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Electric Vehicle Load Estimation at Home and Workplace in Saudi Arabia for Grid Planners and Policy Makers

Abdulaziz Almutairi [1,*], Naif Albagami [1], Sultanh Almesned [2], Omar Alrumayh [3] and Hasmat Malik [4,5]

1 Department of Electrical Engineering, College of Engineering, Majmaah University, Majmaah 11952, Saudi Arabia; n.albagami@mu.edu.sa
2 Department of Educational Sciences, College of Education, Majmaah University, Majmaah 11952, Saudi Arabia; s.almesned@mu.edu.sa
3 Department of Electrical Engineering, College of Engineering, Qassim University, Unaizah 56453, Saudi Arabia; o.alrumayh@qu.edu.sa
4 Department of Electrical Power Engineering, Faculty of Electrical Engineering, University Technology Malaysia (UTM), Skudai 81310, Malaysia; hasmat@utm.my
5 Department of Electrical Engineering, Graphic Era Deemed to be University, Dehradun 248002, India
* Correspondence: ad.almutiri@mu.edu.sa

Abstract: Electric vehicles (Evs) offer promising benefits in reducing emissions and enhancing energy security; however, accurately estimating their load presents a challenge in optimizing grid management and sustainable integration. Moreover, EV load estimation is context-specific, and generalized methods are inadequate. To address this, our study introduces a tailored three-step solution, focusing on the Middle East, specifically Saudi Arabia. Firstly, real survey data are employed to estimate driving patterns and commuting behaviors such as daily mileage, arrival/departure time at home and workplace, and trip mileage. Subsequently, per-unit profiles for homes and workplaces are formulated using these data and commercially available EV data, as these locations are preferred for charging by most EV owners. Finally, the developed profiles facilitate EV load estimations under various scenarios with differing charger ratios (L1 and L2) and building types (residential, commercial, mixed). Simulation outcomes reveal that while purely residential or commercial buildings lead to higher peak loads, mixed buildings prove advantageous in reducing the peak load of Evs. Especially, the ratio of commercial to residential usage of around 50% generates the lowest peak load, indicating an optimal balance. Such analysis aids grid operators and policymakers in load estimation and incentivizing EV-related infrastructure. This study, encompassing data from five Saudi Arabian cities, provides valuable insights into EV usage, but it is essential to interpret findings within the context of these specific cities and be cautious of potential limitations and biases.

Keywords: charging station; electric vehicle; home and workplace; load estimation; peak load; per-unit profiles

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1. Introduction

1.1. Background and Motivation

Transportation electrification is a viable solution to reduce greenhouse gas emissions and enhance energy security [1]. This involves reducing reliance on fossil fuels and shifting towards locally available renewable energy sources. The adoption of electric vehicles (Evs) has significantly increased due to battery technology advancements, interest in sustainable energy, and lower EV costs [2,3]. However, the penetration of Evs is limited in certain regions such as the Middle East. This is primarily due to comparatively lower local fuel prices [4]. Nevertheless, some Middle Eastern countries, including Saudi Arabia, have recently taken significant steps toward technological transformation and energy efficiency. For instance, Saudi Arabia has implemented Corporate Average Fuel Economy (I) standards for new light-duty vehicles since 2016 and launched Vision 2030 to drive further changes in the country [5]. As part of Vision 2030, Saudi Arabia is developing a futuristic smart city called Neom, where autonomous Evs will play a major role in transportation [6]. Despite being one of the highest per-capita motor gasoline consumption countries, Saudi Arabia is taking proactive measures to shift towards a more sustainable transportation system. A recent study estimated that the number of drivers in Saudi Arabia will reach approximately 12.5 million by 2040, further emphasizing the need for transportation electrification [6]. To achieve these benefits, load modeling of Evs is required.

Load modeling of Evs is imperative for effective grid management and promoting the widespread adoption of Evs. As the EV market continues to grow, understanding and accurately predicting the impact of these vehicles on the grid is essential. Load modeling allows grid operators to anticipate and manage increased electricity demand from charging Evs, preventing overloads and ensuring grid stability [7]. Furthermore, it enables policymakers to make informed decisions about infrastructure development and incentives, ultimately accelerating the transition to a more sustainable and electrified transportation system. Therefore, load modeling of Evs is a vital tool that facilitates the seamless integration of Evs into the grid, reduces emissions, and enhances energy security [8].

1.2. Literature Review

The existing studies on EV load modeling can be divided into two main groups. The first group deals with the estimation of EV load with a focus on accuracy. For example, a systematic methodology to predict additional loads resulting from EV charging in the mid-and-long term is developed in [9]. The methodology includes probabilistic models for EV charging profiles and forecast models for future EV ownership. A comprehensive methodology for EV load forecasting at charging stations is proposed in [10], incorporating traffic flow using a deep-learning-based model. A stochastic model is used in [11] to determine the load of fast charging stations in a residential apartment complex. An EV charging load prediction approach is proposed in [12] considering vehicle types, EV ownership estimation, and the Monte Carlo algorithm to model travel and charging characteristics. Finally, an experimentally validated artificial neural network classifier is used in [13] for accurately estimating the state of health of lithium-ion batteries in Evs under varying load conditions.

The second group deals with the analysis of EV loads on the existing power systems. Various cases are analyzed in [14] and concluded that proper management of EV charging is a key consideration to mitigating negative impacts on electric power systems and maximizing the potential benefits they can offer. Similarly, the impact of Evs on a residential power network is analyzed in [15] and Vehicle-to-Grid (V2G) mode is suggested for adjusting grid load based on the uncertain number of Evs. Similarly, the role of Evs and their impact on the grid during major power outages is discussed in [3]. Region-specific analyses are also conducted in the literature. For example, a stochastic model that incorporates social attributes (e.g., age, location, weekday/weekend) and travel data to accurately quantify the impact of Evs on China's electricity load profiles is developed in [16]. A high-resolution (1-min) aggregate mobility model is developed in [17] considering differences in patterns due to weather and socio-economic factors in Europe. The impact of electrifying the Scandinavian and German road transportation sectors on electricity generation capacity investments up to 2050 is analyzed in [18]. The impact of implementing fast charging stations for Evs in the power distribution system of a Latin American is studied in [19], considering social, geographic, and technical aspects.

1.3. Research Gap and Major Contributions

The literature review underscores the inherent need for location-specific studies when estimating EV load profiles and assessing their impact on power networks. This necessity arises from the distinct variations in regional power infrastructures, load patterns, driving behaviors, operational principles, and localized policies. Consequently, conducting region or country-specific analyses becomes imperative to gauge the readiness of existing power systems for the integration of Evs. Local surveys emerge as invaluable tools in this regard, enabling an in-depth examination of local driving patterns, the feasibility of adopting electric transportation, and the projection of EV market shares within specific regions. Such granular insights empower policymakers and grid operators to proactively anticipate the influence of Evs and strategize grid management accordingly.

Furthermore, prior research into estimating EV loads has exhibited a wide array of modeling approaches, datasets, and levels of complexity. This variability presents challenges in terms of replicating and validating results, as well as making meaningful comparisons between different methodologies. Notably, the intricacies involved in estimating EV load profiles stem from multifaceted factors, including consumer preferences, diverse EV product offerings, evolving social dynamics, and the impact of evolving policy landscapes. To address these complexities effectively, it is imperative to harness locally diverse datasets that accurately represent the unique characteristics of each region. Additionally, the incorporation of comprehensive methods capable of capturing uncertainties and stochastic processes is essential for producing robust and reliable EV load estimations. In essence, the thorough consideration of these multifaceted elements is pivotal in advancing understanding of EV load modeling and optimizing grid management for a sustainable EV future.

In an effort to provide valuable insights for researchers and policymakers, particularly in the Middle East with a focus on Saudi Arabia, this study takes a proactive approach by conducting a real survey. The survey data of five major cities are used to extract crucial driving patterns and commuting behaviors exhibited by vehicle drivers. This empirical data, in conjunction with information pertaining to Evs, are employed to accurately estimate the daily energy consumption of these Evs. The EV data are sourced from commercially available EV models up to the present date. The major contributions of this study are as follows:

- This study estimates the EV load profiles in Saudi Arabia based on real survey data conducted in five different regions. Additionally, data from all commercially available EV models (up to the current date) are incorporated into this study.
- Customized per-unit profiles for both residential and workplace charging are estimated to address the charging preferences of the majority of EV owners. This tailored approach ensures that load estimations closely align with actual EV charging behaviors, which is crucial for effective grid management.
- An analysis of diverse building types, including purely residential, purely commercial, and mixed residential/commercial structures, is conducted. These analyses empower policymakers to manage peak EV charging loads effectively under various levels of EV penetration.

This study and its analysis empower policymakers to effectively manage peak EV charging loads under various levels of EV penetration. By aligning policy initiatives with the data-driven findings, this study offers a strategic framework to enhance grid stability, optimize charging infrastructure, and promote sustainable EV adoption in the region.

The remainder of the paper is organized as follows: The Introduction section is followed by driving behavior analysis (Section 2), where various parameters related to vehicle drivers, such as daily arrival and departure times, daily mileage, and parking durations, are extracted from real survey data in Saudi Arabia. It is followed by Section 3, where parameters of Evs, such as usable battery size and energy efficiency are extracted from a database of commercially available Evs. Then, daily energy consumption of Evs is computed. Based on the parameters of previous sections, per-unit profiles of Evs for homes and workplaces are estimated in Section 4. These per-unit profiles are used to simulate various cases, including different locations and types of charging stations, in Section 5. Finally, conclusions, limitations, and future research directions are presented in Section 6.

2. Driving Behavior Analysis

To enable the estimation of the energy demand of Evs for diverse applications, it is essential to gather and analyze two distinct types of data. The first category revolves around the behavioral patterns of vehicle drivers, offering valuable insights into their usage patterns [20]. This encompasses crucial information such as the daily mileage covered by the vehicles, providing a glimpse into the distance they travel regularly. Additionally, the data also capture the arrival and departure timings of the vehicles at their respective home and workplace locations, shedding light on their commuting routines. Furthermore, the duration of their stay at home and workplace is a significant aspect, aiding in understanding the periods when the vehicles might be available for other services.

The step-by-step procedure for survey data processing and estimation of per-unit profiles is shown in Figure 1. The survey data processing is discussed in this section while the per-unit profile estimation is discussed in the subsequent section. The first step is to process the raw survey data. The survey questionnaire consisted of 11 questions covering various aspects related to Evs, details about the survey can be found in [6]. Participants were asked to provide their age, area of residence, and the number of vehicles they had at home. Additionally, the questionnaire sought to gauge their daily traveling mileage and the specific details of each trip, including the origin and destination points.

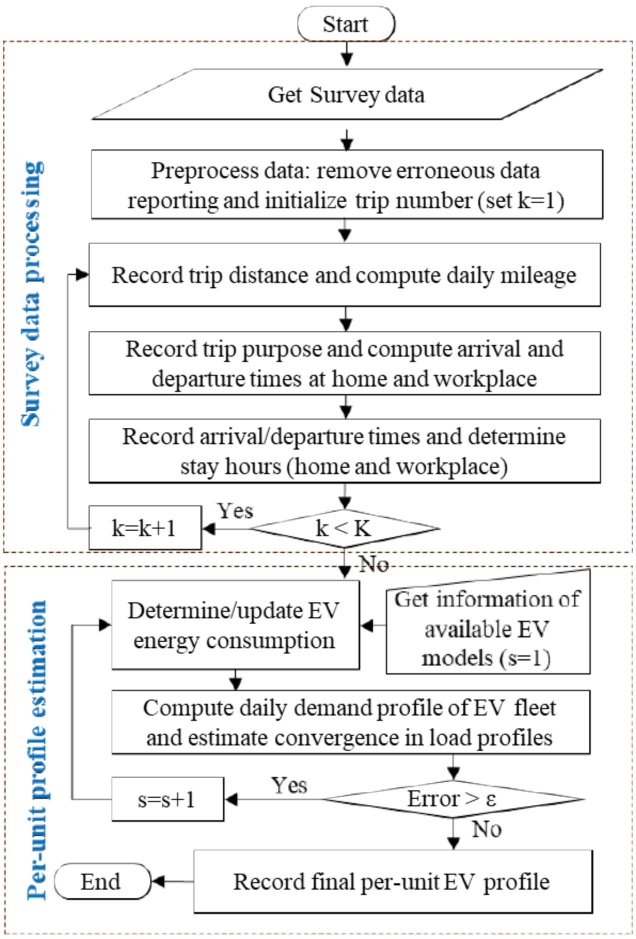

Figure 1. An overview of survey data processing and per-unit profile estimation.

Incorporating participants from five distinct cities across Saudi Arabia, this study sought to encompass a wider spectrum of EV driving behaviors and accommodate regional disparities. It is essential to interpret our findings within the confines of the selected cities, acknowledging that although our sample size may not comprehensively represent all EV driving patterns throughout Saudi Arabia, it nonetheless offers valuable insights into the subject matter.

Another important aspect inquired about was their preference for the location of charging facilities, among other relevant topics related to EV usage and preferences. Most of the users have identified home or workplace as their first choice for charging their Evs [21]. Therefore, data related to these two locations (home and workplace) are analyzed in detail in this paper.

During survey data processing, the first step is to filter out any erroneous data. For example, removal of trips with missing mileage or duration, selecting specific driving modes, elimination of unidentified vehicle IDs, and filtering out trips without origin/destination or day details. Unrealistic speeds are also removed. This ensures a refined and reliable dataset for further analysis. The filtered data are then used to estimate the arrival/departure times at home and workplaces, daily mileages, and parking durations (home and workplace), which are discussed in the following sections.

2.1. Arrival and Departure Times

The pre-processed data are used to extract the arrival and departure times of vehicles at home and workplace. Data on the origin of the first trip reported as the home are filtered first to estimate the home departure time. Similarly, data with the last trip with the destination as home are filtered to estimate the home arrival time. The histogram of data is computed, and probability density functions (PDFs) are estimated. The PDFs are then used to estimate the cumulative density functions (CDFs). An overview of the PDFs and CDFs for home is shown in Figure 2. The same process is repeated for the workplace by filtering data with the origin/destination as the workplace. The obtained results of PDFs and CDFs for the workplace are shown in Figure 3.

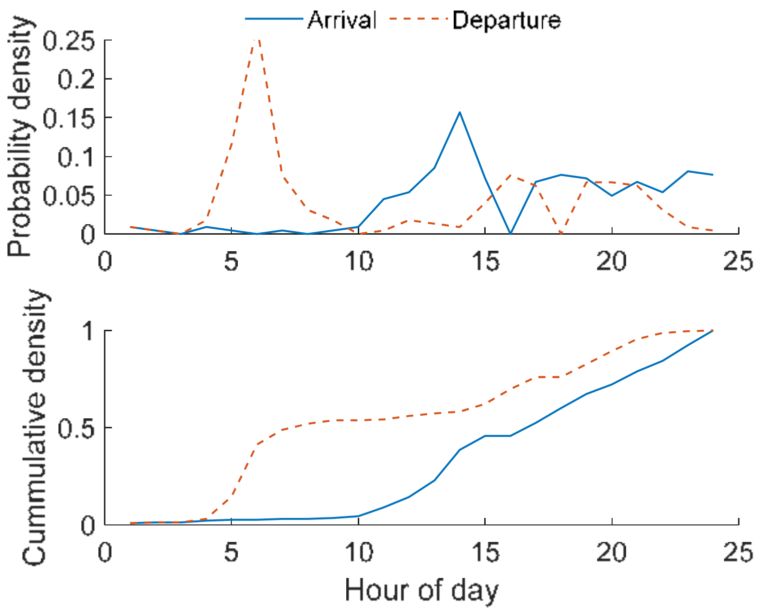

Figure 2. Daily arrival and departure time PDFs and CDFs for home.

Sharp peaks can be observed for workplace arrival and departure, as expected. However, the home arrival PDF shows a scattered distribution with few peaks. This is due to the different working natures of different participants (full-time and part-time). In addition, this scattered distribution is also due to other trips after work such as a visit to groceries, petrol pump, gym, etc.

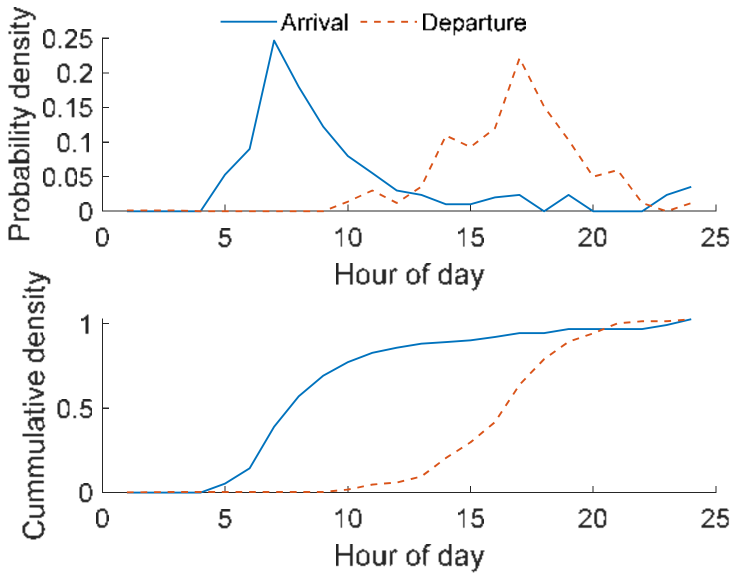

Figure 3. Daily arrival and departure time PDFs and CDFs for workplace.

2.2. Daily Mileage Estimation

The pre-processed data are again used to track the trips of each vehicle during the day. Each vehicle ID is tracked, and the total number of trips completed by each vehicle and the mileage of each trip is recorded to estimate the daily mileage. An overview of the obtained results is shown in Figure 4.

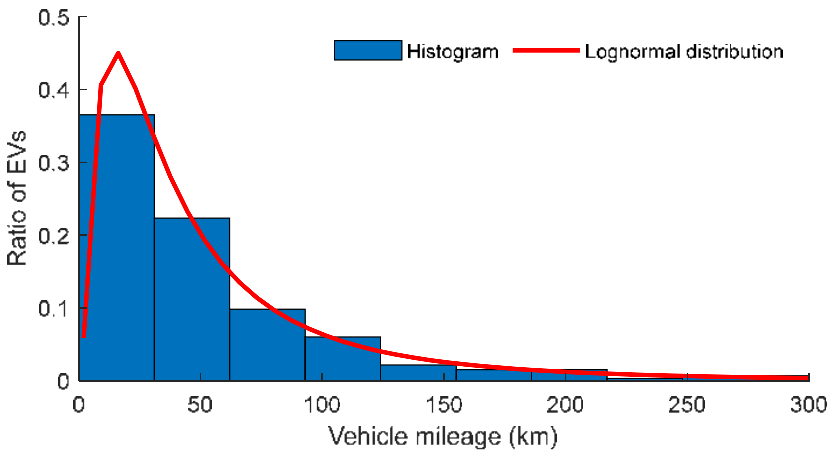

Figure 4. Daily mileage of vehicles.

It can be observed that most vehicles travel under 50 km a day and a very minute number of vehicles travel more than 150 km a day. The daily mileage of vehicles is approximated with a lognormal distribution, and it precisely captures the distribution of daily mileage of vehicles. It is consistent with other studies reported in the literature [22,23].

2.3. Parking Duration Estimation

Finally, the arrival and departure information of the vehicles is used to estimate the parking duration of vehicles at home and workplace. Details about the computation of parking duration for home and workplace can be found in [22]. An overview of the obtained results for the home and workplace is shown in Figure 5.

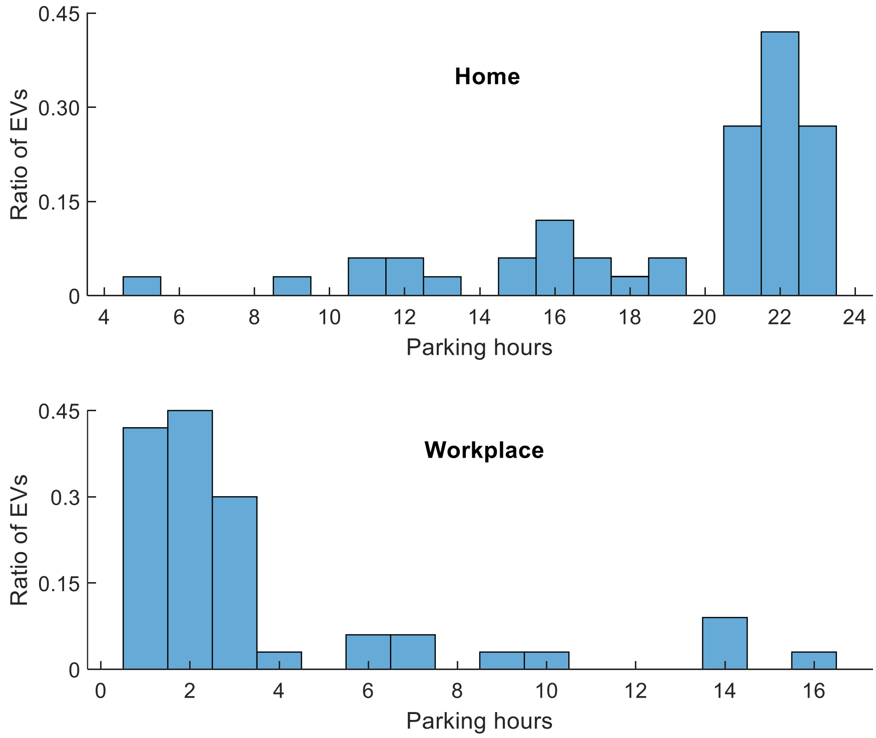

Figure 5. Parking duration of veicles at home and workplace.

It can be observed that the parking duration of the home is concentrated in two clusters, the first one with an average of 16 h and the second one with more than 20 h. This is expected since the stay duration of vehicles at home is higher and usually more than 12 h (night hours) [24]. A very minute number of vehicles have a stay duration less than 10 h. Contrarily, the parking duration of vehicles at the workplace is much lower and no vehicle has a stay duration of more than 16 h, as expected. The lower parking duration clusters at workplace might be due to part-time workers and workers with frequent office trips.

3. EV Parameter Extraction

The second step is to extract the EV parameters from the database of commercially available Evs [25]. The database includes details about various electric vehicle models, their specifications, performance metrics, charging capabilities, battery information, range, pricing, and more. This database serves as a comprehensive resource for individuals, researchers, businesses, and policymakers interested in understanding and comparing different electric vehicles available in the market. It can help consumers make informed choices when purchasing an electric vehicle and provide insights into the advancements and trends within the EV industry. The parameters of interest for this study are usable battery size and mileage efficiency [26], which are discussed in the following sections.

3.1. Battery Size and Energy Efficiency

The usable battery size is the capacity of the battery pack that can be utilized for driving before the battery's state of charge (SOC) drops to a level where performance and longevity might be compromised. EV manufacturers often design their battery packs with a buffer of energy that is not fully accessible to extend the battery's lifespan. This buffer also prevents the battery from being frequently charged to 100% or discharged to 0%, as these extremes can degrade the battery over time [27]. As battery technology advances, the usable capacity of EV batteries has been increasing, leading to improved range and efficiency. Similarly, energy efficiency in electric vehicles is typically measured in watt-hours per kilometer (Wh/km) and serves as a metric to understand how efficiently an EV uses its battery energy to travel a certain distance. This measure is equivalent to the energy required to drive the vehicle for one kilometer.

An overview of usable battery size and mileage efficiency of different EV models available in the database [25] is shown in Figure 6. Both battery size and energy efficiency are approximated with normal distributions, and both seem to follow normal distribution functions. As of August 2023, the typical usable battery capacity for electric vehicles (Evs) stands at approximately 58.4 kilowatt-hours (kWh). Moreover, the average energy consumption of these Evs is recorded at around 195 Wh/km.

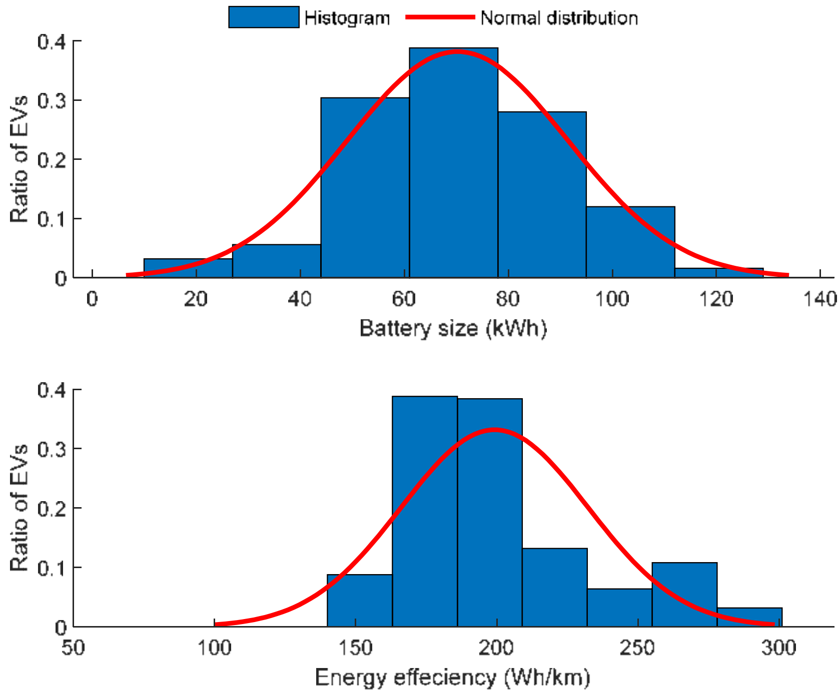

Figure 6. Parameters of commercially available Evs.

3.2. Energy Consumption

The energy consumption of Evs plays a pivotal role in shaping their practicality and sustainability [28]. This metric refers to the amount of electrical energy required to propel an EV over a certain distance. A key factor influencing energy consumption is the daily mileage of the vehicle, as it directly correlates with the frequency of charging. Higher daily mileage would require more energy, while lower daily distances result in reduced energy needs. Mileage efficiency, measured in watt-hours per kilometer (Wh/km), gauges how efficiently the vehicle utilizes its battery energy to cover a specific distance. The initial SOC of the battery before a trip also impacts energy consumption. Starting with a full battery provides the vehicle with more available energy, potentially yielding better efficiency.

In this study also, these factors are utilized to estimate the daily energy consumption of Evs. An EV fleet is formed by allocating different parameters such as daily mileage, initial SOC, and mileage efficiency. The daily mileage of the vehicles extracted from the survey data is utilized while the mileage efficiency of commercially available Evs is randomly allocated to different Evs. It is assumed that battery SOC decreases linearly as a function of traveled distance, similar to [29]. The daily energy consumption of vehicle v (E_v) is given by

$$E_v = (M_v) \cdot \frac{E_v^{pkm}}{1000}, \tag{1}$$

where M_v is the daily mileage of the vehicle and E_v^{pkm} is energy efficiency of the vehicle in Wh/km. An overview of the daily energy consumption of Evs is shown in Figure 7. It can be observed that the daily energy consumption of most of the Evs is lower than 20 kWh.

This is in accordance with the daily mileage (under 100 km for most of the vehicles) and average energy efficiency of Evs (195 Wh/km). The daily energy consumption is also approximated with a lognormal distribution similar to the daily mileage. This correlation stems from the complex interplay of various factors influencing both aspects. A lognormal distribution suggests that while there's an average or typical energy consumption value, there is also variability around this average due to factors like driving conditions, terrain, climate, and individual driving habits.

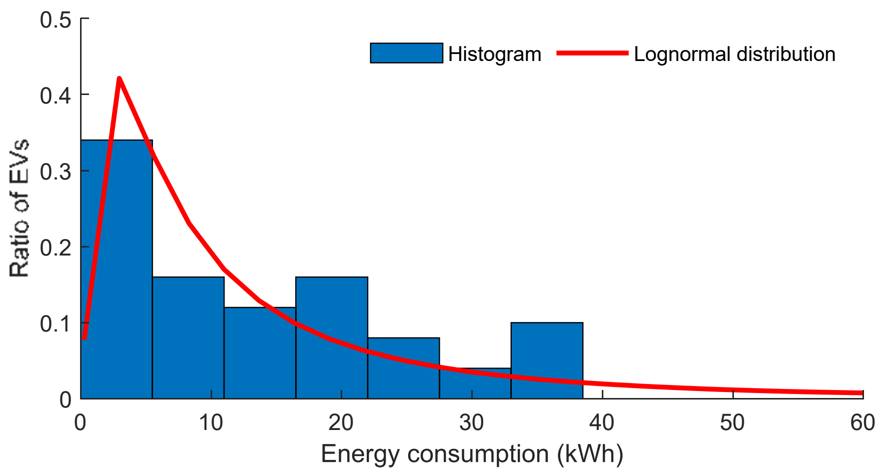

Figure 7. Daily energy consumption of Evs.

4. Per-Unit Profiles

The primary dataset used for assessing the EV load in this study originates from real survey data collected in Saudi Arabia. This dataset encompasses information gathered from households and vehicles within the region, offering valuable insights into the driving behaviors and patterns of different vehicle owners. To ensure the reliability of the data, a meticulous pre-processing procedure is conducted. This involves the removal of incomplete or duplicated records, as well as the focus on specific vehicle categories to maintain data accuracy.

After the data refinement process, the dataset is streamlined to encompass approximately 5000 trip samples, which are deemed suitable for in-depth analysis. The study further considers two prevalent charging levels employed in residential settings [30]: level 1 charging (120 V, 12 A, 1.44 kW) and level 2 charging (240 V, 30 A, 7.2 kW). These charging levels hold significance in evaluating the potential impact of EV charging on the local electric grid infrastructure. By integrating this contextual information, the study aims to present a comprehensive and simulation-driven analysis of EV load patterns in workplaces and homes. This information can be used by grid managers and policymakers to plan future grid operations and incentivize EV charging infrastructure in the future for the region of Saudi Arabia.

4.1. EV Load Profile Estimation

The data utilized for determining the EV load are categorized into two types: data pertaining to EV driver behavior, and data related to the Evs themselves. Within the domain of EV driver behavior, the probability density functions (PDFs) of arrival time, departure time, and daily mileage play a crucial role. On the other hand, data linked to the Evs include information concerning battery capacity, battery efficiency, SOC operating range, and driving range. Additionally, the study considers data on the market share of Evs and the charging level distribution among charging stations.

The study draws information from the current market availability of Evs at a commercial level [25]. Due to the complexity of analyzing individual Evs, the study focuses on broader clusters of Evs. This approach is supported by the observation that numerous Evs share similar attributes, such as battery size and energy required to cover a unit distance (mileage per km), as depicted in Figure 6. The analysis of this data leads to the identification of four distinct clusters utilizing the K-means clustering algorithm. This algorithm efficiently groups Evs with similar features, ensuring a representative categorization without losing the overall generality of the dataset. Details about the clustering process can be found in [31].

Upon acquiring input data concerning EV owners and information about the Evs themselves, the study determines load profiles for individual Evs (P_t^v), which is then used to compute the load of the EV fleet (P_t^{fleet}) as given below.

$$P_t^{fleet} = \sum_{v \in NV} P_t^v \tag{2}$$

Upon arrival, the SOC of v^{th} EV (SoC^v) is determined using Equation (3). Where (R^v) is the range of v^{th} vehicle and (M^v) is the daily miles driven by each PEV.

$$SoC^v = \left(\frac{R^v - M^v}{M^v} \right) \cdot 100 \tag{3}$$

If the SOC is within the defined bounds, the required charging energy (E^v) and charging duration (D^v) of PEV is determined using Equations (4) and (5), respectively. Initially, the required energy is computed using (4) and then based on the required energy, the number of intervals required for charging (D^v) that energy is computed using (5).

$$E^v = (SoC^{\max} - SoC^v) \cdot B^{cap} \tag{4}$$

$$D^v = \frac{E^v}{\eta^v \cdot L^{ch}} \tag{5}$$

In Equation (3), B^{cap} is the capacity of the EV battery in kWh and $SoC^{\max}$ is the maximum SOC of the EV. In Equation (5), η^v is the efficiency of the EV battery and L^{ch} is the charging level of the charging station.

An iterative process is carried out for every scenario (s), with the convergence of the load profile evaluated based on the historical EV profiles up to scenario s. If introducing a new scenario does not result in significant changes to the estimated profile (where the error is lower than a predefined threshold, ε), the process concludes, yielding the final load profile for each individual EV. Conversely, if the inclusion of a new scenario leads to substantial profile changes, the process repeats by incorporating the new scenario. This iterative methodology allows the study to methodically assess and determine load profiles while considering various scenarios and convergence criteria. By iteratively refining the load profiles based on changing scenarios, the study aims to achieve accurate representations of the PEV fleet's electricity demand patterns.

4.2. Per-Unit Load Profile Estimation

The load profiles for the four EV clusters under different charging levels (L1 and L2) are estimated for both home and workplace [32]. It should be noted that the term 'per-unit' refers to per EV in this study. The profiles provide an overview of the temporal distribution of charging load for a single EV across different hours of the day. The An overview of results for the home is shown in Figure 8 and for the workplace in Figure 9. It can be observed that the peak for homes is around 18h and that of the workplace is around 11 h. This is expected since most of the EV owners arrive home in the evening and at the workplace during the morning. The results also show that L2 results in higher peaks for both home and workplace, as expected. This is due to the higher power rating of L2 chargers.

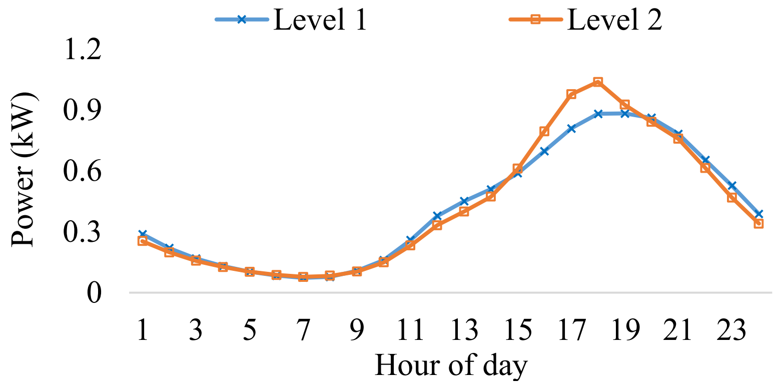

Figure 8. Per-unit load profiles for home.

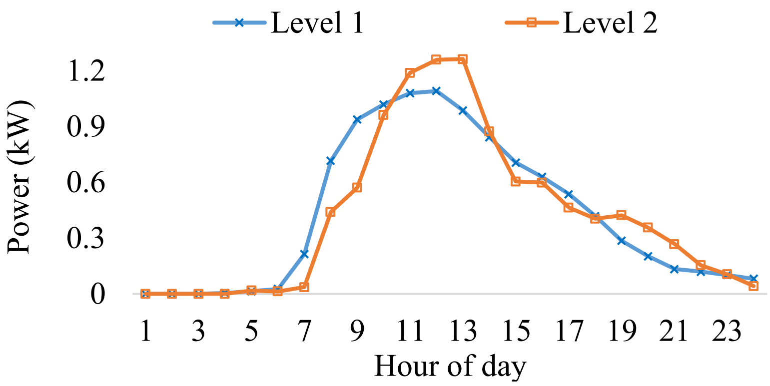

Figure 9. Per-unit load profiles for workplace.

The profiles can be used by policymakers and grid operators for estimating EV load considering different scenarios. These scenarios could include different ratios of charger types (L1 and L2), different types of buildings (residential, commercial, and mixed), and a combination of both. It is expected that most of the EV owners will either charge their Evs at home or their workplace. In addition, most homes and workplaces have L1 or L2 chargers. Therefore, the estimation of per-unit profiles for these two locations considering different charging levels will provide the necessary information for the researcher, policymakers, and grid operators. Some analyses are conducted in the following section to provide an overview of the usage and importance of these per-unit profiles.

5. Analysis and Applications of Per-Unit Profiles

The per-unit profiles hold great potential for accurately estimating loads of diverse EV fleets in various scenarios. By employing per-unit load profiles that reflect the charging behaviors of individual Evs, it becomes feasible to project the aggregated demand on the electric grid for different charging station types and building categories. These load profiles can be particularly valuable when assessing the impact of Evs on the grid within different contexts. For instance, considering different types of charging stations like Level 1 and Level 2 allows us to gauge the varying power requirements and load dynamics based on charging speeds. Furthermore, when analyzing different building types, including purely residential, purely commercial, and mixed-use, the per-unit load profiles enable a detailed understanding of how EV charging interacts with existing energy consumption patterns in each context.

The primary focus of this study Is on residential buildings and workplaces where level 1 and level 2 charging stations are generally used. Therefore, only level 1 and level 2 charging stations are considered in this study. However, the proposed method can be used for fast charging stations as well. In this study, buildings are categorized based on their primary purpose of usage. For example, a residential building is primarily used for living purposes, such as homes, apartments, condominiums, and dormitories. Similarly, commercial buildings are designed primarily for non-residential purposes, such as offices, retail stores, factories, and warehouses. Finally, some buildings may have mixed usage; for example, some portions of the building are used for commercial purposes and some for residential purposes. Examples of mixed-use buildings include apartments, where residential units are on upper floors with retail shops or restaurants on the ground floor. The focus of this study is on shared parking locations, as vehicle arrival and departure times, along with parking hours, are mainly influenced by the community behavior of the residents.

5.1. Charging Station Location-Based Analysis

In this section, the developed per-unit load profiles are used to estimate the load for different types of buildings. Four scenarios are considered in this section and the weightage of each charging station type for each scenario is listed in Table 1. For example, the *100% Each* scenario refers to purely residential and purely commercial buildings. Similarly, the *Workplace Dominant* scenario refers to buildings with more commercial portion than residential; this case simulated 70% commercial and 30% residential situations. The *Home Dominant* scenario is opposite of the *Workplace Dominant* where 70% of the space is for residential and 30% for workplaces. Finally, the *50% Each* scenario refers to buildings with 50% of both types (commercial and residential). The focus of this study is on shared parking locations, as vehicle arrival and departure times, along with parking duration, are primarily influenced by the community behavior of the residents. It should be noted that percentages here refer to the portion of vehicles in each area/building parking space related to different sectors, such as residential and commercial.

Table 1. Weightage of different charging station location for each scenario.

Scenario Name	HL1	HL2	WL1	WL2
100% Each	1	1	1	1
Workplace Dominant	0.7	0.7	0.3	0.3
Home Dominant	0.3	0.3	0.7	0.7
50% Each	0.5	0.5	0.5	0.5

An EV fleet size of 100 Evs is considered for the analysis in this section. An overview of the obtained results is shown in Figure 10. For the sake of visualization, the scale of all figures is kept the same in Figure 10. It can be observed that the peak load is the highest for the *100% Each* scenario. This is expected as all Evs will arrive during the same period and start charging. The highest peak was observed for workplace L2 with a value of 126 kW. Contrarily, the lowest peak was observed for the *50% Each* scenario for *Workplace* L2 with a peak value of 63 kW. The other two scenarios had intermediate peak values. It can also be observed that with the same penetration ratio, the peak load of WL2 is higher compared to the HL2. This is due to the arrival of most of the workers during the same time at the workplace as compared to home. The home arrival time is spread across intervals, as discussed in Section 2.

This analysis shows that purely residential or commercial buildings result in higher peak loads while mixed buildings have lower peak loads with the same EV fleet size. In particular, the lowest peak load was observed when the ratio of commercial to residential usage is around 50%. It is also interesting to note that the power consumption (other than Evs) of these buildings will also follow a similar trend. More energy will be consumed as more people start arriving at home or the workplace.

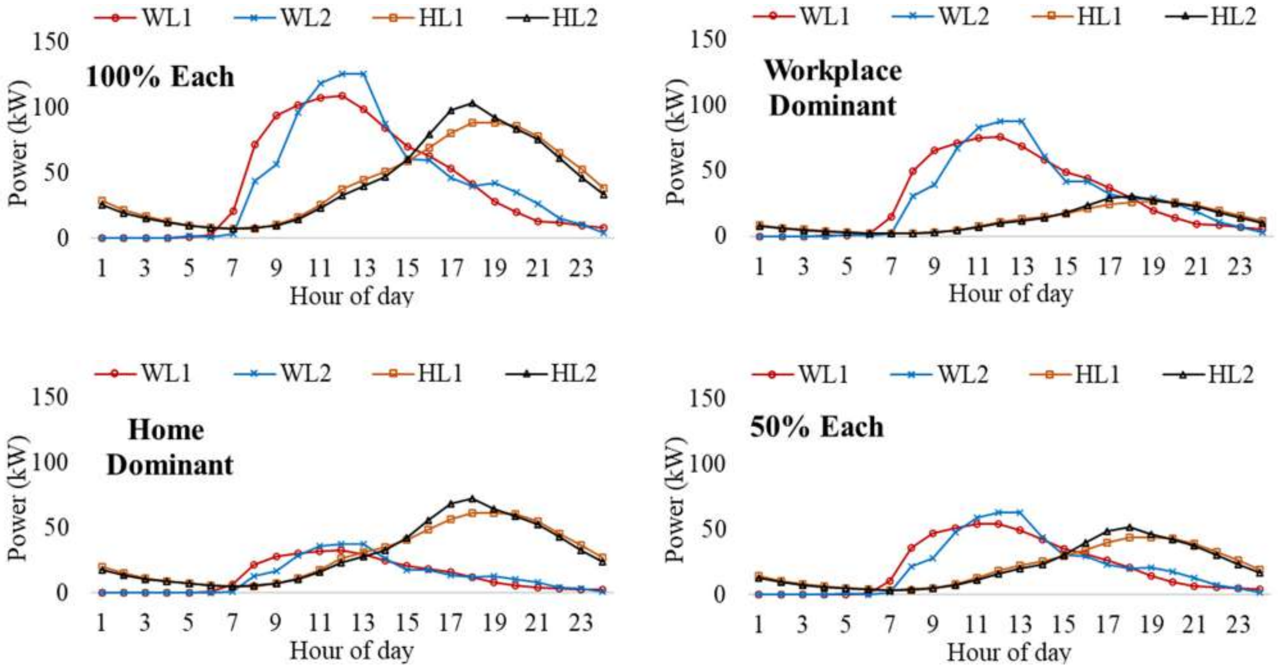

Figure 10. Load profiles of 100 EVs under different location of charging sattions.

5.2. Charging Station Type-Based Analysis

In this section, the estimated per-unit profiles are used to estimate the impact of charging station types (L1 and L2). Four scenarios are simulated by varying the ratio of each charger type. An overview of the weights for each scenario is shown in Table 2. For example, in the case of the *Home* scenario, only home-based charging stations are considered, such as HL1 and HL2. Similarly, for the *Workplace* scenario, only work-based charging stations are considered, i.e., WL1 and WL2. In the case of the *Home Dominant* scenario, 70% of home-based chargers and 30% of work-based chargers are considered. Finally, for the *Workplace Dominant* scenario, 70% of work-based chargers and 30% of home-based chargers are considered.

Table 2. Weightage of different charging station types for each scenario.

Scenario Name	HL1	HL2	WL1	WL2
Home	1	1	0	0
Workplace	0	0	1	1
Home Dominant	0.7	0.7	0.3	0.3
Workplace Dominant	0.3	0.3	0.7	0.7

In each scenario, the ratio of L1 chargers varies between 0% and 100%, and four cases are simulated for a fleet size of 100 Evs. The 0% case refers to all L2 chargers and the 100% case refers to all L1 chargers. The obtained results for all the scenarios are shown in Figure 11. It can be observed that the peak load decreases as we move from case 1 (0%) to case 4 (100%). This is because the peak load of L2 chargers is higher compared with L1 chargers, as discussed in the previous section. The highest peak load was observed for the *Workplace* scenario for 0% of cases with a value of 126 kW. This scenario refers to 100% L2 chargers. The lowest peak was for the *Home Dominant* scenario for 100% case with a value of 74 kW. The other two cases have intermediate peak values.

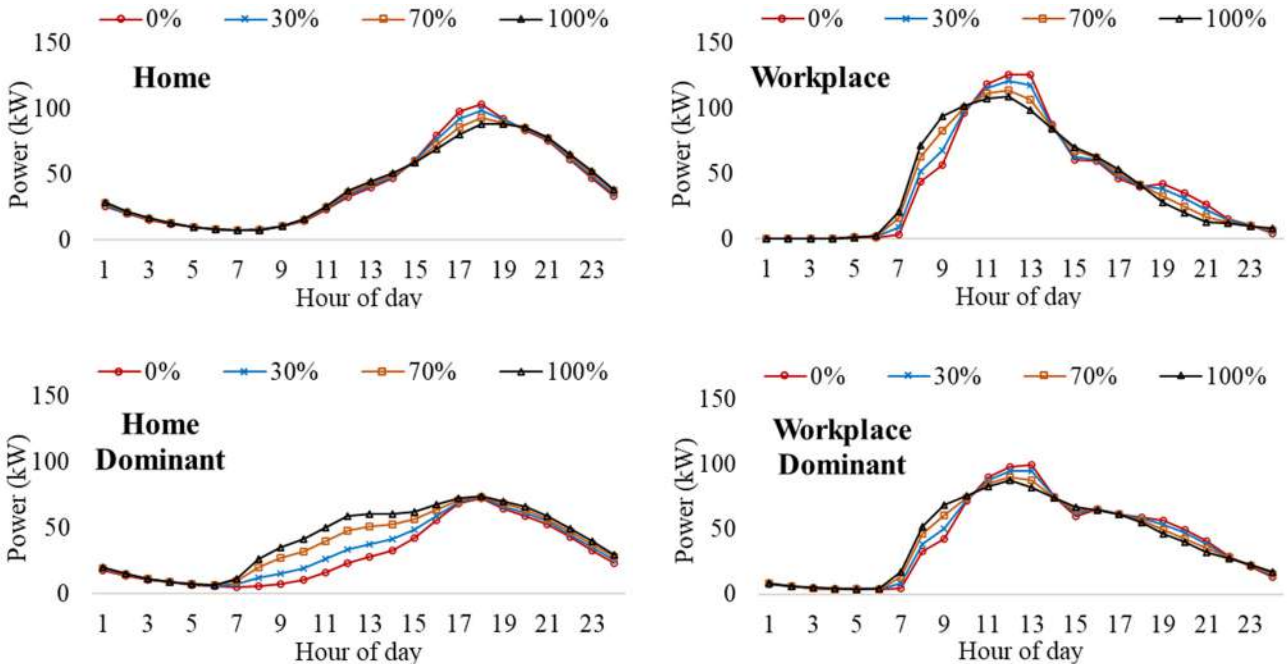

Figure 11. Load profiles of 100 EVs under different charging station types.

It can also be observed from this analysis that the *Home Dominant* scenario has a much flatter curve as compared to the other three cases. It implies that for mixed buildings, all L1 chargers can result in lower peak loads as compared to all L2 or mixed L1 and L2 portfolios. It can be concluded that this investigation sheds light on the direct correlation between charger types and peak loads across diverse scenarios. The findings underscore the importance of selecting appropriate charger configurations based on the charging needs and settings, contributing to effective grid management and optimized EV integration within different charging contexts.

6. Conclusions

In this study, per-unit profiles are estimated for homes and workplaces based on real survey data in Saudi Arabia. The provided profiles hold significant value for policymakers and grid operators, offering essential insights into estimating electric vehicle loads under various scenarios. These scenarios encompass a spectrum of considerations, such as different charger type ratios (L1 and L2), building types (residential, commercial, mixed), and combinations thereof. The profiles are then used to estimate the load of the electric vehicle fleet under different settings. It underscores that purely residential or commercial buildings yield higher peak loads, whereas mixed-use buildings exhibit lower peak loads, even with the same fleet size. Notably, the ratio of commercial to residential usage of around 50% generates the lowest peak load, indicating an optimal balance. Furthermore, this trend extends to power consumption beyond EVs; as more individuals return home or to the workplace, energy consumption also follows a similar pattern. An intriguing observation emerges from this analysis: the *Home Dominant* scenario exhibits a notably flatter curve compared to the other cases. This insight implies that in mixed buildings, employing L1 chargers can result in diminished peak loads. This realization underscores the nuanced influence of charger types on peak loads, and its implications extend to effective grid management and enhanced EV integration in diverse charging environments. Ultimately, this investigation underscores the importance of considering appropriate charger configurations tailored to specific charging contexts, thereby contributing to optimized grid operation and seamless EV integration.

This study relies on survey data collected from five different regions/cities in Saudi Arabia, which offer valuable insights. However, it is important to keep in mind that, like any dataset, they have certain limitations and potential biases. These aspects, while worth acknowledging, can be opportunities for refinement and further investigation, ensuring that our understanding of EV usage in the region continues to grow and evolve. It is important to interpret the findings within the specific context of these cities that were part of the study.

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