Enhancing Electric Vehicle Charging Infrastructure: A Network Analysis Based on Real-time Usage and Geographical Data

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***Abstract*—Electric Vehicle (EV) charging stations have played an important role in recent days for eco-friendly transport solutions. The high usage of electric vehicles in recent days has increased the need for maintaining and improving the charging station infrastructure. In this project, we are analyzing the data from the EV charging station, exploring the real-time usage, user interactions, and geographical considerations. Through the blend of Network analysis using NetworkX Python library, Exploratory Data Analysis using Pandas, Matplotlib, Seaborn libraries in Python, and user behavior analysis using the Tableau dashboard. Using these tools, we aim to derive the analysis, and insights and provide changes in the infrastructure to enhance the customer experience and profit for the EV charging stations.**

Our research focuses on the efficient EV charging landscape and providing a user-friendly charging station environment. Key insights and contributions of this research are:

- **User distribution for the charging station around the country and User behavior analysis.**
- **Understanding the relationship between users and the charging station using network analysis.**
- **Identifying trends, charging habits, and infrastructure evolution using exploratory data analysis.**
- **Providing Infrastructure development recommendations using the insights derived.**

I. Introduction

Electric Vehicles(EVs) are becoming a lot more widespread as an increasing number of people are switching over to them. The benefits of EVs have been instrumental in this shift. But has the infrastructure kept up with the rapid increase? We aim to explore this idea in our project and see if the charging infrastructure is adequate enough for the rapid changes in the EV market. We will explore these ideas in our project, focusing on the location and types of EV charging. We will take the help of maps and real-time data to do thorough research. We will focus on finding out where the charging stations are placed, whether they are an appropriate distance away from each other and how busy they are. We aim to offer recommendations to the charging stations based on our findings on ways to improve and simplify the charging experience for customers. We believe that our project will contribute to creating a better and more sustainable future for everyone.

II. Motivation

The demand for sustainable transportation solutions becomes more urgent due to the swift pace at which the climate of our world is changing, and the burgeoning number of environmental issues. Witnessing this, governments all over the world have been ardently supporting the adoption of electric vehicles (EVs), offering a variety of incentives and benefits.

One of our team members had a personal experience that exposed the shortcomings in the existing charging infrastructure as our team delved more into the realm of electric vehicles. A vacation she went on demonstrated how important it is to have a large network of charging stations in order to make EVs feasible for daily use and long-distance driving. In addition, we found that busy stations offer good chances for supercharger installations, which improve customer satisfaction while simultaneously increasing station revenue.

Ultimately, we want to make sure that electric vehicles (EVs) are more than simply a backup form of transportation when we embark on this project. With the support of a large and effective network of charging stations, we see them as the primary option.

III. Problem Definition

The progression of the shift towards environmentally friendly transportation alternatives is profoundly aided by electric vehicle (EV) charging stations. The efficiency and accessibility of the charging infrastructure are increasingly becoming important as EVs continue to gain popularity.

In this study, we examine real-time user interactions and geographic factors by delving into extensive data from EV charging stations. We hope to shed light on the nuances of EV charging dynamics by combining network analysis with Python-powered data processing utilizing pandas, NumPy, and seaborn, along with visualization tools like Tableau and matplotlib. Our study is at the forefront of creating an efficient and user-friendly EV charging landscape because of this refined approach.

IV. Objective

We aim to derive insights about the electric vehicle charging stations based on the user interaction with the charging station and guide the enhancement of the electric vehicle charging infrastructure. To derive the charging habit insights, we are planning to identify the trends, peak usage times, and user preferences related to EV charging. To understand the infrastructure and provide recommendations, we are planning to assess the current state, distribution, and potential gaps in the charging station networks. Based on the network and exploratory data analysis, we want to craft data-backed strategies to refine and expand the charging station infrastructure.

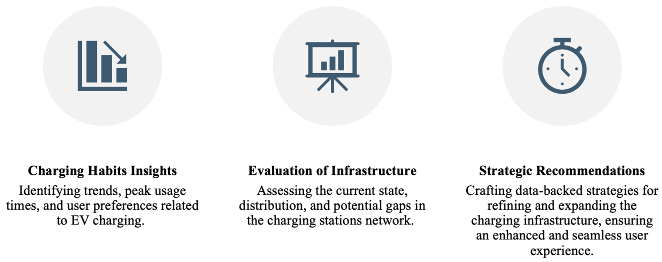

Fig. 1. Objective

V. Literature review

Electric vehicles (EVs) are transforming how we approach transportation. Several significant studies have explored the dynamics of EV adoption.

In the article "Role of workplace charging opportunities on adoption of plug-in electric vehicles – Analysis based on GPS-based longitudinal travel data," the authors highlighted the pivotal role of workplace charging in influencing people to choose EVs. The study found that availability of charging facilities at workplaces encourages those who have longer commutes to consider EVs, as they can recharge their vehicles conveniently during working hours. For our EV project, this emphasizes the importance of collaborating with businesses to install charging stations, ensuring that EV users have convenient access during their work hours.

Another critical study titled "The impact of range anxiety and home, workplace, and public charging infrastructure on simulated battery electric vehicle lifetime utility" delved into the concept of "range anxiety" - the fear of running out of charge. Using the BLAST-V tool, the research indicated that the accessibility of charging stations, whether at home, workplaces, or public areas, significantly alleviates this anxiety. In relation to our EV project, this points to the need for a comprehensive network of charging stations in various locations, ensuring that potential EV users feel confident in their vehicle's ability to meet their daily travel needs.

Furthermore, the study "Within-day recharge of plug-in hybrid electric vehicles: Energy impact of public charging infrastructure," explored the implications of public charging facilities on the usage pattern of EVs. The research concluded that abundant public charging stations encourage more frequent use of EVs, especially those with smaller battery capacities. For our project, this suggests that by establishing more public charging points, especially in busy urban areas, we can significantly enhance the attractiveness and feasibility of using EVs for daily commutes and other short trips.

By combining insights from these studies, our EV project is poised to address key concerns of potential EV adopters and pave the way for a more sustainable transportation future.

VI. Hybrid crisp-DM and Waterfall model

Understanding business requirements: To gain a better understanding of business requirements, we can analyze user charging habits, evaluate the current state of charging infrastructure, and develop data-driven strategies for improving and expanding the EV charging service.

Design plan: We utilized Python for data cleaning, preprocessing, exploratory and network analysis, using libraries such as NetworkX. To present insights derived from data, we leveraged Tableau to create user-friendly dashboards.

Data understanding: We checked the data quality and validity before you start the analysis. We used methods such as df.info(), df.describe(), df.isnull().sum(), df.duplicated().sum(), etc. to get some basic information and statistics about the data and identify any missing, duplicated, or incorrect values.

Data cleaning and preparation: We have replaced null values in the 'Ended by' column with 'Unknown'. Additionally, we have dropped four irrelevant columns that had empty values. As all sessions were from the US, we have used 'USD' for missing values in the 'Currency' column. We have also dropped the rows with missing values in the 'Driver Postal Code' column. To make the data more readable, we have converted the 'User ID' and 'Driver Postal Code' columns to integers. Finally, we have defined a dictionary of time zone abbreviations to standardize session time zones.

Analyzing the data: Analyzing electric vehicle charging data involves studying topics such as descriptive statistics, charging patterns over time, energy consumption habits, environmental savings analysis, and user behavior. Other important areas to consider are high-usage stations, plug type preference, session ending behavior, charging session duration versus energy consumed analysis, user payment behavior, and user behavior based on geographical data.

Creating data visualizations: We have created a variety of visual aids including network graphs, scatter plots, bar charts, histograms, violin plots, heatmaps, and dashboards. These visualizations effectively display the data and the outcomes of our analysis on topics such as charging stations, session duration, energy consumption, session endings, and user distribution.

Generating insights based on data: Throughout our analysis, we found it necessary to create various types of visualizations. These included network graphs, scatter plots, bar charts, histograms, violin plots, heatmaps, and dashboards. Our goal was to display the data and findings of our analysis on topics such as charging stations, session duration, energy consumption, session endings, and user distribution. By examining these visualizations, we were able to gain valuable insights.

Deployment : We created dashboards, reports, presentations, and a video, to share our analysis findings and insights. We posted them on github and youtube.

Fig. 2. Hybrid Waterfall model

VII. Data Process Flow

The data process flow explains the steps we have followed to complete this project. Once the title and goal had been decided to analyze the electric vehicle infrastructure, we started our research to source the right dataset. The dataset used in this project for analysis is sourced from the City of Palo Alto's official data portal.

After data sourcing is completed, the dataset is downloaded in CSV format. Loaded the dataset in Python pandas for further cleaning and preprocessing steps. Once the dataset is cleaned, it has been exported and shared with the team for further analysis.

Fig. 3. Data Process Flow

We have used the NetworkX tool for network analysis and created graph visualization to understand the relationship between users and charging stations and to understand the charging station infrastructure. Once the network analysis was completed, the team moved to do exploratory data analysis using Python Pandas, Matplotlib, and Seaborn libraries. In this step, we have also created a tableau dashboard to understand the user behavior analysis.

After the analysis of the dataset, the insights are derived based on the visualizations and we recommended the infrastructure changes for further development and profit. The report has been compiled and the project has been presented.

VIII. Dataset Description and Collection Methods

Dataset Collection

Data Source:
Data for this project is collected from the City of Palo Alto's official data portal.
https://data.cityofpaloalto.org/dataviews/257812/ELECT-VEHIC-CHARG-STATI-83602/

Dataset:
The "Electric Charging Station Usage (2011 to 2013)" dataset was chosen for analysis.

Tags Used:
Relevant dataset tags: "utilities" and "infrastructure."

Timeframe:
Data is collected from the period of July 2011 to December 2020.

Dataset Description

Our dataset provides a comprehensive overview of interactions between electric vehicle users and charging stations. Sourced from the City of Palo Alto, the dataset encompasses transactions spanning July 2011 and captures essential metrics that underpin our project's objective.

Central to our analysis, the dataset comprises 27 distinct features. The most crucial among them include:
Start Date and End Date: shed light on peak usage times and potential seasonal or daily charging trends.
Total Duration: reflecting the average charging duration and offering insights into user charging habits and station efficiency.
Energy (kWh): a measure of energy consumption for each charging session, indicative of charge requirements and equipment efficiency.
GHG Savings (kg) and Gasoline Savings (gallons): Quantifying environmental benefits is a key parameter for assessing the ecological impact of EVs.
Port Type and Plug Type: Elucidating user preferences and indicating any potential technological or compatibility gaps in the charging process
EVSE ID and Address: Instrumental in spatially mapping the existing charging infrastructure and detecting high traffic zones or network gaps.
Fee: A financial metric that, when analyzed, can influence pricing strategies and gauge user's spending behaviors.
Ended By: Signifying the end-cause of a charging session, it provides a deep dive into user behaviors and station functionality.
User ID: Facilitating user segmentation is a cornerstone for differentiating between habitual and sporadic users.

Harnessing these features, our goal is to fathom the interplay between EV users and charging stations. This understanding is pivotal for us to provide actionable insights for optimizing charging habits, evaluating the adequacy of current infrastructure, and ultimately crafting data-backed recommendations to refine and expand the charging network.

IX. Data Cleaning and Pre-processing

An essential phase in the pipeline for data analysis and visualization is data cleaning. It guarantees that data visualizations convey insights from the data in an accurate and efficient manner, facilitating well-informed decision-making and a deeper comprehension of underlying patterns and trends. Data preprocessing is an initial stage that helps prepare unprocessed data for efficient visualization by cleaning, organizing, and transforming it. Preprocessing quality has a direct impact on the precision, readability, and utility of the data visualizations produced.

Managing Missing Values: Missing values are a common occurrence in real-world datasets. By using techniques like imputation or removal to deal with these missing values, data preprocessing makes sure that the visualizations are founded on accurate and comprehensive data.

Handling Outliers: Outliers can cause visualizations to become distorted and make it difficult to identify significant patterns. Extreme values shouldn't unduly affect the visualization, thanks to data preprocessing techniques like outlier detection, removal, or transformation. Data Transformation and Feature Engineering: By enabling the creation of new features or the transformation of pre existing ones, data preprocessing creates a foundation for visualization that is more informative. Feature engineering can assist in locating hidden relationships or patterns in the data. Parsing Dates and Times: Created a standard format by converting date and time strings. This guarantees that temporal data is represented consistently. Ensuring that all timestamps are in a consistent time zone is known as "standardizing time zones." This is crucial for datasets that contain information gathered from various geographic locations. Regularization: It is the process of transforming irregular time intervals into regular ones. For datasets where measurements might not happen at regular intervals, this is crucial.

- In order to clean up the data, we removed the values from four columns: EVSE ID, County, System S/N, and Model Number.
- Verifying Null values and substituting them with specific parameters. To improve readability when visualizing plots, data types for columns User ID and Driver Postal code are converted from float to integer.
- utilizing dateutil.tz to apply timezone to the transaction date column and the pytz library in Python to correct the DateTime format. Examining the Energy and Location columns for outliers

X. Network Analysis

The electric vehicle infrastructure can be analyzed better by analyzing the networks using graphs. We have used the NetworkX tool to create graph visualization for understanding the relationship between the user and the charging station. We have referred to the book, Network Science with Python by Edward L Platt, to understand bipartite graphs and how to create graphs using the NetworkX tool in Python.

The bipartite graph is a graph with two sets of nodes, and they are independent. The two sets of nodes do not connect with the edge to the same set. The below visualization is created using the bipartite graph concept, here users and charging stations are two sets of nodes. One user does not establish a connection to other users and the same for the charging stations. Edges are established only between users and charging stations. In the visualization, the purple nodes denote the users, and the yellow nodes denote the charging station. In our dataset, we have 5 charging stations and 970 users. The edge width with a thicker line denotes the charging time is higher. The user nodes on the outside of the graph show the users who use only one charging station. The user nodes in the middle of the graph are the users who use more than one charging station to charge their cars.

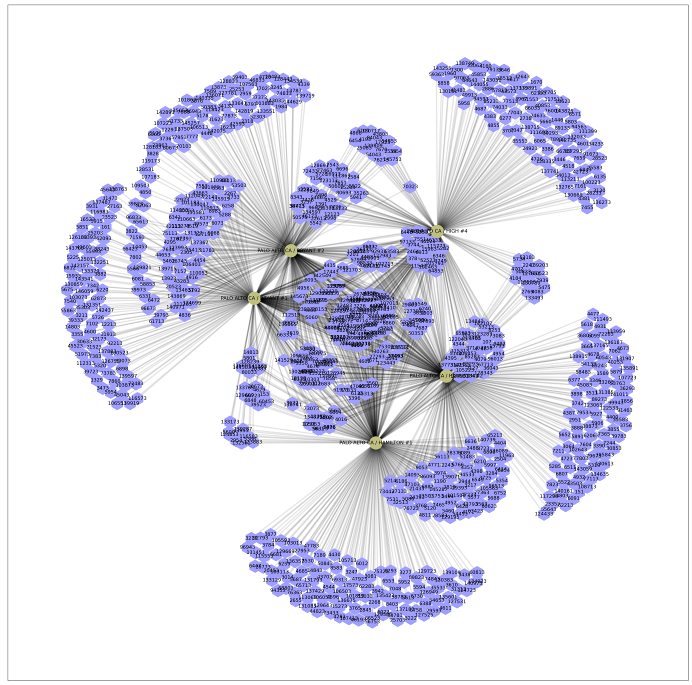

Fig. 4. Bipartite graph with spring layout

The users who used only one charging station to charge their cars are 459 and the users who used more than one charging station to charge their car are 511. The below graph shows the unique users and users who used more than one charging station in Palo Alto city. The purple nodes denote the users, and each node represents the number of times each user visited the charging station to charge their car. The darker purple shade in the user node denotes the user who visited more than one charging station. The lighter purple shade denotes the users who used only one station to charge their cars. This visualization denotes the unique users who visited more times to their station to charge the car and are shown by more light purple nodes compared to darker shades in the visualization.

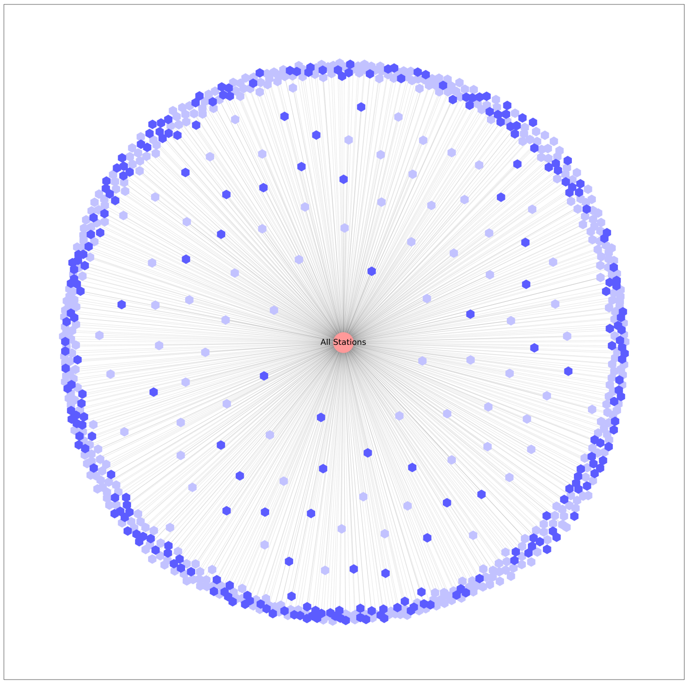

Fig. 5. Unique users versus users who used more than one charging station

As per our analysis, we were able to find the numbers for unique users by each charging station in Palo Alto City. **Unique Users Per Station (Only Visited That Station):**

Station Name	Unique users per station
PALO ALTO CA / BRYANT #1	77
PALO ALTO CA / BRYANT #2	89
PALO ALTO CA / HAMILTON #1	107
PALO ALTO CA / HAMILTON #2	91
PALO ALTO CA / HIGH #4	95

This graph was created with only one node named the charging station. In our dataset, we have five charging stations in Palo Alto city and edges show the number of unique users who used both node charging stations to charge their cars. Based on the visualization, we can derive that the most used two charging stations together by users are Hamilton 1 and 2, and 251 users used these two stations together to charge the cars.

But all the other counts in the graph are also closer to 200 which indicates that the users who come to this city to charge choose any station with an available port. Overall, the users who used more than one charging station chose any station among the five based on availability. The main reason for this behavior might be that all five stations are very close to each other (based on the map view in EDA analysis), and they can choose the station based on their availability.

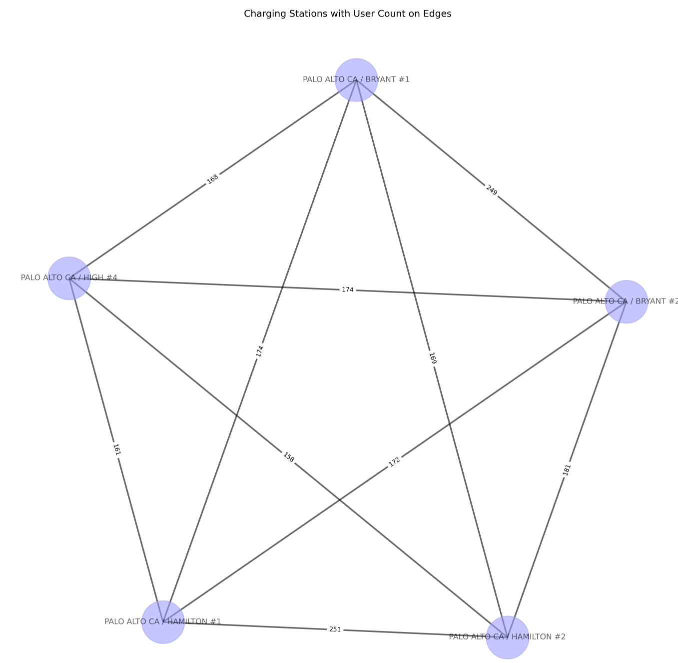

Fig. 6. User count for two charging stations

We also wanted to analyze exactly how many users used two stations, three stations, four stations, or all five stations to charge their cars.

Category	Number of Unique Users
Unique users who use two stations	252
Unique users who use three stations	95
Unique users who use four stations	80
Unique users who use five stations	84

By the above analysis, we can see the number of users who use two charging stations together is more compared to other numbers of stations. This might be because of Bryant 1 and 2 , Hamilton 1 and 2 location which is very nearby (can be viewed in map street view in EDA analysis), the users have more opportunity to choose between these two stations.

XI. EDA Analysis

Descriptive statistics(Analysis of Charging Session Duration vs. Energy Consumed), High-Usage Stations vs. Frequent Users

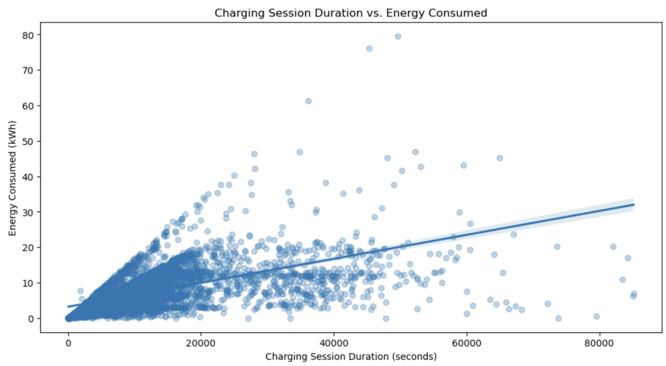

Fig. 7. Charging session duration vs Energy Consumed

The scatter plot of charging session duration vs energy spent for electric cars shows a strong positive correlation, indicating that, on average, longer charging times correspond to higher energy consumption. This alignment represents the basic limitation of electric car batteries, which require longer charging sessions to achieve their restricted capacity. Notably, outliers with long charging times and low energy usage point to a variety of circumstances, such as intermittent charging or high-efficiency charging. These findings highlight the importance of user behavior, battery capacity concerns, and efficiency variables in defining electric car charging patterns. Overall, the scatter plot gives a detailed insight of the relationships between charging session time and energy use, throwing light on prospective electric car charging optimization solutions.

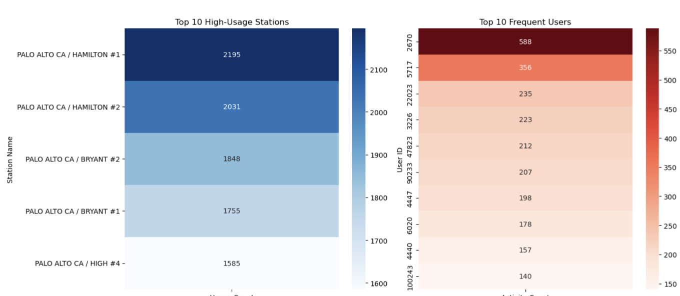

Fig. 8. Usage analysis for station and top 10 users

The heatmap display reveals interesting trends in charging station data. Notably, 'Palo Alto CA/ HAMILTON 1' is the most often used station, with a substantial use count of 2195, closely followed by 'Palo Alto CA/ HAMILTON 2' and 'Palo Alto CA/ BRYANT 2.' The concentration of consumption in Palo Alto, CA, indicates a particular need for charging services. Meanwhile, among the top ten most regular users, User ID 2670 stands out with an unusually high activity count of 588, indicating persistent and frequent use. The diversity of activity counts among users reflects a diverse user base, which might include both individual and business users. These heatmap data provide useful business ideas, such as managing resources at high-traffic stations and personalizing services to fit the preferences of regular customers, thereby improving the overall charging experience for varied user profiles.

Charging Patterns Over Time, Energy Consumption Habits

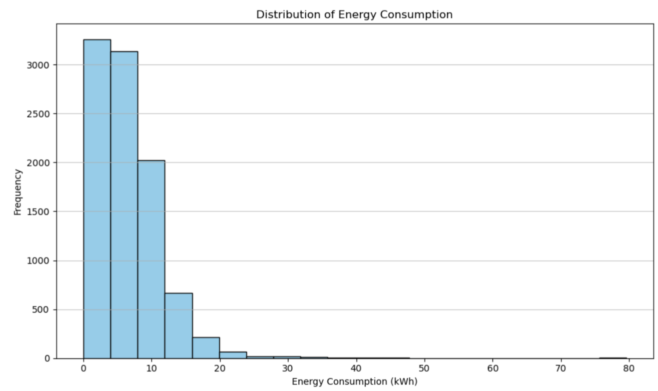

Fig. 9. Distribution of Energy Consumption

As you can see, the distribution of Energy Consumption is extremely right skewed. The frequency of Energy consumption in kWh is highest(over 3000) for when energy consumed is less than 10 kWh. For 10 kWh, the frequency of energy consumption is just over 2000. After that, the frequency per energy consumption keeps decreasing steadily until it reaches close to zero at 30 kWh. After that, the bars have too low of a frequency to be readable, but we can see that the bars continue until 80kWh energy consumption.

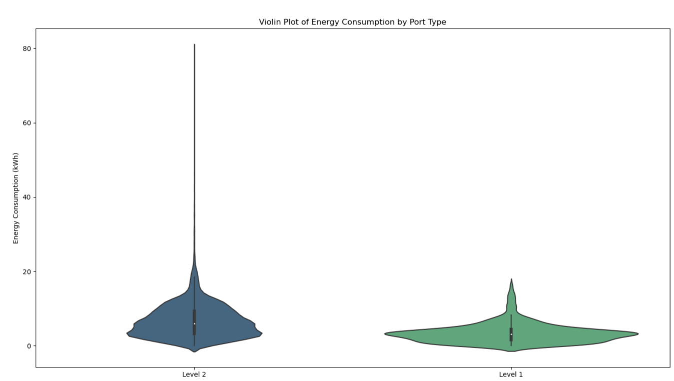

Fig. 10. Violin plot for Energy consumption by port type

Violin Chart of Energy Consumption by Port Type insights: On the X-axis, we have Port Type and on the Y-axis we have Energy Consumption in kWh. First violin is for energy consumption of level 2. The approximate minimum of level 2 port type is less than 0, and the maximum is 80 kWh. The median is approximately 8. The first quartile is approximately

4 and the third quartile is approximately 12. The width or maximum frequency is around the first quartile. After 20kWh, the width of the violin is very less so it looks like a straight line until its maximum around 80kWh.

Second violin is for energy consumption of level 1. The approximate minimum of level 2 port type is less than 0, and the approx maximum is 20 kWh. The median is approximately less than 5kWh. The first quartile is approximately close to 0 and the third quartile is approximately 10. The width or maximum frequency is around the median.

Comparing the two violins, the Level 2 violin has a lesser width than the level 1 violin, but the level 2 violin has a more uniform width as compared to level 1. Level 1 has a sharp width increase near the median, but otherwise is it narrow.

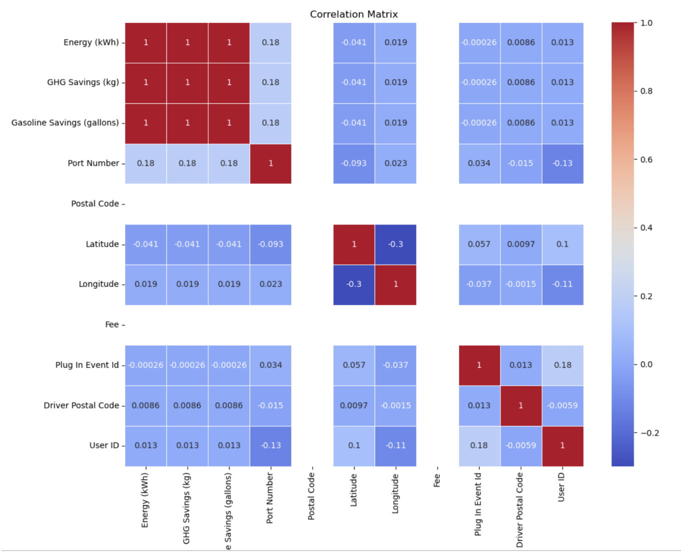

Fig. 11. Correlation Matrix

Correlation Matrix Heatmap of all numerical columns insights: Columns used are: Energy(kWh), GHG Savings(kg), Gasoline Savings(Gallons), Port Number, Postal Code, Latitude, Longitude, Fee, Plug In Event Id, Driver Postal Code, User Id. For Postal Code and Fee, there are gaps in the matrix so there are no correlations for these two columns. The correlation between the first three columns Energy(kWh), GHG Savings(kg), Gasoline Savings(Gallons) is very high with one another. The 3x3 matrix between these three columns has the highest positive correlation possible(1) which is denoted by the color dark red. The lowest correlations are negative correlations of -0.3 between Latitude and Longitude as well as Longitude and Latitude. This is denoted by a cool dark blue color.

Environmental Savings Analysis, Plug Type Preference

The distribution of environmental savings over charging sessions is shown by this histogram. Using electric vehicles and charging stations reduces emissions and has a positive environmental impact, as indicated by the ”Environmental Savings” column. Understanding the distribution can help one understand how the charging sessions have affected the environment as a whole.

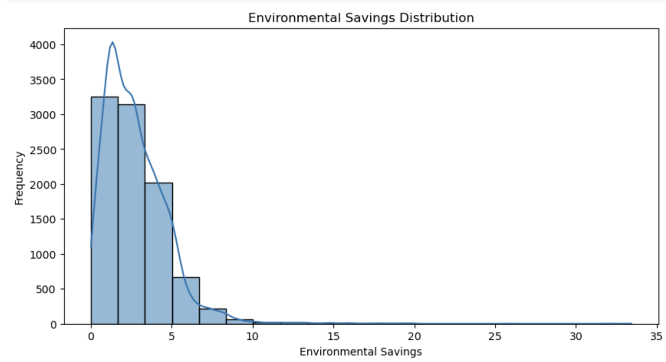

Fig. 12. Environmental savings distribution

Plug Type Reference : The distribution of plug types used during charging sessions is shown in a pie chart. The size of a slice of pie indicates the percentage of charging sessions that utilized a particular plug type, and each slice represents a different plug type. An overview of the popularity of various plug types is provided by this chart.

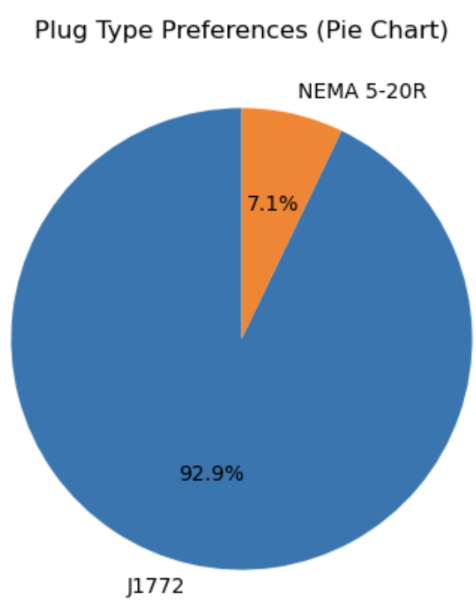

Fig. 13. Plug type preferences

Session Ending Behavior Analysis, Analysis of Charging Session Duration vs. Energy Consumed

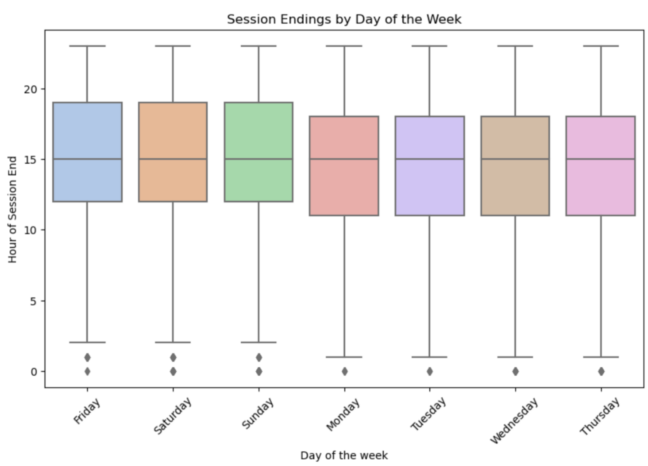

Fig. 14. Session Ending by Day of the Week

Based on the analysis, it appears that consumers tend to be more engaged with the service on Fridays, Saturdays, and Sundays, as evidenced by the higher median session endings on those days. This suggests that they have more free time, interest, or motivation to use the service during the weekend. Conversely, consumers seem to be less engaged on Mondays to Thursdays, as indicated by the lower median session endings on those days. This could mean that they have more obligations, distractions, or alternatives to use the service on those days. Additionally, it seems that consumers exhibit more variability in their engagement on Fridays, as evidenced by the larger interquartile range on that day. This may indicate that they have more diverse, flexible, or uncertain usage behavior. Conversely, consumers have more consistency in their engagement on Mondays, as evidenced by the smaller interquartile range on that day. This could imply that they have more similar, regular, or predictable usage behavior.

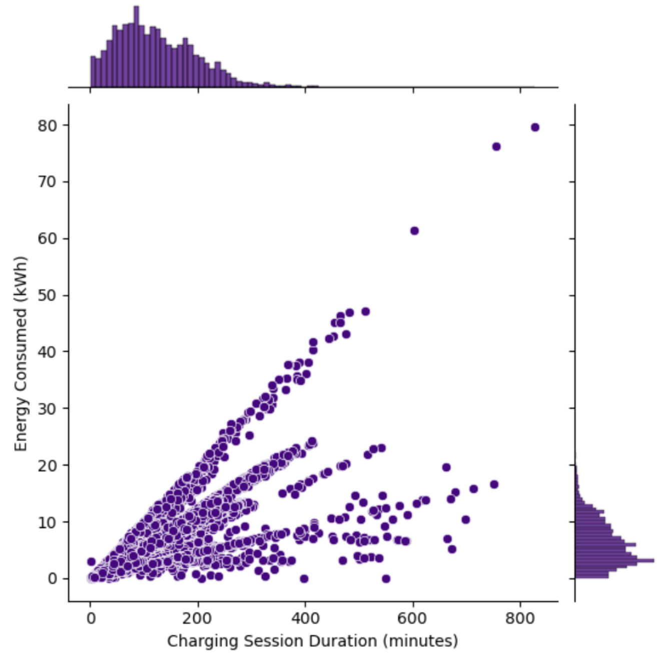

Fig. 15. Joint plot for charging session duration vs energy consumption

When it comes to electric vehicles, consumers tend to charge them for longer periods and consume more energy. This behavior could suggest that either their vehicle has a high battery capacity, they drive longer distances, or they charge their vehicle less frequently. Additionally, the presence of an outlier in the top right corner of the data could indicate a potential anomaly or error. It is possible that this outlier is due to a faulty sensor, a data entry mistake, or a rare event. Therefore, it is important to investigate it further to determine the cause and validity of this outlier.

XII. Dashboard -User behavior Analysis

To understand the user's behavior for the charging station usage, we have used the Tableau tool to create the visualizations.

User Distribution Analysis

The maps have been created in the tableau to understand how users are distributed around the charging station of Palo Alto City, California. The first map shows the users highlighted from other states and different counties and the numbers in the highlighted users indicate the count of users from that state or county. The number and user count from other counties or states is around 20 or less. This indicates that the five charging stations in Palo Alto City are not in the travel route which gets more unique users from different states.

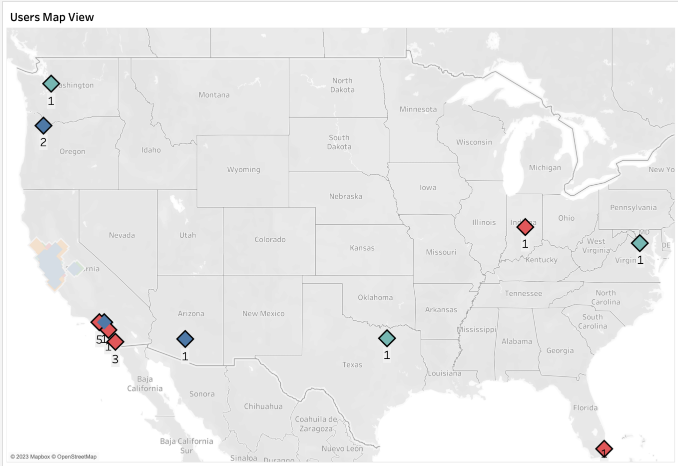

Fig. 16. Country view for users distribution

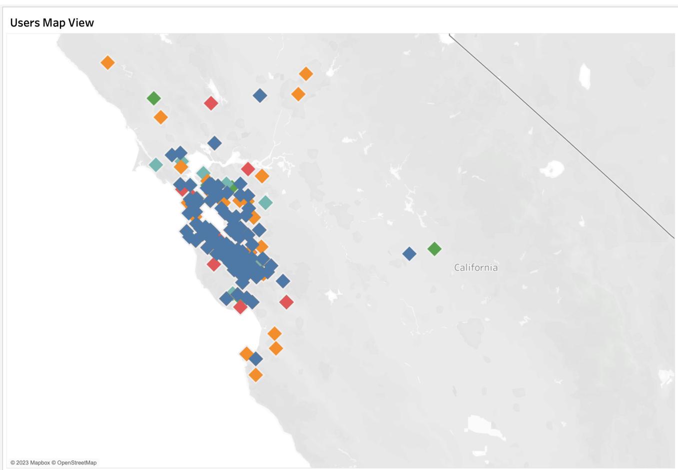

Fig. 17. State view for users distribution

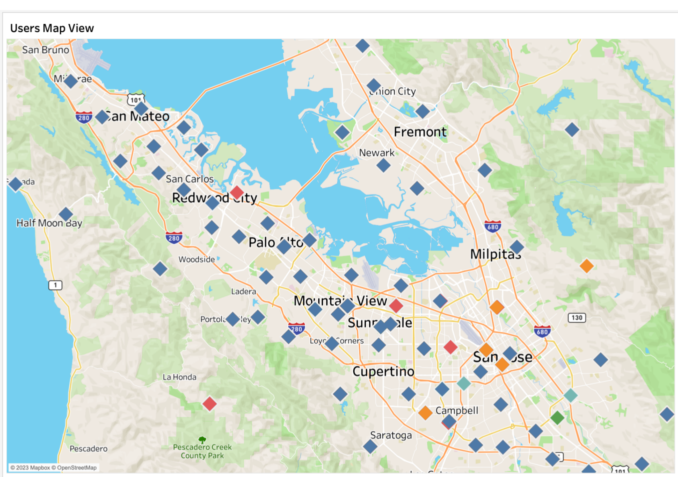

Fig. 18. City view for users distribution

The next two maps show how users are distributed in California and city view for users around Palo Alto city. Most of the users who use the charging station are local users who reside in the same or nearby county. Even though all five charging stations are very close in street view, the users are not from the same streets as the charging station. The users are distributed around the city and nearby cities, which indicates that this station city is getting busy with users who travel to nearby cities for work or other purposes.

User Behavior Analysis

Tableau interactive dashboard was created to analyze the users and their behavior. This dashboard helps us to visualize how users are interacting with the Palo Alto City charging station. The details provided in the numbers are the total time the car is connected in the station, charging time and Idle time is the time the car is connected to the plug even after the car charging is completed. The reason for idle time might be, the users have gone shopping after they parked their car for charging.

The bubble chart shows the user's idle time without charging. The size of the bubble denotes the total amount of time that a specific user is idle in the specific station. The label of the bubble chart shows the user details, charging station details, and total hours the users were idle. The station is assigned a color to differentiate the five stations from each other. The charging station street view shows the street view map, and the five triangle shapes denote the five charging stations.

The bar chart was created to show the total energy used by users in all five stations. The table was created to show the total number of times users visited each charging station. The donut pie chart was created to show the gasoline savings that happened at each station and the total savings done by users. The horizontal bar chart was created to show the plug type and these charging stations have two plug types in total. A density plot was created to show what time the user charged most in the charging station and to find peak hours or busiest hours for the stations.

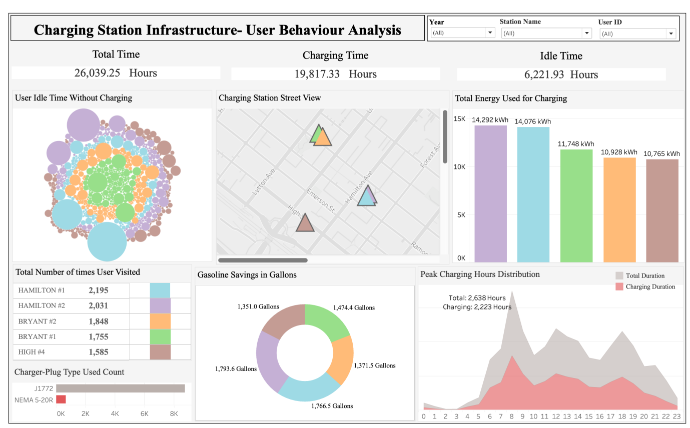

Fig. 19. Tableau dashboard

A Story of User 136695:

From the below visualization, we can understand the behavior of one user with ID 1336695. This user visited all five stations to charge their car. The total charging time is around 120 hours and idle time is around 16 hours. He visited Bryant 1 station around 25 times in the last three years to charge their car. He used both plug types while charging the car and the peak time when the user charged is at 2pm. In his 25 times of charging at Bryant 1 station, he used 502.6 Kwh energy to charge the car and helped the world to save 63.07 gallons of gas.

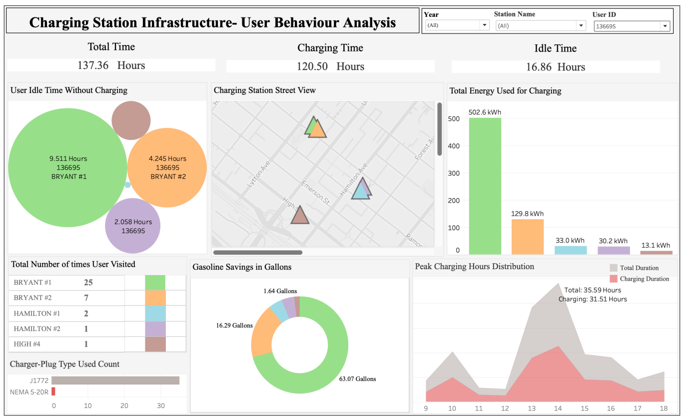

Fig. 20. Tableau dashboard- A Story of User 136695

A Story of User 60023:

From the below visualization, we can understand the behavior of one user with ID 60023. This user visited all five stations to charge their car. The total charging time is around 240 hours and idle time is very high which is close to charging time 113.24 hours. He visited Bryant 1 station around 14 times in the last three years to charge their car. He used one plug type while charging the car and the peak time when the user charged is around 8pm. In his 14 times of charging at Bryant 1 station, he used 239.32 Kwh energy to charge the car and helped the world to save 30.01 gallons of gas.

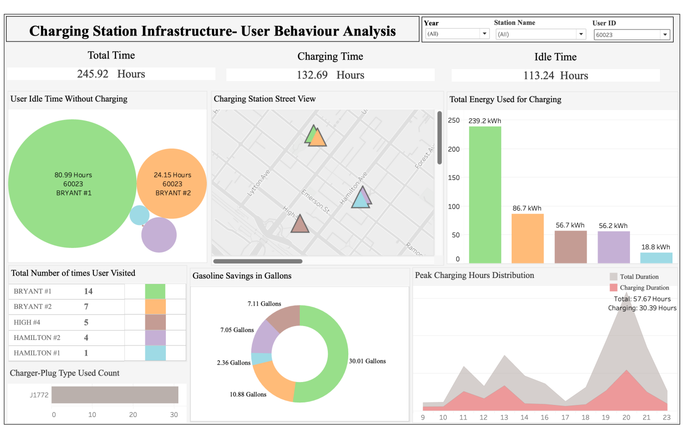

Fig. 21. Tableau dashboard- A Story of User 60023

XIII. Infrastructure Development Recommendation

Based on our analysis of the Palo Alto city electric vehicle charging station dataset for the years 2011, 2012, and 2013, we have given the following recommendations for developing the charging station infrastructure to enhance the user experience and gain more profit:

- **Expand the charging station network:** Based on our network analysis, we were able to derive that users often choose charging stations based on availability. Also, based on our user behavior analysis, we can find all the users are local and from nearby cities. So, expanding more stations in nearby cities could reduce congestion at existing stations in Palo Alto City and provide more options for users.
- **Enhance charging station capabilities:** As per our analysis, there is a significant use of both level 1 and level 2 charging ports. We recommend increasing or upgrading the existing charger with faster charging capabilities, like a supercharger or level 3 charging ports.
- **Implement smart charging system:** The total idle time for all five stations in the last three years is 6221.93 hours. This is the time when the cars remain plugged in after the charging is complete. We can implement a smart charging system that can alert the user when the charging is complete and increase the penalties for occupying the charging spot beyond the charging time.
- **Adding Solar panels and batteries for green energy savings:** This city is in California and is a good place for solar systems. Based on the usage of these stations, we can add solar panels and batteries to store the electricity generated, which will give more profit to the electric vehicle company in the long run.
- **User Engagement and Incentives:** Enhancing the user experience by providing a more user-friendly app or dashboard where they can see the available charging station, charging speed, and nearby locations Since our users use more than one station often, we provide a single account where they can access all station usage details. Apps or digital platforms can be developed for this purpose.

XIV. Conclusion

In conclusion, our analysis of the Palo Alto City electric car charging station dataset from 2011, 2012, and 2013 offered useful suggestions for improving charging station infrastructure. We encourage a multifaceted strategy to improve the user experience and increase revenue. To begin, expanding the charging station network to surrounding cities reduces traffic concerns and gives users more alternatives. Furthermore, improving charging station capabilities by offering faster charging technologies like superchargers or level 3 ports meets the different demands of consumers who rely on both level 1 and level 2 charging. The adoption of a smart charging system, which is designed to reduce idle time and inform users when charging is complete, assures effective station usage. The incorporation of solar panels and batteries corresponds to the

California location, delivering green energy savings for long-term profitability. Finally, increasing user involvement via a user-friendly app or dashboard, in conjunction with a unified account for obtaining station usage information, promotes a smooth and pleasant experience. These proposals together contribute to Palo Alto City's more sustainable, user-centric, and lucrative electric car charging infrastructure.

XV. Future Scope

Analysis of Temporal Trends

Examine historical patterns in the use of charging stations. Determine seasonal variations, peak usage periods, and any new trends.

Regional Evaluation

Examine the usage trends in various cities or regions. Determine which locations are in high demand and whether more infrastructure for charging would be beneficial.

Analysis of User Behavior

Examine user behavior by looking into things like preferred charging times, typical charging times, and how often users charge. This might reveal information about the habits of users.

Impact of Policy Changes

Examine the effects of any incentives or changes in policy for electric vehicles that occurred during the dataset's coverage period on the use of charging stations.

Rate of Charging Station Utilization

Determine and display the charging station utilization rate. Determine which stations are frequently busy or underutilized.

Forecasting through Modeling

Create predictive models using historical data to estimate future demand for charging stations. This could be useful when planning infrastructure.

Analysis of Demographics

Examine the demographic variables affecting the use of charging stations. This may involve factors like population density, income levels, or the availability of incentives for electric vehicles.

Combining Weather Data with Integration

To comprehend how weather affects charging station usage, incorporate weather data into your analysis. Extreme temperatures, for instance, may have an impact on charging behavior.

A Comparative Study Using EV Sales

Compare sales data for electric vehicles with trends in the use of charging stations. Examine whether a rise in charging demand is correlated with higher sales.

Network Accessibility and Connectivity

Analyze how easily accessible charging stations are in various locations. Examine how well both urban and rural areas are covered by the charging network.

Impact of Battery Technology

Examine whether changes in battery technology over time have affected how batteries are charged. For example, a larger battery may have an impact on how often it is charged.

User Input and Contentment

Examine customer reviews or satisfaction surveys about charging stations, if they are available. Determine what needs to be improved upon and evaluate overall user satisfaction.

List of Figures

References

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