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# Analysis of electric vehicle charging station usage and environmental sustainability in the UK

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## Abstract

This dissertation presents an in-depth analysis of electric vehicle (EV) charging station usage across three geographical levels: Scotland, the London Borough of Barnet, and Newcastle University's Urban Science Building. Utilising data from publicly available sources, the study explores patterns in energy consumption, charging station utilisation, and associated carbon emissions. Key trends were identified, including higher usage rates during winter, weekends, post-COVID periods, and late-night charging. The research underscores the environmental implications of these patterns, linking energy consumption with carbon intensity. The findings contribute to the ongoing development of sustainable EV infrastructure in the UK by offering insights into optimising charging networks for both user convenience and environmental sustainability.

**Keywords:** Electric Vehicle Charging, Energy Consumption, Carbon Emissions, Charging Infrastructure, Sustainable Transportation, Post-COVID Trends, Seasonal Variation.

## 1 Introduction

As of 2023, transportation is the major contributor to greenhouse gas emissions in the UK becoming an important factor in climate change, one of the biggest challenges of the 21st century [1]. Electric vehicles (EVs) represent a significant leap towards sustainable transportation, producing zero harmful emissions at the point of use [1]. Some of the leading manufacturing companies of EVs in the UK include big names such as Tesla, MG, Kia, Mercedes and Volkswagen [2]. The government of the UK sets their target for all new cars to be zero emission by 2035 [3]. To fulfil this target the manufacturing of EVs is increasing each year (Figure 1 ) [4, 5]. However, widespread EV adoption depends on developing a robust and efficient charging infrastructure. Designing such an infrastructure presents a complicated challenge [6, 7]. It needs to fulfil the diverse charging needs of EV owners, ensuring convenient access to charging points. At the same time, it must maintain high station utilisation rates to be financially feasible [8, 9]. Most importantly, the infrastructure needs to minimise its overall environmental impact [1].

While the focus often lies on the convenience and affordability of charging, understanding the relationship between charging patterns and carbon emissions is equally important [1]. Traditional gasoline-powered vehicles contribute significantly to greenhouse gas emissions, primarily through the burning of fossil fuels. While EVs themselves produce zero engine out emissions, the environmental impact of charging them depends on the source of the electricity used [1, 6]. Understanding how charging patterns influence energy consumption, and the associated carbon footprint is essential for developing a truly sustainable charging network.

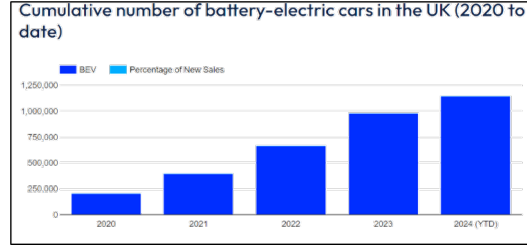


Figure 1: EV sales in the UK 2020-24

This research project aims to leverage the power of data analytics to analyse the EV charging patterns in the UK. A detailed analysis of a comprehensive dataset will be carried out in this project which comprises data like energy consumption, EV arrival times, charger occupancy, and utilisation rates of EV charging sessions at public charging stations in the UK. [6, 4, 7] Various key trends will be identified by analysing these factors, and significant insights will be drawn. Also, the associated carbon emissions data will be analysed to understand the effect of variable energy consumption and utilisation rates on carbon emissions. All these detailed analyses will contribute to understanding the behaviour of EV charging patterns resulting in profitable decision-making of improving the EV infrastructure grid in the UK.

Based on the prominent need to reshape and create new EV grid infrastructure, this project tries to answer these research questions:

1. How can data science help fulfil the primary objective of improving the EV grid infrastructure?
2. What are the past and current situations and trends of EV charging patterns?
3. What is the relation between the energy consumption of EV charging stations and the carbon emissions?

Collectively answering these three questions achieves the stated research goal. This paper is organised to describe the literature review process, the methodology used, the extracted results and insights, and finally, it concludes with the implications of the findings and suggests directions for future work.

## 2 Related Work

The existing literature on electric vehicle (EV) infrastructure and charging behavior provides valuable insights into the environmental impacts and operational patterns of charging stations. Notable studies have explored the emissions associated with EV charging in the UK, such as the work by Daniel, Helen and Iain examines how the source of electricity affects emissions during the charging process.[1] Additionally, research conducted in Germany has analyzed the profitability and usage patterns of charging stations, offering a perspective on the operational efficiency of such infrastructure.[6]. Also, a notable work has been done by Safak Bayram, Ali Saad, Ryan Sims, Colin Herron, and Stuart Galloway to explain the usage analysis of public chargers in the UK but it is confined for AC chargers only.[10] The impact of external factors, like the COVID-19 pandemic, on EV charging behavior has also been investigated, revealing shifts in usage patterns due to societal changes.[11] Moreover, comprehensive studies on EV charging infrastructure have outlined current trends and policy implications, guiding future development efforts.[7] However, these studies largely focus on general usage patterns and lack a detailed analysis of seasonal and weekly variations in charging behavior, especially in relation to carbon emissions.

My research addresses this gap by focusing specifically on the analysis of charging stations with different connector types in the UK, with an emphasis on understanding the seasonal and weekly usage patterns and their relationship with carbon emissions. According to the research done by Safak explains the charging demand in cold weather, but lacks to elaborate the usage and environmental impact of charging at public stations [12]. While data sources like Zapmap provide extensive statistics on EV usage, they do not delve into the temporal variations in usage or how these patterns impact overall emissions.[4] By conducting a detailed analysis of these factors, my research offers

a more nuanced understanding of the environmental impacts of EV charging. This work not only complements the existing literature but also provides critical insights that can inform more effective policy-making and operational strategies for EV infrastructure in the UK.

### 3 Methodology

This research project follows the CRISP-DM (Cross Industry Standard Process for Data Mining) [13] life cycle comprising six phases. The sequence of the phases is not strict and moving back and forth between different phases is usually required.

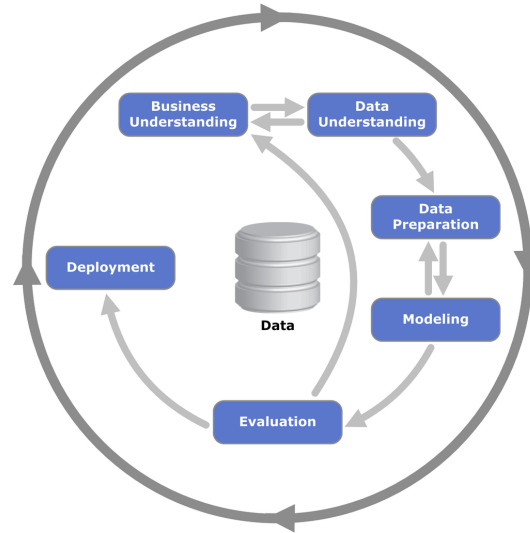


Figure 2: Crisp-DM data life cycle

#### 3.1 Business Understanding

This initial phase focuses on understanding the project objectives and requirements from a business perspective, then converting this knowledge into a data science problem definition and a preliminary plan designed to achieve the objectives. As discussed in the **Introduction** of this project, the primary business objective is to use data science to understand the EV public charging station usage and its profitable contribution to making a sustainable EV grid infrastructure. This research required zero production costs due to publicly available resources. The primary data science goal for this project is to create informative dashboards to extract results from the analysis and further derive significant insights from this process. The analysis of public charging stations at 3 types of geographic levels is carried out in this project:

Country Level – Scotland Regional Level – London Borough of Barnet Site Level – Urban Science Building, Newcastle University, Newcastle

#### 3.2 Data Understanding

The data understanding phase starts with initial data collection and proceeds with activities that enable you to become familiar with the data and identify data quality problems. The EV charging station usage data used for this research is time series data representing the charging sessions of charging stations and other data represents the carbon intensity of that location over time.

##### 3.2.1 Data Collection

The data for Scotland was collected from “*ChargePlace Scotland*” [14] which provided an open dataset of over 3538 individual charge points owned by over 400 different charge point hosts(owners). The regional data for the London Borough of Barnet was collected from the government website -

“Open Barnet” [15] which had over 70 charge points operated by ‘CityEV’. The site-level data of the public charging station at the Urban Science building was obtained from Newcastle University which had 6 different charge points operated by ‘FastNed’. The Carbon Intensity data was extracted from the “Carbon Intensity API” [16] for Scotland, London and North-East (for Newcastle) respectively.

### 3.2.2 Data Description

The EV charging station usage datasets contained information about charging sessions in real-time over 2 to 4 years (varying for each dataset). The Scotland data was recorded with 2.75 million charging sessions from October 2022 to May 2024; The London data was recorded with 6225 charging sessions from January 2020 to March 2022; The USB data was recorded from March 2021 to July 2024 and had at least these columns:

- Charging start date and time
- Charging end date and time
- Charge point ID – The ID of the charger
- Energy Consumption in kWh (kilo-watthour) – The total energy consumed in each session

Additionally, for Scotland and the USB1 dataset, the charger connector types were associated with each record. The Carbon Intensity data had information about the carbon intensity levels at that moment of date and time. The schema was as follows:

- Date Time (UTC) - Date and Time when carbon intensity was recorded.
- Carbon Intensity Level (gCO2/kWh)

### 3.2.3 Data Quality

The EV charging datasets were publicly available but for each month, which further required the merging of multiple files together. The data quality report is presented in Table 1:

## 3.3 Data Preparation

According to the Data Quality Report above, the identified issues are treated in the data preparation process. Data cleaning was carried out to address and remove the null, duplicate and ‘zero’ values from the datasets. Further, Data Wrangling techniques were used to transform the data into a consistent format. The data collected was in multiple sets of files which required Data Integration using the ‘glob’ library in Python. Next, the Carbon Intensity Data was merged with the EV data based on the corresponding date and location. After obtaining a clean and consistent dataset, new features and variables were generated which were necessary for the analysis:

- Connector types were assigned based on energy consumption levels for Scotland EV data for October 2023
- $Charging\ Duration\ (in\ hrs) = Charge\ End\ Date\ and\ Time - Charge\ Start\ Date\ and\ Time$
- $Carbon\ Emissions\ (gCO_2) = Carbon\ Intensity(gCO_2/kWh) * Energy\ Consumption(kWh)$  [17]
- $Time-based\ utilisation\ rate = (Duration\ (in\ hrs) / 24) * 100$  [8, 9]
- For duration > 24 hrs,  $utilrate = [duration / (24 * (no.\ of\ days + 1))] * 100$
- Hour of the day – Extracted from the Charge Start Date and Time
- Day of the Week – Extracted from the Charge Start Date and Time
- Name of the Month - Extracted from the Charge Start Date and Time
- Seasons – The name of the season was assigned to each event based on the name of the month. (Summer, Spring, Winter, Autumn)

The London EV data did not have a connector-type column for the charger IDs; hence they were grouped based on their energy consumption levels as follows:

Table 1: Data Quality Report

Dataset	Data Values	Data Format	Remarks
Scotland EV data	Had null and unknown values for Energy Consumption and had a missing column of “connector type” in October 2023. Many zero values for the ‘Energy kWh’ and ‘Amount’ columns.	The charge starts and end times were not in a uniform date-time format.	Overall, the data requires data cleaning of null values and requires data filtering for zero values. Data wrangling is required for inconsistent format and data generation for connector type.
London EV data	Had null and unknown values for sessions. Many zero values for ‘Energy Consumption’. Contains duplicate values.	The charge starts and end times were not in a uniform date-time format.	Overall, the data requires data cleaning of null and duplicated values. Further, requires data filtering for zero values and data wrangling for inconsistent format.
USB EV data	The data was already filtered out from missing events from the end of August 2023 to the start of September 2023. Many zero values for the ‘Energy kWh’ column. No null values were detected.	The charge starts and end times were not in a uniform date-time format.	Overall, the data requires filtering for zero values and data wrangling for addressing the inconsistent format.
Carbon Intensity data	No null values, but many zero values in the data.	The charge starts and end times were not in a uniform date-time format.	Overall, the data requires filtering for zero values and data wrangling for addressing the inconsistent format.

- Group 1: 5 to 24.99 kWh
- Group 2: 25 to 49.99 kWh
- Group 3: 50 to 74.99 kWh
- Group 4: 75 kWh and above

### 3.4 Modelling - Exploratory Data Analysis

Based on the primary aim of this research project, the modelling step is majorly concerned with the rigorous analysis of the data by creating interactive dashboards to understand the results visually. After preparing 3 clean and sorted datasets, the data was analysed in 4 ways:

1. Statistical Analysis
2. Seasonal Analysis
3. Weekly Analysis
4. Hourly Analysis

### 3.5 Evaluation

At this stage, the data visualisation is completed that appears to have high quality from a data analysis perspective. Before proceeding to deploy these results and making any decisions, significant insights are drawn from the analysis. The descriptive evaluation of results can be seen in the **Results** section of this paper.

### 3.6 Deployment

After drawing some important insights from the results, the stakeholders can make some impactful decisions and necessary actions to fulfil the consumer demand which would turn out to be the achievement of this research. Also, any further steps that can be carried out to make this research better and more useful are discussed briefly in the **Conclusion** of this paper.

## 4 Results

There are four stages of the analysis that are carried out in this research for each dataset separately and the results yielded from these are as follows:

### 4.1 Statistical Analysis

#### 4.1.1 Country Level - Scotland

Table 2 below shows the number of sessions for each connector type along with the average energy consumption and carbon emissions of each connector type. The DC chargers – Ultra-rapid and Rapid chargers have the highest average energy consumption followed by the AC chargers suggesting that faster energy transmission relates to higher energy consumption. The number of sessions for Rapid and AC chargers is the highest identifying them as the most frequently used chargers. Another notable observation is the average carbon emissions from the DC charging sessions are much greater than that of the AC chargers.

Table 2: Statistics for each connector type

Connector Type	Number of sessions	Average of Consumption(kWh)	Average of carbon emission gCO2
Ultra-Rapid	13094	40.68	1880.94
Rapid	1423384	24.19	1118.98
AC	1316360	23.38	1085.32
AC Controller / Receiver	622	20.09	870.21
Total	2753460	23.88	1106.46

#### 4.1.2 Regional Level - London Borough of Barnet

The statistics in Table 3 show that the number of sessions with lower average energy consumption levels is more than those with higher average energy consumption. Although the average carbon emissions show a positive relation with the average energy consumption as the parameters increase in values.

#### 4.1.3 Site Level - USB, Newcastle University

According to Table 4 IEC-62196-T2-COMBO also known as COMBO connector type is the most popular, accounting for most of the charging sessions. However, it also has the highest average energy consumption and carbon emissions per session. Furthermore, there seems to be a positive correlation between average energy consumption and average carbon emissions across connector types. This is expected, as higher energy consumption generally leads to higher emissions.

Table 3: Statistics for each connector type

Energy Consumption Group	Number of sessions	Average of Con- sum(kWh)	Average of carbon emission gCO2
Group 1	4533	13.09	2336.80
Group 2	1454	33.94	6147.42
Group 3	225	57.90	10115.71
Group 4	13	81.42	15360.19
Total	6225	19.73	3535.22

Table 4: Statistics for each connector type

Connector type	Number of sessions	Average of Con- sum(kWh)	Average of carbon emission gCO2
COMBO	24435	34.01	1168.72
T2	1075	15.51	723.87188
CHAdEMO	4264	13.72	576.30
Total	29774	30.44	1067.82

## 4.2 Seasonal Analysis

### 4.2.1 Country Level - Scotland

The chargers are categorized into AC (AC and AC Controller/Receiver) and DC (Rapid and Ultra Rapid) types. Figure 3 shows that AC charger energy consumption has slightly increased yearly, peaking in Winter and dipping in Summer. Carbon emissions also peak in Winter 2022 and 2023, with lower levels in Summer 2023. However, some anomalies exist, such as a sharp drop in carbon emissions from January to March 2024, despite a less dramatic decrease in energy consumption.

Figure 4 illustrates DC charger usage in Scotland. Energy consumption peaked in Winter 2022 at 25.40 kWh and hit a high of 27.20 kWh in October 2023, likely due to more chargers being installed. Consumption dropped in Summer 2023 to 23.56 kWh. Carbon emissions peaked in Winter 2022 and Autumn/Winter 2023, following energy consumption trends, but showed a negative correlation with energy use from January to March 2024 before rising again in April and May 2024.

### 4.2.2 Regional Level - London Borough of Barnet

The seasonal analysis of usage pattern in the London Borough of Barnet is shown in Figure 5, where the energy consumption and carbon emissions are seem to have increased from Summer of 2020 towards the Winter of 2020. Every year the Winter Season is seem to dominate the usage of charging stations along with the peak carbon emissions in the same season. Also, another important factor to notice is the energy consumption and carbon emissions level saw an immense increase at the start of 2021, which is the start of post-COVID period.

### 4.2.3 Site Level - USB, Newcastle University

The USB charging station features three types of connectors. Figure 6 shows that the CHAdEMO DC charger has minimal seasonal variation, with peak energy consumption in Winter 2021 and a low in Spring 2023. Both energy consumption and carbon emissions were highest in 2021, gradually decreasing each year, likely due to the post-COVID surge.

Figure 7 indicates that the IEC T2 AC charger exhibits wide seasonal variation, with lower overall energy consumption compared to CHAdEMO and COMBO chargers. Peaks occurred in Spring 2021 and 2024 at around 23 kWh, and the lowest usage was in Summer 2023. The T2 charger is less popular in Winter, and carbon emissions mirror the energy trend, with a spike in 2021.

Lastly, Figure 8 shows that the COMBO charger, with the highest average energy consumption (25-40 kWh), peaked at 36.82 kWh in December 2022 and was lowest in March 2021. The rise in energy consumption suggests a shift towards high-speed DC charging, with carbon emissions

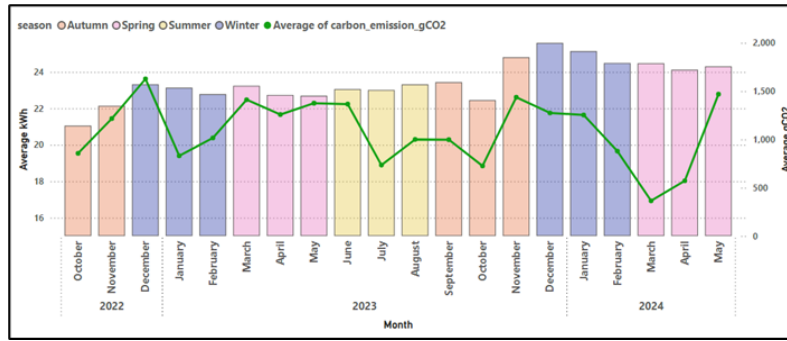


Figure 3: Seasonal Analysis of energy consumption and carbon emissions – AC chargers

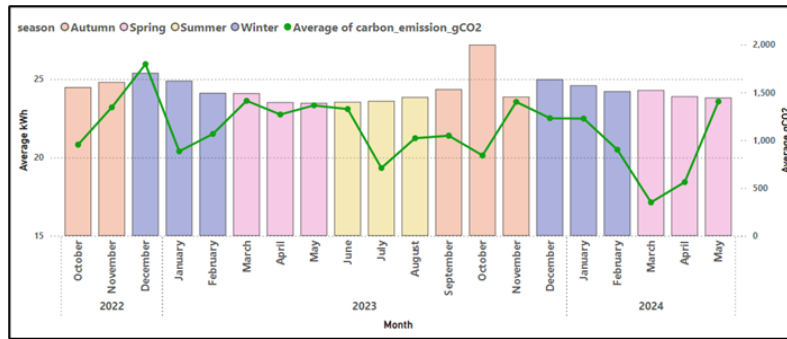


Figure 4: Seasonal Analysis of energy consumption and carbon emissions - DC chargers

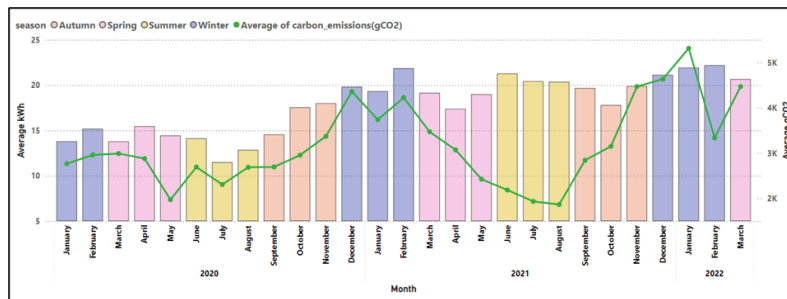


Figure 5: Seasonal Analysis of energy consumption and carbon emissions - London

showing a slight positive correlation in Winter. The 2021 spike likely reflects increased demand and the post-COVID period.

### 4.3 Weekly Analysis

#### 4.3.1 Country Level - Scotland

The charging usage on weekdays versus weekends is depicted in Figure 9. The average energy consumption for AC chargers is more on weekends than on weekdays with a peak of 57.67 kWh on Saturdays of Summer. The DC chargers have shown more average energy consumption on weekdays than on weekends except in the Winter season. The peak average energy consumption for DC chargers occurred on Mondays of the Autumn season that too of 55.45 kWh. The carbon emissions began dropping as approached the middle of the week reaching the lowest of 809 gCO2 in the Winter season and again rising as approached the weekend with the highest of 1352 kWh showing a probable effect of energy consumption.



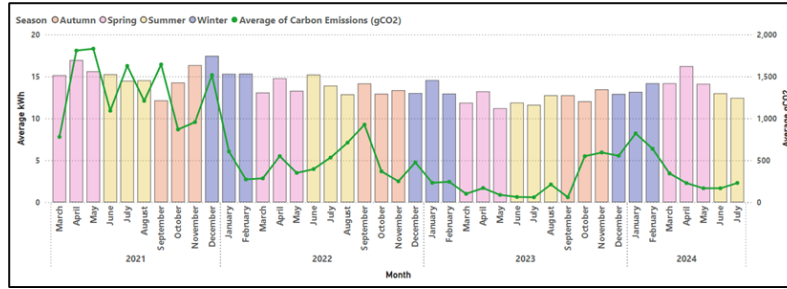


Figure 6: Seasonal Analysis of energy consumption and carbon emissions - CHAdEMO charger

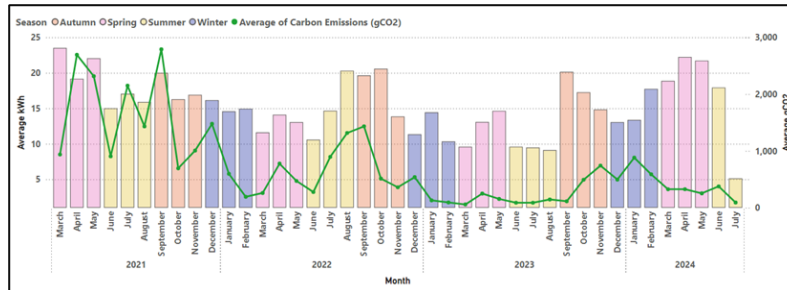


Figure 7: Seasonal Analysis of energy consumption and carbon emissions - IEC T2 charger

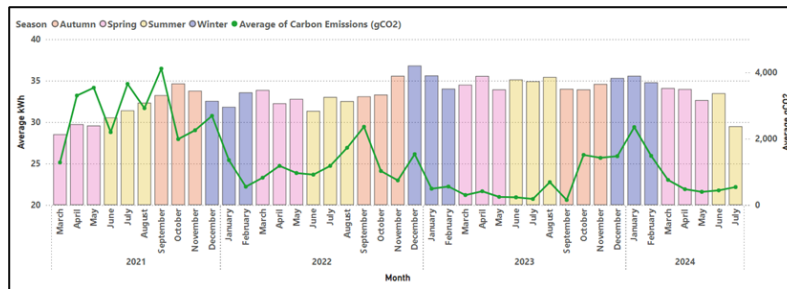


Figure 8: Seasonal Analysis of energy consumption and carbon emissions - COMBO charger

#### 4.3.2 Regional Level - London Borough of Barnet

The usage analysis of charging stations in London on weekdays and weekends can be observed in Figure 10. The Group 1 chargers have shown more average energy consumption on weekdays than on weekends except in the Spring season. The peak average energy consumption occurred on Thursdays of Winter with 14.43 kWh. Group 2 chargers have shown more average energy consumption on weekends than on weekdays with a peak of 36.71 kWh. Group 3 chargers have shown more average energy consumption on weekends than on weekdays except in Summer season. The peak average energy consumption was achieved on Sundays of Spring season with 63.49 kWh. The Group 4 chargers, with highest energy consumption band has shown its presence only in Autumn and Winter season with peak average of 83.45 kWh on Wednesday of the Winter season. Overall, the average energy consumption is more on weekends than that on weekdays. The carbon emissions are seem to be higher on weekdays than on weekends in each season suggesting a positive relation with the energy consumption.

#### 4.3.3 Site Level - USB, Newcastle University

Figure 11 represents the weekly usage analysis of chargers at USB. The COMBO connector which is a DC charger seems to have dominated the weekly usage in each season with a peak of 35.83 kWh on Saturday of Winter. The average energy consumption is higher in each season on weekends than on



Figure 9: Weekly Usage Analysis - Scotland

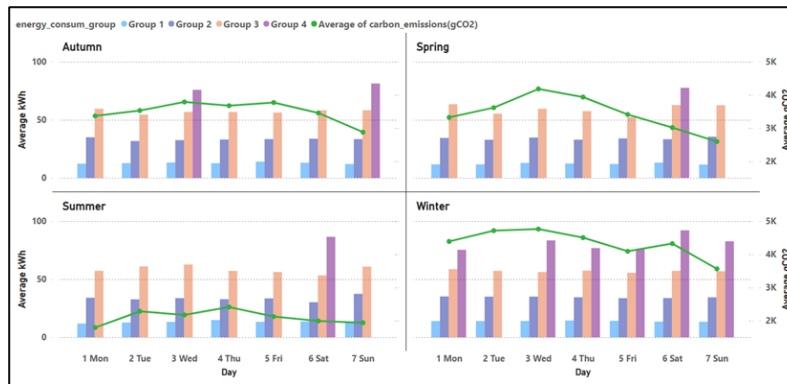


Figure 10: Weekly Usage Analysis - London Borough of Barnet

weekdays except in the Spring season which shows a constant average consumption of around 33 kWh. The second DC charger i.e. CHAdeMO connector shows higher consumption on weekends than on weekdays with the highest consumption of 16 kWh on Sundays of the Winter season. Lastly, the AC charger with T2 connector type shows an opposite usage to DC chargers with higher average energy consumption on weekdays than on weekends. The peak usage of 22.17 kWh was achieved by the T2 type AC charger on Tuesday of the Autumn season. The average carbon emissions seem to be greater on weekdays than on weekends which is a relative trend followed by the weekly usage of DC chargers.

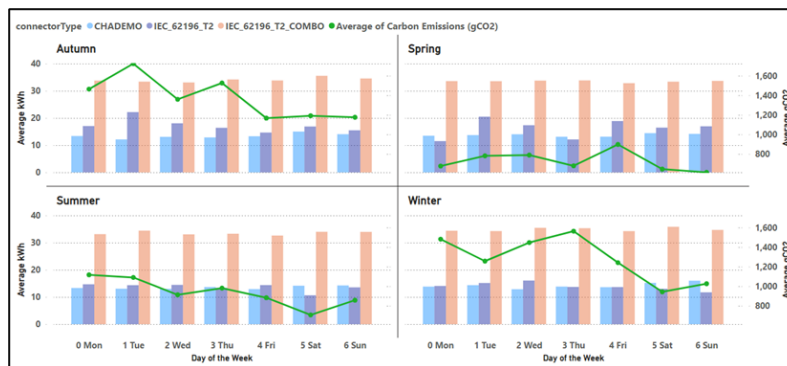


Figure 11: Weekly Usage Analysis - USB, Newcastle

## 4.4 Hourly Analysis

### 4.4.1 Country Level - Scotland

The hourly usage of chargers in Scotland is depicted in Figure 12. The average energy consumption of Ultra-Rapid chargers is the highest among all chargers due to their popular use and high-speed energy transfer rate. The average energy consumption seems to be low in the mid-daytime and increases gradually as nighttime approaches. The peak average energy consumption of 74.37 kWh was observed in the 3rd hour of the day by the Ultra-Rapid charger. The gap in the usage of AC Controller/Receiver suggests that the chargers might be a time-based charger and is offline in these early morning hours. The average carbon emissions very closely follow the usage trend for all types of chargers except for AC Controller/Receiver chargers. The peak average carbon emission of 3655.99 gCO<sub>2</sub> can be seen in the 3rd hour of the day for Ultra-Rapid charger.

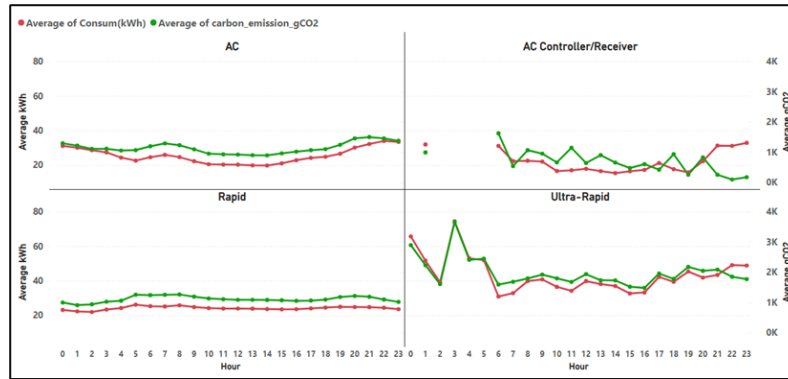


Figure 12: Hourly Usage Analysis - Scotland

### 4.4.2 Regional Level - London Borough of Barnet

In Figure 13, the hourly usage analysis of chargers in the London Borough of Barnet can be observed. As the groups are categorised based on energy consumption levels, the group with higher bands have sessions specifically occurring in a few hours of the day. Groups 3 and 4 with higher energy consumption bands seem to have high average energy consumption after noon. The peak of 99.11 kWh is observed for Group 4 in the 17th hour of the day. Groups 1 and 2 with lower consumption bands have relatively higher average energy consumption in the early morning hours of the day. The average carbon emissions almost follow a similar trend to the usage of chargers. The carbon emissions saw a steep decline on the 12th hour of the day for Group 4 chargers with a value of 7440.25 gCO<sub>2</sub>.

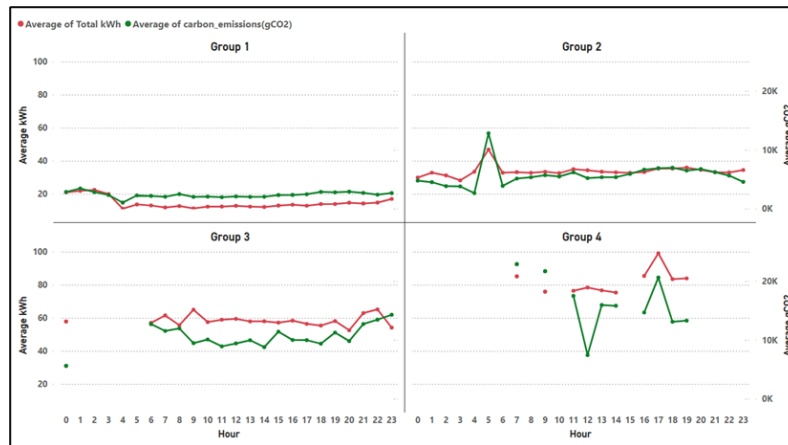


Figure 13: Hourly Usage Analysis - London

#### 4.4.3 Site Level - USB, Newcastle University

The analysis of hourly usage of chargers at the USB in Newcastle is depicted in Figure 14. The hourly average energy consumption is highest for the COMBO connector followed by CHADEMO and T2 connector types. Peak average energy consumption of 37.42 kWh is achieved by the COMBO connector in the 4th hour of the day. The missing sessions for the AC charger - T2, can be possibly the charger being offline along with the low energy consumption in the early morning hours altogether can suggest the probable lesser usage and popularity. The trend of average carbon emissions positively relates to the average energy consumption trend with a peak of 2100.90 gCO<sub>2</sub> on the 20th hour of the day for the T2 connector.

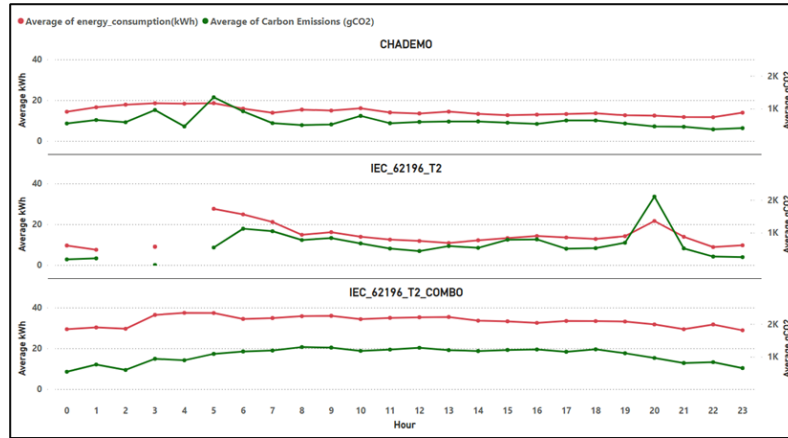


Figure 14: Hourly Usage Analysis - USB, Newcastle

## 5 Conclusion

This study analysed EV charging patterns across three distinct datasets: Scotland, London Borough of Barnet, and the Urban Science Building at Newcastle University. The analysis revealed significant differences in charging behaviours and energy consumption across these regions. In Scotland, the data indicated a wide range of energy consumption, with the highest values associated with ultra-rapid chargers. London exhibited lower overall energy consumption, with most sessions falling within lower energy brackets. Meanwhile, the Newcastle University site showed a higher concentration of charging sessions using the COMBO connector, indicating a preference for this type of charger.

The analysis highlighted several consistent trends across all datasets: higher usage during winter months, increased activity on weekends, and a notable rise in charging sessions during late-night hours. Additionally, post-COVID data showed an increase in charging station utilisation, reflecting the growing adoption of EVs. These findings emphasise the need for charging infrastructure that can accommodate peak usage times and seasonal variations in demand.

Future work should focus on deeper analysis using advanced machine learning models to predict charging demand and optimise the placement and operation of charging stations. By incorporating real-time data and predictive analytics, the efficiency and environmental benefits of EV infrastructure can be further enhanced. These improvements will be critical in supporting the UK's transition to a more sustainable transportation network.

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## References

- [1] Daniel Mehlig, Helen ApSimon, and Iain Staffell. Emissions from charging electric vehicles in the uk. *Transportation Research Part D: Transport and Environment*, 110:103430, 2022.
- [2] Tom Swallow. Top ev manufacturing companies in the uk. EV Magazine, 2023. Retrieved from <https://evmagazine.com/top10/top-10-best-selling-evs-in-the-uk>.
- [3] Department for Transport and Office for Zero Emission Vehicles. Transitioning to zero emission cars and vans: 2035 delivery plan. UK Government, July 2021. Retrieved from <https://www.gov.uk/government/publications/transitioning-to-zero-emission-cars-and-vans-2035-delivery-plan>.
- [4] Jade Edwards. Ev market stats 2024. Zapmap, 2024. Retrieved from <https://www.zap-map.com/ev-stats/ev-market>.
- [5] Transport Scotland. Report on public electric vehicle (ev) infrastructure in scotland: Opportunities for growth. Transport Scotland, 2024. Retrieved from <https://www.transport.gov.scot/publication/report-on-public-electric-vehicle-ev-infrastructure-in-scotland-opportunities-for-growth/>.
- [6] Christopher Hecht, Jan Figgner, and Dirk Uwe Sauer. Analysis of electric vehicle charging station usage and profitability in germany based on empirical data. *iScience*, 25(12):105634, 2022.
- [7] Muhammad Shahid Mastoi, Shenxian Zhuang, Hafiz Mudassir Munir, Malik Haris, Mannan Hassan, Muhammad Usman, Syed Sabir Hussain Bukhari, and Jong-Suk Ro. An in-depth analysis of electric vehicle charging station infrastructure, policy implications, and future trends. *Energy Reports*, 8:11504–11529, 2022.
- [8] Green Finance Institute. Demystifying utilisation. Green Finance Institute, 2023. Retrieved from <https://legacy.greenfinanceinstitute.com/news-and-insights/demystifying-utilisation/>.
- [9] Green Finance Institute. Beyond utilisation: Consumer behaviour and charging infrastructure. Green Finance Institute, 2024. Retrieved from <https://www.greenfinanceinstitute.com/news/beyond-utilisation-consumer-behaviour-and-charging-infrastructure/>.
- [10] Safak Bayram, Ali Saad, Ryan Sims, Colin Herron, and Stuart Galloway. Usage analysis of public ac chargers in the uk. Department of Electronic and Electrical Engineering, University of Strathclyde, 2023. Retrieved from <https://pureportal.strath.ac.uk/files/180297425/Bayram-et-al-IET-EVI-2023-Usage-analysis-of-public-AC-chargers-in-the-UK.pdf>.
- [11] Sakib Shahriar and A. R. Al-Ali. Impacts of covid-19 on electric vehicle charging behavior: Data analytics, visualization, and clustering. *Applied System Innovation*, 5(1), 2022.
- [12] I Safak Bayram. Impacts of electric vehicle charging under cold weather on power networks. In *2021 56th International Universities Power Engineering Conference (UPEC)*, pages 1–6, 2021.
- [13] Peter Chapman. Crisp-dm data life cycle. In *CRISP-DM 1.0: Step-by-step data mining guide*, 2000. Retrieved from <https://api.semanticscholar.org/CorpusID:59777418>.
- [14] ChargePlace Scotland. Monthly charge point performance. ChargePlace Scotland, 2024. Retrieved from <https://chargeplacescotland.org/monthly-charge-point-performance/>.
- [15] Barnet Open Data. Electric vehicle charging transactions. Barnet London Borough, 2022. Retrieved from <https://open.barnet.gov.uk/dataset/exm5m/electric-vehicle-charging-transactions>.

- [16] National Grid ESO, Environmental Defense Fund Europe, University of Oxford Department of Computer Science, and WWF. Carbon intensity data. Carbon Intensity API, National Grid ESO, 2024. Retrieved from <https://carbonintensity.org.uk/>.
- [17] Paul Davis. How to calculate and evaluate a carbon intensity score. PCI Energy Solutions, November 2023. Retrieved from <https://www.pcienergysolutions.com/2023/11/01/how-to-calculate-and-evaluate-a-carbon-intensity-score/>.

## Appendix

### Abbreviation:

1. EV - Electric Vehicle
2. USB - Urban Science Building
3. AC - Alternative Current
4. DC - Direct Current
5. kWh - kilowatt-hour
6. gCO<sub>2</sub> - grams of carbon-di-oxide

### Data Distribution:

#### Country Level: Scotland

The Energy Consumption levels for charging sessions in Scotland range from 5 kWh to approximately 307 kWh which is the highest outlier of the plot. Most of the sessions occur within the energy consumption level under 62 kWh which is the upper fence of the boxplot.

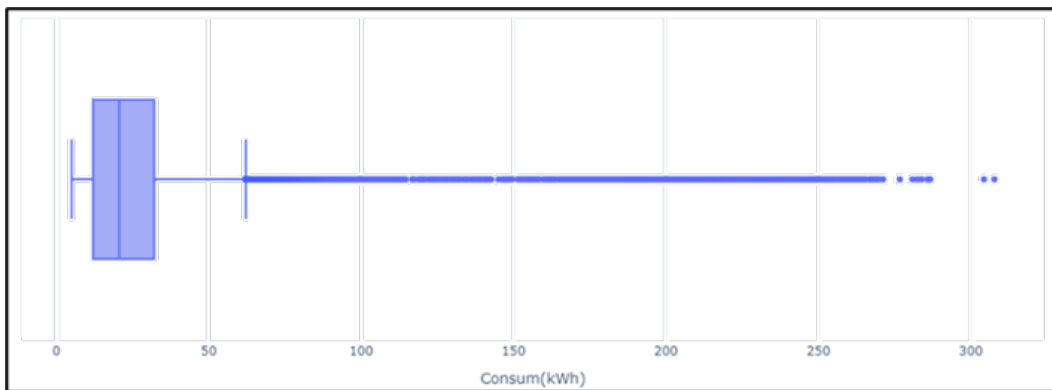


Figure 15: Energy Consumption Level Distribution

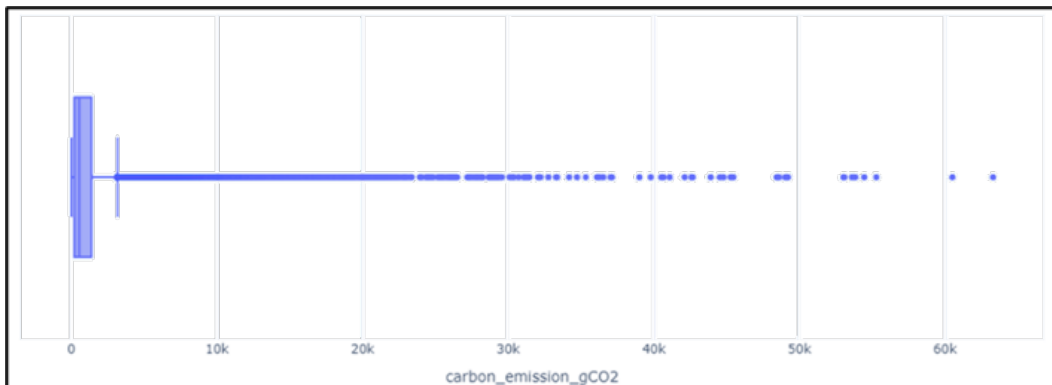


Figure 16: Carbon Emissions Distribution

Overall, the Carbon Emissions range from 0 gCO<sub>2</sub> to a maximum of 63k gCO<sub>2</sub> which is the farthest outlier in the above boxplot. Most of the charging sessions have emitted greenhouse gases under 3167 gCO<sub>2</sub> which represent the upper fence of the boxplot.



### Regional Level- London Borough of Barnet

The energy consumption levels for the London Borough of Barnet lie between 5 kWh to a maximum of 99.5 kWh. The greatest number of sessions lies between the range of 5 kWh to 10 kWh.

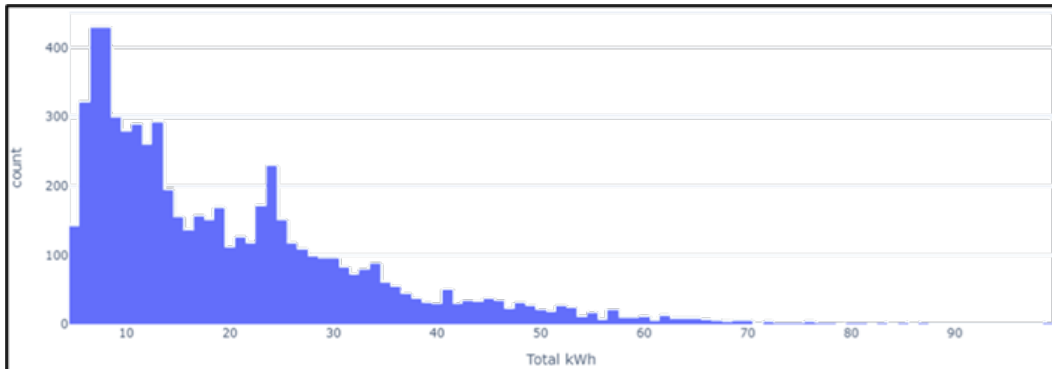


Figure 17: Energy Consumption Distribution

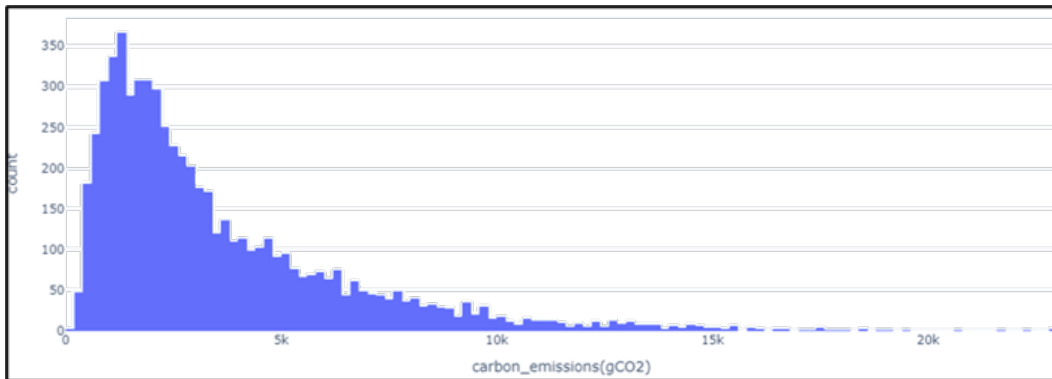


Figure 18: Carbon Emissions Distribution

The carbon emissions lie between the range of 0 gCO2 to a peak of 23k gCO2. Most sessions range from the first 0 to 5k gCO2.

### USB building, Newcastle University

A significant portion of the data falls within the lower energy consumption range (10-20 kWh), implying that most of the observed entities consume relatively less energy. The extreme right end of the graph might contain outliers, representing exceptionally high energy consumption values that deviate significantly from the majority.

The carbon emissions fall under 10k gCO2 and peak emissions can be observed in a range within 2500 gCO2.

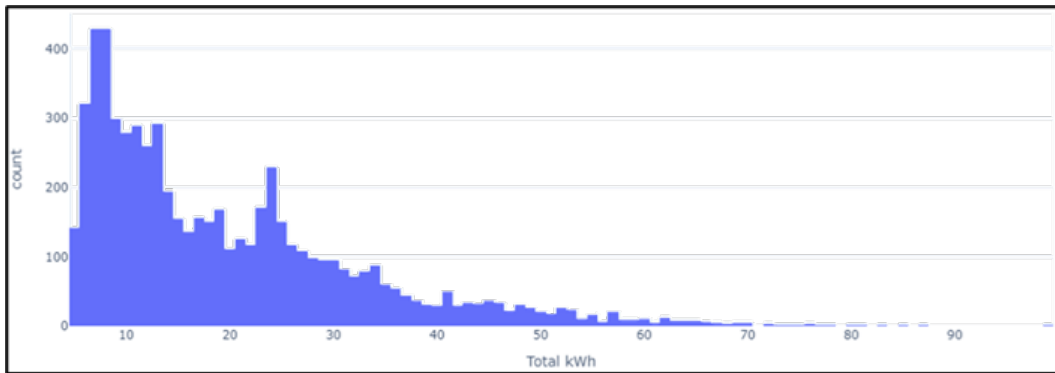


Figure 19: Energy Consumption Distribution

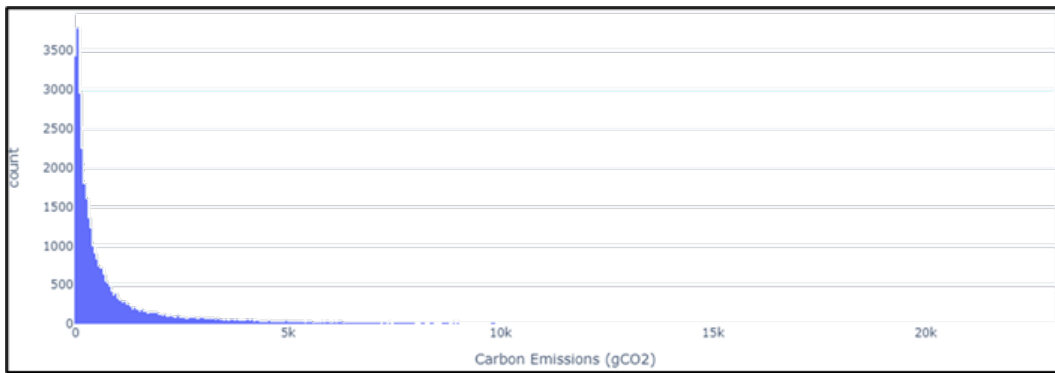


Figure 20: Carbon Emissions Distribution