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Assessing EV Load Uncertainty in Rental Car Fleets: Statistical Insights for Effective Charging Infrastructure

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ABSTRACT

Many countries worldwide are actively working towards achieving the United Nations Sustainable Development Goals (UNSDGs) 2030, focusing on implementing sustainable solutions to environmental, economic, and social issues. One promising and environmentally friendly solution that has gained significant international attention is the use of electric vehicles (EVs), which help reduce emissions and reliance on fossil fuels. This paper presents a qualitative study aimed at assessing the uncertainty surrounding EV load in rental car fleets. As rental agencies increasingly adopt EVs, they face challenges in forecasting charging demand, especially within limited space and infrastructure. By providing valuable data and reliable statistical models, the study estimates EV consumption for car rental companies, which might face difficulties in charging multiple vehicles efficiently. Accurate EV load estimation is essential for designing effective charging infrastructure and developing optimal load management models that reduce technical issues and economic costs. Over twelve statistical functions were tested to capture variables such as fleet size, usage patterns, and charging behavior that influence EV load formation. Additionally, this paper includes case studies to support planners and developers in improving EV charging infrastructure, offering practical insights for scaling EV integration in the rental sector and contributing to broader sustainability goals.

1 | Introduction

1.1 | Background and Study Objectives

Over the last 10 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, EVs 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 (CO_2) emissions and mitigate the global warming and climate change [2]. However, integrating renewable energy with the grid presents certain limitations [3]. In this context, integrating the Saudi code of energy conservation with renewable technologies such as solar PV systems is increasingly recognized as a key enabler of sustainable mobility and EV adoption [4].

Governments around the world have supported the use of EVs and have set ambitious targets to promote their adoption. For instance, Norway and the Netherlands have set targets to achieve 100% EV sales by 2030 [5]. 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 EVs 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 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 EVs on the road. Moreover, the car industries have set targets encompassing various aspects, such as EV sales, model diversity, size, and range.

However, there is a need for further investigation into EV charging infrastructure for rental car fleets. The aim of this paper is to establish a data-driven foundational framework for managing and analyzing centralized EV fleets in car rental operations, enabling reliable vehicle availability and supporting future advanced research and applications.

The specific objectives of this paper are

- To collect, structure, and validate a comprehensive real-world dataset that captures rental contract information, vehicle usage patterns, and charging energy requirements for a centralized EV fleet.
- To develop and apply statistically robust models to characterize rental behavior, driving distances, and charging energy demand through appropriate probability distribution fitting.
- To establish a reusable baseline analytical framework that can support future research on advanced fleet management strategies, charging optimization, and the integration of emerging technologies.

To introduce these objectives and to identify areas where further work is needed, the following section provides state-of-the-art review in EV adoption, fleet management, and charging infrastructure.

1.2 | State-of-the-Art

EV adoption brings both opportunities and challenges regarding grid management, renewable integration, and system reliability and stability. Issues related to power system stability and reliability are due to the fact that 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. Some studies have suggested several solutions: (1) the implementation of demand response programs and (2) the integration of reliable communication systems [10, 11]. These solutions are expected to ensure efficient charging management, grid balancing, and optimization of grid assets. Charging EVs in an uncoordinated manner can harm the power systems, while vehicle-to-grid (V2G) technologies and renewable integration represent reasonable means of enhancing system reliability. Integration of dynamic thermal rating with scheduling of EVs would better the performance at the generation and distribution levels. V2G and dynamic line rating (DLR) are two important emerging technologies that offer increased grid flexibility and reduction of renewable curtailment. A recent survey indicates that coordinated V2G and DLR operation under uncertainty can significantly improve wind power integration while pointing out gaps in co-optimization, battery aging, and lifecycle impacts [12]. Dynamic thermal line rating (DTLR) and EV scheduling in wind-integrated networks have been explored further for their impact on reliability [13]. Coordinated operation of these technologies offers a reduction in Expected Energy Not Supplied (EENS) and improves reliability indices. Furthermore, the integration of wind energy into microgrids via DLR and EV scheduling has been explored, with an aim to decrease operating costs and increase renewable absorption, showing the practical benefits of flexible energy storage and transmission strategies [14]. Similarly, modeling and coordination approaches for DLR, DERs, and EVs have been the subject of systematic reviews [15]. Hybrid frameworks that combine optimization with machine learning can provide better coordination of EVs and DERs. The main challenges involve voltage drops at peak periods of EV charging and a lack of integrated frameworks that manage interactions amongst DLR, DERs, and EVs. These findings set a base for flexible and adaptive power system design. However, these studies do not explicitly consider the operational constraints of vehicle fleets such as rental car services.

Another important aspect of EV–grid interactions involves resilience to extreme weather. A proposed framework for vulnerability assessment in the presence of EVs and energy storage systems considered such parameters as aging, variability of renewables, and hybrid sources [16]. Utilizing a hybrid algorithm supported by simulations on IEEE bus systems, it achieved quantitative risk and grid weak point determination under orderly and uncoordinated EV charging conditions. Advanced coordination schemes using cloud-edge-device collaboration for AC/DC hybrid distribution systems have recently been proposed by Su et al. [17]. These schemes model interactions among the cyber, physical, and social layers to optimize both EV dispatch and renewable energy performance.

Despite all advantages of the adoption of EVs, the widespread use of EVs may raise several challenges represented by technology acceptance and awareness, as well as their integration into the electrical grid. Recent studies have explored stochastic modeling of EV charging behavior and infrastructure, emphasizing the variability in user patterns and its impact on grid loads. For instance, a decision-making trial and evaluation method is used to analyze how personal and social factors influence EV users' charging behaviors, highlighting the complexity of user decision-making in diverse social environments [18]. Bian et al. examined the use of multiagent reinforcement learning approach to achieve a scalable and coordinated energy management system for EVs, aiming to optimize energy distribution and consumption across multiple vehicles [19].

While this research focuses on modeling EV charging, V2G, and DLR integration, the effects of battery degradation on charging uncertainty are not considered in the current work. The impact of battery aging on charging efficiency and energy management strategies will be addressed in future research.

Finally, global EV adoption trends place technical solutions in context. Comparisons between EV and internal combustion engine vehicles show that the rate of adoption is heavily driven by social and economic factors, as well as by policy [20]. Strategies such as promoting the affordable EV models, development of charging infrastructure, incentives, and integration of renewable energy into EV production are all key strategies to be enacted if the world is going to accelerate transportation electrification while ensuring environmental sustainability.

Further advancing the discussion, a novel multiobjective optimization approach is introduced for EV charging and V2G scheduling, balancing multiple objectives to improve overall system performance [21]. This approach reflects the growing need for sophisticated optimization techniques in EV energy management. Addressing infrastructure protection, a research develops a charger current–limiting scheme designed to improve coordination between main and backup overcurrent relays, considering various EV penetration levels [22]. A comprehensive planning framework is proposed for multiregional EV charging and battery swapping stations, addressing the surge in demand due to increasing EV adoption and emphasizing the need for strategic infrastructure development [23].

Recent advances in V2G-aware optimization emphasize the dual challenge of balancing grid support with battery health management in EV fleets. Paparella et al. [24] presented a multiobjective approach towards the implementation of the Mobility as a Service paradigm by integrating respective costs and fees related to the provision of various V2G services while taking into due consideration the respective battery health factors. Their method denotes that the disregard of battery wear may vitiate the economic benefits that accrue through the facilitation of the respective services since the additional costs of battery degradation may potentially nullify the benefits that otherwise accrue to the firm. On similar lines, the approach adapted by Mohseni and Brent [25] attempts to provide optimal solutions for the stochastic EV charging and discharging processes conducted on a microgrid that consists principally of intermittent renewable energy resource inputs and provides a method using a mixed-integer linear program that incorporates the information gap decision theory approach to accommodate the various stochastic processes involved with EV road usage patterns and routes and denotes that risk-sensitivity impacts the profitability of microgrids significantly. Cavus and Bell [26] introduced V2G-HealthNet, a hybrid deep learning framework combining LSTM and transformer-based attention mechanisms to predict state-of-health and remaining useful life of EV batteries.

Similarly, researchers have focused on how smart coordination of EV charging and the use of V2G can avert overloading in the distribution network. Hamim et al. [27] proposed a day-ahead optimization framework to flatten out the demand for residential EV charging, including the use of the genetic algorithm method to plan charging and discharging within operational bounds, in support of V2G. In another related study, Sihawong et al. [28] studied overload and undervoltage issues in an 18-bus low-voltage distribution scenario. Their results showed that running multiple chargers during peak hours can increase energy losses, create voltage sag, and damage equipment, and they proposed a charger management system to avoid such network problems, ensuring a stable and efficient supply.

Despite the significant amount of work on the integration of EVs, V2G, DLR/DTLR, and stochastic models for charging, there still exist a number of challenges. This includes the system's performance with random charging patterns, the interaction with the whole power system, management on the scale of the automotive fleets, optimization with uncertainty, and infrastructure associated with the chargers. All these issues need to be addressed especially with a larger penetration of EVs.

1.3 | Motivation

The research focuses on centralized rental car fleets operating at a single site, where charging infrastructure must support continuous vehicle availability under strict operational and space constraints. Unlike conventional charging scenarios, rental fleets experience unique operational challenges such as high vehicle turnover, variable rental durations, and constrained charging spaces. These factors introduce significant variability in charging demand, making it essential to develop load forecasting models tailored to the operational realities of rental fleets to support effective infrastructure design and load management. Existing EV load forecasting and infrastructure planning studies largely focus on residential users, public charging stations, or homogeneous fleets and therefore do not adequately capture the operational dynamics of rental car fleets.

This work represents the first study of its kind focusing on centralized rental fleets and addresses the practical challenge of ensuring vehicles are available, sufficiently charged, and ready for the next rental trip without service disruptions.

To achieve this, multiple essential variables were considered, like rental contract data (vehicle start and return times), vehicle usage patterns and distances, and energy consumption and charging requirements to ensure readiness for next rentals. It is important to emphasize that such integrated datasets are not readily available in existing literature. It creates a foundational dataset and analytical framework to support future research and real-world applications.

The novelty of this study lies in (i) the use of real-world rental transaction data to characterize EV charging demand, (ii) the development of a stochastic load profile that captures high vehicle turnover and variable rental durations, and (iii) the application of this model to support infrastructure sizing and charging management at rental car offices. To the authors' knowledge, this is one of the first studies to explicitly model EV charging demand in rental car environments under realistic operational constraints.

1.4 | Paper Organization

This paper is organized as follows: Section 2 describes the materials and methods, including data collection and statistical modeling approaches used to evaluate charging load uncertainty in rental car fleets. Section 3 presents the results of the statistical analysis, highlighting key insights related to charging energy requirements, pick-up and drop-off times, and rental durations. Section 4 outlines future research directions, and Section 5 concludes the study, emphasizing the practical implications of the findings for planners and policymakers involved in EV infrastructure development for rental fleets.

2 | Methodology

The following subsections describe the data collection and analysis procedures used to model EV load in rental fleets.

2.1 | Data Preparation and Processing

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

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. This information guided the selection of relevant variables for the study.

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 geographic diversity in the sample.

(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 distribution provides valuable insights for optimizing rental operations and staffing to accommodate peak demand

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 1 | Sample car rental contract used to collect data for the predefined variables.

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 1. 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 times of charging. Another significant random variable represents the pick-up and drop-off dates, which helps identify 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. This information is essential as it directly influences the required energy to charge the EVs for future rentals, as indicated in Equations (1)–(3).

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

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

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

Equations (1)–(3) were developed by the authors as part of the modeling framework proposed in this study.

Here,

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: remaining 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 charge the battery in KWh

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.

2.2 | Statistical Models

Conducting a comprehensive statistical evaluation study plays a crucial role in accurately determining the impact of EV loads.

TABLE 1 | Probability distribution functions (PDFs), related symbol, PDF equations, and parameters [29, 30].

Distribution	Symbol	$f(x)$	Parameters			
			Scale	Shape	Location	Others
Beta	BE	$((x-\alpha)^{\alpha1-1}(b-x)^{\alpha2-1})/((\Gamma(\alpha1)\Gamma(\alpha2))/(\Gamma(\alpha1+\alpha2))(b-a)^{\alpha1-\alpha2-1})$	NA	$\alpha1, \alpha2$	NA	a, b: continuous boundary parameters
Burr	BU	$(\alpha k((x-\gamma)/\beta)^{\alpha-1})/(\beta(1+((x-\gamma)/\beta)^{\alpha})^{k+1})$	β	k, α	γ	ν: degrees of freedom (positive integer)
Chi-squared	CS	$((x-\gamma)^{\nu/2-1}e^{-(x-\gamma)/2})/(2^{(\nu/2)}\Gamma(\nu/2))$	NA	NA	γ	NA
Dagum	DA	$(\alpha k((x-\gamma)/\beta)^{\alpha k-1})/(\beta(1+((x-\gamma)/\beta)\alpha)^{k+1})$	β	k, α	γ	NA
Exponential	EX	$\lambda e^{(-\lambda(x-\gamma))}$	λ	NA	γ	NA
Gamma	GA	$((x-\gamma)^{\alpha-1}e^{-(x-\gamma)/\beta})/(\beta^{\alpha}\Gamma(\alpha))$	β	α	γ	NA
Johnson S unbounded	JSU	$\delta/(\lambda\sqrt{2\pi}\sqrt{z^2+1})e^{(-(1/2)(\gamma+\delta\ln(z+\sqrt{z^2+1})^2))}, z=(x-\xi)/\lambda$	λ	∂, γ	ξ	NA
Johnson S bounded	JSB	$\delta/\lambda\sqrt{2\pi}z(1-z)e^{(-(1/2)(\gamma+\delta\ln(z/(1-z)))^2)}, z=(x-\xi)/\lambda$	λ	∂, γ	ξ	NA
Log-gamma	LGG	$((\ln x)^{\alpha-1}e^{-(\ln x)/\beta})/(x\beta^{\alpha}\Gamma(\alpha))$	β	α	NA	NA
Lognormal	LGN	$e^{(-(1/2)((\ln(x-\gamma)-\mu)/\sigma)^2)}/(x-\gamma)\sigma\sqrt{2\pi}$	σ	NA	μ, γ	NA
Normal	NO	$e^{(-(1/2)((x-\mu)/\sigma)^2)}/(\sigma\sqrt{2\pi})$	σ	NA	μ	NA
Rayleigh	RA	$(x-\gamma)e^{(-(1/2)((x-\gamma)/\sigma)^2)}/\sigma^2$	σ	NA	γ	NA
Weibull	WE	$\alpha/\beta((x-\gamma)^{\sigma-1}/\beta)e^{(-((x-\gamma)/\beta)^{\sigma})}$	β	α	γ	NA

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 1 presents the PDFs of the selected distributions along with their equations and parameters. Further details are discussed in [29, 30].

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 (K–S) test was utilized as it is widely recognized as a reliable goodness-of-fit test in various applications. The K–S test involves comparing theoretical PDFs with experimental (actual) PDFs [24]. 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 K–S 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. Figure 2 presents the methodological framework employed for the statistical evaluation study. The diagram describes the sequential stages of the research process, beginning with systematic data collection and extending to the application of the K–S test. It emphasizes the comparative analysis between theoretical and experimental PDFs, thereby facilitating a rigorous assessment of model suitability. This framework underscores the structured and transparent approach adopted in evaluating the goodness-of-fit between theoretical assumptions and empirical observations.

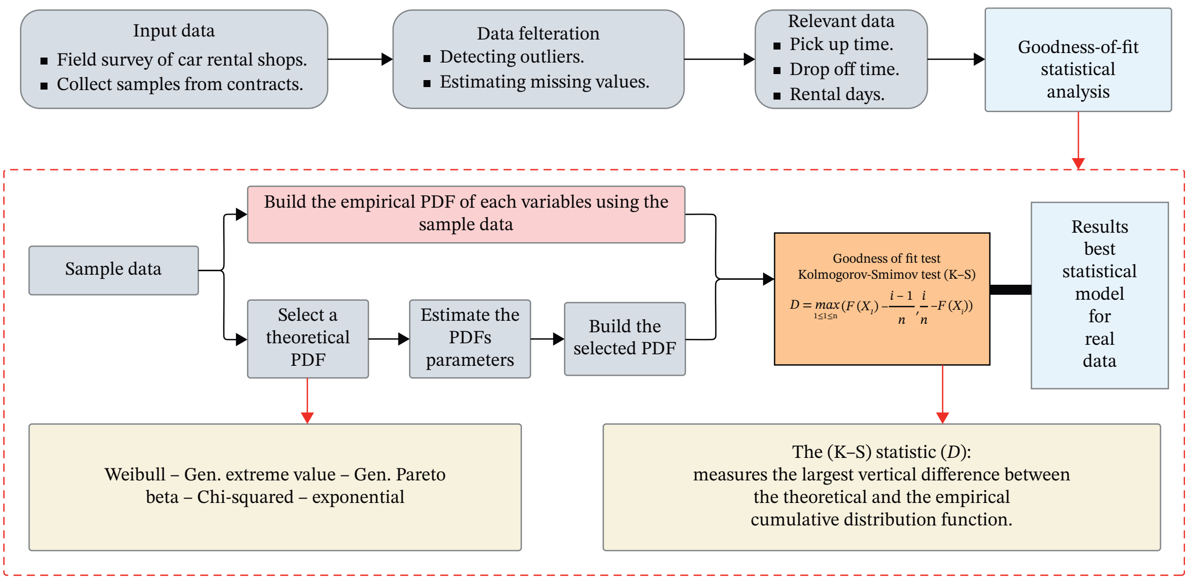

FIGURE 2 | The framework for conducting the statistical evaluation study.

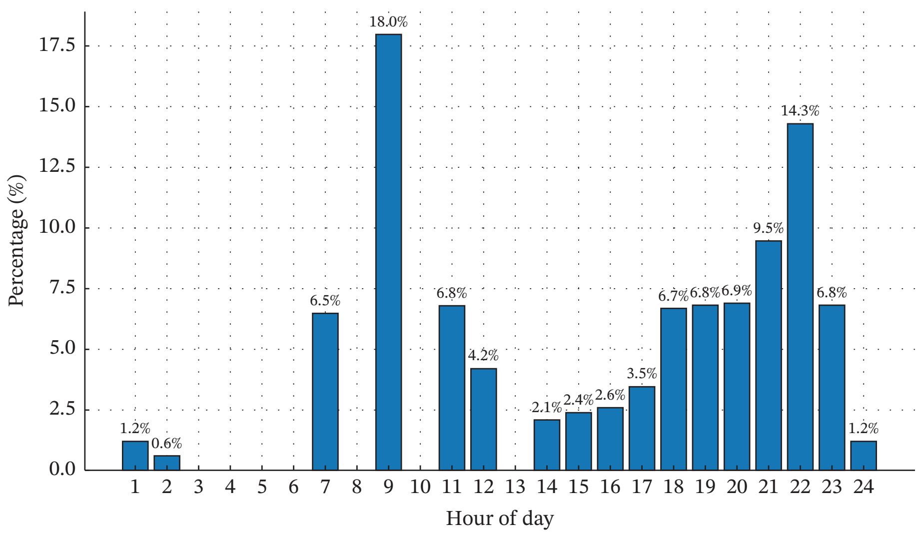

FIGURE 3 | Percentage distribution of rental car pick-ups by hour of the day.

3 | Results and Discussion

This section presents comprehensive results and relevant analyses of the investigated variables. The data were processed and analyzed using Microsoft Excel, while the EasyFit software was employed for statistical analysis and probability distribution fitting [31]. The adopted framework supports a consistent evaluation of the stochastic characteristics of the studied variables and enables reliable interpretation of the results.

3.1 | Pick-Up Times

Figure 3 illustrates the distribution of car pick-up times throughout the day, highlighting key trends in customer behavior. Table 2 presents the hourly distribution of rental car pickup events based on the analyzed dataset. This distribution reflects the temporal variability of vehicle pick-up activity and serves as an input for modeling stochastic charging demand in rental car environments. The most significant peak occurs at 9 a.m., accounting for over 18% of total pick-ups. This aligns with the typical office opening hours, suggesting that many customers, particularly business travelers, prefer to collect their rental cars early in the morning to start their day. Conversely, the lowest percentage of pick-ups is observed between 3 a.m. and 6 a.m., likely due to the closure of rental offices and minimal demand during these late-night hours. However, after midday, there is a significant decline in pick-up activity, reaching its lowest levels between 12 p.m. and 5 p.m. This pattern may be attributed to reduced customer demand during afternoon hours, as users are likely engaged in work, travel, or other activities. In the evening, the pick-up rate rises steadily, forming a second peak between 6 p.m. and 10 p.m. due to that some customers may also choose to pick up their rental cars at night to have them ready for use the next day. These distributions inform the optimization of rental operations and staffing to meet peak demand.

TABLE 2 | Hourly distribution of rental car pick-up events, expressed as a percentage of the total number of pick-up transactions ($N = 400$).

Hour	Pick-up percentage (%)
1	1.0
2	0.5
3	0.0
4	0.0
5	0.0
6	0.0
7	6.5
8	0.0
9	18.0
10	0.0
11	7.0
12	0.0
13	4.0
14	2.0
15	2.0
16	2.5
17	3.0
18	6.0
19	6.0
20	6.0
21	7.0
22	14.0
23	6.5
24	1.0

The goodness-of-fit results for different PDFs for pick-up times are presented in Table 3. The PDFs are ranked based on the lowest statistic obtained from the 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 4 shows how significantly these PDFs are different from the sample data of pick-up times. The K–S test results indicate that the generalized Pareto distribution provides the best fit to the observed pickup time data, yielding the lowest test statistic among the evaluated distributions. This suggests a closer agreement with the empirical data compared to alternative PDFs. 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.

3.2 | Drop-Off Times

Figure 5 presents the distribution of drop-off times along with their corresponding percentages. The data reveal 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. In Figure 6, the results obtained from conducting six different tests using the

TABLE 3 | 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	$k = -0.55119$	$\sigma = 6.8627$	$\mu = 13.908$
Weibull	0.27487	$\alpha = 1.3784$	$\beta = 19.103$	$\gamma = 0$
Chi-squared	0.28258	V = 14	$\gamma = 0$	
Exponential	0.32477	$\lambda = 0.0654$	$\gamma = 0$	

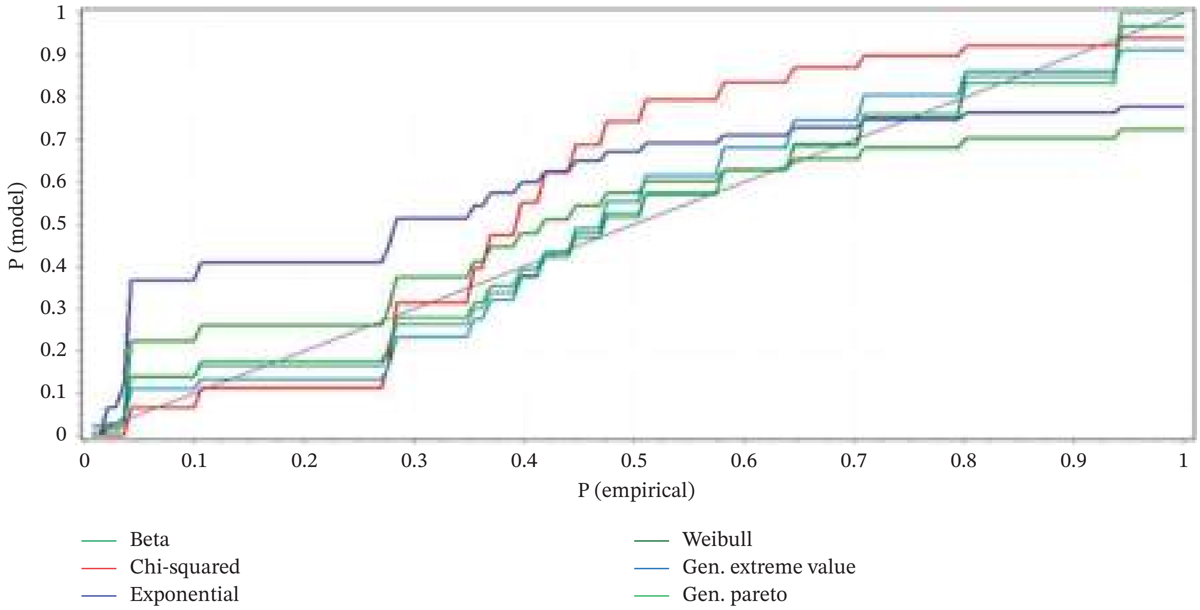

FIGURE 4 | P–P plot for selected PDFs fitted to pick-up.

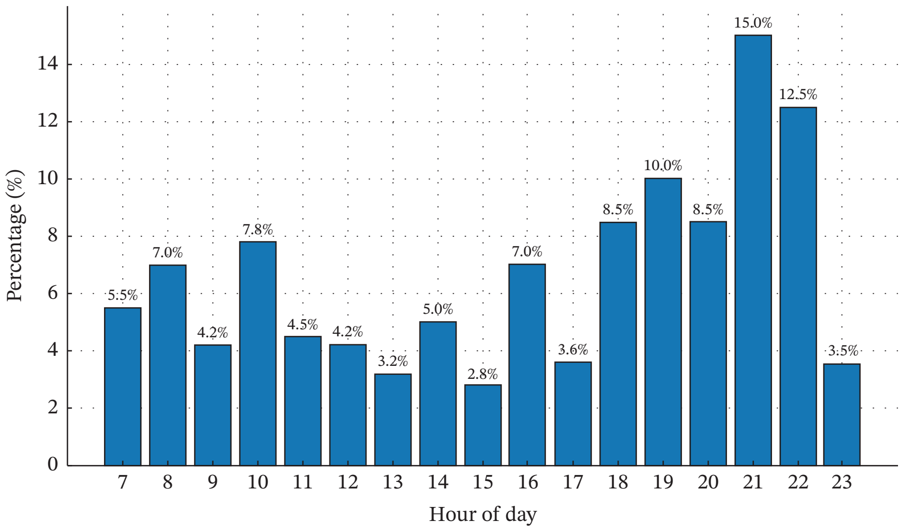

FIGURE 5 | Distribution of drop-off times throughout the day.

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. Several theoretical PDFs were tested for goodness of fit for drop-off times using the K–S test. It can be seen in Table 4 that the generalized extreme value, generalized Pareto, and beta distributions are in closest agreement with the observed data, while Chi-squared, Pareto, and exponential distributions turn in relatively poor comparative performances.

3.3 | Rental Days

Figure 7 illustrates the distribution of rental days along with their respective percentages. The data indicate 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. Figure 8 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 4 ranks the PDFs based on their goodness of fit as determined by the K–S test. Figure 8 visually represents the various fitted PDFs in relation to the actual rental days data. Results show that the generalized Pareto, generalized extreme value, and Weibull distributions provide the best fit to the rental duration data, which is further supported by the K–S test results shown in Table 5. On the other hand, the exponential, beta, and Chi-squared distributions fail to capture the essential stochastic behavior of rental durations.

3.4 | Charging Energy Required to Fully Charging the Battery in KWh

Figure 9 shows the distribution of energy required to achieve a full charge. As presented in Table 6, the data ranges from

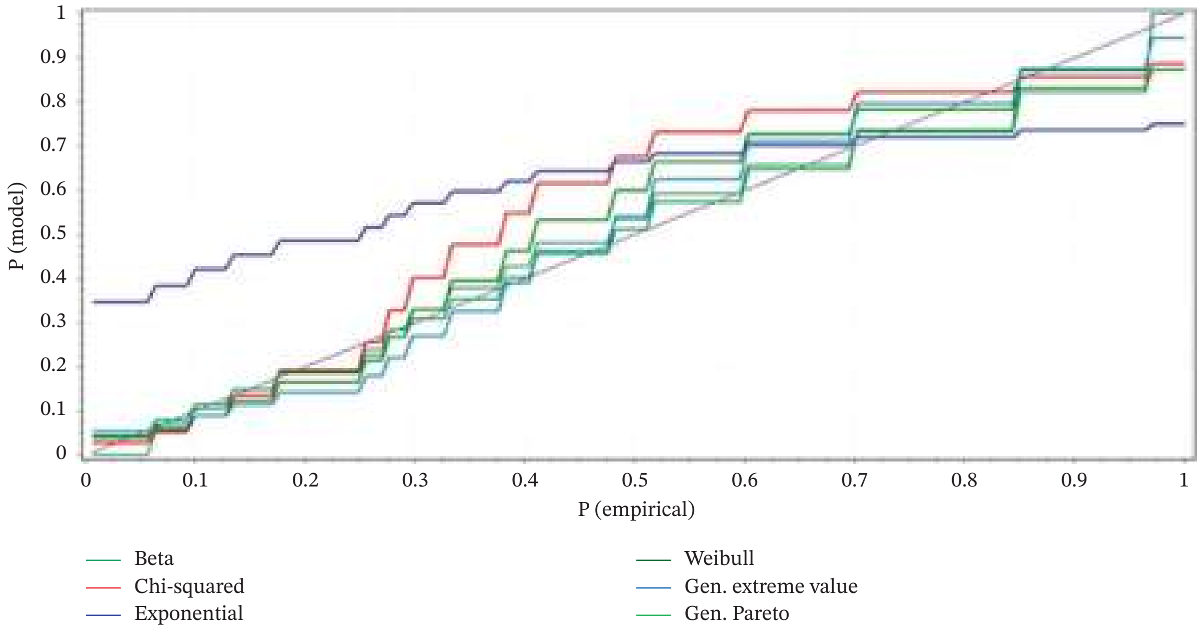

FIGURE 6 | P–P plot for selected PDFs fitted to drop-off times.

TABLE 4 | Goodness-of-fit result for different PDFs for drop-off times.

Critical statistic is 0.11453				
PDF	**Statistical**	**Parameters**		
Gen. extreme value	0.11453	$k = -0.64031$	$\sigma = 5.5912$	$\mu = 15.669$
Gen. Pareto	0.10712	$k = -1.8865$	$\sigma = 31.553$	$\mu = 5.6218$
Beat	0.14306	$\alpha 1 = 0.87095$ $a = 7.0$	$\alpha 2 = 0.58774$ $b = 23.0$	
Weibull	0.14676	$\alpha = 3.3068$	$\beta = 18.5$	$\gamma = 0$
Chi-squared	0.21361	$\nu = 16$	$\gamma = 0$	
Exponential	0.33775	$\lambda = 0.06041$	$\gamma = 0$	

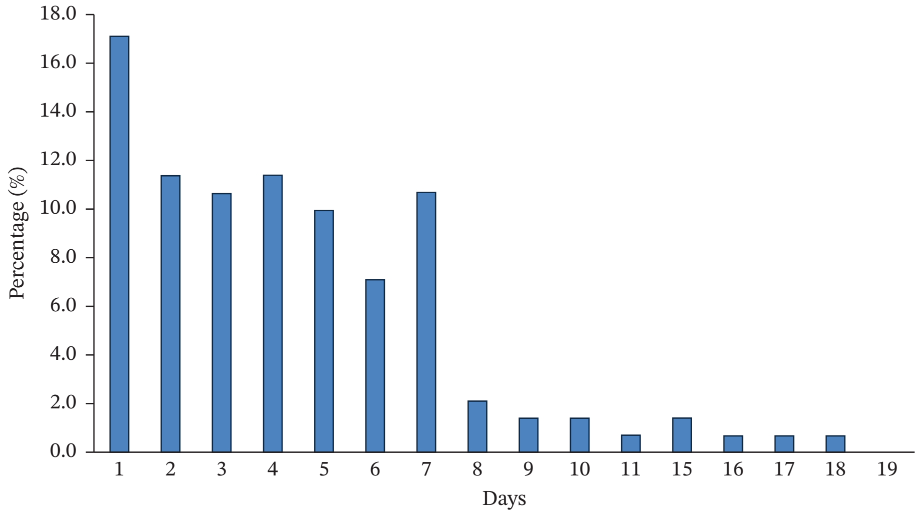

FIGURE 7 | Histogram of number of rental days.

a minimum charge of about 23.97 kWh to a maximum of 112 kWh, with a median value of 68 kWh. The interquartile range spans the values between 62 and 88 kWh, reflecting moderate variability in charging demand, a factor that is of great importance for sizing charging infrastructure and doing capacity planning. The line inside the box represents the median,

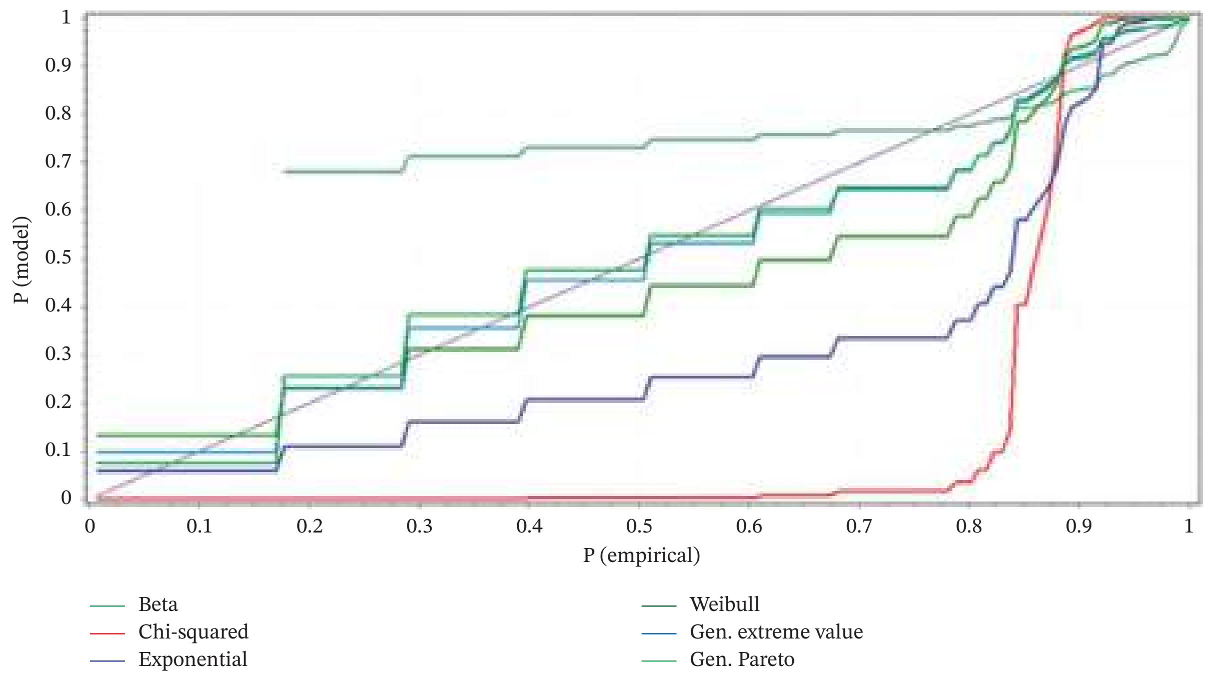

FIGURE 8 | P–P plot for selected PDFs fitted to rental days.

TABLE 5 | Goodness-of-fit result for different PDFs for number of rental days.

Critical statistic is 0.13727				
PDF	**Statistical**	**Parameters**		
Gen. Pareto	0.13727	$k = 0.76125$	$\sigma = 3.955$	$\mu = 0.68995$
Gen. extreme value	0.13766	$k = 0.7856$	$\sigma = 3.4028$	$\mu = 3.1115$
Weibull	0.23556	$\alpha = 0.8809$	$\beta = 9.1935$	$\gamma = 0$
Exponential	0.44667	$\lambda = 0.05795$	$\gamma = 0$	
Beat	0.50281	$\alpha 1 = 0.06731$ $a = 1.0$	$\alpha 2 = 1.5469$ $b = 578.46$	
Chi-squared	0.76797	$\nu = 17$	$\gamma = 0$	

which is the central value dividing the dataset into two equal halves.

4 | Future Research Directions

The analyses and findings suggest several directions for future research, summarized as follows:

1. Developing reliable mathematical models to determine the appropriate EV charging infrastructure designed based on the specific needs of each car rental office.
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.

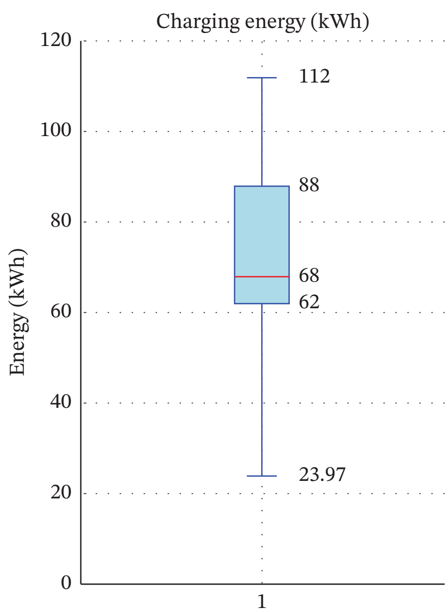

FIGURE 9 | Charging energy required to fully charging the battery.

TABLE 6 | Summary of charging energy statistics (kWh).

Statistic	Value (kWh)
Minimum	23.97
Q1	62.00
Median	68.00
Q3	88.00
Maximum	112.00

5. Developing and validating the proposed data-driven framework in real-world smart city environments and utility-scale pilot program.

5 | Conclusions

This paper proposed statistically validated models for key variables influencing EV charging demand at rental car facilities. A dataset of rental car contracts was analyzed, and stochastic models were developed for pick-up times, drop-off times, rental durations, and charging energy requirements based on goodness-of-fit testing. Each variable was represented by a statistically validated mathematical function. After conducting the necessary statistical tests, the mathematical functions were ranked based on their compatibility with the sample data for each variable.

Key findings showed that the beta distribution provided the best fit for modeling EV energy consumption, outperforming other tested distributions including Weibull, exponential, and Chi-squared. The statistical analysis revealed a median charging energy of 68 kWh, with a maximum recorded value of 112 kWh, and a lower outlier boundary at approximately 24 kWh. These insights are critical for determining the capacity requirements for future charging stations. Moreover, the pick-up time analysis revealed that 9:00 a.m. was the peak hour, representing 18% of all vehicle departures, followed by increased activity during late evening hours (especially around 10:00 p.m.). Understanding these temporal patterns enables rental companies and planners to optimize charger availability and reduce wait times. The analyses and finding merged from this paper serve as an important initial step in estimating the EV loads and preparing plans for proper design and optimal management of EV charging load at car rental offices. It is also anticipated that the outcomes of this paper will be beneficial to researchers, planners, and developers interested in EV charging infrastructure.

Author Contributions

Conceptualization: Abdulaziz Almutairi; methodology: Ahmed Alanazi; writing–original draft preparation: Abdulaziz Almutairi and Ahmed Alanazi; writing–review and editing: Ahmed Alanazi; supervision: Abdulaziz Almutairi; project administration: Abdulaziz Almutairi.

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Disclosure

All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data supporting the findings of this study are available within the article.

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