The Pennsylvania State University
The Graduate School

# ANALYSIS OF FACTORS THAT CONTRIBUTE TO ELECTRIC VEHICLE BEHAVIOR AFTER THE CHARGE EVENT

A Capstone Project in

Geographic Information Systems

by

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*The Federal government is looking to increase the number of EV charging ports in the United States as a part of the strategy to combat Climate. There has been research to help ascertain where to optimally put EV charging ports. This research has focused on EV charging behavior, the economics of owning a charging station and the most efficient use of the electric grid. I propose that we should also look at the behavior of EVs after they are finished charging. Using data in Kansas City and North Kansas City I look at what spatial and temporal factors have an effect. It looks like the land use of the charging port has an effect. EV charging ports on street parking have the EVs stay a significantly less amount of time than other land use types. We do not see an effect by season, but we see an increasing trend over the years. More data will be needed to see if this trend continues after 2020.*

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## 1. Introduction:

The Federal government has set up a target of creating 500,000 new EV charging ports to combat climate change. Public charging points have increased by 6.3%. in the fourth quarter of 2022. Currently they need to build more than that amount to reach the targeted goal. Due to public need researchers have looked at the most efficient way to develop an EV charging infrastructure. Relying on behavior of the EVs that are currently on the road. Looking at where drivers prefer to charge their vehicles. Some attention has been paid to the behavior of the drivers after the charging event. Seeing whether the drivers stay at the charging port after the charge event. However, more attention needs to be given to this area. It is important because many people will use public charging infrastructure and it is important that is available to use when people need it. People staying plugged into the EV charging port when it is no longer needed poses a problem for getting EV drivers in and out as fast as possible. This information can help decision makers see where it is most efficient to build EV charging ports. To see what factors influence this. The scope of this paper will at look at some of these factors. Focusing on the spatial and temporal aspects of this question.

## 2. Literature Review:

EV charging behavior has been looked at to inform the building of new EV charging ports. Studies have been conducted in many cities and countries to find the optimal locations to place them. These studies take into account the impact on the electricity grid, the economics of EV charging ports, constructed models and EV charging behavior.

Morrissey et al. conducted a study in Ireland looked at the preferences of EV owners of where they like to charge their vehicle. They found that the peak of EV charging is found after people arrive home at the end of their day. The authors split up the data by type of charge point, and location of the charging port. There is a preference for people to charge their vehicles at their households. Public charging took place in multiple locations. With the shortest duration at gas stations with a mean of 75 minutes. Car parks and on-street charging had a similar mean with each around 130 minutes. Fast chargers were the most popular type of charge type, with the authors concluding that this is the most viable port type for the future. They concluded that chargers should be given to what they deem strategic locations around Ireland (Morrissey et al 2016).

When a similar study was conducted in England, they found that work was the most popular place for people to charge their EVs. However, this includes organizations. If we only count private residential areas, most charge events happened at home. Followed by work and then in public. On average a public charge event took less time than a home or work charge event. Taking 2.7 hours. The longest being a work charge event taking 3.6 hours (Robinson et al 2013).

Analysis of EV charging behavior have also been conducted in the United States. Hu et al. looked at the occupancy rate and energy use for EV charging ports in Kansas City. They found no monthly pattern in occupancy rates. They did find that before 6am and after 5pm EV charging stations were more likely to be used. The paper also looked at occupancy by land use type. The land use was broken down into 5 different categories:

- Commercial
- Residential
- Industrial
- Transport

- Recreational

Results for this analysis showed a similar pattern for residential use. Though conclusions could not be drawn for any other type of land use. Part of their analysis showed that 60% of vehicles were still plugged into the EV charging port once the charge event had stopped. This paper will investigate the characteristics of the 60% of charge where the vehicle stayed plugged in past a minute (Hu et al 2020).

It is important that we look at the placement of the charging infrastructure with relation to the electric grid. Realizing that if we want EVs to help decarbonize it is important when creating new EV charge points that the electricity that powers them is renewable. The electricity that powers them also needs to be affordable (Mastoi et al. 2022). Research to make sure the system does not use more electricity than necessary was conducted by El-Zonkoly & Coehlo. Algorithms were created to figure out the number and size of parking lots. In addition, the scheduling of resources was done by an algorithm. These algorithms were used on a bus network to minimize energy consumption. The locations that were considered were commercial and parking garages. Variables that were also included in the algorithm were the cost of the electricity and the loss of charge (Zonkoly & Coehlo 2017).

Researchers also looked at the optimal locations of EV charging locations to make sure that the economics work out. Costs need to go down over time so that the owners of the charging stations and the distributors of the electricity can make a profit and continue to operate. The biggest variable was waiting time and the impact it has on the electric grid (Gupta et al 2021). A charging process was developed with a view to increasing profits and decrease wait time to charge.  When the EV driver pulls into a lane the price of the charging is listed in the lane. There are multiple lanes with different prices. The EV driver will use the lane that they want to pay for. A simulation was run showing the results of the different prices showing that there was less delay in waiting in the queue (Rabbie et al. 2018). Policies must be adopted by the government to successfully beat these challenges (Gupta et al. 2021). Another economic factor that effect the owners of the stations is the price of the land that the EV charging ports will be built on (Ahmed et al 2022).

Multiple models have been created to look for optimal placement. One was created to test the optimal distance between the nodes of an EV charging network. Alhazmi et al. created the Trip Success Ratio (TSR) model which is meant to see if the charging stations are convenient for EV drivers.  The first step was to model the virtual trips using survey data and a simulation model. The next part of the model was estimating the Remaining Electric Range (RER). This was done by looking at the capacity of the battery, the charge of the battery and the Tractive Effort Factor (TEF).  These states were estimated for each virtual trip.  The results from this were put into a Maximum Location Covering Problem (MLCP) model. Scenarios were tested to take into account real world factors including construction costs.  They determined that 20km between nodes was the optimal configuration between construction costs and successful trips (Alhazmi et al 2017).  Other models looked at the optimal number of ports as well as location. This includes the Flow Refueling Location Model (FRLM) (Zhu et al.). Other researchers use a hierarchical cluster model to find zones for electric vehicles charging stations. (Bitencourt et al 2021).

## 3. Data:

The data for the paper was the same used by Dr. Xianbiao Hu in an "Analysis of Electric Vehicle Charging Behavior Patterns with Function Principal Component Analysis Approach". The data came from charge point and covers Kansas City from 2014 through 2019. The data

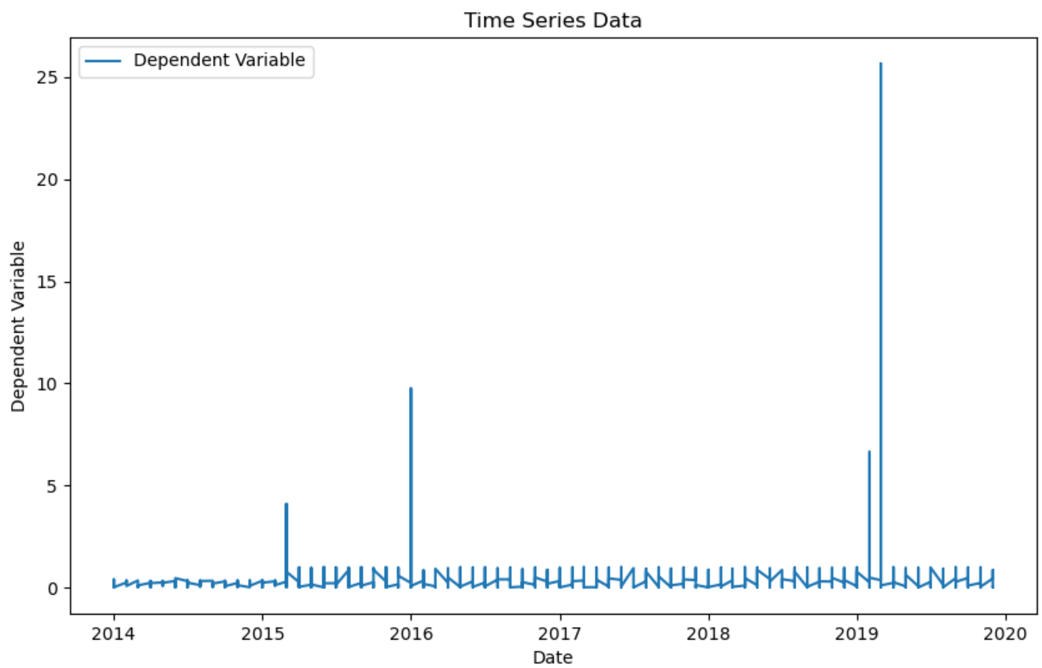


*Figure 1*

comes to a total of X number of data points. It covers the date and time when the EV was plugged into the charge point, when the charged event stopped, and when the EV port was unplugged and the vehicle left. The data covers all of stations in Kansas City. The dependent variable is:

*Table 1*

| Dependent Variable | Dependent Variable Description |
|---|---|

| | |
|---|---|
| Time After Charge(minutes) | The amount of time in minutes that a vehicle has stayed plugged in after the charge event is completed. |

The independent variable are:

*Table 2*

| Independent Variable Name | Independent Variable Description |
|---|---|
| **Land Use** | The type of land parcel the EV charging port is located on. |
| **Month** | The month that the charging event took place. |
| **Day** | The day of the week that the charging event took place. |
| **Season** | Which season the charging event took place. |
| **Hour** | The hour of the day the charging event took place. |
| **Day/Night** | Whether the charging event took place during the day or night. |
| **Port Type** | What type of charging port was used for the charging event. |
| **Weekday/Weekend** | Whether the charging event took place on a weekend or a weekday. |

| | |
|---|---|
| **Plug Type** | What type of plug was used for the charging event. |
| **Port Count** | How many ports are at the charging station where the charging event took place. |
| **Energy** | How much energy was used during charging event. |
| **EVSE_ID** | The identification of the EV charging station. |
| **USER_ID** | The identification of the vehicle during the charging event. |

Each of these variables were chosen because they could plausibly have an effect on the dependent variable. While the paper is meant to look specifically at Land use it is important to look at other variables that may be having an effect.

The Time after charge was calculated by subtracting the total duration the EV was at the charging station from the amount time the EV was charging. This was then converted into the number of minutes to create a standard unit of measurement. The temporal data categories were calculated by extracting the data from the start time of the EV charging data. The start time was chosen because it makes sense to track the time people start charging their vehicle and not when it is finished. Though in most of the cases the data would not be affected, the hour in which the charging occurred may be. It was important to be consistent about what time we started from.

Land use codes for the parcels that the EV charging stations were built on were gotten from the open data Kansas City initiative. There was a total of 66 land used codes. Similar codes were coded the same, creating 16 different categories. This coding is different than the Hu et al. paper where they created 5/6 broad categories. My coding system needed to be more specific because the intent of this paper is to look at the best types of land use to build EV charging ports. So, it needs to be able to discriminate between different types of uses. For example, the difference between an office and a warehouse. This does have the effect of making comparison to previous studies less possible.

*Table 3*

| Land Use Code | Description | Land Use Code | Description |
|---|---|---|---|
| **1** | Residential | **2** | Hotel |
| **3** | Car Dealer | **4** | Office |
| **5** | Warehouse | **6** | School |
| **7** | Government | **8** | Medical |
| **9** | Garage Parking | **10** | Paved Parking |
| **11** | Street Parking | **12** | Travel |
| **13** | Commercial | **14** | Recreation |
| **15** | Miscellaneous | | |

There are some limitations that the data possesses. The main one being is that all the data is before 2020. This then does not take into account changes in behavior that could have possible happened after COVID. While activity will have gone down in 2020 due to COVID we do not have any data about how much the activity returned or if it followed the same patterns.

## 4. Methods:

Three statistical methods were used to investigate the connection between the variables. Each method looks into the question of land use from a different angle.

They were:

- A Random Tree Model
- Time Series Analysis
- Hot Spot Analysis

A linear regression model was first looked at to see if there is any correlation between the different variables. However, the data that we have is not linear. A time cube was created in ArcGIS pro and fed into a curve fit model. It samples 11 locations and 18.18% of the locations had data that fit a linear curve. The majority of locations had data that had an S curve. Meaning the linear regression model would not be able to see if the model would be a good fit. Instead, a Random Forest Model was used to see if the model was a good fit. The Random Forest Model looks to see that land use is part of a model that can explain the variation in data.

A time series analysis will help establish patterns in the data. We will be able to see the temporal patterns in the behavior of EV charging by land use code.  Each land use code will its activity broken out hourly, by type of day and by month. To see if there is a consistent change between type of land use.

The last test conducted was a hot spot analysis. This will help see the relationships between the temporal data and the spatial area. Seeing if there are clusters of data that are alike and there is a statistically meaningful relationship. This test shows us a wider geographic variable than just the land use of charging stations. It will allow us to see if the location in

Kansas City is a significant factor in the dependent variable. Patterns can also emerge to see what land use has a statistically significant number of hot spots.   If so, it could provide future ideas for research into this problem.

# 5. Results:

## 5.1 Statistical Description of the Data:

In total there were 135,688 charge events where the vehicle was still plugged in after one minute. Table x shows that the highest number of charge events took place in the office land use category.  Which had 35,355 charge events occur past the charge event. The category that had the least amount of charge events was government building with 472 charge events. A significant decrease in amount of charge events. The second land use type with the most charge events was land use associated with commercial areas. This includes retail areas, restaurants, and other personal services.  Together they make up nearly 45% of the charge events of the data. Parking areas are another focus and are broken up by type. We see that most charge events took place in garage parking followed by street parking. Paved area parking lots have significantly less charge events.

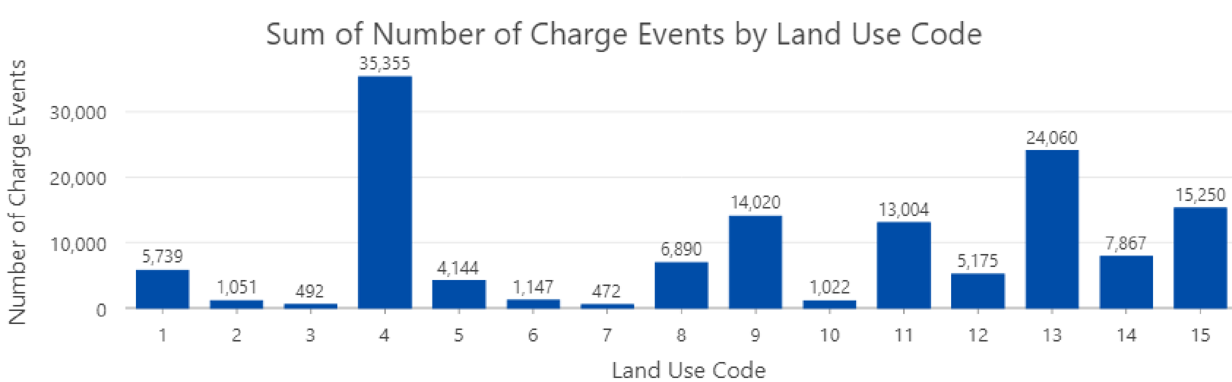


*Figure 2*

Street parking has lower average minutes than garage parking as shown in figure 3. The former has an average time of 215 minutes after charge while the latter has an average of 283 minutes.  Paid Parking has the least number of average minutes with 134 minutes. The travel land use code had the highest average of minutes with 513.

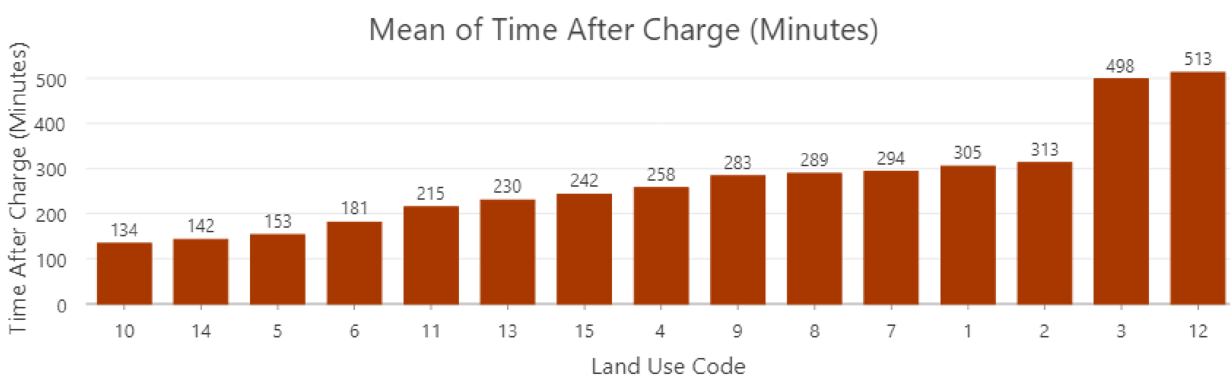


*Figure 3*

*Table 4*

| Row Labels | Sum of Time After Charge Minutes | Count | Minimum | Maximum | Mean |
|---|---|---|---|---|---|
| **1** | 1750864.04 | 5739 | 1 | 1439.24 | 305.08 |
| **2** | 328913.81 | 1051 | 1 | 1435.07 | 312.95 |
| **3** | 245196.57 | 492 | 1.33 | 1401.19 | 498.37 |
| **4** | 9109835.88 | 35355 | 1 | 1439.15 | 257.67 |
| **5** | 632593.91 | 4144 | 1 | 1336.48 | 152.65 |
| **6** | 207335.32 | 1147 | 1.02 | 1420.18 | 180.76 |
| **7** | 138632.80 | 472 | 1 | 957.15 | 293.71 |
| **8** | 1994559.75 | 6890 | 1 | 1438.14 | 289.49 |
| **9** | 3969489.49 | 14020 | 1 | 1433.15 | 283.13 |
| **10** | 136940.09 | 1022 | 1 | 1169.2 | 133.99 |
| **11** | 2794827.97 | 13004 | 1 | 1431.54 | 214.92 |

| | | | | | |
|---|---|---|---|---|---|
| **12** | 2656180.00 | 5175 | 1 | 1439.46 | 513.27 |
| **13** | 5527358.72 | 24060 | 1 | 1428.51 | 229.73 |
| **14** | 1118513.61 | 7867 | 1 | 1433 | 142.18 |
| **15** | 3695773.23 | 15250 | 1 | 1436.12 | 242.35 |
| **Grand Total** | **34307015.19** | **135688.00** | | | **252.84** |

Looking at the distribution of the data we see that the data is not normally distributed. It is right skewed. The mean time a car was still at the EV charging port was 252 minutes past the charge event. The maximum time that an EV vehicle was there was 1,439 minutes after the charge event.

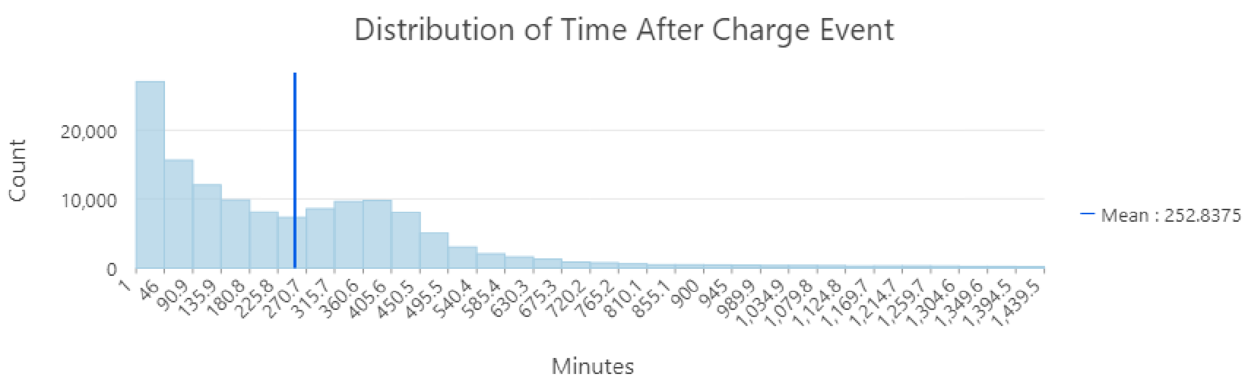


*Figure 4*

Figure 5 shows the data is broken down hourly and we see that that the mean time rises between 0200 and 0400. Between 1100 and 1300 there the mean is the lowest. During the evening the amount time increases. This pattern is very prominent for EV charging stations that are on travel centers. The result is expected since the people are away from their cars for extended period of time.

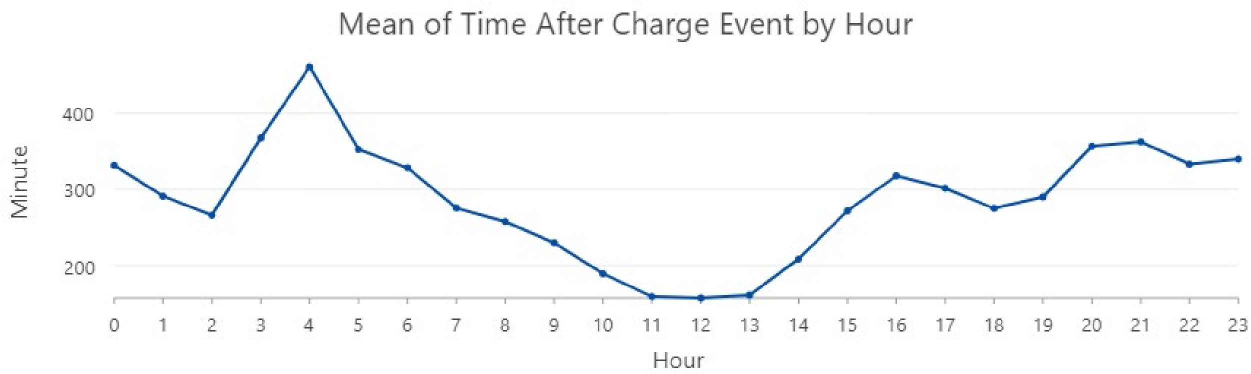


*Figure 5*

When we look at the breakdown of the data by charger type, we see that the vast majority of the charging events are using level 1 chargers. There is a significant difference in the mean between level 1 charging and level 2, and DC fast charging. This is due to the very different amount of charging events and makes them not comparable. We can compare the level 2 chargers against the DC fast chargers. The latter has 600 more charge events yet has a less time parked after the charger event overall. Possibly showing that people tend not to linger at DC fast chargers.

| Row Labels | Sum of Time After Charge Minutes | Count | Minimum | Maximum | Mean |
|---|---|---|---|---|---|
| **DC Fast** | **2059.84** | **972** | **1** | **11.03** | **2.12** |
| Fall | 558.06 | 274 | 1 | 9.03 | 2.04 |
| Spring | 493.26 | 210 | 1 | 9.13 | 2.35 |
| Summer | 576.29 | 281 | 1 | 9.06 | 2.05 |
| Winter | 432.23 | 207 | 1 | 11.03 | 2.09 |
| **Level 1** | **2820.98** | **357** | **1.08** | **318.36** | **7.90** |
| Fall | 475.75 | 82 | 1.08 | 11.23 | 5.80 |
| Spring | 1034.41 | 117 | 1.1 | 318.36 | 8.84 |
| Summer | 653.53 | 88 | 1.34 | 164.29 | 7.43 |
| Winter | 657.29 | 70 | 1.19 | 246.41 | 9.39 |
| **Level 2** | **34302085.29** | **134358** | **1** | **1439.46** | **255.30** |
| Fall | 9624390.01 | 37801 | 1 | 1438.05 | 254.61 |
| Spring | 8630619.5 | 33904 | 1 | 1439.24 | 254.56 |
| Summer | 9357986.82 | 36904 | 1 | 1439.46 | 253.58 |
| Winter | 6689088.96 | 25749 | 1 | 1438.46 | 259.78 |
| **(blank)** | **49.08** | 1 | 49.08 | 49.08 | 49.08 |
| Fall | 49.08 | 1 | 49.08 | 49.08 | 49.08 |
| **Grand Total** | **34307015.19** | **135688** | | | **252.8375** |

*Table 5*

We also do not see a difference in mean of time parked after the charge event in different seasons. They are roughly the same. We can say that the season of the person is in does not have an effect on how this variable.

**5.2: Time Series Analysis:**

For all land uses there seems to be in an increase in the amount of time that an EV vehicle is plugged into the charging port after it has completed its charge event peaking in 2019. There is a lower peak at the end of 2017 going into 2018. There is a dip back to lower levels in 2020 but this could be due to the pandemic. However, when the data is disaggregated different patterns emerge, though will all land use types we still see a spike in 2019.

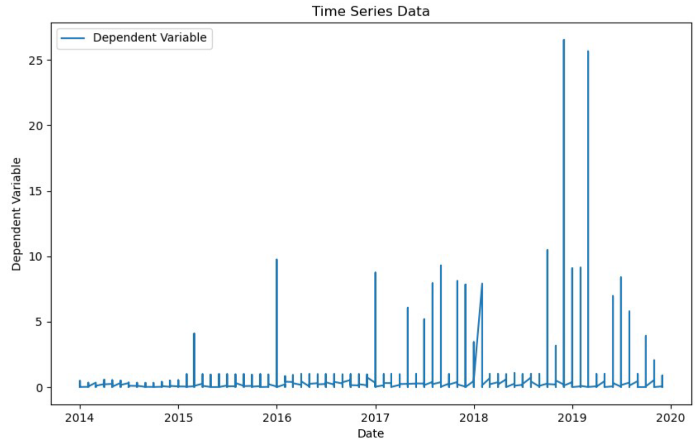


*Figure 6*

When we breakdown the land use of we see different temporal patterns. Land use dedicated to office use has a high in 2019. With slight peaks in 2015 and 2016. Commercial land use is fairly consistent with a peak in 2019.

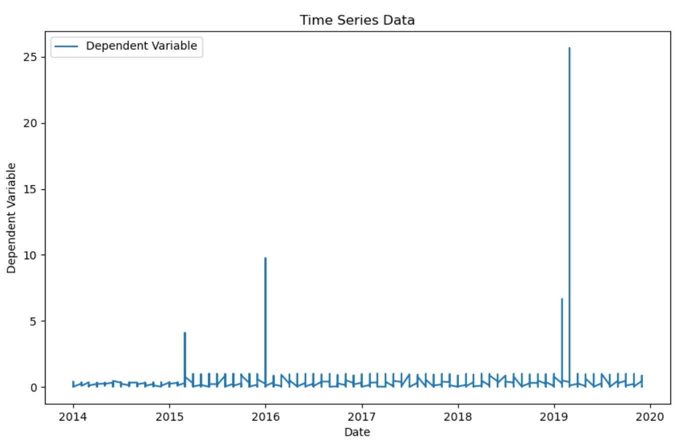


*Figure 7*

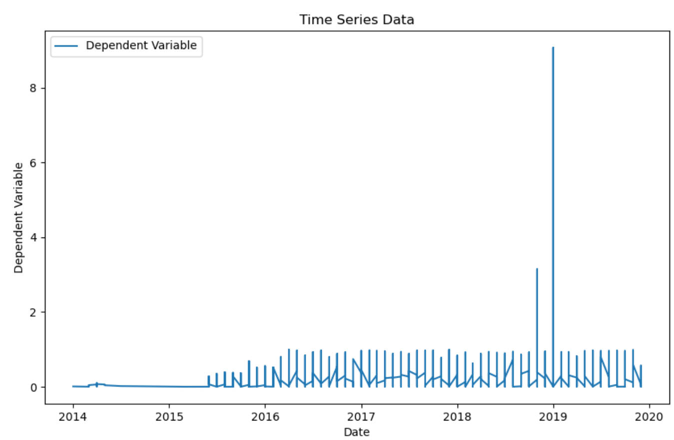


*Figure 8*

Street parking, paved parking and garage parking have similar times series pattern. The time after charge increases around late 2016 and increases until 2020. This is different than most other land uses, where there is a decrease during 2020. The data for paved parking starts in 2017 when the first charging ports were installed then.

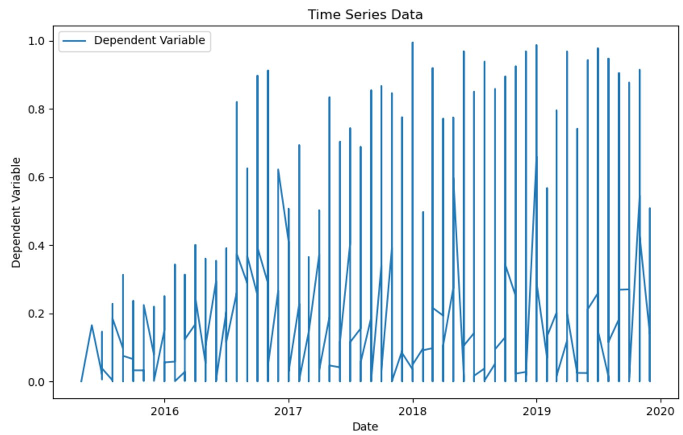


*Figure 9*

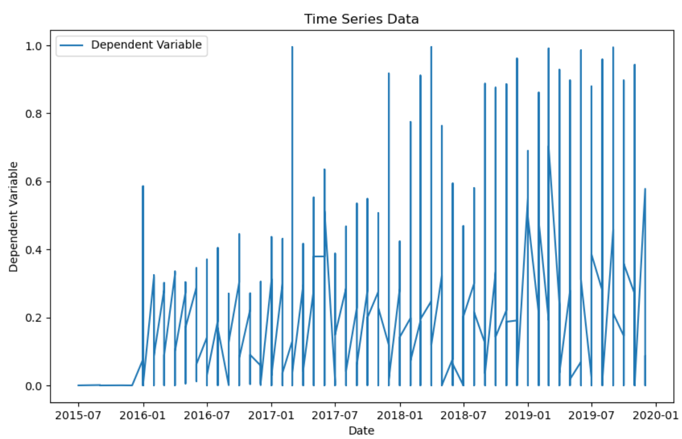


*Figure 10*

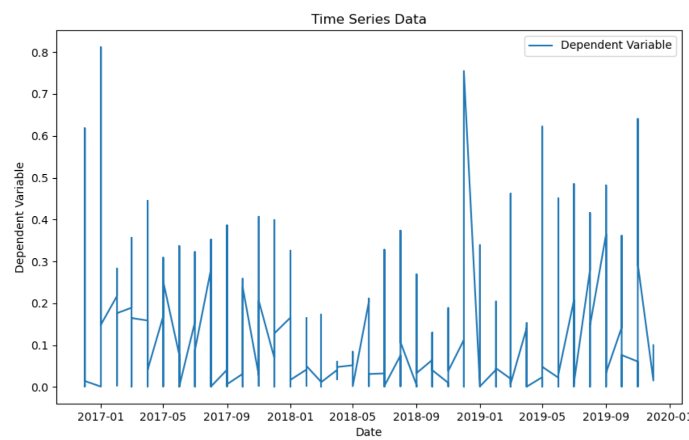


*Figure 11*

## 5.3 Random Forest Model:

A random forest model was used to see if the model was able to explain the variation in the dependent variable. The random forest model turned up a value of R squared = 0.47396460995701295. Meaning that this model explains the significant amount of the variation in data.  There is a good chance that many of the independent variables are statistically significant. This allows us to be confident that the results we see in the data are meaningful.

**5.4 Hot Spot Analysis:**

Patterns emerge both in the different areas of Kansas City and by land use type of the parcels. Hot spots are statistically significant areas where the time parking after charge event is high and the cold spots are statistically significant areas are low.  In the area in and around downtown Kansas City there is a clustering of statistically significant hot spots and cold spots balancing each other out. Whether the charging port is downtown does not seem to be associated with the variable.  South of that there are cold spots. In the northwest of the city the results are more mixed with clusters of hot and cold spots. Around the edges of the city there is not a noticeable pattern.  Geographical areas in Kansas City and North Kansas City do not seem to show a strong pattern.

Cold spots are associated with street parking, recreation areas, schools and warehouses. Hot spots are associated with land uses for hotels, car dealers, garage parking and medical facilities. We can see that the

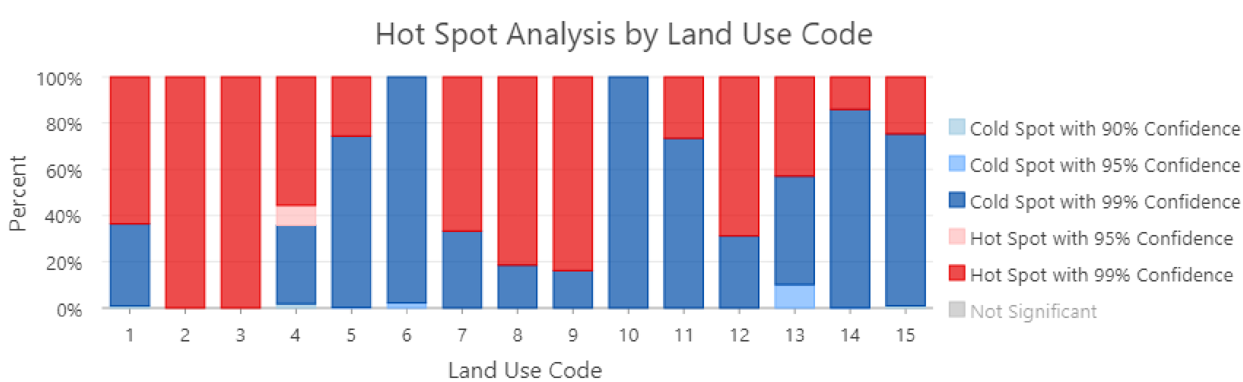


*Figure 12*

### 5.5 Results:

Looking at the results of our analysis we see that street parking is land use most associated with a low time after charge event. Recreation areas also are associated with low time parked after charge event. Making these good areas to place charge ports so that they can be used efficiently.  Garage parking is associated with high time after charge event. Making it a much less efficient use of land for charging ports. Travel areas are the least efficient use of land use for charging, with the highest time parked after charge event. While there may be other reasons to put charge ports in these areas it is important to be aware that they are not the most efficient places to put them, and steps to mitigate this issue must be taken.

## 6. Conclusion:

Overall, there is significant variability in how long an EV vehicle stays at the EV charging port after the charge event has ended. The mean time a car stayed past the charge event changed depending on the type of land use. Land use that is associated with street parking has less time parked after the charge event. The hour that the car is charging seems also to be a significant factor in explaining the dependent variable. The land use of the parcel should be a variable in models for researcher who want to optimize EV charging ports placements. This will help reduce the amount of wait time that an EV driver will have when needing to charge their vehicle. Further research can look into whether the results replicate in other cities or countries. It can also ascertain whether the trends have continued post-COVID.

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