First Assignment

AI-Driven Strategies For Optimal EV Charging Station Deployment

for Electric Vehicle Technologies and Applications WS 24/25

at
Technical University Berlin
Institute of Machine Design and Systems Engineering
Department of Product Development Methods and Mechatronics

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submitted at: January 19, 2025

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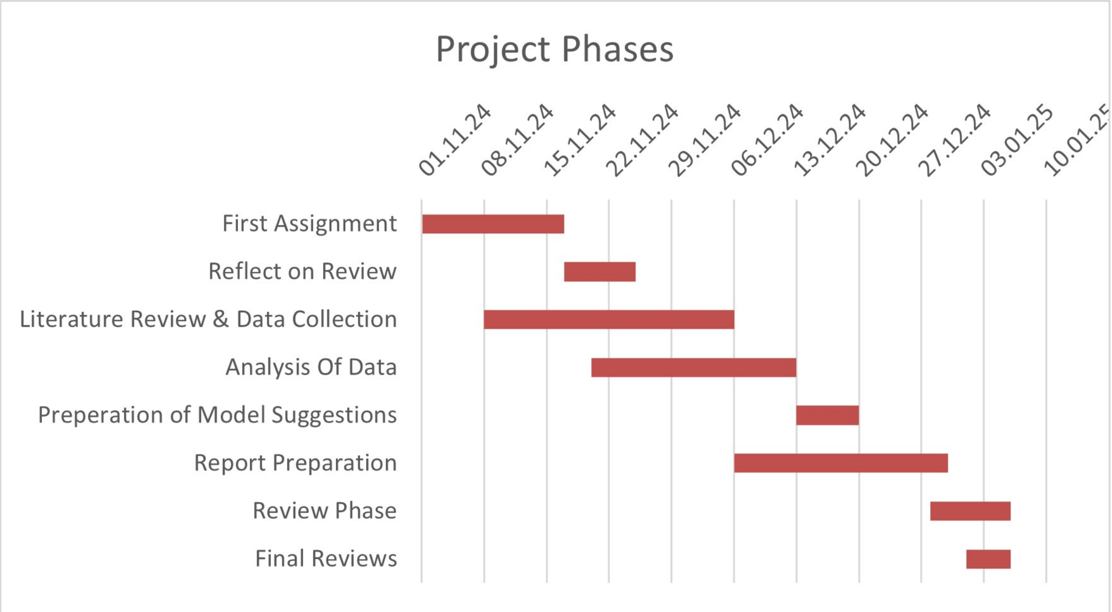

2 Abstract

As the usage of EVs increases globally, efficient deployment of charging station infrastructure has become a critical component of sustainable urban mobility.Determining optimal locations for EV charging stations is crucial for minimizing infrastructure costs and maximizing operational efficiency. Policymakers can leverage data-driven approaches to make informed decisions, ensuring that charging infrastructure meets demand effectively while remaining cost-efficient. This paper focuses on and uses the methods of AI to solve the problem of efficient EV charging station deployment. Utilizing open-access data sources, such as Berlin Open Data, the research analyzes spatial patterns, utilization rates, heatmaps and key factors influencing the efficiency of the locations of charging stations, including geographical, social, and economic determinants. AI methodologies are also weighed against each other to find that supervised learning with neural networks is the most optimal AI methodology for the problem at hand. However, due to data limitations, a real life example is not possible to be built at the time of publishing. A pre-trained supervised learning model developed by Jayanath et al.[22] was used to give insight to optimal EV charger locations but was found to be very biased towards traffic volume. Then an unsupervised learning model was built to find the underlying patterns in existing infrastructure. Using Analytic Hierarchy Process to rank patterns in infrastructure it was made possible to find and visualize the most optimal EV charger locations in Berlin.

Keywords: Electric vehicle charging station deployment, Spatial data analysis, GIS systems, Berlin, Urban planning, Artifical intelligence, Machine learning

3 Introduction

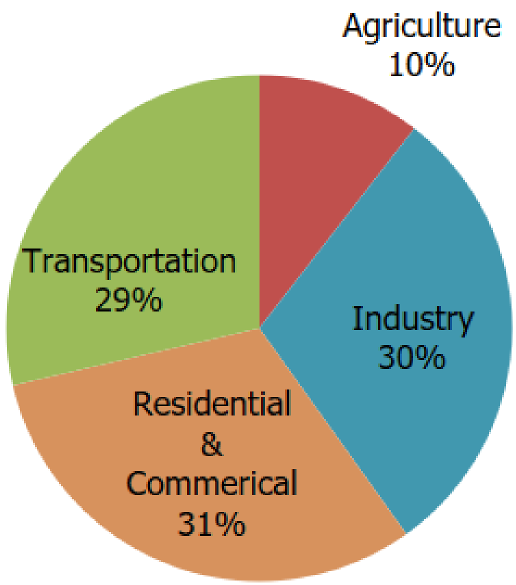

Figure 1: Total U.S Greenhouse Gas Emissions by Economic Sector Including Electricity End-Use Indirect Emissions. [14]

Burning fossil fuels for transportation, including cars, trucks, ships, and planes, produces greenhouse gas emissions. Transportation uses mostly petroleum-based fuel, primarily gasoline and diesel, which cause direct emissions. It is also the second largest direct and indirect greenhouse gas emissions source, and the third largest comes from industry. To process raw materials into finished goods or products, industry also needs energy from burning fossil fuels and which causes greenhouse gas emissions. It is shown above that industry highly contributed of U.S. greenhouse gas emissions. Burning natural gas or petroleum for electric power is less carbon-intensive than coal. In the United States, coal was responsible for 55% of the sector's CO_2 emissions, but only 20% of the electricity generated from coal was generated in 2022 [14]. one of the important steps for more national energy security, less reliance on imported fossil fuels, and an increasingly energy-sustainable future is introducing electric vehicles. Countries can embark on a cleaner transportation future powered by innovation, resilience, and environmental responsibility by working together and collaborating with industry to build the infrastructure needed to achieve that [6].

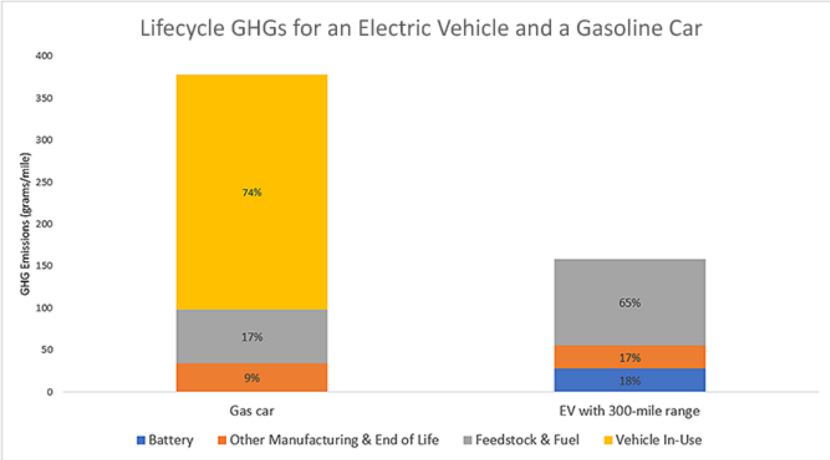

Figure 2: Lifecycle Greenhouse Gases. [13]

In the production of electric vehicles, battery manufacturing is also needed as an important part of it, which is accused of still causing pollution. Throughout the lifetime of electric vehicles, starting from manufacturing then charging and driving, electric vehicles are still calculated to be less in the production of greenhouse gas emissions compared to internal combustion engine vehicles, which can be seen in the following figure where it can be seen a very clear comparison, namely where the gas car during its use contributes 74% in its lifecycle. Unlike gasoline cars, electric vehicles do not produce greenhouse gas emissions during use. Compared to internal combustion engine vehicles (ICEVs), electric vehicles (EVs) have a considerable advantage in terms of energy efficiency. For example, EVs convert 87%–91% of energy from batteries whereas ICEVs can only convert 16–25% of gasoline [13]. Despite the significant advantages that EVs have and their worldwide implementation, the availability and accessibility of EV charging stations are issues, and the cost of batteries is also another obstacle that needs to be faced since batteries are one of the important parts of EVs. Even though installing charging infrastructure at home is possible and inexpensive (ca. 200 EUR), it still doesn't compare to the charging speed of not charging stations. Another problem in introducing electric vehicles is consumer acceptance or customer readiness to adopt EVs due to many considerations, such as performance concerns or, as mentioned above, the availability and accessibility of charging infrastructure. There are also other technical issues such as standardization, Safety requirements for recharging/discharging places, Charging cable at the car or at the recharging station, Periodic inspections and maintenance of recharging places, Cross-national compatibility (re-charging abroad should not be different to recharging at home). Several approaches to help where to place EV charging stations in urban areas have been proposed in response to this issue. Electric vehicles can also be considered to be more environmentally friendly, which can help reduce contributions to greenhouse gas emissions and local air pollution [3].

The EV market has seen more consumers and businesses experiencing rapid expansion

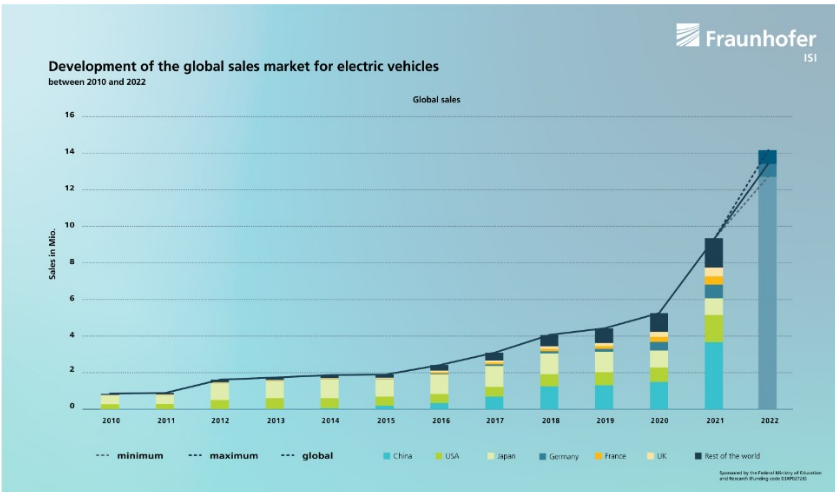

Figure 3: Development of the global sales market for EVs between 2012 and 2022. [21]

as companies and people choose EVs to reduce their carbon footprint and take advantage of financial incentives. Despite the market growth, the efficiency and management of charging infrastructure is still an issue. One of the solutions for this scene is artificial intelligence (AI), which can be promising in optimizing strategies for the deployment of EV charging stations [5].AI can play a major role in maximizing the advantages of electric mobility while searching for a solution to overcome the problem of energy infrastructure [32]. with the help of AI algorithms, it is possible to identify optimal EV charging station deployment and distribution by collecting and analyzing specific data such as traffic patterns, user behaviour, and geographic features. AI will become more important in the future, while the EV infrastructure expands further. To ensure that the energy demand can be accommodated sustainably, AI algorithms can also pave the way to the integration with renewable energy sources, such as solar and wind power. This can lead to lower greenhouse gas emissions and a shift toward a more sustainable energy ecosystem [31].

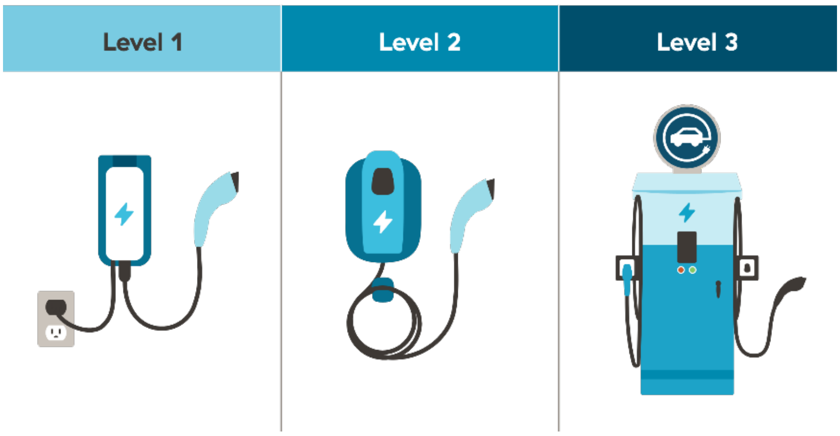

Figure 4: 3 Charging levels for EVs. [33]

The vehicle industry is experiencing rapid development with the emergence of many innovations, one of which is the three different EV charging levels with their objectives, even though these levels are suitable for all EV drivers. The vehicle industry is experiencing rapid development with the emergence of many innovations, one of which is the three different EV charging levels with their objectives, even though these levels are suitable for all EV drivers. Level 1 can be regarded as a basic wall plug. Level 1 EV charging has the slowest case speed, with a power rate of around 1.8kW to 2.4kW. For example, it takes 20 hours to get the capacity that can be used to travel 120 miles. Most public charging stations provide a level 2 charging station with a power rate of 3.6kW to 9.6kW, which is faster than the level 1 charging station. Rather than alternating current that is used for level 1 and level 2 charging station level 3 charging station uses direct current which can charge with high speed with power rate 25kW to 350kW. Due to the high cost and the inadequate electrical infrastructure, a level 3 charging station cannot be installed at home [17, 33].

4 Problem Definition

The main focus of this project is the implementation of AI to optimize EV Charging station deployment in urban areas. This multi-objective problem has various key factors such as traffic flow, parking place, population density, and geographic features. Each key factor has issues that can lead to unideal deployment decisions. With the utilization of AI, it is possible to redefine the placement of EV charging stations in many ways through data analytics from the key factors despite the issues from each factor [41].

4.1 Parking Availability

As the introduction outlines, The EV market has seen more consumers and businesses experiencing rapid expansion. The adequate EV charging infrastructure continues to be one of the limitations for deploying an Urban EV transportation system, particularly in Asian cities with high population densities, such as Singapore, Hong Kong, and Shanghai.[46] The demand for accessible and efficient EV charging stations is rapidly increasing as the global transition to EVs continues expanding. EV charging infrastructure placement is becoming dependent on residential and commercial parking places because parking lots are one of the most strategic places suitable for deploying EV charging stations due to their accessibility and convenience for EV drivers, although there are limited parking spaces [42].

4.2 Traffic Flow

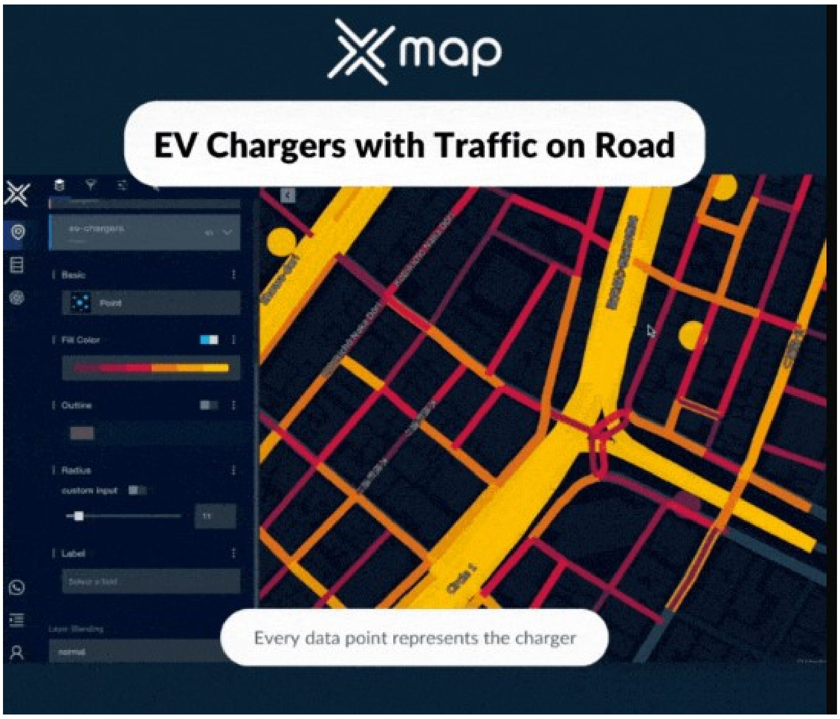

Figure 5: Example of Charging Stations Based on Traffic Flow. [49]

Traffic flow plays a vital role in the optimal deployment of EV charging stations. Collecting other relevant data, such as the landscape of the roads and the mapping of specific areas, enables us to predict the areas with the most demand for charging stations, as EV owners are more likely to stop for charging when passing through this area, and slightly lower the traffic jam. Lowering traffic congestion can also be minimized by the optimal deployment of EV charging stations, where the EV owner can charge the vehicle rather than wasting time in traffic congestion [49].

4.3 Energy Distribution

Energy distribution can be included in the consideration for planning the deployment of EV charging stations. The challenges that will be faced in energy distribution are grid that can be suitable for each customer and every charging station has various energy or electricity capacity due to dependency on the demand at each charging station where the higher the demand the bigger the capacity required. At the same time, this will also cause problems with the cost of the right-sized electric vehicle supply equipment and maintaining the charging station [44].

5 Objectives

The purpose of this project is to explore the use of AI methods for planning EV charging station deployment in urban areas through research and analysis of AI-based models and relevant data sources such as traffic flow, parking, and demographics. This project aims to determine the key factors influencing optimal EV charging station placement in urban areas. With the knowledge of specific factors, relevant data sources and estimates of necessary infrastructure for the future, it is possible to choose the most suitable AI methodologies for charging station deployment planning and compare the approach of AI-driven to traditional planning methods.

6 Data

6.1 Turning the Motivation into Data

6.1.1 What the motivation is:

A standard and publicly available data type is charger utilization rate. Charging stations have to first communicate with the EVs to start the energy transaction as specified by ISO 15118[35] and charging times can be tracked. ISO 15118[35] is a standard that was developed with the goal that allows for a secure and user-convenient way of charging EV's while allowing the user mobility and providing stable and at the same time being stable and energy-efficient. [29].

As shown in this paper that is explaining the overview of ISO 15118 [35] [29], and in the following table it illustrates the organization of the communication protocols between EV and charging stations in OSI (Open System Interconnection) layers.

Between two endpoints that are EVCC (EV Communication Controller) and SECC (Supply Equipment Communication Controller), after the process of all the data that is to be used while charging is done, the communcation between two endpoints happens with either a charging cable or a wi-fi connection.

Through the layer 7 (Application Layer), ISO 15118 logs the data such as:

<table>
<tr><td>Application
OSI layer 7</td><td rowspan="7">ISO 15118-1

General information and use case definition

(merged with contents of ISO 15118-6 for second edition)</td><td rowspan="5">ISO 15118-2

Network and application protocol requirements and ISO 15118-20 2nd generation network and application protocol requirements</td><td colspan="2">Application layer messages (V2G Message),
SDP (SECC Discovery Protocol)</td><td rowspan="5">ISO 15118-4

Network and application protocol conformance tests</td></tr>
<tr><td>Presentation
OSI layer 6</td><td colspan="2">EXI (Efficient XML Interchange)</td></tr>
<tr><td>Session
OSI layer 5</td><td colspan="2">V2GTP (Vehicle-to-Grid Transfer Protocol)</td></tr>
<tr><td>Transport
OSI layer 4</td><td colspan="2">UDP (User Datagram Protocol)
TCP (Transmission Control Protocol),
TLS (Transport Layer Security)</td></tr>
<tr><td>Network
OSI layer 3</td><td colspan="2">IP (Internet Protocol),
SLAAC,
DHCP</td></tr>
<tr><td>Data link
OSI layer 2</td><td rowspan="2">ISO 15118-3</td><td rowspan="2">ISO 15118-5</td><td rowspan="2">ISO 15118-8</td><td rowspan="2">ISO 15118-9</td></tr>
<tr><td>Physical
OSI layer 1</td></tr>
</table>

Table 1: Performance indicators and variables with a timeline of the charging station deployment [35]

- ISO 15118-3: Physical and data link layer requirements
- ISO 15118-5: Physical and data link layer conformance tests
- ISO 15118-8: Physical and data link layer requirements for wireless communication
- ISO 15118-9: Physical and data link layer conformance test for wireless communication
- Start and Ending times of the Charging Session
- Amount of energy transaction during each session
- EV identifiers

Charger utilization rate is derived from this session data, as can be seen in the following formula:

$$Utilization = \frac{\text{Time the charger is active}}{\text{Total available time}}$$

- High utilization rates: suggests adding more chargers

- Low utilization rates: Over-provisioning or poor placement

Through analyzing of the data related to charger utilization rate, it is possible to gauge whether a given charger is excessive or insufficient to meet the demand from its surroundings. Both cases are to be avoided.

6.1.2 How the motivation can be quantified – efficiency score:

To develop and quantify the efficiency score of the utilization measurement for EV charging station deployment, metrics and methodologies that measure the efficiency of a charging station can be analyzed using the relevant data from all of the following indicators shown in the figure [47].

"The results show that a model based on available geographical data and performance metrics of the current network are best combined to predict infrastructure performance."-[47]

For the effectiveness and the optimized deployment of the EV charging stations, the infrastructure should be realized that it is a multi dimensional solution needing problem. Therefore understanding this variables is important to produce effective resolutions, which can be temporal dynamics such as technological developments related to EV's or the charging stations which can be seen in a study that tries to explore the charging behavior of an EV user with a simulation model.[45]

"Overall, the results of the case study indicate a decrease in demand on the charge infrastructure as battery sizes increase and the number of EV's stays the same, which is beneficial for most involved stakeholders."-[45]

This case study and benchmark analysis [48] at 2016 that has been done on the Dutch metropolitan area (The metropole region of Amsterdam, the city of Amsterdam, Rotterdam, the Hague, Utrecht) tries to explore different charge patterns and to establish whether and how charge behavior i.e.: charged volume, capacity utilization, unique users, differs between cities. The study focuses on the deployment of the charging stations regarding the questions of the location selection, timing and which type of charging infrastructure to use such as: (charge station with 2 sockets, charge hubs with 4+ poles or fast charging infrastructure) and the variables of the data that's been used in this benchmark analysis that is related to this paper are start connection date time, end connection date time, connection time (duration), charging time, volume.

Key Performance Indicators were not all measured at the city level but at the parking zone level or the charge point level. One of the goals was sustainability goal – to increase the air quality in the city, when switched to EV's resulting in the decrease of fossil fueled vehicle usage, contributes in this goal. KPI's make it possible to compare the charging behavior between different cities. Another point that stands out on this research and similar literature, is to understand and analyze the pattern of "charging station hogging", which finds out the blocking of charging stations after the charging process is done. [48, 26, 28]

It is important to keep in mind that this research did not include or measured the effects of some factors that could possibly be highly relevant such as income or population density in a city like Berlin where some specific districts compared to other districts has more EV charging stations where it can be assumed to this being related to more dense areas regarding of the population. Which can be important when deciding on the deployment method of the EV charging stations regarding studies like [15] that shows the psychological dynamics of EV users battery charging behavior. Where it is summarized that the typical user in this research mostly charged their EV although substantial battery life was remaining and some of the users generally charged when there was battery warnings.

This city level focused research paper shows that by “identifying relevant KPIs at the city level charge infrastructure policies of different cities can be compared [48]” and one of the roll-out strategies that resulted in “focusing on more strategically placed charge points as in the metro-pole region of Amsterdam result in more effective usage of the charge points when comparing the time actually charging to the time connected”-[48]

6.1.3 Aspects and the methodology of the efficiency score

On a research that has focused on the public charging demand and infrastructure of EV’s and charging stations from the city of Berlin [27], real world data is used to perform an analysis on the weekly charging behaviors. The researchers [27] state that there are “numerous charging stations without available data” and also that “there was no official count of charging stations” until the introduction of the Berlin Model, which is a official requirements that charging stations have to fulfill. These requirements states that infrastructure must be accessible to all EV users, and the operator of the infrastructure is irrelevant. Also the charging stations record charging information and this paper used the data that is resulting from this Model, between December 2016 and March 2018.

Type of Current	**Charging Type**	**Charging Power**
Alternating Current (AC)	Normal charging	2.3 kW - 22 kW
Direct Current (DC)	Fast charging	22 kW - 350 kW

Table 2: Types of Charging Currents and Power Ranges

As it can be seen from [12], the speed of the charging and the charging power is directly related to the type of charging, which requires different type of plugs, such as Type 2 Plug (AC charging) and Combo2 Plug (allows AC charging and fast DC-charging from the same port) or CHAdeMO (is not compatible for Type 1 and Type 2 charging) (a DC-fast charging standard that is released before the CCS). CCS charging is more commonly used in Germany.

[27] used the peak power to distribute charging power, which represents these connector types that are being used in Berlin. They cleaned the data by removing inactive sessions and possible misusage and the result was 50.491 charging events and 221 charging stations.

By the end of 2020, there was a total of 1.140 charging points [20]. As of 20th April 2024, the city of Berlin has 25000 available charging points, of which around 3850 of the charging points are publicly accessible, from the official website of Berlin [10].

Peak Power	Connector Types	Charging Mode	Use Case	Standard
3.6 kW	Type1 SAE J1772 Type2	AC, slow	Home Low-power public charging	IEC 62196-2 SAE J1772
11 kW	Type 2 (Mennekes) Tesla (NACS)	AC, fast	Home Public AC charging	IEC 62196-2 SAE J3400
40 kW	CCS (Combo1, Combo2) CHAdeMO	DC, fast	Public fast-charging	IEC 61851-23 IEC 62196-3 (CHAdeMO)

Table 3: Charging points Information .[10]

Focused areas on the data were infrastructure supply, infrastructure utilization, infrastructure efficiency.

Conclusion from this research tells that although the charging stations were unevenly distributed, the utilization is relatively equal. It is confirmed by the analysis that the charging station utilization is under its capacity, related to “charging station hogging”, also another important point that allows to understand and analyze the charging station utilization rate and therefore the data related to charging station efficiency, similarly mentioned in the research on the Dutch metropolitan area [48].

6.2 Identifying Necessary Data

6.2.1 What data types are used in similar literature

The data needed in this project can be open-access database, such as GIS (geographic information system), e.g. for Berlin it is available through Berlin Open Data [8] or in Poland, BDOT10k (Polish National Databases of Spatial Data) [9].

GIS-based method can be helpful for the open source projects, low-funded volunteers or startups that are trying to support or build a project during the process of analyzing and finding the most optimal locations for EV charging stations, when it is publicly available without additional costs.

There are some key aspects when trying to determine the locations of EV charging stations, such as,

- Spatial Data: road system, attributes of the following: type, power, connection type

- Social determinants: availability, demand
- Mobility patterns: types and modes of travel
- Type of chargers: charging infrastructures
- Economic Aspects: costs, profits

And this list can be extended as far and as detailed as is expected. In a study conducted to determine new locations for electric vehicle charging stations using GIS [39], these key aspects can be seen more in-depth and in detail. This list also aligns with the data types used in the study such as the research of the Dutch metropolitan area [48].

Spatial data are widely available, and for this reason it creates an advantage to choose it as the data source to determine the optimal locations for EV charging stations. Integrating social determinants with spatial data allows the ability to predict future demand for EV charging infrastructure. For instance, although this is just an assumption, areas with high residential density and limited parking space may exhibit different charging patterns compared to commercial zones, an that can be a factor to use when deciding for the optimum infrastructure locations.

6.2.2 Table and chart of the data type distribution

Data Type	**Purpose**	**Example Sources**
Spatial Data	Identify optimal station locations	GIS, OpenStreetMap
Social Data	Determine user demand	Surveys, open data
Traffic Data	Analyze mobility patterns	Traffic sensors, GPS data
Energy Data	Assess grid readiness	Utility providers, energy reports
Economic Data	Evaluate cost-effectiveness	Financial reports, policy papers

Table 4: Data type distribution and possible sources

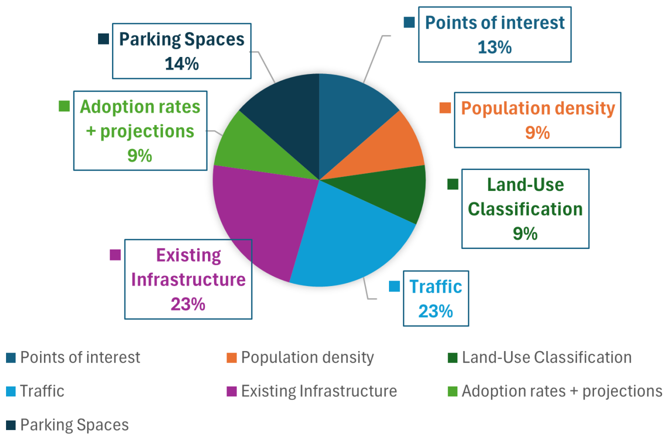

Figure 6: Pie chart of frequency of used data types in similar literature [16][22][4][7]

6.3 Collecting Data

6.3.1 Availability of the aforementioned data types for Berlin

For example, this data [11] which its key topics are presented in different spatial units is just available at Berlin Open Data with a quick search including the keywords "ladeinfrastruktur,elektro,auto", Locations of the EV charging stations, Electricity consumption of the e-charging stations per district with the attributes of the EV charging station locations. For instance [48] used variables such as RFID, Start Connection Date Time, End Connection Date Time and Charging Time when they collected the data from the charging sessions.

There are also some private applications which show the EV charging station locations on the map. They can be used to analyze the current situation regarding the situation of the charging station depending on the user reviews.

In Berlin-based studies, the Berlin Open Data platform provides information on parking zones; however, detailed information on individual parking spots is not available through this source. Alternatively, parking spot-specific data can be accessed via Parkplatz Transform.

6.3.2 Table for available data sources

Data Source	Type of Data
Berlin Open Data	- Points of interest[36] - Population density[40] - Land-Use Classification[36] - Existing Infrastructure[37] - Adoption rates + projections[38] - Traffic
Parkplatz Transform	- Parking Space[43]

Table 5: Berlin suitable possible data sources for spatial data

6.3.3 How GIS systems are used to gather the data

There's typically two category that spatial data is referring to about the information for specific locations: raster and vector. They can combined with attributes, e.g. address or postal code, and location of a EV charging station can be the spatial data.

- **Raster Data** is simply a grid based form of spatial data that is a combination of pixels or cells, where each of them represents a geographic location, and their values correspond to the information of that location such as temperature, elevation, or land cover. It is suitable for the usage e.g. satellite images or climate models.
- **Vector Data** represents geographic features through discrete points, lines, or polygons. A point on a vector data can represent a specific location like a tree or in this case a charging station, a line can represent a road or river, and a polygon can represent an area like a city boundary or a land parcel. While raster data is ideal for analyzing continuous phenomena, vector data excels at representing precise, discrete features.

Berlin Open Data datasets, which cover most of the datasets used in this paper, are Web Feature Service(WFS) endpoints. They are essentially links that can send data to Geographical Information Systems(GIS) like QGIS and ARCGIS. Unfortunately, most of the data represent areas and thus are vector data. Since most of the operations on the data will require querying the surrounding area of an EV charger to gather data within the search window, vector data adds another dimension of complexity to operations. Therefore in this paper all spatial information was reduced to their respective center points.
Another issue is that all of the available data is in another geographical projection than the projection used in the map that will be created in section 7. The data is in the EPSG:25833 projection and the map uses EPSG:4326 projection.
These both points can be remedied by using the field calculator in QGIS which applies a formula to all the data entries in the map. For raster data the formula

`x(transform($geometry, 'EPSG:25833','EPSG:4326'))` will suffice whereas for the vector data the formula `x(transform(centroid($geometry), 'EPSG:25833','EPSG:4326'))` is needed to find the centroid of the area that the vector represents.
After these steps, the datasets can then be exported using QGIS in a more conventional file format like a Comma-Seperated Values(CSV).

6.4 Analyzing and cleaning the Data

The effectiveness of the strategies which will be outlined in this paper for optimal EV charging station deployment relies heavily on the quality of the data used. Reviewing the data is crucial to ensure the accuracy, reliability, and applicability of the results. This section evaluates the datasets utilized, identifying potential limitations and discussing the implications these factors may have on the findings. By addressing data quality, transparency and a solid foundation can be established.

6.4.1 Combining the data

To perform future operations on our data, it is very important to combine the data into aa single data structure. This enables easier manipulation of EV charger data as each EV charger itself holds its data. To achieve this, `pandas` Python programming language package can be used. Exported data which is saved in `csv` files can be loaded into memory using the `read_csv` function. As the foundation for the combined data, EV charger information will be used because we're examining the data surrounding EV chargers. Then the EV adoption data can be merged with it based on the post code column.
Adding other data isn't straightforward. All the other data types have their values paired with a latitude and longitude for the center of the geometry they represent. These coordinates are not necessarily coincident with the EV charger coordinates. Therefore a custom function is used to gather data from surrounding areas.

```python
import numpy as np
# Euclidian distance function
def dist(x1, y1, x2, y2):
return np.sqrt((x1-x2)**2 + (y1-y2)**2)

'''
    PARAMETERS:
        table: The table the information should be gathered from
        attr: Column that holds the desired data
        lat, lng: Coordinates of the origin point of the search
        distance: Side length of the n x n square that the search
        will be conducted in(in kilometers)
        first: Whether only the nearest match should be returned
```

```
    '''
    def get_attr_area(table, attr, lat, lng, distance=0.5, first=False):
        # Make a rough calculation of defining coordinates of the search square
        new_lat  = [lat  - (distance / 6378.137) * (180 / math.pi),
        lat + (distance / 6378.137) * (180 / math.pi)];
        new_lng = [lng - (distance / 6378.137) * (180 / math.pi) / math.cos(lng * math.pi/180),
        lng + (distance / 6378.137) * (180 / math.pi) / math.cos(lng * math.pi/180)]
        # Fetch the data in the table that lies inside the square
        result = table.query(f'{new_lat[0]} <= lat <= {new_lat[1]} &
        {new_lng[0]} <= lng <= {new_lng[1]} ').copy()
        if first:
            # Find distance of each finding, sort it and
            return the first(smallest distance) result
            result['dist'] = result.apply(lambda x: dist(x.lng, x.lat, lng, lat), axis=1)
            result.sort_values('dist', inplace=True)
            return result.iloc[0][attr]
        return result[attr]
```

After using this function to gather data, each EV charger holds the variables of its surrounding region and the data is now in a much more suitable form for AI training methods.

6.4.2 Data quality

The data quality was assessed across four key dimensions:

1. **Accuracy:** The datasets used contain a low number of evidently wrong data.
2. **Completeness:** Most of the datasets used contain data for the entire Berlin area. One exception is the parking information. As it is crowd-sourced, data for lesser populated areas is missing.
3. **Consistency:** The datasets used are mostly consistent. The data for geographically close points do not increase or fall sharply and are generally intuitive.
4. **Balance:** The data is not uniformly distributed within their respective ranges. This leads to many outliers and affects the accuracy of AI models.
5. **Timeliness:** The most up-to-date dataset used was from 2020, with others being from previous years. The datasets are not consistent in terms of timeliness.

6.4.3 Relevant data types

Although all the data collected in section 6.3 will be utilized, not every data type is required for building an AI-driven strategy. Determining which data types are the most relevant is extremely important because AI models do not understand which inputs are relevant and will try to find relationships between all of them. This will also help the performance as less data will be moved around. Considering the most used data types in existing literature explained in section 6.2, the following data types were determined to be relevant:

Data Type	Variable Name
The percentage of EV vehicles compared to all vehicles in the postcode area (EV adoption)	p_EV
Nearby population	pop_near
Nearby parking spots	park_near
Nearby yearly traffic	traffic_near
Nearby EV chargers	charger_near
Land-use classification	class

Table 6: Chosen data types and how they will be referred in code

6.4.4 Correlation analysis

Correlation analysis is a critical step in understanding data relationships, refining models, and making informed decisions. If highly correlated independent variables are included in an AI model, it can lead to loss of accuracy or inclusion of redundant features that don't add unique information but increase model complexity.
One contentious point could be inclusion of both population and EV adoption data types as one can argue that the latter is the result of the behavior of the former which can be uniformly distributed. To check if these data types are correlated, a scatter plot can be created.

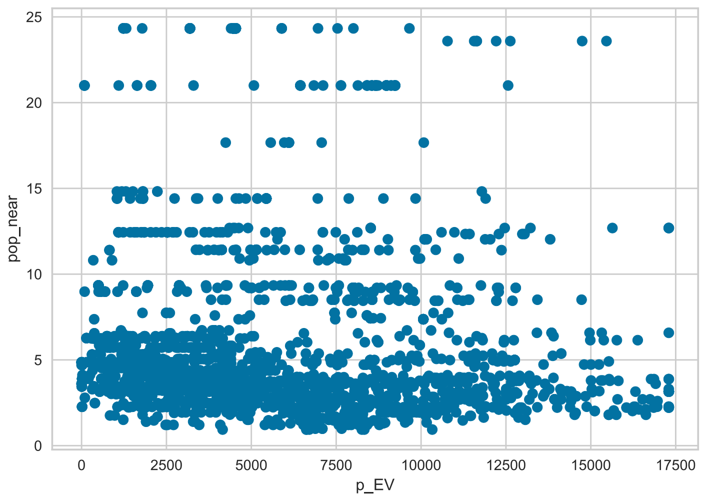

Figure 7: Scatter plot between EV adoption(y-axis) and nearby population(x-axis)

The points are widely dispersed, and there doesn't appear to be a clear pattern, such as a linear or nonlinear trend. Therefore inclusion of both data types is valid.
It would also do well to do correlation analysis on the entire dataset to check for further correlations that may exist. This can be done by using the `corr` method on our `pandas DataFrame` and visualizing it with `heatmap` function from the `seaborn` Python package.

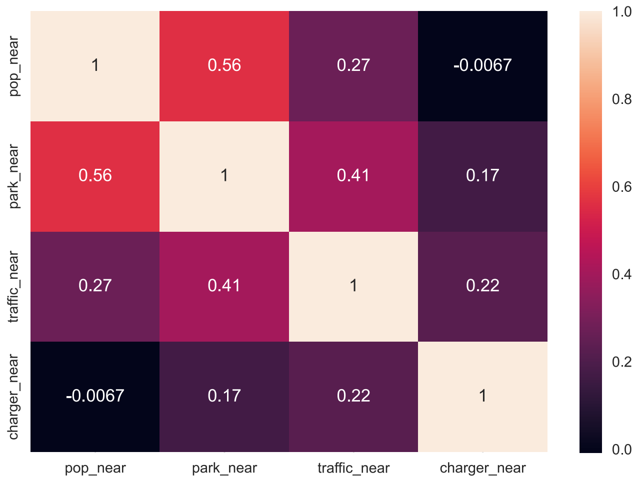

Figure 8: Heatmap of the correlations in the dataset

On this graph, the values on the intersection of the labels represent correlation between the data types. The values range from -1 to 1. The highest correlation value in our dataset is 0.56 which is at worst a moderate correlation. This set of data types is eligible for employing an AI-driven strategy.

6.4.5 Outlier detection and Winsorization

As mentioned in section 6.4, the data is imbalanced and even has a few blatantly wrong entries. These extremities should be taken care of before applying any AI methodology. To get rid of wrong data the following data entries were dropped from the dataset:

- Entries with non-valid Berlin postcode
- Entries with 0 EV adoption
- Entries with 0 nearby traffic
- Entries which have Null or NaN in one of their values

After these operations number of rows in our dataset reduced from 2717 to 2439. Now the outliers should be filtered. The outliers can be seen by using `boxplot` from `seaborn`

Python package. It should be kept in mind that EV adoption is a percentage and thus does not have a big range and can be excluded. Furthermore, land-use classification is categorical data. It should not be treated as real numerical values and must also be excluded from outlier filtering.

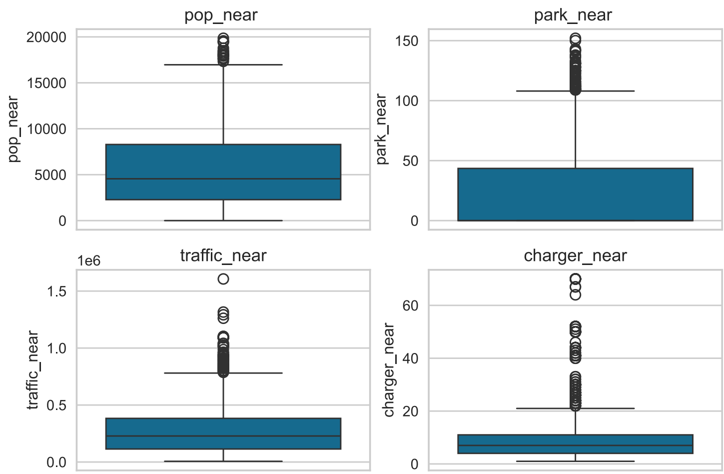

Figure 9: Box plot of original data

Key elements of the plot:

- The boxes signify the interquartile range(IQR) between 25th(Q1) and 75th(Q3) percentiles.
- The lines extending from the boxes are called whiskers and show $1.5 \times IQR$ beyond Q1 and Q3.
- Values beyond the whiskers are considered outliers(shown with circles).

These outliers can be drawn back into acceptable ranges using Winsorization. Winsorization is a mathematical technique that replaces extreme outliers with less extreme values. Outliers in our data can be replaced with their whiskers' limits.

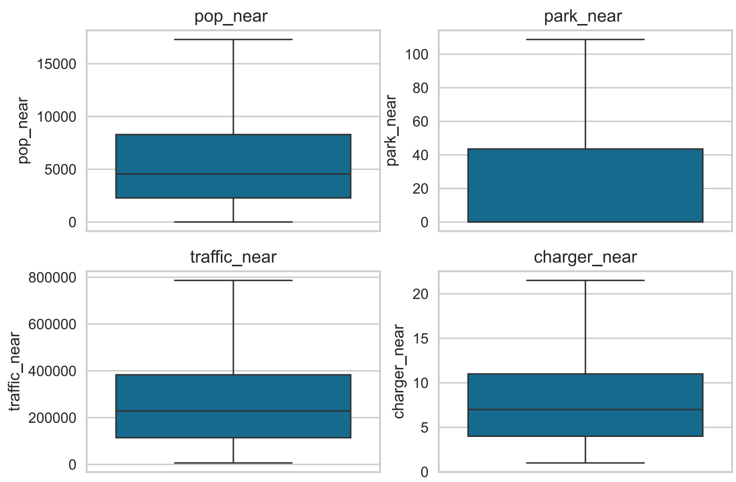

Figure 10: Box plot after Winsorization

Now the data is ready for operation and will provide much more accuracy to the models that learn from it.

7 Visualization

Visualization is key to understanding and interpreting the results of possible strategies. Available data and the algorithmic outputs are too complex and highly dimensional to gain insights easily. Visualization helps bridge the gap between data and actionable information. Through clear interpretable visuals, stakeholders which are policymakers, urban planners, researchers and other roles that are are involved in creating EV charging infrastructure can gain highly valuable intuition. Also since the matter is tightly tied to geography, visualization is highly in order. This section focuses on the visualization techniques employed to illustrate available data and key findings.
Most common visualization methods are geographic heatmaps, bar charts, and network diagrams. Geographic heatmaps are particularly effective for displaying the spatial distribution of data points, enabling planners to identify high-demand areas or underserved regions. Bar charts can create comparative analyses and network diagrams highlight relationships between different types of data. The visualization method most suited for the purposes of this paper are heatmaps as they excel in highlighting spatial patterns and density variations in a single glance.
Creating heatmaps can be achieved using specialized tools such as Geographic Information Systems(GIS) or by leveraging web-based libraries like `Leaflet.js`. GIS platforms, such as QGIS and ArcGIS, offer robust functionality for handling large spatial datasets, including layering, geoprocessing, and advanced spatial analysis. On the other hand,

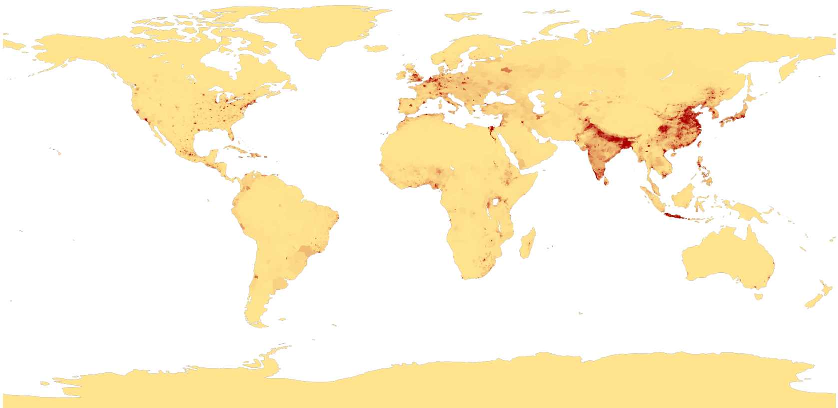

Figure 11: 1990 population density heatmap by NASA[30]

`Leaflet.js` offers unmatched flexibility and interactivity, making it ideal for custom web-based applications. Its extensive documentation, active community support, and ecosystem of plugins simplify the development process while providing powerful features like dynamic updates and user interaction. Web based solutions also allow sharing data more easily as the only software needed to view the data is a web browser which is remarkably more widespread compared to standalone GIS software.

7.1 Creating a Heatmap

To create the heatmap, first, a map should be created. After creating empty HTML, CSS and JavaScript files, creating any map with `Leaflet.js` can be achieved with very few lines of code. To enable `Leaflet.js`, it is sufficient to include an HTML tag to fetch the necessary resources from a content delivery network(CDN). `leaflet.heat.js`, which is the community plugin for creating can also be fetched via CDN. Then in the JavaScript file the following steps should be taken:

1. Create a variable `map` with `L.map(mapName)` function and use `.setView([lat, lng] ,zoom)` to initialize the map view to start at specified coordinates with the specified zoom.

2. Using `L.tileLayer` function to fetch the map tiles from OpenStreetMap tiling service. Add it to the `map` object using `.adddTo(map)` method.

3. Create an array for the heatmap. The array items are in `[latitude, longitude, intensity]` format. `intensity` is optional and determines the opacity and color of the point. Note that when zooming out, the points and their intensities get combined.

4. Create a heatmap using `L.heatlayer(array, {options})` function and use the `.addTo(map)` method again. `options` used were `{radius: 15, minOpacity: 0, maxZoom: 30}`.

These steps and explanations of options can be found in Leaflet[2] and Leaflet.heat[1] documentations respectively.
If the EV charger data collected in section 6.1.2 was plugged into the heatmap array with the same intensity for each charger, the density map of EV chargers in Berlin can be created.

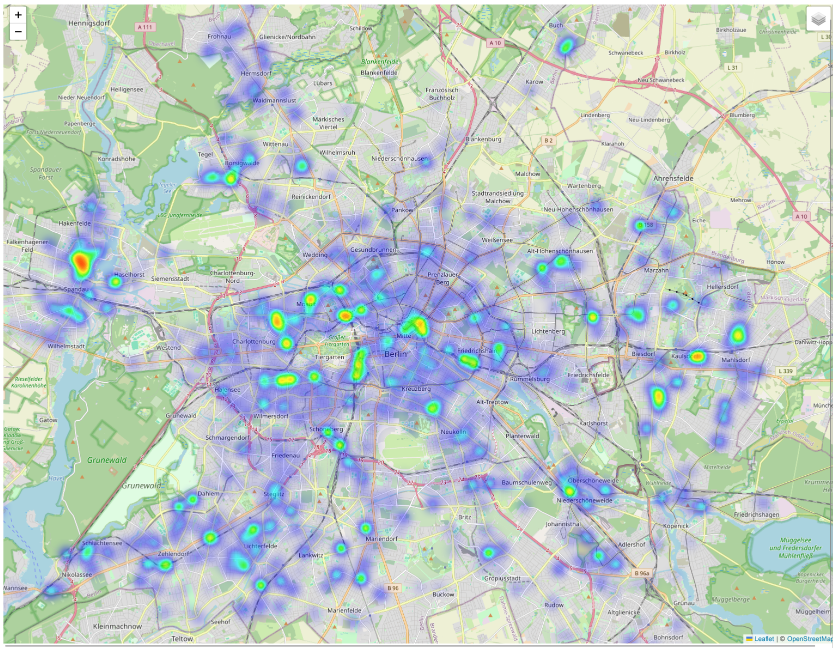

Figure 12: EV charger heatmap of Berlin
The colors scale with count and are in the following order: Blue - Green - Yellow - Red

7.2 Adding individual EV charger data

It could also serve useful to add EV charger locations themselves with their data to confirm that the heatmap is correctly generated and is in accordance with the data. This can be accomplished by creating `L.marker` objects and using `.bindPopup` method to bind a mark-up text to be displayed when an EV charger is clicked on. It is also possible to add a custom icon to the EV charger markers with the `L.icon` function.
However as there are 2439 EV chargers in the dataset, the performance becomes a concern with these markers. To alleviate the performance problem, the `Leaflet.markercluster`[25] plugin can be added via CDN. When markers are added to the `markercluster` created

by `L.markerClusterGroup`, the markers that are close together are combined to a single marker, resulting in improved performance. The hidden markers can be revealed by zooming in or clicking on the group marker.

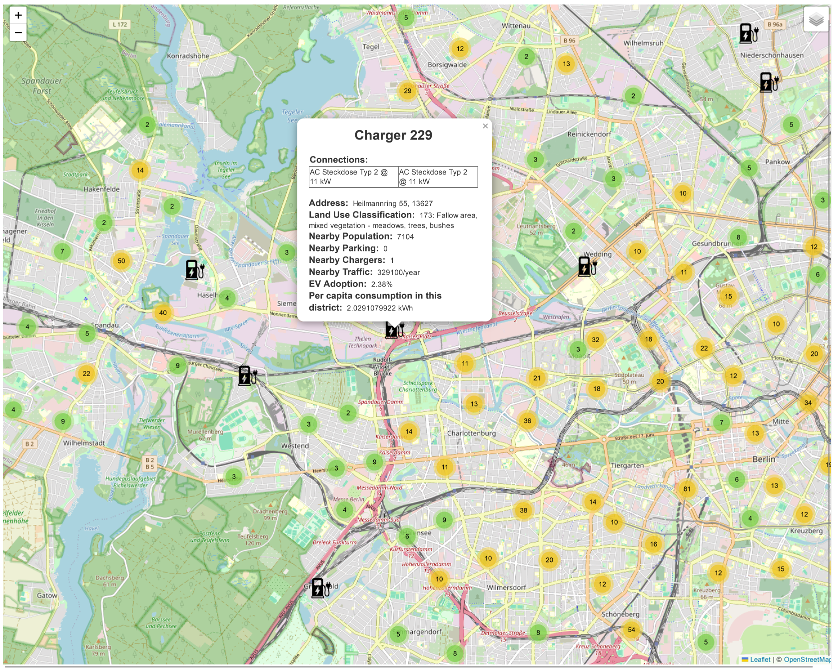

Figure 13: Single and grouped charger markers with custom popup

8 Methodology

8.1 AI Methodologies

Machine learning and deep learning, which is a subset of machine learning, have been proven to be efficient in finding correlations between large data points. By objectively assigning weights to variables, the high-dimensional task of finding a function to predict optimal EV charger locations can be carried out by many members of the machine learning toolchain.[24] In this section, which AI models are applicable for the task at hand will be explored.

8.1.1 Supervised Learning

Supervised learning is a type of learning paradigm that is trained on labeled data. This means that the training set includes both input features and output values. The goal is to find a function that maps the input to the output by adjusting weights of the input features in a linear equation in an iterative process using techniques like gradient descent. The biggest component of supervised learning is also its biggest drawback: the requirement for large amounts of labeled data. With a small dataset, a supervised learning model can over-fit the data, meaning that it can memorize the data set rather than recognize underlying patterns. In real life scenarios, this can be quite time-consuming or expensive. Combined with neural networks, which will be explained later, more complex tasks can be tackled, making supervised learning the best candidate for predicting optimal locations of EV chargers. The exact approach on how to train a supervised learning neural network will be detailed in Section 8.2.

8.1.2 Unsupervised Learning

Unsupervised learning is a type of machine learning in which the model is trained on unlabeled data. The model must find patterns and structure on its own to gain insight and make predictions. Unsupervised learning is also used in marketing, anomaly detection and image processing.
There are many unsupervised learning techniques, and among the most common is clustering. Clustering tries to group the data points together into clusters. The model trained by unsupervised training can then predict which clusters the new data points belong to. Then it is potentially possible to use a multiple-criteria decision analysis to rank the clusters, reducing the human involvement in the decision making immensely.
Unsupervised learning does not have the precision supervised learning has and therefore it is difficult to assess how well the model is performing. Additionally, the patterns that a unsupervised learning model finds might be superficial and may not necessarily represent a real world correlation.

8.1.3 Reinforcement Learning

Reinforcement learning is a type of machine learning where a model(agent) interacts and makes decisions about data to achieve a goal. The agent receives rewards and punishments for its decisions based on how wrong the decision was. It is inspired by how humans and animals learn by trial and error.
Though it's possible to have the agent go through the trial and error by simulating the environment, the simulation is out of scope for this paper. This approach is more efficient for the modelable problems in the EV landscape.

8.1.4 Conclusion

In section 6.1 the degree of optimality of an EV charger was squeezed down to single numerical value. And that value is in a spectrum, namely between 0 and 1. Supervised learning algorithms are the best option for linear regression, which is predicting continuous, non-binary outcomes.
A machine learning architecture will be proposed using supervised learning and neural networks. However, as explained in section 6.1.2, all available charger utilization datasets are either anonymized(location unknown) or not publicly available. Therefore a real

example is unable to be demonstrated. The details of training a model will instead be explained in section 8.4.2 for an unsupervised learning model.

8.2 Neural Network to Predict Efficiency

8.2.1 How a Neural Network Works

A neural network is a type of learning structure that is inspired by the human brain. A neural network consists of interconnected neurons that alter and pass on information. Neural networks can handle complex tasks compared to other methods and neural networks are the backbone of deep learning.

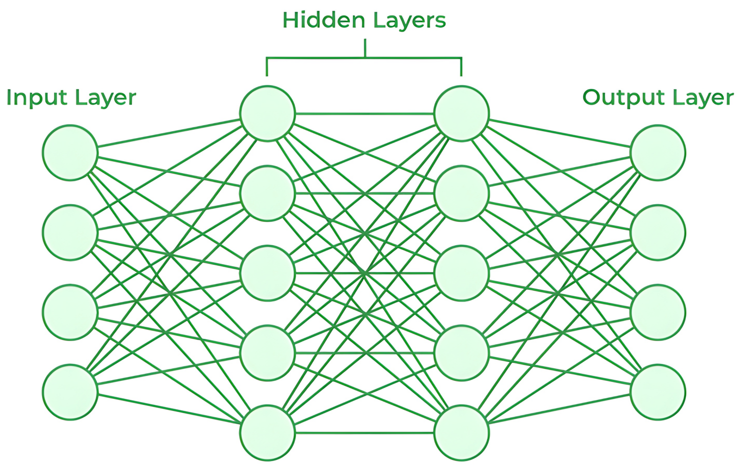

Figure 14: Structure of a neural network[19]

A neural network is made up of 5 components:

1. **Neurons:** Each neuron recieves an input, alters it and then passes the value onto the next neuron. All neurons in a layer are connected to all neurons in the previous and the next layer.

2. **Layers:** A layer is a group of neurons. A network has input, output and hidden layers. More hidden layers contribute to better accuracy but gives back diminishing returns at the cost of performance.

3. **Weights:** A neuron's each connection has its own weight which the value in the neuron is multiplied by.

4. **Bias:** Each neuron has a bias term that is added to the value in the neuron

5. **Activation function:** Weighted sums are then put through activation functions to introduce non-linearity. Most common examples of activation functions are Rectified Linear Unit(ReLU) and sigmoid functions.

Neural networks are trained in 3 steps:

1. **Forward Propagation:** Input data is passed onto the input layer and then forward through the hidden layers.
2. **Loss Function:** The model's prediction is compared to the actual result using a loss function(like Mean Square Error, Binary Cross-Entropy etc.), which measures the error between the predicted output and the expected output.
3. **Backpropagation:** The network adjusts the weights and biases using an optimization algorithm to minimize the error.

Neural networks are an excellent choice for handling high dimensional data like all the features of an EV charger location and learning non linear relationships.

8.2.2 Neural Network Architecture Proposal

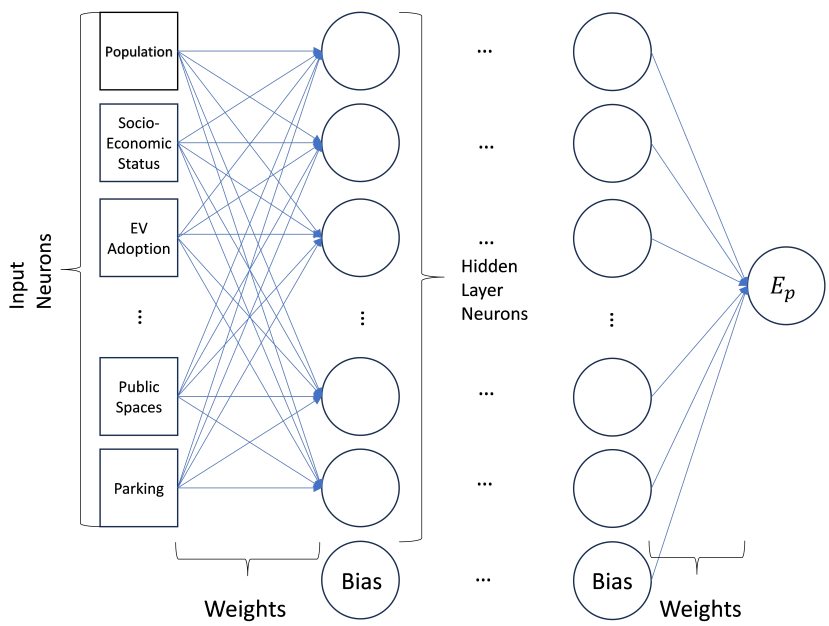

Figure 15: Neural Network Architecture Proposal

In this model, the EV charger data will be fed to input neurons. It is important here to recognize that though the land use classification is represented by a numerical value, it is a categorical value in actuality. The model should not treat it as a number and as

such, should not perform mathematical calculations on it because, for example, adding the category "Housing Area" to "Industrial Area" is not possible. One of the most common ways to circumvent this is using One-Hot Encoding. One-Hot Encoding turns categorical data into a binary vector. In programming languages this is represented by an array like `[1, 0, 0]`. The position of 1 determines the category. This achieves many things. Firstly, now the data has no implicit ordering, meaning that they have no numerical relationship and are independent from each other. Secondly, the encoded data is equidistant and has no ranking or hierarchy. These achieve individuality in data and the model no longer assumes relationships between categories.
After the input data is propagated, they arrive in the hidden layers. For the purposes of predicting it is sensible to use 2-4 hidden layers with 64-128 neurons each with ReLU activation function to strike a balance between learning prowess and computational overhead.
On the output layer there will be a single neuron which holds the predicted efficiency score. Sigmoid can be used for activation function because of its suitability for regression of bounded values.

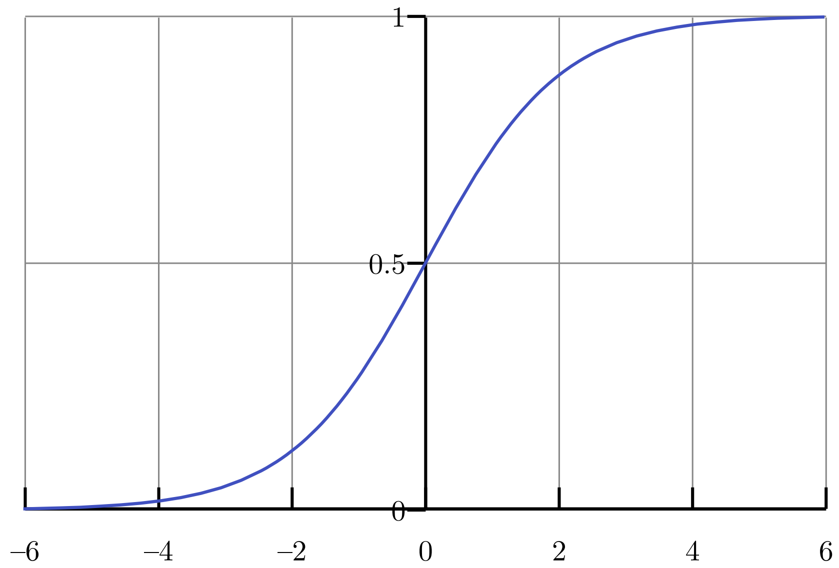

Figure 16: Sigmoid function[34]

For the loss function, mean squared error is more suitable for regression. Although not mentioned in section 8.2.1 as a necessary part of a neural network, the Adam(Adaptive Moment Estimation) optimizer can be used as the optimization method. The Adam optimizer is an algorithm commonly used for updating weights and biases during training. In the end the trained model will be able to take in new data and output a prediction based on the training data.
All of the necessary tools are present in various libraries for programming languages. These tools remove a lot of development burden and enable training a model with

relatively few lines of code.

8.3 Grid Partition Method for Results

Grid partition method refers to the process of dividing a geographical area into smaller, separate grid cells. To figure out which parts of a geographical area(Berlin in the case of this paper) are more suited for deploying EV chargers, a trained model can be used to evaluate each grid cell. The result of the evaluation would be the predicted efficiency score an EV charger placed in the center of that grid would have. Logically, a more divided grid results in more granular data but the compute times can get overbearing fast. The exact grid partition method used in following sections is as follows:

1. Berlin is divided into $n \times n$ squares. The grids' center coordinates are saved.
2. A function is used to consolidate data within a $500m \times 500m$ square centered around the EV charger candidate location.
3. The collected data for each grid is fed through the trained model and the prediction is saved.
4. The predictions are scaled into valid ranges and visualized on the map

8.4 Working with Open Data

One of the challenges in deploying AI-driven strategies for EV charging station optimization is the absence of publicly available data on charger utilization. This limitation necessitates leveraging alternative methodology and open data sources to approximate demand and make informed deployment decisions. Open data — ranging from traffic and population density to existing charging infrastructure and points of interest—offers a valuable foundation for analysis. With these datasets, it is still possible to generate meaningful insights despite the gaps in charger-specific data. This section explores methods for processing open data to support model development in the context of EV infrastructure planning.

8.4.1 Using A Pre-Trained Model to Predict Demand

One of the ways of working around missing data is synthesizing the data. Using a pre-trained model developed by Jayanath et al.[22] it is possible to generate general information about charging events of an EV charger using surrounding area information. Jayanath et al. collected information about a network of 12 direct current fast charging(DCFC) sites in the province of Nova Scotia in Canada. They then trained a supervised learning model to map 4 data sets to charger utilization data. This charger utilization data is also not publicly available.
The data points used by Jayanath et al. were:

- Traffic volume: Average daily traffic(passing vehicle) count scaled down by a factor of 1000

- Local population: Nearby population scaled down by a factor of 1000
- Interprovincal highway: This feature is special to Canada and its geography and city design. A city like Berlin is more interconnected thus when considering inside areas of Berlin, interprovincal highways have much less weight in the matter of charger utilization.
- Competition defined as:

$$Comp = \frac{\sum_{n=1}^{N}(P_{kW_n}) \times (25 - Dist_{minutes})^2 \times PlugFactor_n}{P_{kW_{here}} \times 25^2}$$

  - P_{kW} denotes the total wattage of a charger
  - $Dist_{minutes}$ denotes the distance to competing charger in minutes. Because finding out the distance in minute requires interacting with an external application programming interface(API), here distance in kilometers were preferred. As the target, 1km was set.
  - $PlugFactor$ denotes what fraction of EV fleet the DCFC charger can serve if it has a proprietary connector that is not compatible with all EVs. This information is not available for Berlin.

One concern around using this model is the gaps in data. Therefore this model should and will only be used to enable making more informed decisions when utilization data is absent. The results should be seen as relative or some sort of ranking between EV chargers.
Jayanath et al. trained a regression model using these data points and published the regression coefficients. The results are as follows:

Variable	Units	Lower a	Best a	Upper a
Traffic, a_1	$Events/10^3 \cdot ADT$	17	35	53
Population, a_2	$Events/kPop$	-23	8	39
Competition, a_3	$Events/Comp$	-152	-77	-2
InterProv, a_4	$Events/InterProv$	980	1335	1690

Table 7: Regression coefficients for each of the four geographic explanatory variables, with 95th percent confidence interval coefficients, Jayanath et al.[22]

The predicted number of daily charging events per year can be expressed as:

$$Pred_i = a_21 \times Traf_i + a_2 \times Pop_i + a_3 \times Comp_i + a4 \times InterProv_i$$

After normalizing the data and using a similar function to the the efficiency score function in section 6.1, the vacancy heatmap of EV chargers in Berlin can be generated.

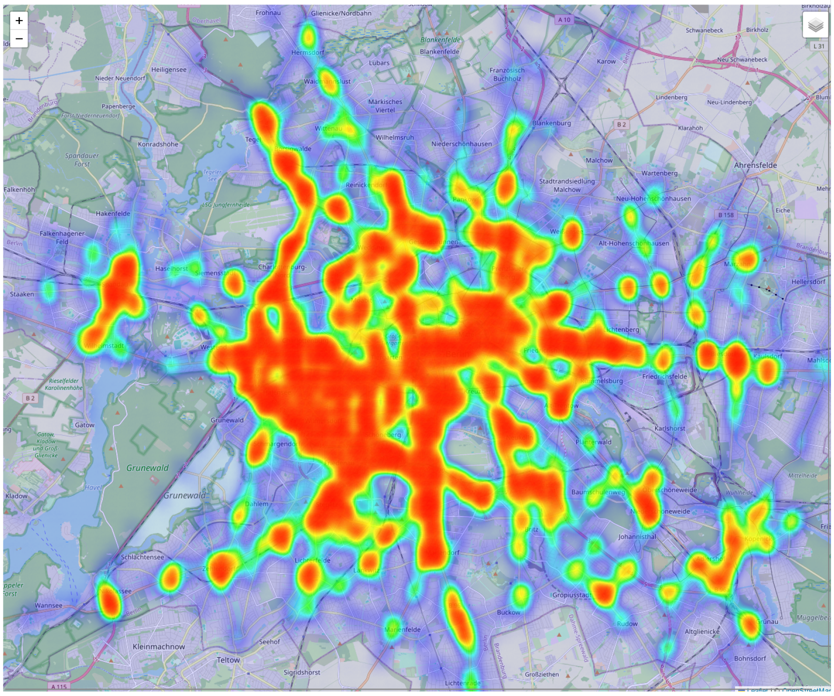

Figure 17: Heatmap of Berlin using the regression model by Jayanath et al.[22] and scoring.
The colors scale with score and are in the following order: Blue - Green - Yellow - Red

Note that this map doesn't show absolute efficiency but rather it highlights EV chargers that lie around 50th percentile of predicted yearly charging events.
From the regression coefficients it is abundantly clear that Jayanath et al.'s model is highly biased towards traffic hotspots and the map reflects this tendency. Such skewed performance can lead to unintended consequences, including the misallocation of resources or inaccurate predictions in areas with lower traffic density. For instance, the model may overestimate traffic congestion in peripheral areas or fail to identify emerging congestion patterns. Addressing this issue would entail a more dimensional model that is trained with more diverse data such as the one proposed in section 8.2.2.

8.4.2 Unsupervised Learning

An unsupervised learning model is the model that can provide most insight with the available, unlabeled data. This section focuses on the steps that were taken to train an unsupervised learning model from the ground up using publicly available data for Berlin. The model was coded with the Python programming language and the packages used were `yellowbrick, scikit-learn` and `matplotlib`.
Machine learning models work best with data that lies within the same numerical range.

One data point ranging in a disproportionately bigger spectrum can cause learning errors as the data point with bigger values would have a bigger impact on the regression equation. Therefore it is of immense importance to fit all the data points into the same range. This can be achieved with the following code:

```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler((0, 1))
scaled_data = scaler.fit_transform(data)
```

First a `MinMaxScaler` object was initialized with tuple of the preferred range of 0 to 1. Then the `fit_transform` method was used to scale the data from 0 to 1. With the data properly scaled, building the model can commence.
For the unsupervised learning technique, clustering explained in section 8.1.2 was chosen. As for the clustering method, the K-Means method was chosen for its simplicity and and faster performance. The K-Means method however requires predetermining how many clusters there should be. To help with this decision, the "elbow" method is the most commonly used[18]. The elbow method works by calculating the within-cluster sum of squares (WCSS) for each number of clusters k. WCSS measures how tightly points are grouped within a cluster, with smaller values indicating better clustering. To figure out the optimal number of clusters for our data, `KElbowVisualizer` module can be used.

```
from yellowbrick.cluster import KElbowVisualizer

kmeans = KMeans()
elbow = KElbowVisualizer(kmeans, k=(2, 20))
elbow.fit(scaled_data)
elbow.show(block=True)
```

Outputs the following graph:

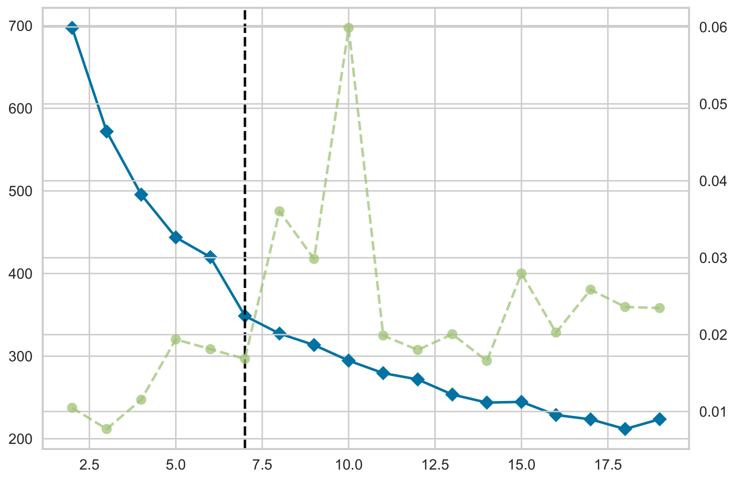

Figure 18: Distortion score elbow for K-Means clustering

Elements of the graph are:

1. **Distortion score** which is depicted as the y-axis on the left. The distortion score is the WCSS.
2. **Fit time** which is depicted as the y-axis on the right(in seconds). The fit time is how much time it takes for the model to learn the data.
3. **Number of clusters(k)** which is the x-axis
4. **Blue line** which is distortion score versus number of clusters
5. **Green line** which is fit time versus number of clusters
6. **Dashed black line** which is the elbow point

The elbow point which lies at $k = 7$ for this particular dataset is the point where distortion point stops decreasing significantly as k increases. Adding more clusters beyond this points increases fit time with diminishing returns. Although the fit time suggests that it is less than tenth of a second even for higher clusters number, it is important to set an optimal number of clusters for better scalability without sacrificing accuracy.
With the number of clusters determined, the model can be initialized and trained with just 3 lines of code:

```
from sklearn.cluster import KMeans

```

```
kmeans = KMeans(n_clusters=7)
data['cluster'] = kmeans.fit_predict(scaled_data)
```

This code trains the model and adds the cluster information to the data. The criteria for each cluster can be shown with the following code:

```
data[['anteilelektrogesamt','traffic_near','pop_near','charger_near',
'park_near', 'class','cluster']]\
.groupby('cluster')\
.agg({'max', 'min'})
```

This outputs the following table:

p_EV			traffic_near			pop_near			...
mean	min	max	mean	min	max	mean	min	max	...
4,08	0,94	14,82	134.182,72	7.900,00	403.500,00	3.444,92	0,00	11.629,00	...
6,38	1,64	24,33	355.282,84	23.200,00	786.450,00	10.721,11	1.088,00	17.295,75	...
16,11	5,24	24,33	662.738,67	332.400,00	786.450,00	4.122,35	85,00	11.640,00	...
4,78	0,94	17,67	213.193,26	6.400,00	664.700,00	3.950,57	0,00	16.416,00	...
12,75	1,94	21,00	364.321,37	164.900,00	786.450,00	8.095,70	1.760,00	12.754,00	...
4,50	1,35	21,00	458.312,69	167.100,00	786.450,00	7.411,93	6,00	16.620,00	...
4,34	1,94	14,41	169.064,54	11.000,00	514.600,00	3.601,63	19,00	11.033,00	...

Table 8: Criteria for clusters 0-6(truncated).

Any EV chargers with data that falls within values of a row gets grouped into its respective cluster.
Geographical data is not random; it is inherently structured and influenced by underlying patterns, processes, and relationships. Therefore some clusters are inevitably more populated than others. The distribution of clusters can provide valuable insights into existing infrastructure. Clusters shrink massive raw data into a more digestible size. They also signal which patterns are significant enough for a machine learning algorithm to classify it as a cluster. Now that the model learned from the data and assigned each entry a cluster, the distribution of clusters can be visualized with the following code.

```
import seaborn as sns

# Defines the color palette
pal = ["#682F2F","#B9C0C9", "#9F8A78","#F3AB60"]

# Create the count plot
pl = sns.countplot(x=combo["cluster"], palette= pal)
```

```
    pl.set_title("Distribution Of The Clusters")
    plt.show()
```

This outputs the following graph:

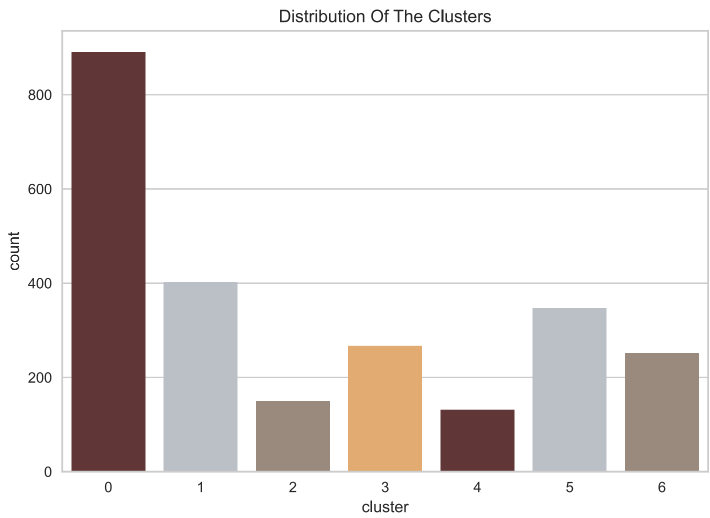

Figure 19: Distortion score elbow for K-Means clustering

It is clear from the graph that the distribution is not uniform. This is to be expected from the geographical data of a big area. If a more uniform distribution is desired for more granular information, it can be achieved by doing one or a combination of the following:

- Using a smaller area
- Using stricter outlier detection
- Increasing the number of clusters
- Balancing the data by resampling - Resampling means reducing the number of entries in the dominating data range and/or increasing the number of entries in minority data ranges by duplication or synthesis
- Using a different initialization method for K-Means - Can be passed to `KMeans()` function as optional argument to maximize distance between clusters
- Splitting the clusters manually post-training
- Using an alternate clustering method

Now that the training is complete, new data can be passed to the model to predict its cluster using the following code:

```
# Create a new entry as pandas DataFrame with appropriate columns
new_entry = pd.DataFrame([[4.07, 12322.0, 7.0, 4540, 5.0, 10]], columns=['p_EV', 'traffic_near',
'pop_near', 'charger_near', 'park_near', 'class'])

# Create a scaler and scale the entry
scaler = MinMaxScaler((0, 1))
new_entry_scaled = sc.fit_transform(ls)

# Predict the new entry's cluster
cluster = kmeans.predict(new_entry_scaled)
display(cluster)

# Output: array([0])
# This means that the model predicted this new entry to belong to cluster 0
```

Splitting Berlin into a 250×250 grid using the grid partition method explained in section 8.3, which parts fo Berlin belong to which cluster can be determined. To visualize this, each cluster can be associated with a color and put into an 250×250 image where each pixel represents a cell on the grid using the following code:

```
from PIL import Image
# Dictionary that associates a cluster with a color(RGBA values)
cluster_color = { 0: (199, 44, 72, 120), 1: (123, 104, 238, 120), 2: (49, 145, 119, 120),
3: (204, 119, 34, 120), 4: (137, 207, 240, 120), 5: (152, 119, 123, 120), 6: (240, 220, 130, 120)}

# Set pixel values of each cell
pixels = grid_cells['cluster'].copy(deep=True)
pixels = pixels.apply(lambda x: cluster_color[x])
pixels = pixels.to_numpy()

# Generate and save the image
img = Image.new('RGBA', (500, 500))
img.putdata(pixels)
img.save('path/to/save/to')
```

The generated image can then be laid over the Berlin map using the `L.imageOverlay(image , [coordinates])` from the `Leaflet.js` library. The resulting image is as follows:

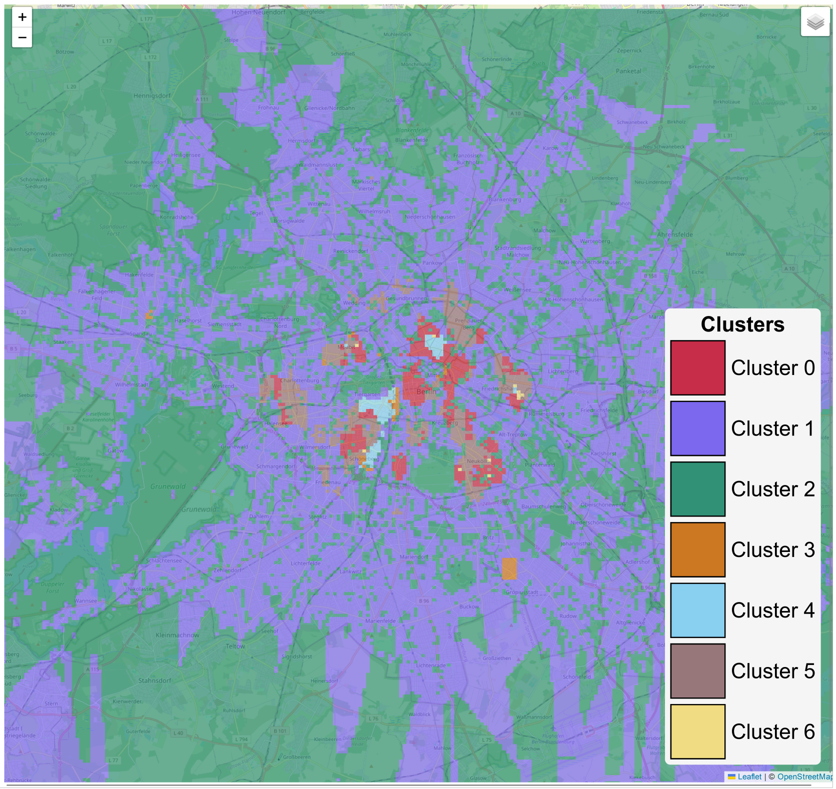

Figure 20: Clusters in Berlin

The information these results provide can be taken even further by employing the Analytic Hierarchy Process(AHP). AHP is a structured decision-making framework developed by T. Saaty in the 1970s at the Wharton School of the University of Pennsylvania. AHP consist of comparing criteria pairwise and giving them relative values(X is k times more important than Y). These relative values are then combined to assign an absolute weight to all the criteria[23]. This breaks complex decisions down into smaller, more manageable components.
As an example, the following values were chosen:

p_EV	traffic_near	charger_near	pop_near	park_near	class
1,5	1,2	2	1,2	1,2	

Table 9: Relative importance values. Each value represents how much more important the criterion is than the next criterion

Extrapolating these values into a square matrix and finding the eigenvector of said matrix gives absolute weights for each criterion. This can be proceeded by multiplying the weights with each cluster's mean or median values to come up with a numerical representation of that cluster's importance[18]. After modifying these numbers using a similar function to the the efficiency score function in section 6.1, it can be used along with grid data to generate a heatmap.

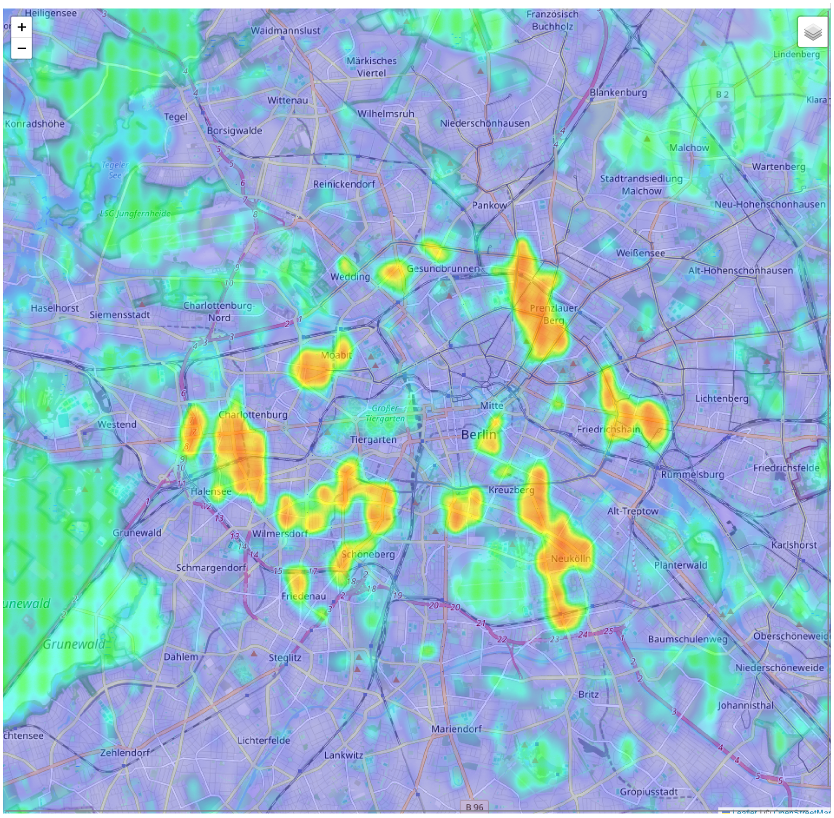

Figure 21: Heatmap with modified AHP results
The colors scale with score and are in the following order: Blue - Green - Yellow - Red

This map can be tweaked by tuning the relative weights in the AHP. This aspect makes unsupervised learning using AHP very versatile and able to adapt to new revelations in EV charger data.

9 Conclusion

This study shows a strategic framework for the planning and optimization of electric vehicle (EV) charging infrastructure in Berlin, underlines environmental adaptation, AI-driven resource allocation, and sustainable development. Below is a detailed look at the main results, the limits, things that were not included, and ideas for future research.

9.1 Evaluation of Key Results and Model Comparison

The study combines environmental data, traffic flow analysis, and machine learning to find the best places for EV charging stations. Main results include:

- **AI-Driven Model Efficiency:** Supervised learning and neural networks gave strong predictions for charging station efficiency. The station is placed in the best spots to be used more. The models study traffic and population trends to make sure charging stations are in busy areas. This helps avoid crowding and makes the user experience better.

- **Environmental Impact Reduction:** High-emission zones were effectively aimed for EV infrastructure expansion, demonstrating the potential for significant CO_2 reduction in urban centers. This not only improves public health but also arranges with wider global sustainability goals.

- **Comparative Performance:** The supervised learning approach was more accurate than unsupervised methods. It was very helpful for guessing how people will use the stations and choosing the best places for them. However, both approaches offered valuable insights into infrastructure planning and resource allocation.

Even with these successes, using pre-trained models caused some problems. They were not designed for specific areas, so they might not work well everywhere. This shows the need for local data and better algorithms in the future.

9.2 Discussing Limitations

While the study presents promising strategies, several limitations were defined:

- **Data Gaps:** There wasn't enough detailed, real-time data about how chargers are used or how users behave. Because of this, the study had to rely on guesses and publicly available data. These gaps can be used to collect better data, such as using IoT-based monitoring systems.

- **Weather Adaptability:** The study overlooked at environmental factors like rainfall and temperature. But it did not have detailed data on how charging stations work in extreme conditions over a long time. The proposed solutions effect the reliability.

- **Model Limits:** Models created in this paper do not account for how demand changes within a year. Areas which spike in popularity in small time frames can afford to have non optimal utilization during those periods.

- **Infrastructure Scalability:** The study uses a simple model that assumes expansion will be smooth. It might miss problems like limits in the power grid and challenges with energy distribution on a larger scale. Solving these challenges requires collaboration between urban planners, utility companies, and policymakers.

9.3 Future Research and Improvement Areas

Some aspects were not covered in the study but could still play a key role in improving EV infrastructure:

- **Using Renewable Energy:** Incorporating renewable energy sources into the data can show which areas are more decarbonized. This can help policymakers make decisions.

- **Forecasting Demand:** Incorporating another AI model that predicts future regional and socioeconomic developments to forecast the next in-demand areas can help decision makers look into the future.

- **Improving Charging Information:** Developing a standard for gathering information about EV chargers can increase the breadth of the available data.

9.4 Final Remarks

This research shows how environmental data, strategic planning, and AI-based solutions can help create a sustainable electric vehicle (EV) charging network. Berlin can become a green transportation leader by solving challenges such as limited data, weather changes, and resource management. These strategies will help the city achieve its climate goals and improve urban living. This approach could serve as a model for other cities looking to adopt environmentally friendly transportation systems. Future technology and research can help EV infrastructure improve and support sustainable, modern cities.

10 Data and Code Availability

- All the data used are available to public for free in their cited resources.

- All the code and results will be published later in `https://github.com/8ugr4/evtech01_2025`

- All the visualizations will be published later in `https://aytacaydin.com/evtech/`

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Table of abbreviations

AC . . . . Alternative Current

AHP . . . . Analytic Hierarchy Process

CDN . . . . Content delivery network

CSV . . . . Comma-Seperated Values

DC . . . . Direct Current

DCFC . . . . . . Direct current fast charging

EV . . . . Electric vehicle

GIS . . . . Geographic information system

ICEV . . . . . . Internal Combustion Engine Vehicles

IQR . . . . Interquartile range

KPI . . . . Key Performance Indicator

Q1 . . . . First quartile

Q3 . . . . Third quartile

ReLU . . . . . . Rectified Linear Unit

WCSS . . . . . . Within-cluster sum of squares