KINDOM OF SAUDI ARABIA
Ministry of Higher Education
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Department: Electrical Engineering

Efficient EV load Estimation for Rental Car Areas in Saudi Arabia

By

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Supervisor

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بسم الله الرحمن الرحيم

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Recommendation of the Committee:

The Committee has approved this dissertation as a partial completion of the requirement for the Master Degree in Science in Renewable Energy Engineering REE

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DEDICATION

To My Dear Parents

My Lord! Have mercy upon them, as they did care for me when I was little as they still care for me when I am grown up.

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Novel Framework for Modeling Electric Vehicles Load at Rental Car Areas

By

Ahmed Ali Alanazi

* Abstract

This research presents a novel framework that employs unique approaches and innovative models to accurately determine the load profiles of plug-in electric vehicles (PEVs) in rental car areas. The primary objective of this study is to develop a probabilistic model for PEV charging loads, considering realistic estimates of the charging process characteristics and explicitly addressing the uncertainties associated with the random variables involved. To achieve realistic load profiles for PEVs, the study undertakes the following activities. Firstly, high-quality data from various sources are utilized and analyzed. Vehicle mobility data is employed to capture renters' behaviors, providing valuable insights into the charging process, such as travel distances and pick-up/drop-off times. Additionally, data related to conventional car types are examined and aligned with EVs, while manufacturers' data is used to obtain information on battery technologies, including capacities and PEV ranges. Charging rate standards are also consulted to gather data on different charging levels. Furthermore, a dependable stochastic model is developed using Monte Carlo simulation (MCS). This approach enables the simulation of input variables necessary for evaluating PEV charging loads, taking into account the inherent uncertainty of the random variables. By generating and assessing numerous scenarios, the MCS technique enhances the accuracy of the proposed framework. The findings of this study contribute to the understanding of PEV charging behavior and provide valuable insights for the planning and management of charging infrastructure in the rental car industry.

Keywords:

EVs charging loads; probabilistic model; rental car areas; Monte Carlo simulation; data analysis; charging infrastructure

Chapter 1

1. Introduction

1.1. Motivation

Over the last ten years, the global car industry has witnessed a remarkable transition into electric vehicles (EVs), and this is to help achieving a more sustainable transportation. The environmental benefits, independency on fossil fuels, and mitigating the adverse effects of climate change are the key drives of the widespread of EVs. Unlike conventional vehicles, EV produce almost zero emissions, which help minimizing air pollution and improving life and health quality [1]. Additionally, electrifying the transportation sector along with the global aim of transitioning to renewable energy sources in the energy sector will significantly reduce the carbon dioxide (CO2) emissions and decline the global warming and climate change [2]. However, the integration of renewable energy with the grid has some of its own limitations [3]. Governments around the world have supported the use of EVs and have set ambitious targets to promote their adoption [4].

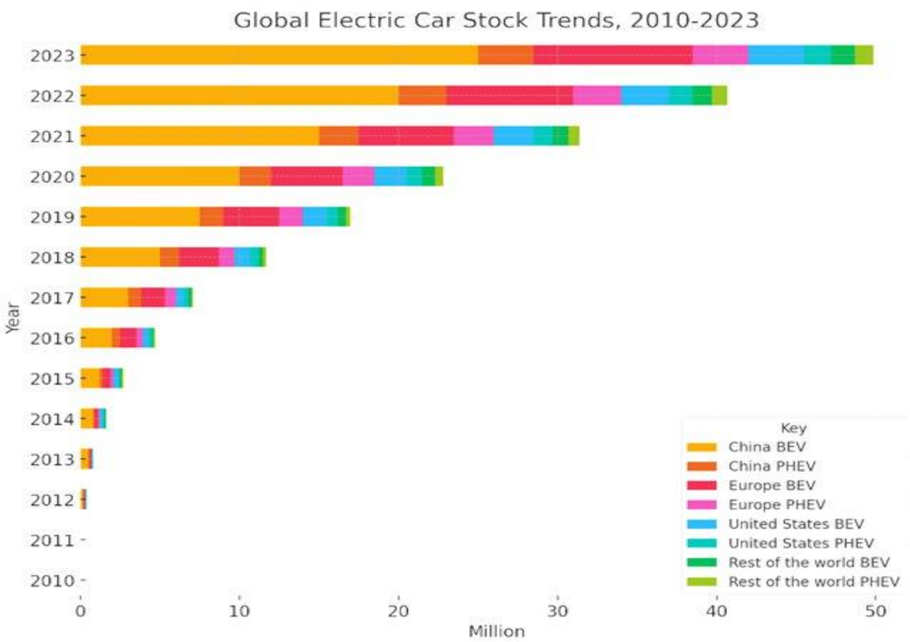

Figure 1. The global EV stock trends for the period from 2010 till 2023 [5].

Figure 1. shows the global EV stock trends for the period from 2010 till 2023 [5]. For instance, Norway and the Netherlands have set targets to achieve 100% EVs sales by 2030 [4]. China, United States, Germany, and France have implemented policies to encourage the development and production of EVs, these countries are now leaders in the EV market [6]. Recently, countries such as the KSA and the UAE have developed ambitious strategies to promote technical advancement and improve energy efficiency. Examples of this shift in KSA include the introduction of Corporate Average Fuel Economy (CAFE) regulations for new light-duty cars in 2016 (NHTSA, 2021) and the execution of Vision 2030 [7]. The CAFE model was implemented because of the similarity in the fleet composition of KSA and the United States. Neom, a progressive smart city, is currently under development in KSA as a part of Vision 2030. Neom will mainly depend on autonomous Personal Electric Vehicles (PEVs) as its main means of mobility.

Saudi Arabia ranks as the third highest country in terms of per-capita motor gasoline consumption, following the USA and Canada. It is also the ninth largest user of motor gasoline globally [8]. According to a study conducted in 2020, it is projected that the number of drivers in the KSA will reach around 12.5 million by 2040, considering the recent policy changes [9]. Therefore, it is crucial to urgently adopt electric transportation in the KSA in order to decrease the reliance on fossil fuels. National targets also focus on expanding the charging infrastructure network to support the growing number of electric vehicles on the road. Moreover, the car industries have set targets encompass various aspects, such EV sales, model diversity, size, and range.

Despite all advantages of the adoption of EVs, the widespread use of EVs may raises several challenges represented by technology acceptance and awareness, as well as their integration into the electrical grid. The widespread and availability of charging stations is still limited, and this is recognized as a primary challenge limiting people willingness to switch from conventional vehicles to EVs

[6]. Significant attempts have been made in expanding charging infrastructure, however; there is still a need for further investment to establish a more and convenient charging stations. Another significant barrier for many people to accept the EV technology is the development of battery technologies include the electric range, charging time, and overall performance [10]. Therefore, the advancement of battery technologies and lowering the cost of EVs help addressing people concerns and make EVs more competitive with conventional cars. Hence, continued research and industrial development in battery technology are essential to overcome these challenges.

Large penetration of EVs is expected to add more difficulties in power system stability and reliability [3,11,12]. This is due to the EV load is larger than any other home appliances and behaves far differently than the conventional loads. Examples of the expected stability issues are overloading, voltage fluctuations, and sudden interruptions [13]. The impact EV charging load on the electrical grid and potential solutions has been extensively studied. A great deal of studies has suggested several solutions include: 1) the implementation of demand response programs and 2) the integration of reliable communication systems [10,11]. These solutions are expected ensure efficient charging management, grid balancing, and optimization of grid assets.

However, there is a need for further investigation into EV charging infrastructure for rental car offices due to the unique challenge of accommodating many EVs within a limited local area. This thesis aims to contribute answering the research questions pertaining to determining the expected charging load profile, designing an optimal charging infrastructure plan, and managing the charging load to ensure economic and technical viability in rental car areas.

Based on our knowledge, there is no previous study that has discussed the loads of EVs in car rental companies. In fact, such topics are highly important for several reasons. Firstly, there is a significant trend among car rental companies to transition to EVs rentals. Secondly, the number of vehicles in rental cars companies is large, and they need to be charged in limited time and locations. Thirdly, the interest in providing charging infrastructure in car rental companies is linked to economic returns. Therefore, it is crucial to discuss this topic and develop reliable models to estimate the EV consumption in car rental companies. Subsequently, the appropriate infrastructure can be designed and developed. This is the focus of the contribution presented in this academic thesis.

1.2. Research Objectives

In this study, the proposed framework incorporates unique approaches and innovative models to accurately determine the load models of PEVs in rental car areas. The primary research goal is to create a probabilistic model for PEV charging loads that incorporates realistic estimates of the factors that characterize the charging process, while explicitly considering the uncertainties associated with the random variables involved. The following activities are undertaken to develop realistic load profiles for EVs:

1) Performing qualitative study that aims to provide valuable data and reliable statistical models that can be utilized to estimate variables shaping the EV consumption at car rental offices. Over twelve statistical functions were tested to represent various variables that significantly shape the formation of EV loads.
2) Utilizing high-quality data: This thesis draws and analyzes research data from four main sources. Firstly, vehicle mobility data is used to capture renters' behaviors accurately, which are crucial for understanding the charging process (e.g., distance traveled, pick-up and drop-off times). Secondly, data related to conventional car types are examined and aligned with PEVs. Thirdly, manufacturers' data is utilized to obtain information on battery technologies,

including capacities and PEV ranges. Lastly, charging rate standards are consulted to gather data on different charging levels.

3) Developing a dependable stochastic model: Monte Carlo simulation (MCS) is employed to simulate the input variables necessary for evaluating PEV charging loads, taking into account the inherent uncertainty of the random variables. This approach generates and assesses numerous scenarios for PEV charging loads.

1.3. Thesis Outline

The remainder of the thesis is organized as follows:

Chapter 2 presents background information pertaining to the EV from different aspects. This chapter provides general information about the batteries characteristics, EV types, charging levels, and charging strategies. It also discusses the expected effects of the integration of EV on the electrical grid.

Chapter 3 presents statistical analysis for evaluating groups of PDFs in order to determine the models that best reflect the main variables influencing the demand profile of EVs at rental car areas.

Chapter 4 introduces the methodology of the proposed framework for simulating the estimated load profiles for EVs at rental car areas. It also presents a collection of case studies to contribute to the understanding of EV charging behavior and provide valuable insights for the planning and management of charging infrastructure in the rental car industry.

Chapter 5 presents the thesis summary, conclusion and suggested future work.

Chapter 2
2. Background and Literature Review

2.1. Introduction

The previous chapter presented the research motivations and objectives. Moving forward, this chapter addresses the relevant information and available technologies with regard to the EVs and their charging infrastructures.

This chapter is divided into several sections; the first is a review of EVs, starting from their history to the types of EVs. The following section covers the types of batteries, their characteristics, and their components. The charging standards and strategies are discussed, afterwards. Lastly, the effect of EV charging the electricity grid. This covers the impact of EVs on grid stability, power quality, load profile, and power loss and overloading.

2.2. The History and Evolution of EVs

Electric vehicles (EVs) and hybrid electric vehicles (HEVs) have been around for a while and are currently experiencing increased demand. They have a long history, dating back to the mid-19th century, and are closely tied to the development of batteries. In 1859, Gaston Planté, a Belgian inventor, introduced the first lead-acid battery, which played a significant role in the development of cars, especially those powered by internal combustion engines (ICE). Karl Benz pioneered the creation of such engines in 1879, leading to the mass production of ICE-powered vehicles [14].

In 1901, Thomas Edison invented nickel-iron batteries for EVs. These batteries had a 40% higher storage capacity than lead batteries but were more expensive to produce. During the early 19th century, there was competition among three propulsion systems in the vehicle market: electric, steam, and gasoline cars [15]. The most active decades for EV development were the 1880s and 1900s. In

1903, steam-powered vehicles accounted for 53% of registered vehicles in New York City, while petrol-powered vehicles represented 27%, and electric vehicles made up the remaining 20%. The popularity of EVs in the United States reached its peak in the 1910s, with 3,000 electric cars on the road. However, the EV market declined due to several factors, including the discovery of oil in Texas, which caused a drop in petrol prices; the introduction of the electric starter, which replaced the crank trigger ignition; the expansion of US highways, which required vehicles with higher autonomy; and Henry Ford's mass production system, which made petrol cars much cheaper than electric ones. After World War II, EVs gained popularity in Japan due to fuel scarcity but their production was halted in the 1950s when rationing ended [14].

In the 1960s, increasing environmental concerns sparked significant interest in EVs among major automakers. The discussions on energy production and usage took climate change into account. It is worth noting that 27% of the world's greenhouse gas emissions are attributed to fossil fuel use in transportation. Despite attempts to reintroduce pure electric cars and hybrids to the market during this time, they couldn't compete with conventional automobiles [15].

In the late 1980s, the growing concerns about pollution in major cities brought EVs into the spotlight as a means of achieving sustainable development. This attention was driven by the adoption of alternative energy sources and new technology [16]. According to Browne et al. (2012), barriers to adopting environmentally friendly fuels, cars, and policies that promote innovative technologies for sustainable development are influenced by geographical boundaries, consumer preferences, legal jurisdictions, and technological advancement [17].

During the 1990s, the Hybrid Electric Vehicle (HEV) was introduced through collaborative efforts between various companies in the public and commercial sectors. Honda became the pioneer in introducing a hybrid vehicle to the American market in 1999, which was met with immediate success. Throughout the 2000s, numerous automobile manufacturers introduced hybrid electric vehicles (HEVs) and EVs to the market. The resurgence of these vehicles in the United States was primarily driven by the goal of enhancing energy security by substituting imported oil from politically volatile regions with domestically generated power [18].

When it comes to sustainable development in developing nations, EVs have the potential to be a game-changer, including in countries that are part of BRICS (Brazil, Russia, India, China, and South Africa). Implementing regulations that support the growth of electric vehicle fleets would bring long-term strategic and environmental benefits. Instead of concentrated emissions in urban centers, pollution would be directed toward energy-generating sources when power is produced from fossil fuels such as coal and natural gas [19].

2.2.1. Types of EVs

This section provides an overview of different types of electric vehicles (EVs) and highlights their distinctive characteristics. EVs come in several variants, each with its own engine specifications, and can be categorized into five types [20].

1) Battery Electric Vehicles (BEVs):

   BEVs operate solely on electric energy and do not have an internal combustion engine (ICE) or rely on liquid fuel. They typically utilize large battery packs to ensure an adequate range [20].

2) Plug-In Hybrid Electric Vehicles (PHEVs):

   PHEVs combine electric motors with conventional ICEs and can be charged from standard wall outlets. By drawing energy from the grid, PHEVs significantly reduce fuel consumption in everyday driving situations [21].

3) Hybrid Electric Vehicles (HEVs):

   HEVs utilize both an electric motor and a conventional ICE. Unlike PHEVs, HEVs are not dependent on the grid. The vehicle's combustion engine generates power that the electric engine draws from the battery. Modern HEVs can also recharge their batteries through regenerative braking, a process that converts kinetic energy into electrical energy [22].

4) Fuel Cell Electric Vehicles (FCEVs):

FCEVs are powered by an electric motor that runs on a mixture of pressurized hydrogen and oxygen from the air supply, producing only water as waste. While these vehicles are often referred to as having "zero emissions," it's important to note that while green hydrogen exists, the majority of hydrogen used is derived from natural gas [20]. Summary of EVs types of EVs is given in Table 9.

Table 9. A summary of EVs types [20].

Type of Vehicle	Range on Single charge (km)	Example	Example Range and Specification	Key Feature
BEV	160-250 Max. 500	Nissan Leaf	360 km 62-kWh	100% Electric
PHEVs	Hybrid	Mitsubishi Outlander	12-kWh	Hybrid
HEVs	Hybrid (25 km on battery)	4^{TH} Gen Toyota Prius	1.3 kWh	
HEVs	600 miles	Hyundai Nexo		
FCEVs	260 km	BMW i3	42.2 kWh	additional 130 km

5) Extended-Range EVs (ER-EVs):

ER-EVs share similarities with BEVs but are equipped with an auxiliary ICE that can be used to recharge the vehicle's batteries as needed. This engine is not directly connected to the car's wheels but is solely responsible for charging, unlike PHEVs and HEVs [20].

2.3. Batteries

In this section, information regarding EV batteries will be presented. Notably, there has been remarkable progress in battery development in recent years. The production of batteries specifically designed for EVs has also experienced a substantial increase on a global scale, reaching a notable 66% [23]. This growth can be attributed to the surge in EV sales, and predictions suggest that the demand for batteries will continue to rise. In fact, it is expected that the demand and supply of EVs will witness significant growth in the coming years. Figure. illustrates the timeline of EV batteries from 2015 to 2022.

When discussing the key attributes of batteries, the following points deserve attention [2] :

Capacity: Storage capacity of battery and its pricing are significant challenges in the world of EVs. Consequently, substantial financial investments are being made to advance batteries with improved efficiency and reliability, thereby enhancing their storage capacity. The capacity of a battery refers to the maximum amount of energy it can store under specific conditions. It is commonly measured in ampere-hours (Ah) or watt-hours (Wh), with Wh being the more prevalent unit of measurement in EVs. Battery capacity plays a crucial role in determining the range of an EV, making it vital for the success of these vehicles. Notably, the capacity of batteries is steadily increasing, and it is expected that soon there will be vehicles with capacities surpassing 100 kWh [24,25,26].

State of Charge: This term describes the battery's current state relative to its full capacity.

Energy Density: Achieving maximum energy density is a critical factor in battery development. It refers to the ability of a battery to store more energy within the same size and weight parameters. Energy density is typically measured in watt-hours per liter and is an important consideration in battery design.

Specific Energy: Specific energy, expressed in watt-hours per kilogram, represents the amount of energy a battery can deliver per unit of mass. This characteristic is sometimes referred to as energy density and can be measured in units of Wh/L or Wh/kg.

Specific Power: Specific power, denoted as power density, indicates the amount of power a battery can deliver per unit of weight (W/kg).

Charge Cycles: A charge cycle is considered complete when a battery has been fully discharged or charged to 100% of its capacity.

Lifespan: The number of charging cycles a battery can endure is an important factor in determining its lifespan. The goal is to identify batteries with greater durability in terms of charging and discharging cycles.

Internal Resistance: Batteries exhibit resistance to the flow of electricity due to non-ideal conductive properties of their components. During charging, some energy is dissipated as heat, resulting in thermal loss. The rate of heat production is directly related to power dissipation in the resistance. Hence, internal resistance significantly impacts high-power charging [22]. Batteries need to withstand high temperatures caused by internal resistance during fast charging. Additionally, the time required to charge current EVs is a drawback that could potentially be addressed by reducing resistance.

Efficiency: Battery efficiency refers to the amount of power a battery can produce in relation to the energy input required for charging. By considering these attributes, battery technology can be enhanced to meet the evolving demands of electric vehicles [24,25,26].

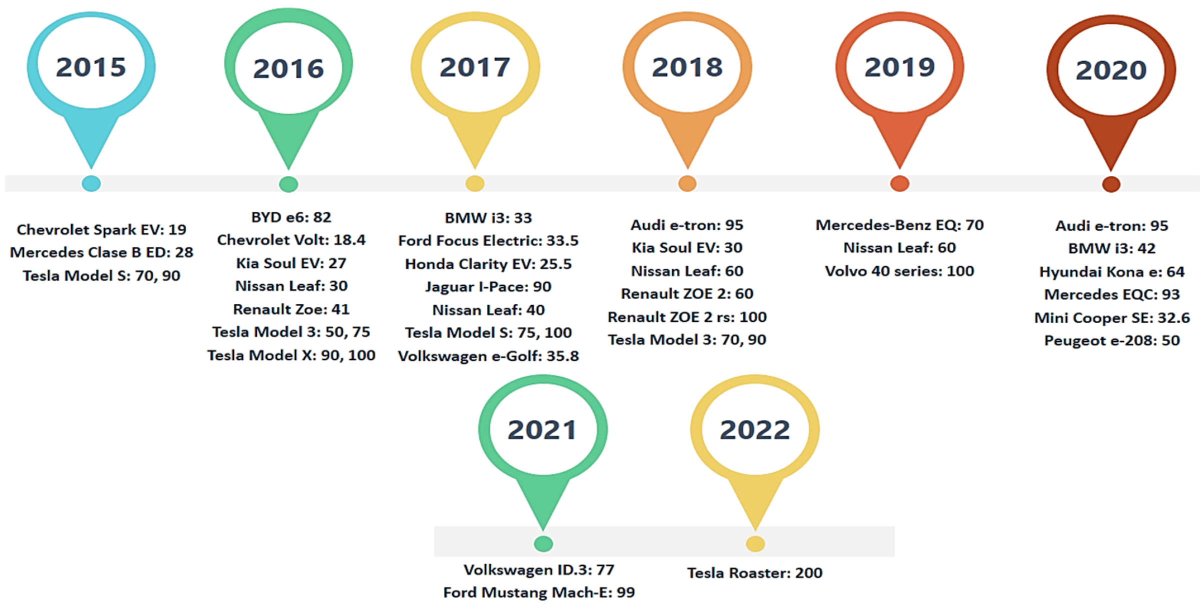

Figure 2. The battery capacities of various EVs Since 2015 [24,25,26].

2.4. Chargers Standards

Charging duration and charging capacity are crucial factors to consider for widespread use of EVs. To ensure the widespread success of EVs, it is essential for customers to have access to fast and convenient charging methods. This involves the installation of charging infrastructure in residential areas and the establishment of electric charging stations that support rapid charging for daily commuting needs. The existing standards and regulations for EV charging technology are outlined below, including an explanation of different charging modes and an overview of the connectors used.

EV charging standards vary depending on the geographical region of use. In North America, particularly in the Pacific zone, the SAE-J1772 standard is utilized. In Europe, the IEC-62196 standard is commonly implemented, while China follows the GB/T 20234 standard. The distinguishing feature of the GB/T 20234 standard is that it categorizes charging modes based on the charging power used, in contrast to the SAE-J1772 and IEC-62196 standards, which categorize charging modes based on the type of power (DC or AC).

2.4.1 SAE-J1772 standard

The SAE-J1772 standard, introduced in 1996 and endorsed by SAE International, is a widely adopted standard in the United States and Japan. This standard defines the following charging modes, which are further detailed in Table 10.

1. Alternate Current Level 1: This mode uses a standard AC power outlet capable of handling currents up to 16 A and a voltage of 120 V, resulting in a maximum power output of 1.9 kW.

2. Alternate Current Level 2: In this mode, the electrical outlet is a conventional type that supplies a voltage of 240 V AC and a maximum current of 80 A, providing a maximum power output of 19.2 kW.

3. Level 1 Direct Current: This mode represents the first level of DC charging. By connecting an external charger to an electrical outlet capable of handling currents up to 80 A and voltages up to 500 V DC, it is possible to receive up to 40 kW of electricity.

4. Level 2 Direct Current: The maximum input voltage and current allowed by the external charger in this mode are 500 V DC and 200 A, respectively. It offers a maximum output power of 100 kW.

By understanding and adhering to these charging standards, the EV industry can ensure convenient and standardized charging options for EV owners worldwide.

Table 10. SAE-J1772 Chargers standards (SAE International Technical Standard, 2017)

Characteristics	**AC level**		**DC level**	
Charge Method	Level 1	Level 2	Level 1	Level 2
Current $_{max}$ (A)	16	80	80	200

Voltage (V)	120	240	200 to 500	200 to 500
Power $_{max}$ (kW)	1.9	19.2	40	100

2.4.2. IEC-62196 standard

For the purpose of charging EVs in China and Europe, the International Electrotechnical Commission (IEC) developed the IEC-62196 standard in 2001. Among the essential aspects of the charging process that are defined by the IEC-62196 standard is the means of energy supply. Based on the nominal power and, consequently, the charging time, this standard, derived from IEC-61851, offers an initial classification of the charging type [16].

- Mode 1, refers to the slow charging method. It is characterized as a way of charging for household use, with a maximum current of 16 A, and it utilizes a normal power outlet that contains one or three phases, a neutral wire, and a protective earth conductor. This approach is the most commonly utilized in our households.
- Mode 2, which is a semi-fast charging option, can be used in both public and private spaces. The highest possible intensity it can handle is 32 A. It follows the same pattern as the previous mode in that it makes use of normal power outlets that have phase, neutral, and earth protection wires.
- Mode 3, refers to the fast-charging option. The appliance is capable of providing current intensities ranging from 32 to 250 amperes. To charge EVs, this mode necessitates the utilization of an EV Supply Equipment (EVSE), a dedicated power supply designed for this purpose. The EVSE is a device that communicates with the vehicles, keeps an eye on the charging process, integrates safety features, and halts the flow of energy when it detects no connection to the car.

- Mode 4, refers to the ultra-fast charging option. The IEC-62196-3 standard defines this specification as a way to directly connect an EV to a DC supply network. The rated current and voltage for this mode are 400A and 1000 V. Means the current can reach a maximum of 400 amperes, while the highest voltage is 1000 volts. This enables a peak charging capacity of 400 kilowatts. Further, an external charger is required for these modes; this charger not only protects the vehicle but also allows it to communicate with the charging port. IEC-62196 charge rating are given in Table 11.

Table 11. IEC-62196 Charge Rating (Acharige et al., 2023)

Mode of charging	Voltage $_{max}$ (V)	Current $_{min}$ (A)	Power $_{max}$ (kW)	Phase
Mode 1	230-240	16	3.8	AC single
	480		7.6	AC three
Mode 2	230-240	32	7.6	AC single
	480		15.3	AC three
Mode 3	230-240	32-250	60	AC single
	480		120	AC three
Mode 4	600-1000	250-400	400	DC

2.5. Impact of EVs on Power System

The extensive adoption of EVs has profoundly transformed the existing business strategies of electric utilities. EV charging may potentially breach power grid limitations at a local or regional level. In addition, the distribution grid's stability, power losses, load profile, frequency and voltage imbalances, and harmonic injection could be negatively impacted by the unplanned and uncontrolled integration of EVs into the network. Numerous studies have already identified a wide range of potential grid effects. The summary of the potential effects of EV charging on the power grid and propose strategies to address these effects is illustrated in Table 12. Overall, these studies cover various aspects of the impact of EVs on power system stability, power quality, demand, losses, and infrastructure. They provide insights into the challenges and potential solutions associated with integrating EVs into the electrical grid.

Table 12. Summary of references discussing impact of EVs on power systems

References	Summary
Dudurych, 2021 [27]	Discusses impact of EVs on power system stability, which refers to a power system's ability to return to its steady-state condition after a disturbance. System instability has led to increased power system blackouts, highlighting the importance of researching system stability.
Sayed et al., 2010 [28]	Emphasizes that EVs have distinct properties as nonlinear loads and can put pressure on the power system. EVs consume electricity rapidly during charging, posing concerns about the grid's reliability and stability.
Onar & Khaligh, 2010 [29]	Investigates the impact of EV charging loads on the electrical system's stability. The results indicate that the inclusion of EV charging loads decreases stability compared to the system without EVs.
Said & Mouftah, 2020 [30]	Proposes a peak load management model to improve EV adoption and ensure smart grid reliability. The model instructs EVs to charge or discharge based on parameters such as power usage, time, and location.
Tavakoli et al., 2020 [31]	Highlights the potential harm to power grid stability caused by the combination of EVs and renewable energy sources (RESs) like photovoltaic and wind systems. The

	intermittent nature of RESs and the unpredictability of EV loads contribute to this instability.
Sivaraman & Sharmeela, 2021 [32]	Discusses the negative effects of variable EV charging characteristics on the distribution network, including overloading, harmonic disturbances, and inadequate voltage profiles.
Rodriguez-Pajaron et al., 2021 [33]	Introduces a probabilistic methodology by to evaluate the impact of EVs and nonlinear loads on the power quality of low-voltage residential networks. The focus is on quantifying harmonics and voltage imbalance.
Qian et al., 2011 [34]	Presents a study that simulates and assesses the distribution system demand caused by charging EV batteries. The results indicate that unregulated residential EV charging can lead to significant increases in daily peak electricity demand.
Zhanng et al., 2014 [35]	Presents a study that suggests the attributes of EV users significantly influence the timing and magnitude of daily charging demand, particularly Social and demographic characteristics.
Islam & Mithulananthan, 2016 [36]	Focuses on predicting the daily load profile for multiple EVs at corporate premises. The study suggests that overall power demand correlates with the extent of EV adoption.

Foley et al., 2013 [37]	Examines the impact of EV charging on Ireland's power system. Charging during off-peak times is preferable, reduces emissions, and has a positive effect on the system.
Antoun et al., 2020 [38]	Proposes a real-life assessment to examine the effect of uncontrolled level 2 EV charging on electrical utilities. The study considers the load profile at home and evaluates the impact of EV penetration and level 2 charger adoption.
Galiveeti et al., 2018 [39]	Presents a method to measure distribution network energy losses as a function of varying EV adoption rates. The study shows a potential increase in energy losses and investment expenditures for the distribution system.
Apostolaki-Iosifidou et al., 2017 [40]	Conducts an experimental analysis of a grid-integrated EV system's power losses. The study highlights the lowest electronics efficiency during discharging and proposes a dispatch algorithm to reduce losses.
Deliami & Muyeen, 2020 [41]	Introduces the concept of coordinating EV charging to optimize real-time energy generation costs, including energy losses.
Karmaker et al., 2019 [42]	Discusses the potential overloading of transformers due to clusters of EV charging stations. It highlights the increased heating losses and reduced transformer kVA rating caused by harmonic currents.
Hilshey et al., 2013	Suggests an approach to estimate the effect of EV charging on overhead distribution transformers. The study finds that

[43]	delaying charging until after midnight can reduce transformer aging.
Mobarak & Bauman, 2019 [44]	Proposes a smart charging strategy that reduces the aging rate of transformers due to increased EV adoption. The strategy is effective for both short-range and long-range EVs.
Lunci Hua et al., 2014 [45]	Examines the effects of uncoordinated EV charging during peak hours on cable loads. The study indicates that the current cable infrastructure can handle a certain penetration level of EV charging, beyond which it becomes overwhelmed.

All these studies have addressed the inclusion of EV loads and the analysis and evaluation of their impact on the electrical grid from several aspects, considering various assumptions such as charging at homes, charging at fast commercial stations, or charging at workplaces, and others. However, none of these studies have analyzed and evaluated the EV loads in car rental areas, which is the core of the study presented in this thesis.

Chapter 3

3. Estimating Statistical Models for Different Variables Shaping the EV load at Car Rental Offices

This chapter presents a qualitative study that aims to provide valuable data and reliable statistical models that can be utilized to estimate EV consumption in car rental offices. These offices face a significant challenge in charging multiple vehicles within limited space. Therefore, it is crucial to take the initial steps of accurately and logically estimating the EV load and then relying on it to design the charging infrastructure or develop optimal load management models that ensure minimal technical issues and economic costs. Over twelve statistical functions were tested to represent various variables that significantly shape the formation of EV loads. Additionally, this chapter offers a collection of case studies that are expected to serve planners and developers interested in EV charging infrastructure.

3.1. Introduction

This chapter aims to contribute answering the research questions pertaining to determining the expected charging load profile, designing an optimal charging infrastructure plan, and managing the charging load to ensure economic and technical viability in rental car areas. To accurately determine the expected charging load profile at rental car areas, several factors need to be considered. These include the number of EVs in the rental car fleet, the driven mileage of the vehicles, the rental duration, and the pick-up and drop-off times. There is a primary aim of this study that is collecting real-world data from rental car offices that can provide insights into the charging patterns and usage characteristics of EVs in this specific context. This data can be used to develop load profile models that capture the variability and peak charging demands at rental car locations. This is the core contribution of the proposed work in this Thesis.

3.2. Methodology

This part of the chapter discusses the major procedures and relevant research activities needed to achieve the main goal of proposed study.

3.2.1. Data Preparation and Processing

Following subsections present more details about each procedure for the research chapter that involves collecting and analyzing data pertinent to several factors shaping the EV load on rental cars area:

3.2.1.1. Identifying the determinants and factors

The first step in the research under study is to identify the determinants and factors that influence the formation of the charging load curve of EVs in the areas of car rental companies or offices. Based on this, we have identified the pick-up and drop-off times, pick-up and drop-off dates, driven mileage, and number of rental days. With this information, we will be able to focus on the type of data we aim to provide serving the study's objective.

3.2.1.2. Sampling Strategy

The second step in the research methodology is the sampling procedure, which was conducted as follows:

a) Sample Collection: Samples were collected from four car rental offices located in different regions. This approach ensures the inclusion of diverse geographical areas, allowing for a more comprehensive representation of the original population.

b) Random Selection of Rental Contracts: The selection of rental contracts was performed in a random manner to include various car types and rental periods. This random sampling technique helps in obtaining a representative sample that reflects the different types of cars available for rent and the varying rental periods.

3.2.1.3. Data Collection

To gather the relevant data associated with the predetermined variables identified in the first step, 400 samples were collected from car rental contracts depicted in Figure. Additionally, a correlation was established between conventional cars and their corresponding EVs to determine battery sizes and the distance they can drive in electric mode. The random variables representing the pick-up and drop-off times provide insights into the expected start and end time of charging. Another significant random variable that are representing the pick-up and drop-off dates, which help identifying whether there is a need for daily charging or specific charging intervals on a weekly or monthly basis. Furthermore, the random variable representing the driven mileage at pick-up and drop-off determines the state of battery charge (i.e. remaining energy in the EV battery) at the time of EV return. These information are essential as they directly influence the required energy to charge the EVs for future rentals, as indicated in (1-3).

$$K_u = K_d - K_p \tag{1}$$

$$K_r = \begin{cases} 0 & K_u \geq K_e \\ K_e - K_u & K_u < K_e \end{cases} \tag{2}$$

$$CE = \begin{cases} B_s & K_r = 0 \\ \frac{B_s}{K_e} \times K_u & K_r > 0 \end{cases} \tag{3}$$

Where:
K_u : Used kilometers during the renting time.
K_d: Kilometers recorded at the drop-off time.
K_p: Kilometers recorded at the pick-up time.
K_r: Reaming Kilometers recorded at the drop-off time.
K_e: Kilometers driven by the battery if it is fully charged.
B_s: Energy capacity of the battery in KWh.
CE: Charging Energy required to fully charging the battery in KWh.

Car Rental Contract			
Customer Data		**Rental Term**	
Customer Name:		Required Duration:	
Customer Number:		Car Exit:	
Nationality:		The Date:	
Proof of Identity:		The Time:	
Type:		Kilometer:	
The Number:		Return Car:	
Place of Issue:		The Date:	
Release Data:		The Time	
Driving License:		Kilometer:	
Type:		**Accounting Data**	
Place of Issue;		The Number of Days:	
The Address:		Hours and Minutes:	
Additional Driver:		How Many Users:	
Vehicle Data		Free Sleeve:	
Type:		How Much Plus:	
Number of Plate:		The Amount Of Rent:	
Model:		Return Amount:	
Free Sleeve:		Excess Amount:	
Daily Car Rental:		Number of Accidents:	
Excess Amount:		Other Amount:	
Return Amount:		Total Contact:	

❖ **Important Notes:**

A. The specific areas for vehicle use during the contract period are
B. The possibility of returning the car before the end of the contract period without the lessee bearing the value of the remaining period
C. The car may be used outside the Kingdom of Saudi Arabia as agreed
D. The tenant is obliged to review the lessor monthly for periodic maintenance work, otherwise he bears full responsibility for engine malfunctions of all kinds

Figure 3. One of the collected and analyzed samples

3.2.1.4. Data Presentation and Analysis

The final step is the presentation of data using visual analysis. Histograms are well-known analysis tools commonly used in visualizing and analyzing data quickly and effectively. Histograms are graphical representations that display the distribution of a dataset allowing researchers to observe the shape, central tendency, and spread of the data. By utilizing histograms, researchers can gain insights into the patterns and characteristics of the collected data. They provide a visual summary of the data distribution, enabling the identification of outliers, skewness, or any other significant features.

3.2.2. Statistical Models

Conducting a comprehensive statistical evaluation study plays a crucial role in accurately determining the impact of electric vehicle (EV) loads. This involves assessing a wide range of theoretical probability density functions (PDFs) to identify the most suitable model that effectively captures the random characteristics of each variable. In this research, twelve different PDFs were selected and examined to evaluate their goodness of fit with observed samples of various behavioral variables. Among the PDFs considered, some are commonly employed to represent a diverse range of variables across different fields, such as the normal, lognormal, and beta distributions. Additionally, several recently developed PDFs were explored, holding potential to serve as underlying distribution models for the variables under investigation. Table 13 presents the PDFs of the selected distributions along with their equations and parameters. Further details are discussed in [13,46].

Table 13. Probability distribution functions (PDFs), related symbol, PDF equations, parameters.

Distribution	**Symbol**	**f(x)**	**Parameters**			
			Scale	**Shape**	**Location**	**Others**
Beta	BE	$\dfrac{(x-\alpha)^{\alpha 1-1}(b-x)^{\alpha 2-1}}{\dfrac{\Gamma(\alpha 1)\Gamma(\alpha 2)}{\Gamma(\alpha 1+\alpha 2)}(b-a)^{\alpha 1-\alpha 2-1}}$	NA	$\alpha 1$, $\alpha 2$	NA	(a , b) continuous boundary parameters
Burr	BU	$\dfrac{\alpha k\left(\dfrac{x-\gamma}{\beta}\right)^{a-1}}{\beta\left(1+\left(\dfrac{x-\gamma}{\beta}\right)^{a}\right)^{k+1}}$	β	k, α	γ	ν - degrees of freedom (positive integer)
Chi-Squared	CS	$\dfrac{(x-\gamma)^{\frac{\nu}{2}-1}e^{-\frac{(x-\gamma)}{2}}}{2^{\frac{\nu}{2}}\Gamma\left(\frac{\nu}{2}\right)}$	NA	NA	γ	NA

Dagum	DA	$\dfrac{\alpha k\left(\frac{x-\gamma}{\beta}\right)^{\alpha k-1}}{\beta\left(1+\left(\frac{x-\gamma}{\beta}\right)\alpha\right)^{k+1}}$	β	k, α	γ	NA
Exponential	EX	$\lambda e^{(-\lambda(x-\gamma))}$	λ	NA	γ	NA
Gamma	GA	$\dfrac{(x-\gamma)^{\alpha-1}\, e^{-(x-\gamma)/\beta}}{\beta^{\alpha}\Gamma(\alpha)}$	β	α	γ	NA
Johnson S unbounded	JSU	$\dfrac{\delta}{\lambda\sqrt{2\pi}\sqrt{z^2+1}} e^{\left(-\frac{1}{2}\left(\gamma+\delta\ln\left(z+\sqrt{z^2+1}\right)^2\right)\right)}, z=\dfrac{x-\xi}{\lambda}$	λ	ð, γ	ξ	NA
Johnson S bounded	JSB	$\dfrac{\delta}{\lambda\sqrt{2\pi}z(1-z)} e^{\left(-\frac{1}{2}\left(\gamma+\delta\ln\left(\frac{z}{1-z}\right)^2\right)\right)}, z=\dfrac{x-\xi}{\lambda}$	λ	ð, γ	ξ	NA
Log-Gamma	LGG	$\dfrac{(\ln x)^{\alpha-1}\, e^{-(\ln x)/\beta}}{x\beta^{\alpha}\Gamma(\alpha)}$	β	α	NA	NA
Lognormal	LGN	$\dfrac{e^{\left(-\frac{1}{2}\left(\frac{\ln(x-\gamma)-\mu}{\sigma}\right)^2\right)}}{(x-\gamma)\sigma\sqrt{2\pi}}$	σ	NA	μ, γ	NA
Normal	NO	$\dfrac{e^{\left(-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right)}}{\sigma\sqrt{2\pi}}$	σ	NA	μ	NA
Rayleigh	RA	$\dfrac{(x-\gamma)e^{\left(-\frac{1}{2}\left(\frac{x-\gamma}{\sigma}\right)^2\right)}}{\sigma^2}$	σ	NA	γ	NA
Weibull	WE	$\dfrac{\alpha}{\beta}\dfrac{(x-\gamma)^{\sigma-1}}{\beta} e^{\left(-\left(\frac{x-\gamma}{\beta}\right)^{\sigma}\right)}$	β	α	γ	NA

In the literature, numerous criteria and techniques have been proposed for assessing the goodness of fit between theoretical PDFs and observed data. These tests aim to gauge the degree to which theoretical PDFs accurately represent a given set of observations. In the present study, the Kolmogorov-Smirnov (KS) test was utilized as it is widely recognized as a reliable goodness-of-fit test in various applications. The KS test involves comparing theoretical PDFs with experimental (actual) PDFs [47]. It utilizes the K-S statistical equation (D), which quantifies the largest vertical discrepancy between the theoretical and experimental cumulative distribution functions. By employing the KS test, the researchers were able to assess the degree of fit between different PDFs and the observed data, providing valuable insights into the suitability of each PDF to represent the variables of interest. The steps for collecting and analyzing data are explained in the Figure.

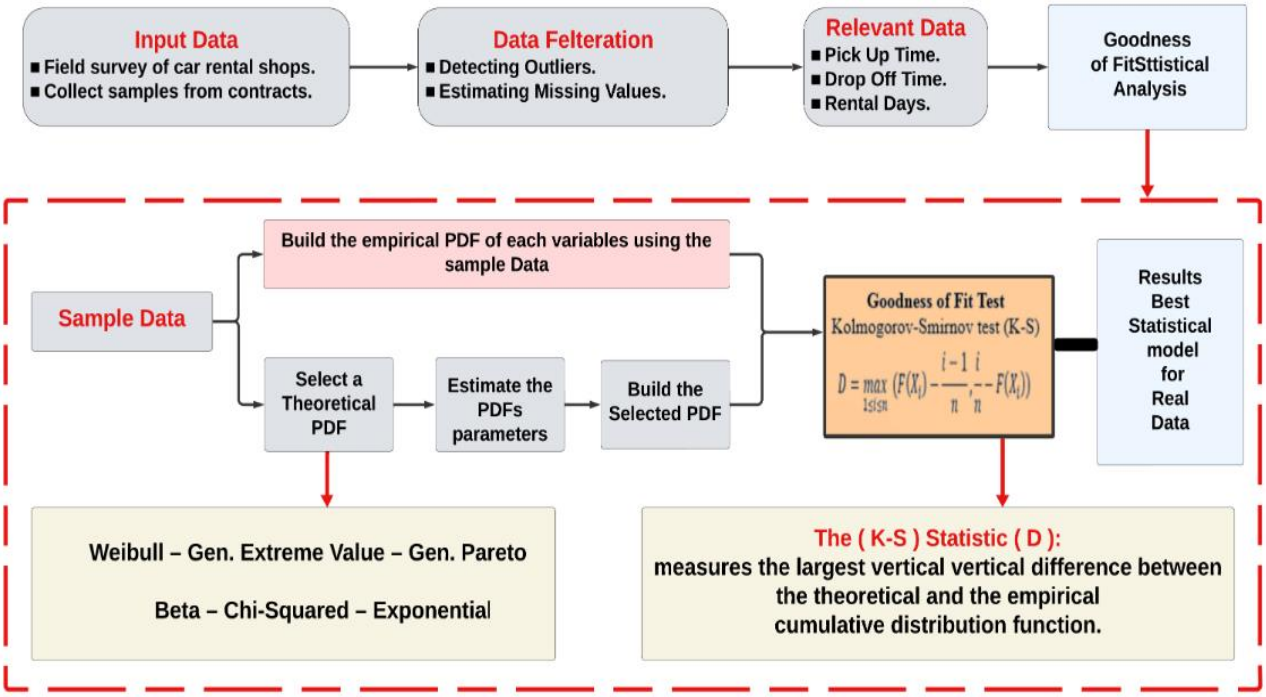

Figure 4. The framework for conducting the statistical evaluation study

3.3. Results

In the remaining sections of the chapter, a comprehensive data and highly useful information regarding the variables under investigation are presented. It is important to note that the data was thoroughly analyzed using Microsoft Excel as a widely utilized software program for its extensive capabilities in data analysis. Additionally, EasyFit program is used to ensure the accuracy and reliability of our findings regarding the statistical tests on a multitude of PDFs related to the studied variables [48]. This way of treatment is not only enhancing the credibility of the presented study but also leading to robust conclusions based on the analyzed data.

3.3.1. Pick-up Times

The histogram depicted in Figure illustrates the distribution of pick-up times along with their corresponding percentages. It reveals that the pick-up time at 9 a.m has the highest percentage, start time of usual opening office time, whereas the lowest percentage occurs between the hours of 3 a.m and 6 a.m. It can be observed that the evening period witnesses a large number of car pickups, which is consistent with the fact that a considerable percentage of renters are from outside the area. After securing accommodation in hotels in the afternoon, they proceed to pick up their cars. Another percentage of people rent a car in the evening to keep it with them for the next day and return it in the evening after finishing their work. Figure displays the results obtained for six different tests using the Easy Fit program, the best three fitted PDFs along with least three fitted ones. Among these PDFs, the Gen.Pareto model closely aligns with the actual data, demonstrating a remarkable proximity to the observed trends.

The goodness of fit results for different PDFs for pick-up times are presented in the Table 14. The PDFs are ranked based on the lowest statistic obtained from the Kolmogorov-Smirnov (K-S) test. Among the tested PDFs, the Generalized Pareto distribution had the lowest statistic of 0.10274, followed by the Beta distribution with a statistic of 0.11453. The Chi-Squared and Exponential distributions had higher statistics of 0.28258 and 0.32477, respectively. Figure shows how significantly these PDFs are different from the sample data of pick-up times.

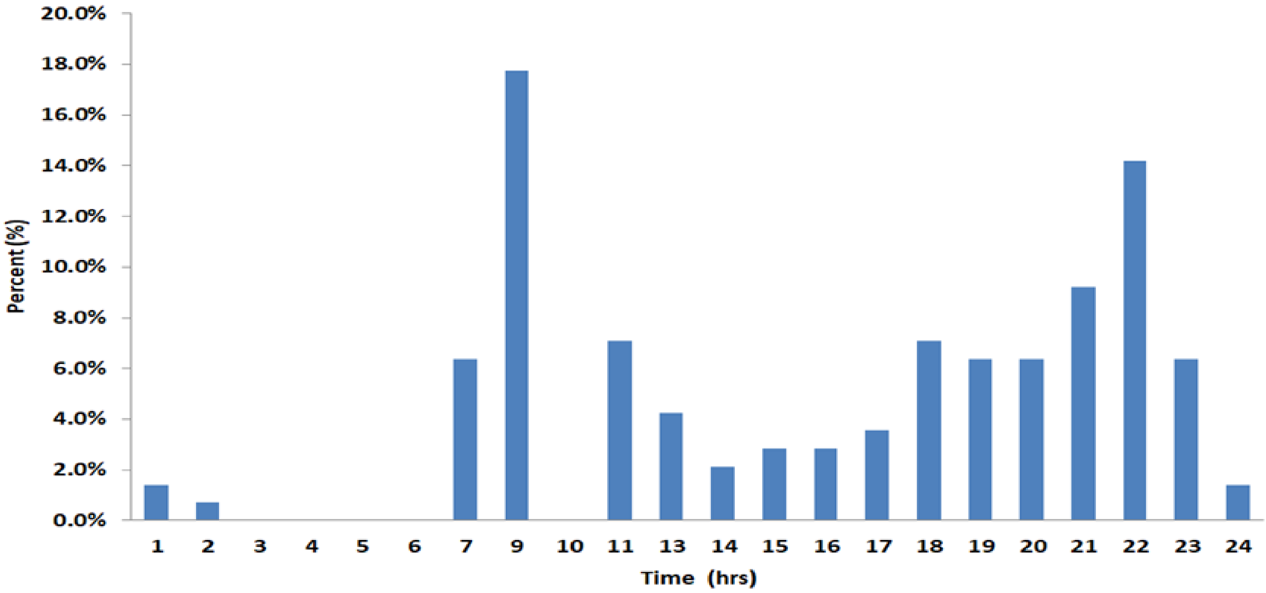

Figure 5. Histogram of Pick-up times.

As stated earlier, the goodness of fit statistic obtained from the K-S test indicates how closely the observed data matches the expected distribution. A lower statistic suggests a better fit. In this case, the Generalized Pareto distribution yielded the lowest statistic among the tested PDFs, indicating that it provides a closer match to the observed pick-up times data compared to the other distributions. The Generalized Pareto distribution is a flexible distribution that can model a wide range of data patterns. It is commonly used for modeling extreme events and tail behavior, making it suitable for capturing the characteristics of pick-up times, which may exhibit heavy-tailed or extreme behavior.

Table 14. Goodness of fit result for different PDFs for Pick-up times

Critical Statistic is 0 .10274				
PDF	**Statistical**	**Parameters**		
Gen. Pareto	0.10274	k = -1.6465	σ = 33.918	μ = 2.4747
Beat	0.11453	$\alpha1$ = 1.3333 a = -1.1999E-14	$\alpha2$ = 0.67219 b = 23.0	
Gen. Extreme Value	0.13727	k = - 0.55119	σ = 6.8627	μ = 13.908
Weibull	0.27487	α = 1.3784	β = 19.103	γ = 0
Chi-Squared	0.28258	ν = 14	γ = 0	
Exponential	0.32477	λ = 0.0654	γ = 0	

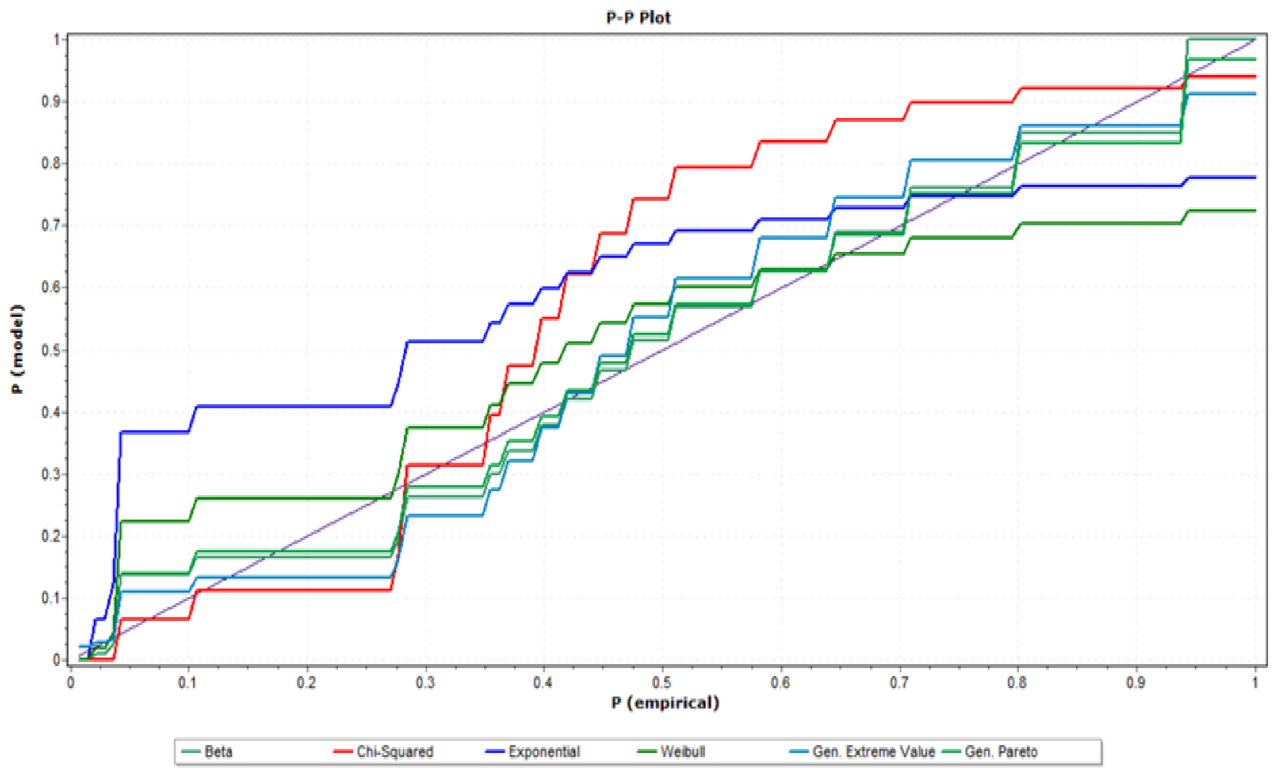

Figure 6. P–P plot for selected PDFs fitted to pick-up.

3.3.2. Drop-Off Times

Figure presents the distribution of drop-off times along with their corresponding percentages. The data reveals that drop-off time spans from 7 a.m. to 11 p.m. The highest percentage of drop-off time occurs at 9 p.m., while the period between 12 a.m. and 6 a.m. shows nearly zero drop-off percentage.

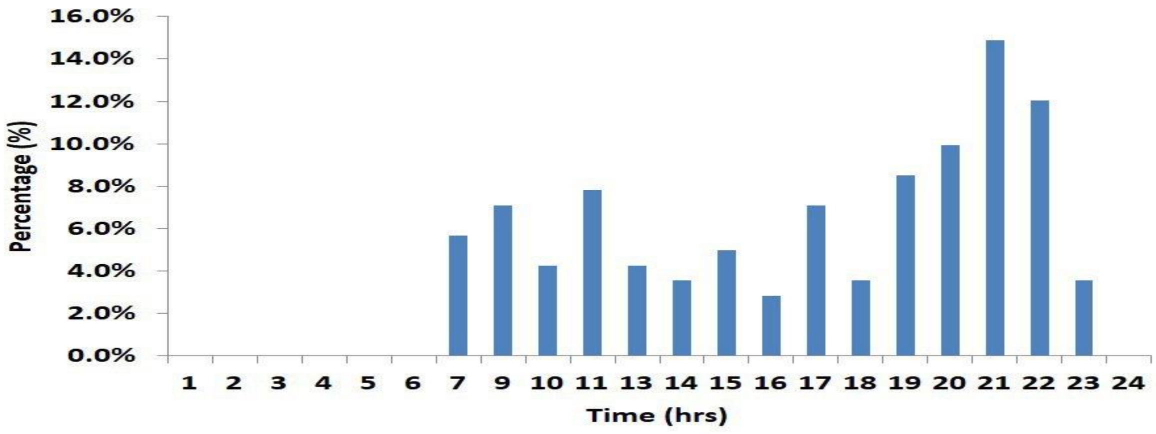

Figure 7. Histogram of drop-off times.

In Figure, the results obtained from conducting six different tests using the EasyFit program are displayed. Among these tests, the Gen. Extreme distribution closely aligns with the actual data, demonstrating a remarkable similarity to the observed trends. This case was conducted to assess the goodness of fit of the selected theoretical probability density functions (PDFs) to the data of drop-off times.

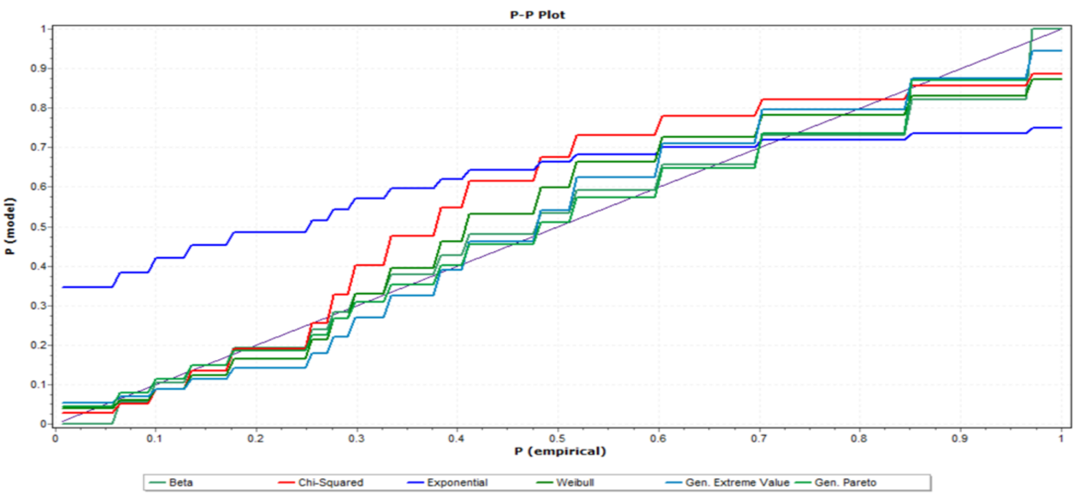

Figure 8. P–P plot for selected PDFs fitted to drop-off times.

The PDFs are ranked based on statistical values obtained from the K-S test, as presented in **Table 15**. The table clearly shows that Gen.Extreme Value, Gen.Pareto, and Beta are the best-fitted PDFs. Figure 6 also illustrates that these PDFs closely match the pattern of the real data. Conversely, Chi-Squared, Pareto, and Exponential PDFs, as shown in the same figure, are the worst-fitted. Consequently, using these PDFs to model the drop-off times may significantly impact the accuracy and validity of the intended results.

Table 15. Goodness of fit result for different PDFs for drop-off times

Critical Statistic is 0 .11453				
PDF	**Statistical**	**Parameters**		
Gen. Extreme Value	0.11453	k = - 0.64031	σ = 5.5912	μ = 15.669
Gen. Pareto	0.10712	k = -1.8865	σ = 31.553	μ = 5.6218
Beat	0.14306	$\alpha1$= 0.8 a = 7.0	$\alpha2$ = 0.58774 b = 23.0	
Weibull	0.14676	$\alpha = 3.3068$	β = 18.5	γ = 0
Chi-Squared	0.21361	$\nu = 16$	γ = 0	
Exponential	0.33775	λ = 0.06041	γ = 0	

3.3.3. Rental Days

Figure depicts a histogram illustrating the distribution of rental days along with their respective percentages. The data indicates that the highest percentage, at 17%, corresponds to car rentals for one day. Renting cars for durations ranging from 2 days to 1 week varies between 7% and 11%. Rentals for a month or longer are estimated to account for approximately 12% of the total. Moving on to Figure, it displays the results obtained from applying six different PDFs to the variable associated with rental days using the EasyFit program. Gen.

Pareto exhibits a close resemblance to the actual data. Table 16 ranks the PDFs based on their goodness of fit as determined by the K-S test. Figure visually represents the various fitted PDFs in relation to the actual rental days data. It is evident that Gen. Pareto, Gen. Extreme Value, and Weibull are the PDFs that closely align with the observed data and therefore provide the best fit. This conclusion is further supported by the test results presented in Table 16. Conversely, Exponential, Beta, and Chi-Squared are the least fitting PDFs, indicating their inability to adequately capture the stochastic nature of the driver behavior variable.

Table 16. Goodness of fit result for different PDFs for Rental Days

Critical Statistic is 0 .13727				
PDF	**Statistical**	**Parameters**		
Gen. Pareto	0.13727	k = 0.76125	σ = 3.955	μ = 0.68995
Gen. Extreme Value	0.13766	k = 0.7856	σ = 3.4028	μ = 3.1115
Weibull	0.23556	$\alpha = 0.8809$	β = 9.1935	γ = 0
Exponential	0.44667	λ = 0.05795		γ = 0
Beat	0.50281	α1= 0.06731 a = 1.0	α2 = 1.5469 b = 578.46	
Chi-Squared	0.76797	$\nu = 17$		γ = 0

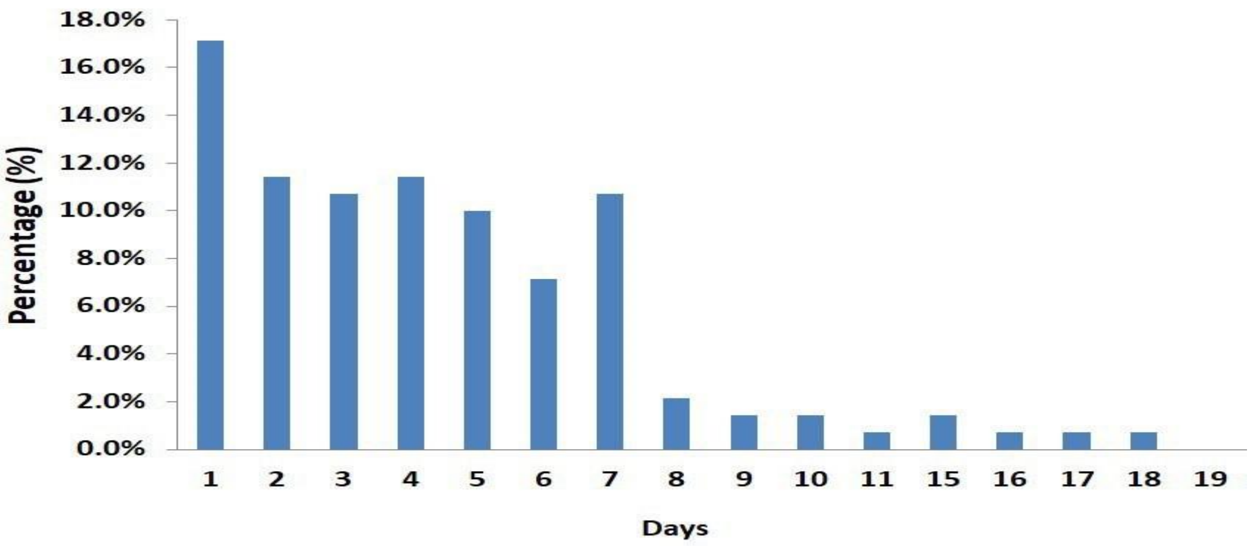

Figure 9. Histogram of number of rental days

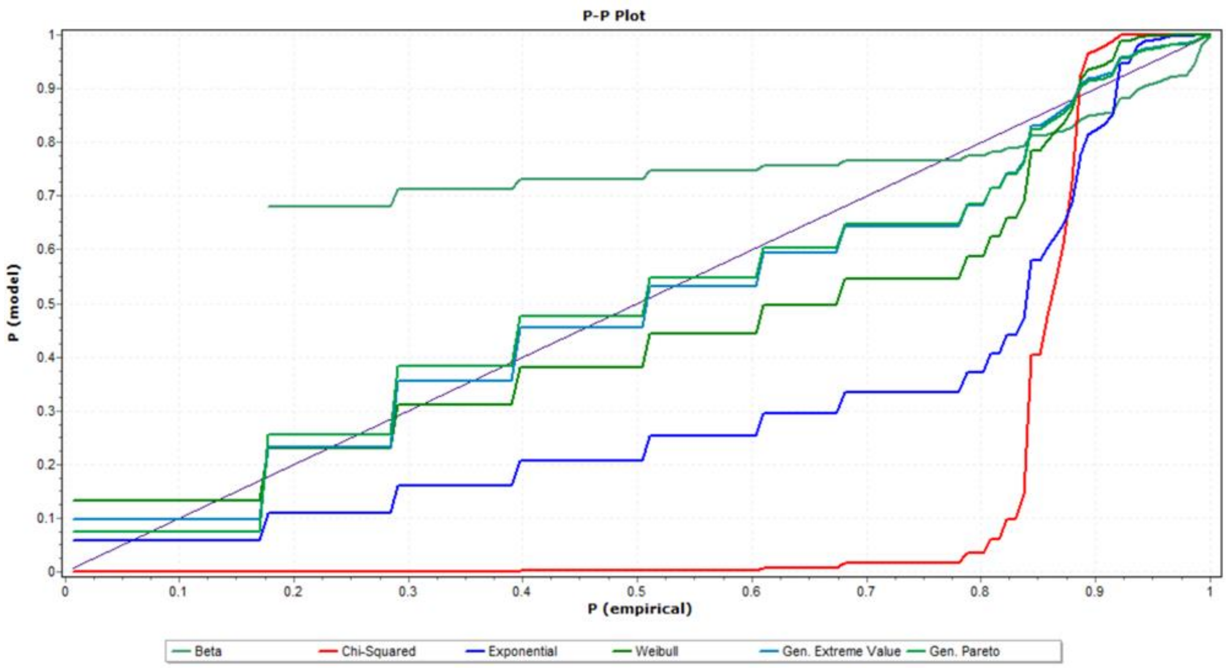

Figure 10. P–P plot for selected PDFs fitted to rental days.

3.3.4. Charging Energy Required to Fully Chargung Battery in KWh

The box plot presented in visually depicts the distribution of Charging Energy values required for charging electric vehicles (EVs) at rental car offices. The plot showcases the highest value recorded as 112 and the lowest value as 24. Divided into quartiles, the numbers 62, 68, and 88 represent the first quartile (Q1), median (Q2), and third quartile (Q3), respectively. The box in the plot spans from Q1 to Q3, indicating the interquartile range (IQR) and encompassing the middle 50% of the data. The length of the box provides insights into the spread of Charging Energy values within this range. The line inside the box represents the median, which is the central value dividing the dataset into two equal halves.

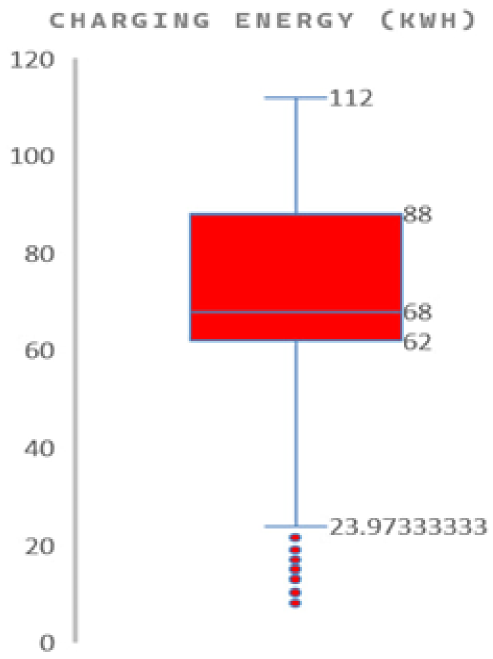

Figure 11. Charging Energy Required to Fully Charging the Battery

Chapter 4

4. Probabilistic Framework for Modeling EV Charging Loads in Rental Car Areas

This chapter presents a novel framework that employs unique approaches and innovative models to accurately determine the load profiles of plug-in electric vehicles (PEVs) in rental car areas. The primary objective of this study is to develop a probabilistic model for PEV charging loads, considering realistic estimates of the charging process characteristics and explicitly addressing the uncertainties associated with the random variables involved.

4.1. Introduction

One of the viable solutions to reduce greenhouse gas emissions and enhance energy security is reducing reliance on fossil fuels and transitioning to locally available renewable energy sources [49]. In 2022, plug-in electric vehicles (PEVs) experienced a record year in sales despite supply chain issues, macroeconomic and geopolitical uncertainties, and rising commodity and energy prices. EV sales grew in shrinking markets globally. More than 26 million electric vehicles were on the road in 2022, a 60% increase compared to 2021 and more than five times the stock in 2018 [50]. Government initiatives and technological advancements are driving the rapid adoption of PEVs [51].

While PEVs offer significant advantages, their integration poses unique challenges and concerns for the energy and transportation sectors. Many technical, economic, and social barriers still need to be addressed and further developed for EV adoption [52].

These challenges arise from two main factors that differentiate PEV loads from conventional loads. Firstly, PEV charging loads are larger and can place significant demands on electrical power networks. Secondly, PEV loads are still in the early stages of development, resulting in uncertainties related to driver behavior, data penetration levels, technological advancements, and charging infrastructure [53]. There is a recognized need to accurately estimate the expected PEV load, address challenges associated with PEV charging, and study their impact on the electric grid [54]. To achieve this, a comprehensive framework is required. This framework should consider the representation of charging process elements, the availability of sufficient and relevant data, and the development of a probabilistic model that accounts for the inherent variability and randomness of PEV profiles [55]. Such a framework would assist system planners and decision-makers in quantifying the effects of PEVs on system reliability and stability, determining necessary grid actions and upgrades, and updating policies to accommodate PEV charging loads [56].

Numerous research studies have extensively examined the development and implementation of models for estimating the charging load of plug-in electric vehicles (PEVs) and their impact on power systems. For instance, the authors of focused on developing a deterministic PEV model for residential charging in a specific region of the United States, with a specific emphasis on discussing its reliability implications [57]. Other studies have been conducted to estimate PEV loads in various settings, such as homes, workplaces, and fast charging stations, utilizing probabilistic and simulation-based models [58]. Furthermore, a significant body of previous research has concentrated on investigating the integration of PEVs into electric systems, addressing both short-term and long-term planning issues [59]. These studies have also explored the dynamic performance of power systems when incorporating PEVs, as well as conducting economic and financial analyses and examining electricity market policies and opportunities [60]. Moreover, many studies have underscored the importance of coordinated and controlled charging techniques to enhance power reliability and stability [61]. These studies have explored strategies for arranging and organizing the charging process to ensure optimal power utilization and minimize potential adverse impacts on the grid.

Based on the authors' knowledge, there is no previous study that has discussed the loads of PEVs in car rental companies. In fact, such topics are highly important for several reasons. Firstly, there is a significant trend among car rental companies to transition to PEVs rentals. Secondly, the number of vehicles in rental cars companies is large, and they need to be charged in limited time and locations. Thirdly, the interest in providing charging infrastructure in car rental companies is linked to economic returns. Therefore, it is crucial to discuss this topic and develop reliable models to estimate the PEV consumption in car rental companies. Subsequently, the appropriate infrastructure can be designed and developed. This is the focus of the contribution presented in this academic article.

In this study, the proposed framework incorporates unique approaches and innovative models to accurately determine the load models of PEVs in rental car areas. The primary research goal is to create a probabilistic model for PEV charging loads that incorporates realistic estimates of the factors that characterize the charging process, while explicitly considering the uncertainties associated with the random variables involved. The following activities are undertaken to develop realistic load profiles for PEVs:

1) Utilizing high-quality data: This thesis draws and analyzes research data from four main sources. Firstly, vehicle mobility data is used to capture renters' behaviors accurately, which are crucial for understanding the charging process (e.g., distance traveled, pick-up and drop-off times). Secondly, data related to conventional car types are examined and aligned with PEVs. Thirdly, manufacturers' data is utilized to obtain information on battery technologies, including capacities and PEV ranges. Lastly, charging rate standards are consulted to gather data on different charging levels.

2) Developing a dependable stochastic model: Monte Carlo simulation (MCS) is employed to simulate the input variables necessary for evaluating PEV charging loads, taking into account the inherent uncertainty of the random variables. This approach generates and assesses numerous scenarios for PEV charging loads.

4.2. Data preprocessing and Treatments

This section of the chapter discusses the key procedures and research activities necessary to achieve the main objective of the proposed study.

1. Data Preparation and Processing:

The following subsections provide more detailed information on each procedure involved in collecting and analyzing data related to various factors that influence the load curve of electric vehicles (EVs) in rental car areas.

a) Identifying the determinants and factors:

The initial step in this research is to identify the determinants and factors that impact the formation of the charging load curve for EVs in car rental areas. These factors include pick-up and drop-off times, pick-up and drop-off dates, driven mileage, and rental duration. By understanding these factors, we can focus on collecting data that aligns with the study's objectives. Samples were collected from four car rental offices located in different regions. This approach ensures that a diverse range of geographical areas is represented, providing a more comprehensive understanding of the overall population. The rental contracts were randomly selected to include various car types and rental periods. This random sampling technique ensures that the sample reflects the different types of cars available for rent and the varying rental durations. This part is thoroughly discussed in the previous chapter.

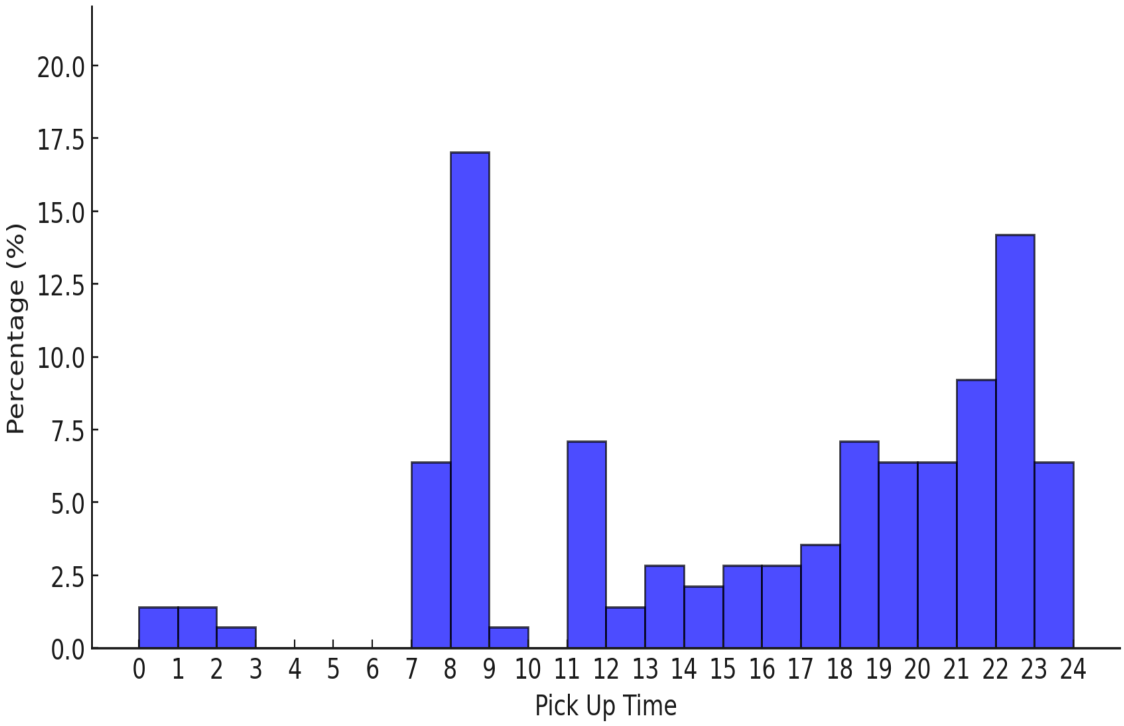

Figure 12. Histogram of Pick Up time.

Table 9. The models of cars and EV Batteries types

Type OF Cars	Models	Pick Up Time PT	Pick Up Date	Drop Off Time DT	Drop Off Date	NO. Days During Rental	Kilometers At Pick Up KP	Kilometers At Drop Off KD	Used Kilometers During Renting KU	Type EVs Cars	Size Of Batteries for EVs Cars	Kilometers For each Charge
Toyota Camry	2013	6	16/04/2015	22	24/04/2015	8	60648	61512	864	Tesla S	98	535
Toyota Corolla	2019	7	04/04/2022	11	25/05/2022	51	69915	77899	7984	MG4 EV	62	450
Hyundai Accent	2023	22	03/07/2023	21	14/07/2023	11	34028	36258	2230	Hyundai - Ioniq 5	68	230
Kia Sportage	2012	17	22/08/2015	20	23/08/2015	1	97398	98123	725	Volvo - XC40	78	412
Hyundai Sonata	2016	18	13/12/2015	17	20/12/2015	7	246	2155	1909	Tesla S	98	535
Honda Accord	2012	0	16/08/2012	22	26/08/2012	10	52434	53963	1529	Tesla S	98	535
Renault Megane	2021	8	31/01/2023	10	06/02/2023	6	24600	25472	872	Lucid - Air	88	684
Kia Cerato	2022	22	08/08/2022	21	10/08/2022	2	23230	23343	113	Kia - Niro EV	65	385
Kia Rio	2022	23	08/09/2022	14	11/09/2022	3	10519	11218	699	Hyundai - Ioniq 5	68	230
Toyota Yaris	2016	14	28/02/2020	10	13/06/2020	106	142203	145274	3071	Toyota - BZ4X	67	460

b) Statistical Models:

Conducting a comprehensive statistical evaluation study is essential for accurately assessing the impact of EV loads. This involves evaluating various theoretical probability density functions (PDFs) to identify the most suitable model that captures the random characteristics of each variable. In this research, twelve different PDFs were selected and analyzed to assess their goodness of fit with observed samples of different behavioral variables. The PDFs considered include commonly used distributions like normal, lognormal, and beta distributions, as well as recently developed distributions that show promise for modeling the investigated variables. Table 10. provides the PDFs of the selected distributions, along with their equations and parameters. Additional details can be found in the previous chapter.

Table 10. Parameters of the fitted PDFs for each driver behaviour variable

	Fitted Distribution	**Statistical**	**Parameters**			
Pick-up	Gen.Pareto	0.10274	k= -1.8865	σ= 31.553	μ =5.6218	
Drop-off	Gen. Extreme Value	0.11453	k= -1.8865	σ= 31.553	μ =5.6218	
CE	Beta	0.15063	α1=5.2809	α2=2.4038	a= - 40.11	b=116.28

4.3. Simulation of EV Charging Model

MATLAB was used to program and write the mathematical model to determine the energy consumption of electric vehicles when using chargers with a specified capacity. Based on the data collected and analyzed previously, such as the daily energy consumption of a group of vehicles and their pick up droop off times, the programming was developed accordingly.

The programming begins by defining the basic variables such as charger power, the number of vehicles, and the total hours. It then calculates the required charging duration for each vehicle based on its daily energy consumption and the charger's power. Vehicles are prioritized starting with those that need the longest charging time and ending with those that need the shortest.

Subsequently, a charger is allocated to each vehicle to charge as many vehicles as possible with minimal wait time. The energy demand and charger usage are updated for each hour of the day based on this scheduling. Two types of chargers were used: the first with a capacity of 7.2 kW and the second with a capacity of 50 kW. Several scenarios were considered for each charger. For the first charger with a capacity of 7.2 kW, five scenarios were tested, each with specific results: the first scenario with 10 chargers, the second with 20 chargers, the third with 30 chargers, the fourth with 40 chargers, and the fifth with 50 chargers.

4.3.1. General Overview of the Developed Model

The provided MATLAB model simulates the demand profile for charging EVs based on given drop-off times, pick-up times, and required charging energy. The model aims to optimize the charging schedule, considering constraints such as the availability of chargers, charging power, and the need to fully charge vehicles before their pick-up times.

4.3.2. Detailed Explanation of the Code

- **Data Initialization**: The code begins by initializing arrays for the pick-up times (PT), drop-off times (DT), and required charging energy (REC) for each EV.
- **Constants Initialization**: Key constants such as the number of chargers, charger power, and simulation duration are set.
- **Charging Calculation**: The code calculates the required charging time for each EV based on its required energy and the charger power.

- **Priority Sorting**: EVs are sorted based on their priority for charging, which is determined by the required charging time and the interval between drop-off and pick-up times.
- **Charging Scheduling**: The code assigns chargers to EVs based on their priorities and the availability of chargers within the allowed time frame.
- **Simulation of Charging**: The charging process is simulated over a 48-hour period, tracking the energy served, energy not served, and the utilization of each charger.
- **Output Results**: The code calculates and displays the total energy served, energy not served, and the utilization of each charger.

4.3.3. Mathematical Formulation of EV Charging Demand Profile

Table 11. displays the parameters used in the programmed code, while Table 12. explains the variables present in the code and research in general.

Table 11. Parameters used in programmed.

Parameters	
N	Number of EVs.
C	Power of each charger (kW/h).
$\boldsymbol{P_{power}}$	Total simulation time in hours (48 hours).
Hours	Total simulation time in hours (48 hours).
$\boldsymbol{PT_i}$	Pick-up time for the (i-th) EV (hours since start of period).
$\boldsymbol{DT_i}$	Drop-off time for the (i-th EV) (hours since start of period).
$\boldsymbol{RCE_i}$	Required charging energy for the (i-th) EV (kWh).

Table 12 Parameters used in programmed.

Variables	
$\mathbf{T_{start,i}}$	Start time of charging for the (i-th) EV.
$\mathbf{T_{end,i}}$	End time of charging for the (i-th) EV.
$\mathbf{E_{served,i}}$	Energy served to the (i-th) EV (kWh).
$\mathbf{T_{not\ start,i}}$	Energy not served to the (i-th) EV (kWh).
$\mathbf{S_{c,t}}$	Amount of energy served by charger (c) at time (t).

- **Objective**

Maximize the total energy served to all EVs while respecting the charger constraints and ensuring EVs are ready by their pick-up times.

Constraints

- ❖ **Charging Time Calculation**:

$$T_{charge,i} = \left\lceil \frac{RCE_i}{P_{power}} \right\rceil$$

This determines the minimum required charging duration for each EV.

- **Charger Assignment and Scheduling**:

Each EV (i) is assigned a charger (c) such that:

$$T_{start,i} \geq DT_i$$

$$T_{end,i} = T_{start,i} + T_{charge,i} \leq PT_{i\,+}\,24$$

- **Charger Availability**:

For each charger (c) and any time (t) ;

$$\sum i\text{: } using\ c\ [T_{start,i} \leq t < T_{end,i}] \times P_{power} \leq P_{power}$$

This ensures that no charger is used beyond its capacity at any time.

- **Energy Tracking**:

$$E_{served,i} = min\big(REC_i, \big(T_{end,i} - T_{start,i}\big) \times P_{power}\big)$$

$$E_{not\ served,i} = REC_i - E_{served,i}$$

This tracks the actual energy each EV receives and the shortfall, if any.

- **Demand Profile Computation**

For each hour tt in the simulation period,

$$T_{c,t} = \sum i\text{: } using\ c\ [T_{start,i} \leq t < T_{end,i}] \times P_{power}$$

$$Total\ Energy\ at\ (\ t\ ) = \sum_{c=1}^{c} S_{c,t}$$

4.4. Results and Analysis

The following subsections presents the results of using two charging levels (7.2 kW and 50 kW as the most common candidate charging levels for this kind of services.

4.4.1. Energy Served & Not Served for Chargers ٧.2 kW

Below is the discussion of the analysis of ES and ENS across different Scenarios, as depicted in Figure 16.

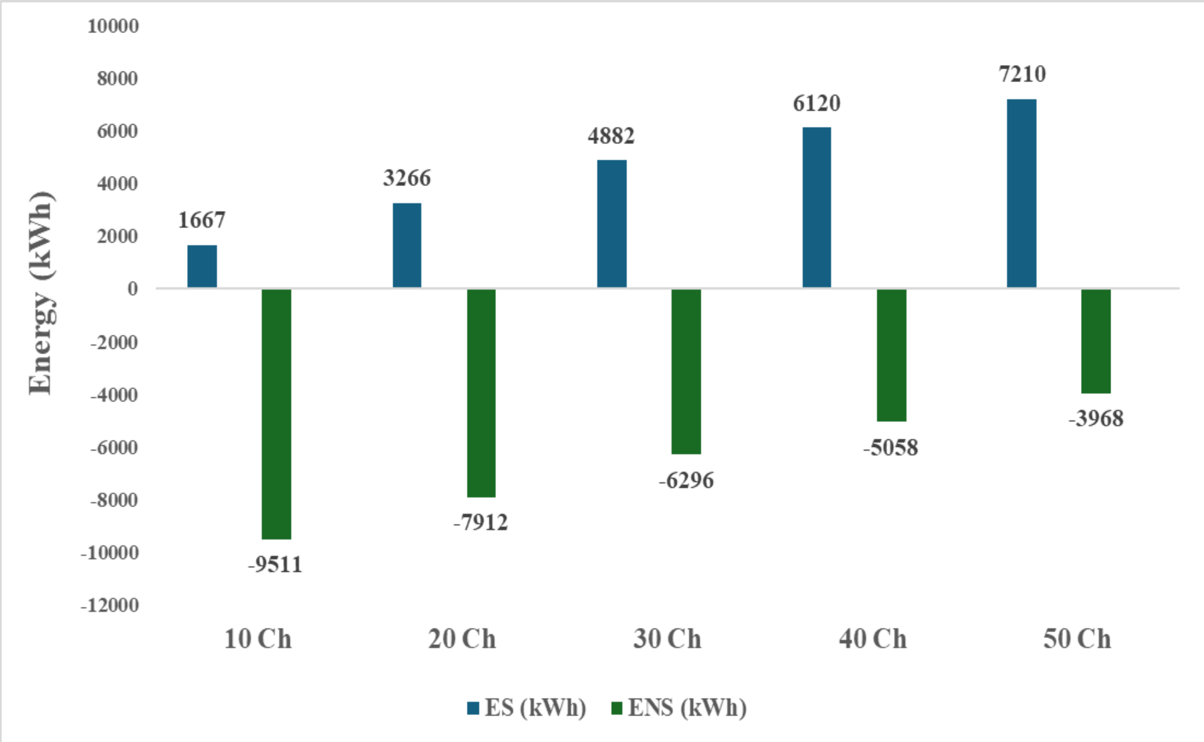

Figure 13. Energy Served and not Served for each Scenarios (7.2 Kw).

In the first scenario with 10 chargers, the ES was 1667 kWh, while ENS was -9511 kWh, indicating that the demand for charging significantly exceeded the available capacity, resulting in a high amount of unserved energy. In the second scenario with 20 chargers, the ES increased to 3266 kWh, and the ENS decreased to -7912 kWh, suggesting an improvement in the network's ability to meet the demand. The third scenario with 30 chargers showed a further increase in ES to 4882 kWh and a decrease in ENS to -6296 kWh, reinforcing the trend of improving charging capacity. Similarly, the fourth scenario with 40 chargers saw the ES rise to 6120 kWh and the ENS fall to -5058 kWh, indicating a notable improvement in the network's ability to meet demand. Finally, in the fifth scenario with 50 chargers, the profile achieved the highest level of ES at 7210 kWh and the lowest level of

ENS at -3968 kWh, suggesting that the distribution capacity has reached a satisfactory level.

In conclusion, as the number of chargers increased from 10 to 50, there was a significant improvement in the amount of energy served and a consistent decrease in the amount of unserved energy. This indicates that the charging infrastructures can better meet the demand with an increasing number of chargers, enhancing the effectiveness and capacity of the network to provide service.

4.4.2. Energy Served & Not Served for Chargers 50 kW

Below is the discussion of the analysis of ES) and ENS across different Scenarios, as depicted in Figure 17.

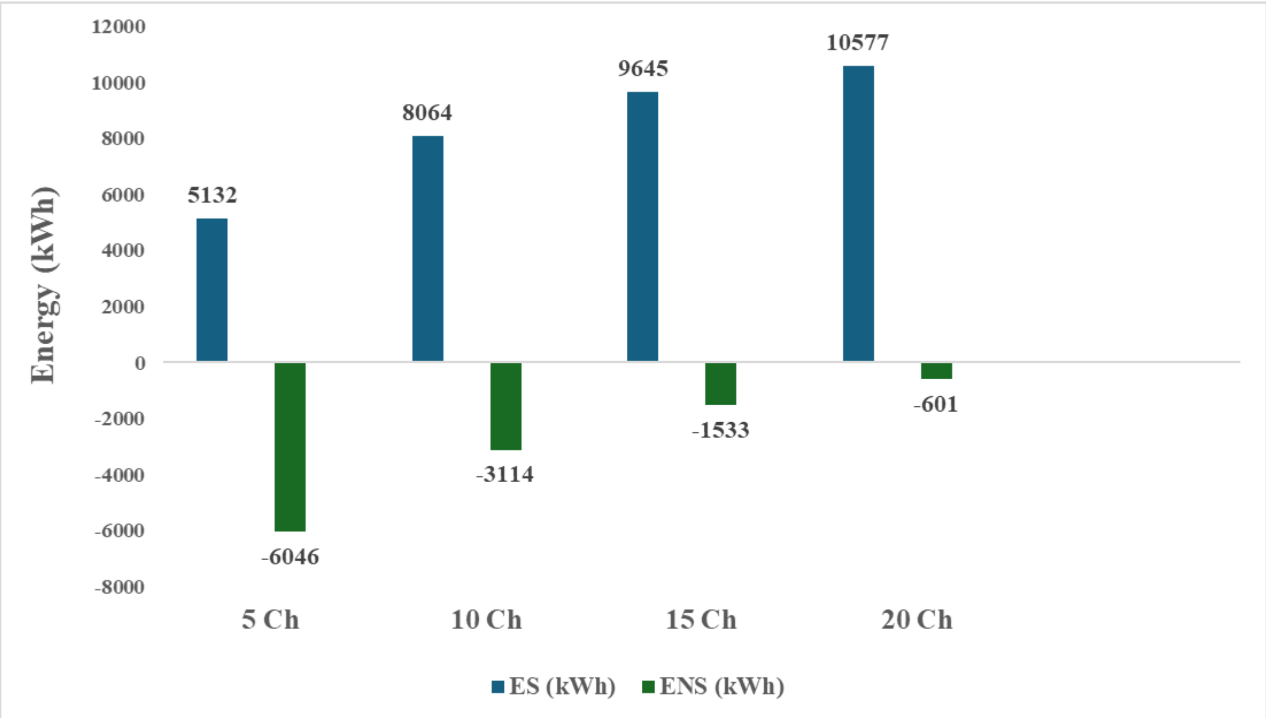

Figure 14. Energy Served and not Served for each Scenarios (50 kW).

In the first scenario with 5 chargers, the ES was 5132 kWh, while the ENS was -6046 kWh, indicating that the demand for charging significantly exceeded the available capacity, resulting in a large amount of unserved energy. In the second scenario with 10 chargers, the ES increased to 8064 kWh, and the ENS decreased to -3114 kWh, suggesting a significant improvement in the chargers' ability to meet the demand. The third scenario with 15 chargers showed a further increase in ES to 9645 kWh and a decrease in ENS to -1533 kWh, reinforcing the trend of improving charging capacity. Similarly, the fourth scenario with 20 chargers saw the ES reach its highest level at 10577 kWh and the ENS drop to its lowest level at -601 kWh, indicating a significant improvement in the chargers' ability to meet the demand. It is clear that as the number of chargers increased from 5 to 20, there was a significant improvement in the amount of energy served and a consistent decrease in the amount of unserved energy.

4.4.3. Hourly Demand for Chargers (7.2) and (50) kW

The two Figures 18 and 19 display the daily patterns of EV charging profiles over a 24-hour period under different scenarios. For the sake of compression, it is important to mention that these profiles are presented as per-unit referring to the rated power the chargers in each scenario can provide. For example, in first scenario, ten 7.2 kW chargers can provide up to 72 kW. A value of 1.0 means all chargers are in use, and a lower value means fewer chargers are being used. For all scenarios, the high usage of all chargers is recorded, indicating full usage at 1 AM. Around the middle of the day, there is a significant drop in usage across all scenarios, reaching a low point. Towards the evening of the day, the profiles increase again, indicating higher demand for charging in the evening. This behavior is somehow correlated with drop-off time of the EVs. With more chargers being used (40 and 50 chargers), a slightly more gradual decline is observed compared to lower number of chargers, indicating a better distribution of charging demand.

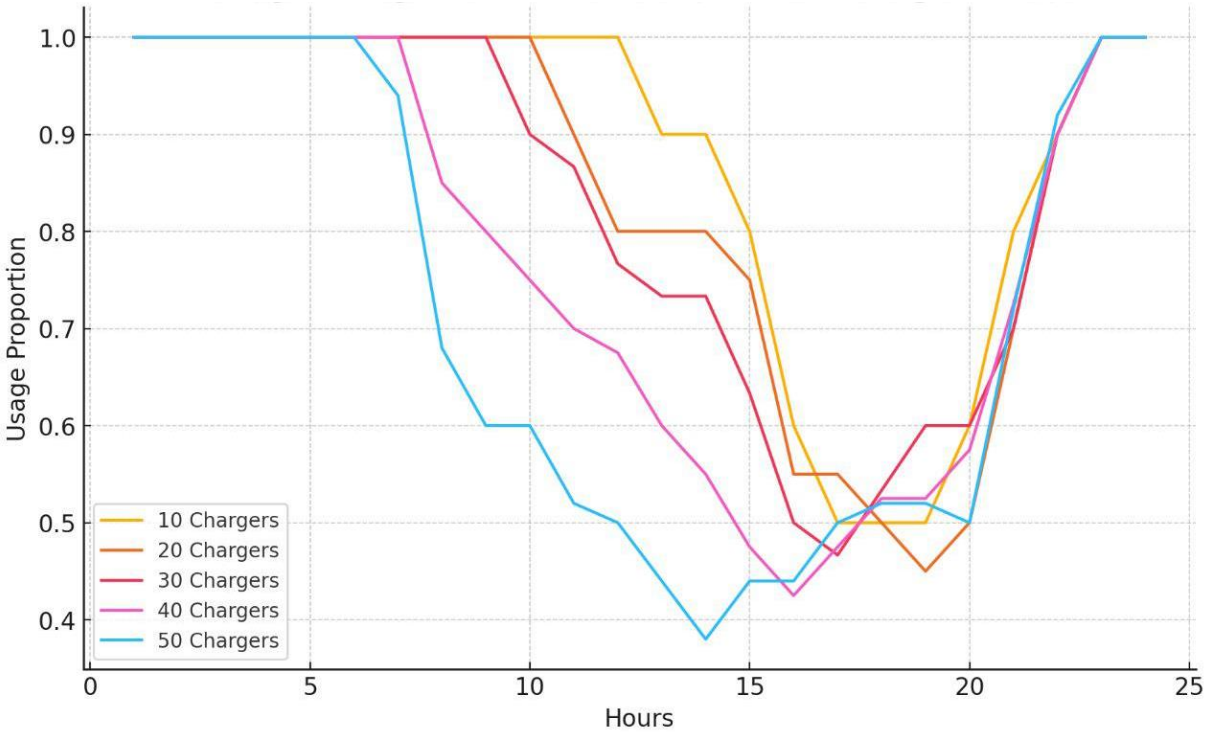

Figure 15. Hourly Demand for the Charger (7.2 kW).

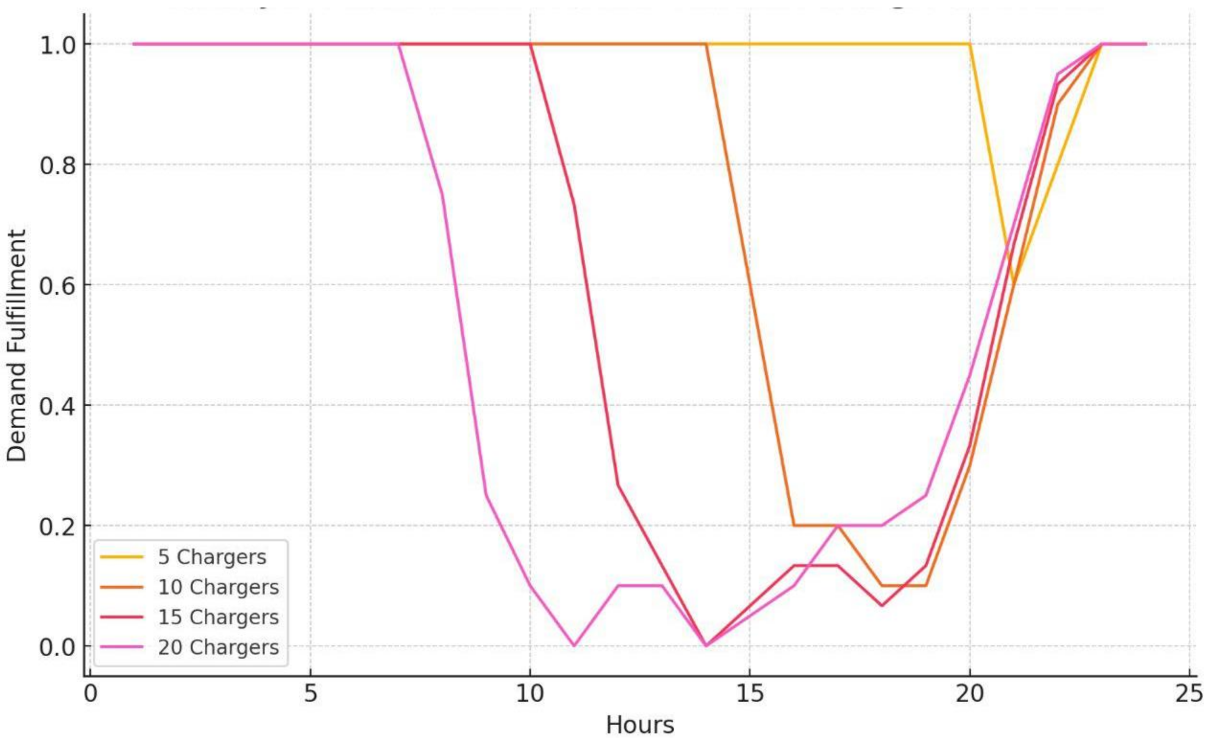

Figure 16. Hourly Demand for the Charger (50 kW).

The 7.2 kW charger scenarios in Figure 18 shows more gradual changes in usage, while the 50 kW charger scenarios Figure 19 exhibit sharper changes in demand. Higher counts of chargers result in better distribution of usage and fulfillment, highlighting the importance of sufficient charging infrastructure to meet varying demand throughout the day. In conclusion, these charts provide valuable insights into the temporal patterns of EV charger usage and demand fulfillment, emphasizing the need for strategic planning in charger deployment to optimize resource utilization and meet user demand efficiently.

4.4.4. Chargers' Usage (Case 1: 7.2 Kw)

Table 13 contains usage ratio data for a 7.2 kW charger across five different scenarios (10, 20, 30, 40 and 50 chargers). The data includes columns showing the chargers usage percentage during the day (i.e. 24 hrs.). If the usage percentage is one, it indicates that the charger is operating and charging EVs over the 24 hours. If the ratio is less than 1, it signifies that the charger is operating for a part of the day.

Table 13. Chargers usage percentage over different scenarios (7.2 kW)

Chargers	S10	S20	S30	S40	S50
Ch-1	1.00	1.00	0.79	0.79	0.83
Ch-2	1.00	1.00	0.79	0.79	0.83
Ch-3	0.79	0.79	0.83	0.83	0.96
Ch-4	0.79	0.79	0.83	0.92	0.96
Ch-5	0.83	1.00	1.00	0.96	1.00
Ch-6	1.00	0.79	0.79	0.83	0.83
Ch-7	1.00	0.79	0.79	0.83	0.83
Ch-8	0.79	0.83	0.83	0.38	0.38
Ch-9	1.00	0.88	1.00	1.00	1.00
Ch-10	0.79	0.79	0.83	0.83	0.96
Ch-11		0.79	0.83	0.83	0.92
Ch-12		0.79	0.79	0.83	0.83
Ch-13		1.00	0.79	0.83	0.83
Ch-14		1.00	1.00	1.00	1.00
Ch-15		1.00	1.00	1.00	0.83
Ch-16		0.88	1.00	0.79	1.00
Ch-17		0.83	0.92	0.38	0.38

Ch-18	0.79	0.83	0.96	0.96
Ch-19	0.88	0.88	1.00	0.71
Ch-20	0.83	0.83	0.96	0.96
Ch-21		0.96	1.00	0.83
Ch-22		0.88	1.00	1.00
Ch-23		0.88	1.00	1.00
Ch-24		0.96	0.42	0.42
Ch-25		0.96	0.96	0.83
Ch-26		0.96	0.96	1.00
Ch-27		0.83	0.88	0.88
Ch-28		0.96	0.42	0.42
Ch-29		0.96	1.00	0.88
Ch-30		0.88	0.88	0.96
Ch-31			0.83	0.88
Ch-32			0.88	1.00
Ch-33			0.88	0.88
Ch-34			0.88	0.96
Ch-35			0.88	0.88
Ch-36			1.00	0.88
Ch-37			1.00	0.83
Ch-38			0.88	0.88
Ch-39			0.42	0.42
Ch-40			0.42	0.42
Ch-41				0.42
Ch-42				0.88
Ch-43				1.00
Ch-44				1.00
Ch-45				1.00
Ch-46				0.42
Ch-47				1.00
Ch-48				0.42
Ch-49				0.88
Ch-50				0.88

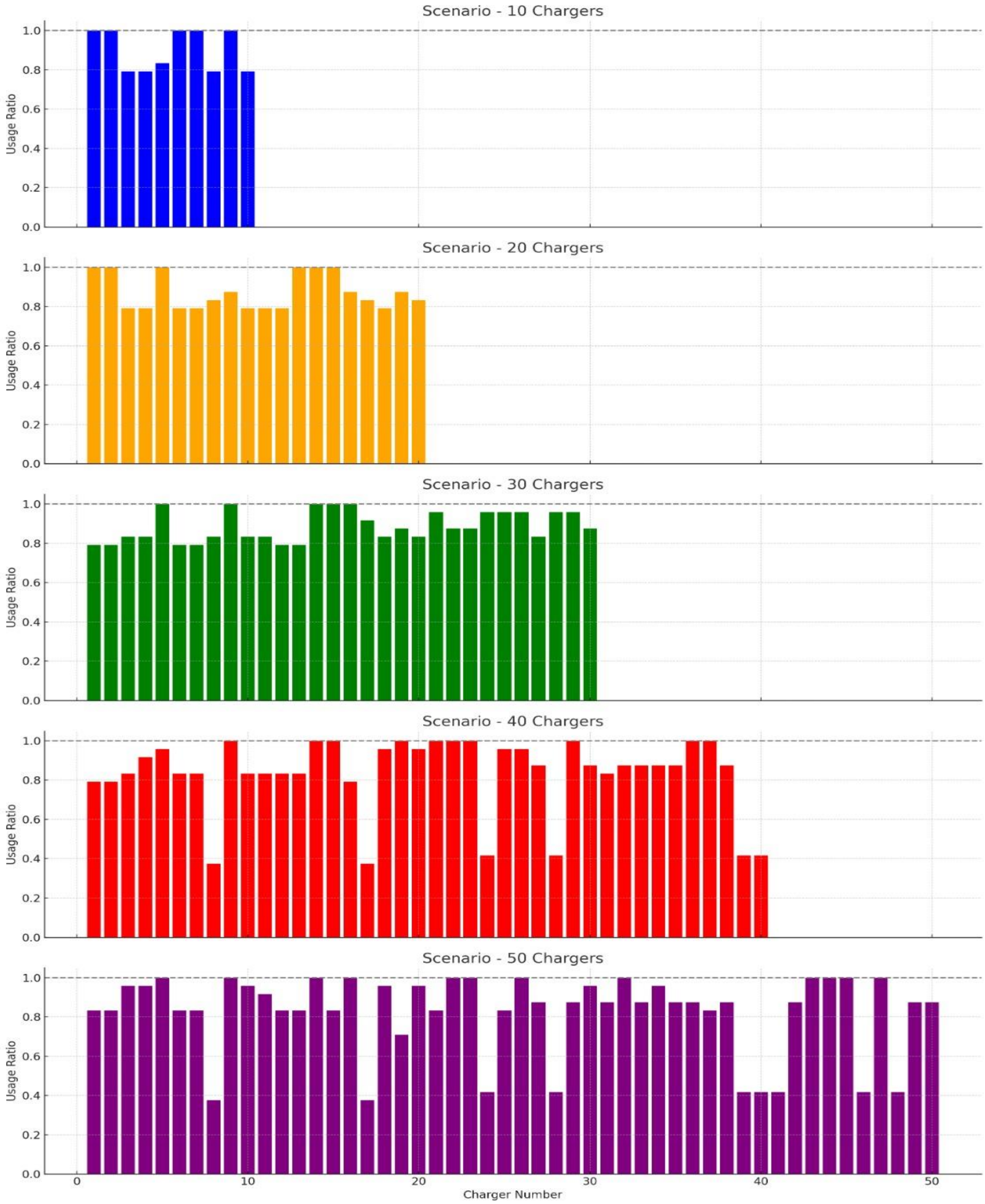

Figure 17. Simulation Chargers Usage 7.2 kW.

Figure 14 illustrates the usage ratio of EV chargers (i.e. 7.2 kW) across five different scenarios with varying numbers of chargers: 10, 20, 30, 40, and 50. Each scenario is analyzed to understand the distribution of charging demand among the available chargers, aiming to optimize energy consumption and efficiency. In the 10 chargers scenario, the usage ratios are consistently high, with most chargers operating near full capacity (0.8 to 1.0), indicating that the system is under sever demand and this is confirming the large amount of ENS. Doubling the number of chargers to 20 helps distribute the charging load more evenly, though the overall usage remains high. With 30 chargers, the load is distributed more effectively, resulting in reduced pressure on individual chargers and increased availability for EVs needing to charge. Increasing the number of chargers to 40 and 50 further improves the distribution of charging demand, with a noticeable decrease in the average usage ratio, indicating a well-balanced system where the charging load is effectively managed.

The analysis of these five scenarios highlights the critical role of the number of available chargers in managing the demand for EV charging. As the number of chargers increases, the system can distribute the load more evenly, reducing the operational stress on individual chargers. This leads to improved efficiency, lower energy consumption per charger, and increased overall system reliability. The study demonstrates that increasing the number of EV chargers significantly enhances the management of charging demand, underscoring the importance of adequate infrastructure planning in the deployment of EV charging networks to ensure sustainability and reliability.

4.4.5. Charger Usage 50 kW

Table 13 contains consumption data for a 50 kW charger across five different scenarios (5, 10, 15, and 20 chargers).

Table 14. Chargers usage percentage over different scenarios (50 kw)

Chargers	S5	S10	S15	S20
Ch-1	1	0.87	0.66	0.5
Ch-2	1	0.83	0.75	0.66
Ch-3	1	0.75	0.70	0.5
Ch-4	1	0.83	0.75	0.66
Ch-5	0.91	0.66	0.625	0.41
Ch-6		0.75	0.66	0.66
Ch-7		0.91	0.75	0.75
Ch-8		0.83	0.66	0.5
Ch-9		0.75	0.58	0.5
Ch-10		0.83	0.66	0.58
Ch-11			0.66	0.625
Ch-12			0.58	0.54
Ch-13			0.58	0.5
Ch-14			0.66	0.66
Ch-15			0.58	0.5
Ch-16				0.5
Ch-17				0.41
Ch-18				0.5
Ch-19				0.5
Ch-20				0.5

Figure 18. Simulation Chargers Usage 50 kW.

Figure 15 shows the usage ratio for each charger in four different scenarios with varying numbers of chargers: 5, 10, 15, and 20. In the 5 chargers scenario, all chargers operate at high efficiency and are nearly fully utilized 24 hours per day, indicating that the number of chargers is insufficient to meet the demand fully. Increasing the number of chargers to 10 reduces the load on each charger, but they are still nearly fully utilized, suggesting a high demand for charging. With 15 chargers, the distribution of the charging demand improves, reducing the load on each charger, and this number starts to approach the optimal to meet the demand. Expanding to 20 chargers further distributes the demand effectively, significantly reducing the load on each charger and indicating that the number of chargers is more than sufficient to meet the current demand.

Based on these results, several suggestions can be made to optimize the EV charging infrastructure. These include optimizing the number and capacity of chargers to reduce congestion in high-demand areas, encouraging balanced usage through incentives for off-peak charging, and implementing smart charging technologies to manage and optimize load distribution across chargers. By analyzing the current data, informed decisions can be made to improve the efficiency of energy consumption and ensure the overall sustainability of the EV charging infrastructures.

Chapter 5

5. Conclusion and Future Work

5.1. Summary and Conclusion

The research presented in this thesis has provided a comprehensive examination of EV charging infrastructure at rental car areas and the factors influencing charging loads. Chapter 1 and 2 reviewed the history and types of EVs, as well as the characteristics and components of various battery technologies. It also covered the charging standards and strategies, while exploring the potential impacts of EV charging on the electricity grid, including grid stability, power quality, load profiles, and potential overloading.

Building upon this foundation, Chapter 3 aimed to develop accurate data and reliable statistical models to represent the key variables influencing EV charging loads at car rental facilities. By collecting sample contract data and utilizing statistical analysis tools, the research was able to generate validated functions for factors such as pick-up times, drop-off times, and rental durations. These findings serve as an important initial step in estimating EV charging loads and informing the design and management of charging infrastructure at car rental locations. Furthermore, Chapter 4 introduced a novel probabilistic framework to determine EV charging load profiles of rental car offices, accounting for the uncertainties inherent in the charging process. The outcomes of this research are anticipated to benefit researchers, planners, and developers working to advance EV charging infrastructure and support the broader adoption of electric mobility.

5.4. Future Work

The analyses, approaches, and discussions presented in this thesis will open the doors to many future research studies. We can summarize some of them in the following points:

1. Developing reliable mathematical models to determine the appropriate EV charging infrastructure designed based on the specific needs of each car rental office, taking into account factors such as the socioeconomic nature of the region.
2. Designing the EV charging infrastructure from the technical aspects and identifying the required cables, transformers, and other components.
3. Developing an economic model to calculate the economic costs and balance them with the technical and technological standards to determine the appropriate options.
4. Studying the integration of a renewable energy system in car rental areas as an option to meet the demands of EVs.

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