Analysis of Charge Ahead Colorado Grant Program Electric Vehicle Charging Stations

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1 Abstract

This report summarizes and provides analysis for data gathered from Colorado Energy Office (CEO) electric-vehicle charging stations from May to December 2019. We emulated a third-party report which summarized similar data from May 2016 to April 2019 [1], and verified that annual trends observed in the report continued through 2019. The CEO is also concerned with identifying peak demand times as a means of reducing demand charges. We were able to conclude that peak demand-times differ on weekdays from weekends, and identified peak demand-time intervals. Peak demand-times occur near midday on weekdays.

*Jarrid Carroll-Frey - Bar Chart and Pie Chart Analysis, Monthly Energy Draw Analysis for different Venue Types, Peak Demand analysis with total charging time using 15 minute intervals, max time function that returns array of peak times across all files. Contributed to writing Sections 2, 3.1, 3.7, 4.1, 4.2, and notebook Sections 2, 6.1, 6.3, 7, 12, 13, 14.

†Gabby Harrison - Data summarizing and categorizing different CSV files, annual analysis, venue column analysis, station analysis, and start time hourly peak demand. Contributed to report Sections 2, 3.1–3.7, 5.2, 5.4, 5.6 and notebook Sections 2, 3, 4, 5, 6.2–6.6, 7, 9, 11, 15.

‡Priscilla Moreno - Summarizing, categorizing and choosing the CSV files for our analysis. Created Python code to concatenate and validate the transfer of data into a single file. Created visualizations, organized the final code notebook. Contributed to report Sections 3.6, 5.1–5.9, and notebook Sections 1, 2, 5, 6.1, 7.1, 7.2, 7.5, 7.6, 8, 9, 10.1, 14, 15.

§Cameron Steenblock - Research, concatenation of data, creating code for visual representations of data. Contributed to report Section 6, and notebook Sections 1, 2, 10.2.

¶Amy Thompson - Contributed to file read-in and concatenation, start and end time columns, start and end time plots, ZIP code and weekday dataframes, writing and editing reports. Contributed to report Sections 1, 2, 3.5, 4.1–4.8, 5.1–5.3, 6, and notebook Sections 1, 2, 3, 10.1, 11.

2 Introduction

Charge Ahead Colorado is a Colorado Energy Office program that was created to support the goal of reducing greenhouse gas emissions and consumer energy costs in the state. The program achieves this by distributing grants for electric vehicle (EV) charging stations to grantees within Colorado.

Colorado Energy Office is concerned with identifying peak demand times as a means of reducing demand charges for its grantees. Demand charges are fees charged by the utility to the grantee as a result of transactions that occur during time intervals when energy demand is high. The occurrence of demand charges is a problem for grantees because the cost can outweigh the benefit of an EV charger grant.

This report summarizes data gathered from sponsored stations from May to December of 2019, and builds on the third-party report previously commissioned by CEO which covers data from 2016 to April 2019 [1]. Each transaction recorded includes a start time, duration, energy used in kW h, "greenhouse" gas (GHG) savings, customer Id, and other information pertinent to the location of the station.

We first categorized each of the stations as one of seven different venue types in order to analyze demand in terms of location and understand an ideal location type for placing these charging stations. Venue types were chosen by the address of the station and the nearby venue type. The data demonstrate the behavior of consumers; they are suggestive that consumers are more likely to use certain venues overall or during different parts of the day. The analysis of venue type could help inform decisions about where to place new EV charging stations in the future.

The plots provided in this report will provide an understanding of changes in demand throughout the day, as well as differences in demand between weekdays and weekend days. These findings can be used to produce effective policy for reducing the burden of peak demand.

3 Methods

3.1 Description of Data

Our data is recorded in of 54 unique "comma-separated value" (.csv) files and 24 Microsoft Excel (.xlsx) files. During the process of cleaning the data, the 24 .xlsx files were excluded because many had inconsistent columns or blank information. The 54 .csv files were then concatenated into one .csv file so that we could analyze all of the data together. Combining all the files enabled us to view and analyze the data as a whole, and identify trends across all stations. Each .csv file contained more than one station and was provided to CEO by a unique grantee. The combined file has a total of 37,194 rows and 31 columns. The rows represent the number of transactions in our .csv file, and transactions span 244 days from May 2019 to December 2019.

The 31 columns are different descriptors of the transactions. We removed 22 columns that we determined to be irrelevant to our analysis for peak demand. We then added 17 additional columns for each transaction which were pertinent to our data. These include venue type, venuenum (0=Apartment, 1=Hotel/Resort, 2=Leisure, 3=Municipality Building, 4=Parking Garage/Lot, 5=Retail, 6=University/Medical Campus and 7=other), a new end time as a function of start time and charge time, day of the week, start time rounded to the nearest 15 minutes, hour of day in which the charging began, weekday (0) or a weekend (1), and the month the transaction occurred.

Of the columns we used, station name, organization name, station Id number, ZIP code, latitude and longitude, address, city, county and venue are all categorical types of data, which give location descriptions for each transaction. Our data includes 28 Colorado counties in the CEO's jurisdiction, spanning across 143 stations and 57 ZIP codes. Noticeably, very few stations in our data that are located in the city of Denver. This is due to the fact that data for stations in most of Denver are unavailable, as the stations are not solely in the jurisdiction of the CEO.

Start date, end date, total duration, charging time, start time, end time, day of week, hour, and weekend/weekday are all numerical data type columns that give date and time descriptions for each transaction. Start Date and End Date include the time of day as well as the date each transaction occurred. For our peak demand analysis, we created a column with start time, and used charging time to find when the car stopped charging, which we then used to create an end time column. This distinction between charging end time and unplug time is significant because plugged in non-charging vehicles do not produce demand charges. We also analyzed peak demand-time using charging duration time, to include instances in which the charger is being occupied even though it is no longer charging. The hour column was added in order to extract data for hourly analysis plots.

We created the day-of-week column to identify the day each transaction occurred on. A 0 in this column corresponds to Monday, and continues through 6 which corresponds to Sunday. We also added in a column that determines if a transaction occurs on a weekday or weekend day. A 0 in this column corresponds to a weekday, and a 1 corresponds to a weekend day. The energy column describes how many kW h were used in each transaction.

3.2 Data Tables

We created tables to organize and group our data based on annual change and venue type. In our venue table, we were able to summarize the number of stations, number of transactions, energy usage, average energy per station, and average energy per transaction for each venue type.

3.3 Pie Charts

The consultant report we emulated incorporated pie charts when comparing qualitative data, such as venue type. We incorporated this into our report to visualize the proportions of energy and transactions drawn from each venue type. We also used pie charts to compare the number of transactions and energy drawn monthly for all stations combined. These plots demonstrate trends dependent on a station's venue type, as well as what times of year are associated with higher or lesser usage at these stations.

3.4 Bar Charts

Bar charts are useful tools when comparing or demonstrating trends in data. We used bar charts to combine our 8 months of data with the data in the consultant report to measure changes from year to year. We also used bar charts to show monthly growth over the span of our data, from May 2019 to December 2019. Bar charts were also useful when analyzing the different ZIP codes and counties, to see which regions of Colorado had highly active stations. From there, we utilized sorted horizontal bar charts to find the top and bottom performing stations included in our data.

When beginning our peak demand analysis, bar charts were useful when comparing the hourly start times for each transaction, which we then took further by comparing each day of the week, as well as weekdays to weekends. This allowed us to see when the initial start time peaks occurred, and how hourly trends changed in relation to day of week.

3.5 Box-and-Whisker Plots and Histograms

Box-and-whisker plots are used to visualize the quartiles of the transaction data, and histograms estimate the distribution of the data. More specifically, the box-and-whisker plot graphically shows the 25th percentile which is also known as Q1, the 50th percentile which is also known as Q2 or median, and the 75th percentile which is also known as Q3. The box represents the interquartile range (IQR) which is where the bulk of the values lie. Q1, which is the line at the bottom of the box, shows the middle number between the smallest value (not the minimum) and the median of the dataset. Q2 or median is the green line inside the box, which represents the middle value of the data set. Q3 is the upper line where the box ends, and represents the middle values between the median and the highest value (not the maximum). The bottom whisker is the minimum value which does not include outliers, and is calculated as follows: $Q1 - 1.5 * IQR$. The top whisker is maximum value, once again not including outlier, is calculated as follows: $Q3 + 1.5 * IQR$. We also used a triangle symbol to plot the mean value.

We utilized both of these models to examine all the transactions that occurred in each venue type, and compare the range of energy use. This gave us an idea of maximum and mean energy used per transaction. The histograms

Table 1: Totals Across All Stations

Number of charging stations	143
Number of transactions	37,194
Number of ZIP codes	57
Number of counties	28

then provided us with the frequency of the different sizes of transactions and whether the majority of these transactions tend to use less or more energy.

3.6 Bubble and Heat Maps

We used both a bubble and heat map to get a visualization of the transactions, and magnitude of these transactions, based on energy (kW h), throughout Colorado. The purpose of these maps is to see which regions are more active, as well as to see low-activity regions.

3.7 Curve Plot

We used a line plot to demonstrate demand during a 24-hour time interval. We broke the day into 15 minute intervals, or 96 different "bins" over which a transaction can span. Based on start time and total charging time, each transaction was placed into its respective bins, populating every bin between its start time and end time. The line plot showed us which of these bins are peak demand times. We also created a second line plot to demonstrate peak demand time based on start time and end time, which possibly includes a time in which the vehicle was still plugged in but no longer charging. Both plots were used for the combined data as well as each individual .csv files.

4 Results

4.1 Summary of Data

Tables 1 and 2, and Figure 1 show overall results from data-summarizing methods. Transactions grew 60% from 2018 to 2019, while energy only grew by 38%.

4.2 Monthly Energy Draw

Figures 2, 3, 4, and 5 describe the data in terms of monthly usage. "None" in 5 represents a single transaction that occurred in January 2020.

Table 2: Summary by Year

Year	Transactions	Energy (kW h)
2016	6474	70917.000
2017	15121	174770.000
2018	32933	451108.000
2019	52621	623135.894

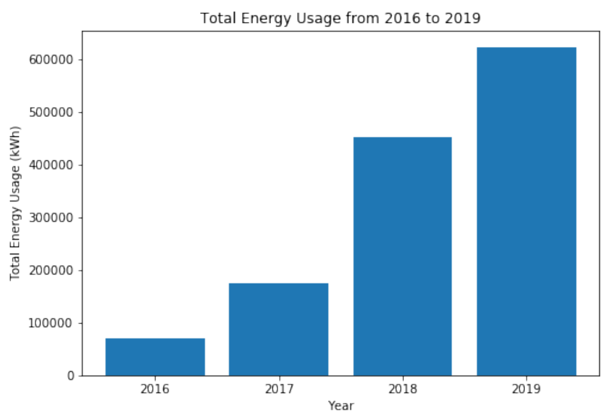

Figure 1: The increase in energy use between 2016 and 2019 can be attributed to the stations that were added over the time the data was collected.

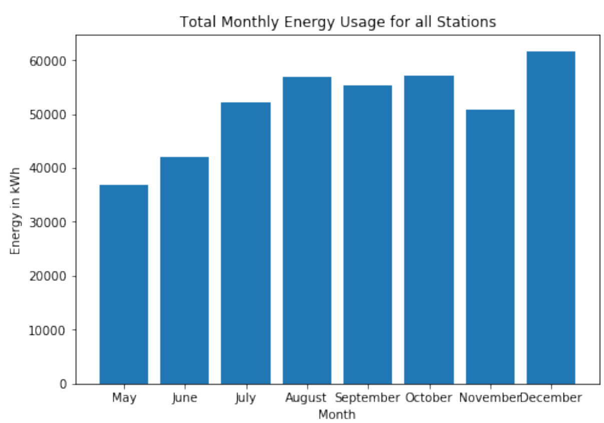

Figure 2: Energy use is lower in the earlier months, and appears to increase throughout each year. This finding was consistent with the results from the consultant report.

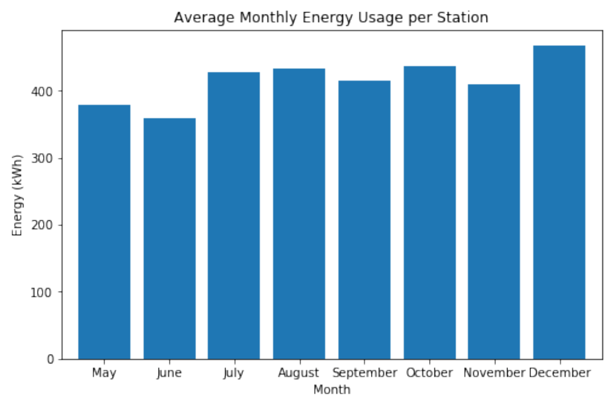

Figure 3: This plot shows average energy used per station per month. This shows that energy appeared lower in earlier months, because there were less active stations.

4.3 Top and Bottom 10 Stations

Figures 6, 7, 8, and 9 show an analysis that gives top and bottom 10 stations for number of transactions and energy use.

4.4 Analysis by Venue Type

All stations were classified as a venue type. Figures 10, 11, 12, 13, 14, and 15 show an analysis based on these venue types. There could be a degree of variability regarding venue types due to the fact that two types could overlap, such as a medical campus also being a workplace.

4.5 Peak Demand analysis by Geographical Location

Figures 16, 17, 18, 19, 20, 21, and 22 show the results from peak demand analysis by ZIP code, county, and longitude and latitude.

4.6 Peak Demand Analysis by Start Time

Figures 23, 24, 25, 26, 27, and 28, show analysis of transactions based on the time of day at which they were initiated.

4.7 Peak Demand Analysis: Binning Method

Figures 29, 30, 31, and 32 show the results from the binning method we developed to show peak demand-times based on the number of active transactions throughout the day.

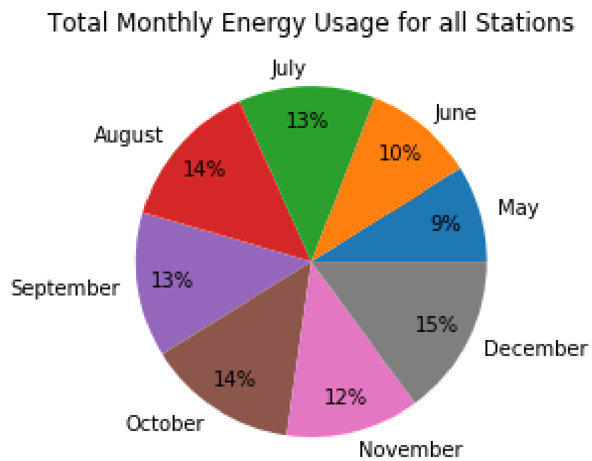

Figure 4: Energy use varies little over the months, but May represents the least percentage of overall use, while December represents the largest percentage.

4.8 Analysis of Non-Charging Time

Non-charging time refers to the time interval beginning when the EV stops charging, and ending when the EV is unplugged. Figures 36, 37, and 38 describe the the shape of non-charging time.

4.9 Linear Correlations Between Descriptors

Figures 39 and 40 show preliminary investigations of linear correlations for a regression analysis.

5 Discussion

5.1 Summary of Data

We first compared our newer data to the previously commissioned consultant report [1], which contains similar data spanning from 2016 through April of 2019. As noted in that report, there is an increase in both transactions and energy usage from 2016 to 2019, but the growth rate was also shown to be diminishing. For example, Table 2 shows that the total number of transactions increased by 118% from 2017 to 2018, but only by 60% from 2018 to 2019. Total energy usage on the other hand increased by 158% from 2017 to 2018, yet only by 38% between 2018 and 2019. It is significant that between 2018 and 2019, total energy usage grew by only 38%, while the transactions still increased by 60%. This may be reason to analyze the placement of the more recent stations and analyze the times a vehicle is charging versus how long it was occupied. It is

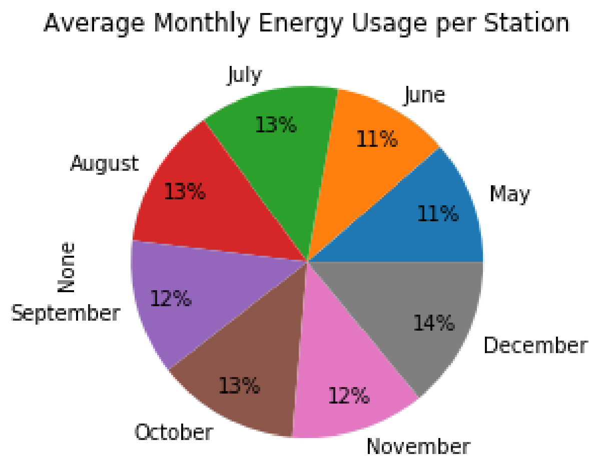

Figure 5: This pie chart shows the average monthly use per station, or total energy divided by number of stations. "None" represents a single transaction that occurred in January 2020.

also important to note that there was a recent change in the format of tracking these transactions, from .xlsx to .csv files.

5.2 Monthly Energy Draw

At first, the graph of the monthly energy draw demonstrated that there may be a correlation between time of year and energy use, but we were unable to come to a definitive conclusion. Interestingly, our data show a similar curve to that of previous years, shown in the consultant report. Both reports indicate that usage is lower in the earlier months of the year, increasing as the year progresses. Since the grant program has been adding stations every year, we can't definitively conclude if this increase is cyclical or not, but the data we have are suggestive of a cyclical increase. From the data collected since 2016, we can conclude that more energy is likely to be used later in the year, shown in Figure 2.

The chart in Figure 4 shows the percentage of total annual energy use, categorized by month. December shows the highest monthly share of energy in 2019, at about 15 percent, but because next two largest months are August and October at 14 percent, peak time of the year does not seem significant.

The charts in Figure 3 and 5 show the average monthly energy usage, with the number of active stations during each month taken into account. By doing this, we were able to see if the increase in energy usage later in the year was due to more stations being added each month. December is still the month with the highest energy, and the earlier months, May and June, remain the lowest,

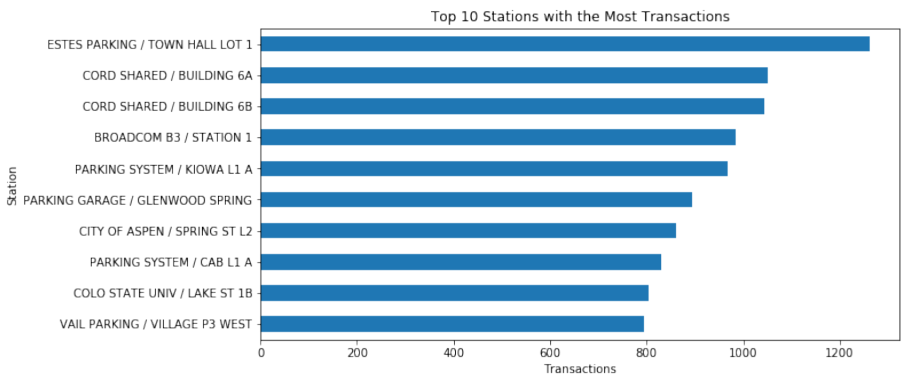

Figure 6: Nine of the top-10 most-used stations show similar use, but the station with the most transactions is Estes Parking / Town Hall Lot 1.

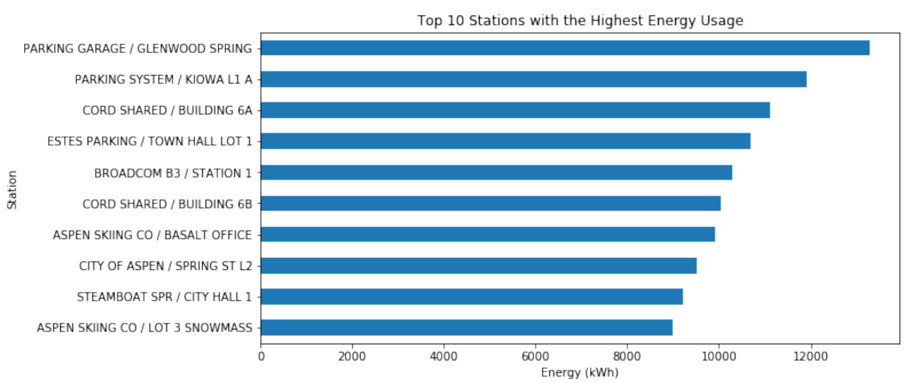

Figure 7: The station with the most energy use is Parking Garage / Glenwood Spring.

although there was an increase in these months when number of active stations were taken into account. This further shows that peak time of the year does not seem significant.

5.3 Top and Bottom 10 Performing Stations

We found that overall, all stations combined recorded more transactions in 2019 than in previous years. A comparison of top and bottom stations in the scope of energy usage produces two different lists of stations. The station with the largest number of transactions is Estes Parking/Town Hall Lot 1, while the station with the most energy use is Parking Garage/Glenwood Spring. These findings are consistent with both our bubble map measuring energy by latitude and longitude, as well as the venue type analysis of parking garage/lots, but it

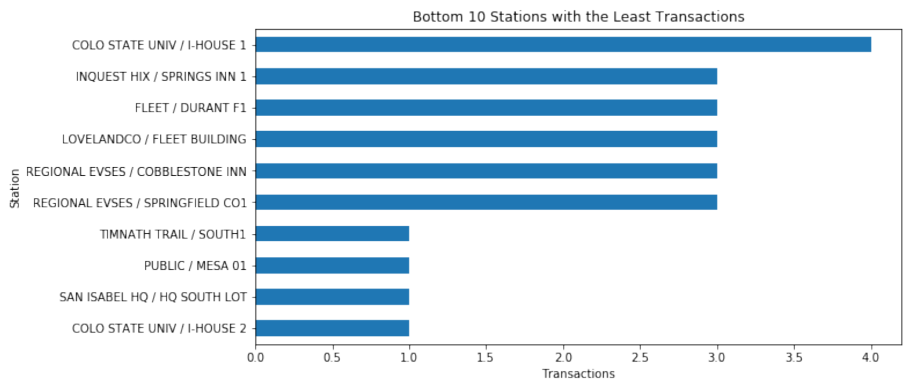

Figure 8: The stations which used the least kW h are Timnath Trail/South1, San Isabel HQ/HQ South Lot, Public/Mesa01, and Colo State Univ/I-House 2.

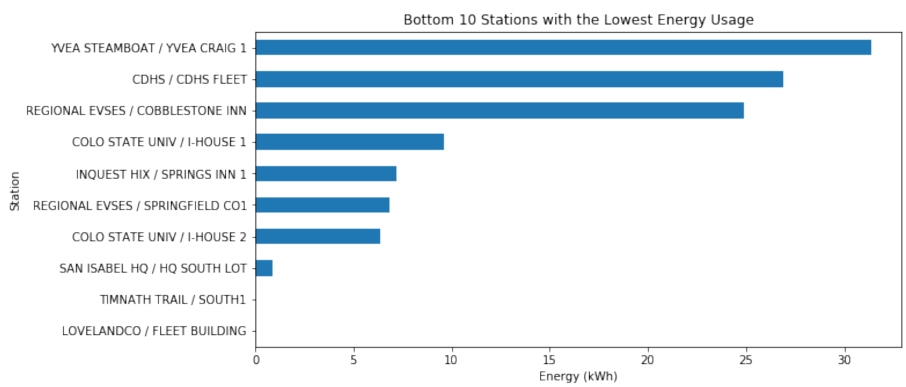

Figure 9: More than one station had 0 kW h use.

should be noted that a large number of stations in City of Denver's jurisdiction were excluded due to the data being unavailable. All 10 stations with the least transactions registered 4 or fewer transactions, and 3 stations recorded less than 5 kW h. See Figures 6, 7 , 8 and 9 which labels the stations by the names listed in the .csv file.

5.4 Analysis by Venue Type

Figure 13 summarizes each venue type and shows that stations are more commonly found near municipality buildings, workplaces, and parking garages/lots. Figures 10 and 12 demonstrate that these venue types have higher numbers of transactions, which has a correlation to higher energy usage. There are fewer stations at retail locations and apartment complexes. Figures 10 and 12 show that these venue types account for fewer transactions, and thus less energy us-

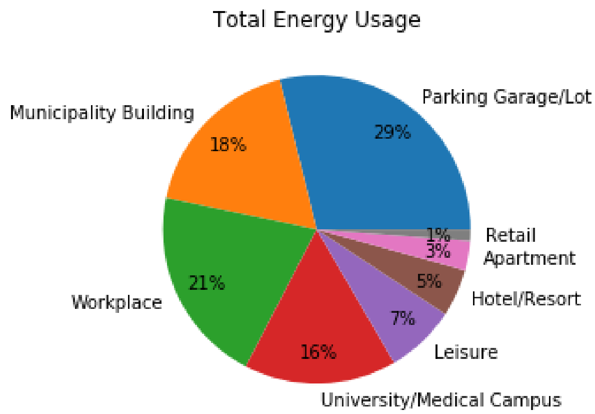

Figure 10: Parking garage/lot venues used more energy than any other venue, while retail and apartment venues used the least.

age.

Figure 11 shows stations' average energy usage for each venue type. These results are different from the above plots which only shows the total energy per venue type. The percentages change according to the number of stations in that type of venue. By comparing Figures 10 and 11, we notice that the percent of energy used overall by parking garage/lot venues drops from 29 to 22 %. This means that there are probably stations in that venue type which use little energy. Parking garages and lots and workplace stations still account for high energy usage, but so do apartment and university and medical campus stations, though there are fewer stations in these venue types. We can conclude that increasing the number of stations in these venue types might alleviate usage and therefore peak demand at other stations.

Figures 10 and 11 show the variation and distribution of every transaction completed in each venue type. Figure 11 shows that the average energy usage per transaction is largest for hotel and resort venue types. Figure 10 demonstrates the distribution of transactions and shows that there are more high-energy transactions for this venue type. We can conclude that consumers who use these stations are more likely to plug their cars in for longer periods of time, and because these stations are at hotels and resorts, consumers may be leaving their cars charging for extended periods such as overnight. The average use appears to be lowest for municipality stations, which suggests that new stations at these venue types may not be as high-priority as others.

5.5 Peak Demand Analysis by Geographic Location

For charging time analysis of location, we plotted both energy usage and total transactions against stations' ZIP codes, counties, and longitude and latitude.

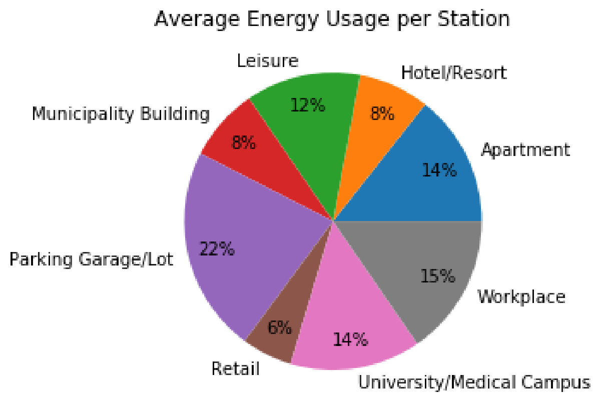

Figure 11: The plot shows average energy use per venue type per station. Parking venues showed the most energy consumption compared to all other venues.

Venue	Venue Type	Number of Stations	Number of Transactions	Total Energy (kWh)	Avg. Energy (kWh) per Staion	Avg. Energy (kWh) per Transaction
Municipality Building	Municipality Building	42	7403	73716.693	1755.159357	9.957678
Workplace	Workplace	25	7377	85287.597	3411.503880	11.561285
Parking Garage/Lot	Parking Garage/Lot	24	10408	119125.355	4963.556458	11.445557
University/Medical Campus	University/Medical Campus	21	6074	66107.705	3147.985952	10.883718
Hotel/Resort	Hotel/Resort	12	1523	20520.593	1710.049417	13.473797
Leisure	Leisure	11	2848	30370.118	2760.919818	10.663665
Apartment	Apartment	4	1103	12735.351	3183.837750	11.546102
Retail	Retail	4	458	4879.482	1219.870500	10.653891

Figure 12: Apartment venues had the most transactions per station, indicating that there may be a demand for more stations in apartment areas.

Figures 16 and 17 show energy usage and transaction for each ZIP code in our data. Figures 18 and 19 show energy usage and transaction by county. Figure 20 is a bubble map where bubble sizes correspond to energy usage per transaction at each longitude and latitude point. All plots have consistent data. They point at Larimer, Eagle, and Pitkin counties being the counties that consume the most energy in regards to EV charging. These include Vail, Aspen, and Fort Collins. Since Hewlett Packard Enterprise and Colorado State University are both in Fort Collins, it makes sense that these venues provide more EV charging stations and therefore used the most energy according to our data. Aspen and Vail are vacation spots with stations in parking garages, so they are available to the public. Since there are over 30 energy suppliers in Colorado, the CEO can use this analysis to determine where they should place new stations with peak demand as a consideration.

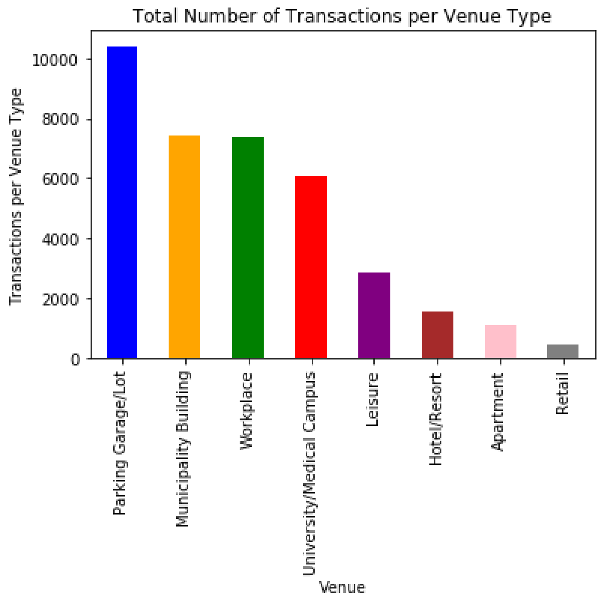

Figure 13: Parking Lot transactions served the highest number of consumers by far, while retail comprised the least percentage of transactions.

Transactions by Venue Type

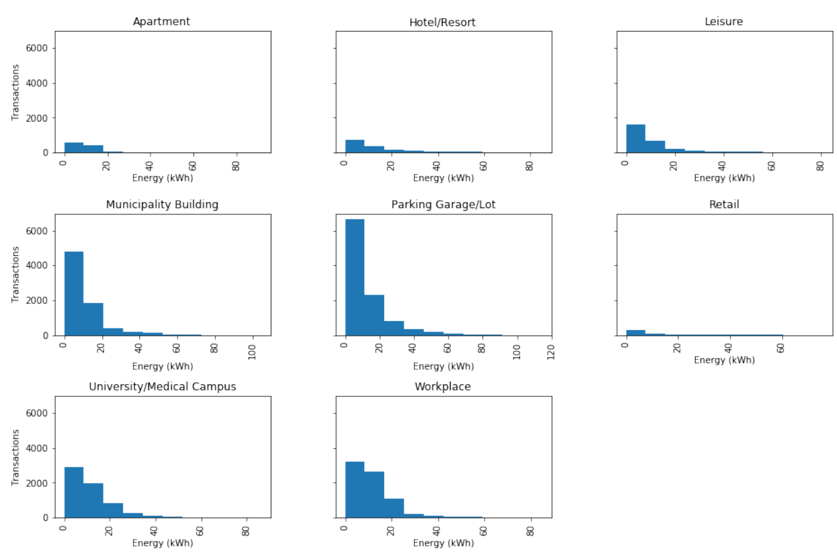

Figure 14: Though the average energy used is similar across transactions for all venues, the distribution of energy use varies.

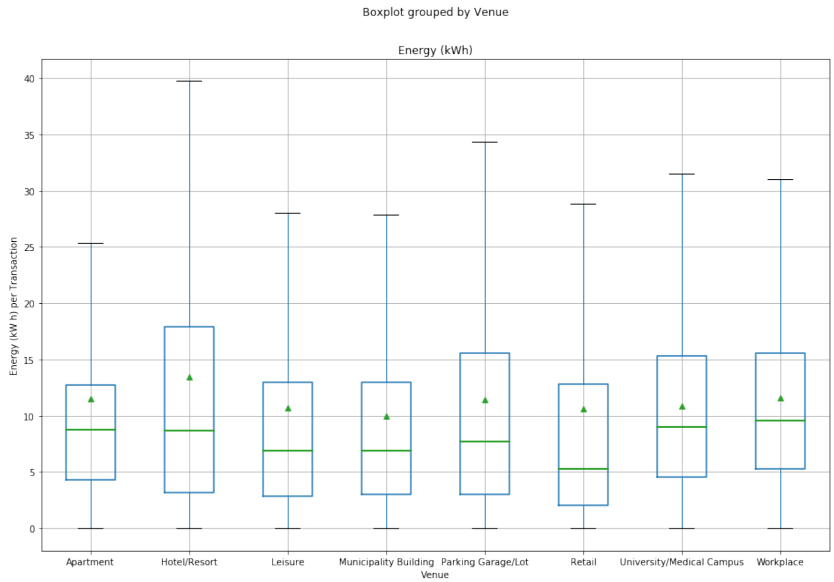

Figure 15: This box-and-whiskers plot illustrates Energy usage per transaction for each venue type. The line represents the median and the triangle represents the mean. Despite the median values being below 10 kW h for all venue types, there were a large number of outliers (not shown) reaching nearly 400% of the median.

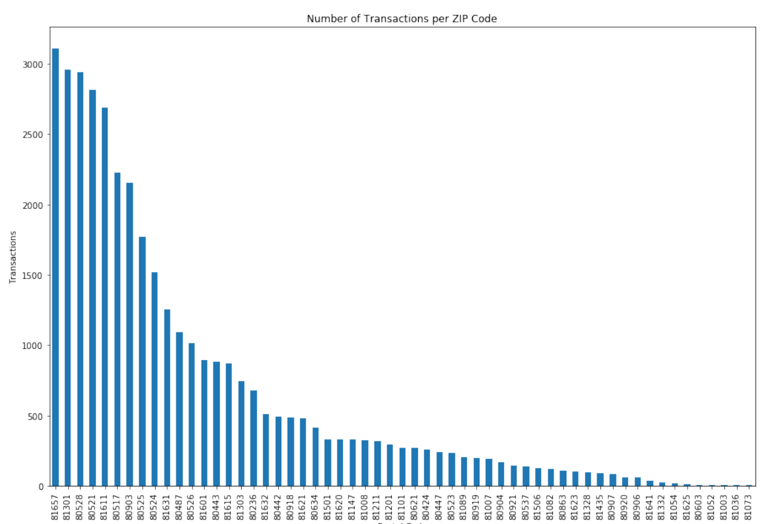

Figure 16: This plot shows the number of transactions based on ZIP code. ZIP code 81617 had the most transactions.

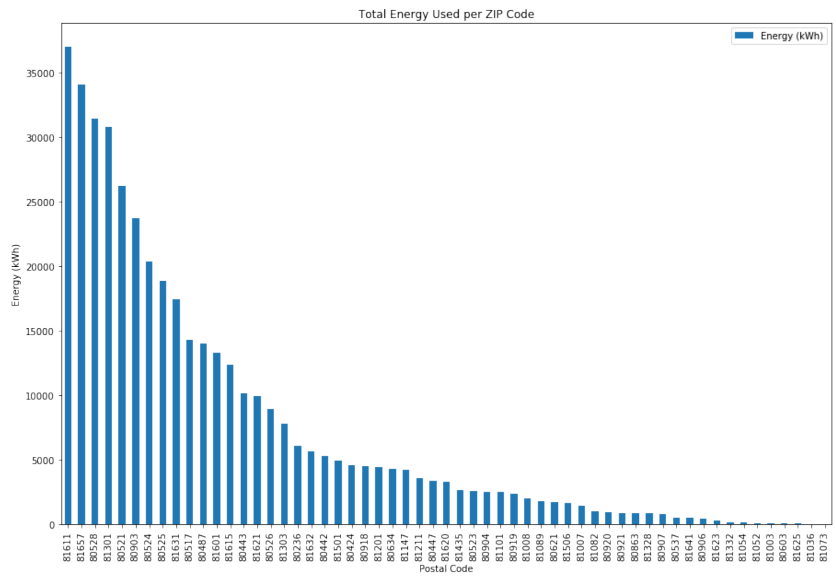

Figure 17: This plot shows energy usage based on ZIP code. ZIP code 81611 had the most energy usage.

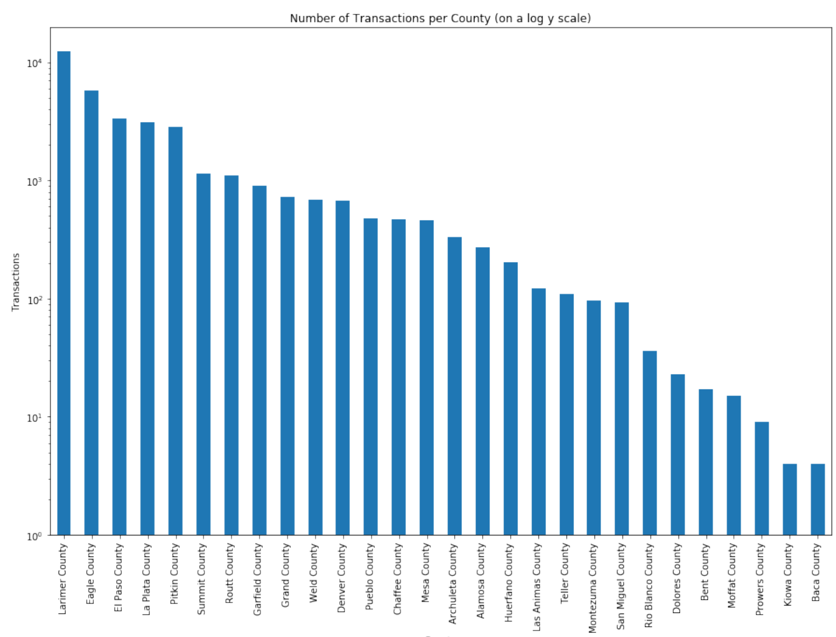

Figure 18: This log scale plot shows the number of transactions based on county. Larimer county had significantly more transactions than any other county.

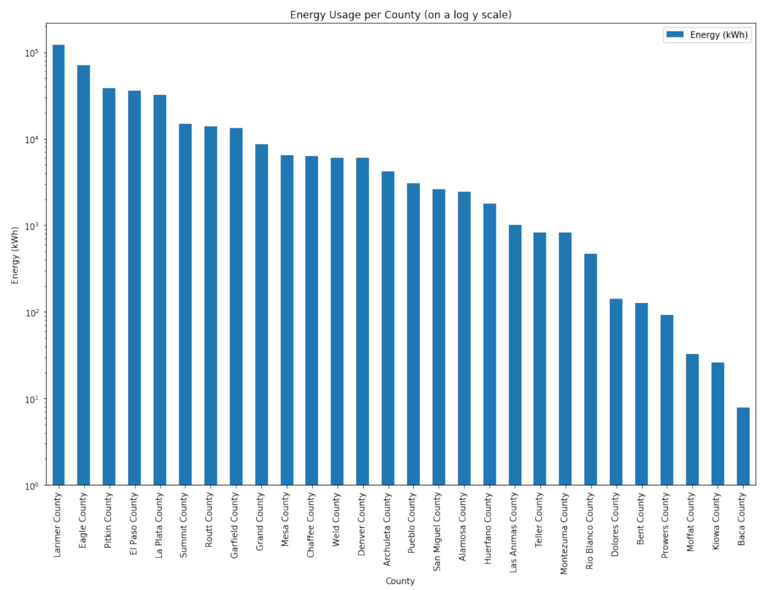

Figure 19: This log scale plot shows energy usage based on county. Larimer county had the most energy usage.

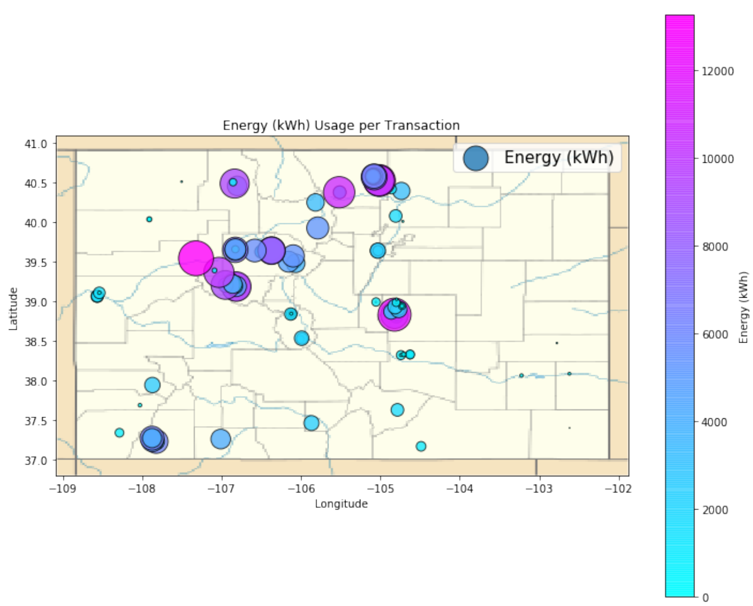

Figure 20: This map shows a distribution of energy use across all the stations throughout Colorado. Areas with higher use could benefit from additional stations.

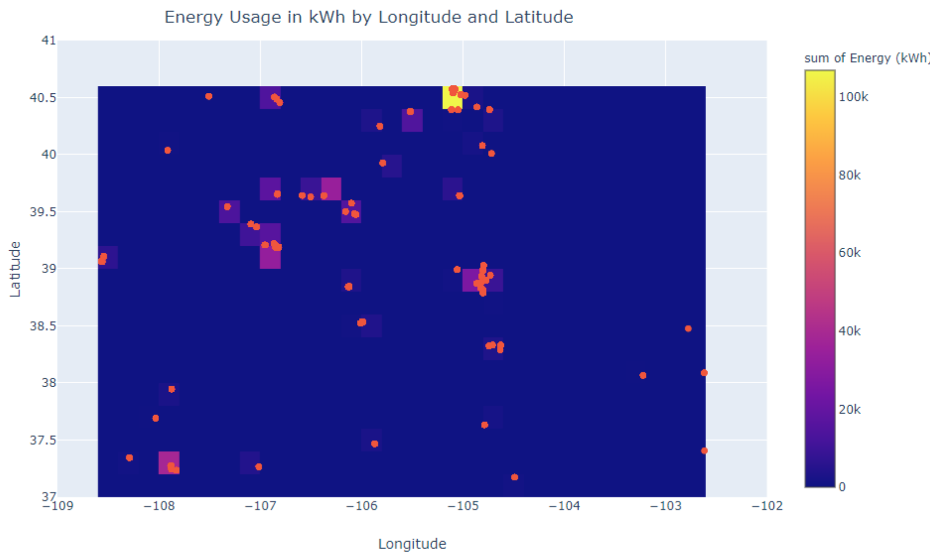

Figure 21: This map shows how much energy has been used in certain areas of Colorado. It also shows how many stations are in these high energy areas.

5.6 Peak Demand Analysis by Start Time

This analysis shows the time of day consumers choose to start charging their EV. Figures 23, 24, 25, 26, 27, and 28 show how many transactions were initiated each hour.

Figure 23 shows the distribution of transaction start times during each day of the week. On weekdays, most consumers start charging their cars between 7:00 a.m. and 8:00 a.m., with another smaller peak time around 12:00 p.m. This suggests that most consumers choose to charge their cars before work, or possibly during a lunch break, rather than after work.

Figures 24, 25,and 26, show weekend day transactions. There is less consistency on the weekends, with peak times occurring between 10:00 a.m. and 12:00 p.m. Figures 27 and 28 compare the work-week transactions to the weekend transactions. Figure 28 shows the weekdays in red and weekends in blue. Consumers are more likely to charge their cars during the week rather than on the weekends. There is a significant decrease in EV charger use on weekends compared to weekdays.

5.7 Peak Demand Analysis: Binning Method

Figure 29 shows a peak demand curve based on the total charging duration time for each transaction. In other words, the value for each time interval shows the number of active transactions at that time. The x-axis is broken into

Figure 22: This map is an accompaniment to the previous Figure. It shows the position of every charging station's location, as well as the venue type for each location. This shows that both the number of stations and venue type are important for determining energy usage.

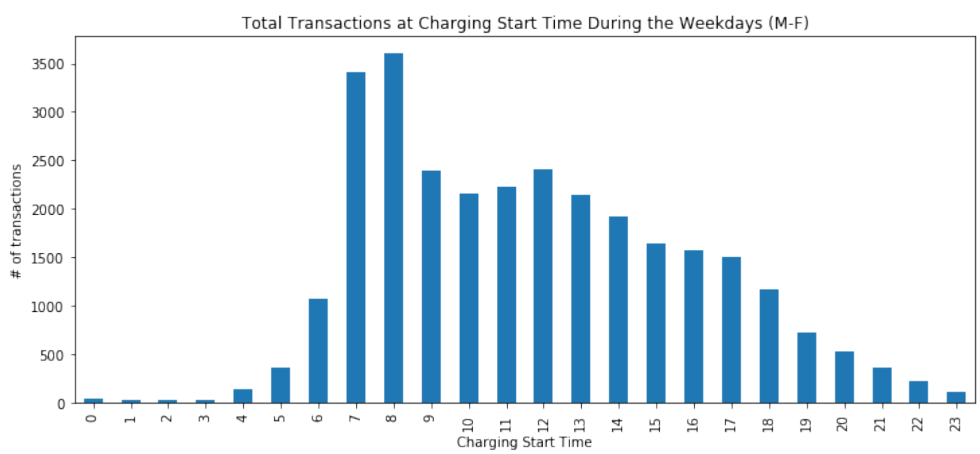

Figure 23: This chart shows that consumers are most likely to plug into a charger between 7:00–9:00 a.m. during the week. A second, much smaller peak of transactions start between 12:00–1:00 p.m.

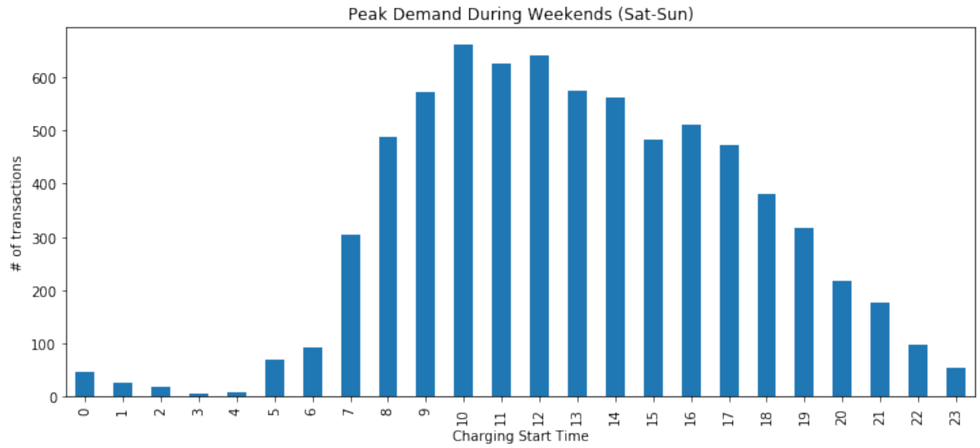

Figure 24: This plot shows the number of transactions started during a given hour in the day. Weekend days show a delayed plot compared to that of weekdays, and also shows a significantly lower number of transactions overall.

15-minute intervals, equaling a total of 96 consecutive bins. Peak demand was then analyzed in terms of charging time as well as total duration. The peak demand time for charging time occurs at about 9:45 a.m. These results are different than the start time peak demand analysis, which showed a peak demand between 7:00 a.m. and 8:00 a.m. This is consistent with our finding that most transactions are relatively short, therefore while many transactions start at 7:00 a.m. or 8:00 a.m., the time in which there are the most simultaneous users is around 9:00 or 10:00 a.m. Although there are a few longer transactions spanning several hours or even days, these transactions are outliers. For total duration, it was found that the peak demand time was the interval 11:00 am to 11:15 am. As was the case with the charging time, while many transactions started earlier, the time in which there were the most users was around 11:00 am. Figure 31 shows the peak demand curve for each of the individual .csv files that were concatenated into our concatenated .csv file. Most of the individual .csv files also show peaks between 11:00 a.m and 1:00 a.m. This can be verified with the histograms found in figure and . Some smaller .csv files from lower-volume stations have small peak demand times late in the afternoon or very early in the day, but this data is skewed by the fact that few data points exist. Figure 31 shows the peak demand curve for each of the individual .csv files that were concatenated into our concatenated .csv file. Most of the individual .csv files also show peaks between 11:00 a.m and 1:00 a.m. This can be verified with the histograms found in figure $_and.Somesmaller.csvfilesfromlower-$ $volumestationshavesmallpeakdemandtimeslateintheafternoonorveryearlyintheday,butthisdataisskewedbyt$

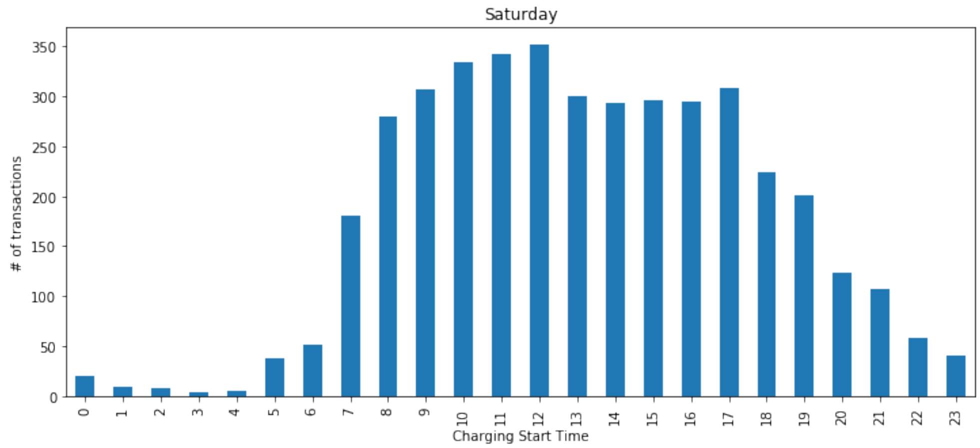

Figure 25: Transaction start times on Saturdays follow a bell-shaped curve, peaking around 12:00 p.m.

5.8 Analysis of Non-Charging Time

For this analysis we found the duration time between when a transaction stops charging and the time it is unplugged. This is a function, End Date minus the Start time plus charging-duration time. We will call this Non-Charging Time. We ran across a single transaction that came back with a negative non-charging time and concluded it was an error, since charging cannot happen un-plugged, so We disregarded it. The histogram 36 of Non-charging Time shows in its first bar that most of the transactions, nearly 35,000, recorded with less than 7 hours non-charging time. Around 1,000 transactions recorded a non-charging time of 7 to 15 hours. This accounts for only 3 percent of all transactions. The histogram also shows that several 10s of transactions out of our 37,194, spent over 100 hours not charging i.e. approximately 4 days. The max Non-Charging time was 26 days and 18 hours while the mean Non-charging time was 2 hours and 55 minutes. We also found that total non-charging time added up to 4537 days, out of the 13,176 days worth of data. The days worth of data account for 244 days for each of the 54 stations. This means that 34 % of the time a transaction is happening, the vehicle is not charging or using energy.

Figure 38 is a box-and-whiskers plot of Non-Charging time by Venue Type.The y-axis is being measured in nanoseconds or 10^{-9}seconds, so at 10^{13}, it is equivalent to 2.78 hours. This shows that Apartment station types have the highest mean non charging time at around 5 hours, with 3 quarters of their transactions under 8 hours, meaning the last quarter or 25 percent of transactions fluctuate all the way up to 20 hours. If we include the 8 hours on average it takes to charge a vehicle starting from no charge, this means 75 percent of transactions in apartment type leave their cars plugged in at most 16 hours. This can be overnight while they sleep. The upper quartile, the last 25 percent leave their cars plugged

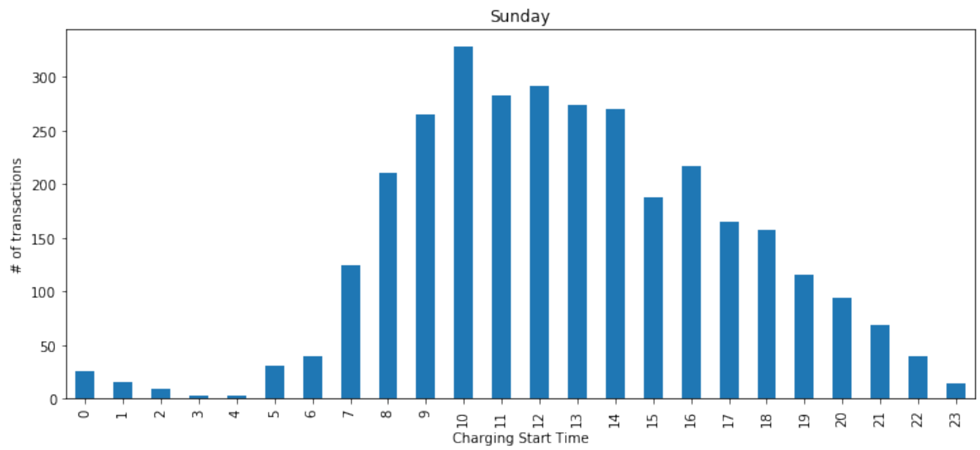

Figure 26: Transaction start times on Sundays differ from Saturdays, showing a peaking earlier around 10:00 a.m.

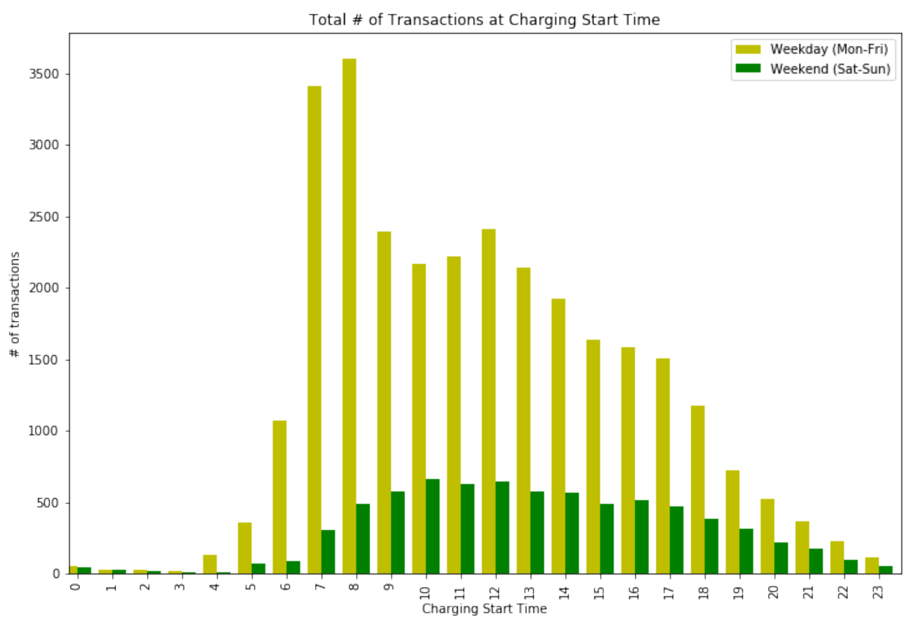

Figure 27: This plot compares the total number of active transactions during a given hour on weekdays versus weekend days. As expected, weekday transactions far outweigh weekend transactions, and indicate a different peak times.

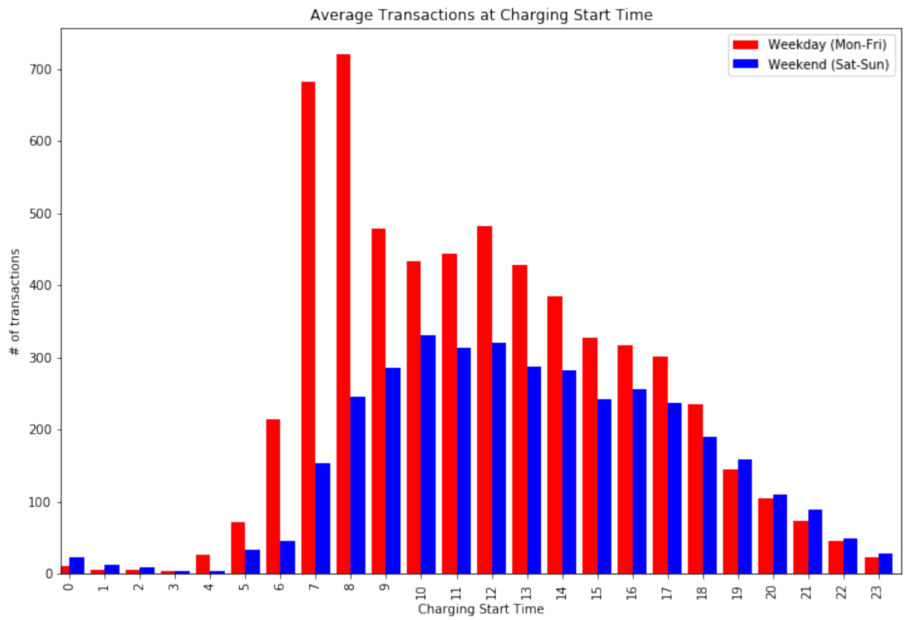

Figure 28: This plot shows the average number of active transactions during a given hour on weekdays versus weekend days. Peak time for weekdays occurs between 7:00am–9:00a.m. Peak time on weekends occurs much later around 10:00a.m.–12:00 p.m.

in, including charging for at most 28 hours, not including any outliers. These may be instances when the transaction is parked over the weekend.....(This is inconsistent with the other box and whiskers so must rethink.)Universities have the next highest variation, 75 percent of their transactions though, still are less than 2.78 hours. Their mean non-charging time is about 2.08 hours. Municipality has a mean time of 8 hours, due to the very high outlying transactions, but again most of their non charging time is under 2 hours. It also seems obvious to us that leisure and retail type non charging time is very small, since usually that time is limited.

Figure 37 shows the box-and -whiskers plot of Non-Charging time for day of the week. It shows that there is larger variation in the non-charging time between the week-day and the weekend. The y-axis is measured in the same way as Figure . Most of the weekday transaction non-charging times are under 100 minutes or 0.6×10^{13}. During the weekend they are less than 17 minutes. Thursday has the most outliers which is why the mean time for Thursday is at about 4 hours of non-charging time.

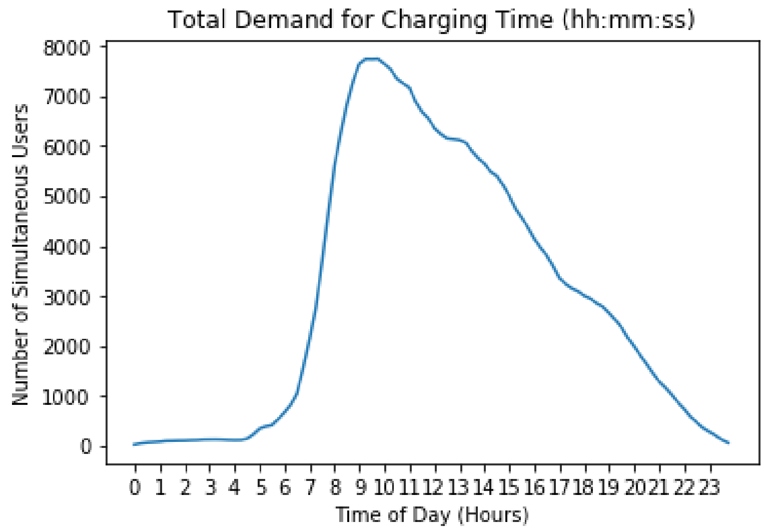

Figure 29: This plot shows the number of active (plugged-in and charging) transactions during a given 15-minute interval for time of day, and includes all transactions in our data.

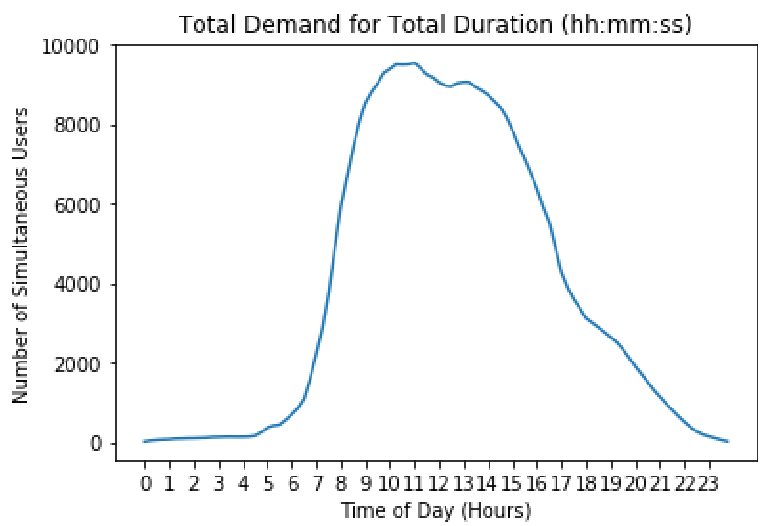

Figure 30: This plot shows the number of plugged-in (both charging and non-charging) transactions during a given 15-minute interval for time of day, and includes all transactions in our data..

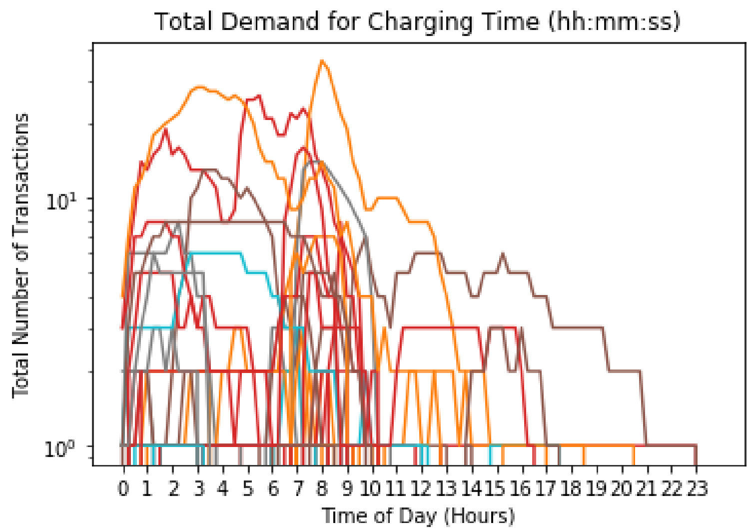

Figure 31: This log scale plot shows the number of active (plugged-in and charging) transactions during a given 15-minute interval for time of day. Each color represents a different file, and indicates that different stations have different peak times than others. Overall, stations experience a surge in demand between 7:00–9:00 a.m., with a peak occurring right around 8:00 a.m.

5.9 Linear Correlations Between Descriptors

In order to determine if we could create a predictive model, we compared certain descriptor columns against each other. Our intent was to find a linear correlation between them and continue from there. The columns we compared were Total Energy, Start Time Min (start time in minutes), and Non-Charging Time in Hours. The scatter matrix in Figure 39 shows the results of these descriptors mapped against one another. We found no significant correlations. The only relationship we noticed was based on the scatter plot of Start Time and Non-Charging time, which shows that most transactions starting between 8:00 a.m. and 4:00 p.m. have longer non-charging times, but there was not enough evidence to create a prediction. The patterns do suggest that some sort of transformation may linearize them.

For our second attempt see Figure 40. We grouped our data into peak start times for all 143 stations and plotted them against the number of transactions at that peak start time (in minutes). We found no significant correlation between the number of transactions at start peak time and its peak time. In other words, there does not appear to be a relationship between how busy a station is and when its peak start time is.

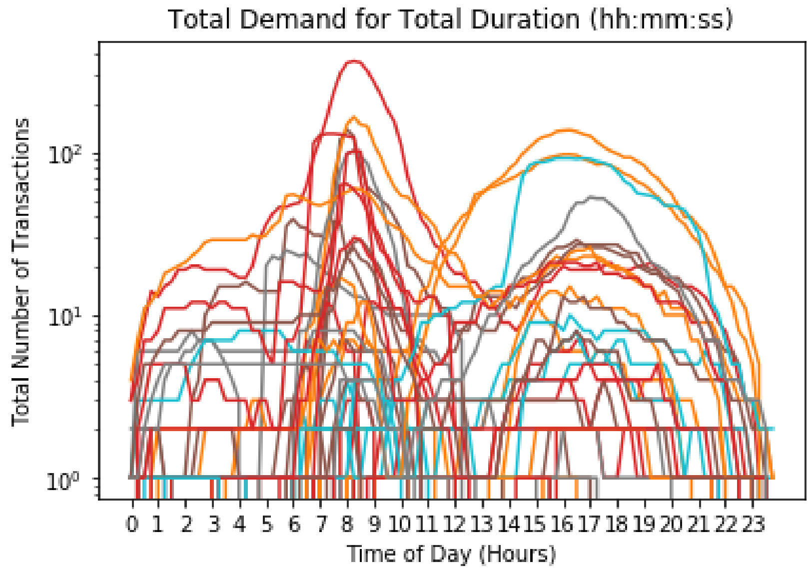

Figure 32: This log scale plot shows the number of transactions during a given 15-minute interval for time of day, including duration, where the EV is plugged in but not charging.

6 Conclusion

Our goal was to identify peak demand time(s) in order to help the Colorado Energy Office make informed policy decisions to affect peak demand charges. Our analysis allowed us make some key conclusions for dealing with this task. We were able to verify the continuation of trends presented in the consultant report [1], but some of the increases were diminishing. The most significant was the change in percentage of total energy used from 2018 to 2019, compared to 2017 to 2018. The annual increase changed from 258% to only 38%. This growth is contingent upon the overall health of the economy, since if the economy were in recession than less people would be able to afford an electric cars, and thus this analysis may not be applicable to an economy in recession or in otherwise vastly different health compared to the economy from 2016 to 2019. We were also able to identify and visualize trends in peak demand-times across a number of categories such as venue, ZIP code, and day of week.

Peak times display trends in terms of months, days, and 15-minute intervals. The most prominent months of usage are consistently later in the year, with a small peak occurring mid-year and a large peak occurring at the tail end of the year. We have four years of data to give this conclusion a high degree of certainty, although factoring in the number of active stations showed that the

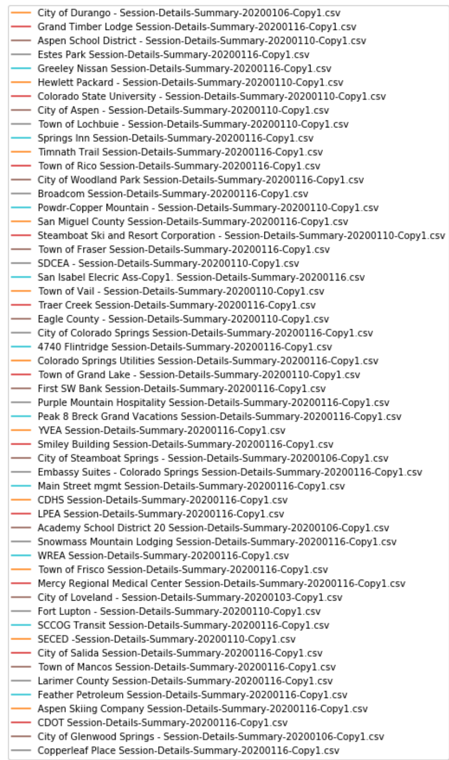

Figure 33: This figure shows the legend for Figures 31 and 32.

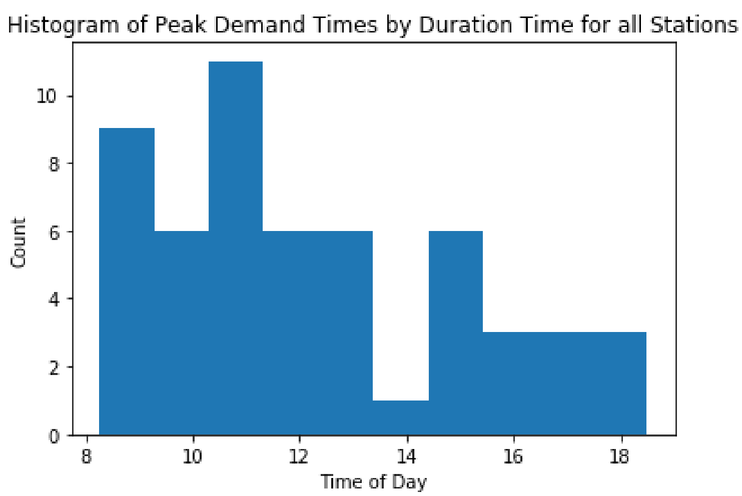

Figure 34: This plot shows the count of stations at each peak demand start time.

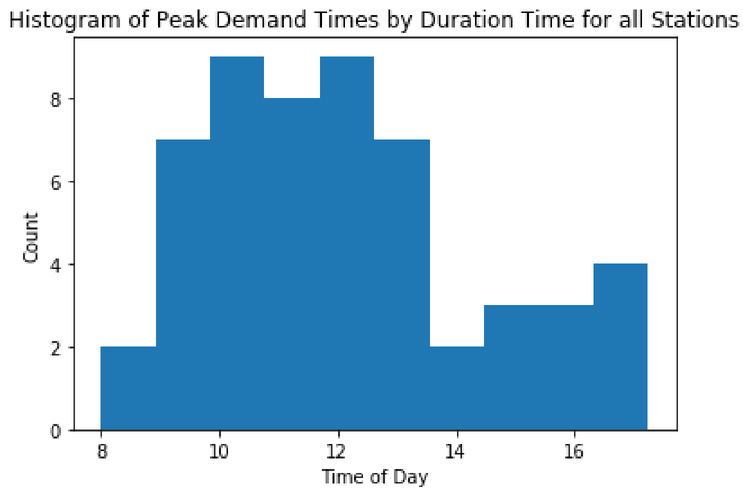

Figure 35: This plot shows a histogram of peak demand time based on duration and on time of day.

annual peaks are not significant. We concluded that there are more transactions during the weekdays than the weekends, and that the peak start time during weekdays is 7:30–7:45 a.m. Policy developed for the purpose of reducing peak demand charges should discourage consumer use during the peak demand time, for example by charging for use of charging stations during these peak times on the appropriate days.

We also concluded that the location and venue type of a station does influence use in terms of energy used and frequency of use. We know both the top and bottom performing stations, counties, and ZIP codes in Colorado. The Colorado Energy Office can utilize these insights when making decisions about new EV charger placements.

References

[1] 2019. *CEO Charging Station Report: May 2016 thru April 2019*. Denver, Colorado: Colorado Energy Office

Required Files

- https://math-hub.ucdenver.pvt/aime/user/priscilla.2.moreno/notebooks/team1/data/January_2020/CEOfiles/Final%20CEO%20notebook.ipynb
- Jupyter notebook is named "Final CEO notebook.ipynb" can be found at /team1/data/January_2020/CEOfiles

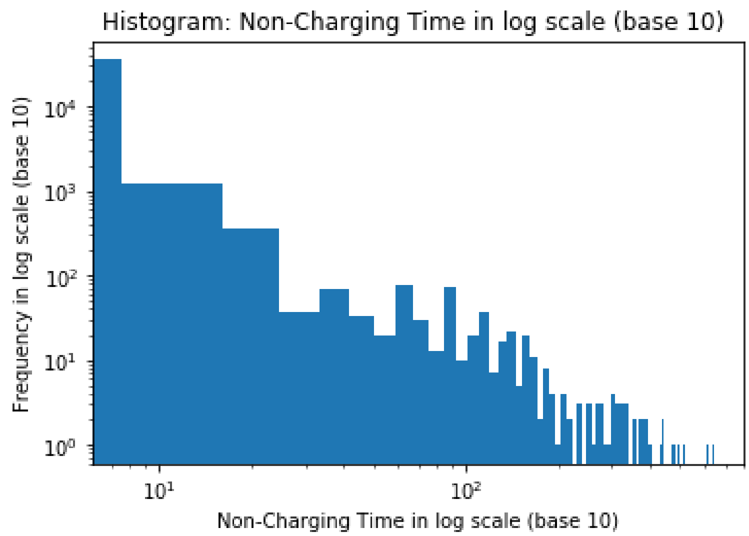

Figure 36: This plot shows the frequency of different lengths of non-charging duration.

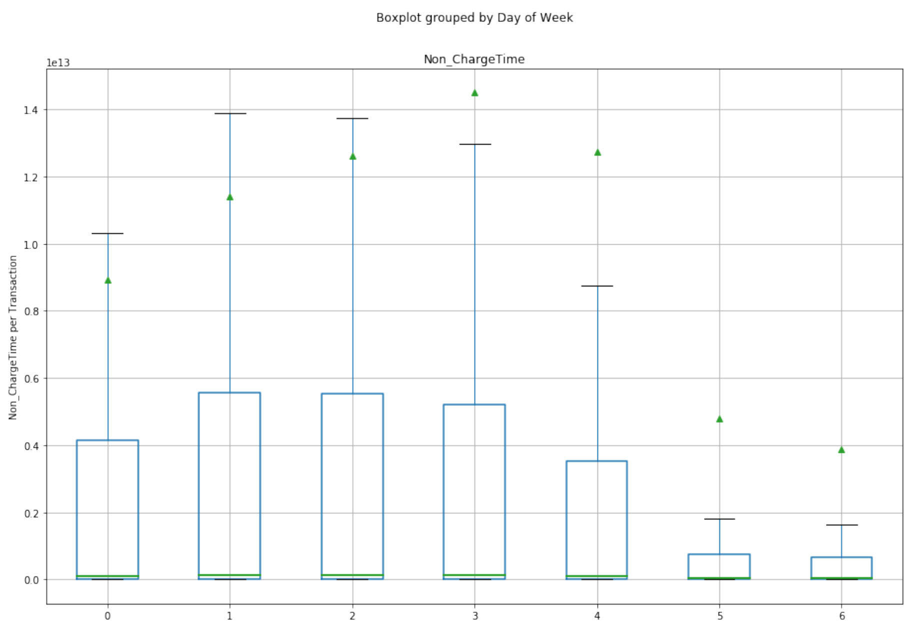

Figure 37: This box-and-whisker plot illustrates non-charging time (in hours) per transaction for each day of the week. The line represents median and the triangle represents mean.

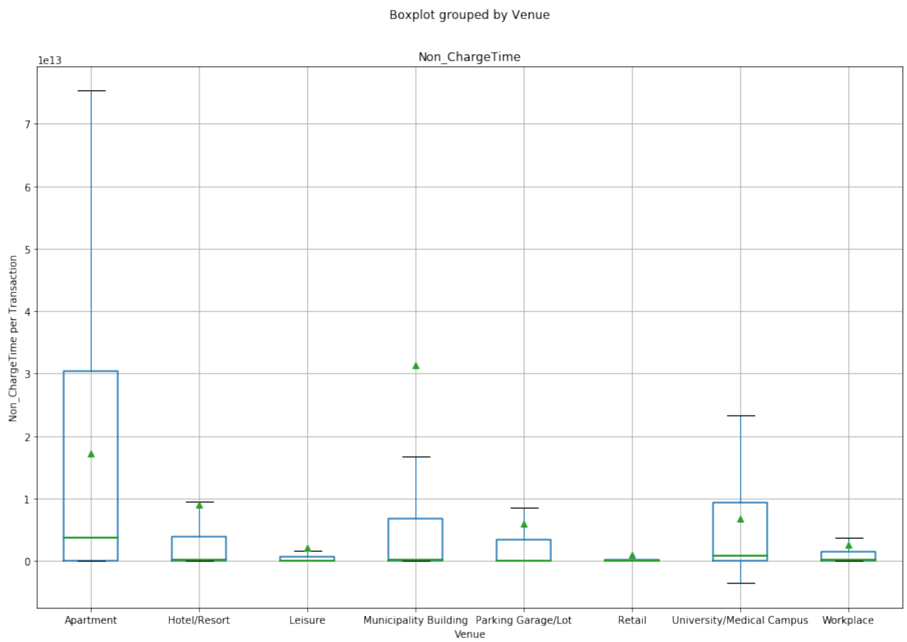

Figure 38: This box-and-whisker plot illustrates non-charging time (in hours) per transaction for each venue type. The line represents median and the triangle represents mean.

- ”CEO files” is the directory which includes the 54 .csv files provided by CEO. It can be found at /team1/data/January_2020/CEOfiles
- Colorado3.png is the bubble map image of Colorado. It can be found at /team1/data/January_2020)

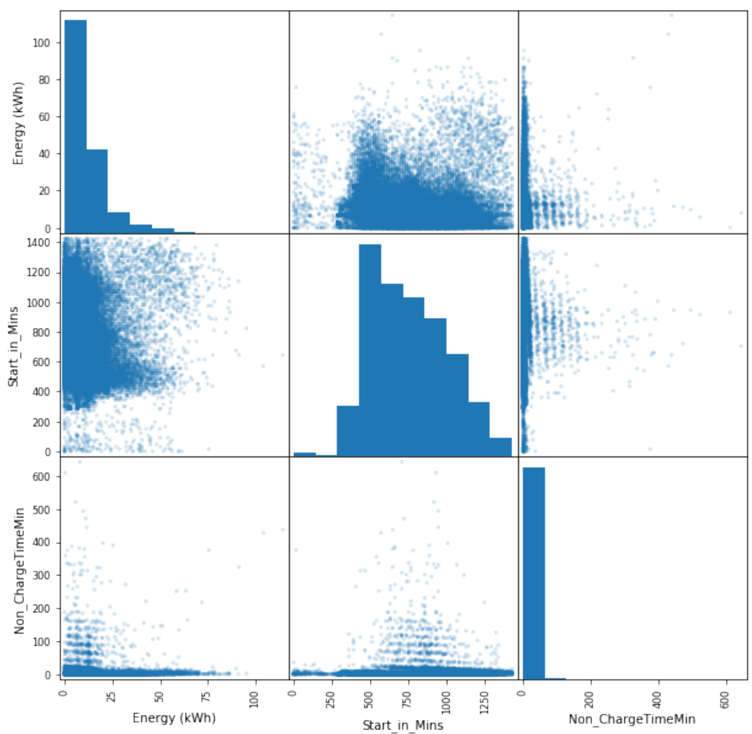

Figure 39: This scatter matrix shows several variables plotted against one another.

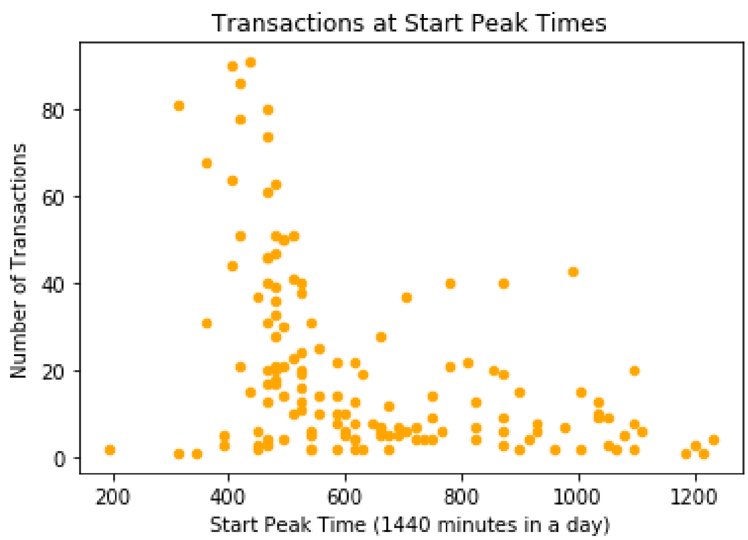

Figure 40: Each dot on this plot represents the 143 different stations. It plots each station's peak start time against its total number of transactions.