Siting Charging Stations for Electric Vehicles Data Analysis

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***Abstract*—This study addresses the optimization of electric vehicle (EV) charging station placement in Denmark. Through a comprehensive analysis of data provided by Norlys A/S, the usage patterns of existing charging infrastructure are assessed, and the influence of pricing schemes on user behavior. Our mixed-method approach includes data cleaning, spatial analysis of charging station distribution, and temporal analysis of charging patterns. The findings reveal that while the demand for charging correlates with commute times, pricing strategies do not necessarily reflect real-time electricity spot prices, suggesting that operators prioritize operational simplicity and demand management. The research concludes that the optimal placement of new stations should integrate these user behavior patterns to enhance the EV charging network's efficiency. Future work will explore the integration of these insights into predictive models for station placement.**

***Index Terms*—electric vehicles, charging stations, charging behavior, charging infrastructure**

I. Introduction

One of the most pressing political challenges that the world currently is presented with is the urgent need to reduce carbon emissions to combat the rapid climate change that is unfolding throughout the world. A major source of carbon emissions is vehicles. As the general wealth is increasing the demand for personal vehicles is the highest it has ever been. Therefore the transition from traditional internal combustion engine vehicles to electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEVs) is becoming a fundamental strategy towards combating carbon emissions. One of the leading countries in both renewable energy and the conversion towards EVs is Denmark. Yet transportation accounts for approximately one-third of the total energy consumption in Denmark, with nearly 95% of that third consisting of fossil fuels. [1]. In response, the Danish government has set an ambitious target of having 1 million EVs and PHEVs on the roads by 2030. The landscape of Denmark's roads is changing rapidly, with a significant increase in the adoption of electric vehicles (EVs) and plug-in hybrid electric vehicles (PHEVs) since 2020. This growth reflects a strong shift in consumer preferences towards more sustainable transportation options [2]. The upward trend in the percentage of new cars being of either PHEV or EV, along with the target set by the government, a requirement for improved charging infrastructure is apparent. Therefore, the development of a readily accessible and effective public charging network is essential to accommodate the rising demand.

Identifying this growing demand, this study aims to conduct data analysis of the existing charging infrastructure in Denmark, specifically the publicly available charging stations. This analysis includes gaining insight into the existing capacity of chargers, along with the corresponding utilization of said charging stations. Gaining knowledge of the current charging infrastructure, understanding user behavior, and identifying potential bottlenecks in the road infrastructure will assist in suggesting optimal locations for introducing new charging stations and expanding the already existing infrastructure.

The paper is organized in the subsequent sections: Section II provides an overview of the already existing research on charging infrastructure and EV owners' behavioral tendencies. Additionally, the section gives an overview of methods that have previously been used for suggested solutions to similar problems. Section III presents the data that has been provided and used for the duration of this study. Section IV describes the data cleaning and preprocessing pipeline instantiated to prepare the data for analysis. Section V shows the results of the data analysis and highlights key observations and patterns. Section VI entails a discussion of the findings, along with considerations towards further development of the study. Finally, section VII concludes upon the results found throughout the study.

II. Related Studies

For the past decade, multiple studies have been completed to identify and understand charging infrastructure across the world. Most of such studies have focused on topics such as understanding usage patterns of EVs, eliciting user preferences and desires, and estimating the energy consumption of deploying charging station infrastructure. They all have in common, that they stand as a contribution to gaining insight towards the new domain of EV charging. Before deploying a fully fetched infrastructure, it is important to understand the user behavior by analyzing the usage pattern of the already existing charging stations. Van den Hoed et. al. (2013) analyzed the public charging station usage patterns in Amsterdam. The study indicated that a rapid expansion in the number of charging stations led to a relatively high average capacity usage of the entire infrastructure. It is proposed that the findings of expanding the charging infrastructure could be an effective approach to solving what is stated as a ”chicken and egg” problem, compared to waiting for EVs to constitute a larger portion of the city’s traffic. Nevertheless, the study was limited to inspecting four highly dense areas in Amsterdam, with regards to charging infrastructure, why more limited areas remain untested [3].

Another study looking into the general user behavior elsewhere was conducted by Almaghrebi et. al. (2019) which looked into close to 18.000 charging sessions in the state of Nebraska. The findings showed a peak demand for public parking was at 1 p.m., which is located around the lunch break. More interesting, the study showed that only one-quarter of the time spent connected to a charging station was used for actually charging, while the remaining 77% of time was used for only parking. As such, the study showed in dispute with the previously mentioned study, that increasing the amount of charging stations in an area might not lead to a significant increase in charging demand in terms of kWh [4]. A similar study conducted by Jiang et. al. (2016) examining 19.000 charging events at the University of California, found that a vast majority of 90% of those charging events transferred less than or equal to 12 kWh. Another consideration showed that 67% of EV charging sessions lasted less than four hours while nearly 90% lasted less than 7 hours. Even though it is expected that charging sessions do not last over longer durations, the study suggests that efficient and high-capacity charging stations seem purposeful. Additionally, the study discovered that the time slot between 7 a.m. and 10 a.m. acquired the peak demand for energy, indicating that many EV owners choose to either charge on their way to work or find a parking spot with a belonging charging stand. The combination of peak hours at the morning traffic and lunch break suggests that locating charging stations at large public parking areas such as hospitals, universities or shopping malls seems ideal [5].

Looking into studies related to general user behavior for EV users, and the placement of potential new charging stations is paramount for investing in a more sustainable future. Therefore it is also important to look for differences in a geographical aspect. As this study will be conducted in Denmark it is only appropriate to investigate the local EV user behavior. Anders Fjeldbo Jensen et. al. (2020) has questioned the reasoning behind the adoption of EVs in Denmark. The first question raised revolved around the choice of routes for 107 vehicle-owning households. A large-scale experiment was set up looking into the difference of routing choice when driving an EV contra an internal combustion engine vehicle. The research indicated that participants driving electric vehicles (EVs) showed greater sensitivity to travel time and trip length, typically using EVs for shorter journeys. This trend could be linked to the belief that EVs consume less energy than internal combustion engine vehicles. Nevertheless, the study also pointed out that the driving range of EVs has markedly increased in recent years, suggesting that drivers might not need to alter their route selection preferences as much as this study suggests when using EVs [6]. Two years later, Jensen et. al. (2022) carried out both qualitative and quantitative evaluations to gain insights into electric vehicle (EV) user preferences. This research included conducting interviews with 11 EV users and performing statistical analyses on data obtained from Stated Choice (SC) experiments and discrete choice modeling. The study’s primary findings emphasized the significance of cost and convenience in users’ decisions regarding charging, such as the need for compatibility among various charging providers. Notably, it was also found that users were prepared to take longer routes to reach charging stations equipped with fast charging capabilities [7]. Including user preferences in the decision-making process when debating an expansion of the EV charging station infrastructure, enhances the probability of positively expanding such infrastructure.

In Denmark the existing research has primarily concentrated on examining user preferences and behaviors concerning EVs as opposed to fossil-fueled vehicles. This study aims to bridge this gap by conducting a detailed data analysis of the public charging infrastructure in Denmark. This will offer a thorough understanding of the current state of the EV charging network, complementing the existing focus on user perspectives.

III. Dataset

The following section aims to explain the dataset that is collected, processed, and analyzed for conducting the initial phase of this project. The section will display the structure of the data that is provided by Norlys A/S, along with giving an in-depth explanation of each unique column in the data.

To give an overview of the dataset, it consists of multiple files and file formats, namely a series of JSON files and a Parquet file. Each JSON file contains metadata for each of the charging stations covered by the dataset, while the Parquet file consists of time-series data for all the stations. For more detail about the data in each of the formats, refer to the sections III-A and III-B.

A. JSON

As mentioned, the JSON files contain metadata for each of the observed charging stations. The metadata is stored in classical JSON format and includes a variety of relevant information, yet part of the original metadata is not relevant to the scope of this study. As a result, a number of the properties were ignored or even removed to simplify and minimize the data. A copy of the original data is maintained and can be viewed at Tab.I. An example of the cleaned data is given by III-A. The remainder of this section will aim to explain those properties of the JSON files that are maintained.


```
{
    "slug": "xpyrz2",
    "location": {
        "latitude": 55.712846,
```

```
        "longitude": 10.014387
    },
    "locationAddress": {
        "city": "Juelsminde",
        "country": "Denmark",
        "countryCode": "DK",
        "county": "",
        "street": "Rousth js Alle 4",
        "full": "Rousth js Alle 4,
            Juelsminde, Denmark",
        "zip": "7130"
    },
    "owner": "Base2Charge",
    "minCapacity": 22,
    "maxCapacity": 75,
    "plugType1": 0,
    "plugType2": 4,
    "plugType3": 0,
    "plugTesla": 0,
    "plugCCS": 4,
    "plugChademo": 0,
}
```

The first Key-Value pair encountered has the Key identifier ”slug”. The slug key is used to uniquely identify each charging station. Important to note is that each charging station may consist of one or multiple charging stands or power outlets. For future reference, ”charging station” will refer to the entire cluster of stations tied to a single unique slug value, while the term ”charging stand” will pertain to an individual power outlet. The ”slug” property in the JSON metadata not only exists on its own but also connects the metadata to the Parq file, which showcases a column of matching slug IDs. The ”location” property provides information about the location of the associated charging station. The location is defined by a pair of coordinates, with the first coordinate defining the latitude position, and the second coordinate defining the longitude position for the associated charging station.

The third property in the JSON object is named ”locationAddress” and contains a list of key-value pairs, which in combination provides the location of a charging station by a full address, including both values for country, city, street address, and zip code among others. The next property is ”owner” which simply indicates which company is the owner of the charging station. The next two properties are in close relation as they provide the minimum and maximum capacity for the charging station. If there’s a discrepancy between the minimum and maximum capacities, the charging rate relies on the maximum capacity for a limited number of charging stands. Once this limit is surpassed, the minimum capacity dictates the charging rate. The capacities are given in kilowatts (kW). The remaining properties are used to identify the amount of each type of charger stand in the cluster, hereby implicitly providing the number of stands associated with a given charging station.

Status: 2	Available
Status: 3	Occupied
Status: 5	Unavailable
Status: 0	Unknown

TABLE I: Status value definitions

B. *Parq*

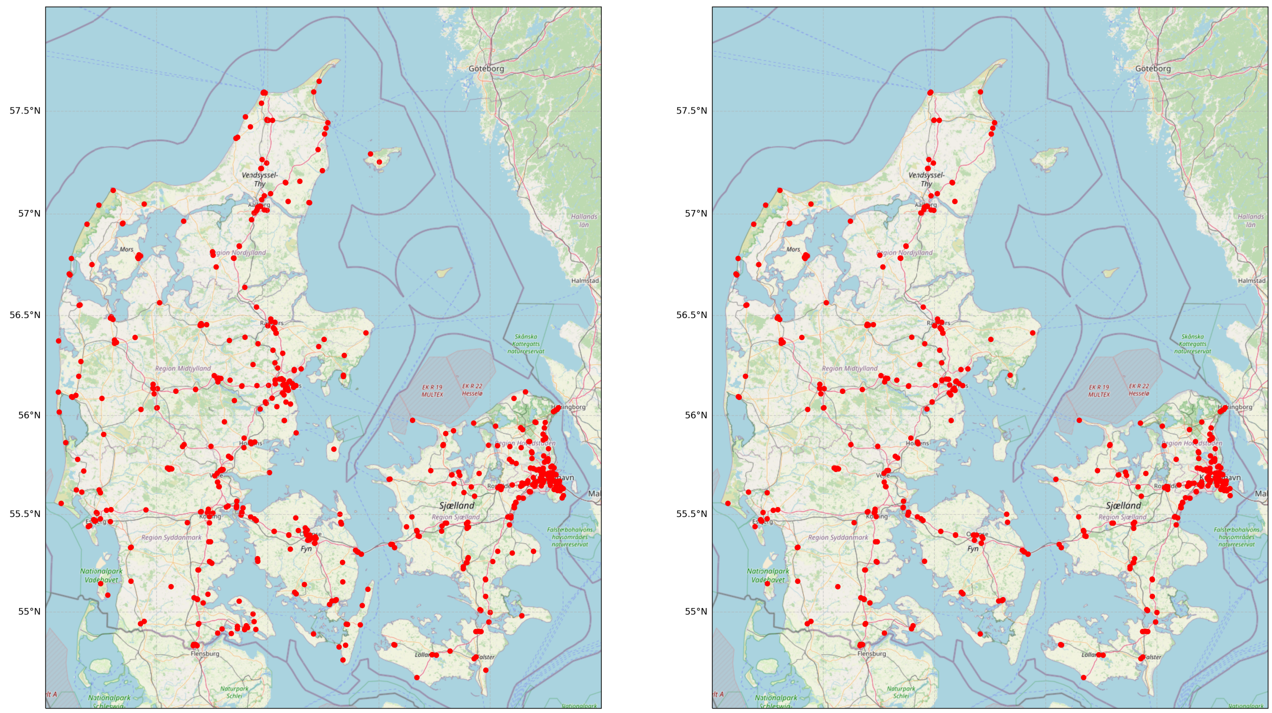
The Parq file consists of time-series data extracted from each of the observed charging stations, and covers one month, with the earliest timestamp being sampled at 2023-08-10 13:33:13 and the latest at 2023-09-11 12:01:17. The data is collected into three columns, Slug, Stander, and Timestamp.

Starting again at the Slug column, which represents the charging stations under observation. Again this is used for two purposes, first and foremost to associate a time-series data point with a charging station, and additionally to allow for connectivity of the associated metadata from the JSON file as described previously. The Stander column consists of a list of varying information about each charging stand within the associated charging station. An example of a modified single entry in the list of a single data point is listed in III-B.

```
{'id': 'DK*CKE*E170*3',
'status': 2,
'price': '3.99 DKK/kWh',
'info': 'Available since: 5 min',
'tariffs': [{'name': 'Circle K','
    costKwh': '3.99'},
              {'name': 'Circle K Drop-In'
                 , 'costKwh': 4.99}]}
```

The modification entails only including the ”info” property since there are no samples where both ”price” and ”info” coexist. The listing shows 5 key-value pairs, starting with an ”id”.
”id” determines which of the charging stands is under focus. The ”id” property exists in all of the successfully extracted data points. Similarly, the second key-value pair, ”status” is present in every successful sample. The ”status” key may obtain one of four values, which are presented in Tab. I. The significant values for this study are values, 2 and 3 corresponding to Available and Occupied respectively. Neither status code 5 nor 0, provides any information relevant to the aim of this project, meaning any occurrence of these status codes is neglected. The above-mentioned properties are the only two present at every successful reading, while the remaining values are present only for a subset of data points. This is due to the variance in information provided by sampling data from charging stations with different owners.

However, the remaining properties may still have relevance for this study, which is the reason they have not been removed. The ”price” entry shows the current price for charging at the stand. Even though there exists a price property, many owners provide information about tariff prices. The tariffs typically



(a) Here are the stations before the cleaning of the Parq

(b) Here are the stations after the cleaning of the Parq

Fig. 1: Map of charging stations in Denmark

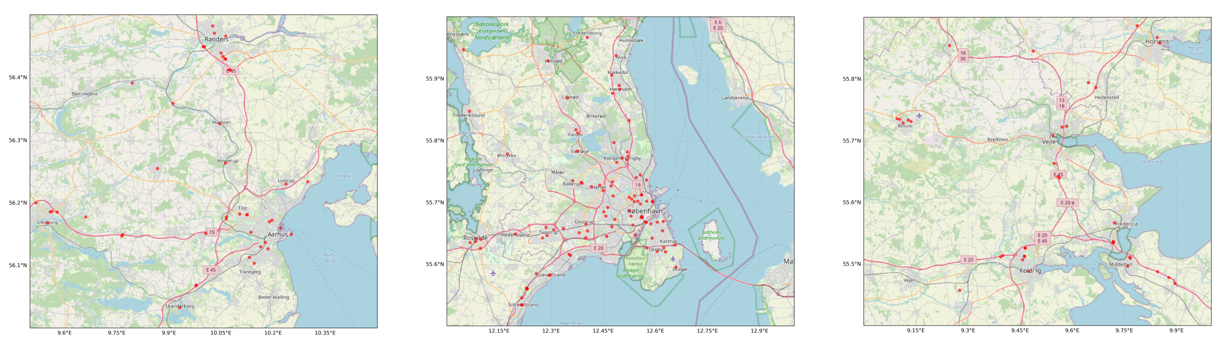


Fig. 2: Map of charging stations in in dense area

indicate if there are varying prices for charging at the station while being subscribed to the owning firm, and provide a price for non-subscribers indicated as a Drop-In price. Finally, the "info" key contributes information regarding the duration in which a charging stand has been either occupied or available. The final column indicates the time at which the sample has been collected. Unfortunately, the dataset only contains readings from public stations and data samples are gathered only in the time interval from 06:00 am-11:15 pm.

IV. Data Cleaning

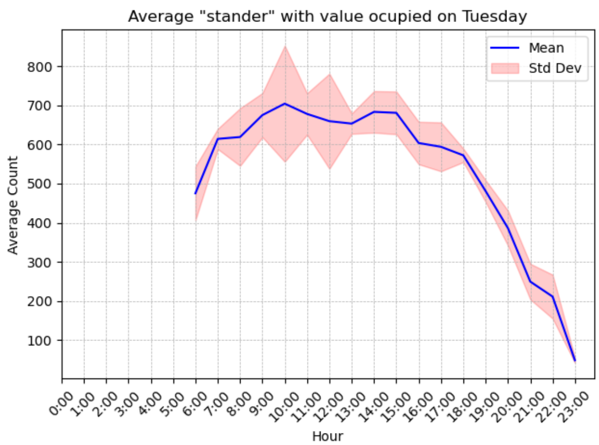
This section aims to describe the process of cleaning the data such that redundant and lackluster data has been removed. This process is done before entering the data analysis phase, such that the data patterns detected are only from useful and appropriate data.

A. JSON

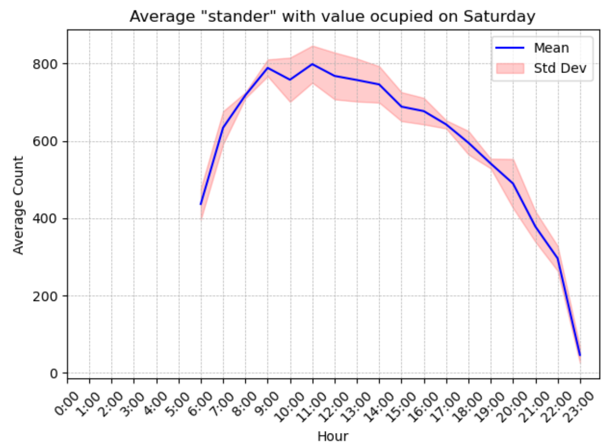
At first glance of the JSON files, it was apparent that the metadata was divided into multiple files, each representing a region of Denmark. The data was split between a total of 7 files, namely:

- bornholm.json
- fyn.json
- nordjylland.json
- nordsjaelland.json
- soenderjylland.json
- storkopenhavn.json
- sydsjaelland.json

Looking into the data within each of these files it quickly became apparent that the data did not consistently match the regions described by the naming convention of the files.



(a) Average occupied stands on a weekday Tuesday with variance



(b) Average occupied stands on a weekend Saturday with variance

Fig. 3: Average of used occupied stands

For instance, the bornholm.json file is expected to include information about charging stations located in Bornholm, however, no charging stations in Bornholm are observed. Instead, the charging stations included in bornholm.json were stations located in central Copenhagen. Data in the remaining files mostly match the expected regions, yet stations located near the intersection between regions tend to have duplicate data, as the data is included in both region files. An additional inconsistency is present in soenderjylland.json, where a number of the properties included in the remaining files are missing. Yet, none of the missing properties appear to have an impact on the outcome of this study, why the anomaly is mostly neglected. Additionally, a bunch of the charging stations that are described in soenderjylland.json appeared in one of the other files, resulting in having the complete version of the object elsewhere. Therefore, the files containing the entire list of properties were included first, when redundant charging stations were sorted, with the intent of keeping as much information on as many charging stations as possible. Finally, some of the observed stations were located near the Danish border in Sweden and Germany. These were removed as the scope of the study is limited to Denmark.

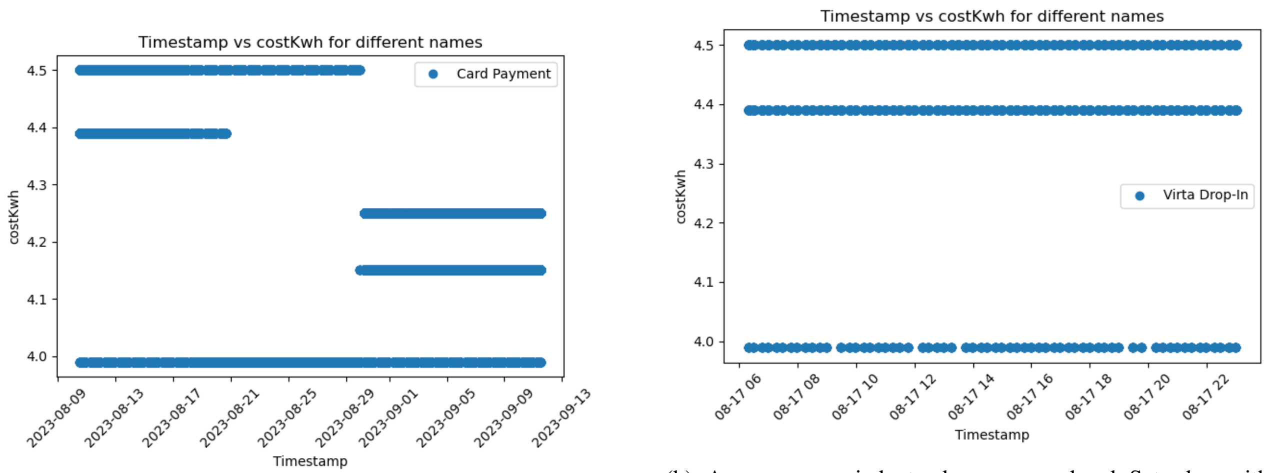
w. List of tariffs/price	w. Info	Discard
Circle K	Allego	Base2Charge
E.on	Clever	Better Energy
Monta	Drivee	CloudCharge
Q8	EVBox B.V	Jysk Energi
Spirii	IONITY	Norlys
Tesla (Open for all EV)	Shell Recharge	OK
Tesla		Shell Recharge DK
		Uno-X
		Sperto

TABLE II: Group owners by the information they provide

B. Parq

An initial look at the time-series data showed instances where data was either absent or an error occurred during the sampling process. Therefore, the foremost step in our data cleaning process involved removing any rows that displayed these discrepancies. Removing these entries of the data, simultaneously discarded data for some of the owners. As some owners did not provide any information, all of the charging stations with such owners were removed from the data. A list of the removed owners can be found in the rightmost column of Tab. II. There are two inconsistencies in the table, Sperto and CloudCharge. From the observed charging stations, only one was under CloudCharge ownership. As a result, it was decided to remove this station from the dataset. The reasoning behind removing all Sperto-owned stations from the dataset lies in the rate of samples. Most of the stations had a total of approximately 2000 responses over the entire period, while all Sperto-owned stations had only around 700 responses. Therefore, to maintain consistency all stations with less than 1500 updates were removed, and these consist primarily of Sperto-owned stations.

The next step in the cleaning process was to inspect the variance of data displayed in the ”stander” column. As mentioned earlier, the data which is included in this column varies. This inconsistency can be attributed to the practices of the respective charging station owners. While some disclose information on pricing and tariffs, others give insights into the length of availability or occupancy. The leftmost and middle columns of Tab. II have sorted owners based on the information associated with the ”stander” column. One owner, ”E.on Drive and Clever” is not found within the table, as only ”id”, and ”status” codes are informed. However, it is decided to maintain the inclusion of the associated stations to maximize the amount of charging stations included in the study.



(a) Price over time for Q8

(b) Average occupied stands on a weekend Saturday with variance

Fig. 4: Price over time one day for Q8

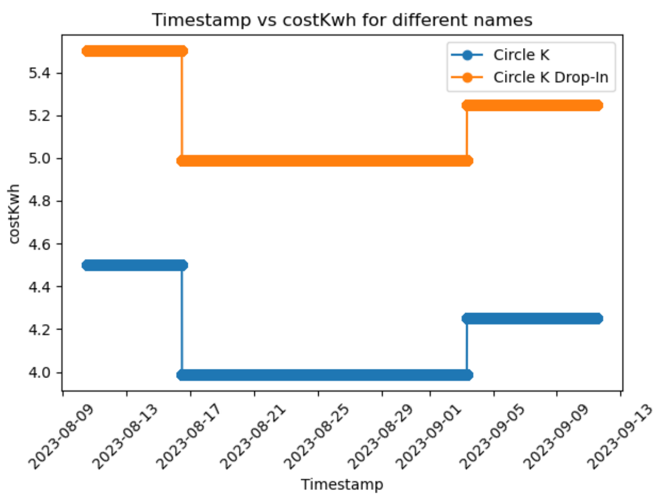


Fig. 5: Charging price over time for Circle K

The stations before and after cleaning the data are visualized in Fig. 1. Each dot represents a charging station. The data is visualized with the intent of finding dense areas, to narrow down the area of interest. On the left-hand side, all stations in the original data are depicted, while the image on the right-hand side depicts the stations that remain in the data after cleaning. Inspecting the location of the removed stations indicates that the removed stations have an even distribution across Denmark and that the integrity of the data regarding dense areas is maintained.

V. Data Analysis

This section covers the analytical aspect and aims to explain the tendencies that exist within the dataset. The purpose is to understand what information can be extracted from the collected data and to narrow down the area of focus for future modeling accordingly.

A. Status

The analysis phase started by assessing the tendency in the occupancy of charging stations. To understand this, the number of charging stands that reported occupancy at each sample for each day of the week was plotted. This is illustrated in Fig. 3. The figure demonstrates the mean charging stand occupancy by hour, meaning that up to four readings by each stand are included. On the left-hand side, the occupancy tendency for all Tuesdays is depicted. A clear trend is found where the amount of reported occupied charging stands is relatively low in the very early morning hours and rises throughout the morning hours between 6 am and 10 am. Between 10 am and 3 pm, the amount of occupied stands is relatively stable, while a steady decrease in occupied stands occurs throughout the afternoon and evening hours. The red area describes the standard deviation between the samples from all of the Tuesdays throughout the observed time interval. Even though there is a relatively large variance, the tendency appeared more or less similar for each Tuesday. Therefore the depiction is deemed representative. On the right-hand side, the occupancy is showcased for a Saturday. Noticeably the number of charging sessions on public stations is generally higher throughout the day, indicating that people are more inclined to charge at public stations during weekends. A smaller interval in the standard deviation indicates that the behavior regarding the use of public charging stations is more consistent on weekends The tendencies shown are replicated for the remaining days of the week, such that each weekday, Monday through Friday, share the same tendencies, while the days during the weekend, Saturday and Sunday have similar tendencies.

B. Price

Another interesting aspect that might influence the behavior of charging sessions is the cost. The price for charging fluctuates depending on multiple factors. First and foremost, each provider has their price range. While some owners have the same price for every station in the country, other owners have different models for determining the price at each charging station. These models may depend on multiple factors: Time of day, Location of the station, and the general price of electricity. Two different examples of pricing models are depicted in Fig. 5 and Fig. 4. Starting with the model used by Cirkel K, where each station regardless of its locale, demands an identical price for each kWh throughout the country. Two prices are available, one price, for drop-in charging and the other for subscribing customers. However, both these prices follow the same regulation, where a fixed rate is determined for a period of time.

The competing provider Q8 uses an alternative model, where the price depends heavily on the location of the station. Q8 operates with three different prices simultaneously, which are deployed to each station based on location. The most expensive price is deployed to stations located along highways and near bottlenecks in the road infrastructure, i.e. at the bridges between Jutland, Funen, and Zealand. Stations that are located around larger cities such as Aarhus or Copenhagen demand a slightly lower price, while stations that do not fit in either of the above categories seem to be deployed with asking a base price. The more expensive prices seem to fluctuate based on some conditions seemingly related to the electrical arrangement Q8 has negotiated.

Investigating the pricing structure of various charging stations led us to test a hypothesis regarding the impact of electricity spot prices on usage patterns. Our analysis revealed that there is no direct correlation between the spot price of electricity during the observation period and charging behavior. While it was noted that the peak usage hours of charging stations coincided with times when the electricity spot price was lower, this alignment appears to be coincidental. The peak usage hours primarily correspond with morning and evening commuting times. This suggests that the high demand for charging sessions is more closely tied to the daily travel patterns of users, occurring when traffic is heaviest and people are commuting to and from work. Meanwhile, the peak in spot prices for electricity generally aligns with the highest overall electricity consumption, which typically occurs in the hours surrounding the standard working day.

C. Narrowing inspection area

Even though the study aims to cover the EV charging mechanisms for the entire country, it seemed necessary to try and narrow down the area of inspection, such that the selected areas could provide some information about similar dense locations elsewhere in the country. Narrowing down the inspection area was done by determining the most station-dense areas, to try to ensure continuity in the samples.

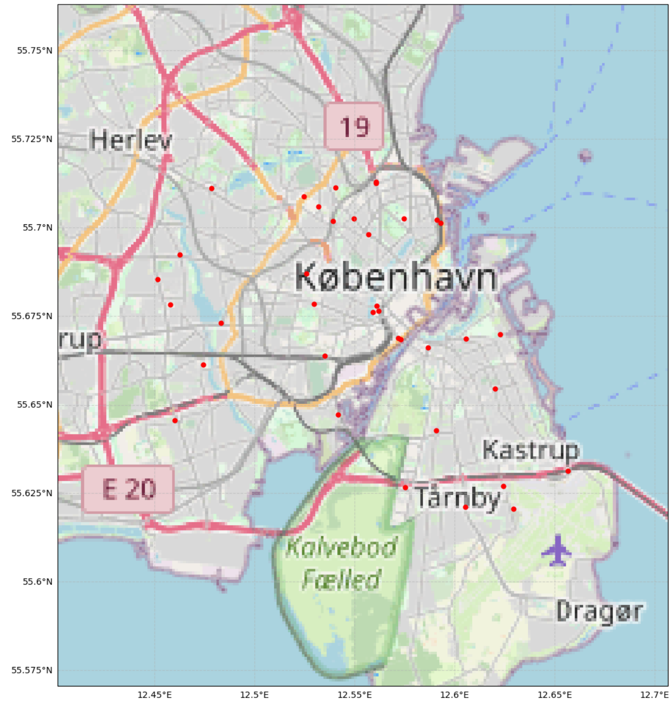


Fig. 6: Charging stations in and around Copenhagen. The image is padded for quality purposes.

Therefore, the primary inspection area was narrowed down to charging stations in and around Copenhagen. The area covers approximately 236.822 km^2 and is bound by the longitude and latitude coordinates:

- Longitude 1: 12.438°
- Latitude 1: 55.568°
- Longitude 2: 12.658°
- Latitude 2: 55.718°

Inspecting the area shows that a total of 37 charging stations are within the boundaries, and cover the innermost city of Copenhagen including stations in near approximation. The stations' locations are illustrated in 6. The 37 stations were distributed across seven different providers: ['Allego', 'Circle K', 'Clever', 'E.ON', 'Monta', 'Q8', 'Spirii']. To understand the interconnectivity between the stations, the distance between each station was calculated. The calculation was done by finding the shortest path in terms of travel time following the road infrastructure in and around Copenhagen. The calculation was done by retrieving data about the round infrastructure in Denmark from Geofabrik. Then the data was spun up on a localhost server, where requests could be sent to find the distance between each station. The distance was then measured using the shortest distance method from the OSRM python package.

VI. Discussion

The purpose of this paper is to understand the user behavior of EV owners in terms of using public charging stations. To generalize it is important to either include all public charging stations in the area of interest or to include a significantly large random sample, which is representative. The data used for this study has included 598 charging stations, with these stations being spread across Denmark. Each of these 598 stations reports the use of anywhere between one to ten charging stands, averaging at about 4 stands per station indicating approximately 2400 charging stands. The exact amount of public charging stands in Denmark as late of June 2023 amounted to a total of 13.100. This means that the sample of examined stations constitutes 18.5% of the total amount of public charging stands. However, the distribution that is present in the random sample matches the distribution of all charging stands across Denmark, maintaining similar dense locations.

The data generally lacks consistency meaning that a lot of information provided by parts of the data has either been discarded or inspected in isolation. This has resulted in not being able to fully use the information that is present in the Data, as it would breach the data integrity. One of the main concerns with said data is correlated to sampling. The intent was to have time-series data with a sample rate of 15 minutes. Yet there is an inconsistency when inspecting the actual sample rates of each data point in the sample, where samples of the same stations fluctuate in time, resulting in unevenly spaced time-series data. As a result of having unevenly spaced time-series data, a limitation is set when building a model for the prediction of the optimal placement for introducing new charging stations. Additionally, each station returns its current state upon receiving a sampling request, meaning that what happens in between requests remains unknown. As a result, charging sessions that last less than 15 minutes might be a blind spot to the sample. However, the indication in both the data used and other referenced studies indicate that even though charging sessions appear to be ”short”, a session typically lasts longer than the 15-minute sample rate.

Another limitation about the data lies in the hours of sampling. As previously mentioned the sample covers only the time-frame between 6 a.m. and 11 p.m., which leaves a rather large undiscovered period. This may also lead to user behavior patterns during the late-night and early-morning hours. This is apparent in the data, as the general response in occupied charging stands is higher at the first response of the day when compared to the last response from the previous day. While the dataset is limited to sampling hours between 6 a.m. and 11 p.m., thus omitting late-night and early-morning user behavior, the available data still holds significant value. Notably, the behavior patterns observed at the boundaries of our time-frame, suggest that the observed hours encompass user behavior during peak usage time.

Interestingly the observed patterns are similar for all weekdays, while weekend days are also similar to each other, yet not completely identical to the weekdays. This indicates that there is a change of behavior when entering the weekend. Notably, the data shows a higher overall occupancy rate across all hours, which remains more constant than on weekdays. The observations also indicate that the standard deviation of the data is smaller during weekends, implying that the behavior is more consistent. Therefore, for the continued work with this study, looking into incorporating these differences into a model when determining an optimal location for introducing new charging stations. Overall, this data can be extremely useful for planning purposes. It can inform the scheduling of utility load management, and potentially the strategic placement of new charging stations to meet higher demand during peak usage times. Additionally, these trends can assist in predicting future charging station requirements as the adoption of electric vehicles continues to grow.

Looking into the pricing scheme, adopted by various owners of charging stations in Denmark, it is apparent that different strategies are incorporated. Cirkel K’s strategy, as described, is uniform across all stations. Such a model is straightforward, with fixed rates set, likely making it easier for the customers to understand and predict their charging expenses. This approach might appeal to customers who value consistency and simplicity in pricing, and those who frequently use the same locations for charging. In contrast, Q8’s pricing model is more dynamic and location-based, with three distinct pricing tiers. The highest price is reserved for strategically important locations such as highways and road infrastructure bottlenecks, reflecting higher demand and possibly the convenience factor of these locations. A slightly lower price is applied to stations in large cities, where the demand is also high but perhaps slightly less critical. The base price is allocated to stations that do not fall into these two categories, likely reflecting a standard rate of service.

This paper is written as initial documentation, describing the initial steps that have been performed to gain insight towards understanding what data is included in the study, along with observing the patterns that can explained with the information provided by said data. The paper works as the first of two iterations, where the second iteration will aim to include selecting and developing a model for determining the optimal placement of new charging stations. The focus of this paper is therefore to understand the data and determine which parts of the data are both meaningful and complete enough to base such a model upon.

VII. Conclusion

The contents of this paper are to statistically describe usage patterns and correlations that should be incorporated into predicting optimal placements for new charging stations with the intent of optimizing infrastructure load balancing. Our investigation into the utilization patterns of EV charging stations across Denmark has yielded an understanding of current infrastructure and user behavior. The data provided has been thoroughly analyzed with the intent of discovering both the limitations and possibilities in predicting the optimal placement of future EV charging stations. State-of-the-art methods for analyzing EV charging utilization have been revisetoto assist the direction of this research. The results of this research showcase EV charger utilization in Denmark, while also testing for correlation with both pricing schemes and the electricity spot price. Additionally, a data processing pipeline has been created such that future data can be cleaned, processed, and later analyzed. Despite the limitations that have been identified, it has been concluded that there is justification for working further towards developing a predictive model.

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