboard View : Phase One Visualization

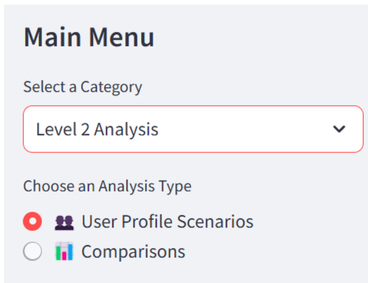

Figure 5.4: Dashboard View : Phase Two Visualization

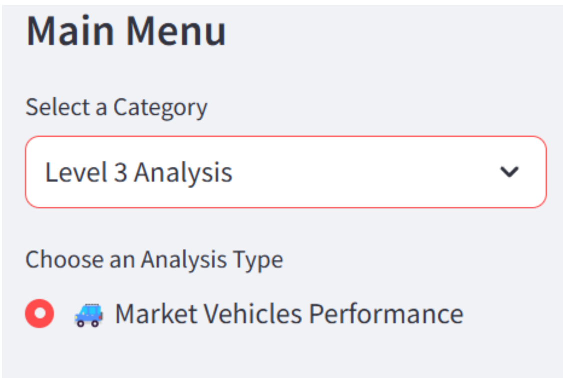

Figure 5.5: Dashboard View : Phase Three Visualization

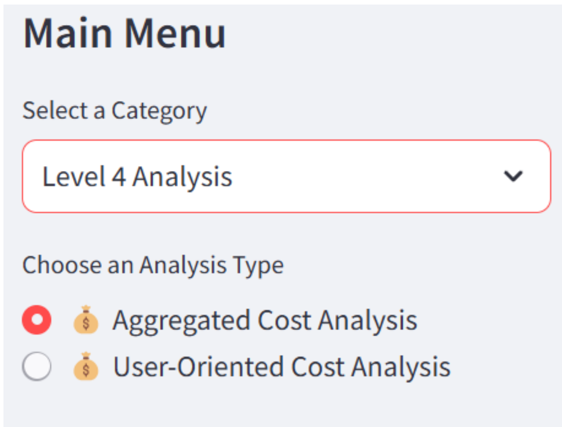

Figure 5.6: Dashboard View: Cost Analysis

As shown in the figures 5.2, 5.3, 5.4, 5.5 and 5.6, the main menu section allows users to select the analysis level they wish to explore. The first option, "Sample Characterization," provides a comprehensive overview of the sample on which the research is based. The plots shown in "**Data Exploration**" in Dataset Management chapter (Chapter 3) were created from this menu. Subsequent options correspond to the different phases of the simulation process, as discussed in the Methodology chapter (Chapter 4). Each phase is presented separately in the figures, allowing for a detailed exploration of the results. As shown in the figures, the dashboard features various drop-down menus that allow users to select their preferred values for visualization. The following figures are taken from the "Level 3 Analysis" which corresponds to the visualization of phase three of the simulation. The first drop-down menu (figure 5.7) enables the selection of **Scenario(s)** related to different charging scenarios. The next step, as shown in the subsequent figure (figure 5.8), involves selecting the **car brand(s)** (figure 5.8), followed by the option to choose the specific **car model** (figure 5.9) from the selected manufacturer.

The dashboard also provides the option to track the performance of either all users within the sample or a specific user, which can be selected from a corresponding drop-down menu. The next step allows users to specify the **charging power**, choosing between **AC** or **DC** charging (figure 5.11 and figure 5.12) , which are selected separately. Finally, users can choose the desired **metrics** (figure 5.13) and **plots** (figure 5.14). The combination of these selections corresponds to a specific simulation, which is then ready to be displayed and analyzed. This dashboard can be utilized as tool for providing a practical way to explore and understand the simulation results in different scenarios and from various perspectives.

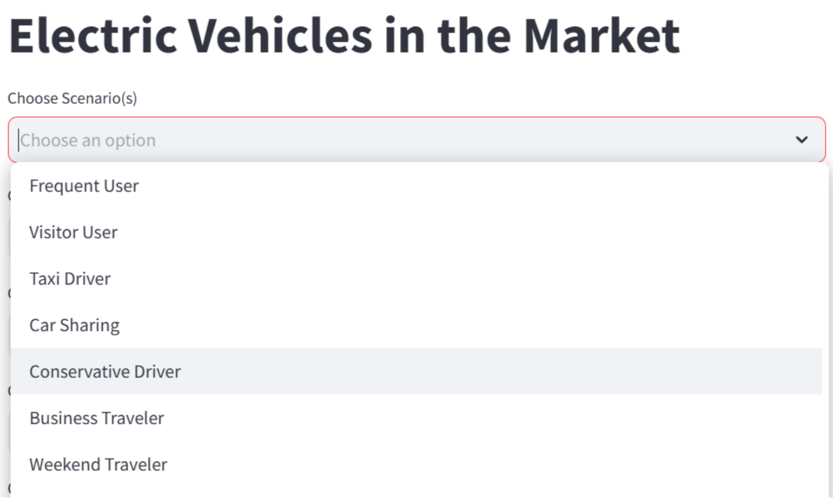

Figure 5.7: Drop-down menu for selecting different charging scenarios

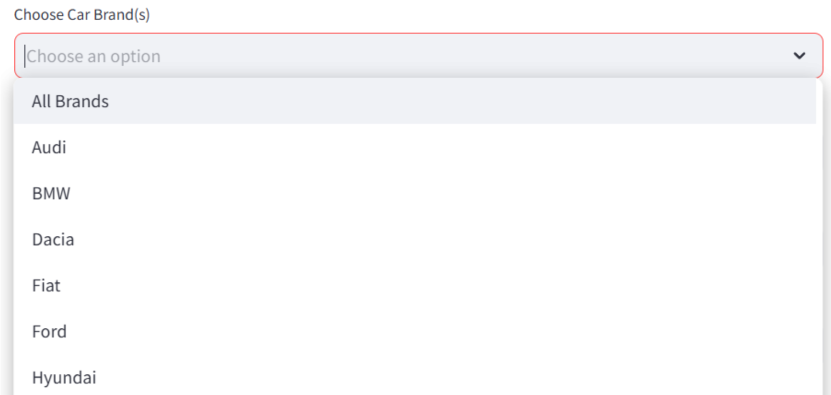

Figure 5.8: Drop-down menu for selecting a specific car brand

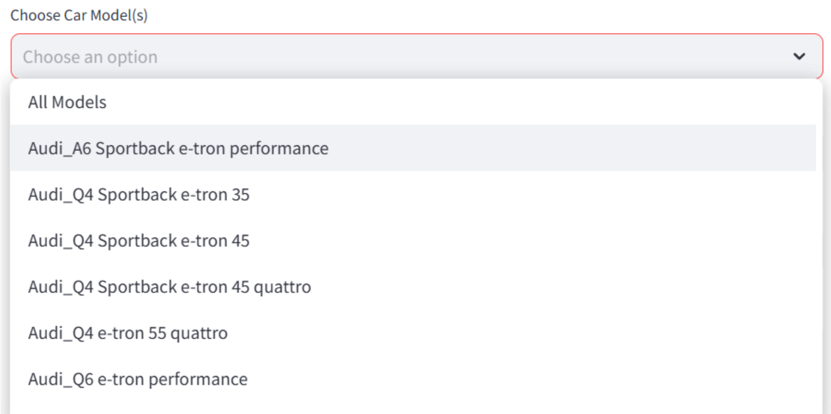

Figure 5.9: Drop-down menu allowing users to select a specific car model

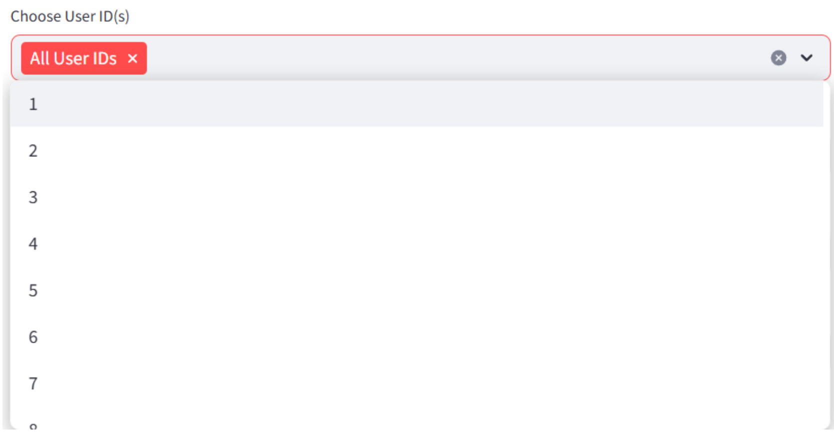

Figure 5.10: Drop-down menu for selecting User IDs.

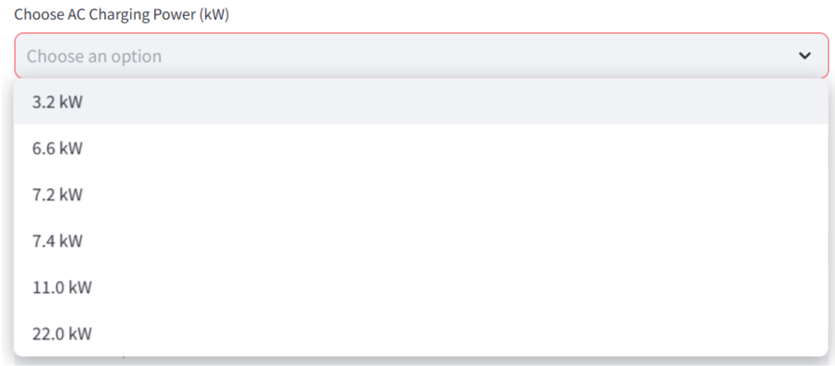

Figure 5.11: Drop-down menu for selecting the AC charging power (in kW)

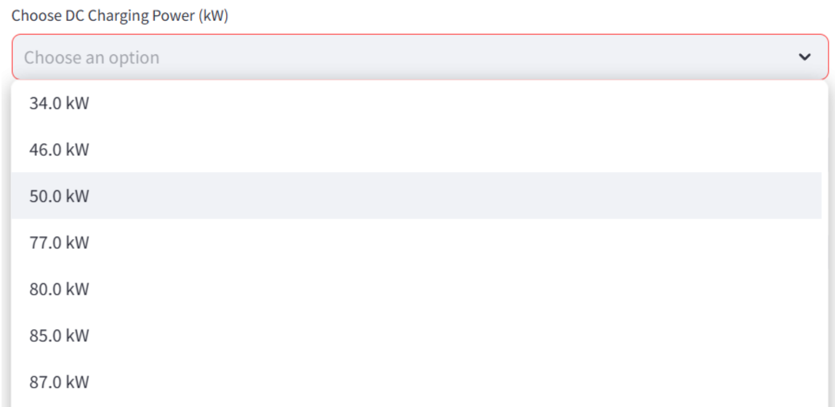

Figure 5.12: Drop-down menu for selecting the DC charging power (in kW)

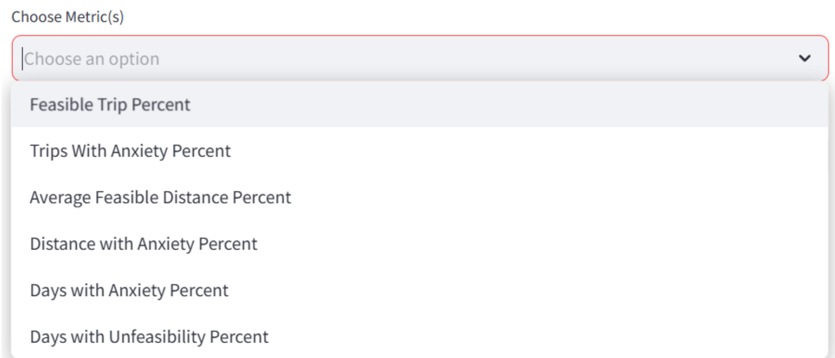

Figure 5.13: Drop-down menu for selecting metrics

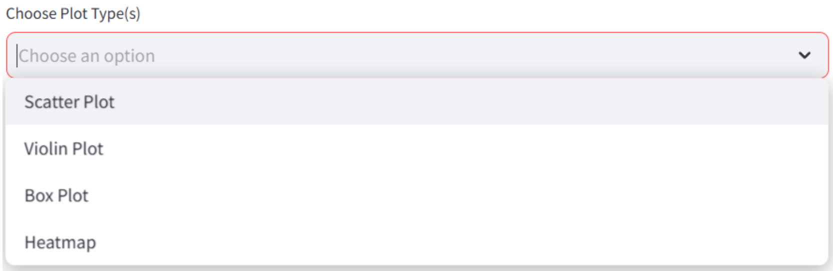

Figure 5.14: Drop-down menu for selecting plot types for visualization

In the cost analysis section 5.24, users can filter vehicles based on an initial budget, categorized by the purchase price of electric vehicles. These prices are grouped into intervals of 10,000 euro, ranging from 10,000 - 20,000 euro to 80,000 - 90,000 euro. This segmentation allows users to focus on vehicles within their affordability range.

The cost metrics analyzed include various charging scenarios:

- **Daily Charging Costs**: These are calculated based on whether the user charges their car at home or on the street.
  - **Street Charging Costs**: Differentiated between AC and DC charging power. If the charging scenario for a conservative driver is selected, the analysis considers costs for both AC and DC charging.
  - **Home Charging Costs**: Assume a lower bound of 0 euro, reflecting the possibility of using renewable energy sources such as solar panels.
- **Cost per Kilometer**: This metric is particularly useful for users who wish to compare the costs of operating an electric vehicle with traditional fuel expenses (e.g., petrol or gas). It provides a tangible and comparable value that can aid decision-making.

The price ranges considered for this analysis are as follows:

- **Street DC Charging Power**: 0.80 to 1.00 euro per kWh
- **Street AC Charging Power**: 0.38 to 0.80 euro per kWh
- **Home Charging**: 0 to 0.30 euro per kWh

This detailed analysis provides users with a clear understanding of daily operational costs and cost efficiency, aiding them in making informed decisions about electric vehicle ownership and usage.

Figure 5.15: Interactive Dashboard - Cost Analysis

5.2 Simulation Results

5.2.1 Phase One

Since the first phase of the simulation operated at an abstract level, without considering specific vehicle details, the results can be used to analyze the influence of various factors, such as battery capacity and charging power, on different performance metrics. These results offer a general overview of the system's behavior under idealized conditions, assuming that vehicle owners have continuous access to charging stations and charge their vehicles at every parking event, provided it meets the pre-defined conditions for charging duration.

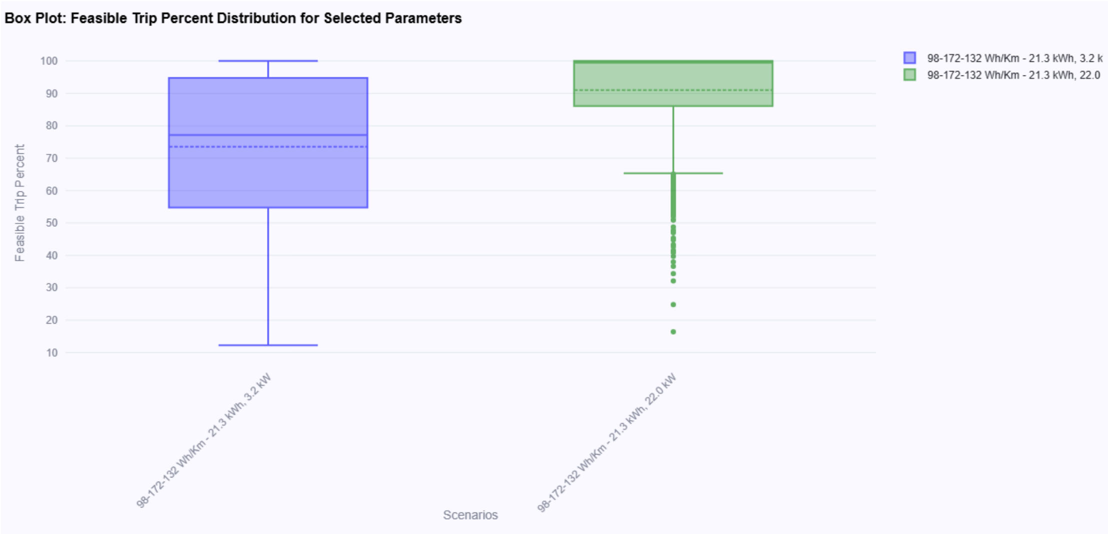

Figure 5.16: Box plot showing the distribution of Feasible Trip Percent for a battery capacity of 21.3 kWh with charging powers of 3.2 kW and 22 kW. The results are based on all users, considering a constant consumption rate of 98-172-132 Wh/km and a minimum charging duration of 20 minutes.

The boxplot in Figure 5.16 shows the distribution of feasible trip percentages while keeping energy consumption and battery capacity constant and minimum charging duration is assumed 20 minutes. In this case, the only variable changing between scenarios is the charging power, making it a clear illustration of how charging power affects trip feasibility.

The 22kW charging rate consistently achieves higher feasible trip percentages compared to 3.2kW, demonstrating the benefit of faster charging during parking events. The 3.2kW scenario shows greater variability, with a wider interquartile range (IQR), suggesting that slower charging can lead to inconsistent performance, especially during shorter parking durations. In contrast, the 22kW charging scenario has a narrower IQR and a higher median feasible trip percentage, indicating more reliable performance and reduced range anxiety.

However, outliers in the 22kW data suggest that, despite the higher charging power, there are instances where feasibility drops below 20%. This low percentage may be attributed to the high utilization rate of vehicles in the sample, as discussed in the Dataset Management chapter. Similarly, the 3.2kW scenario occasionally results in feasibility as low as 10 - 20%, which creates a particular issue for users with frequent or long trips, displaying the limitations of slower charging speeds.

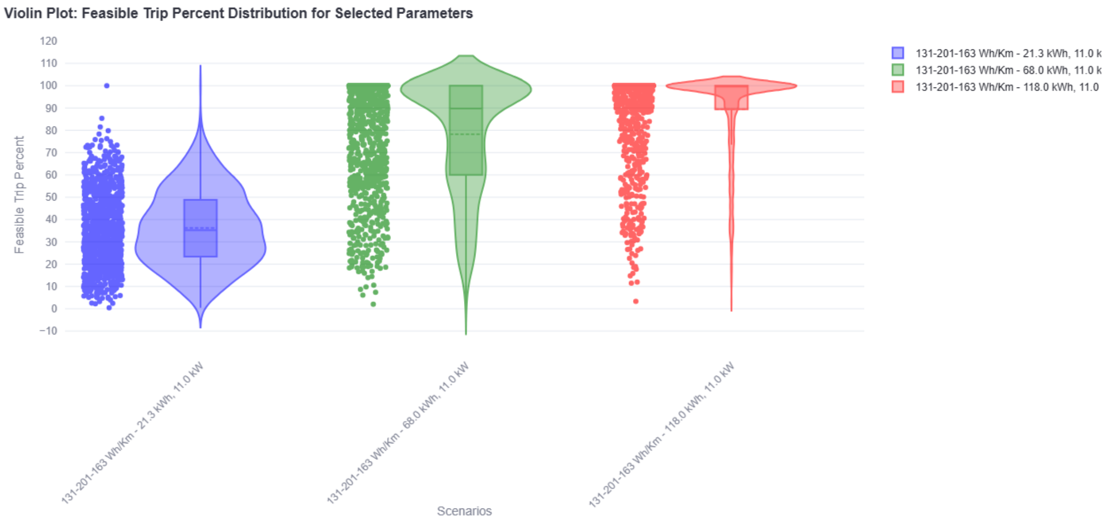

Figure 5.17: Violin plot showing the distribution of Feasible Trip Percent for battery capacities of 21.3 kWh, 68.0 kWh, and 118.0 kWh, all with a charging power of 11.0 kW, by considering all users, with a constant consumption rate of 131-201-163 Wh/km and a minimum charging duration of 8 hours.

The violin plot (figure 5.17) shows the distribution of the Feasible Trip Percent metric across three different scenarios, each varying by battery capacity while maintaining a constant charging power of 11.0 kW and energy consumption rates of 131-201-163 Wh/km.

In the blue violin with a 21.3 kWh battery, the distribution is highly variable with a wider spread, often approaching 0% feasibility, which highlights the struggle of smaller capacities to support longer or more energy-intensive trips. Increasing the capacity to 68.0 kWh (green plot) narrows the distribution, indicating more consistent performance and a generally higher range of feasibility that better accommodates diverse trip profiles. The red plot with a 118.0 kWh battery shows a sharply concentrated distribution near 100%, displaying superior performance with minimal variability, which illustrates it can support even the most demanding trips.

While the charging power remains constant across scenarios, its positive impact is amplified with higher battery capacities.The plot highlights that low battery capacities are associated with high variability and limited feasibility, while medium capacities, as shown in the green plot, offer more balanced performance. The median value of 90% indicates that half of the users achieve more than 90% satisfaction. High capacities consistently outperform lower ones, emphasizing that selecting the right battery capacity is crucial for meeting user needs.

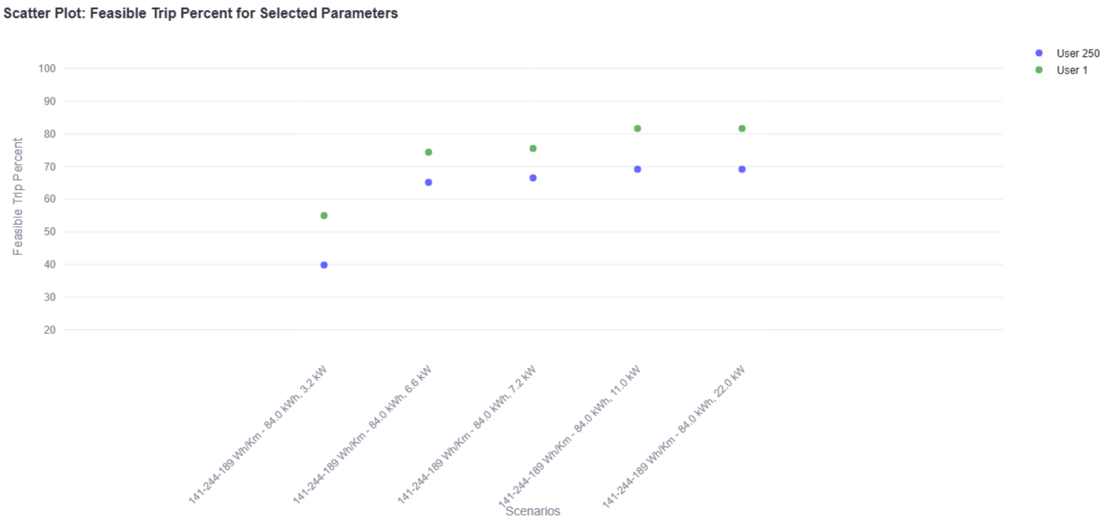

Figure 5.18: Scatter plot showing the Feasible Trip Percent for two selected users (User 1 and User 250) across different charging power scenarios (3.2 kW, 6.6 kW, 7.2 kW, 11.0 kW, and 22.0 kW) with a battery capacity of 84.0 kWh, with a constant consumption rate of 141-244-189 Wh/km and a minimum charging duration of 8 hours.

As mentioned earlier, the interactive dashboard allows users to track the behavior and status of individual users across various scenarios. The scatter plot in Figure 5.18 shows the relationship between charging power and Feasible Trip Percent for two users, User 1 and User 250, under a fixed 8 hour charging duration. In this analysis, both battery capacity and energy consumption are kept constant across the five scenarios.

It reveals that increasing charging power from 3.2 kW to 7.2 kW significantly improves feasibility, but further increases beyond 7.2 kW offer only marginal benefits due to a saturation effect. After 8 hours, moderate power levels nearly fully charge the batteries, and additional power has little impact.

User 1 generally achieves higher trip feasibility than User 250, but both experience diminishing returns beyond a certain power threshold. These results suggest that, with longer parking durations, very high charging rates offer limited extra benefit. In this analysis, only two randomly selected users were examined, highlighting the dashboard's ability to track individual user performance. The findings stress the importance of considering user-specific behaviors such as parking time and trip patterns when optimizing charging infrastructure, rather than focusing solely on increasing power, to ensure cost-effectiveness.

5.2.2 Phase Two

Moving on to the second phase, users have the option to select charging scenarios based on various predefined conditions. This phase is closer to real-world scenarios, as it considers more than just the minimum charging duration to determine whether charging occurs. Here, users can compare different strategies and observe how these strategies impact key metrics. For detailed explanations on each charging scenario check Phase Two 4.1.2 section in the Methodology chapter.

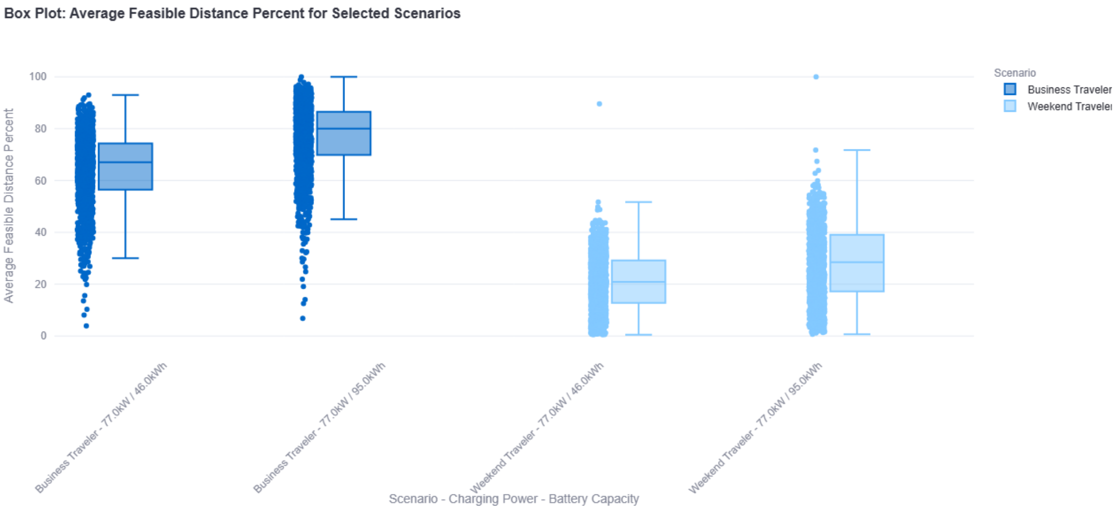

Figure 5.19: Box plot showing the Average Feasible Distance Percent for business and weekend travelers across two battery capacities (46.0 kWh and 95.0 kWh) with a charging power of 77.0 kW, by considering All Users, with a constant consumption rate of 120-200-154 Wh/km

The box plot 5.19 compares the average feasible distance percentage for business and weekend travelers across two battery capacities (46.0 kWh and 95.0 kWh) with a constant charging power of 77.0 kW. It reveals that increasing battery capacity from 46.0 kWh to 95.0 kWh significantly improves trip feasibility for both traveler profiles by providing better range and reducing the likelihood of infeasible trips.

Business travelers consistently achieve higher feasible distance percentages than weekend travelers, due to the fact that business travelers charge their vehicles on every working day during the week. In contrast, weekend travelers, who charge only on weekends, exhibit more variability in trip feasibility, especially with the smaller 46.0 kWh battery. This pattern is likely because their infrequent charging opportunities make them more sensitive to battery capacity and charging power. Outliers, particularly for business travelers with the 95.0 kWh battery, suggest extreme cases where even high capacity may not ensure trip feasibility, possibly due to unusually high consumption.

In conclusion, investing in higher battery capacities generally improves trip feasibility, especially for business travelers. However, for weekend travelers the frequency of charging switching from charging two days a week to five can significantly impact trip feasibility, proving the importance of consistent charging opportunities for optimal performance.

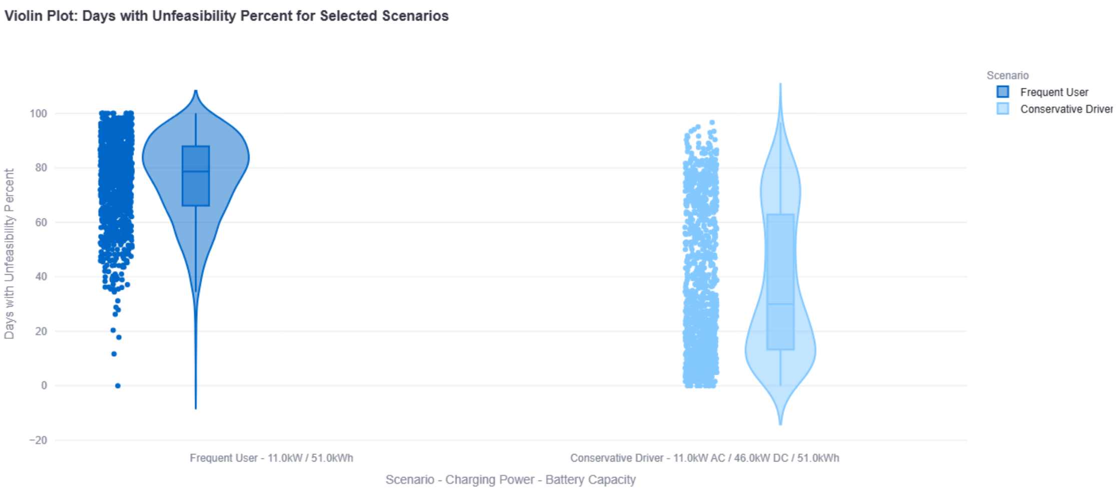

Figure 5.20: Violin plot showing the distribution of days with unfeasibility percent for two scenarios with battery capacity of 51.0 kWh: Frequent User (11.0 kW charging power) and Conservative Driver (11.0 kW AC/46.0 kW DC charging, by considering All Users, with a constant consumption rate of 114-187-150 Wh/km

Based on violin plot 5.20, both scenarios share the same battery capacity (51 kWh) and energy consumption rates and the key difference lies solely in their charging behaviors:

Frequent users based on the assumption made, primarily charge their vehicles using 11 kW Level 2 AC chargers, typically overnight at home, with additional charging on weekends. Despite regular use, their reliance on a single charging mode results in significant variability in the percentage of days with infeasible trips, with many days experiencing high levels of infeasibility (80-90%).

This variability highlights the limitations of depending solely on moderate AC charging. The high median infeasibility indicates that, even with extended charging periods, users frequently struggle to ensure trip feasibility, pointing to the challenges of relying solely on this charging method.

Conservative Drivers, on the other hand, use AC chargers (11 - 22 kW) but also supplement with 46.0 kW DC fast charging in emergencies. This mixed charging strategy provides more flexibility and faster top-ups when needed, despite having the same battery capacity and consumption rates. As a result, their distribution is narrower, with a lower median infeasibility percentage, indicating a more consistent and reliable travel experience. The addition of DC fast charging helps to bridge the gap during longer trips or unexpected high energy demands, reducing the likelihood of infeasible days.

In conclusion, even with identical battery specifications and energy consumption, distinct charging behaviors relying only on moderate AC charging versus combining it with faster DC options lead to different outcomes in trip feasibility. The Conservative Driver's access to faster charging reduces variability and infeasible days, emphasizing the important role of charging behavior in optimizing electric vehicle use.

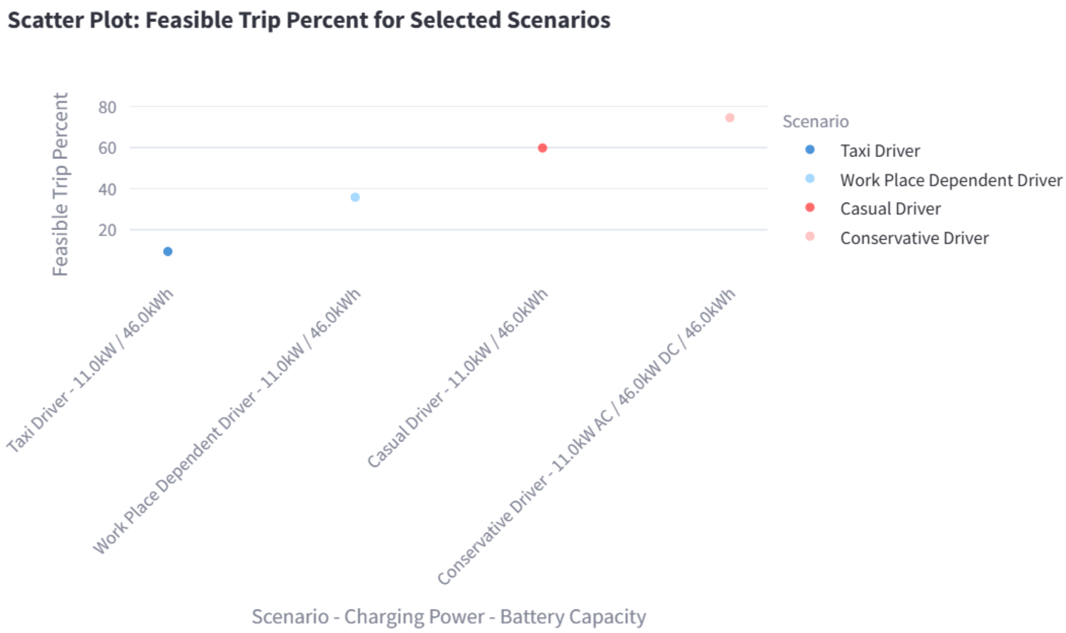

Figure 5.21: Scatter plot showing the Feasible Trip Percent for User ID 480 across different driver scenarios: Taxi Driver, Workplace Dependent Driver, Casual Driver, and Conservative Driver. Assuming battery capacity of 46.0 kWh, charging power of 11.0 kW, and a constant consumption rate of 120-200-154 Wh/km.

The scatter plot (Figure 5.21) shows the Feasible Trip Percent for different driver scenarios simulated for a single user (User ID 480). In all scenarios, the battery capacity is fixed at 46.0 kWh, with a charging power of 11.0 kW and a constant energy consumption rate of 120-200-154 Wh/km. The four scenarios examined are Taxi Driver, Workplace Dependent Driver, Casual Driver, and Conservative Driver.

Key insights from the plot reveal that the Taxi Driver scenario results in the lowest feasible trip percentage, around 20%, suggesting that this charging behavior does not work well for User 480.

In the Workplace Dependent Driver scenario, the feasible trip percentage increases to about 40%, benefiting from workplace charging during long parking periods.

The Casual Driver scenario shows an even higher feasible trip percentage of nearly 60%, thanks to less frequent trips and moderate energy consumption. The Conservative Driver scenario yields the highest feasibility at 70%, though this still indicates room for improvement, even under optimal charging behavior. This suggests that User 480 should carefully plan travel patterns and charging strategies when transitioning from a combustion engine vehicle to an electric vehicle.

Overall, the plot highlights the noticeable impact of charging strategies on trip feasibility. Even with a constant energy consumption rate, varying charging patterns lead to different results.

5.2.3 Phase Three

This result is derived from Phase Three of the analysis, where the simulation incorporates real-world vehicles, making the findings more relatable and intuitive for readers and users. Unlike the previous phases, this phase eliminates assumptions about battery capacities and energy consumption rates. Instead, each vehicle model has been assigned its actual specifications, including maximum battery capacity, realistic energy consumption rates, and the highest charging speed it can accept. By working with real vehicles and familiar names such as the Fiat 500e Hatchback, the results presented in this phase are not only more grounded in reality but also carry greater practical implications. This approach ensures that readers can better understand the trade-offs between different vehicle configurations and user profiles, offering insights that are directly applicable to real-world scenarios.

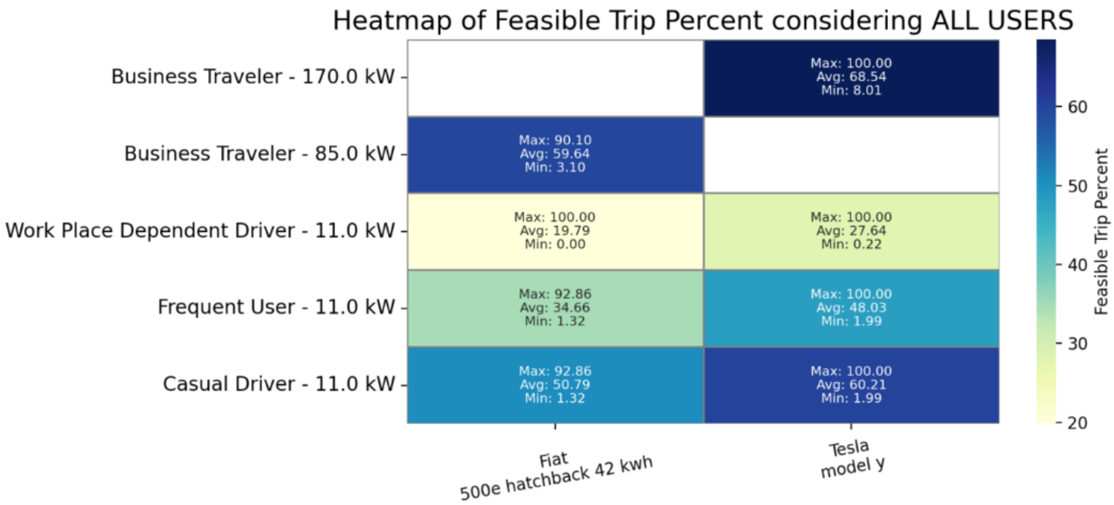

Figure 5.22: Heatmap of Feasible Trip Percent for all user profiles, comparing two vehicle models: Fiat 500e Hatchback (42 kWh battery) and Tesla Model Y.

The heatmap 5.22 visualizes the distribution of Feasible Trip Percent for different driver profiles across two vehicle models Fiat 500e Hatchback (42 kWh) and Tesla Model Y under various charging scenarios.

While it's clear that the Tesla Model Y outperforms the Fiat 500e across most scenarios, one interesting observation is the large gap between the two vehicles at lower charging power (85 kW and 11 kW). The Fiat 500e experiences significant drops in trip feasibility, especially with low charging power, which is not as apparent at first glance. This suggests that for certain vehicle models with smaller batteries, the need for faster charging infrastructure is more critical to maintain feasible trips.

The Workplace Dependent Driver scenario with 11 kW charging power shows the Tesla achieving relatively higher feasibility percentages, but it's important to note that even the best performing scenario (Tesla Model Y at 11 kW) still results in lower feasibility for the Fiat 500e. This indicates that while workplace charging during long parking sessions helps, it may not be sufficient for the sample which was used for this study, because the exploration on the dataset showed that the utilization rate is quite high in this sample.

At higher charging powers (85 kW and 170 kW), increasing power shows decreasing returns for the Tesla Model Y in some scenarios. This indicates that beyond a certain point, charging power doesn't significantly improve trip feasibility, particularly when the battery is nearly full. This highlights the need to balance power and efficiency when optimizing charging infrastructure.

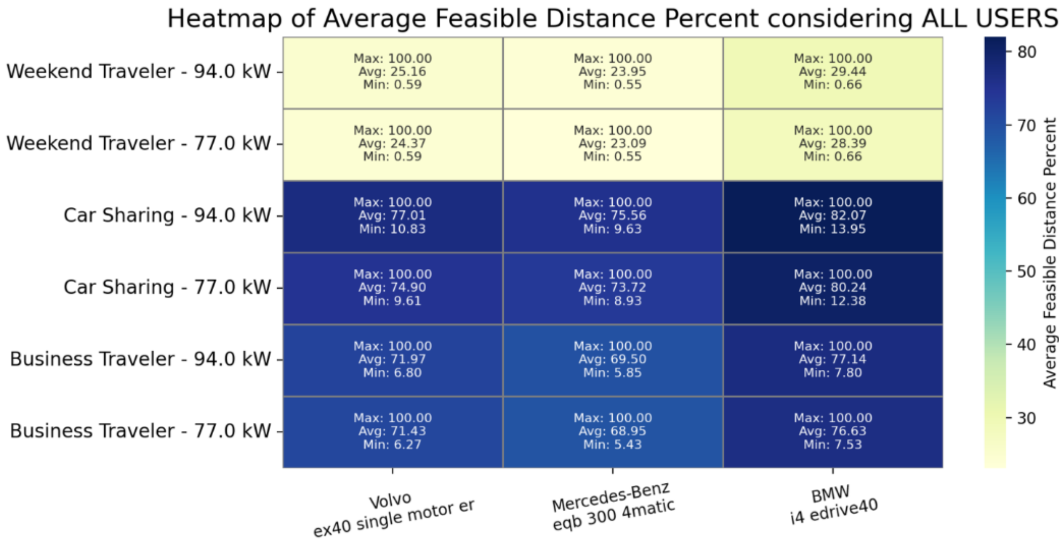

Figure 5.23: Heatmap of Average Feasible Distance Percent considering all users across various driver scenarios and vehicle configurations. The rows represent charging scenarios with charging powers. The columns indicate vehicle models.

Car sharing scenarios show high feasibility with both 77.0 kW and 94.0 kW charging, maintaining strong feasibility which is above 70%). This suggests that car-sharing charging scenario could work well on the existing sample and their trips pattern.

The BMW i4 eDrive40 performs consistently across different charging powers and user profiles, with average feasibility between 60% and 70%. This makes the BMW i4 a versatile model, offering stable feasibility regardless of user behavior and charging options.

The Mercedes-Benz EQB 300 4MATIC tends to underperform compared to other vehicles, especially with moderate charging power (77.0 kW). This highlights how vehicle-specific factors like efficiency and energy consumption can impact performance.

These insights show that trip feasibility depends not only on battery size or charging power but also on charging behavior, and vehicle-specific attributes, all of which are crucial when designing EV ecosystems.

5.2.4 Cost Analysis

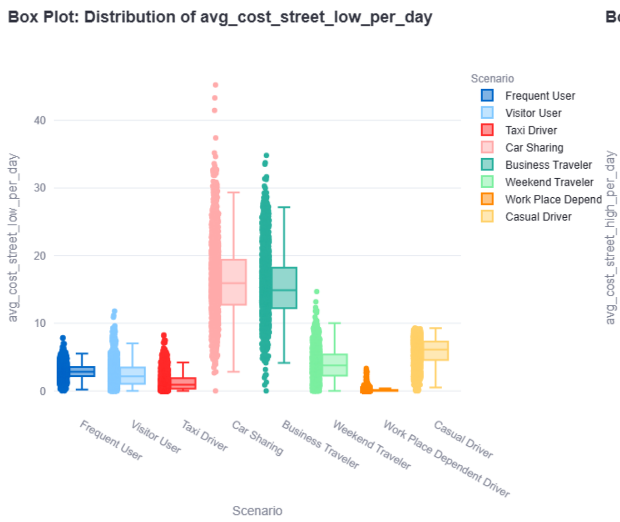

Figure 5.24: The distribution of the lower bound of daily average street charging costs across various user scenarios.

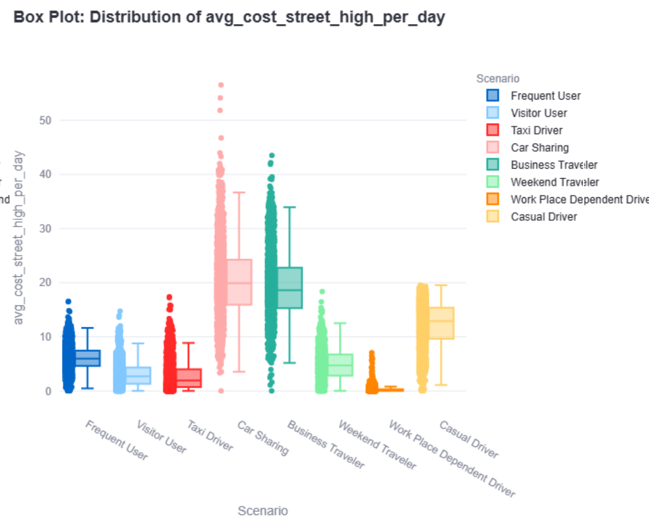

Figure 5.25: The distribution of the upper bound of daily average street charging costs across various user scenarios.

These box plots in figure 5.24 illustrate the distribution of street charging costs across different charging scenarios by considering the lower bound of prices. For scenarios like **Frequent Users** and **Casual Drivers**, which typically use AC chargers, the prices fall within a range of 1 to 10 euros per day. However, for **Business Travelers** and **Weekend Travelers**, who rely on DC fast chargers, the distribution shows larger values due to the higher cost associated with fast charging. The car model selected for generating these plots is the **Dacia Spring Electric 45**.

The **Car Sharing** and **Business Traveler** scenarios display higher charging costs, as both assume the use of DC fast chargers, which are naturally more expensive. Additionally, the **Car Sharing** strategy assumes that vehicles are kept at a full charge to ensure they are always available for shared use. As a result, the median charging cost in the **Car Sharing** scenario is higher than in the other charging scenarios.

The box plots in Figure 5.25 displays the distribution of street charging costs across various charging scenarios, focusing on the upper bound of prices. As with the previous plot, the car model used for generating these box plots is the **Dacia Spring Electric 45**. As anticipated, both the **Car Sharing** and **Business Traveler** scenarios exhibit the highest average charging costs, ranging from 0 to 50 euros per day. For the other charging scenarios, the prices generally remain within the 0 to 10 euros per day range. However, for **Casual Drivers**, the median price rises to approximately 15 euros per day, indicating a noticeable increase in charging costs compared to other user groups.

Chapter 6

Conclusion

6.1 Discussion

6.1.1 Key Findings and Implications

This study explored how electric vehicle (EV) charging behaviors, user profiles, and infrastructure requirements interact, using a three-phase simulation framework. The findings provide valuable insights into the factors that influence EV adoption and offer actionable recommendations for infrastructure development and policy-making.

Phase One: Abstract Scenarios In the first phase, the simulations used generalized battery capacities and charging power levels to explore key trade offs. The results showed that higher charging power generally improved trip feasibility, particularly when parking durations were shorter. However, beyond a certain threshold such as 11 kW for overnight charging there were diminishing returns, meaning that additional charging power didn't significantly improve feasibility. When it came to battery capacity, larger batteries made a substantial difference in the percentage of feasible trips. Smaller batteries, on the other hand, resulted in more variability and lower reliability, especially for users who relied on them for longer trips. This phase emphasized the need for a balance between battery size and charging speed to effectively meet user needs.

Phase Two: Behavioral Nuances The second phase introduced nine distinct user profiles, which demonstrated how charging behaviors critically shape EV feasibility. For example, **Frequent Users**, who rely solely on moderate AC charging, experienced greater variability in trip feasibility, as their trips were more susceptible to charging limitations. In contrast, **Conservative Drivers**, who combined AC charging with DC fast charging, had more consistent trip feasibility. Additionally, user profiles like **Business Travelers** and **Weekend Travelers** highlighted the importance of tailoring infrastructure. For high-mileage users, such as business travelers, DC fast charging was essential to ensuring trip feasibility. These findings underscore the need for flexible charging strategies that cater to diverse user behaviors and travel patterns.

Phase Three: Real-World Vehicles Incorporating real world EV specifications in the third phase provided practical insights into vehicle performance and infrastructure compatibility. For instance, **Tesla Model Y** consistently outperformed smaller vehicles like the **Fiat 500e Hatchback**, achieving better trip feasibility and covering more distance. The results also emphasized that charging infrastructure needs to be matched to a vehicle's specifications to optimize user satisfaction and system efficiency. This phase bridged the gap between theoretical models and real world applications, offering practical, data driven recommendations for stakeholders.

Cost Analysis The cost analysis revealed some important trends in charging and operational costs. While DC fast charging incurred higher costs, it provided critical flexibility for high-mileage users, making it a necessary option for those with demanding travel needs. On the other hand, home charging remained the most cost-effective choice, particularly when paired with renewable energy sources. Additionally, the cost per kilometer metric allowed users to compare the operational costs of EVs with traditional fuel expenses, helping them evaluate the financial viability of EV adoption. These insights are crucial for potential EV adopters and policymakers, as they provide a clearer understanding of the financial implications of different charging strategies.

6.1.2 Broader Implications

The findings of this study offer valuable insights for several stakeholders.

For **infrastructure development**, it is clear that investments should focus on high power DC fast chargers along highways and in urban centers, while also ensuring that moderate AC chargers are readily available in residential areas. This would create a more accessible and efficient charging network for all users.

In terms of **policy**, there are opportunities to incentivize the installation of home chargers and the integration of renewable energy sources. These measures could help reduce costs and further promote the adoption of electric vehicles (EVs).

Lastly, for **consumers**, providing personalized recommendations based on individual driving patterns could be beneficial. Customized advice on EV models and charging strategies will help users make informed decisions that best suit their needs and lifestyles.

6.2 Limitations

While this research offers valuable insights into electric vehicle (EV) charging behaviors and infrastructure planning, it is important to recognize several limitations that may affect the generalizability and accuracy of the findings.

One key limitation is the use of simplifying assumptions in the simulation. For instance, the model assumes charging availability at every parking location, as precise geographic data was not available. While this assumption helps streamline the analysis, it overlooks real-world constraints such as charger availability, network distribution, and local grid capacity, all of which can significantly influence the feasibility of EV charging in practice.

Another limitation arises from the generalization of user profiles. The charging behaviors modeled in the simulation are based on literature and hypothetical constructs, which may not fully capture the diverse and evolving range of real-world user behaviors. In dynamic urban environments, where driving patterns and charging habits can vary widely, these profiles may not be representative of all users, especially as behaviors continue to evolve.

Additionally, the dataset used for the simulation is derived from internal combustion engine (ICE) vehicles, rather than actual EVs. While the simulation provides valuable insights, the differences in driving patterns, energy consumption, and charging habits between ICE vehicles and EVs may not be fully accounted for, potentially affecting the accuracy of the results.

The simulation also relied on static parameters, such as fixed consumption rates, battery capacities, and charging powers, in the initial phases. In reality, factors such as fluctuating energy prices, weather conditions, and advancements in battery technology can all influence energy consumption and charging efficiency. These dynamic variables were not incorporated into the simulation, limiting its ability to reflect real-world conditions.

Although later phases of the simulation introduced more realistic specifications, the model still assumes idealized conditions. It does not account for issues such as charger malfunctions, maintenance downtime, or deviations from typical usage patterns. These factors, while often overlooked, can play a crucial role in determining the effectiveness of EV charging infrastructure.

Finally, the scope of the analysis was primarily focused on energy metrics and cost implications. While these are important considerations, other aspects such as environmental impacts, policy changes, and socio-economic factors influencing EV adoption were not explored in depth. A more comprehensive analysis would include these broader aspects to better understand the full range of factors affecting EV adoption and infrastructure development.

6.3 Future Work

Building on the findings of this study and acknowledging the limitations, several promising avenues for future research and improvements can be pursued.

One key area for enhancement is the **integration of real-time data**. By incorporating dynamic factors such as weather conditions, traffic patterns, and fluctuating energy prices, the simulation accuracy can be significantly improved. Additionally, utilizing real-time data streams would allow for adjustments in consumption rates and the availability of charging infrastructure, making the simulation more reflective of actual conditions.

Another important direction is the **enhancement of user profiling**. To refine and expand user profiles, empirical data on EV user behaviors could be gathered through surveys or observational studies. Developing more detailed profiles that account for a wider variety of lifestyles, socio-economic factors, and geographic differences would provide a more comprehensive understanding of how different users interact with EVs.

Further, the **simulation scenarios** could be advanced to include a broader range of situations. For example, incorporating emergency scenarios, charger malfunctions, and deviations from typical user behavior would provide a more realistic view of charging dynamics. Additionally, exploring scenarios with varying grid capacities and renewable energy integration would help assess the resilience of infrastructure under different conditions.

In addition to technical factors, future research should also consider **environmental and policy influences**. Analyzing the environmental impacts of different charging strategies and infrastructure choices could offer insights into the sustainability of EV adoption. Investigating how government incentives, policy changes, and market dynamics affect EV adoption and charging behaviors would also be valuable in understanding the broader societal context.

An **extended cost analysis** is another crucial area for future work. Conducting more detailed cost-benefit analyses, considering long-term operational costs, maintenance, and potential savings from optimized charging strategies, would provide a deeper understanding of the economic implications of EV adoption. Comparing simulation results with real-world cost data would also help validate and refine the economic models.

Lastly, the **scalability of the study** and application to different regions is essential. By applying the simulation framework to various regions or cities, the research can better account for local infrastructure, regulations, and user behavior variations. Expanding the study to include larger datasets and more diverse vehicle models would enhance the generalizability and applicability of the findings.

In conclusion, this study provides a framework for understanding the relationship between EV user behaviors, vehicle specifications, and charging infrastructure. By addressing barriers like range anxiety and charging accessibility, it offers insights to accelerate EV adoption and achieve broader environmental and public health benefits. Future research should focus on integrating real-time data, enhancing behavioral profiling, and incorporating dynamic variables to improve the impact and relevance of these findings.

Appendix A

Market Vehicle Specifications

This appendix provides a comprehensive table of real-world electric vehicle specifications employed during Phase Three of the methodology in this study. The table encompasses key attributes for a diverse range of electric vehicles, including usable battery capacity, maximum charging power (both AC and DC), energy consumption rates under city, highway, and combined driving conditions, as well as the price for each model. All specifications have been meticulously extracted from *ev-database*[1], ensuring that the study's findings are anchored in current and reliable market data. These realistic parameters and constraints have informed the subsequent analysis and simulations, thereby establishing a robust foundation for the research conclusions.

The table below summarizes the essential columns, which have been abbreviated for clarity and formatting purposes:

1. **Brand:** The name of the automotive manufacturer.
2. **Model:** The specific model designation of the vehicle.
3. **Battery:** The usable battery capacity measured in kilowatt-hours (kWh).
4. **AC Charger:** The maximum compatible alternating current (AC) charging power in kilowatts (kW).
5. **DC Charger:** The maximum compatible direct current (DC) charging power in kilowatts (kW).
6. **City Consumption:** The estimated energy consumption in watt-hours per kilometer (Wh/km) under mild weather conditions in urban settings.
7. **Highway Consumption:** The estimated energy consumption in watt-hours per kilometer (Wh/km) under mild weather conditions on highways.

[1] https://ev-database.org

8. **Combined Consumption:** The estimated energy consumption in watt-hours per kilometer (Wh/km) under mild weather conditions combining both urban and highway driving.

9. **Price:** The vehicle's price reported in euros. Prices sourced from the German market on the website have been selected, assuming they are closest to the pricing in Italy.

Definitions:

- **Mild Weather:** Refers to optimal conditions characterized by a temperature of 23 degrees Celsius with no use of air conditioning (A/C).

- **Highway Consumption:** Assumes a constant driving speed of 110 km/h. Energy usage may vary based on factors such as speed, driving style, climate conditions, and route characteristics.

These standardized conditions ensure consistency and comparability across the dataset, facilitating accurate analysis and interpretation of the vehicles' performance metrics.

Table A.1: Real Market Vehicle Specifications

Brand	Model	Battery	AC	DC	City	Highway	Combined	Price
Audi	Q4 Sportback e-tron 45	80	11	175	121	190	154	54.950
Audi	Q4 Sportback e-tron 45 quattro	77	11	175	131	203	164	56.950
Audi	Q4 e-tron 55 quattro	77	11	175	134	211	171	59.000
Audi	SQ8 e-tron	106	11	168	163	255	206	98.100
Audi	Q4 Sportback e-tron 35	52	11	145	120	189	153	47.600
Audi	A6 Sportback e-tron performance	94.9	11	270	112	165	137	75.600
Audi	Q6 e-tron performance	94.9	11	260	134	213	171	68.800
BMW	i4 eDrive35	67.1	11	180	108	164	134	57.500
BMW	i4 eDrive40	81.3	11	207	109	166	136	60.500
BMW	iX xDrive40	71	11	148	138	215	175	77.300
Dacia	Spring Electric 45	25	6.6	34	98	172	132	16.900
Fiat	500e Hatchback 42 kWh	37.3	11	85	105	173	138	34.990
Fiat	Grande Panda	43.8	7.4	100	112	190	148	24.000
Fiat	500e Hatchback 24 kWh	21.3	11	50	101	170	133	30.990
Fiat	600e	50.8	11	85	108	178	141	36.490
Ford	Explorer Extended Range	77	11	135	122	195	156	48.510
Ford	Mustang Mach-E ER RWD	91	11	150	129	207	165	58.500
Hyundai	INSTER Long Range	46	11	85	102	170	133	27.000
Hyundai	Kona Electric 65 kWh	65.4	11	105	113	184	145	47.190
Kia	Niro EV	64.8	11	80	112	183	146	45.690
Kia	EV6 Standard Range 2WD	54	11	175	120	193	154	46.990
Kia	EV6 Long Range AWD	80	11	263	127	203	162	58.000
Mercedes-Benz	EQB 250+	70.5	11	102	116	183	147	53.514
Mercedes-Benz	EQE SUV AMG 43 4MATIC	90.6	22	173	150	232	189	124.920
Mercedes-Benz	EQT 200 Standard	45	22	80	134	225	176	39.623
Mercedes-Benz	EQB 300 4MATIC	66.5	11	112	133	211	168	55.519
MG	MG4 Electric 51 kWh	50.8	6.6	87	114	185	147	34.990
MG	MG4 Electric 77 kWh	74.4	6.6	144	119	191	152	45.990
MG	MG MG4 Electric XPOWER	61.7	6.6	142	130	213	169	46.990
Peugeot	e-208 50 kWh	46.3	7.4	101	108	175	138	35.975
Peugeot	e-208 51 kWh	48.1	7.4	100	103	169	134	40.875
Peugeot	e-3008 73 kWh	73	11	160	132	212	170	48.650
Peugeot	e-5008 97 kWh Long Range	96.9	11	160	137	220	176	60.000
Peugeot	e-308	50.8	11	100	114	185	147	44.765

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Table A.1 – continued from previous page

Brand	Model	Battery	AC	DC	City	Highway	Combined	Price
Renault	Megane E-Tech EV60 220hp	60	22	129	105	171	136	46.600
Renault	Megane E-Tech EV40 130hp	40	22	85	103	167	133	42.000
Renault	Scenic E-Tech EV87 220hp	87	22	150	123	198	158	48.900
Renault	5 E-Tech 52kWh 150hp	52	11	100	107	176	141	32.900
Skoda	Enyaq 85	77	11	135	117	186	148	48.900
Skoda	Enyaq 60	60	11	124	117	187	151	44.200
Skoda	Skoda Enyaq Coupe RS	77	11	175	117	179	145	63.300
Skoda	Enyaq iV 85x 4x4	77	11	175	120	190	152	51.150
Skoda	Enyaq iV CoupÃ© 60	58	11	124	112	173	140	46.850
Tesla	Model Y	57.5	11	170	113	177	142	45.970
Tesla	Model Y Long Range	75	11	250	118	185	149	55.970
Tesla	Model Y Performance	75	11	250	124	195	156	60.970
Tesla	Model 3	60	11	170	93	142	116	40.970
Tesla	Model 3 Long Range Dual Motor	75	11	250	98	148	122	49.990
Volvo	EX40 Single Motor ER	79	11	205	134	219	174	55.490
Volvo	EX30 Single Motor	49	11	134	121	196	156	36.590

Appendix B

Code Repository

This appendix includes the implementation of the simulation framework, along with detailed documentation and scripts, supporting the methodologies outlined in the main chapters. It ensures the reproducibility and transparency of the results. For access to the complete code, please visit the researcher's GitHub repository at https://github.com/homa-jamalof/Trip-Simulator.

Explanation of the Code Snippet (1)

This section of code is designed to identify when an electric vehicle (EV) is likely being charged at a workplace, reflecting typical charging behavior for workplace-dependent drivers. The code begins by importing necessary libraries and defining a standard office hours window from 8:00 AM to 6:00 PM.

The core of this snippet is the `flag_workplace_charging` function. This function examines each row of trip data to determine if the parking event aligns with a workplace charging scenario. Specifically, it checks:

- Whether the vehicle was parked for at least 6 hours (360 minutes).
- If the parking occurred on a weekday (Monday to Friday).
- If the parking period started and ended within the defined office hours (between 8:00 AM and 6:00 PM).

If all these conditions are met, the function returns `True`, flagging the event as a potential opportunity for workplace charging. Otherwise, it returns `False`.

In simple terms, this code filters the dataset to pinpoint parking events that are long enough, occur during working days, and fall within typical office hours circumstances under which a driver is likely to charge their EV at work. This logical check is essential for the simulation to accurately model and analyze charging behaviors specific to workplace dependent drivers.

```
import pandas as pd
from datetime import time
```

```python

# Define time window
start_window = time(8, 0)  # 8 AM
end_window = time(18, 0)   # 6 PM

def flag_workplace_charging(row):

    # Calculate the total parking duration in minutes and start/end times
    total_charging_duration = row["park_dur_min"]
    start_charging_time = row["start_parking_time"]
    end_charging_time = row["end_parking_time"]

    # Check if charging is on a weekday, within 8 AM - 6 PM, and is at least 6 hours
    if (
        total_charging_duration >= 360 and  # minimum 6 hours (360 minutes)
        start_charging_time.weekday() < 5 and  # Monday to Friday
        start_window <= start_charging_time.time() <= end_window and  # Starts within office hours
        end_charging_time.time() <= end_window  # Ends within office hours
    ):
        return True

    return False
```

Listing B.1: Code Snippet (1)

Explanation of the Code Snippet (2)

Purpose: The `calculate_charging` function estimates the energy (in Wh) charged during a parking session based on the parking duration, charging parameters, and battery constraints. It only computes charging if permitted and ensures the charged energy does not exceed the battery's capacity.

Parameters:

- `park_dur_min (float):` The duration of the parking session in minutes.
- `charging_estimations (dict):` A dictionary containing:
  - `battery_capacity_kwh`: Battery capacity in kWh.
  - `charging_power_kw`: Charging power in kW.
- `battery_capacity (float):` The total battery capacity in Wh (not directly used in this function).
- `charge_flag (bool):` A flag indicating whether charging is allowed.

Logic and Workflow:

1. **Key Normalization:** The function begins by converting all keys in the `charging_estimations` dictionary to lowercase. This ensures robust access to dictionary values regardless of key capitalization.

2. **Default Charging Value:** It initializes `charge_kwh` to 0, representing no energy charged by default.

3. **Conditional Charging Calculation:** If `charge_flag` is **True**, the function calculates the energy that can be charged:

$$\texttt{charge\_kwh} = \left(\frac{\texttt{park\_dur\_min}}{60}\right) \times \texttt{charging\_estimations['charging\_power\_kw']}$$

   This equation converts the parking duration from minutes to hours and then multiplies by the charging power to obtain the energy charged in kWh.

4. **Capacity Constraint and Return:** Finally, the function returns the minimum of:

$$\texttt{charge\_kwh} \times 1000 \quad \text{and} \quad \texttt{charging\_estimations['battery\_capacity\_kwh']} \times 1000$$

   This ensures that the calculated energy does not exceed the battery's maximum capacity and converts the energy from kWh to Wh.

```python
def calculate_charging(park_dur_min, charging_estimations, battery_capacity,
    charge_flag):
    # Normalize the keys in the charging estimations dictionary to lowercase
    charging_estimations = {k.lower(): v for k, v in charging_estimations.items()}

    # Default to zero charge if no charging occurs
    charge_kwh = 0

   # Charge if the charge flag is True:
    if charge_flag:
        # Calculate the energy charged using the charging power and duration
        charge_kwh = (park_dur_min / 60) * charging_estimations['charging_power_kw']

    # Ensure that the charged energy does not exceed the battery's total capacity
    return min(charge_kwh * 1000, charging_estimations['battery_capacity_kwh'] *
        1000)  # Return in Wh
```

Listing B.2: Code Snippet (2)

Explanation of the Code Snippet (3)

The `calculate_energy_remained` function analyzes trip data stored in a DataFrame to compute energy consumption, update the vehicle's state of charge (SoC), and assess trip satisfaction and range anxiety. It uses specified consumption rates and charging parameters to simulate charging events and energy usage across multiple trips.

Key steps of the function include:

- **Initialization:** The function normalizes keys in the charging estimation dictionary, extracts battery capacity (converted to Wh), charging power, and sets a "range anxiety" threshold at 10% of battery capacity. It also initializes consumption rates for highway, urban, and other roads and sets up arrays to store calculations for each trip.

- **Consumption Calculation:** It computes energy consumed on different road types for each trip and sums these to find total trip consumption, also determining the total distance per trip.
- **Trip-by-Trip Processing:** For each unique vehicle:
  - The function iterates over each trip, starting with a full battery.
  - It calculates the post-trip SoC by subtracting the trip's energy consumption.
  - If charging is allowed (based on a flag), it calls `calculate_charging` to compute energy gained during parking.
  - It updates the SoC after parking by adding the charged energy, ensuring it does not drop below zero.
  - It computes the vehicle's autonomy based on remaining energy, determines the percentage of the trip that can be satisfied, and checks if the trip meets satisfaction criteria.
  - The function flags trips with range anxiety if SoC falls below the 10% threshold and calculates how many kilometers were driven under such conditions.
  - SoC values and other metrics are stored in pre-initialized arrays for each trip.
- **DataFrame Update:** After iterating through all trips, the function adds new columns to the DataFrame for pre- and post-trip SoC, energy gained during parking, autonomy, percentage of satisfied distance, trip satisfaction, range anxiety, and kilometers driven with anxiety.

The function concludes by returning the enhanced DataFrame, which now contains detailed energy profiles, trip satisfaction indicators, and range anxiety assessments for further analysis in the simulation.

```python
def calculate_energy_remained(df, consumption_combination, charging_estimation):

    # Normalize the keys in charging_estimation dictionary to avoid case
        sensitivity
    charging_estimation = {k.lower(): v for k, v in charging_estimation.items()}

    # Extract battery capacity and charging power from the dictionary
    Battery_Capacity_wh = charging_estimation['battery_capacity_kwh'] * 1000  #
        Convert kWh to Wh
    charging_power_kw = charging_estimation['charging_power_kw']

    # Combined consumption rate for other roads (Wh/km)
    combined_consumption_per_km = consumption_combination['combined']

    # Define a threshold for "range anxiety" (10% of the battery capacity)
    anxiety_threshold_wh = 0.1 * Battery_Capacity_wh

    # Default initial SoC is the full battery capacity in Wh
    Pre_Trip_SoC_default = Battery_Capacity_wh

    # Calculate energy consumption for different road types in Wh
    df['Highway_Consumption(Wh)'] = df['dis_highway_Km'] * consumption_combination
        ['highway']
```

```python
    df['Urban_Consumption(Wh)'] = df['dis_urban_Km'] * consumption_combination['city']
    df['Other_Road_Consumption(Wh)'] = df['dis_other_Km'] * combined_consumption_per_km
    df['Trip_Consumption(Wh)'] = df['Highway_Consumption(Wh)'] + df['Urban_Consumption(Wh)'] + df['Other_Road_Consumption(Wh)']

    # Calculate the total distance for each trip
    df['distance_per_trip'] = df[['dis_highway_Km', 'dis_urban_Km', 'dis_other_Km']].sum(axis=1)

    # Initialize arrays to store calculated values for each trip
    num_rows = len(df)
    pre_trip_soc_wh = np.full(num_rows, Pre_Trip_SoC_default)
    post_trip_soc_wh = np.zeros(num_rows)
    post_parking_soc_wh = np.zeros(num_rows)
    autonomy_km = np.zeros(num_rows)
    satisfied_distance = np.zeros(num_rows)
    satisfied_trip = np.full(num_rows, 'No', dtype=object)
    trip_with_anxiety = np.full(num_rows, 'No', dtype=object)  # Initialize as 'No' for all trips
    kilometers_with_anxiety = np.full(num_rows, 'N/A', dtype=object)  # Initialize as 'N/A' for all trips
    park_energy_wh_array = np.zeros(num_rows)

    # Extract relevant columns as numpy arrays for efficiency
    vehicle_ids = df['vehicle_id'].values
    trip_consumptions = df['Trip_Consumption(Wh)'].values
    park_durations = df['park_dur_min'].values
    charging_flags = df['charge_flag'].values  # Charging flag column
    distance_per_trip = df['distance_per_trip'].values

    # Process each vehicle individually
    unique_vehicle_ids = np.unique(vehicle_ids)

    for vehicle_id in unique_vehicle_ids:
        # Select trips for the current vehicle
        vehicle_mask = vehicle_ids == vehicle_id
        vehicle_indices = np.where(vehicle_mask)[0]

        Pre_Trip_SoC_Wh = Battery_Capacity_wh  # Start with full battery for each vehicle

        # Iterate over each trip for the current vehicle
        for idx in vehicle_indices:
            trip_consumption = trip_consumptions[idx]
            park_duration = park_durations[idx]
            charge_flag = charging_flags[idx]  # Get the charging flag for the current trip

            # 1. Calculate post-trip State of Charge (SoC) after consumption
            post_trip_soc = Pre_Trip_SoC_Wh - trip_consumption

            # 2. Check if charging flag is True
            if charge_flag:
                # The car needs to charge
                park_energy_wh = calculate_charging(park_duration, charging_estimation, Battery_Capacity_wh, charge_flag)
            else:
                # No need to charge
                park_energy_wh = 0

```

```
            park_energy_wh_array[idx] = park_energy_wh

            # 3. Calculate post-parking SoC by adding energy gained from charging
            post_parking_soc = max(0, post_trip_soc + park_energy_wh if post_trip_soc >= 0 else park_energy_wh)

            # 4. Calculate autonomy (distance the vehicle can travel based on SoC)
            autonomy_km[idx] = Pre_Trip_SoC_Wh / combined_consumption_per_km

            # 5. Calculate % of trip that can be satisfied based on available SoC
            satisfied_distance[idx] = min((autonomy_km[idx] / distance_per_trip[idx]) * 100, 100) if distance_per_trip[idx] > 0 else 0

            # 6. Check if the trip is satisfied (i.e., enough energy for the whole trip)
            satisfied_trip[idx] = 'Yes' if Pre_Trip_SoC_Wh >= trip_consumption else 'No'

            # 7. Determine if the trip has "range anxiety" (SoC falls below 10%)
            if satisfied_trip[idx] == 'Yes' and post_trip_soc < anxiety_threshold_wh:
                trip_with_anxiety[idx] = 'Yes'
            elif satisfied_trip[idx] == 'No':
                trip_with_anxiety[idx] = 'N/A'  # Anxiety is irrelevant if the trip isn't satisfied

            # 8. Calculate kilometers driven with range anxiety, if applicable
            if satisfied_trip[idx] == 'Yes' and Pre_Trip_SoC_Wh > anxiety_threshold_wh:
                remaining_soc_before_anxiety = Pre_Trip_SoC_Wh - anxiety_threshold_wh
                km_before_anxiety = remaining_soc_before_anxiety / combined_consumption_per_km
                kilometers_with_anxiety[idx] = max(0, distance_per_trip[idx] - km_before_anxiety)
            elif satisfied_trip[idx] == 'No':
                kilometers_with_anxiety[idx] = 'N/A'  # No anxiety for unsatisfied trips

            # 9. Update SoC for the next trip
            pre_trip_soc_wh[idx] = Pre_Trip_SoC_Wh
            post_trip_soc_wh[idx] = post_trip_soc
            post_parking_soc_wh[idx] = post_parking_soc

            # 10. Prepare for the next trip by updating Pre_Trip_SoC
            Pre_Trip_SoC_Wh = post_parking_soc

    # Add calculated values to the DataFrame
    df['Pre_Trip_SoC_Wh'] = pre_trip_soc_wh
    df['Post_Trip_SoC_Wh'] = post_trip_soc_wh
    df['Post_Parking_SoC(Wh)'] = post_parking_soc_wh
    df['Park_Energy(Wh)'] = park_energy_wh_array
    df['Autonomy_Km'] = autonomy_km
    df['%Satisfied_Distance'] = np.round(satisfied_distance, 2)
    df['Satisfied_Trip'] = satisfied_trip
    df['Trip_with_anxiety'] = trip_with_anxiety
    df['Kilometers_with_anxiety'] = kilometers_with_anxiety

    # Reorder and return the DataFrame with the new calculated columns
    df = df[[
        "vehicle_id", "trip_id", "start_trip", "end_trip", "dis_highway_Km",
        "dis_urban_Km", "dis_other_Km", "distance_per_trip", 'Pre_Trip_SoC_Wh',
```

```
        "Trip_Consumption(Wh)", 'Post_Trip_SoC_Wh', "park_dur_min", 'Park_Energy(
            Wh)',
        'Post_Parking_SoC(Wh)', 'Satisfied_Trip', 'Trip_with_anxiety',
        'Kilometers_with_anxiety', "Autonomy_Km", "%Satisfied_Distance"]]

    return df
```

Listing B.3: Code Snippet (3)

Explanation of the Code Snippet (4)

The functions demonstrate the process of running simulations for scenarios, such as workplace-dependent drivers, by systematically varying consumption and charging parameters:

generate_table_name: This function constructs a descriptive filename based on specific energy consumption rates (city, highway, combined) and charging parameters (power and battery capacity). The generated name uniquely identifies the simulation scenario, making it easier to organize and reference output files.

run_simulation: This function iterates over lists of consumption and charging parameter combinations. For each pair, it:

- Runs the energy calculation simulation using `calculate_energy_remained`.
- Generates a unique table name for the scenario using `generate_table_name`.
- Saves the resulting DataFrame to a CSV file with a filename that reflects the simulation parameters.

Together, these functions automate the simulation process, generate well-labeled output files, and facilitate analysis of different driving scenarios by exploring various consumption and charging configurations.

```
def generate_table_name(consumption_combination, charging_estimation):
    city = consumption_combination['city']
    highway = consumption_combination['highway']
    combined = consumption_combination['combined']
    charging_power = charging_estimation['Charging_Power_kW']
    Battery_Capacity = charging_estimation['Battery_Capacity_kWh']

    # Return the table name
    return f"Profile8_Sim_{city}_{highway}_{combined}_{charging_power}kW_{
        Battery_Capacity}kWh"


def run_simulation(df, consumption_combinations, charging_estimations):
    for consumption_combination in consumption_combinations:
        for charging_estimation in charging_estimations:
            # Ensure we pass the correct structure to calculate_energy_remained
            result_df = calculate_energy_remained(df, consumption_combination,
                charging_estimation)

```

```
            # Generate table name for the output file based on consumption and
                charging
            table_name = generate_table_name(consumption_combination,
                charging_estimation)
            file_name = table_name + ".csv"

            # Save the result DataFrame to a CSV file
            result_df.to_csv(file_name, index=False)
```

Listing B.4: Code Snippet (4)

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