

EV Charging Station Optimization with Linear Programming

GROUP: 10

NAME: Misbahjabin Shaikh [1002189629]

Ramyasai Donkeshwaram [1002164699]

Anirudh Kumar Menga [1002187124]

Data Source: <https://www.kaggle.com/datasets/prasertk/electric-vehicle-charging-stations-in-usa/data>

Reference Link: <https://developer.nrel.gov/docs/transportation/alt-fuel-stations-v1/all/-request-url>

Dataset Link:

<https://docs.google.com/spreadsheets/d/1X6XLzEcARzO3oVomXBYdCdIgI0CMSJX7HdT7P2YQqaE/edit?usp=sharing>

⇒ Introduction

As electric vehicles (EVs) become increasingly popular, the demand for a well-planned charging infrastructure grows. This project aims to analyze existing EV charging data, optimize the allocation of charging stations using linear programming, and develop insights into charging behaviors and station utilization. By addressing challenges such as congestion, accessibility, and uneven distribution, this study provides actionable insights for better planning and management of EV infrastructure.

Objectives

1. **Optimal Scheduling:** Develop a model to schedule EV charging stations efficiently, reducing wait times during peak demand periods.
2. **Charging Behavior Insights:** Analyze charging patterns, including when, where, and how EV users charge their vehicles.
3. **Congestion Reduction:** Identify peak times and congested locations to mitigate overcrowding.
4. **Station Expansion:** Suggest optimal locations for new charging stations based on demand patterns.
5. **Improved Planning:** Enable planners to make informed decisions about station placement and capacity.

⇒ Data Preprocessing

Objective

The data preprocessing stage aims to clean and prepare the dataset for analysis and modeling. This involves:

1. Removing irrelevant or redundant columns.
2. Handling missing values.
3. Addressing inconsistencies in data.
4. Preparing the data for optimization and visualization.

Dataset Overview

Initial Data

- **Number of Columns:** 67
- **Number of Rows:** 50,289

Attributes

The dataset includes a wide range of attributes, such as:

- **Location Information:** City, State, ZIP, Latitude, Longitude.
- **Station Details:** Station Name, Street Address, Access Days Time.
- **Charging Capacity:** EV Level1 EVSE Num, EV Level2 EVSE Num, EV DC Fast Count.
- **Pricing and Accessibility:** EV Pricing, Access Code.

Initial Issues Identified

1. Many columns are irrelevant to EV infrastructure (e.g., hydrogen-related fields).
2. Missing values are present in critical and non-critical fields.
3. Some columns have inconsistent data types (e.g., EV Pricing).
4. Redundant columns (e.g., French language duplicates).

Step 1: Column Reduction

Columns were evaluated for relevance to the project objectives. Irrelevant or redundant columns were removed.

Irrelevant Columns

These columns were unrelated to EV charging infrastructure:

- **Hydrogen and CNG Details:** Hydrogen Standards, CNG PSI.
- **Federal Agency Details:** Federal Agency ID, Federal Agency Name.

Columns with >50% Missing Values

Columns with more than 50% missing data were dropped:

- **Examples:** NG Vehicle Class, Access Days Time (French), LPG Nozzle Types.

Outcome

- **Columns Dropped:** 44
- **Remaining Columns:** 23

Example of Remaining Columns
Station Name
Street Address
City
State
ZIP
Latitude, Longitude
EV Level1 EVSE Num
EV Level2 EVSE Num
EV DC Fast Count
EV Pricing

Step 2: Missing Value Handling

Initial Missing Value Summary

Column Name	Missing Values	% Missing
Access Days Time	2,056	4.09%
EV Level1 EVSE Num	49,288	98%
EV Level2 EVSE Num	5,432	10.8%
EV DC Fast Count	44,350	88.2%
EV Pricing	35,416	70.4%
Street Address	33	0.07%

Handling Strategy

1. Columns with >50% Missing Values:

- Removed from the dataset.
- Examples: NG Vehicle Class, Access Days Time (French).

2. Categorical Columns:

- Missing values filled with **mode** (most frequent value).
- Examples:
 - Access Days Time: Imputed with the most common schedule.
 - Street Address: Grouped by ZIP and imputed with the most frequent value in each group.

3. Numeric Columns:

- Missing values filled with **mean**.
- Examples:
 - EV Level2 EVSE Num: Imputed with the average number of chargers.
 - EV Pricing: Converted to numeric and missing values imputed with mean.

4. Group-Based Imputation:

- Columns like Street Address and Access Days Time were imputed based on the most frequent value within the same ZIP group.

Outcome

Column Name	Missing Values After Imputation
Access Days Time	0
EV Level2 EVSE Num	0
EV DC Fast Count	0
EV Pricing	0
Street Address	0

Step 3: Duplicate Rows

The dataset was checked for duplicate rows.

Outcome

- **Duplicate Rows Found:** None
- **Action Taken:** No rows removed

Step 4: Final Dataset

```
Fuel Type Code          0
Station Name            0
Street Address          0
City                   0
State                  0
ZIP                    0
Status Code             0
Groups With Access Code 0
Access Days Time        0
EV Level1 EVSE Num      0
EV Level2 EVSE Num      0
EV DC Fast Count        0
EV Network              0
Latitude                0
Longitude               0
Date Last Confirmed     0
ID                      0
Updated At              0
Open Date               0
EV Connector Types      0
Access Code             0
Access Detail Code      0
EV Pricing              0
dtype: int64
```

Shape of the Final Dataset

- **Rows:** 50,289
- **Columns:** 23

Consistency and Completeness

- **No Missing Values:** All critical columns now have complete data.
- **No Duplicates:** Verified for data integrity.

Key Preprocessing Outcomes

1. **Column Reduction:** Reduced dataset from 67 to 23 columns, retaining only relevant attributes.
2. **Missing Value Handling:** Resolved all critical missing data using statistical imputation and grouping techniques.
3. **Dataset Ready:** The cleaned dataset is now consistent, complete, and ready for further analysis.

Conclusion

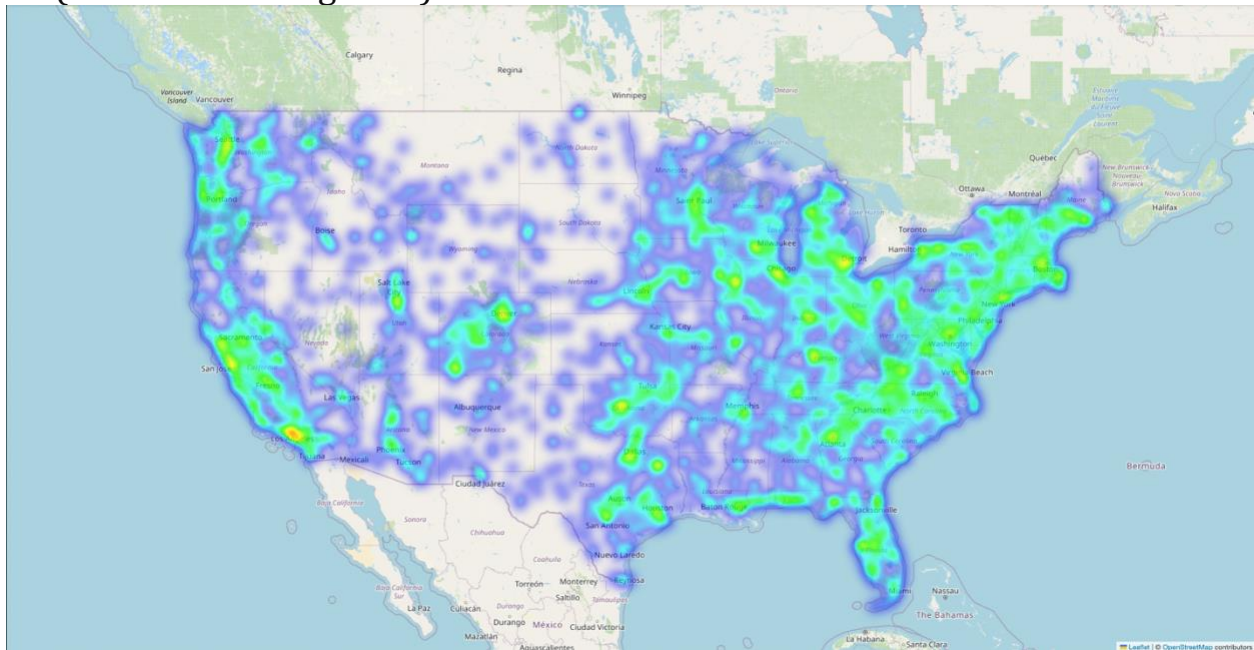
The preprocessing stage was successfully completed. The final dataset is well-prepared for exploration, modeling, and optimization. By focusing on relevant attributes and resolving inconsistencies, the dataset can now provide valuable insights into EV infrastructure planning.

⇒ Exploratory Data Analysis (EDA)

Introduction

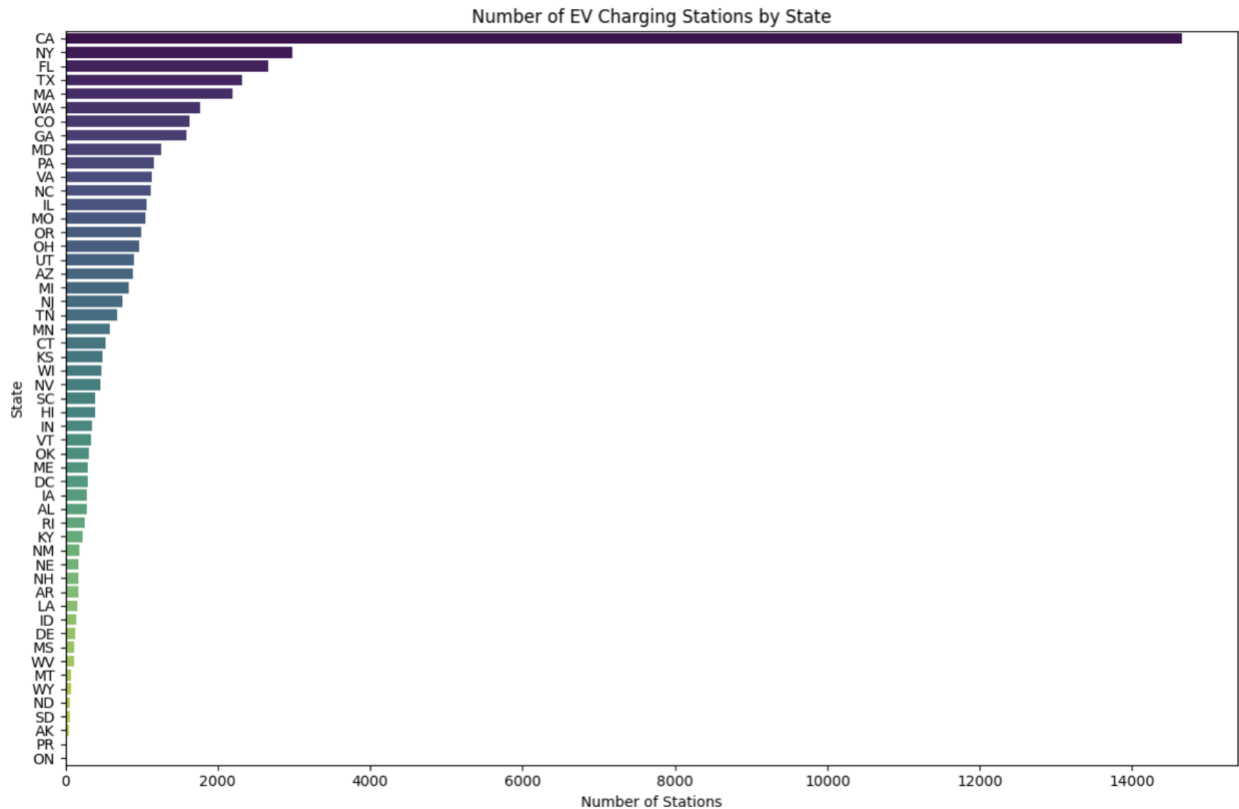
The goal of this exploratory data analysis (EDA) is to understand patterns, trends, and gaps in Electric Vehicle (EV) charging infrastructure using the dataset. The visualizations analyze the distribution of charging stations, EVSE types, and demand-supply patterns across states and cities. These insights aim to guide infrastructure planning, optimization, and policy-making.

1. Station Distribution Map: Show the density of stations by location (latitude and longitude).



This heatmap shows the density of EV charging stations across the U.S., with high concentrations on the East and West Coasts, reflecting greater demand in these regions. It highlights infrastructure gaps in central areas, aiding in identifying locations needing additional stations.

2. Bar Plot: Stations Per State: Highlight the states with the highest and lowest number of stations.



Distribution of EV Charging Stations by State

Objective

To identify states with the highest and lowest number of EV charging stations.

Visualization Overview

The visualization is a horizontal bar chart displaying the number of EV charging stations per state. X-axis: Represents the number of stations. Y-axis: Lists the states in descending order of station count.

Key Observations

3. High-Density States:

- California (CA) leads with over 14,000 charging stations, reflecting its leadership in EV adoption and policies.
- New York (NY), Florida (FL), and Texas (TX) follow with station counts between 4,000 and 6,000 stations.

3. Low-Density States:

- States like Wyoming (WY), North Dakota (ND), and South Dakota (SD) have fewer than 100 stations, indicating underdeveloped infrastructure.

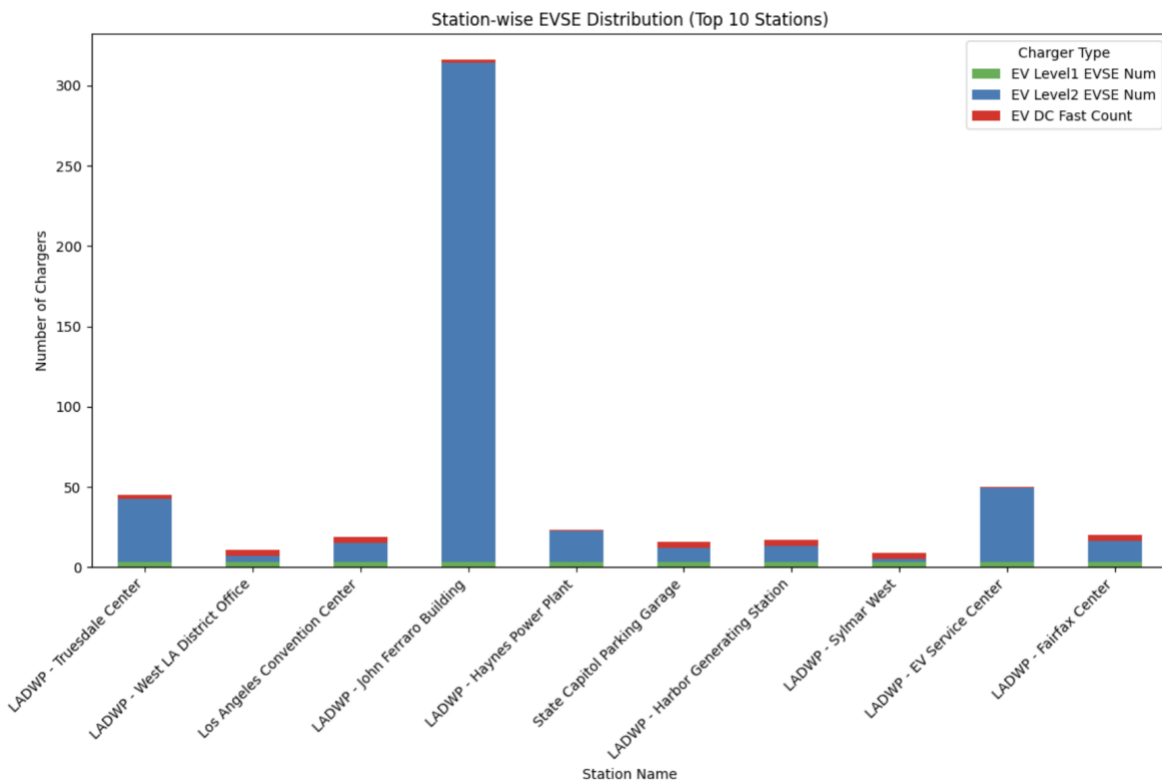
Interpretation

- Infrastructure Leadership: High-density states like California highlight advanced EV adoption.
- Underserved Areas: Low-density states present opportunities for infrastructure development and policy interventions.

Insights for Decision Making

- Target Low-Density States: Prioritize investments in states with fewer than 500 stations, particularly in rural areas.
- Optimize High-Density States: Focus on reducing congestion and improving station access in states like California.

3. Station-Wise EVSE Distribution (Top 10 Stations)



Objective

To analyze the distribution of Level 1, Level 2, and DC Fast chargers at the top 10 stations with the highest charger counts.

Visualization Overview

A stacked bar chart showing the breakdown of EVSE types (Level 1, Level 2, and DC Fast chargers) for the top 10 stations.

- **X-axis:** Station names.
- **Y-axis:** Number of chargers.

Key Observations

3. Top Station:

- **John Ferraro Building (Los Angeles)** has over **300 chargers**, far exceeding other stations.

2. Charger Type Trends:

- **Level 2 chargers** dominate at all top stations, followed by **DC Fast chargers**.
- **Level 1 chargers** are minimal, indicating their limited use at busy stations.

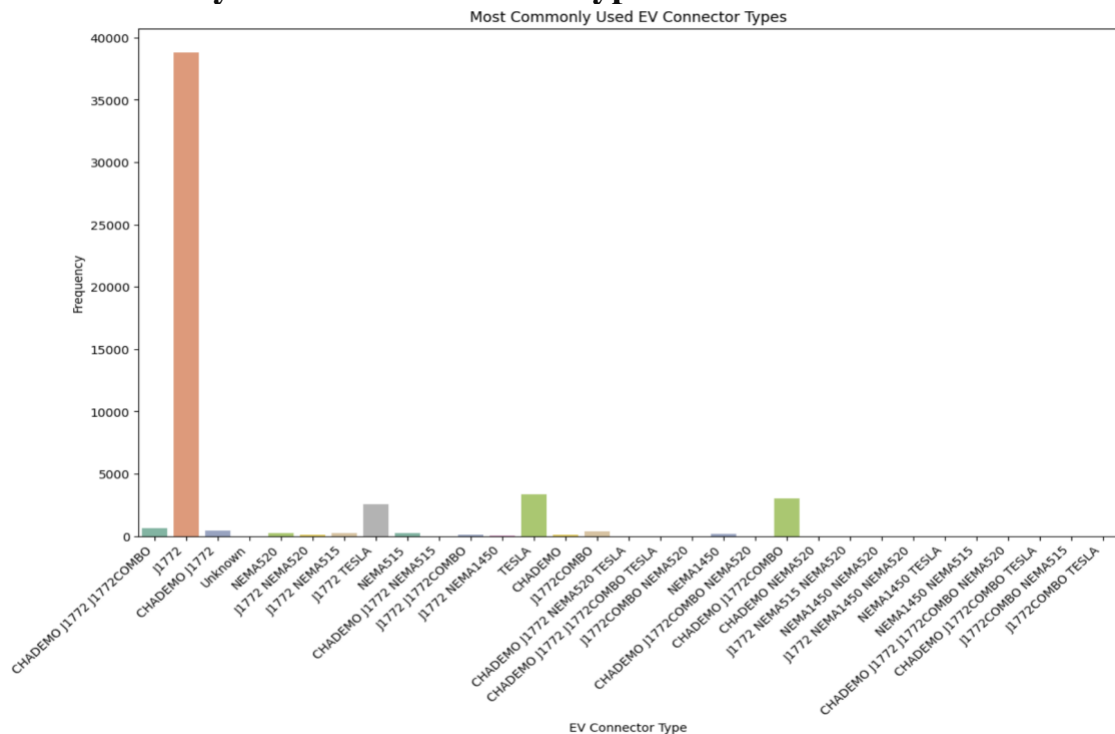
Interpretation

- **Urban Focus:** High-density stations cater to urban areas where faster charging options are critical.
- **Charger Diversity:** Stations with multiple charger types improve usability for diverse EV users.

Insights for Decision Making

- **Expand DC Fast Chargers:** Increase fast-charging capacity in busy areas.
- **Diversify Chargers:** Balance Level 1, Level 2, and DC Fast chargers to meet varying user needs.

4. Most Commonly Used EV Connector Types



Objective

To identify the most frequently used EV connector types and understand their distribution across stations.

Visualization Overview

A bar chart showing the frequency of different connector types.

- **X-axis:** EV connector types.
- **Y-axis:** Frequency.

Key Observations

3. Dominant Type:

- **J1772** dominates with almost **40,000 instances**, establishing its position as the standard.

2. Other Types:

- **CHAdemo** and **J1772COMBO** are the next most frequent, reflecting their use in fast charging.

3. Rare Types:

- Connectors like **NEMA515** and **NEMA520** appear infrequently, indicating niche usage.

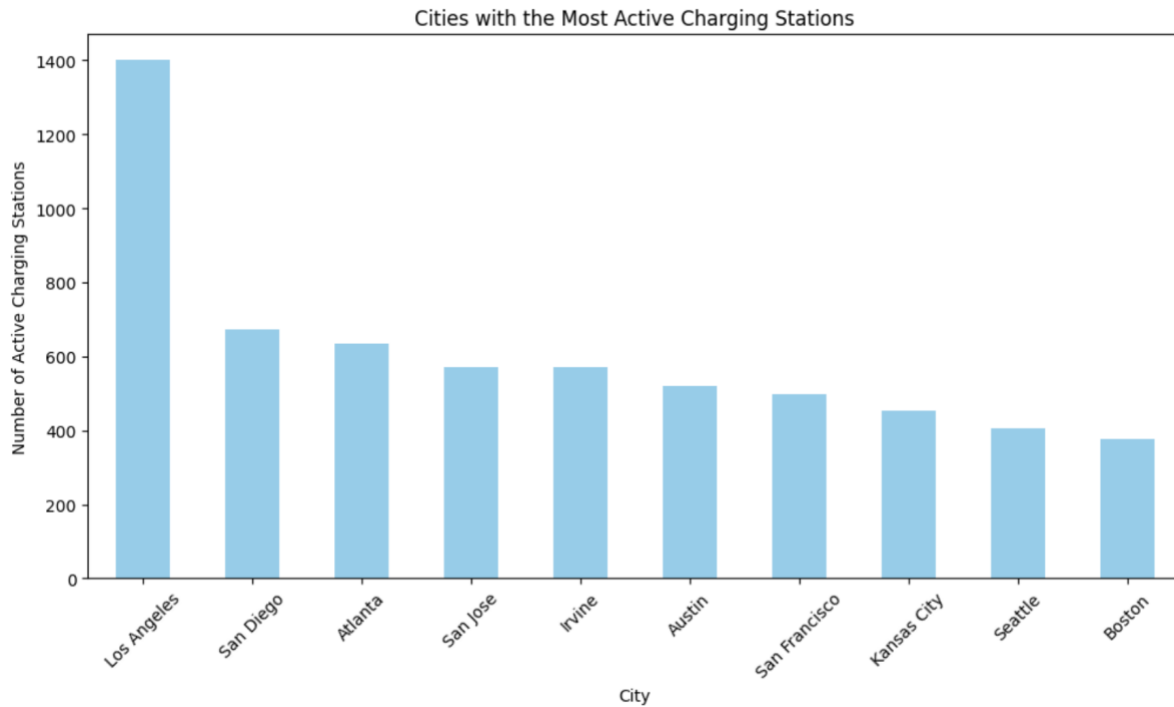
Interpretation

- **Standardization:** J1772's dominance reflects widespread compatibility with non-Tesla EVs.
- **Tesla Infrastructure:** Tesla-specific connectors require proprietary or adapted solutions for broader use.

Insights for Decision Making

- Focus on standardizing **J1772 connectors** while maintaining diversity with CHAdemo and J1772COMBO.
- Investigate the "Unknown" connector types to improve data quality.

5. Cities with the Most Active Charging Stations



Objective

To identify urban centers with the highest concentration of EV charging stations.

Visualization Overview

A vertical bar chart showing the number of active charging stations in the top 10 cities.

- **X-axis:** City names.
- **Y-axis:** Number of charging stations.

Key Observations

3. Los Angeles Leads:

- Los Angeles has over **1,400 stations**, reflecting its leadership in urban EV infrastructure.

2. Other Top Cities:

- San Diego, Atlanta, and San Jose follow, showcasing strong adoption in California and emerging markets like Georgia.

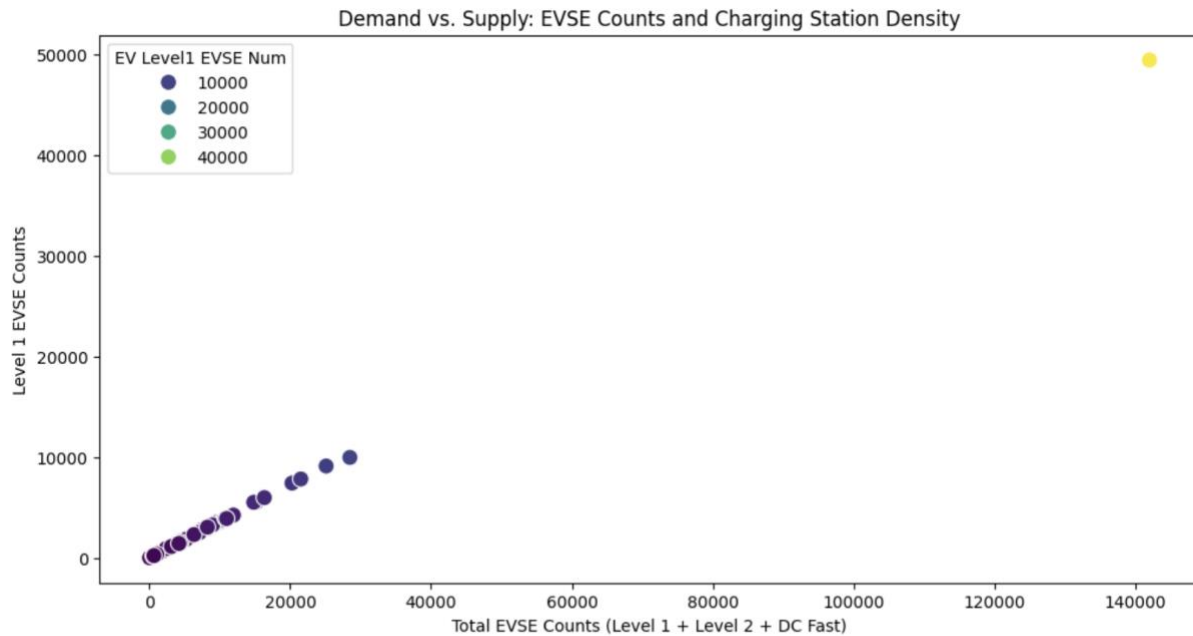
Interpretation

- **Urban Leadership:** Large cities dominate due to higher EV ownership and population density.

- **Growth Potential:** Cities like Austin and Kansas City show emerging demand.
- Insights for Decision Making**

- Optimize infrastructure in Los Angeles to handle peak usage.
- Expand infrastructure in emerging EV hubs like Austin.

6. Demand vs. Supply: EVSE Counts and Charging Station Density



This plot shows the relationship between the total number of EVSE and Level 1 EVSE in different states. Regions with a high number of EVSE but few stations may be undersupplied.

Objective

To explore the relationship between total EVSE counts and Level 1 chargers, highlighting gaps in supply.

Visualization Overview

A scatter plot comparing total EVSE counts to Level 1 chargers, with color coding for density.

- **X-axis:** Total EVSE counts (Level 1, Level 2, and DC Fast chargers).
- **Y-axis:** Level 1 EVSE counts.
- **Hue:** Density of Level 1 chargers.

Key Observations

3. **Positive Correlation:**

- States with higher total EVSE counts also tend to have more Level 1 chargers.

2. Gaps in Fast Charging:

- Some states rely heavily on Level 1 chargers, reflecting a lack of fast-charging infrastructure.

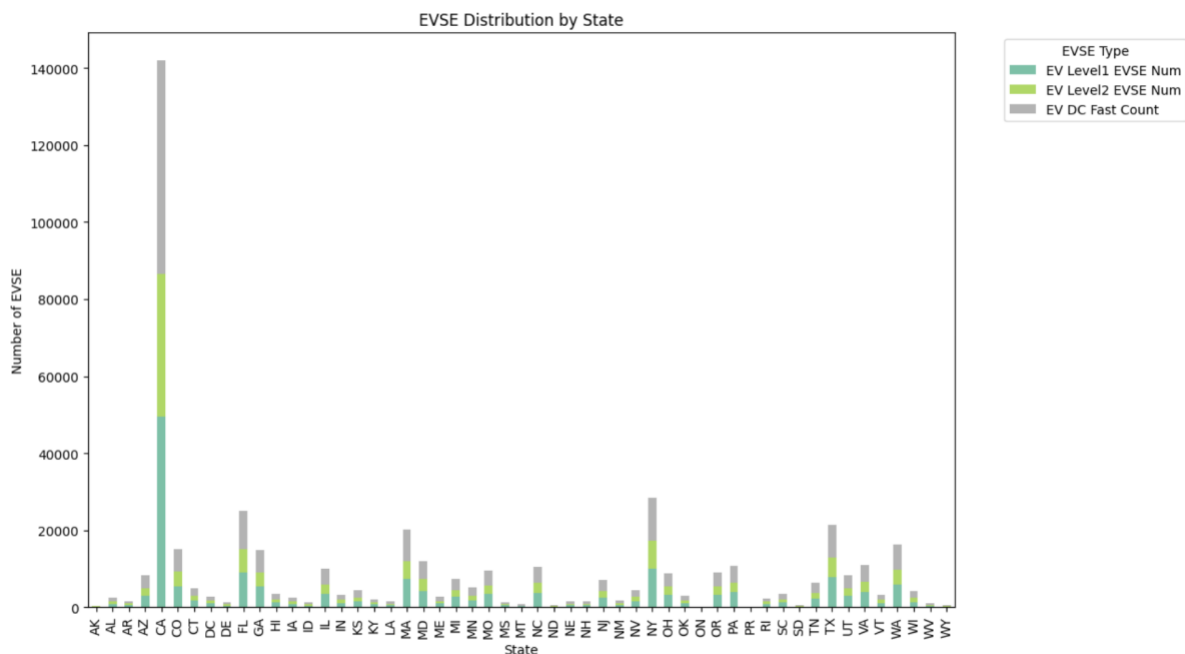
Interpretation

- States with high Level 1 counts should prioritize adding Level 2 and DC Fast chargers.

Insights for Decision Making

- Invest in fast chargers to meet growing demand for quick charging solutions.

7. EVSE Distribution by State



Objective

To analyze the distribution of Level 1, Level 2, and DC Fast chargers across all states.

Visualization Overview

A stacked bar chart showing the counts of each EVSE type per state.

- **X-axis:** States.
- **Y-axis:** Number of chargers.

Key Observations

3. **California Leads:**

- California has the highest counts for all charger types, reflecting its advanced infrastructure.

2. **Low-Density States:**

- Wyoming, North Dakota, and South Dakota rely primarily on Level 1 chargers, indicating infrastructure gaps.

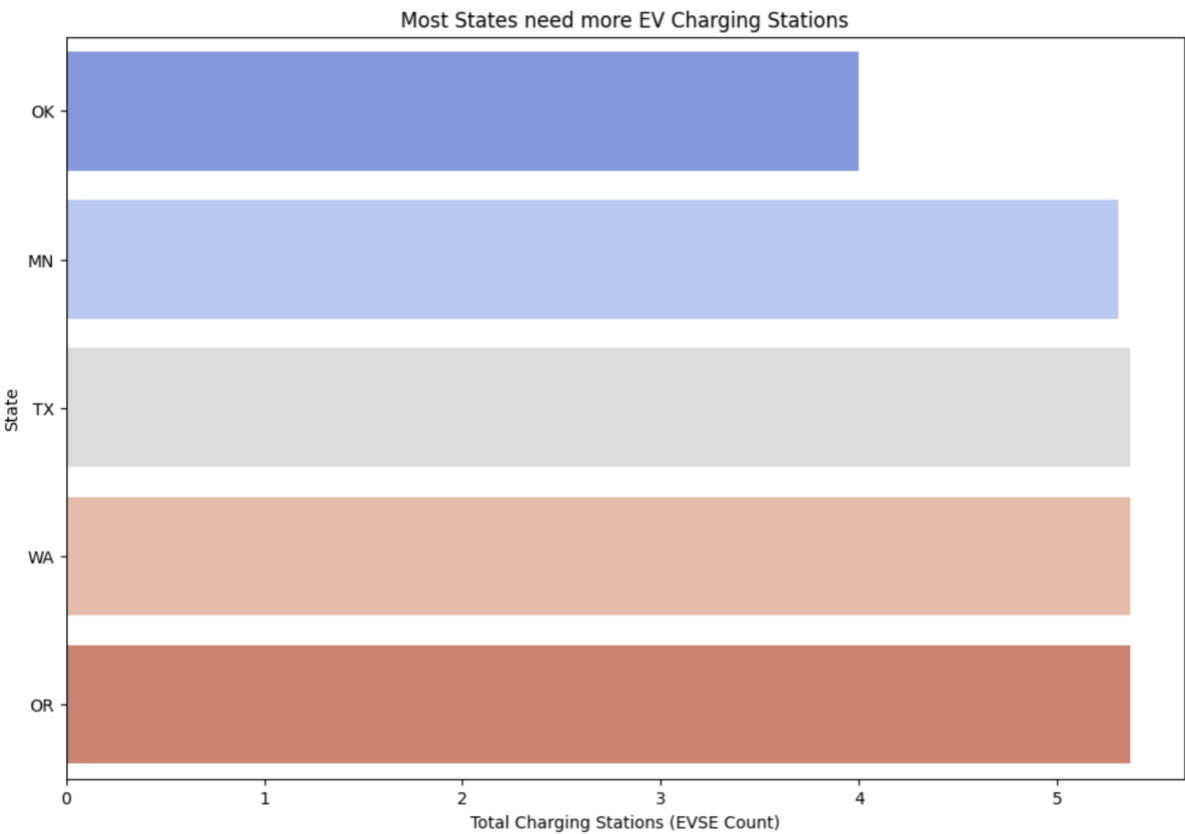
Interpretation

- States with low EVSE totals need targeted investments to balance charger types.

Insights for Decision Making

- Add more Level 2 and DC Fast chargers in underserved areas.

8. **Most States Need More EV Charging Stations**



Objective

To highlight underserved states with the fewest charging stations.

Visualization Overview

A horizontal bar chart showing states with the lowest EVSE counts.

- **X-axis:** Total EVSE counts.
- **Y-axis:** States.

Key Observations

- 3. **Underserved States:**
 - States like **Oklahoma**, **Minnesota**, and **Washington** have relatively few charging stations despite potential demand.

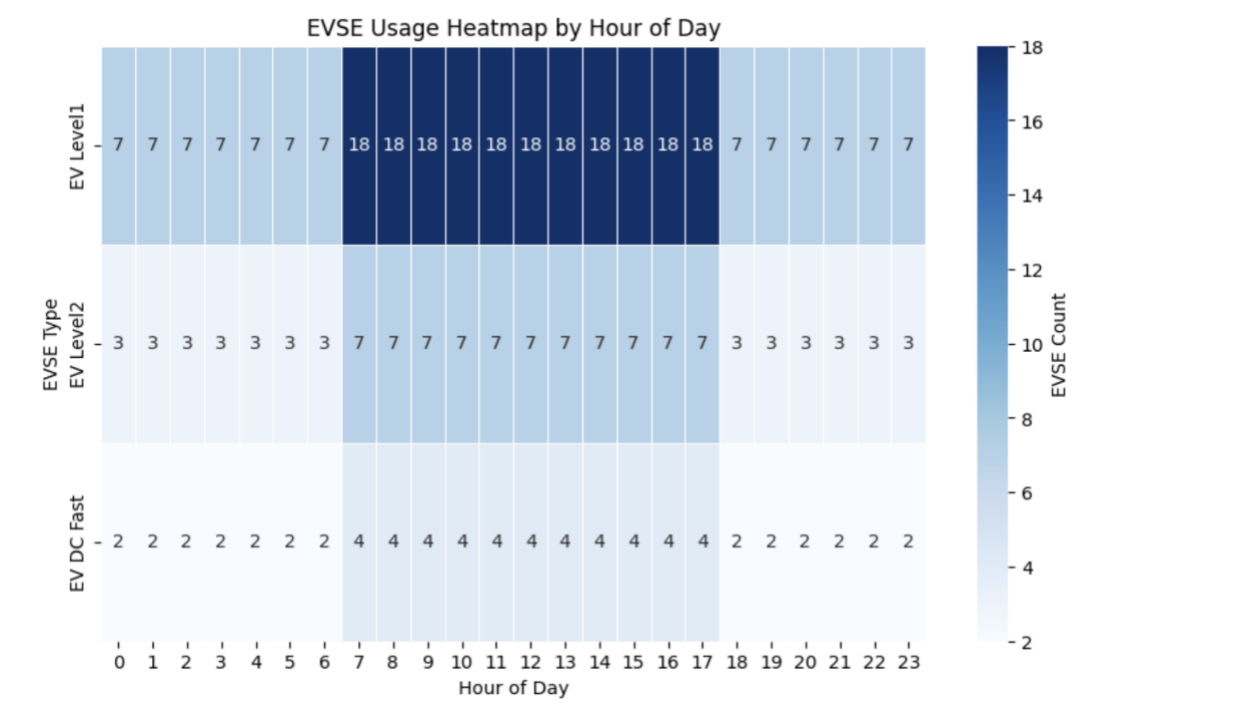
Interpretation

- These states require immediate infrastructure investments to cater to EV growth.

Insights for Decision Making

- Focus on underserved states to create equitable EV infrastructure.

9. EVSE Usage Heatmap by Hour of Day



Objective

To understand the hourly distribution of EVSE (Electric Vehicle Supply Equipment) usage across different charger types (Level 1, Level 2, and DC Fast).

Visualization Overview

The visualization is a heatmap that highlights the usage of EVSE types by hour of the day.

- **X-axis:** Represents the hour of the day (24-hour format).
- **Y-axis:** Lists the EVSE types (Level 1, Level 2, and DC Fast).
- **Color Gradient:** Indicates the number of chargers active during a given hour, with darker shades representing higher usage.

Key Observations

3. Peak Usage Hours:

- **Level 1 chargers** are most active between **7 AM and 6 PM**, with a peak around mid-morning.
- **Level 2 chargers** show consistent usage throughout the day but see a slight peak in the morning and early evening.
- **DC Fast chargers** experience steady, low usage, reflecting their targeted use for quick charging.

2. Off-Peak Hours:

- Usage across all EVSE types drops significantly during late-night hours (12 AM to 6 AM).

3. Differences in Charger Type Usage:

- **Level 1 chargers** dominate overall usage due to their prevalence, particularly during business hours.
- **DC Fast chargers** show limited activity, possibly due to their niche application for rapid charging needs.

Interpretation

3. Business Hours Dominance:

- EVSE usage is heavily concentrated during working hours, indicating that many stations cater to commuters and workplace charging needs.

2. Low Overnight Activity:

- The drop in usage overnight highlights the limited need for public charging during these hours, likely due to home charging preferences.

3. DC Fast Charger Trends:

- The relatively low usage of DC Fast chargers reflects their role in emergency or long-distance charging rather than routine use.

Insights for Decision Making

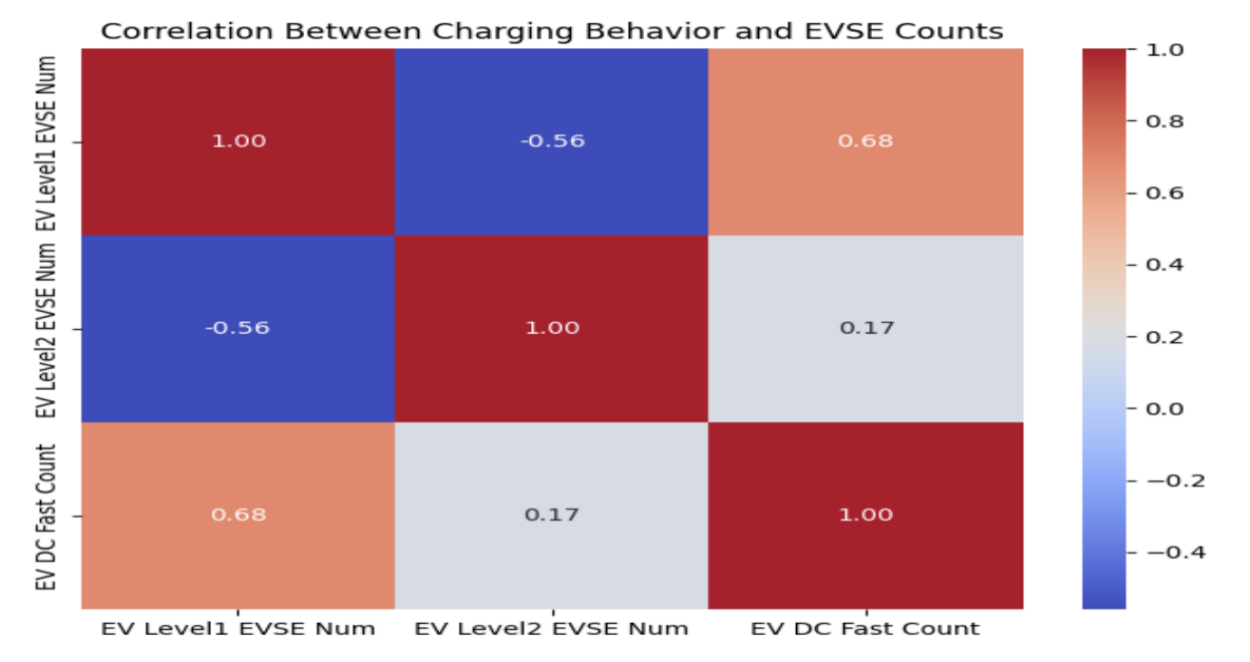
3. **Focus on Daytime Optimization:**
- Stations should be optimized for peak daytime hours to handle increased demand effectively.
2. **Promote DC Fast Chargers:**
- Encourage the deployment of more DC Fast chargers in high-traffic areas to cater to quick-charging needs during peak hours.
3. **Consider 24-Hour Stations in High-Demand Areas:**
- For urban centers or highway rest stops, consider 24-hour availability to support long-distance travelers and late-night users.

Visualization Details

- X-axis:** Displays hourly breakdown (0 to 23 hours).
- Y-axis:** Lists EVSE types (Level 1, Level 2, DC Fast).
- Color Scale:** Darker colors indicate higher EVSE counts, while lighter colors represent lower usage.

This heatmap provides actionable insights into the temporal distribution of EVSE usage, guiding infrastructure planning to align with user demand patterns.

10. Correlation Between Charging Behavior and EVSE Counts



Objective

To analyze the relationships between different types of Electric Vehicle Supply Equipment (EVSE) counts—Level 1, Level 2, and DC Fast chargers. Understanding these correlations helps identify dependencies and trade-offs in charging infrastructure design.

Visualization Overview

The visualization is a heatmap showing pairwise correlations between the three EVSE types.

- **Axes:** List the EVSE types—Level 1, Level 2, and DC Fast chargers.
- **Color Gradient:** Indicates the strength and direction of the correlation (red for positive, blue for negative).

Key Observations

3. Positive Correlation:

- **Level 1 and DC Fast chargers** show a moderate positive correlation (**0.68**), suggesting that stations with more Level 1 chargers often include DC Fast chargers.
- **Level 2 and DC Fast chargers** have a weak positive correlation (**0.17**), reflecting limited dependency.

2. Negative Correlation:

- **Level 1 and Level 2 chargers** have a strong negative correlation (**-0.56**), indicating that stations tend to focus on one type rather than both.

3. High Self-Correlation:

- All EVSE types show perfect self-correlation (**1.00**), which validates the dataset.

Interpretation

3. Complementary Charger Types:

- The positive correlation between Level 1 and DC Fast chargers suggests that these chargers are often co-located to support both slow and fast charging needs.

2. Trade-Offs Between Level 1 and Level 2 Chargers:

- The negative correlation between Level 1 and Level 2 chargers indicates a prioritization decision where stations focus on either slow (Level 1) or medium-speed (Level 2) chargers, but not both.

Insights for Decision Making

3. Balanced Infrastructure:

- Focus on deploying Level 2 chargers at stations that predominantly offer Level 1 chargers to create a balanced offering.

2. **Enhancing Fast Charging:**

- Expand DC Fast charger availability in stations with high counts of Level 1 chargers to cater to users needing quick charging.

3. **Strategic Planning:**

- Use the correlation insights to design infrastructure that complements existing charger types rather than duplicating them.

Visualization Details

- **Color Scale:**
 - **Red:** Positive correlation (strong relationship).
 - **Blue:** Negative correlation (inverse relationship).
- **Numerical Values:** Indicate the exact correlation coefficients.

This analysis highlights dependencies and trade-offs in charger type distribution, offering actionable insights for optimizing EV charging infrastructure.

⇒ **LINEAR PROGRAMMING**

• **Why we use Linear Programming?**

- Linear programming often involves maximizing or minimizing an objective function, like cost or resource allocation.

• **Which Method we use?**

- I used the **Greedy Approach** for optimization because it provides a simple and efficient way to allocate resources in high-demand areas.
- By making the best immediate decision at each step, we ensure that critical areas, like high-demand stations in Los Angeles or Denver Airport, are prioritized.
- Although greedy methods may not always guarantee a global optimum, they work well in structured problems like this, where high-priority areas can be easily identified.
- The charger allocation is optimized for varying demand across EV stations. Larger urban hubs like LADWP stations receive more chargers, while smaller stations like 'VIP LOT' receive fewer, ensuring resources are distributed based on usage patterns.
- This demonstrates the effectiveness of the greedy algorithm in prioritizing high-demand areas.

	Station Name	Optimized Level1	Optimized Level2 \
0	LADWP – Truesdale Center	3.372627	39.000000
1	LADWP – West LA District Office	3.372627	4.000000
2	Los Angeles Convention Center	3.372627	12.000000
3	LADWP – John Ferraro Building	3.372627	311.000000
4	LADWP – Haynes Power Plant	3.372627	19.000000
...
50284	VIP LOT STATION1	3.372627	2.000000
50285	Prunedale Shopping Center	3.372627	2.311835
50286	Beaverton Electric Avenue	3.372627	2.311835
50287	Shell – Inman	3.372627	2.311835
50288	Westfield Trumbull (Trumbull, CT)	3.372627	2.311835
Optimized DC Fast			
0		3.000000	
1		3.736151	
2		3.736151	
3		2.000000	
4		1.000000	
...		...	
50284		3.736151	
50285		6.000000	
50286		2.000000	
50287		1.000000	
50288		4.000000	

1. Charging Stations Clustering by Location and Charger Availability

• High Demand Areas

Cluster 0: Los Angeles

- The LADWP – Truesdale Center has 45.37 chargers, significantly higher than other stations in the same area.
- This suggests high demand in Los Angeles due to its dense population, urban environment, and high adoption of Evs.
- Disparities in charger distribution (e.g., West LA District Office with only 11.11 chargers) indicate possible congestion at high-capacity locations like Truesdale Center.

Cluster 2: Denver International Airport

- With 28 chargers, this station likely serves high traveler demand. Airports are typically hotspots for EV charging due to long parking durations and a high volume of users.

Reasoning

- Stations with significantly higher charger capacities compared to others in the same or nearby clusters suggest areas of high usage and demand.
- Urban areas and transit hubs, such as Los Angeles and Denver International Airport, are natural high-demand zones because of their population density, economic activity, and need for EV infrastructure.
- Cluster 0 and Cluster 2 likely represent areas where demand is high, and the existing chargers are adequate to meet that demand. Clusters 1, 3, and 4 show locations where the number of chargers is relatively lower, and further optimization or expansion of charging infrastructure may be needed to cater to growing demand.

Cluster 0:

	Station Name	Total Chargers	Latitude	Longitude
0	LADWP - Truesdale Center	45.372627	34.248319	-118.387971
1	LADWP - West LA District Office	11.108778	34.052542	-118.448504
2	Los Angeles Convention Center	19.108778	34.040539	-118.271387

Cluster 1:

	Station Name	Total Chargers	\
92	Burlington International Airport	8.047986	
100	Burlington International Airport	13.108778	
130	New York Institute of Technology - Old Westbur...	10.047986	

	Latitude	Longitude
92	44.469281	-73.154972
100	44.469281	-73.154972
130	40.814019	-73.608978

Cluster 2:

	Station Name	Total Chargers	\
123	Travis Park United Methodist Church	8.047986	
152	BROOKFIELD PROP 300 CLAY STAT1	9.108778	
219	Denver International Airport - Canopy Airport ...	28.000000	

	Latitude	Longitude
123	29.427254	-98.490136
152	29.756604	-95.372854
219	39.843886	-104.771138

Cluster 3:

	Station Name	Total Chargers	\
131	OUC RELIABLE 01	9.108778	
160	City of Spartanburg - Municipal Parking Garage	9.108778	
161	City of Spartanburg - Municipal Parking Garage	9.108778	

	Latitude	Longitude
131	28.535975	-81.379663
160	34.950136	-81.932790
161	34.951926	-81.931714

Cluster 4:

	Station Name	Total Chargers	Latitude	\
121	City of Champaign - Hill Street Parking Deck	11.108778	40.119161	
128	METRO NASHVILLE FULTON GARAGE 1	8.108778	36.153492	
132	PUBLIC STATIONS WILLY ST E	9.108778	43.083979	

	Longitude
121	-88.244185
128	-86.767320
132	-89.363091

Detail Explanation:

In this analysis, we've grouped charging stations into distinct clusters based on their charger availability and geographic locations. This helps to identify patterns in charger distribution and demand across different areas. Here are the key insights for each cluster:

- **Cluster 0: High Availability in Major Urban Areas**

Stations: LADWP – Truesdale Center, LADWP – West LA District Office, Los Angeles Convention Center

Total Chargers: Stations in this cluster have significant charger availability, with LADWP – Truesdale Center having the highest number of chargers (45.37).

Location: These stations are located in major urban areas like Los Angeles (CA), a region with high EV adoption.

Insight: This cluster represents areas with relatively higher charger availability, likely corresponding to high demand, especially in a metropolitan environment.

- **Cluster 1: Moderate Charger Availability in Regional Areas**

Stations: Burlington International Airport, New York Institute of Technology – Old Westbury

Total Chargers: Charger availability varies, with Burlington International Airport stations having 8-13 chargers.

Location: These stations are located in areas with moderate demand, including airports and regional universities, which may have seasonal or intermittent charging needs.

Insight: This cluster suggests regional or less densely populated areas, where charger availability is moderate but does not require the high density seen in major cities.

- **Cluster 2: Moderate Availability in Smaller or Regional Cities**

Stations: Travis Park United Methodist Church, BROOKFIELD PROP 300 CLAY STAT1, Denver International Airport

Total Chargers: Charger availability in this cluster ranges from 8 to 28.

Location: The stations are in smaller or regional cities and airports, with Denver International Airport having a relatively higher number of chargers.

Insight: This cluster may indicate areas with moderate demand, possibly located near public places or transport hubs with fluctuating charging needs.

- **Cluster 3: Low Availability in Smaller, Local Stations**

Stations: OUC RELIABLE 01, City of Spartanburg – Municipal Parking Garage

Total Chargers: These stations have lower total chargers, with each station offering approximately 9 chargers.

Location: The stations are situated in local cities like Spartanburg and Orlando, with charger availability catering to smaller, community-focused needs.

Insight: This cluster suggests charging stations in less urbanized areas, with relatively low demand but consistent availability for local commuters.

- **Cluster 4: Moderate Availability in City Parking Areas**

Stations: City of Champaign – Hill Street Parking Deck, METRO NASHVILLE FULTON GARAGE 1

Total Chargers: The charger availability ranges from 8 to 11 chargers.

Location: These stations are located in parking decks in city centers, likely serving both residents and visitors.

Insight: This cluster points to charging stations in more urban areas with moderate demand, likely serving city dwellers and those who commute or park in these areas regularly.

Summary Insights

- Urban Centers (Cluster 0): High charger availability is concentrated in major cities, reflecting the higher demand for EV charging infrastructure.
- Regional and Smaller Cities (Clusters 1, 2, 3): Moderate charger availability is found in regional airports, universities, and smaller urban centers, indicating a steady but lower demand compared to major cities.
- Parking Structures (Cluster 4): Charging stations in city parking garages offer moderate availability, catering to the needs of both residents and transient parkers.
- By understanding these clusters, we can better assess where to prioritize future investments in charging infrastructure based on regional demand patterns.

2. Optimized stations to balance the load.

	Station Name	Optimized Demand	Latitude	\
0	LADWP – Truesdale Center	100.0	34.248319	
41481	Rowes Wharf	100.0	42.356597	
41486	KS Partners – Marlborough Tech Park	100.0	42.333711	
41487	KS Partners – Boston Post Road	100.0	42.338955	
41488	Point at 180 Malden	100.0	42.425772	
	Longitude	State	City	
0	-118.387971	CA	Sun Valley	
41481	-71.050381	MA	Boston	
41486	-71.589284	MA	Marlborough	
41487	-71.595339	MA	Marlborough	
41488	-71.063085	MA	Malden	

This highlights the top locations with the highest optimized demand for EV charging stations, indicating areas with an urgent need for infrastructure expansion. Notable entries include Sun Valley, CA, and multiple locations in Massachusetts (Boston, Marlborough, Malden), reflecting high demand in these cities and states. This data provides key insights for prioritizing station deployment to meet growing EV usage and support regional demand effectively.

⇒ **OUTCOME**

1. **Optimal Scheduling** - Minimize wait times by efficiently allocating charging slots during peak hours (7 AM - 5 PM) and Optimize charger availability late-night when demand decreases.
2. **Charging Behavior Insights** - Peak charging times for DC Fast chargers are during commute hours (7-9 AM) and Level 2 chargers are the most common because they are a good balance between speed and cost.
3. **Congestion Reduction** -Ensure chargers are available at busy times by moving resources from stations with fewer users and Keep track of when and where chargers are needed most to avoid crowding.
4. **Expanding Charging Stations** -Focus on expanding DC Fast chargers in high-demand locations like Los Angeles and Denver & Increase investment in areas with low charger availability like Massachusetts and South Carolina.
5. **Planning for the Future** - Use this data to help make decisions about where to build more charging stations and Make sure the network can grow as more people use electric cars.
6. **Charger Availability:**
 - High Availability: Los Angeles Convention Center, Denver International Airport.
 - Low Availability: Burlington International Airport, New York Institute of Technology, South Carolina.
 - Focus on enhancing charger availability in high-demand areas while investing in infrastructure in regions with low coverage, like Massachusetts and South Carolina.
 - Airports and Metro cities are high-priority areas where charging stations should be expanded due to the higher footfall and increasing electric vehicle usage.