Electric Vehicle as a Mobile Energy Storage: Market Analysis and Grid Integration Challenges

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***Abstract*—The UK is on an ambitious journey towards net-zero emissions by 2050, with the transportation sector contributing 29 percent of GHG emissions. This paper provides an overview of the current state of Battery Electric Vehicles (BEVs/EVs) on UK roads, focusing on the statistical distribution of battery capacity, price, efficiency, and Vehicle-to-Everything (V2X) compatibility. The study analyses the potential of EVs, particularly V2X-compatible ones, to enhance grid stability and facilitate the integration of renewable energy sources.It projects EV growth by 2035 using historical trends and UK government targets. An EV mobility model was created using national travel data to simulate daily EV usage profiles in the UK transport sector. The study highlights the importance of strategic EV integration for achieving a flexible, sustainable, and reliable energy system.**

***Index Terms*—Battery Electric Vehicles (EVs), Electrification, EV as a Mobile Storage (EVaaMS), Grid Integration, Vehicle-to-Grid (V2G)**

I. Introduction

Electric Vehicles (EVs) have received significant support from governments worldwide as part of efforts to meet net-zero targets and advance sustainable development goals. In June 2019, the UK Parliament went beyond its previous commitment to an 80% reduction in greenhouse gas (GHG) emissions from 1990 levels by enacting legislation to achieve net-zero carbon by 2050 [1]. This ambitious goal is particularly critical in the context of the domestic transport sector, which is responsible for 29% of the country's total GHG emissions [2]. Among various modes of transportation, cars and vans contribute the largest share, accounting for 57% of the sector's emissions. Notably, cars make up more than 80% of the total number of registered vehicles in the UK [3]. This underscores the importance of electrifying the car fleet as a central strategy to meet the UK's net-zero targets and combat climate change.

The National Energy System Operator (NESO) estimated that 37.4 million EV would be on the roads by 2050 [4]. Concerns have arisen regarding the widespread uptake of EVs and the subsequent increase in demand, as the capacity of the distribution network and power generation may struggle to cope with the rise in charging demand; between 2022 and 2023, electricity demand from EVs in the European Union tripled, while global demand doubled, reaching a total of 97 TWh [5]. Considering millions of EVs will enter the market in the coming years to achieve net-zero targets, the EV market should be analysed to determine how parameters such as battery capacity, range, efficiency, and driving and charging patterns can be integrated into the electricity market and power grid to utilise Low Carbon Technologies (LCTs). In [6], a review of various mathematical models for EV adoption is presented, highlighting the lack of a specific model that accounts for the mobile nature of EVs. With the introduction of bidirectional chargers and Vehicle-to-Grid (V2G) compatible EVs, it is expected that EV as a Mobile Storage (EVaaMS) will pave the way for the participation of EVs in the energy and flexibility markets as emerging mobile prosumers through V2G, helping the power grid reduce peak loads while also providing financial benefits to owners to support electrification and decarbonisation [7].

Given that mass integration of BEVs is still in its early stages, the existing dataset is either inadequate or fails to sufficiently represent EV mobility at scale. Moreover, distribution network operators (DNOs), aggregators, and policymakers require clear insights into how these mobile storage resources travel and connect to the grid to support smooth market integration. To resolve this 'chicken-and-egg' issue, leveraging data from National Travel Surveys (NTS) [8] can serve as a cost-effective approach to modelling vehicle behaviour from a top-down perspective enabling the evaluation of the potential for mass EV adoption before they become prevalent. In addition, it enables the simulation of their integration into the power system, thereby providing valuable insights ahead of their widespread adoption. The contributions of this paper are as follows:

- Presents a novel EV mobility model that integrates available public datasets, results from NTS and national vehicle statistics to simulate different parameters of EVs available in the UK market, focusing on BEVs.
- Based on the developed mobility model, the market composition of BEVs in the UK market is analysed
- The correlation between different BEV parameters is presented
- The availability of V2G-enabled EVs in the market and their potential for grid integration are assessed
- Future projections of BEVs analysed

II. EVIF: EV Integration Framework

The majority of research on the integration of EVs can be classified into two primary groups. The first focuses on modelling the electrical attributes of EVs, while the second looks into the behaviour of EV owners. However, relatively few studies consider both aspects simultaneously. For example, in [9], the calculation of EV fleet flexibility incorporates influencing factors such as mobility patterns and plug-in behaviour. Similarly, [10] separates EV charging and movement dynamics to develop an EV agent model. The tools used in Papers [11] and [12] were based on the German household travel survey (MiD), but there is no similar tool available for UK NTS data. We introduce the EVIF concept to address the potential flexibility enabled by V2X for the large-scale integration of EVaaMS. This framework was developed to fill the research gap, as no prior studies have specifically designed an EVIF for large-scale EV integration while considering driver behaviour.

A. EVIF Definition

As illustrated in Fig. 1, the integration of EVaaMS comprises two primary components:

- **EV Mobility Model (EVMM)**
- **EV Stationary Model (EVSM)**

The **EVMM** emphasises the attributes of EVs as a mobile object, which is divided into two distinct entities. The first entity covers ***EV parameters*** that include manufacturer-defined characteristics such as battery capacity, efficiency, and range, which collectively capture the mobility features of the EV. The second entity addresses the ***EV owner's driving style***, encompassing travel patterns and mileage. These aspects determine how EVs and their batteries are utilised during travel.

The **EVSM** focuses on the characteristics of EVs in the stationary state, e.g., when parked at a charging point, driveway, or parking lot, and explores how the EV owner interacts with the stationary vehicle, the charger, and the power grid. The ***EV owner's charging behaviour/habits*** include the EV's charging frequency and connection duration. Assuming the varying charging behaviours of EV users, the time when an EV is parked and available for grid services becomes critical. This time frame (T_{Parked}), as shown in Fig. 2, extends from the moment an EV arrives at a charging point to its departure. However, because several factors influence connection time, this duration is not guaranteed for providing flexibility

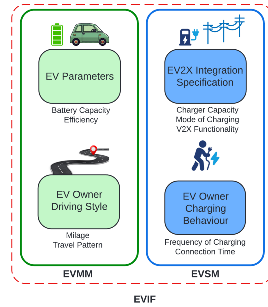


Fig. 1: EVIF, EVMM on the left and EVSM on the right.

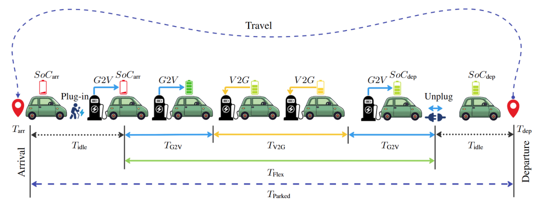


Fig. 2: EV flexibility period

services. These considerations include the idle time (T_{idle}) before connecting the EV to the charger, the availability of charging points, and the owner's decision to delay charging for a lower price. Even within the time frame when an EV is connected to the grid, the ability to interact with the grid, either in V2G or charging mode, depends on user needs, market conditions, grid requirements, and tariff structures. The last entity, ***EV2X Integration Specifications***, demonstrates the connectivity of EVs to the grid through chargers. For instance, charger capacity may constrain the EV's flexibility in terms of charging or discharging power. Additionally, V2X compatibility, the charging mode or EV Battery Management System (BMS) and the onboard charger may restrict charging rates and impede the realisation of V2X functionalities.

B. Public EV charging datasets

Table I of Appendix B lists several publicly available EV charging datasets. However, many of these datasets possess inherent limitations that make them insufficient to develop an EVMM. These datasets often contain the measurement results of pilot projects with a small number of vehicles with a specific make and manufacturer for EVs and chargers, which restricts their applicability. Most datasets lack mobility characteristic of EVs, such as mileage ($D_{n,i}$), usable battery capacity ($E_{\max,n}$) or trip schedule. Privacy concerns and General Data Protection Regulations (GDPR) also prevent the collection of a vehicle user ID ($\mathbf{ID}_{\text{n}}$) or Vehicle Identification Number (VIN), which is essential for the mobility model to illustrate the behaviour of individual EVs based on their battery capacity, range, and performance. Most public datasets are missing the state of charge (SoC), which is crucial for evaluating the flexibility they could provide to the market. Understanding the arrival/departure SoC ($SoC_{\text{arr},n,c}$/$SoC_{\text{dep},n,c}$), battery capacity ($E_{\max,n}$), and EV flexibility period ($T_{\text{Flex},n,c}$) can help model EVs' driving patterns and the available flexibility they can

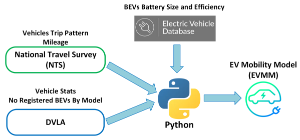


Fig. 3: Data collection and data sources

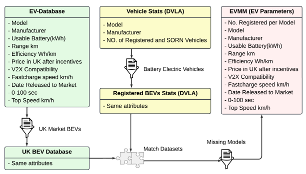


Fig. 4: EVMM (EV Parameters) Dataset Integration and Matching Process

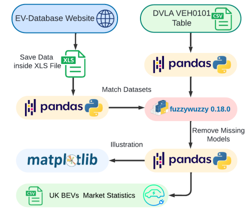


Fig. 5: UK BEV Dataset file structure

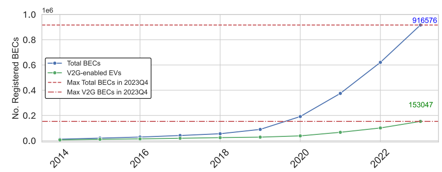


Fig. 6: Registered BEV in UK between 2014 and 2023

deliver to the network. Furthermore, some datasets, such [13], present aggregated load data from fleet chargers, making it impossible to accurately represent individual EV owners' behaviour. Additionally, these datasets fail to adequately describe the range and battery capacity of EVs currently on the market and lack the most recent measurements of these electric vehicles.

III. EVMM

A. EVMM Development

As illustrated in Fig. 3, three distinct datasets were utilised to develop the EVMM: the National Travel Survey (NTS) [8], conducted by the Department for Transport (DfT), which encompasses various data fields related to mileage, trip patterns along with other associated data. The vehicle statistics [14] , supplied by the DVLA (Driver and Vehicle Licensing Agency), indicate the quarterly number of registered vehicles in the UK, along with the battery sizes of each EV model and their V2G compatibility sourced from the EV-Database [15], which is a publicly available website.

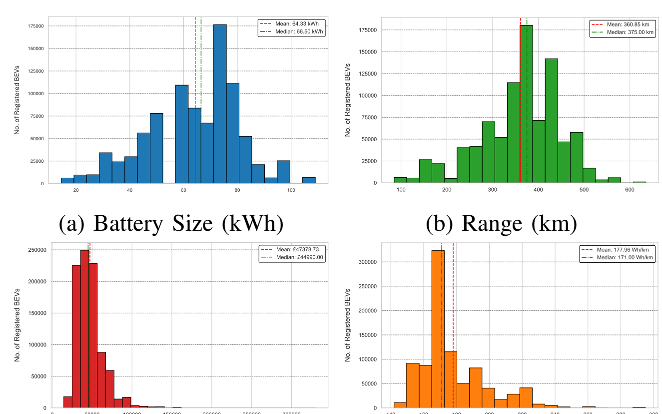
B. EVMM: EV Parameters

Fig. 4 shows the dataset integration process, combining DVLA statistics with EV-Database to create a comprehensive dataset for EVMM parameters that captures the key manufacturer-defined parameters. By cross-referencing these datasets, the EVMM parameters accurately represent the UK BEV market composition and vehicle-defined mobility characteristics, allowing for statistical analysis of the BEVs' potential for grid integration. Fig. 5 depicts the library and file structure used for EVMM EV parameters.

C. Statistical Analysis of the current BEVs market composition in the UK

1) Analysis of BEV Adoption and V2G Integration in UK: Fig. 6 illustrates the growth of BEVs and V2G-enabled BEVs in the UK from 2014 to 2023. While the number of registered BEVs nearly doubled between 2021 and 2023, reaching approximately one million, V2G-compatible BEVs accounted for only 16% of the total. This highlights a significant gap in V2G adoption and underscores the substantial progress required to achieve full electrification of the current car fleet.

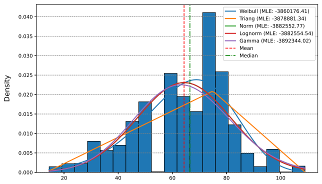
2) Price, Efficiency, Range, Price, and Battery Size Distributions: Fig. 7 highlights key features of BEVs; battery size follows a right-skewed distribution with a peak around 75 kWh, indicating most BEVs have mid-sized batteries; the range is also right-skewed, centered around 375 km. While larger battery capacities generally enable greater ranges, differences in vehicle efficiency and body type variations, which result in different ranges for BEVs with the same battery size. This indicates that factors beyond battery capacity significantly influence range performance. Price distribution is highly concentrated, suggesting affordability plays a significant role in adoption, While these values are tightly clustered around 171 Wh/km, they are based on ideal conditions reported by OEMs. However, actual efficiency can vary significantly depending on real-world factors such as weather conditions, driving, vehicle load, battery age, etc. These insights are crucial for optimizing charging infrastructure, load forecasting, and planning V2G



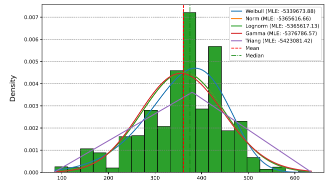
(a) Battery Size (kWh) (b) Range (km)

(c) Price (£) (d) Efficiency (Wh/km)

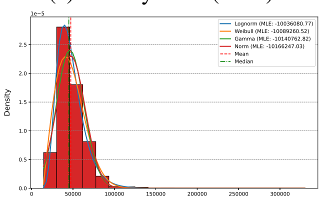
Fig. 7: Statistical Distributions of BEV Characteristics



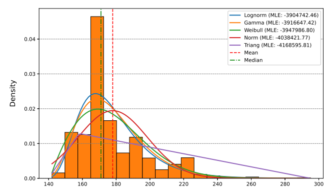
(a) Battery Size (kWh)



(b) Range (km)



(c) Price (£)



(d) Efficiency (Wh/km)

Fig. 8: Comparison of Statistical Distributions for BEV Characteristics

integration strategies.

3) Statistical Modelling of BEV Battery Size, Efficiency, Price and Range: The Maximum Likelihood Estimation (MLE) was applied to several statistical distributions, including Weibull, Triangular, Normal, Log-normal, and Gamma, to determine the best fit for the registered BEVs distributions. As shown in Fig. 8, the Weibull distribution yielded the best fit for battery size and range. For efficiency and price, the Log-normal distribution provided the most accurate representation of the data. These results are supported by a comparison of MLE values and the visual inspection of the distributions' fits to the data.

4) Correlations Among Key Variables: The scatter plots for the BEV manufacturers in Fig. 9 highlight significant correlations between key BEV characteristics. Battery size and range exhibit a strong positive correlation, indicating that larger batteries typically support longer ranges, although variations exist due to differences in efficiency and body type. It can also be observed that manufacturers often use the same capacity of batteries across their EVs but differentiate them by variations in body design and drivetrain configurations, thereby targeting different segments of the market. Price trends suggest that premium manufacturers frequently set higher price points, reflecting the integration of advanced technologies and luxury features, which contribute to deviations from the observed correlations. Additionally, vehicles with the same battery size show varying ranges due to differences in body design and efficiency, emphasizing the importance of using EVMM to account for simultaneous variations in efficiency, range, and battery size.

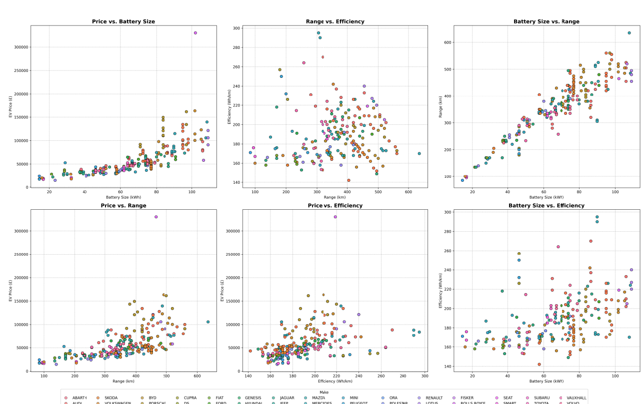


Fig. 9: Correlation of Battery Size, Range, Price, and Efficiency

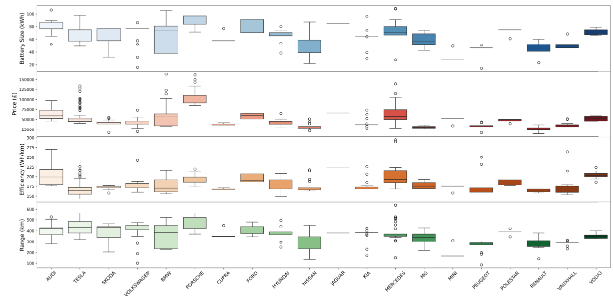


Fig. 10: Comparing battery size, price, and efficiency across top 20 EV manufacturers

5) Comparative Analysis of Battery Size, Price, and Efficiency Across Top 20 Manufacturers: The box plots in Fig. 10 provide a comparative analysis of battery size, price, and efficiency (Wh/km) across EV manufacturers, illustrating distinct market strategies. Tesla and Porsche demonstrate the largest median battery sizes, exceeding 75 kWh, reflecting their focus on long-range EVs, while Volkswagen and Nissan exhibit a broader range, catering to diverse market segments. In contrast, MG and MINI offer smaller, more consistent battery capacities, aligning with affordable and compact vehicle designs. Regarding price, Porsche and Mercedes lead with the highest medians, which is consistent with their luxury branding. In contrast, Tesla's broad price range reflects its diverse lineup, spanning entry-level to premium models. Skoda, Renault, and Vauxhall emphasize affordability with narrower ranges and lower median prices. In terms of efficiency, Tesla vehicles exhibit lower energy consumption, highlighting advanced optimization, whereas Nissan and Mercedes show greater variation in efficiency spreads due to differences in design and model types. MG and Renault achieve consistently lower Wh/km values with minimal variance, aligning with their focus on compact and economical designs. These observations underscore the trade-offs and strategic positioning among manufacturers in balancing battery size, price, and efficiency for their EV offerings. EVMM can further enhance these analyses by enabling the simulation of manufacturer-defined parameters, allowing researchers to explore a wide range of variations in efficiency, range, and battery size simultaneously.

6) Projections of V2G-Enabled BEV: The S-Curve model, often used to represent the adoption of new technologies, captures the growth pattern of BEVs as a function of market saturation, starting with slow adoption, followed by rapid

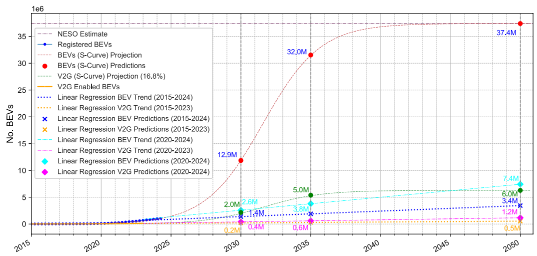


Fig. 11: Projected adoption of BEVs and V2G-enabled BEVs in the UK from 2015 to 2050.

growth, and eventually levelling off [16]. This approach was used to project the adoption of BEVs and V2G-BEVs in Fig. 11, with the NESO saturation level. We also applied linear regression to analyse trends over two distinct periods. The lowest trend (2015–2024) projects that approximately 0.5 million V2G-BEVs will be on the market by 2050. In contrast, by considering the current share of V2G-BEVs, the S-Curve projection estimates that approximately 6 million V2G-BEVs will be on roads by 2050. The S-curves demonstrate rapid growth around 2030, with a significant acceleration by 2035, reflecting the impact of banning petrol and diesel cars. In the most pessimistic scenario, where only 0.5 million V2G-BEVs are on the roads by 2050, the expected EVaaMS capacity would be approximately 32 GWh, assuming an average battery size of 64 kWh. However, in a full electrification scenario, the expected capacity would reach 2.39 TWh, highlighting the significant potential of EVaaMS in supporting grid flexibility and renewable energy integration.

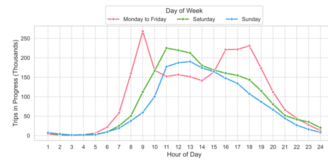
D. EVMM: EV Owner's Driving Style

This section encompasses travel patterns and mileage provided by NTS. How cars travel within the UK is determined by these aspects. As no data-rich repository contains this data for BEVs, it is assumed that owners exhibit the same behaviour after electrification, and this behaviour is generalised from current cars to BEVs.

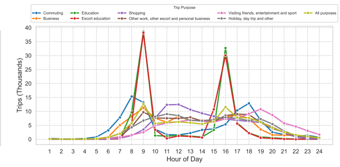
1) Trips in Progress by Car Drivers (NTS0501): The hourly distribution of trips reveals distinct peaks during the morning (8–9 AM) and evening (4–6 PM) hours, corresponding to typical commuting patterns. Weekday trips are more frequent and concentrated during these peak hours, while Sunday exhibits a more evenly distributed pattern with a later start, reflecting recreational travel behaviour.

2) Trips by Purpose and Start Time (NTS0502b): Trip purposes vary significantly throughout the day. Commuting dominates during peak hours, particularly in the morning. Business-related trips and personal errands also align with standard working hours, while leisure trips are more evenly spread into the evening. This suggests that EVs are more likely to be connected to the grid during non-peak driving times, creating opportunities for V2G services.

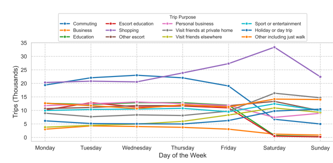
3) Trips by Purpose and Day of the Week (NTS0504b): The data highlight the variability in trip purposes across the week. Commuting remains consistent from Monday to Friday, with a sharp decline over the weekend. Conversely, leisure and shopping trips peak on Saturdays, demonstrating a shift in travel behaviour. This pattern suggests that weekday evenings and weekends are ideal for utilising parked EVs as grid resources.



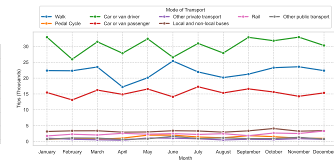
(a) Trips in progress by car driver



(b) Trips by purpose and start time



(c) Trips by purpose and day of the week



(d) Trips by mode and month

Fig. 12: NTS Trip Data Tables

4) Trips by Mode and Month (NTS0504c): Seasonal variations in trip modes indicate that private car use is consistent throughout the year, with minor peaks in summer months likely due to holiday travel. Public transport and other modes exhibit minimal seasonal variation, underlining the dominance of private vehicles for daily mobility. The alignment of trip patterns with typical EV usage scenarios enhances the feasibility of predicting flexibility windows. By incorporating these behavioural trends, the EVMM can be further refined to optimise EV integration into the energy market, aligning charging schedules with grid needs while maintaining user convenience.

IV. Conclusion

The rapid electrification of the transport sector presents advantages and obstacles for the power grid. This study analysed the current state of EVs in the UK, focussing on their market structure, vehicle characteristics, and the potential for grid integration through V2G technology. By developing an EVMM, we determined key mobility and travel behaviour patterns, yielding insights into the viability of EVs as versatile energy storage options and how they can be modelled specifically for power system integration with real travel pattern data. Our findings indicate that while the UK EV market has undergone significant expansion, the uptake of V2G-enabled vehicles remains limited. The analysis highlights the need for targeted initiatives and incentives to accelerate the deployment of V2G-capable EVs that will support the grid with their potential flexibility. Future research should focus on the simultaneous evaluation of EV mobility patterns and power system constraints to enable large-scale EV integration.

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Appendix

A. Abbreviations

- t : index for time period
- i : index for trip
- n : index for EV
- c : index for charging session
- $T_{\text{Parked},n,c}$: EV stationary time period
- $T_{\text{idle},n,c}$: EV idle time period
- $T_{\text{Flex},n,c}$: Flexibility availability time period
- $T_{\text{V2G},n,c}$: Discharging period in V2G mode
- $T_{\text{G2V},n,c}$: Charging period in G2V mode
- $E_{\text{del},n,c}$: Total energy delivered (kWh)
- $E_{\text{del},n,c}(t)$: Instantaneous delivered energy (kWh)
- $E_{\text{G2V},n,c}(t)$: Instantaneous energy in G2V (kWh)
- $E_{\text{V2G},n,c}(t)$: Instantaneous energy in V2G (kWh)
- $SoC_{\text{arr},n,c}$: EV SoC at arrival time (%)
- $SoC_{\text{dep},n,c}$: EV SoC at departure time (%)
- $SoC_{n,c}(t)$: Instantaneous SoC during charging (%)
- $SoC_{n,i}(t)$: Instantaneous SoC during trip (%)
- $E_{\text{max},n}$: Maximum usable battery capacity (kWh)
- $S_{n,i}$: EV trip schedule
- $D_{n,i}$: Mileage of EV n for trip i (km)
- ID_n : EV user ID
- VIN : Vehicle Identification Number
- V2G : Vehicle-To-Grid functionality

B. Public EV Charging Datasets

TABLE I: Public EV Charging Datasets

Dataset	**Ref**	$\mathbf{D_{n,i}}$	$\mathbf{S_{n,i}}$	$\mathbf{E_{max,n}}$	$\mathbf{SoC_{n,i}(t)}$	$\mathbf{T_{Flex,n,c}}$	$\mathbf{T_{G2V,n,c}}$	$\mathbf{E_{del,n,c}}$	$\mathbf{E_{del,n,c}(t)}$	$\mathbf{SoC_{n,c}(t)}$	$\mathbf{ID_n}$	**V2G**	**Charger**	**Date**	**Country, City**
ACN	[17]	✘	✘	✘	✘	✓	✓	✓	✘	✘	✓	✘	Campus Workplace Workplace	2018-2019	USA Pasadena CA La Canada CA Silicon Valley
Multi-faceted Analysis of EV	[18]	✘	✘	✘	✘	✓	✓	✓	✘	✘	✓	✘	Public	2021-2022	Korea
OLEV	[19]	✘	✘	✘	✘	✓	✘	✓	✘	✘	✘	✘	Public Fast Chargers	2017	UK
EV Fleet Measurement	[13]	✘	✘	✘	✘	✘	✘	✘	✓	✘	✘	✘	EV Fleet to Grid Coupling Point	2018-2020	N/A
Pecan Street	[20]	✘	✘	✘	✘	✓	✘	✓	✘	✘	✓	✓	Domestic Wall Box	2011-2024	USA Puerto Rico New York California Austin
Catapult	[21]	✘	✘	✘	✘	✘	✘	✓	✘	✘	✘	✘	Public Workplace Domestic	2022	UK-N/A
NREL	[22]	✘	✘	✘	✘	✓	✓	✓	✘	✘	✓	✘	Workplace	2016-2021	USA-N/A
ELAAD	[23]	✘	✘	✘	✘	✓	✓	✓	✘	✘	✓	✘	Public	2019	Netherlands
Boulder	[24]	✘	✘	✘	✘	✓	✓	✓	✘	✘	✓	✘	Public	2018-2023	USA Colorado