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Electric Vehicle Charging Behavior in Existing Infrastructures: A Rhode Island Case Study

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ELECTRIC VEHICLE CHARGING BEHAVIOR IN EXISTING

INFRASTRUCTURES: A RHODE ISLAND CASE STUDY

BY

ROXANA VOSS URQUIDI

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE

REQUIREMENTS FOR THE DEGREE OF

MASTER OF SCIENCE

IN

SYSTEMS ENGINEERING

UNIVERSITY OF RHODE ISLAND

2018

MASTER OF SCIENCE THESIS

OF

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ABSTRACT

The global trend toward a more sustainable future, based on economics and societal behavior, have assisted in making electric vehicles (EV) more attractive to consumers. New technology implemented in EVs continuously improves their range, charging time, and battery capacity. Therefore, the number of EV sales increased significantly within the last few years. In order to handle the demand from the growth in EV sales, the development of a user-orientated distribution of charging stations is needed which requires substantial knowledge about user patterns in charging behavior. Understanding real data from existing charging stations that is analyzed with rigorous statistical methods gives valuable insight for the development of empirical models of charging behavior.

In order to initiate this work, a case study approach of public Level-2 charging stations in Rhode Island (RI) were analyzed. Research questions range from how charging stations are being used to which kind of areas influence this behavior and what patterns exist toward calendar dependence. After processing the data, single charging stations were classified into functional areas followed by statistical analysis performed with descriptive statistics, visualizing data, hypothesis testing, clustering, regressive models, and forecasting.

Based on the data, there is a strong connection between the total duration of charging events, actual charging time, and the amount of charging events. Not only are chargers utilized differently based on frequency and location, many users use charging stations as parking spots. This pattern exists regardless of charging fees. The charging behavior varies greatly between the different functional areas. Geographical areas seem

to have less influence on charging behavior, seemingly more like a mixture of functional areas. Approximately, only about one third of the RI EV drivers are using RI charging stations. There is mainly a decreasing median amount of charges per user, which speaks to either more home charging or larger battery capacity. Areas in which people are working have less charging events on weekends and have a strong peak of charging events in the morning. Areas in which people are spending their free time have the same amount or more charges on weekends and do not have peak times. Timeseries forecasting models found that, both currently and in the near future, there are enough charging stations in RI. However, this does not imply that all the charging stations are in the correct locations, just that the volume of plugs available in RI is sufficient for the current EV charging population.

Knowing how people charge their EVs is vital to understanding and implementing a new sustainable transportation infrastructure at a critical time when the monumental paradigm shift has relatively just begun.

ACKNOWLEDGMENTS

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CHAPTER 1 – Introduction

1.1 BACKGROUND

The electric vehicle (EV) market is rapidly growing, in the first quarter of 2018, 312,400 EVs have been sold worldwide reaching 59% more than last year (EV-Volumes, n.d.). Around 200,000 battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) were sold in the United States (U.S.) in 2017, with over 55,000 in the first quarter of 2018 (EVAdoption, 2018; InsideEVs, 2018). EV sales significantly increased in 2016 to nearly 160,000 vehicles, when EVs already hit the 1% market share in the U.S. (Howell, Boyd, Cunningham, Gillard, & Slezak, 2017; Klippenstein, 2017; U.S. Department of Energy, 2017).

In 2016, the number of registered BEVs was 362 (0.04% market share), and PHEVs 835 (0.09% market share) in Rhode Island (RI) (Auto Alliance, 2016). However, with the initiation of the RI DRIVE rebate program (circa 2016) by the RI Office of Energy Resources (OER), the sales and leases increased by 32 percent. One RI dealership ranked fourth nationally in EV sales behind the first three ranked in California (Faulkner, 2017; Office of Energy Resources, 2018a, 2018b).

New technology implemented in EVs has made transitioning for consumers more feasible by increasing driving range and battery capacity while decreasing charging time (Howell et al., 2017). A prudently designed infrastructure of charging stations is required to effectively serve this growth. EV charging stations are traditionally installed based on property owner interest (ChargePoint, 2018) or algorithms (i.e., simulations, optimizations) with very little to no on user behavior or user expectations, which can lead to increased

infrastructure costs further down the road (Chen, Kockelman, & Kahn, 2013; McKerracher, 2016; Wang, Xu, Wen, & Wong, 2013; Wood, Rames, & Muratori, 2018; Xi, Sioshansi, & Marano, 2013). Requiring charging stations that people can easily access regardless of their location, is not the solution, because people are not randomly distributed nor, do they move randomly, and most likely they plan to charge based on their daily habits. To accurately develop a robust, consumer-centric charging station infrastructure requires: (i) knowledge of how users utilize the current public and private EV stations and (ii) how that corresponds to their charging expectations and demand. This research explores the relationship patterns between how *public* EV charging stations are being utilized via charging *demand* in Rhode Island.

This research's outcomes will provide a better understanding of consumer charging behavior based on real data from public stations in Rhode Island. In addition, these outcomes will assist the RI Office of Energy Resources (OER), RI Department of Transportation (RIDOT), and RI Department of Environmental Management (DEM) to understand their customer and to make consumer-centered charging infrastructure decisions. Results will establish knowledge for future analysis of the charging infrastructure use and demand at various location types. This information can assist in determining the need for public charging demand and promote charging infrastructure installation at various parking facilities. Overall, conclusions of state trends in charging behavior will be established and considered within the context of national trends. Additionally, the information would be valuable to improve the sustainable transportation infrastructure for all users and the potential to integrate future parties, such as autonomous vehicles.

1.2 RESEARCH GOALS

The goal of this research is to develop a set of empirical models describing charging behavior by providing a statistical analysis on data collected from existing EV charging stations throughout Rhode Island. Charging patterns are examined with a summary utilization of the entire RI charging infrastructure and pattern recognition based on the different location types of charging stations. The study observes public, Level-2 charging station locations throughout RI and analyze them in three ways: (i) how they are distributed, (ii) which different kinds of areas they are in and (iii) how they can be divided. A consistent method of clustering them is determined, all Rhode Island charging stations are divided into certain areas of interest (e.g., institutional, commercial, industrial, residential) and analyzed under specific conditions.

The research objective of this study is to analyze charging station data for the OER and RIDOT which allows for better infrastructure forecasting. The 2013-2017 RI Charging Station database obtained from OER will be analyzed in order to help future infrastructure decision making. Therefore, the following research questions will be explored throughout this thesis:

> *Research Questions 1: (a)* How are charging stations being utilized and *(b)* how frequently? *(c)* Since parking is a valuable commodity, are EV users using charging stations as parking spots?

> *Research Question 2:* Does the type of areas in which the charging stations are located influence the patterns of charging behavior?

Research Questions 3: What pattern distributions exist, such as *(a)* calendar dependent (i.e., weekly, daily, or hourly), *(b)* seasonality, and *(c)* can they predict future usage trends?

The next chapter, Chapter 2, explores knowledge about the topic via a literature review on EV-market evolution, EV charging in general and related studies. The data analysis methodology is described in Chapter 3 with the necessary tools and software packages (i.e., Excel, Minitab and R). Methods like forecasting models, hypothesis testing, comparison tests, and mapping are discussed in Chapter 3 then applied in Chapter 4. A R script was generated where updated data can be implemented and analyzed the same way as older versions of the dataset. Within this R script, descriptive statistics (e.g., mean, standard deviation) to understand the data are part of this script. Furthermore, comparisons were applied to answer specific research. Finally, seasonal forecasting was applied to explore the future evolution of charging events in certain areas. The results and discussion of this analysis can be found in Chapter 4. After that, conclusions can be drawn about the overall usage of the charging stations in Chapter 5. Since there is high potential for additional studies with this data, Chapter 5 also gives a summary about its limitations and future work.

The outcome of this research will be published in form of a journal paper(s).

CHAPTER 2 – Literature Review

The popularity of EV's continues to grow and is expected to gain a commanding market share in the near future (Lienert, 2013), as either a bridge to or in lieu of autonomous vehicles (AVs) for private, single users. To make EVs available for the mass market, overall costs have to be reduced (e.g., vehicle and insurance costs, financial incentives), which can happen by improving the transportation system instead of simply investing in larger batteries (Morrow, Karner, & Francfort, 2008). Additionally, lithium-ion battery costs are projected to decrease, reducing production costs thus making EVs even more attractive (Dinger et al., 2010). This can lead to decreasing insurance costs which are high due the possible battery damages.

The capacity, and location of charging stations must be carefully considered in order to effectively support this growth in the EV market, thus the charging station location selection problem becomes an important field of interest (Chen et al., 2013).

2.1 EV-MARKET EVOLUTION

Within the last decade the EV-market has grown a lot, but internal combustion engine (ICE) vehicles are still dominating the market with 95% in 2017 (U.S. Department of Energy, 2018). However, there is a significant growth expected within the next years. In 2017 alone, one million EVs were added on the roads globally, making the total global market three million. Europe (yellow), China (blue), and the United States (green) are leading in EV sales right now and are expected to continue growing within the next 20

years, see Figure 1 (Bloomberg New Energy Finance, 2017). Based on projections, this implies that in the U.S. alone there will potentially be one million EVs on the road by 2020.
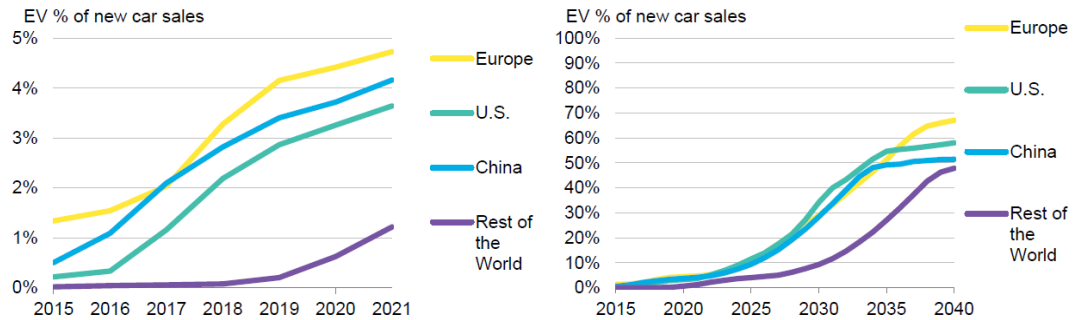
Figure 1: EV sales penetration by geographical area (Bloomberg New Energy Finance, 2017)

Additionally, the number of EV models is growing based on manufacturers' sustainability goals. There were over 10 new models available in 2017, 41 in total and the number is growing based on support from Volvo, BMW, Volkswagen, Telsa, and more(ChargePoint, 2017); within a matter of a few years, there should be model for every use and personal preference (ChargePoint, 2017). Unfortunately, some states have special restrictions for EVs; Tesla for example is not available in every state, due to dealer franchise laws (Gatti, 2017).

The causes of this fast-paced growth is, but not limited to, the new technology implemented in EVs and the fast falling battery costs, which will make EVs become price competitive. Trends like car sharing, and vehicle-as-a-service (e.g., leases with a monthly mile limit) models will influence the market as well, much earlier in adoption and market penetration timing than autonomous vehicles (Bloomberg New Energy Finance, 2017).

However, all these trends are influenced by numerous factors that can change quickly by introducing new policies or new national climate targets, for example (Bloomberg New Energy Finance, 2017).

A preference for BEVs over PHEVs is expected to strengthen. Drivers in Washington state already prefer BEVs, even though the numbers of BEVs and PHEVs are fairly evenly split in the U.S. right now (ChargePoint, 2017; Nigro & Frades, 2015). With respect to the engineering complexity of the dual powertrains and vehicle platforms, the costs for PHEVs are higher over BEVs, making them initially less attractive to customers (Bloomberg New Energy Finance, 2017). BEVs, however, are more dependent on a good distribution of charging infrastructure and are only cost effective in the U.S. based on current financial incentives. Additionally, on a higher systems scale of the intersection between transportation and energy sectors, the electricity consumption for EVs will rise due to larger batteries, demand for fast charging and higher power draws, with higher numbers of EVs on the road. Utilities need to provide and manage (e.g., queuing, off-peak charging) a prudent infrastructure of charging stations to help limit the costs and high demand variability (Bloomberg New Energy Finance, 2017).

2.2 EV CHARGING

EV charging is an important aspect to EVs in general as it is the only source for 'fueling'. Most vehicles are parked over 90% of the time and a lot of parking spaces could become a charging opportunity (ChargePoint, 2017). At the moment there are a lot of different provider on the U.S. market, the biggest one is ChargePoint, followed by Tesla and later Blink, but there is also a high percentage of unaffiliated providers (21.7%)

(EVAdoption, 2017). This can be inconvenient for users because they have to create different user accounts for using the different provider. Public charging stations can be found easily with mobile apps (e.g., PlugShare, ChargePoint, ChargeHub or GoogleMaps) and deliver real-time status if they are occupied or not. Once the driver arrives at the spot, the driver must identify by swiping the costumer card or via NFC (Near Field Communication), after which that the car just needs to be plugged in. The whole process takes about one minute or less, and the user can just let car charge automatically while it is parked.

Another important factor is cost, with an EV the costs per mile driven are significantly lower than miles driven with a conventional ICE. EV drivers pay about 60-100% less per mile driven, but that depends strongly on the vehicle and the daily oil price(ChargePoint, 2017). Considering that many charging stations take no free at all. Additionally, the maintenance costs for a new EV are approximately 2% of the maintaining costs for a new gas vehicle (ChargePoint, 2017).

Charging opportunities close to work and home are important to most user, but not all buildings are EV-ready (ChargePoint, 2017). A lack of home charging can strongly impact the adoption of EVs as well, this barrier will restrict EV sales to reach 100% (Bloomberg New Energy Finance, 2017).

Investing in the charging infrastructure also count for investing in the EV market in general, see Figure 2. EVs are dependent on charging, and charging stations only justify themselves when there are enough EVs. Investments in charging infrastructure must be made before they are needed to initiate this loop, what causes a utilization gap at the beginning of the implementation, see Figure 3. That implies that there have to be stations,

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even if they are not used yet; charging infrastructure needs to be available, for people to even consider buying an EV. However, there will be a market pull after EVs reach a certain percentage of market share, and prior investments will no longer be needed. After enough investments in the EV-market has been done it will continue to grow by its own, within a reinforcing loop, see Figure 2 (Meadows, 2009; Wood, Rames, & Muratori, 2018).
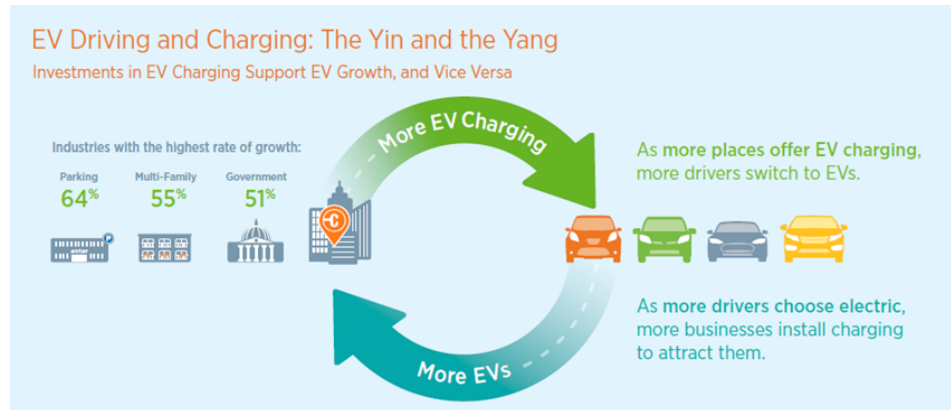
Figure 2: EV sales penetration by geographical area (ChargePoint, 2017)
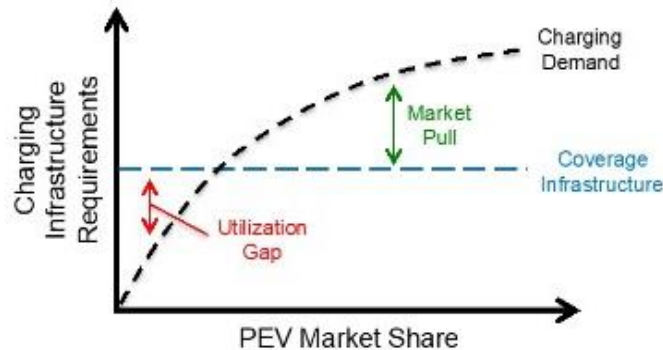
Figure 3: Correlation of charging infrastructure requirements (Wood et al., 2018)

Charging stations are currently available at three different types: (1) Level-1 takes up to 22 hours charging time and is mostly used residentially (home charging), through a convenient household outlet; (2) Level-2, with approximately four to eight hours charging time, is used primarily for commercial charging and is the most common in RI, but they

can also be purchased for residential charging; (3) the DC Fast charger charges 80% in 20-30 minutes, but not all EVs are equipped with this port and charging fees are higher (ChargePoint, 2017; Dong, Liu, & Lin, 2014; McKerracher, 2016; U.S. Department of Energy, 2011) In Figure 4, the voltage, amps, charging loads and average charging time are summarized for the three type of stations. Most cars use an on-board charger inside the car to charge the battery, this technique only works for the Level-1 and the Level-2 charger (ChargePoint, 2017). DC Fast charge has a special, additional plug that pairs with the traditional charger in order to feed the EV power faster.

AC Level One	AC Level Two	DC Fast Charge
VOLTAGE 120v 1-Phase AC	**VOLTAGE** 208V or 240V 1-Phase AC	**VOLTAGE** 208V or 480V 3-Phase AC
AMPS 12–16 Amps	**AMPS** 12–80 Amps (Typ. 32 Amps)	**AMPS** <125 Amps (Typ. 60 Amps)
CHARGING LOADS 1.4 to 1.9 KW	**CHARGING LOADS** 2.5 to 19.2 kW (Typ. 7 kW)	**CHARGING LOADS** <90 kW (Typ. 50 kW)
CHARGE TIME FOR VEHICLE 3–5 Miles of Range Per Hour	**CHARGE TIME FOR VEHICLE** 10–20 Miles of Range Per Hour	**CHARGE TIME FOR VEHICLE** 80% Charge in 20–30 Minutes

Figure 4: Three types of EV charging stations (Brodd, 2017)

Home charging is an important topic. According to recent research from the U.S. Department of Energy (DOE) Office of Energy Efficiency & Renewable Energy (EERE) the charging load profile from home dominant EVI-Pro simulations show that 88% of charges are done at home by a Level-1 or Level-2 chargers, see Figure 5 (Wood et al., 2017). Home charging directly influences the use of public charging stations, but due to limitations of data, the focus of this research is on public Level-2 charging.
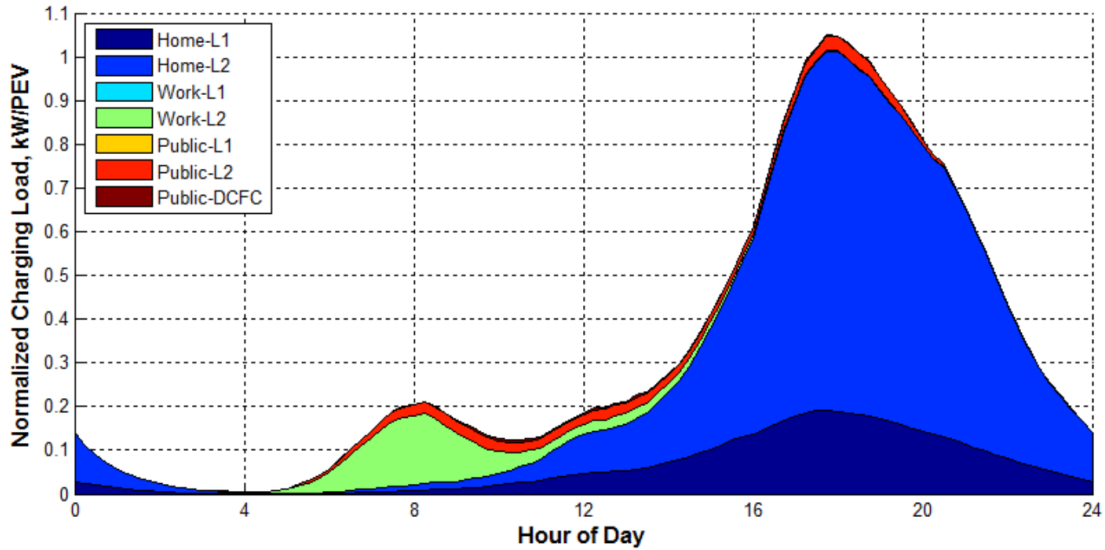
Figure 5: Nominal charging load profile from EVI-Pro simulations (home dominant charging behavior) (Wood et al., 2017)

2.3 EVS IN RHODE ISLAND

Rhode Island has visions about the future development and the City of Providence, as its capital, has set a statement in writing about self-improvements. There are three attributes they want to identify with, mentioned in the Comprehensive Plan of Providence are, they want to be more "green", with a healthy natural environment and a sustainable city design. Also, Providence wants to be more "efficient", a fiscally sound city, providing high-quality and cost-effective services. In their guiding principles, the City of Providence also mentions "sustainability", regarding climate change and the uncertainties within the oil market. Therefore, Providence wants to promote alternatives to the conventional traveling patterns (Taveras, 2014)

Regarding the chosen attributes, a growing trend in transportation with EVs has to be considered. Transportation is the costliest energy sector in Rhode Island (Office of Energy

Resources, 2016). Zero Emission Vehicles are one of the most promising technologies to reduce greenhouse gas emissions and the effects of global warming within this sector. Vehicle electrification, instead of driving conventional vehicles, can save emissions by up to 73% and would be the key pathway to clean up the transportation sector (Office of Energy Resources, 2016)

Rhode Island promoted the EV market with the Rhode Island DRIVE program funded through 2018 and the RI Zero Emission Vehicles Actions (Faulkner, 2017; Office of Energy Resources, 2016). Rhode Island signed the "State Zero-Emission Vehicle Programs" Memorandum of Understanding in October 2013, along with California, Connecticut, Maryland, Massachusetts, New York, Oregon and Vermont. The ultimate goals of the Memorandum of Understanding are to reduce greenhouse gas and smog causing emissions by fostering energy independence by transforming the transportation sector, with actions and programs to address barriers in Zero Emission Vehicle deployment (Office of Energy Resources, 2016). For example, these goals are stated in the RI Zero Emission Vehicle Action Plan regarding EV charging (Office of Energy Resources, 2016):

- Section 5.2: "Promote the installation of charging infrastructure and adoption of ZEV's for commuters at public transit hubs"

- Section 6.1: "Research driver charging behavior to determine the need for non-residential charging, including the level of charging and importance of location"

- Section 6.3 "Coordinate with researchers to undertake multi-state mapping and modeling analyses to inform the design and implementation of efficient corridor charging networks."

In total, there are public 198 charging plugs at 82 charging station locations in RI, 178 are Level-2 charging ports with in average of 2.4 plugs per station, 20 charging ports are DC-Fast charging ports with an average of 2.5 plugs per station (Alternative Fuels Data Center, 2018). Most of the public charging stations were installed in 2013. OER worked together with ChargePoint and National Grid to install 50 charging stations around the state, starting in 2013 (Elsworth, 2016).

2.4 CHARGING STATION LOCATION MODELS

There are different approaches to examining the problem of charging station location selection. Existing studies use mathematical models, studies which use linear programming, analyzing driving and charging behavior to work on this problem. Primarily, researchers create mathematical models to simulate the problem in order to solve for potential solutions. There are multi-objective planning models (e.g., gas-station demands, power grid infrastructure) to layout charging station distributions, in some studies they also determine scheduling of charge and operation costs (Chen, Kockelman, & Kahn, 2013; McKerracher, 2016; G. Wang, Xu, Wen, & Wong, 2013; Wood, Rames, & Muratori, 2018; Xi, Sioshansi, & Marano, 2013). Simulation-optimization models determine where to locate EV charging stations in order to maximize the use for privately owned EVs (Xi et al., 2013). There are also studies which utilize multi-objective planning models to improve the transport system efficiency, as well as improve the grid system operations (Luo, Zhu, Wan, Zhang, & Li, 2016).

Other studies use linear programming to include electricity price variation, the capability of EVs to charge and discharge when desired, called Vehicle-to-Grid technology

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(Kristoffersen, Capion, & Meibom, 2011; Srivastava, Annabathina, & Kamalasadan, 2010). Further research on vehicle-to-grid technology provided evidence that this approach was not viable due to high infrastructural costs and significantly shortened lifespan of EV batteries by the higher number of charge/discharging cycles (Göthel & Bräul, 2012; Mullan, 2012), but there are still stakeholders (ChargePoint, 2017). Certain station location selection models are based on existing optimization routines or heuristics that can find charging locations based on reducing queuing times via prediction of existing data from non-EV vehicles (Chen et al., 2013; De Weerdt, Gerding, Stein, Robu, & Jennings, 2012; Worley, Klabjan, & Sweda, 2012). Yet, these algorithms or models still barley consider EV users preferences, behavioral patterns, and functional areas analysis. Additionally, EV charging is different than refueling an ICE vehicle, therefore studies should focus on EV driving patterns.

Another approach to the problem is by analyzing driving behavior from the EV driver: analyzing their driving, parking, and charging patterns. This level of research has been attempted by making test drives or tracking fleet vehicles (Smart & Schey, 2012; Speidel & Bräunl, 2014). In Australia, they observed EV driving and charging behavior of a fleet of eleven EVs at 23 Level-2 Charging stations. They assessed the state of charge (SOC) before and after the charging events, charging time, time the vehicles are plugged in at the station and energy consumption. No categorizations of public level-2 changing stations exist based on location (Speidel & Bräunl, 2014). Additionally, fleet vehicles are operated differently than consumer-owned EVs, so their behavior may not transition to predictions of charging station locations. Another study, performed in the U.S., with 2903 privately owned Nissan LEAFs looked at SOC and the number of charging events; they only differ

between home charging and "away-from-home location" (Smart & Schey, 2012). Overall, only a few studies insert real charging data beyond commercial, medium duty EVs or fleet vehicles (Duran, Ragatz, Prohaska, Kelly, & Walkowicz, 2014; Smart & Schey, 2012; Speidel & Bräunl, 2014). However, there are many ways to process driving and charging behavior.

Another way is through the combination of the different approaches is the 2018 released projection tool from the U.S. DOE EERE. It is based on data of personal vehicle travel patterns, EV attributes, and charging station characteristics in bottom-up simulations. The used data is out of studies from Columbus, Ohio, Massachusetts, and California (Wood, Rames, & Muratori, 2018). EVI-Pro estimates the quantity and type of charging infrastructure: Workplace Level-2, Public Level-2, and Public DC Fast Charging Plugs. The input variables a user of the projection tool can insert are: "Number of vehicles to support", "Vehicle Mix" (Percentage BEV and PHEV), "Support of PHEVs", and "percentage of driver with access to home charging" (U.S. Department of Energy, 2018). The EVI-Pro tool forecasts quantity and type of charging plugs, there are no behavioral recommendations and no functional area considerations for charging station locations.

Therefore, personal use of EVs are considered limited with respect to charging behavioral patterns even with current growth, use, and installations throughout the literature.

CHAPTER 3 – Methodology

This chapter describes the methods that have been used to analyze the data and discusses the motivating factors for this specific approach. The flow of this chapter starts with describing the data and its processing, followed by the classification of functional areas, and ended up with the specific methods of statistical analysis which have been applied.

3.1 DATA AND DATA PROCESSING

Data from 50 Level-2 public stations out of 73 Level-2 public stations statewide, was available to be analyzed, which can provide a representative overview about the charging behavior at Level-2 charging stations in RI. The data utilized for this study was provided by the Office of Energy Resources with all locations verified by ChargePoint. The data was stripped of user identification information prior to dissemination; the only unique identifiers were through an encoded user identification number (User-ID) and postal zip code. It is assumed that multiple users do not share User-IDs, have only one EV, and are permitted use of all charging stations within the dataset.

A total of 38,685 charging events have been collected at 55 charging stations, they provide two 7.2 kW (208/240V at 30A) Level-2 charging ports (ChargePoint, 2018a). Forty-five of the charging stations were installed in 2013, one more in 2015, three more in 2016 and the remaining six in 2017. Five stations are restricted to state government employees; they are newly implemented in 2016 and 2017. The charging stations for

governmental use only are excluded in this analysis because they are not public. All the fifty other stations are free for public use, the remaining total of charging events is 37,620. Only three of the observed charging stations charge fees: one station charges $0.10/kWh and the other two stations are free the first 4-hours and after that they charge $1/hr. Since they are public stations they are included in this analysis, if a different behavior is conjecturable in certain cases are analyzed separately.

At the beginning it appeared that there was data of 57 charging stations but while verifying the locations one was identified with only two test charges; this station will not be part of the analysis. Another station appeared twice in the data set, because the owner and the name changed, the station data was classified as one.

3.2 CLASSIFICATION OF FUNCTIONAL AREAS

Every city and town in RI classifies their areas into different functional districts by their zoning ordinance to control the land use. The following items are covered in a RI Zoning Ordinance: site layout requirements, requirements for structure characteristics, permitted use, and procedural matters (Atash, 2017). Every RI city and town publishes their zoning map and explanations online for anyone to find a location's zone classification and its regulations. The location for every charging station was established with respect to their functional zone and added to the dataset. For example, the City of Providence has 20 charging stations available, with 40 charging ports in total, located and distributed in different functional districts classified by the City of Providence Zoning Ordinance committee. This zoning ordinance information will be examined to see if charging stations in different functional areas are utilized differently. A detailed

analysis of these types of zones/functional areas for charging stations occurred for the City of Providence.

The City of Providence is regulated by their zoning ordinance and represented in the zoning maps as eight districts which individually have more subdivisions (City of Providence Zoning Ordinance, 2017). There are "Residential Districts" (yellow to brown, Figure 6) with different dimensional standards and housing types. "Commercial Districts" (pink to red, Figure 6) with medium-scale to intense commercial use and design standards. The "Downtown District" (gray, Figure 6) has a special focus in the Comprehensive Plan of Providence as it is a mixed-use district with special regulations. All new developments in the "Downtown District" have to be compatible with existing historic buildings while encouraging day and night time activities, entertainment, and housing. Also, greenways and open spaces are incorporated into the "Downtown District". The design of the exterior of all buildings, open spaces and all exterior physical improvements has to be regulated and approved through development plan review in accordance with the provisions of this area. Furthermore, there are two "Institutional Districts" (blue, Figure 6) in Providence: one with a special focus on healthcare and one with a special focus on education. The "Industrial Districts" (violet, Figure 6) incorporate light to heavy intensity industrial uses, some of which are mixed-used and includes also residential or commercial use. The "Waterfront District" (turquoise blue, Figure 6) incorporates residential, commercial and industrial uses with special restrictions regarding the waterfront. "Open Space and Public Space" (green, Figure 6) are summarized as one zone. Open spaces include parks, wetlands, floodplains, cemeteries, and conservation areas. Public Spaces are areas for public

buildings and facilities such as parks and recreation areas or schools. The last zone incorporates the "Special Purpose Districts" which have intense focus on certain areas of interest to the City of Providence (City of Providence Zoning Ordinance, 2017a).
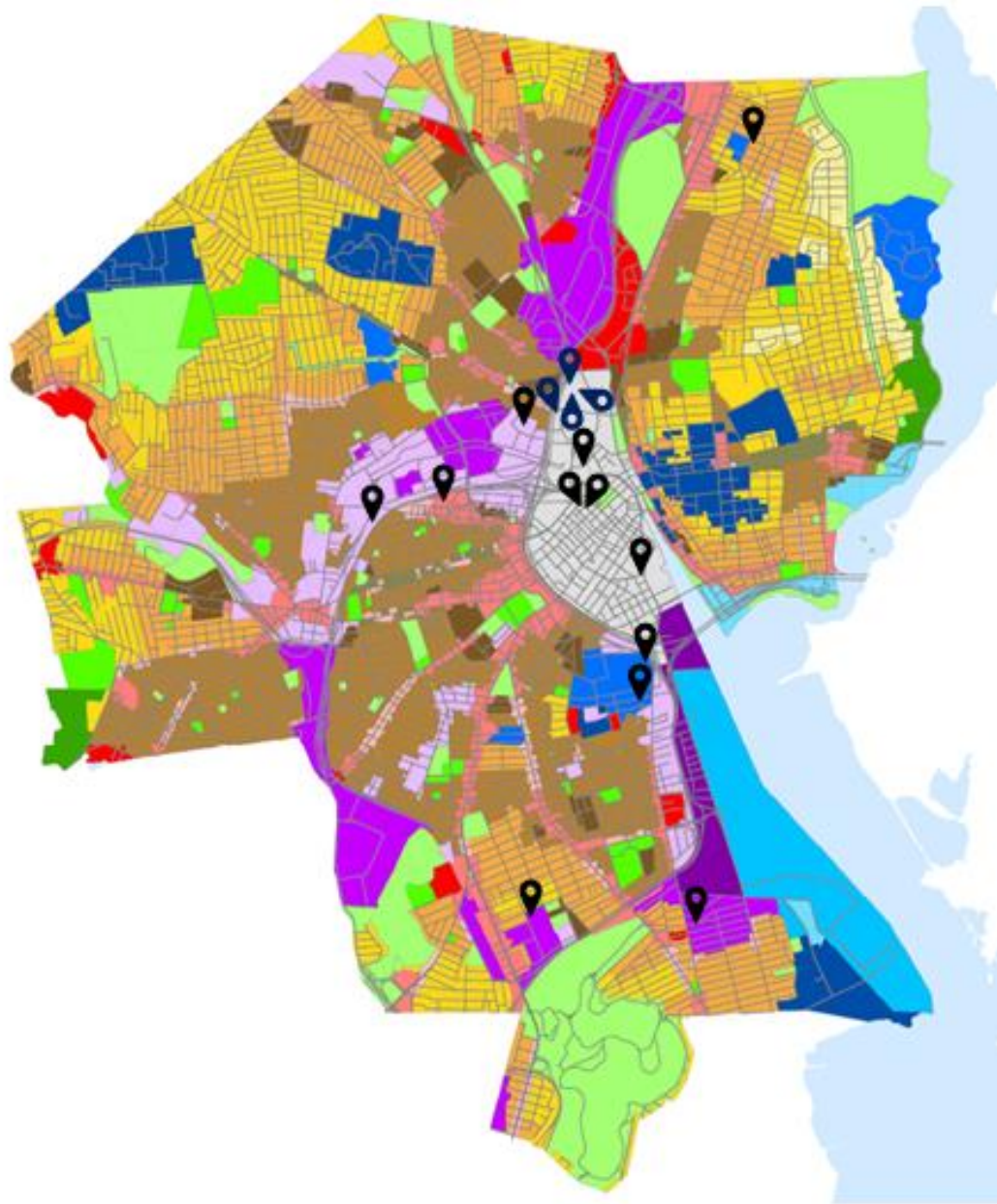
Figure 6: Zoning Map of Providence with charging station locations (City of Providence Zoning Ordinance, 2017c)

All of the 20 charging stations are distributed in five out of the eight districts (see Figure 6). One charging station is in a Residential District, one are located in Commercial Districts, 12 (including the 5 government ones) are located in the Downtown District (the four upper locations, in dark blue have two stations per location); fife out of 12 are for governmental use only, two are located in Institutional Districts and four are located in Industrial Districts (see Figure 6).

This functional classification has been assessed for every city and town with charging stations in the dataset. However, there are slight differences in the classification of the districts, because every city and town can name their own districts. This required reconciling these differences between word choices and zoning types for a more unified approach. Examples of these differences and how they were reconciled are articulated as the following:

(1) Barrington has one charging station in a "Business Districts", for commercial and retail activities (Town of Barrington Zoning Ordinance, 2003). This is assumed to be an equivalent to a "Commercial District", since Barrington has not classified any "Commercial Districts"; this appears to be a different designation for the same kind of district. The same classification adjustment was made for Narragansett, Warwick and West Greenwich (City of Warwick Zoning Ordinance, 2018; Town of Narragansett, 2012; Town of West Greenwich Zoning Ordinance, 2017).

(2) In Lincoln there is one charging station in a "Manufacturing District". Since there is no district classified as an "Industrial District", it assumed that manufacturing is an industrial use and therefore now classified as an

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industrial area (Town of Lincoln Zoning Ordinance, 2015).

(3) In the Town of Smithfield, home to Bryant University with two charging stations, the town has not classified any districts as "Institutional Districts". Yet, a University is definitely institutional, that is why the charging stations at the Bryant University are clustered as Institutional (Smithfield Zoning Ordinance, 2018).

(4) The T.F. Green Airport in Warwick has two charging stations, it is classified as a "Intermodal District". Since the use of an airport is other to any of the other mentioned districts, the T.F. Green Airport has keeps this classification (City of Warwick Zoning Ordinance, 2018).

(5) All "Open Space" and "Public Space" are as in the plan of Providence grouped together.

The locations of the charging stations in all other cities and towns could be classified into the previously used areas: "Commercial District", "Downtown District" (only applies to Providence), "Industrial District", "Institutional District", "Intermodal District" (only applies to Warwick), "Open Space and Public Space", "Residential District" (Bristol Zoning Ordinance, 2018; City of Cranston Zoning Ordinance, 2018; City of Newport Zoning Ordinance, 2014; Department of Planning East Providence, 2003; North Providence Zoning Ordinance, 2014; Portsmouth Zoning Ordinance, 2002; Town of Charlestown Zoning Ordinance, 1991; Town of Glocester Zoning Ordinance, 2015; Town of North Kingstowntown, 2008; Town of South Kingstown Zoning Ordinance, 2015; Town of Westerly, 2010; Zoning Ordinance of the Town of Burrillville., 2018)

3.3 STATISTICAL ANALYSIS

The statistical analysis of this data is the corner stone of this research. For that reason, a goal was it to make the analysis understandable and replicable for other researchers and OER. For this reason, most of the research was executed with the statistical program R within R-markdown (Appendix 1 the code, Appendix 2 the knitted version). R-Markdown has the advantage that this code is clustered in discrete chunks that may be ran individually. The user is able to evaluate the output step-by-step to ensure proper functionality, then view and safe the results under the code and have explanations between the code chunks. The final code can be knitted to a Portable Document Format (PDF) or Word to have a presentable version of the code with all results and explanations. Future researchers can then load in an updated version of the data, follow the instructions, and reconstruct the analysis as needed.

3.3.1 DESCRIPTIVE STATISTICS

Descriptive statistics are a necessary internal step to understand the data and provide an overview about what is included in the dataset. Summary statistics explores the factors and measurements within the dataset. This includes simple, although highly informative statistics, such as sample size, arithmetic standardized means, standard deviation, minimum, and maximum of certain observations. The descriptive statistics in this analysis are performed with the statistical program R, version 1.1.447 – © 2009-2018 RStudio, Inc..

3.3.2 VISUALIZING DATA

As part of understanding the data plotting and mapping is a helpful tool to visualize data. It can present a helpful overview about the collected data, by revealing overarching trends and patterns in the data. This contains descriptive charts like bar graphs, line plots or pie charts which have been generated with R or Excel. Box-plots have been created with R, to compare the median of factors in different areas. To present certain graphs they are shown as single graph or as small multiples to compare different conditions.

Geographical maps have been created with R, there are a few packages (i.e., *maptools, zipcode, maps,* and *mapdata*) which provide data to generate geographical maps. They mark locations with longitude and latitude data either based on that specific data or converted zip codes. Locations were marked in different forms and colors.

3.3.3 HYPOTHESIS TESTING & CLUSTERING

To evaluate results clustering and hypothesis testing can be useful to identify patterns.

Many tests require normal distribution for their test variables; the Anderson-Darling test was used for larger sample sizes and the Shapiro-Wilk test was used smaller sample sizes. If normality was held, hypothesis testing was executed using equal variance via a Tukey test for comparison of means. If the variable was not normally distributed, a Mann-Whitney Wilcox test for comparison of means was used when its assumptions were met: (1) there has to be one dependent variable that is measured at the continuous or ordinal level; (2) the data consist of two categorical, independent groups; (3) there has to be independence of observation; and (4) it has to be determined

if the distribution of score has the same shape or a different shape (Laerd Statistics, 2018). Spearman's Correlation, another non-parametric test, was used if its following assumptions are met: (1) the variables are measured at a continuous level; and (2) there is a monotonic relationship between the two variables (Groß, 2010). Spearman's Correlation was applied in Chapter 4.1 since all three variables meet both assumptions. In Figure 7, the monotonic relationships between each of the variables are illustrated. For the comparison of proportions, a two-sample proportion test was ran using Minitab.
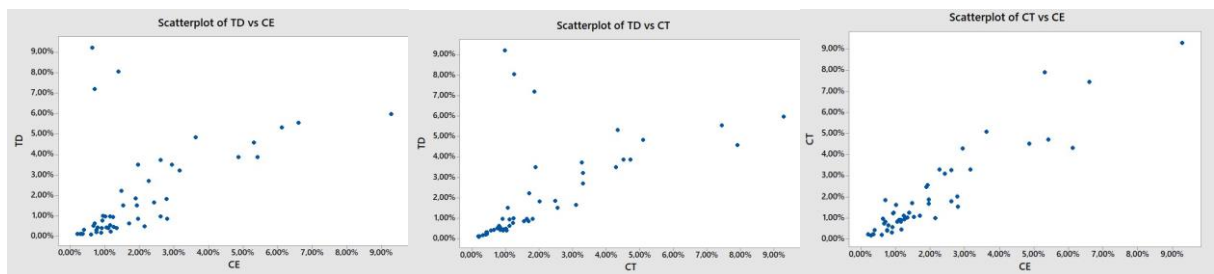
Figure 7: Relationship between Total Duration (TD), Charging Events (CE) and Charging Time (CT)

With hierarchal clustering, findings can be grouped within a tree-structured cluster dendrogram generated with R or Minitab. There are different options that can be chosen: complete linkage (i.e., similarity of the furthest pair); single-linkage (i.e., similarity of the closest pair); group average (i.e., similarity between groups); centroid similarity (i.e., iteration merges the most similar central point). For this thesis complete linkage was used, because it voids a drawback of clusters formed via single linkage, which can appear when single elements are close to each other. Complete linkage usually finds compact clusters of approximately equal diameters (Groß, 2010).

3.3.4 TIME SERIES - REGRESSIVE MODELS & FORECASTING

A time series consists observations of a variable $x_1 \ldots x_n$, which have been collected at equidistant and consecutive time points. Usually the observations are not independent to each other, which requires special methods that explicitly consider stochastic dependence (Groß, 2010). Since, the data was collected at any time a charging event happens and summarized into various time groups (e.g., years, month, days…), they can be treated via timeseries.

If the data is summarized in fixed time intervals k (in this case years or month) there can be a linear dependence, called autocorrelations with lag k, which can be tested with an autocorrelation function. The data summarized as days has significant noise, which makes timeseries analysis with this data inaccurate; thus, it will not be assessed at the daily level. With the Box-Pierce and Ljung-Box test, based on an autocorrelation function (ACF), the data can be tested as to whether the observations can be treated as independent variables or not. If they are independent, special time series analysis is not necessary. Box-Pierce and Ljung-Box tests were performed with a 95% confidence level throughout this thesis (Groß, 2010).

A regression model investigates the relationship between an independent (predictor) and dependent variable (target) and is a predictive modelling technique. It can give valuable information about modeling, time series, and forecasting. If the Box-Pierce and Ljung-Box tests confirms independence of observations, a simple regression model could be applied, such as a linear regression model. If this is not the case an autoregression (AR) model needs to be applied, it regresses on a linear combination of previous values to forecast. AR models can give very good forecasting for shorter terms,

for longer term forecasting in can be inaccurate (Groß, 2010; Pennsylvania State University, n.d.; Ray, 2015).

The analyzed data summarized in months is non-stationary because the mean value from the given data is changing over time; tested with Augmented Dickey-Fuller test "$adf.test()$" in R ($p = 0.08977$; fail to reject H_0; thus, the data is non-stationary). An ARIMA (autoregressive integrated moving-average) model can be fitted on non-stationary data; otherwise an ARMA model works with stationary data. In a ARIMA model tree values (p, d, q) must be chosen wisely to get the best fit for the model. If there is an upwards or downwards trend in the data noticeable, which is given in the dataset, an ARIMA $(p, 1, q)$ model can be used. An alternative would be differencing the data first and using an ARMA (p, q) model or ARIMA $(p, 0, q)$ model. The AR-coefficient (p) (order of autoregressive terms) and the MA-coefficient (q) (number of lags on the MA component) can be achieved with computing the maximum likelihood estimators with the ACF and the PACF (partial autocorrelative-function) (Brockwell & Davis, 2002; Groß, 2010).

To find values (p, q) which could give a good fit the ACF and PACF of the given time series can be plotted; this study performed it in R. The procedure performed for ARMA (p, q) models which is stationary data, with differencing non-stationary data can become stationary which is done prior plotting ACF and PACF. An alternative to this procedure is the R function "$auto.arima()$" which shows the probably most suitable model (Brockwell & Davis, 2002; Groß, 2010).

After that the models with good fit can be tested with the R-function "$Arima()$". The model with the smallest AIC (Akaike Information Criterion) is the preferred model,

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the AIC is a measure of quality for the fit of a model in the maximum likelihood principle. An ARIMA $(p, 1, q)$ model works with differenced data, to reveal the trend again, the drift can be included, this can also improve the AIC value. After that the fit with the chosen model can be proofed visually with the R function "$tsdiag()$". The standardized residuals should look kind of like white noise; in the ACF of residuals there should be no value be over the blue dotted line after lag 0; the p-values for Ljung-Box statistics should be over the blue line. If all these conditions are fulfilled the model has a good fit (Brockwell & Davis, 2002; Groß, 2010).

If a good fitting model is found the values can be predicted with the R function "$predict()$", the periods (in this case number of month) which should be predicted ahead can be chosen. Also, the forecasting can be visualized with the function "$plot(forecasting())$", the number of periods ahead can be chosen and if all data should be included.

For seasonal forecasting a SARIMA (seasonal ARIMA) can be applied. A periodic seasonal pattern has to be noticeable which is in correlation with a constant time period s, this is not the case in the given dataset. Otherwise a SARIMA $(p, d, q)X (P, D, Q)_s$ model could have been applied (Groß, 2010).

CHAPTER 4 – Results & Discussion

This chapter seeks to answer the research questions from Chapter 1. All the findings are out of the provided dataset of 50 public Level-2 stations and analyzed with the mentioned tools in Chapter 3. The fee operated charging stations are within the data but will be part of some additional analysis.

4.1 GENERAL USAGE OF CHARGING STATIONS

This section focuses on answering *Research Questions 1: (a)* How are charging stations being utilized and *(b)* how frequently? *(c)* Since parking is a valuable commodity, are EV users using charging stations as parking spots?

This section provides an overview about the RI data in general and compares it to nationwide trends. Firstly, all the energy savings (i.e., energy used, greenhouse gas [GHG] savings, and gasoline savings) and time factors (i.e., duration plugged in, charging time, and parked after fully charged) are examined with descriptive statistics for all the charging stations. Table 1 shows the mean value, the standard deviation (SD), the minimal value (Min), the maximal value (Max) and the total of all charging events. The measured factors are the energy consumption of the charging events in kilowatt-hours (kWh), GHG savings in kilograms (kg) due to the gasoline savings in gallons, and the total duration that the vehicles have been plugged in at the station. In addition, the actual charging time and the time an EV driver parked at the charging spot after they were fully charged is also measured and documented in common time format. The RI charging stations total use has saved the emissions from around 64 ICE passenger

vehicles driven for 1-year since their installation (US Environmental Protection Agency, 2017).

A notable finding is that the mean charging time almost equals the mean parking time. In earlier studies on charging behavior, users were spending only about 10% of the time for charging out of the total time plugged into a charging station, while in our dataset the mean charging time was very similar (1:55:52) (Speidel & Bräunl, 2014). This could show a shift of usage trends; this will be explored later.

Table 1: Descriptive statistics about measured charging factors

Type	Units	Mean	SD	Min	Max	Total
Energy Used	kWh	7.125	7.380	0	99.843	268,045.200
GHG Savings	kg	2.993	3.100	0	41.934	112,580.500
Gasoline Savings	gallons	0.894	0.926	0	12.530	33,639.640
Total Duration Plugged In	hh:mm:ss	03:41:26	03:38:17	00:00:00	23:58:55	15 years 194 days 03:24:08
Charging Time	hh:mm:ss	01:54:00	01:29:27	00:00:00	14:51:02	7 years 363 days 12:19:02
Parked After Fully Charged	hh:mm:ss	01:47:26	03:00:57	00:00:00	23:11:47	7 years 195 days 15:05:06

The 50 charging stations observed different frequencies of use. Figure 7 illustrates the sum of the charging events (CE), sum of total duration (TD), and sum of charging time (CT) as percent of their corresponding totals occurring in 2017. It is notable that all three factors appear to behave similarly with minor alterations, supported by the Spearman Correlation test (H_0: There is no association between the two variables) which demonstrates that there is a significant correlation between all three variables ($p < 0.001$

for all 3 comparisons, reject H_0, there is a correlation between the variables; TD & CT r = 0.883; TD & CE r = 0.695; CT & CE r = 0.893). CT and CE show 96.73% similarity; TD shows major distinctions for three stations but still has 76.75% similarity to the other two variables, from the complete cluster analysis. To avoid multiple redundant iterations, this research will focus on one of these variables (i.e., Charging Events) with additional analysis with the other two variables as needed (i.e., Total Duration and Charging Time).

The two overall most used stations are in Providence industrial districts, whereas the two least used are in Open Space District in Charlestown and in Commercial District in Warwick.
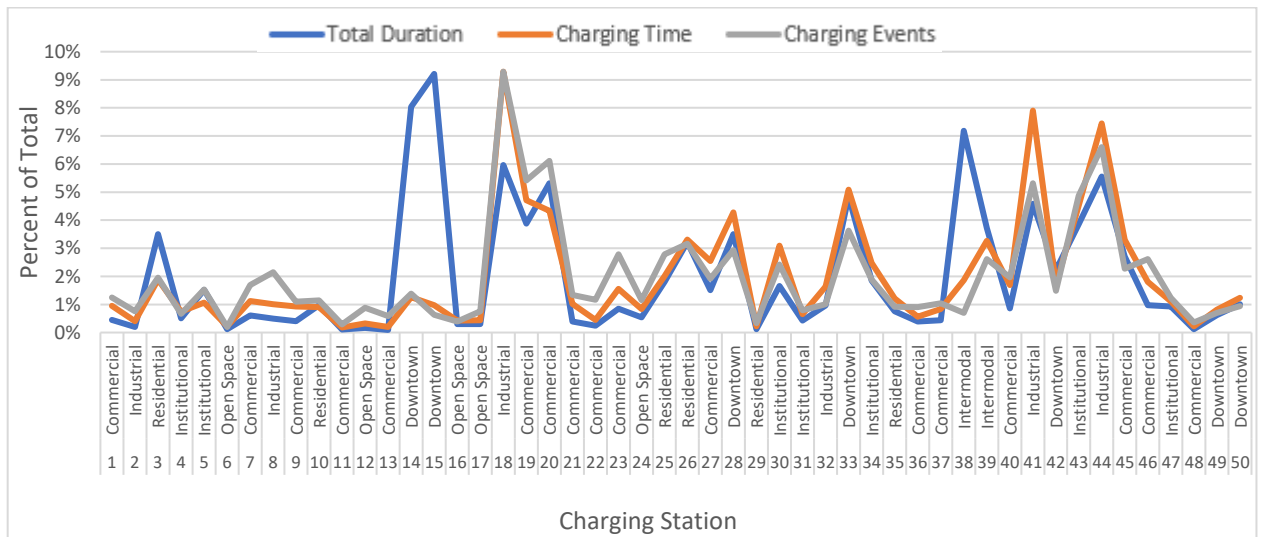

Figure 8: Percent of total charging per station in 2017

The total duration is classified at the time the vehicle is plugged in during a charging event. Figure 9 shows the total duration divided by the total time installed the year 2017, except for stations 24, 37, 49 and 50 which were newly implemented in 2017. A charging station could be occupied 100% of the time but based on the lack of charging traditionally from 11pm to 5am a realistic utilization per charging station is 75% (Figure 9 station 37). Only three stations have a utilization over 50% (Figure 9 gray line)., with the maximum being stations 37 at 78.32% of the time. The median utilization is 6.40% (Figure 9 light blue line), the mean utilization 15.57% (Figure 9 light green line) (Standard Deviation 17.89%); concluding that the majority of RI charging stations are not frequently utilized to their potential.
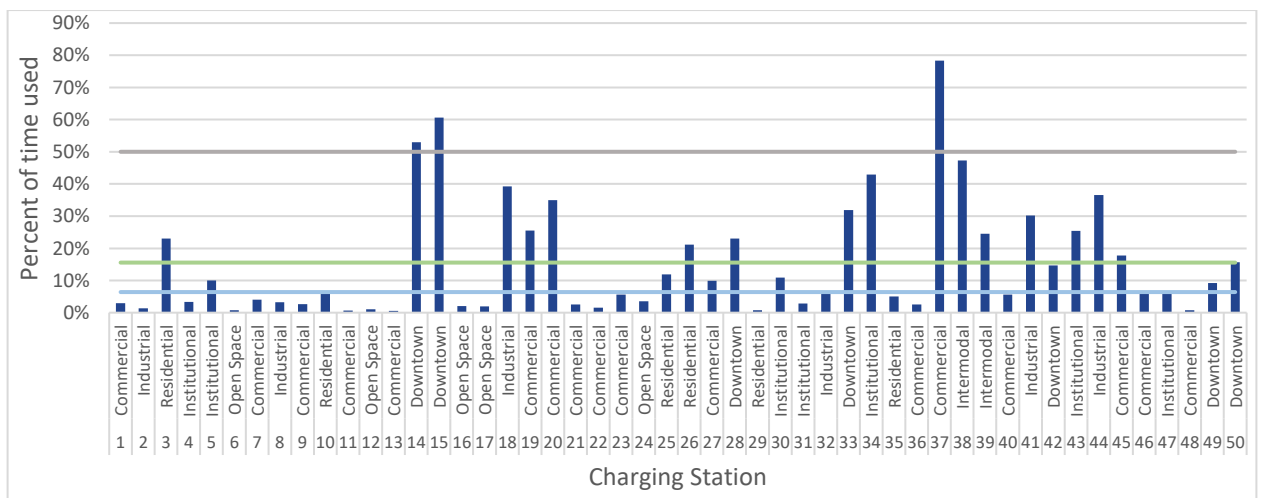
Figure 9: Percent of time charging stations are utilized

The Pareto Principle, also known as the 80-20 Rule, states that 80% of effects come from 20% of their causes. Applied to this case it would imply that 80% of the charging events are done at the 20% most popular charging stations. This principle is not represented in this data set. 20% of the most used stations were responsible for 48% of all charging events, 56% of the total plug in time, and 55% of the total charging time.

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The RI charging stations are distributed across 20 different cities, seven functional areas, and five different counties. The map in Figure 10 shows exactly where each charging stations is located (dot) with the color representing the count of charging events in 2017. There is a noticeable higher density of charging stations around Providence (longitude 41.8, latitude 71.42) than the rest of the state; which makes sense based on Providence's status as the state's capitol and only metropolitan area.
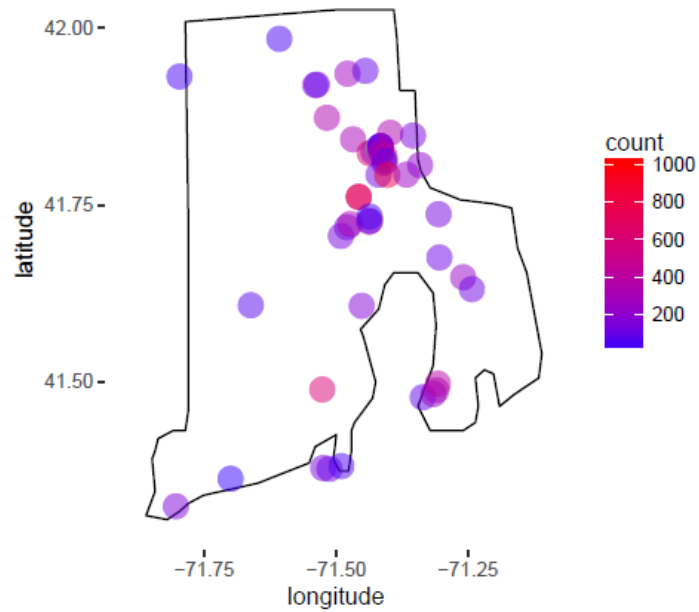
Figure 10: RI map with charging station locations and amount of charges

EV drivers using RI charging stations come from several different locations around the country. Figure 11a shows a U.S. map indicating the area corresponding with the zip code of the registered users and the quantity of charging events they did at the 50 RI charging stations. Most of the more frequent users are from RI and nearby New England states, as visible in the zoomed in map in Figure 11b.

Figure 11: (a: top) U.S. map of users of RI charging stations (b: bottom) New

England and Mid-Atlantic map of users of RI charging stations

In 2017, there are 429 users from RI this are 0.0405% of the RI population is using RI charging stations. This does not fit together, with the number of registered EVs in 2016 where 362 BEV (0.04% market share) and 835 PHEVs (0.09% registered) (Auto Alliance, 2016). But in 2016 there were 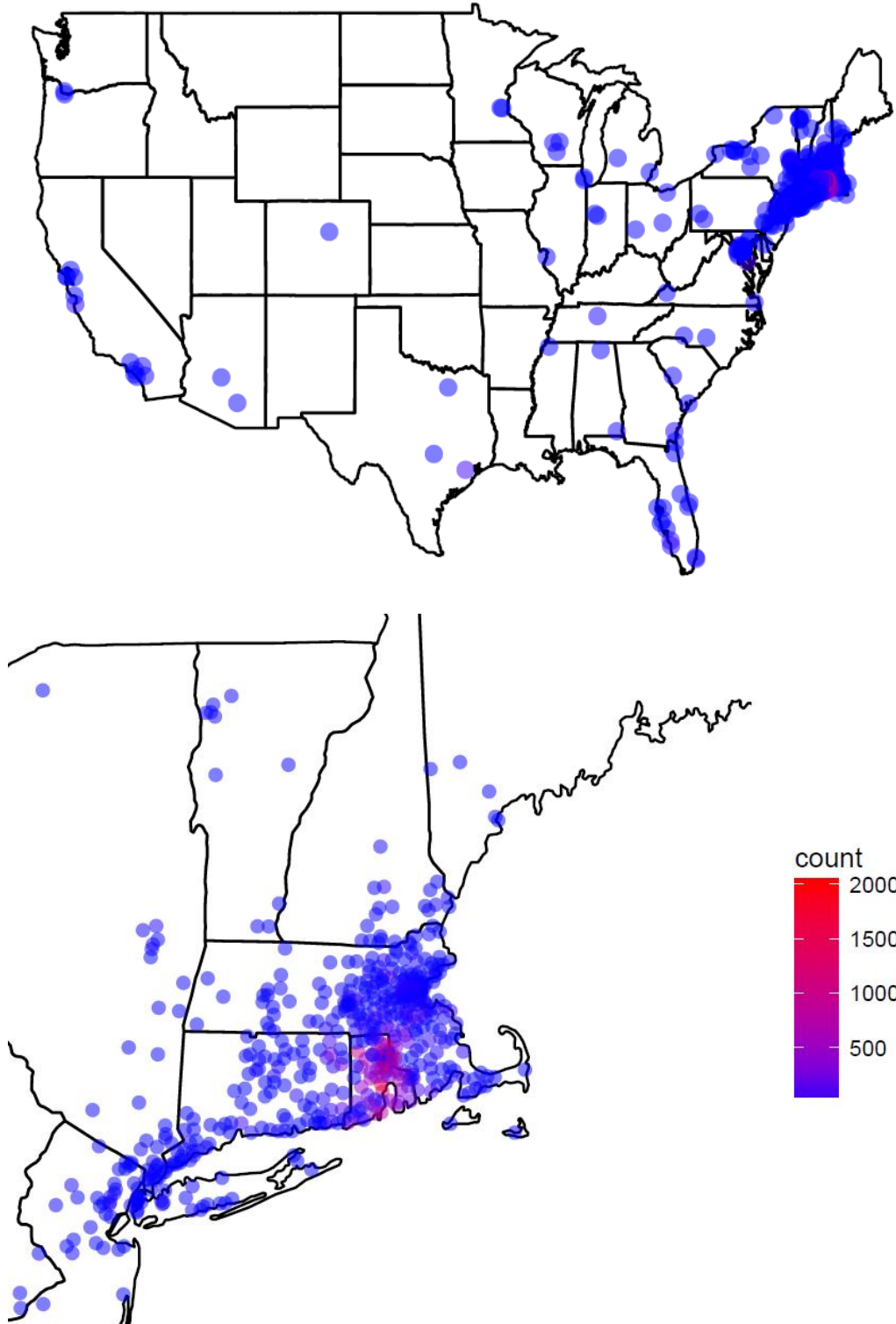only 295 users from RI charging at RI charging stations. That implies that not even a fourth of EVs driver have used RI charging stations in 2016.

In 57% of the charging events, users in RI are leaving the charging station within 30 minutes after they are fully charged. This is not unusual since ChargePoint, the webservice for these chargers, sends users a request to leave within 30-minutes post fully charged. However, there are no further consequences of leaving cars at the station beyond scheduled, repeated warnings. The other 43% of the charging events pertain to users staying more than 30 minutes after their EV is fully charged and using the charging spots as traditional parking spots.

Is the charging behavior the same for stations with fees? Only three of the observed charging stations charge fees: one station charges $0.10/kWh (the fifth most frequently used station) and the other two stations are free for the first 4-hours with a $1/hr charge onwards (third and fourth frequently used charging stations). To answer whether the duration of parking time on charging stations vary based on the price of charging, a hypothesis was tested using test of two proportions (H_0: The variables are not significantly different).

Null hypothesis (H_0) is that the station is not significantly different. One station in an industrial area charges $0.1/kWh, it is expected the station is not significantly different to the others since they do not pay anymore after they are fully charged since

58% of the users at this station leave within 30 min and 42% stay longer. This station is not significantly different to the general non-fee use; with a p-value of 0.5, it fails to reject the H_0 hypothesis.

The other two stations are in a commercial area located next to each other, the first 4-hours are free and after that the charge is \$1/hr. As expected, this cost model appears to prevent users from occupying the station for too long. At these stations 70% and 71% use the charging stations just to charge and 30% and 29% stay longer than 30-minutes after they are fully charged. This is better than the other stations, but it could also be due to the area in which the stations are located. With an p-value under 0.001 for both tested, this rejects the H_0 hypothesis for the stations with a \$1/hr fee after the fourth hour, they are significantly different from the general use non-fee chargers. These two stations are not significantly different to each other ($p = 0.55$), but the they are significantly different to the other payed station with \$0.1/kWh ($p < 0.001$ for both).

It was found that one charging station with fee is used like they are generally used in RI. The other two charging stations with a different fee model (fee after 4-hours) behave differently. But that is not necessarily only due to the fee, it can also be due to the functional area in which the charging stations are located. To test if this is the reason for the different behavior, further analysis will be made in Chapter 4.2.1.

4.2 USAGE WITH LOCATIONS AS A FACTOR

The location seems to have strong impact on the user behavior at charging stations. In this section discusses *Research Question 2:* Does the type of areas in which the charging stations are located influence the patterns of charging behavior?

4.2.1 FUNCTIONAL AREAS

A map was created to get an idea where the charging stations are located and their functional areas. The RI map in Figure 12 shows each of the 50 charging stations as dots, colored according to their area type and their size representing how many charging events occurred in 2017.
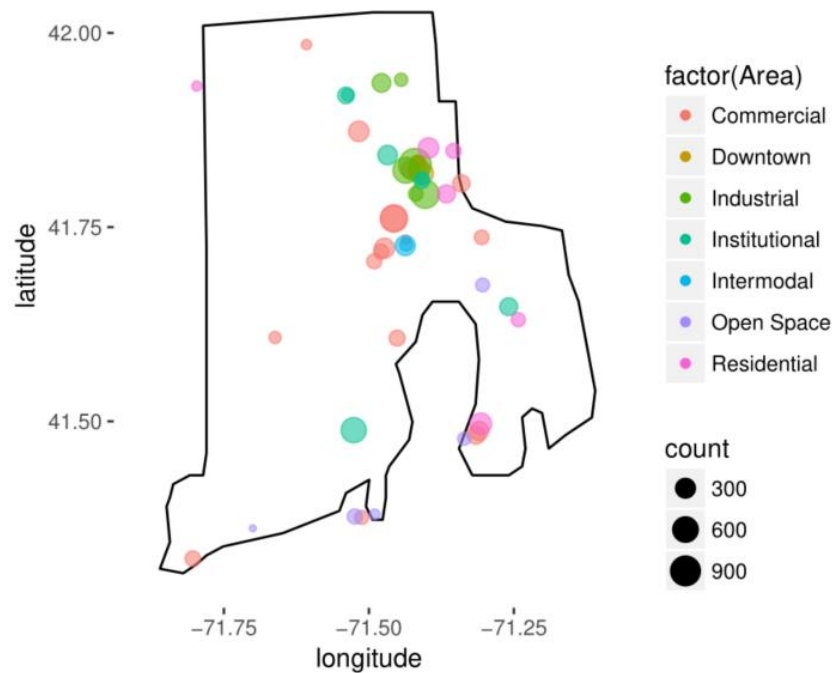

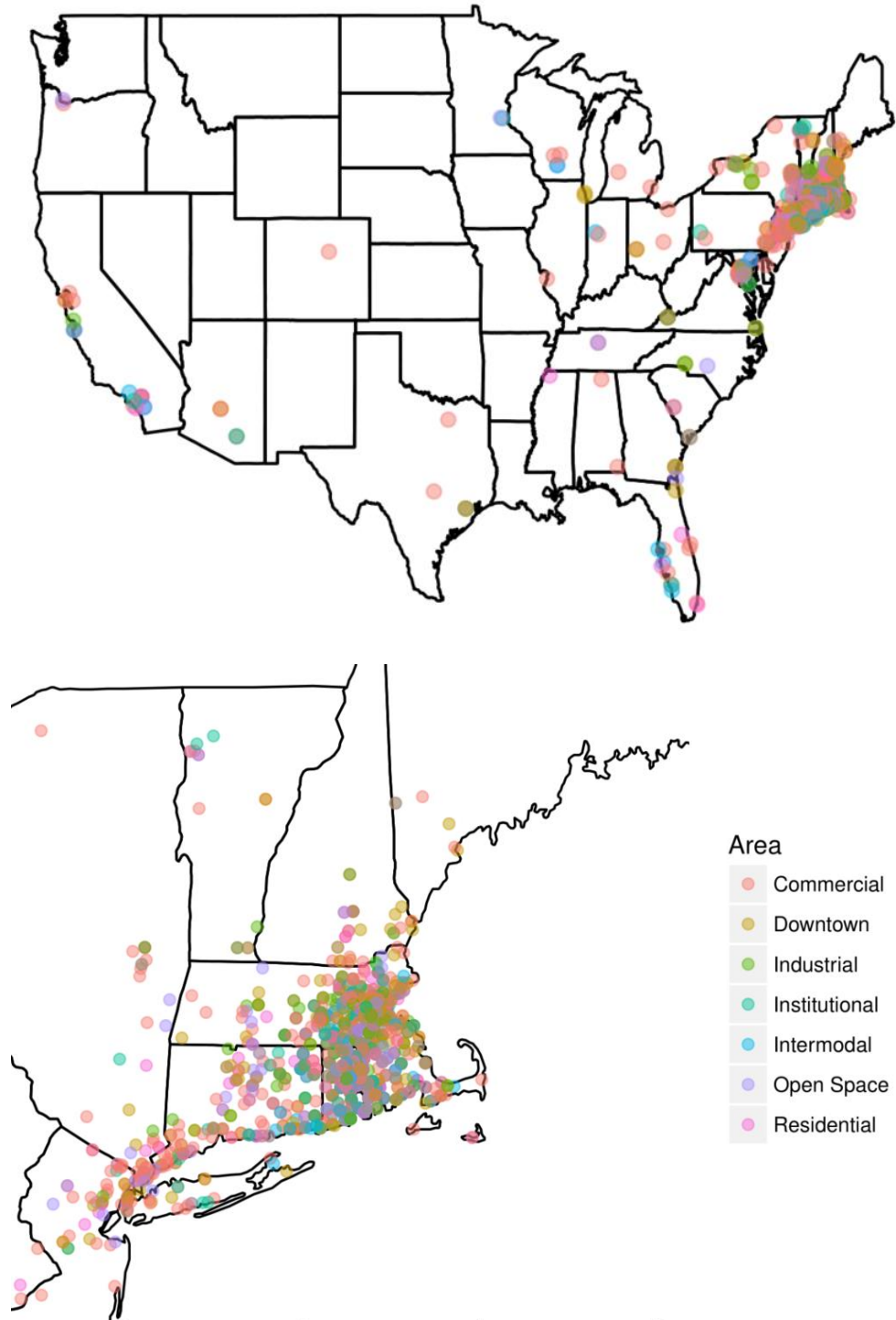Figure 12: RI map with charging station locations and classified areas

Figure 13: (a: top) U.S. map of users of RI charging stations colored in functional areas (b: bottom) New England and Mid-Atlantic map of users of RI charging stations colored in functional areas

Is there a connection between a charging station's area and geographical origin of the user? To investigate this, the U.S. map plotted in Figure 13a with the zip codes of the registered users of the charging stations represented by dots colored to indicate the functional area in which they have been charging. As noticeable in the Figure 13a&b, there is no pattern recognizable, no connection between these two factors can be drawn.

There are 17 charging stations located in commercial districts, 7 charging stations in downtown districts, 6 stations in industrial districts, 7 stations in institutional districts, 2 charging station in intermodal districts, 5 charging stations in open space districts, and 6 charging stations in residential districts. Figure 14 compares the amount of charging stations in certain areas and charging. The noticeable differences are that industrial areas seem to be more popular as there are more charging events (Figure 14b) per station (Figure 14a), and open space areas seem to be less popular with less charging events (Figure 14b) per station (Figure 14a) as in the other areas; all other areas seemed to be relatively balanced.
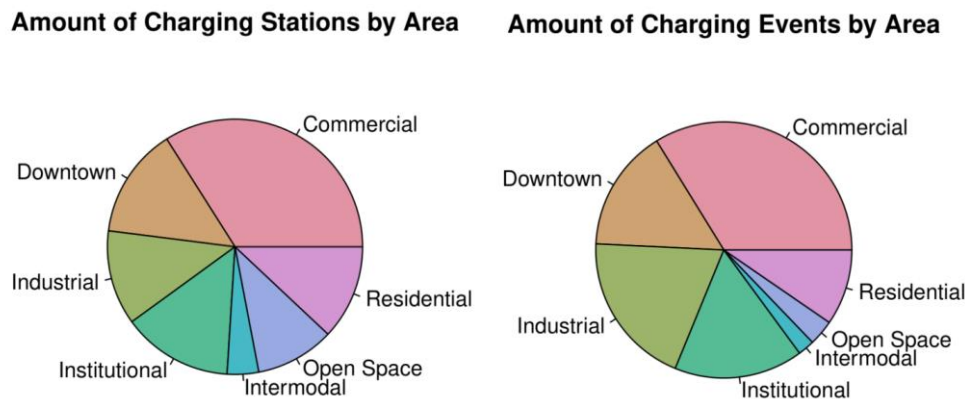
Figure 14: (a: left) Amount of Charging Stations by functional area (b: right) Amount of Charging Events by functional area

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Taking a closer look at the single stations in the certain areas, see Figure 15, one can see in which type of area the more popular, and less popular stations are located. But each area has more and less used stations; what does this implies for the stations over all?
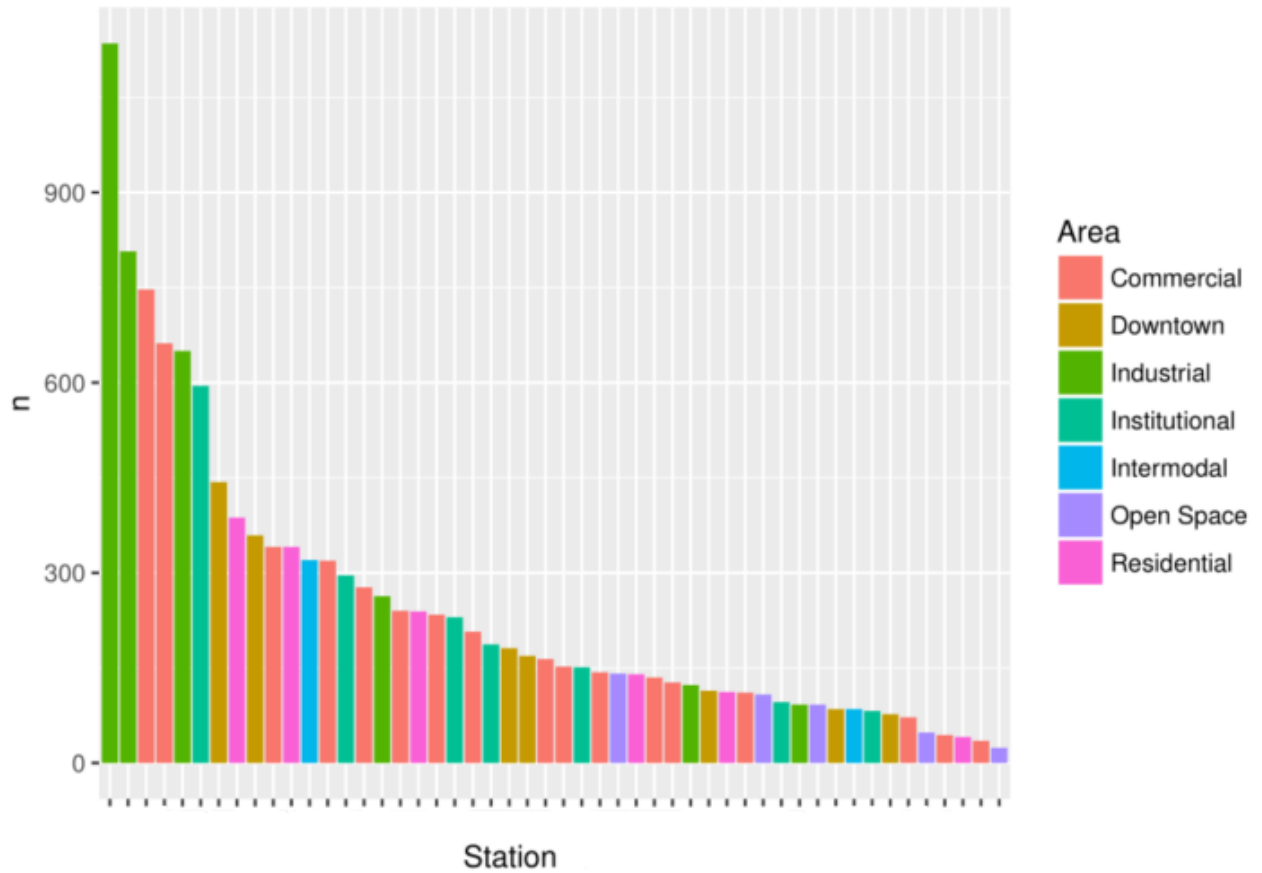
Figure 15: Amount of charges (n) per station colored in area type

In the next step the areas are visualized as box-plots (Figure 16). It is noticeable that the highest median use of single charging station is at industrial areas, followed by downtown areas, institutional areas, commercial areas, residential areas, intermodal areas, and finally open and public space areas. In the charging stations located in industrial and institutional districts are respectively one charging station that is extraordinary heavily used, marked as an outlier. Comparing the functional areas with a Kruskal-Wallis Test (H_0: The samples [groups] are from identical populations), they are not significantly different to each other ($p = 0.2204$; fail to reject Null hypothesis [H_0]; they are from identical population).

Figure 16: Box-plot about the amount of charges (n) by functional area

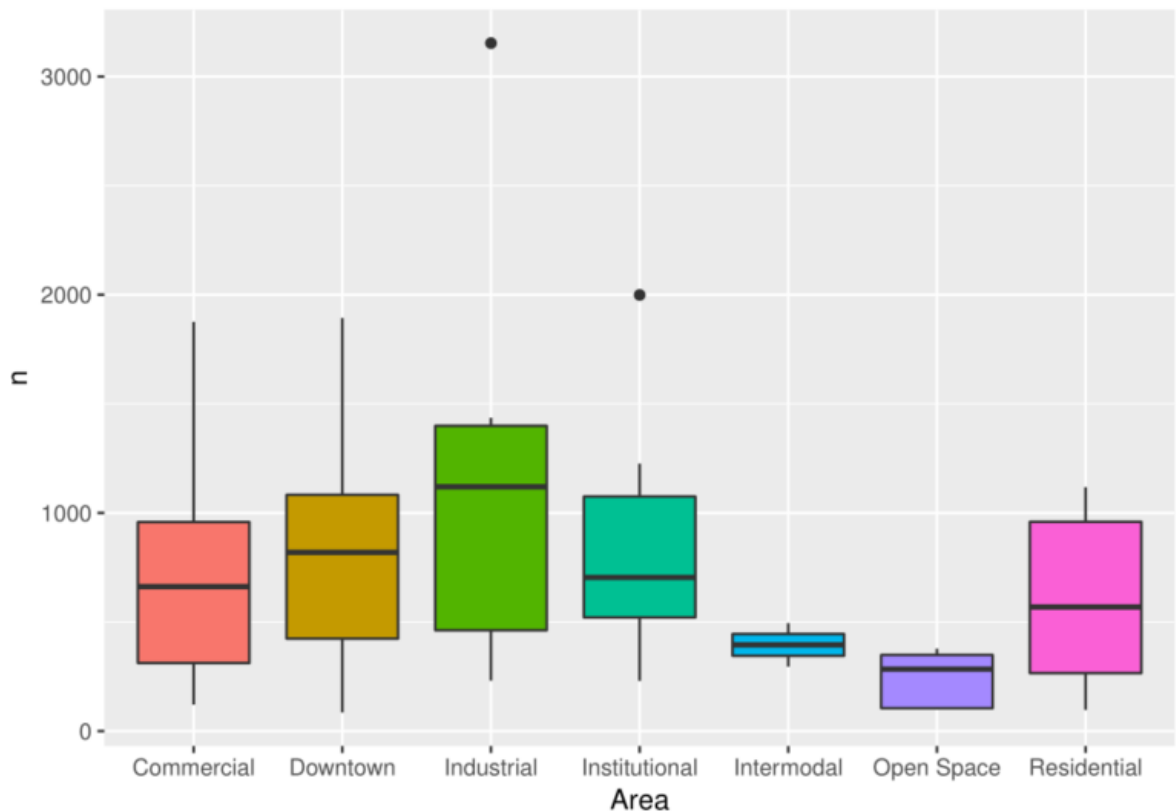In Table 2 are descriptive statistics about the total duration of charging events, charging times, and amount of charges per station in functional areas. The mean value, the standard deviation, and the maximum value are given; no minimum value is shared since it is always zero. It is quite notable that these values vary drastically between functional areas.

Table 2: Descriptive statistics of functional areas

Factor	Area	Mean	SD	Max
Total Duration [hh:mm:ss]	Commercial	02:26:37	02:56:32	23:53:28
	Downtown	06:08:59	04:29:00	23:54:59
	Industrial	03:27:03	03:14:50	23:58:55
	Institutional	04:12:04	03:05:40	20:10:44
	Intermodal	04:26:45	04:31:55	23:03:54
	Open Space	02:05:05	02:52:45	20:03:21
	Residential	04:28:00	03:50:36	23:51:42
Charging time [hh:mm:ss]	Commercial	01:37:55	01:24:43	14:51:02
	Downtown	02:15:30	01:43:37	14:36:27
	Industrial	02:06:07	01:28:31	14:19:15
	Institutional	01:58:12	01:13:42	11:40:10
	Intermodal	01:54:05	01:46:44	13:56:26
	Open Space	01:28:42	01:39:01	13:39:14
	Residential	01:55:21	01:30:59	12:27:25
Amount of charges per station	Commercial	235.8824	197.7704	747
	Downtown	204.0000	142.1795	443
	Industrial	511.6667	420.4567	1135
	Institutional	233.8571	175.7967	595
	Intermodal	202.5000	166.1701	320
	Open Space	82.6000	46.8380	141
	Residential	210.0000	135.9382	387

When comparing those results from Table 3 with the results from Chapter 4.1, it is noticeable that the stations which charge a fee, fits into the patterns of the functional areas in which they are located in. The hypothesis tested two proportions, H_0: The variables are not significantly different. At the station with a fee in an industrial area

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which charges \$0.1/kWh, 58% of the users at this station leave within 30-minutes and 42% stay longer. This is not significantly different ($p < 0.001$ with test of two proportion) to the behavior in industrial areas. At the other two fee conditional stations in a commercial area, 70% and 71% use the charging station just to charge and 30% and 29% stay longer than 30min after they are fully charged. At these stations, users park more than usual in commercial areas, but still they are not significantly different ($p < 0.001$ for both with test of two proportion) to the behavior in commercial areas. Overall, charging fees at EV charging stations seems not to influence the charging behavior when considering functional area.

In the cluster dendrogram in Figure 17 paired with Table 3, it is observed that commercial and open space areas are clustered together, hence used similarly. Industrial and intermodal areas are clustered together and eventually clustered together with institutional and residential areas. Therefore industrial, intermodal, institutional, and residential areas are similarly used. The functional area not clustered with less similarity toward the others is the downtown area. The downtown area is used extraordinary often as a parking spot in over 70% of the cases.

Table 3: Usage as charging and parking by functional area

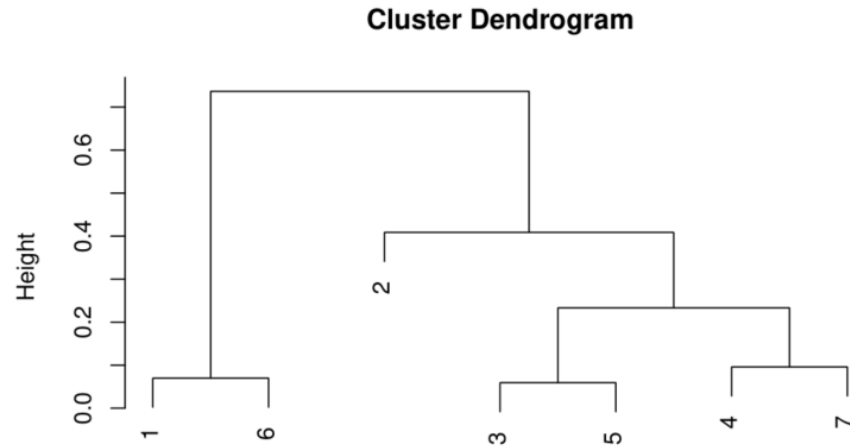| Area	Charging	Parking
1 Commercial	76.46%	23.54%
2 Downtown	29.30%	70.70%
3 Industrial	58.20%	41.80%
4 Institutional	41.70%	58.30%
5 Intermodal	54.01%	45.99%
6 Open Space	81.40%	18.60%
7 Residential	48.49%	51.51%

Cluster Dendrogram

Figure 17: Complete Cluster dendrogram about usage as charging or parking by functional areas

It has been found that the charging behavior and frequency is different in each functional area. However, some of them show similarity to each other. The three stations which charge a fee are not significantly different to the general usage in the area in which they are located, in case of using the charging stations as parking or charging spot.

4.2.2 GEOGRAPHICAL AREAS

In this chapter the focus is on geographical areas, thus the five counties (i.e., Bristol, Kent, Newport, Providence, and Washington) of Rhode Island. Providence County is the largest county in RI with around 637,357 people living there in 2017 and home of the capital City of Providence, and the only county in which the population is continuously growing within the last few years (Cubit Planning, Inc., 2018). Following counties are listed in decreasing population size: Washington County (126,150),

Newport County (83,460), Kent County (63,760), and Bristol County (48,912) (Cubit Planning, Inc., 2018).

The distribution of the various types of charging stations based on functional areas within each county is as follows: Bristol County has three stations: one in open space, one in institutional, and one in commercial areas; Kent County has seven stations: five in commercial and two in intermodal areas; Newport County has five stations: one open space, two in commercial, and two in residential areas; Providence County has 28 stations: six in commercial areas, seven in downtown areas, six in industrial areas, five in institutional areas, and four in residential areas; Washington County has seven stations: three in commercial, three in open space, and one in an institutional areas. Comparing the amount of charging events by county from Figure 18, Providence has the most charging events, percentage wise even more than charging stations. All other counties have percentage wise less charging stations as charging events.
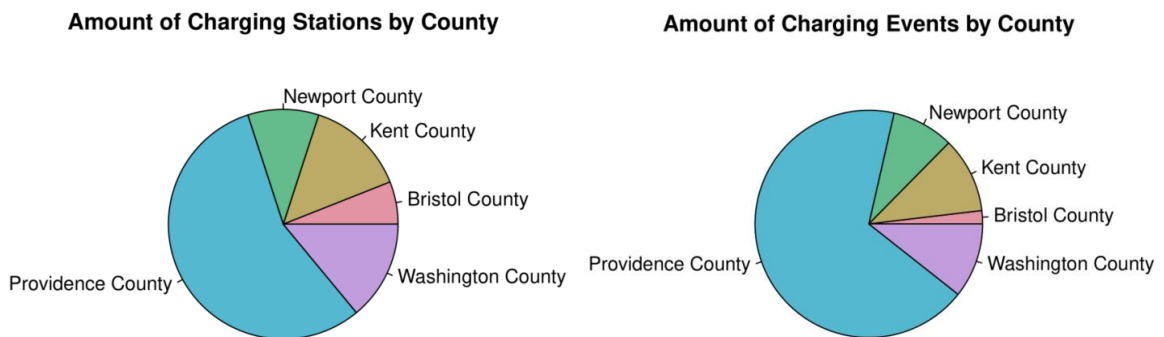

Figure 18: (a: right) Amount of Charging Stations by County (b: left) Amount of Charging Events by County

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Divided in single stations by county, see Figure 19, one can see in which county the most frequently used and least frequently used stations are located. Considering each county has more and less used stations, what does this imply for the stations over all?
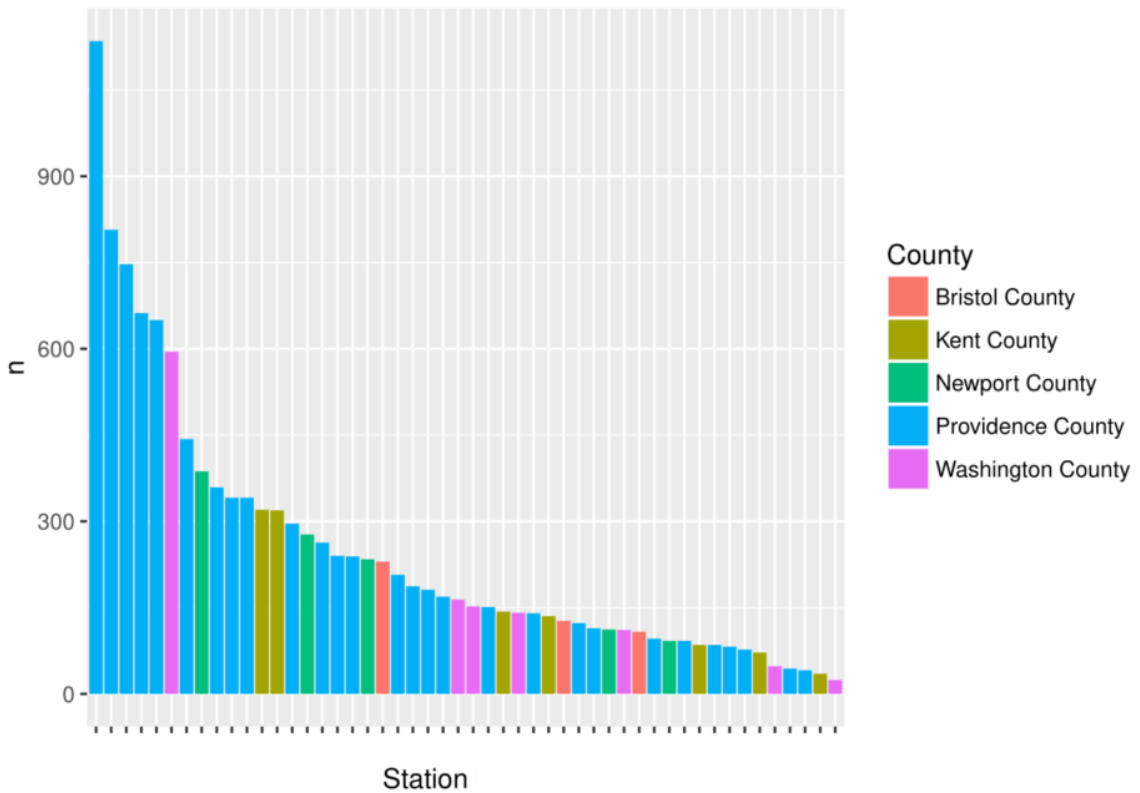

Figure 19: Amount of charges per station colored in different county

Looking at the single stations as box-plots in Figure 20, the highest median use of a single charging station is in Providence County followed by Newport County, Kent County, Washington County, and Bristol County. Providence and Washington County each have one charging station that is extraordinarily heavily used, shown as the outliers in Figure 19. Comparing the geographical areas with a Kruskal-Wallis Test, they are not significantly different to each other ($p = 0.1546$; fail to reject Null hypothesis [H_0]; they are from identical population).
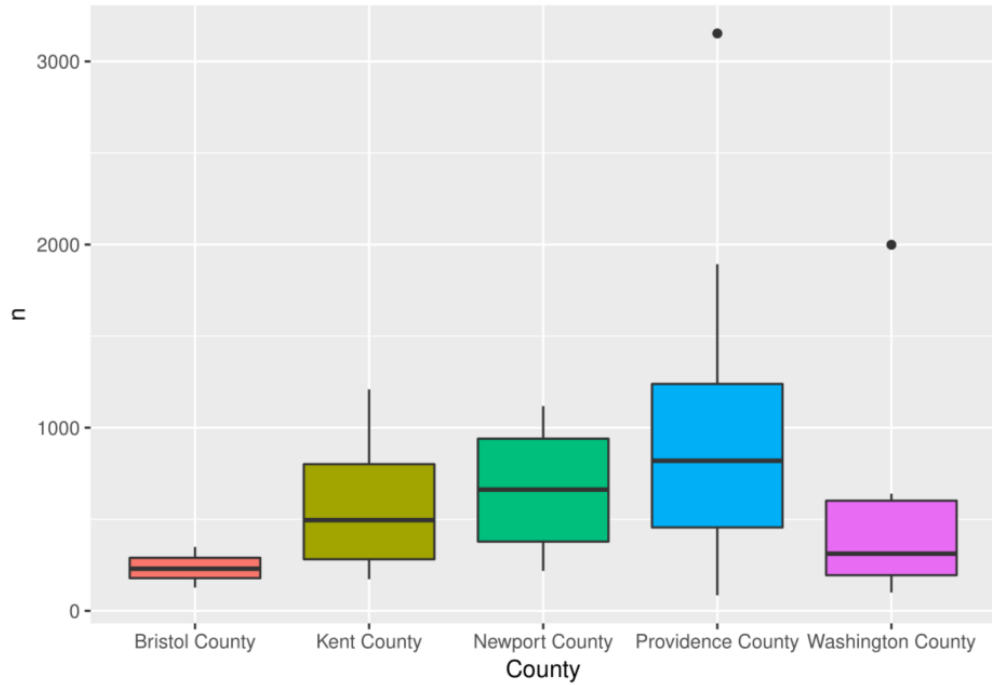
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Figure 20: Box-plot about the amount of charges by county

Further observing about the development of the counties have been made; how different is the EV adoption in each county? To analyze that question, small multiples of RI with its counties were plotted, in which the color changes depend on the amount of charges per year (Figure 21). Of course, Providence County has the most charging events, as already previously established in Figure 18. Yet, regardless of county, RI shows a continuous growth over the last five years with respect to EV adoption.
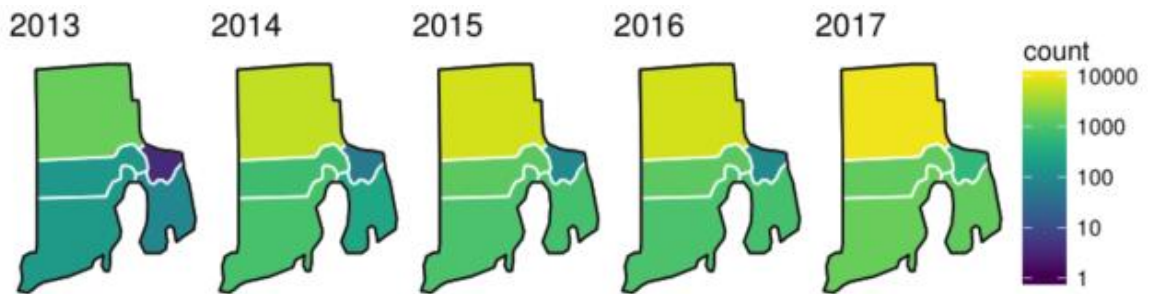

Figure 21: Amount of charging events done in each county over the years

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But, how much is the number of users from each county changing? To answer this question, the number of users from each county is divided by the population and visualized in Figure 22. It is noticeable that in all counties, the number of EV users per population is growing. The slowest growth is in Providence and Kent Counties, since EVs are still more expensive than ICE vehicles, this could be linked to fact that these two have the lowest median household income in RI (Providence County $50,637, Kent County $65,592). Bristol County shows a really strong growth from 2016 to 2017 (median household income $73,096); also, a good growth but more continuous shows Washington's count (median household income $74,302). Somewhere in between these growth patterns is Newport County with a median household income of $71,347. There are a lot of other factors that could potentially influence EV adoption that would require additional exploration in future work to understand these particular nuances per county.

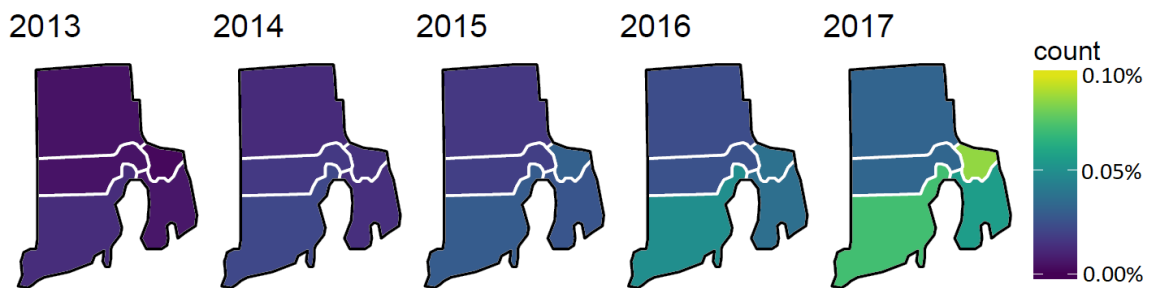Figure 22: Number of users by county normalized by population over year

Figure 21 represents the number of EV charging station users by county normalized for the population, but Figure 23 visually represents how the median number of charging events per user changes over the years. After 2013 there is a decrease in median charging events per user noticeable in all counties except for Kent County, in

which the median amount of charging events increased. Two factors in particular could have influenced this trend; there could be more home charging, or it could be due to better batteries implemented in EVs. (Note: Bristol County is gray in 2013 because there was only one user who did 90 charges this year, the scale was chosen regardless of this behavior to have a better contrast).
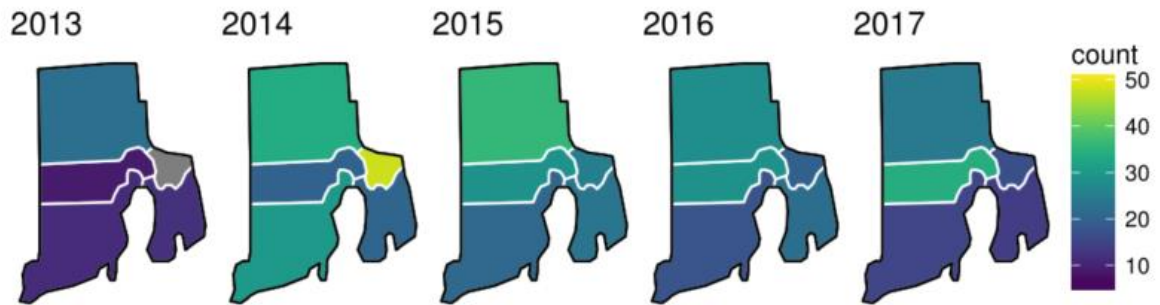
Figure 23: Median number of charging events per user by county over year

The RI counties are different frequently used; Providence County has the highest amount of charges and charging stations, but also the highest population. The amount of user per population form each county varies and follows a different trend as the amount of charges. Overall the charging events per user decreased over the years in all counties except of Kent County.

4.3 TIME DEPENDENT TRENDS

This chapter answers the *Research Questions 3:* What pattern distributions exist, such as *(a)* calendar dependent (i.e., weekly, daily, or hourly), *(b)* seasonality, and *(c)* can they predict future usage trends?

Working with time series requires caution, because they usually are dependent on time. Looking at the number of charging events (n) per day (Figure 24) there is already a trend noticeable, but for working with time series this form is not ideal because there is a lot of noise due to daily variation. Summarizing the data further can be helpful to be less affected by outliers.
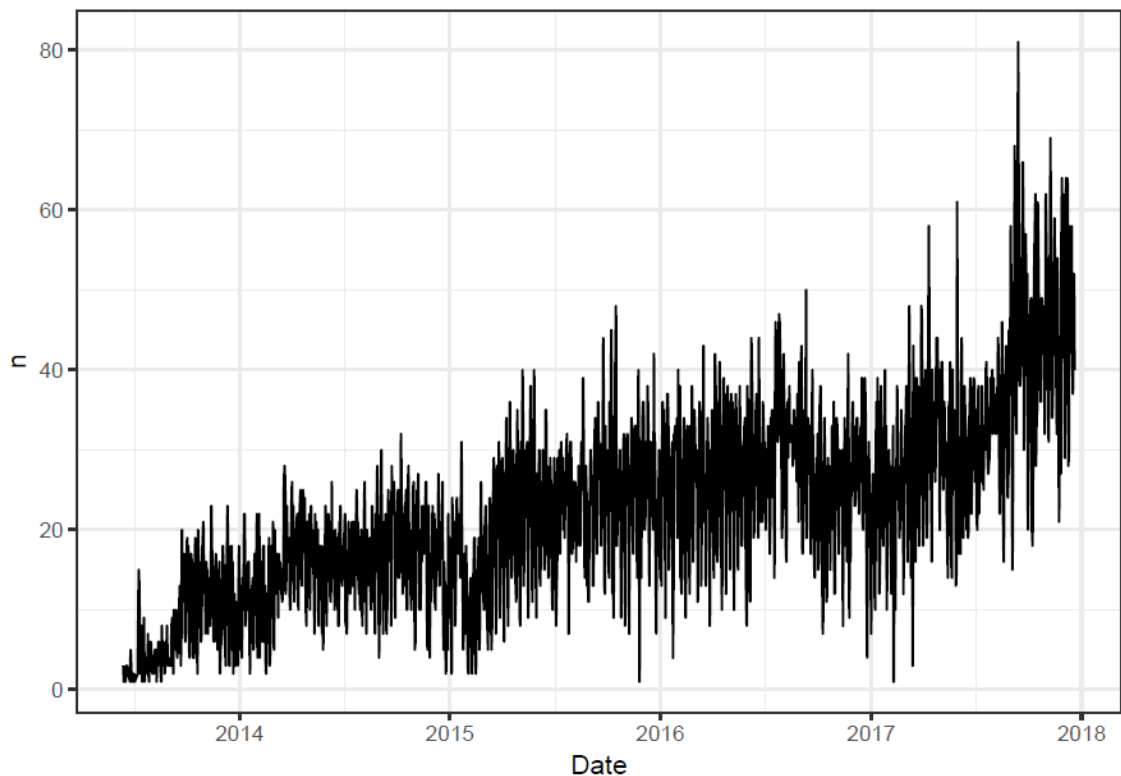
Figure 24: Charging events per day

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The RI charging stations get used mostly from Monday to Friday, less charging events happen on Saturday and Sunday (Figure 25). This conforms with the U.S. wide statistics ChargePoint released 2016 that more charging at public stations occurs during the week and less on the weekends. Yet Rhode Island has percentage wise more charging events during the weekends than the rest of the U.S. this is shown in the ChargePoint statistics (McKerracher, 2016).

Figure 25: Amount of charging events by weekday

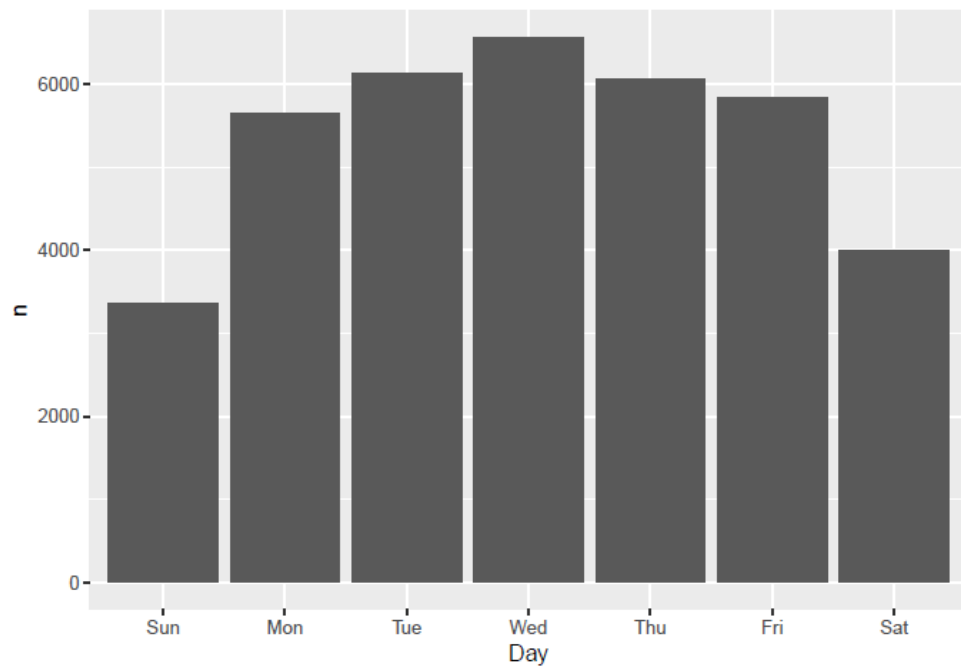To analyze the similarities and differences in functional areas, they have been summarized in weekdays. In Figure 26 you can see how different it looks in the certain areas per weekday. It is noticeable that downtown, industrial, and institutional areas have more charging events from Monday to Friday and less at the weekends, this could be attributed to people working in these districts. Commercial and intermodal areas do not show strong differences between weekends and the rest of the week, people go shopping every day, and also using the airport at any day. Residential areas are more inconsistent, because this is usually the origin of drives. Open space areas show a different pattern, there are more charging events during the weekends compared to other days, possibly because people visiting these areas more often at weekends.
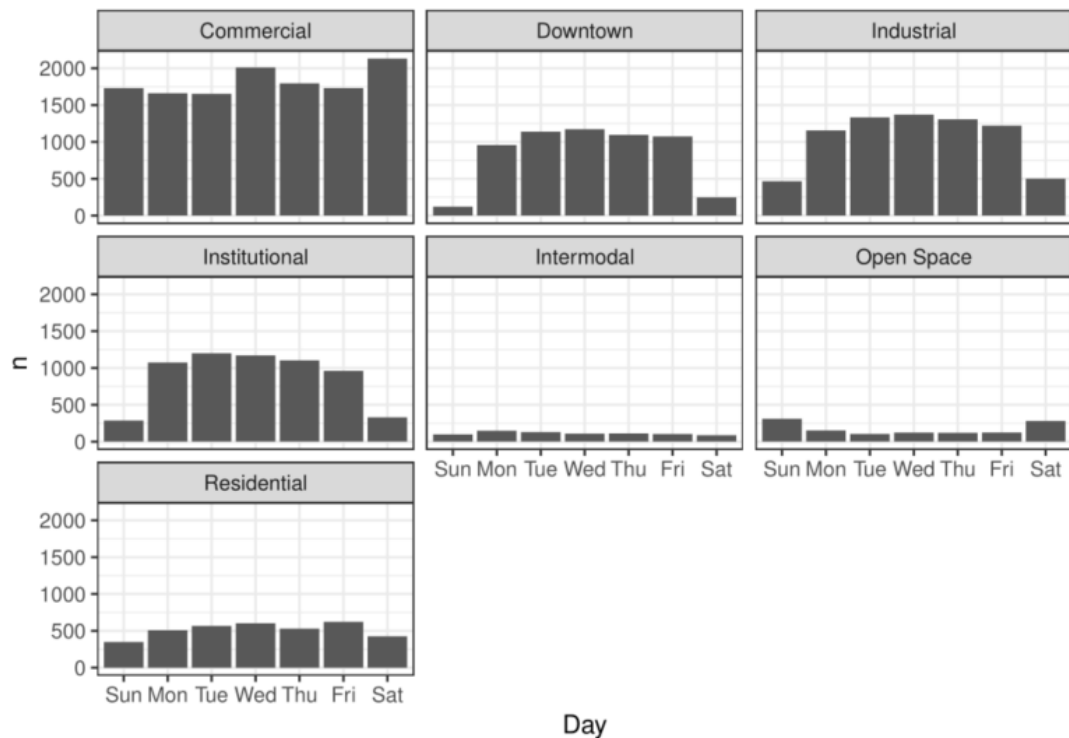
Figure 26: Amount of charging events (n) per day of the week in functional areas

To compare this observation, the correlation of the areas has been verified using clustering (Figure 27). The similarity of downtown, industrial, and institutional areas has been confirmed as having similar weekly patterns of use. Residential areas are 93% similar to these ones as well, intermodal joins this group with a similarity level at 67% similarity. Commercial and open space areas are 66% similar. These clustering are similar to charging versus parking, except for downtown now relates a group.
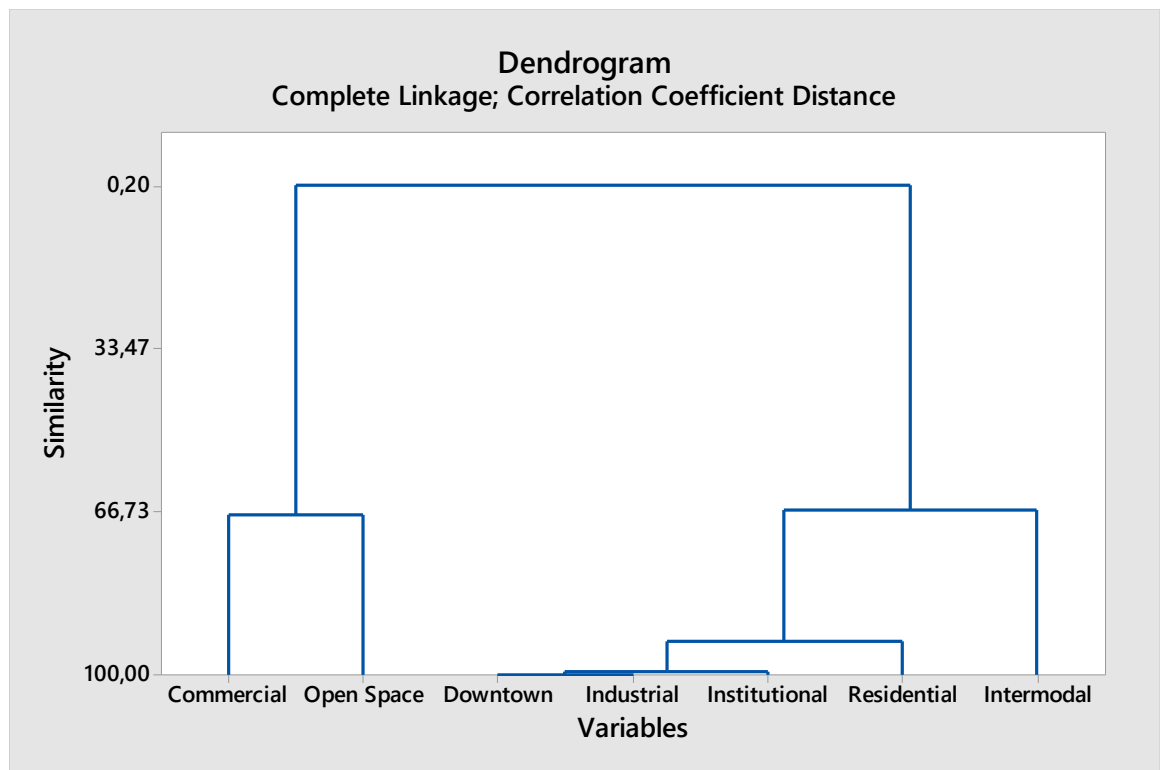
Figure 27: Cluster diagram of charging behavior at weekdays in functional areas

In Figure 28 the amount of charges per weekday is visualized for each county. Kent County, for example, has five commercial stations and two intermodal stations which do not show strong differences between weekdays. Providence County has 18 stations in downtown, industrial or institutional areas, all show less charging events on weekends, six stations in commercial districts that stay more or less the same amount through the weekends and weekdays, the remaining four are in residential areas. The amount of charging events per weekday seems to be strongly dependent on in which functional areas the stations are located over their county.
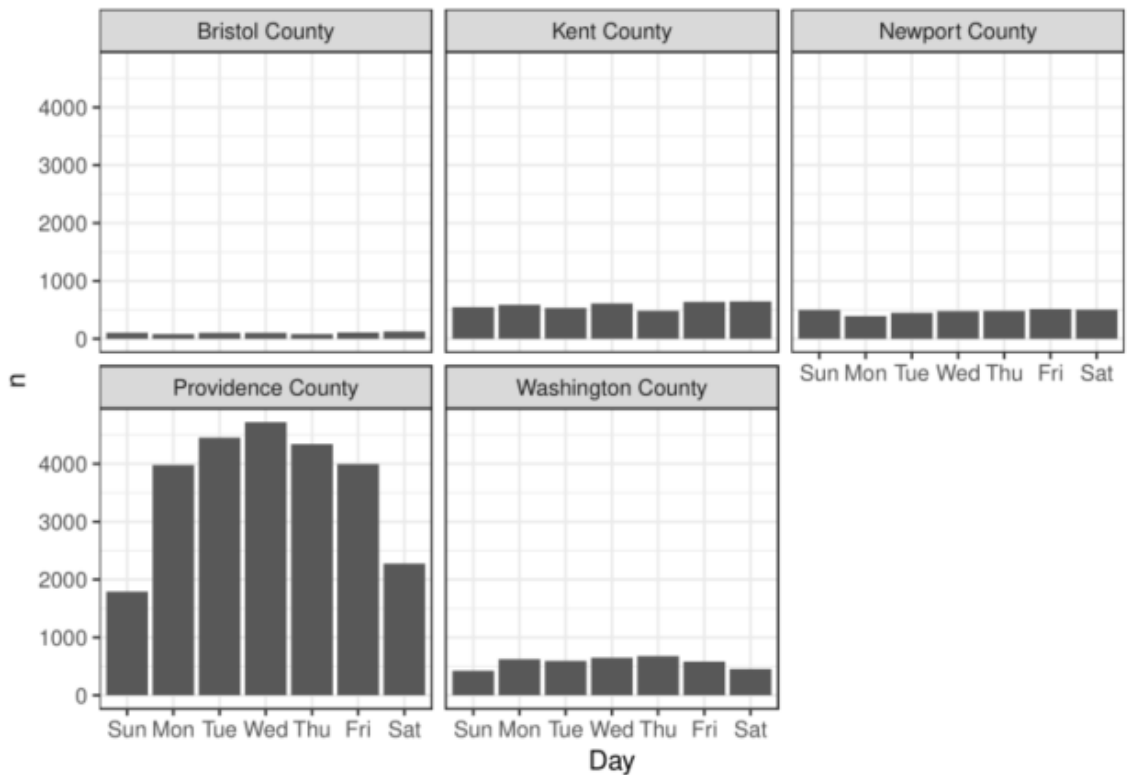
Figure 28: Amount of charging events (n) per day of the week in geographical areas

Charging station users are primarily using the RI charging stations mostly between 7am and 7pm with a peak at 8am (Figure 29). In comparison with the nationwide trends, published from ChargePoint 2016, the usage in RI shows slight differences. The top 8 charging times from 7am to 2pm are very similar, however in RI there is another uptick peak at 5pm where in the rest of the U.S. the amount of charging events is constantly falling from 2pm (McKerracher, 2016). This pattern is similar to that in a study from Australia but 1 hour delayed, peak time at 9am comparing to 8am in RI, after 2pm constantly falling (Speidel & Bräunl, 2014).
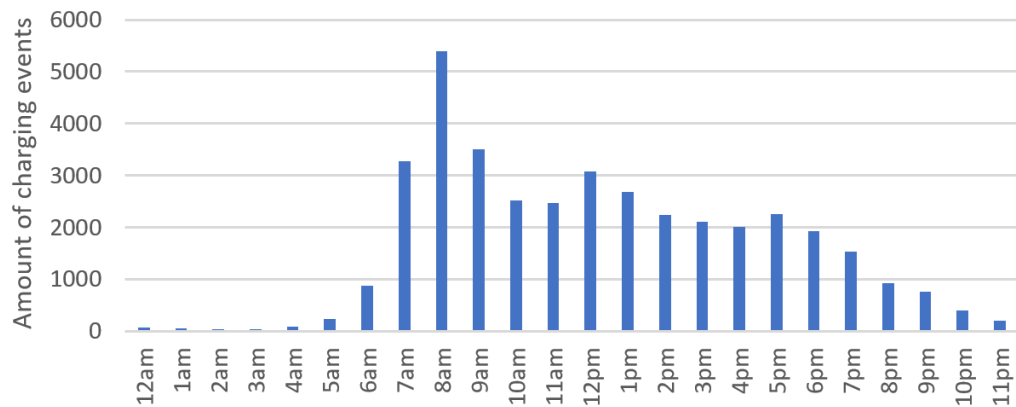
Figure 29: Amount of charging events throughout the day

Now the focus is the number of charging events (n) per hours of the day (Figure 30) for the different functional areas. Downtown areas have their peak time between 7am and 8am in the morning, with lower peaks after lunch time around 2pm and 3pm. Yet industrial and institutional areas follow a similar downtown trend but have another uptick in the evening around 5pm. Commercial, intermodal, and open spaces are more evenly spread during the day. Residential areas do not appear to follow a district pattern.
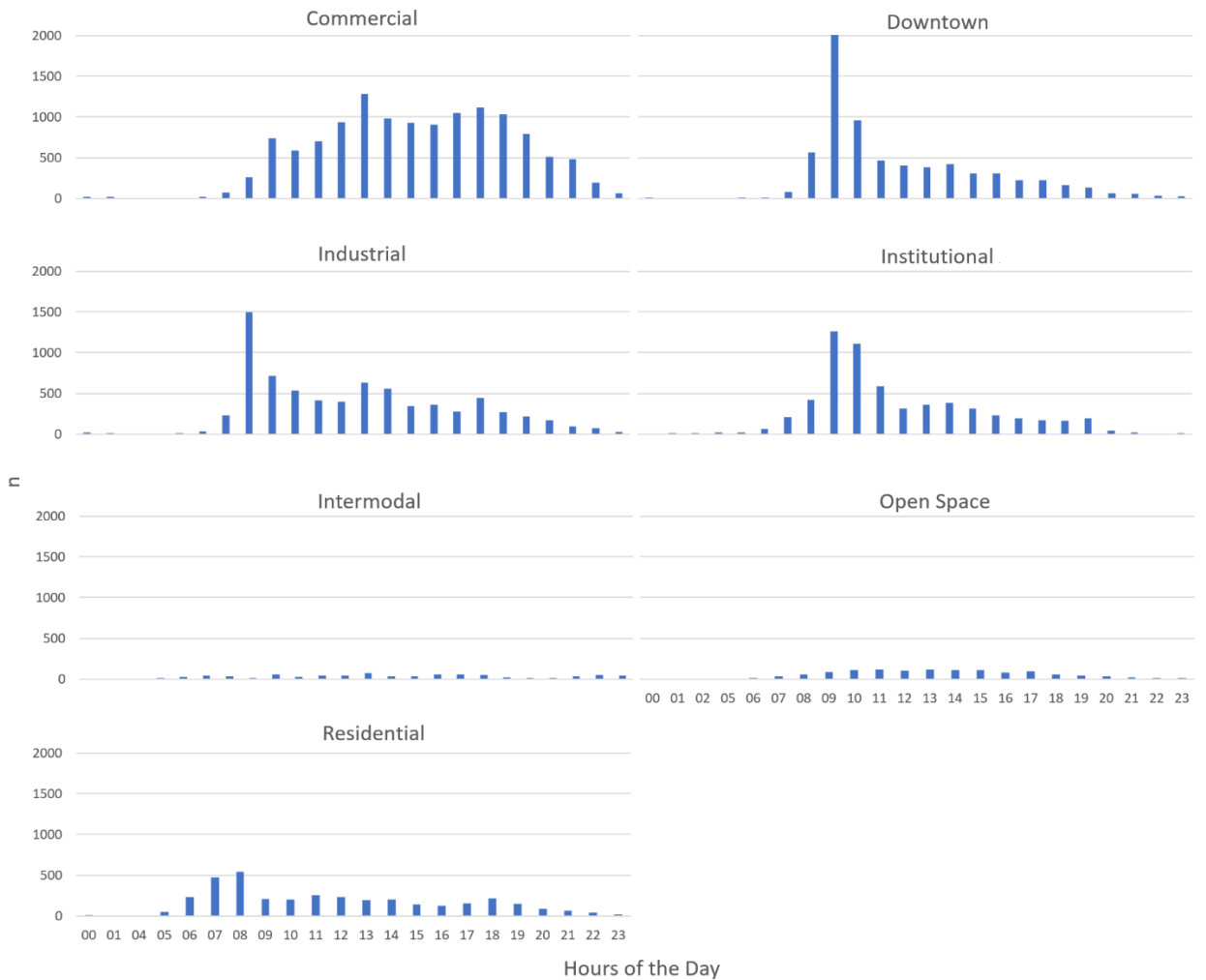
Figure 30: Number of charges by hours of the day in functional areas

The clustering of the functional areas by daytime to validate observations it can be seen in Figure 31's dendrogram. Figure 30 illustrates a strong relationship with 94% between commercial and open space areas, which link with the intermodal area at 76% similarity. Downtown and institutional areas have 97% similarity, industrial and residential areas 94%, this both groups link with 80% similarity. All areas have 61% similarity to each other. These groupings are slightly different than previous clustering groups with intermodal left the larger group to joining commercial and open spaces.
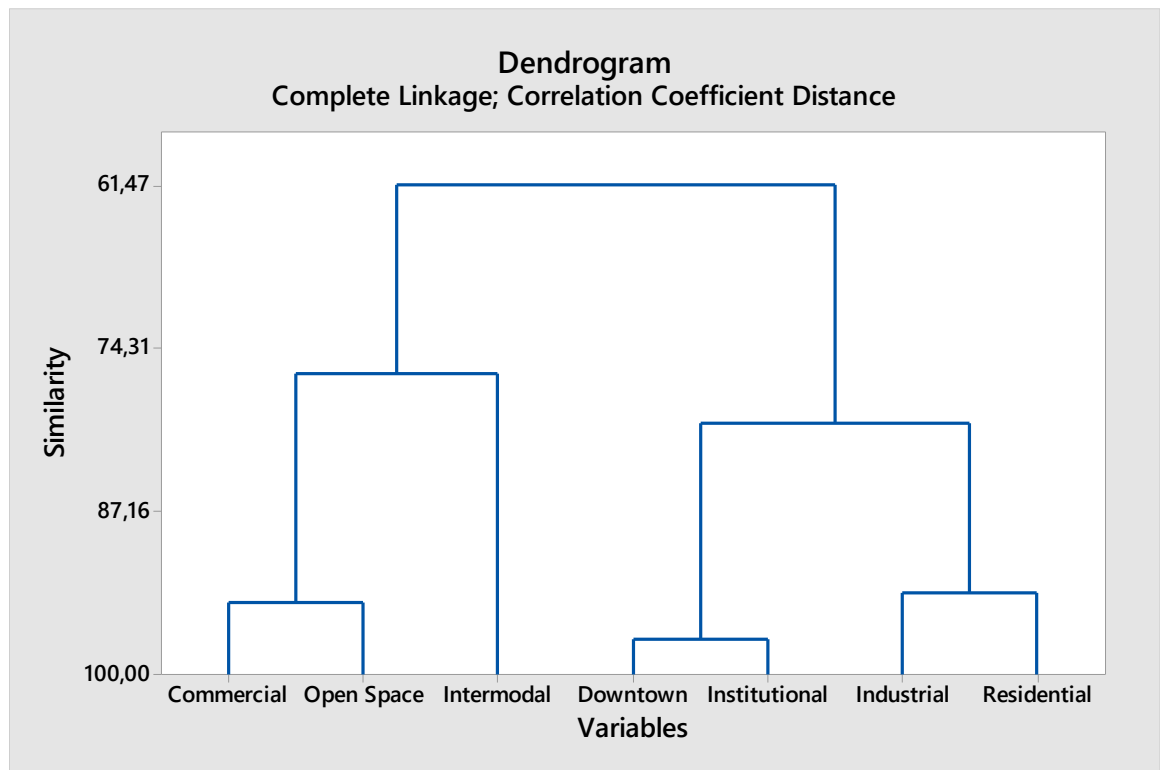
Figure 31: Cluster diagram of charging behavior by daytime in functional areas

For seasonal forecasting a periodic seasonal pattern has to be noticeable which is in correlation with a constant time period (s). Figure 32 shows the charging events per month, it is noticeable that there is always a dip in February, but this is not enough for seasonal forecasting. When divided in functional areas (Figure 33) there is also in no recognizable seasonal trend. Additionally, the RI counties are not showing any seasonal trends either as seen in Figure 34.
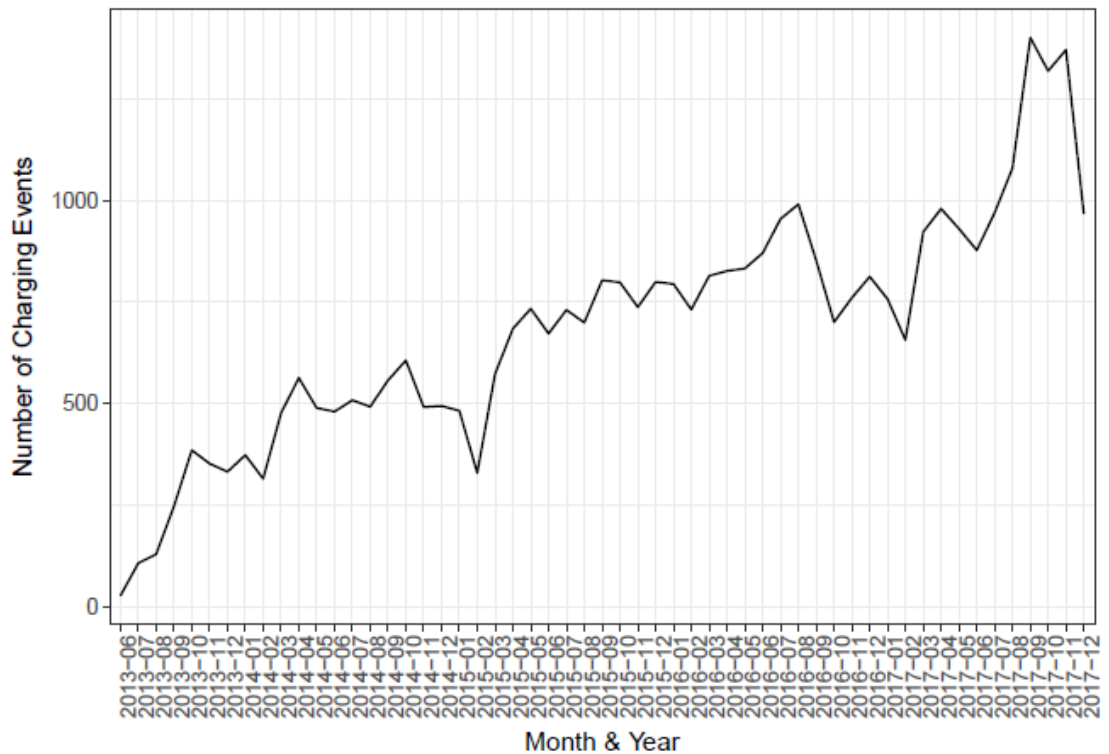
Figure 32: Number of charging events per month
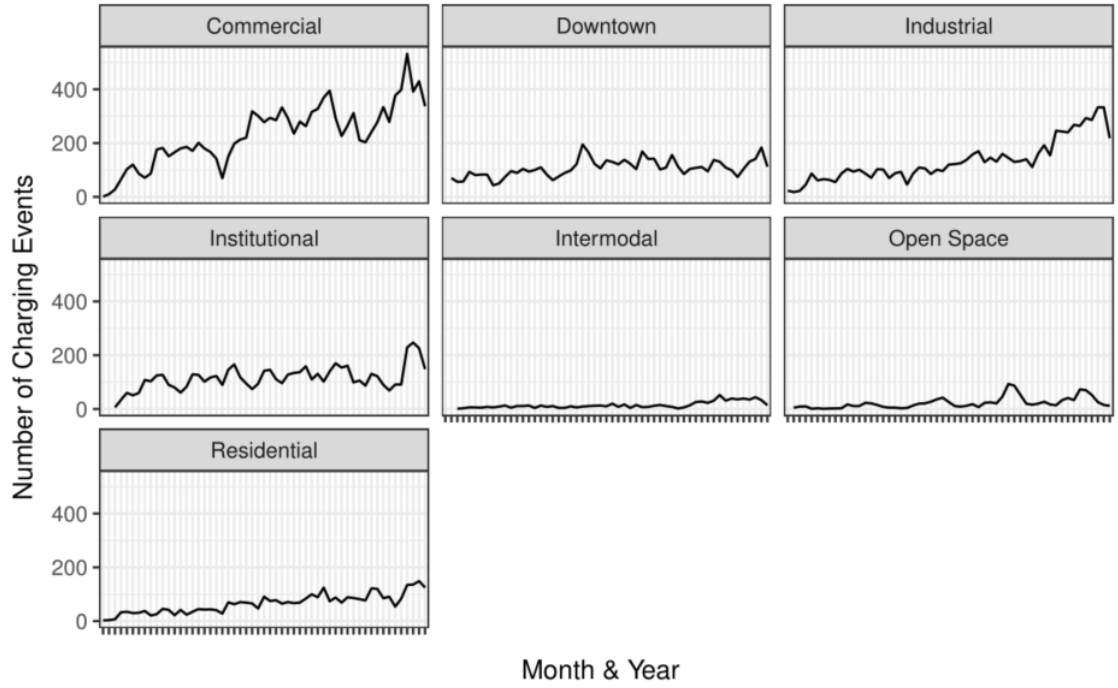
Figure 33: Number of charging events per month by functional areas
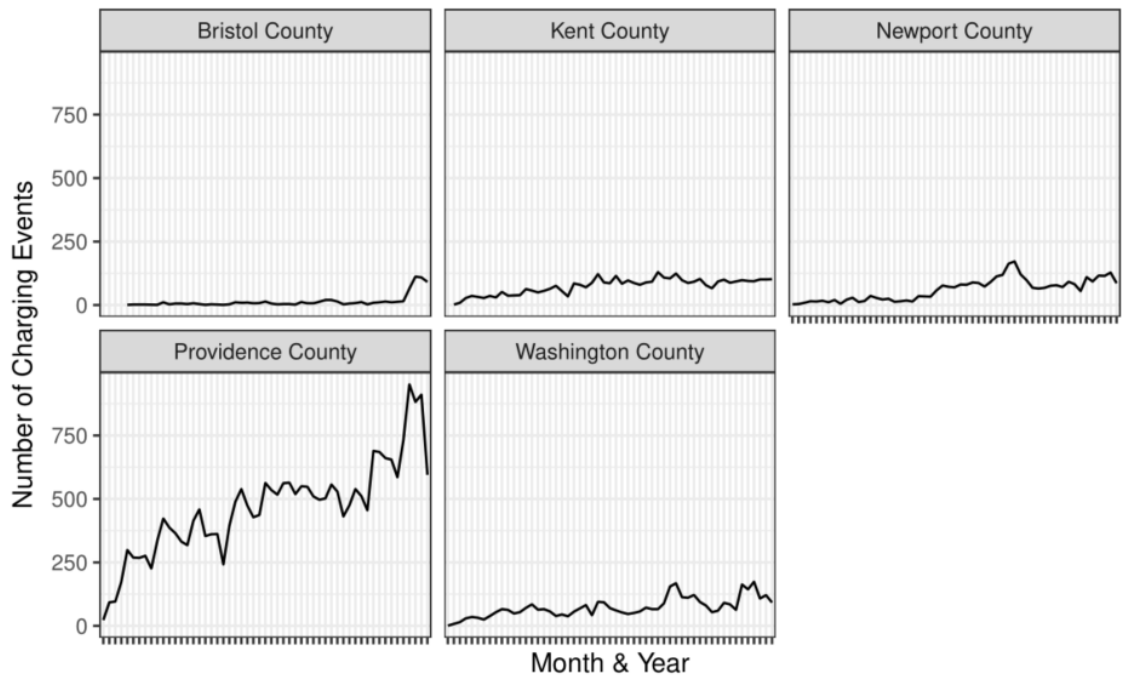
Figure 34: Number of charging events per month by county

The number of annual charging events for each function area. Now the number of charging events in certain areas are plotted in different colors over the years (Figure 35). It is notable that all functional areas show a clear upwards trend, especially with industrial and intermodal areas which show a strong growth within the last year. In industrial areas there are six charging stations, three of which are used below median (under 6.4% of the time). The other three used above the average since 2014. Two of these stations have strong growth from 2016 to 2017, expanding utilization from 15% to 29% and from 10% to 35%. In intermodal areas, the only two charging stations are at the T.F. Green Airport. One charging station was always utilized above median (13% to 55%), whereas the other one has strong growth from 2016 to 2017 from 4% utilization to 24%. These differences can be due to their location in different parking lots with different pricing per hour. Commercial and residential areas are contentiously growing, whereas downtown, institutional and open space were not growing in the last year.
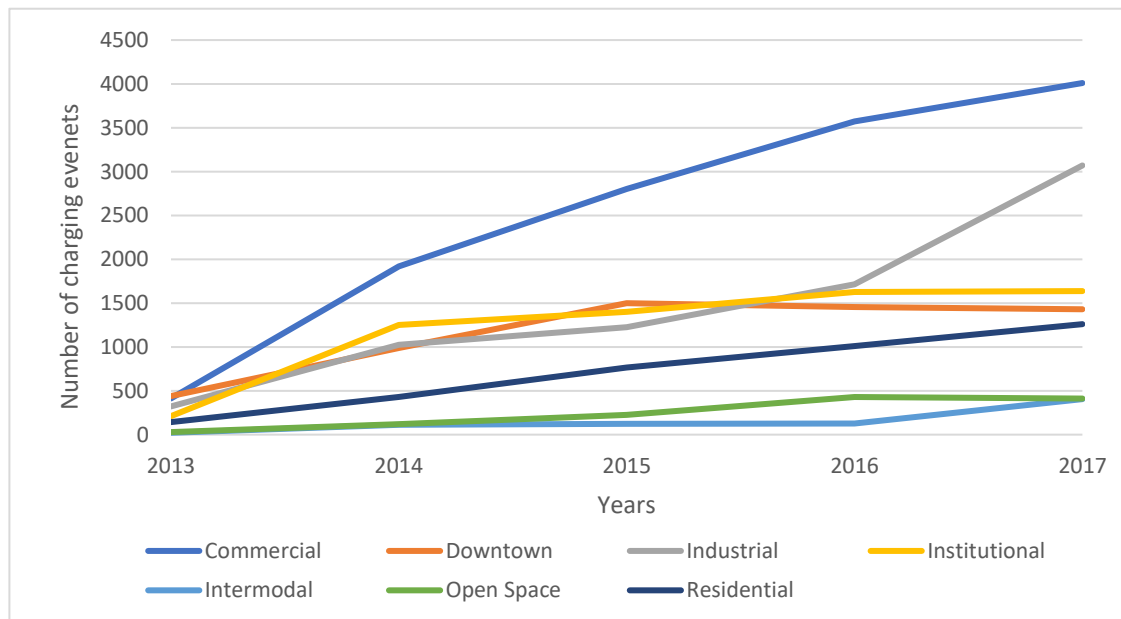
Figure 35: Number of charging events over the years is different areas

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The complete clustering of these areas confirms the visual observations of the last paragraph (Figure 36). Commercial and residential areas are continuously growing, with a similarity of 99.18%; the open space area joins this group with a similarity of 97.88%. Downtown and institutional areas show a similarity of 97.41% and join the already mentioned areas with a similarity of 92.05%. Industrial and intermodal areas show a strong growth within the last year, they show a similarity of 98.36%; all areas show a similarity of 79.00%.
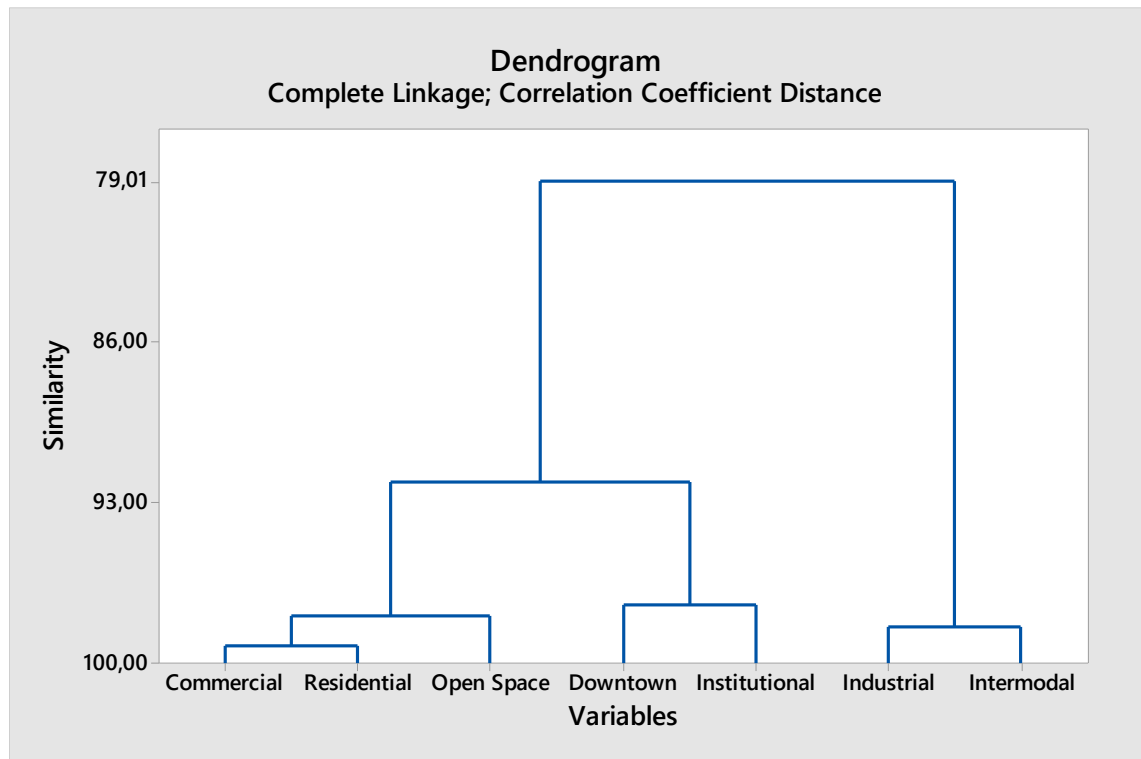
Figure 36: Cluster diagram of yearly trends in functional areas

The charging events per year for the different counties can be seen in Figure 37, most of them showing an upward trend. However, in Kent County, there are actually less charging events in 2017 as of 2016 even though, it has five stations commercial and two stations intermodal area. Yet, both functional areas of commercial and intermodal areas, display a clear, overall trend. Kent County is also the only county where charges per user are increasing, which does not fit together well, be connected with the usage of the airport. Newport County also shows a decrease of charging events in 2017.
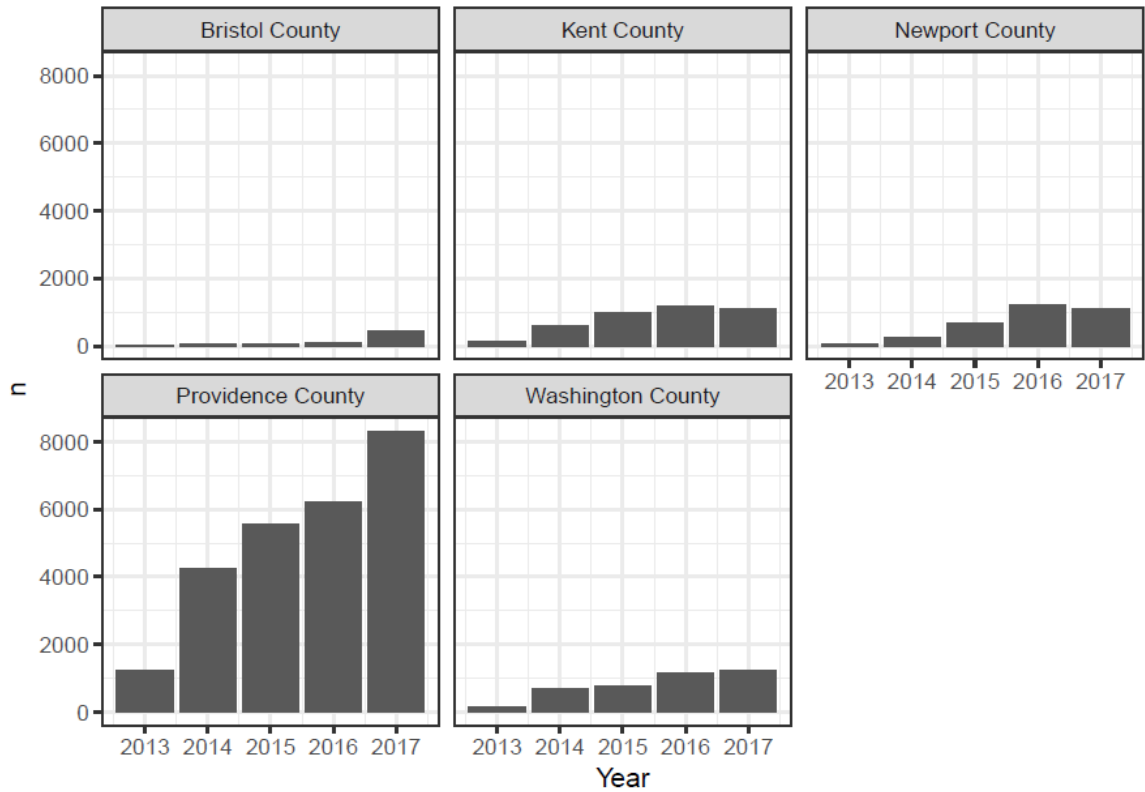
Figure 37: number of charging events over the years in geographical areas

The null hypothesis for Box-Pierce and Ljung-Box is that observations can be treated as independent. When the amount of charging events is summarized by month, the p-values for Box-Pierce and Ljung-Box are both $p < 0.001$ which rejects the null hypothesis; thus, the observations cannot be treated as independent. Therefore, an ARIMA model will be fitted, the analyzed data summarized as month is non-stationary, the mean value from the given data is changing over time based on the Augmented Dickey-Fuller test "$adf.test()$" in R ($p = 0.08977$; fail to rejectH_0; data is non-stationary). In the data there is a noticeable upwards trend, an ARIMA $(p, 1, q)$ model will be used. The maximum likelihood estimators AR-coefficient (p) (order of autoregressive terms) and the MA-coefficient (q) (number of lags on the MA component) are found with looking at the ACF and PACF. Therefore, first the data has been differenced and tested again with the Augmented Dickey-Fuller test ($p = 0.01$; rejectH_0; data is stationary). In Figure 38, it is noticeable that there are no significant values after lag 0 in both the ACF and the PACF, which implies that an ARIMA (0,1,0) could be a good fit. The same model has been advocated by the R function "$auto.arima()$".
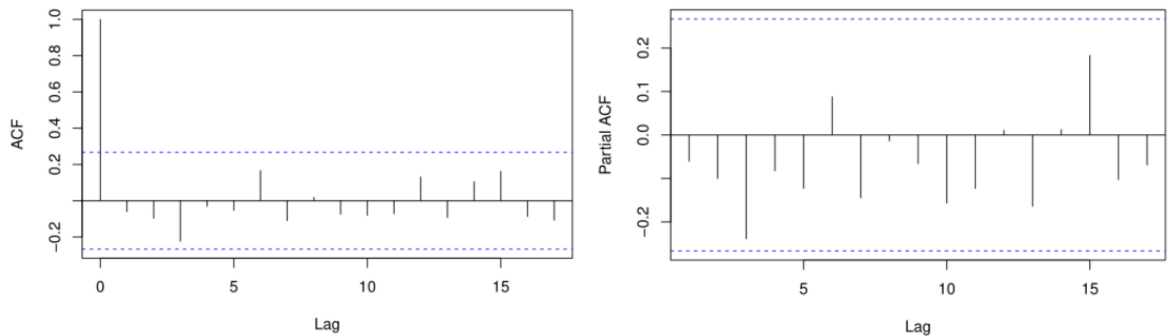
Figure 38: ACF and PACF of differenced timeseries data of charging events per month

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The "$arima()$" model with drift gives an AIC of 666.43 with other models having tested but resulting in the value being consistently higher. The fit with the chosen model is checked visually with the R function "$tsdiag()$" in Figure 39. The first plot Figure 39a, shows standardized residuals, they look like white noise; the ACF of residuals (Figure 39b) shows no value over the blue dotted line after lag 0; all the p-values for Ljung-Box statistics (Figure 39c) are over the blue line. All these conditions speak for a good fit for this model.

Figure 39: Test functions to proof a good fit for ARIMA (0,1,0) model (a: top) Standardized Residuals (b: middle) ACF of Residuals (c: bottom) p-values for Ljung-Box statistics

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Now the ARIMA function can be run on the time series by month. A period of 36 months has been chosen to predict ahead until 2020. Figure 40 shows the forecasting for the next 36 months with upper and lower prediction limits, with a noticeable upwards trend. According to this model there could be 1592 charging events in December 2020 (lower limit: 80%: 726, 95%: 268; upper limit: 80%: 2458, 95%: 2916).

Forecasts from ARIMA(0,1,0) with drift
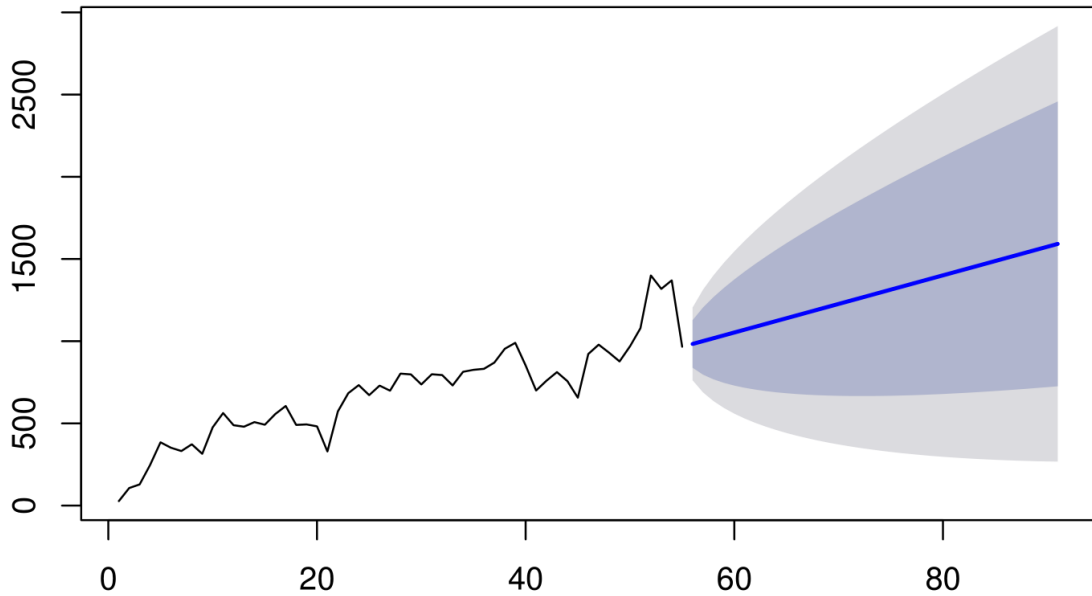
Figure 40: 36 months timeseries forecasting for charging events per month

Improving the forecasting by putting in more data is tried, there for the charging events are now summarized as weeks. The null hypothesis for Box-Pierce and Ljung-Box is that observations can be treated as independent, both ($p < 0.001$) rejected the null hypothesis, the observations cannot be treated as independent. Therefore, also as sums of weeks an ARIMA model can be fitted. The analyzed data seemed to be stationary and confirmed via the Augmented Dickey-Fuller test ($p = 0.03678$; reject H_0, data is stationary). The mean value from the given data is changing over time and visually there is a perceivable trend. Looking at the ACF in Figure 41, the trend is also noticeable with many significant values, the PACF has significant values at lag one and two. The ARIMA (1,1,1) model has an AIC value of 2265.56 which was the lowest for this model between all the different models tested.
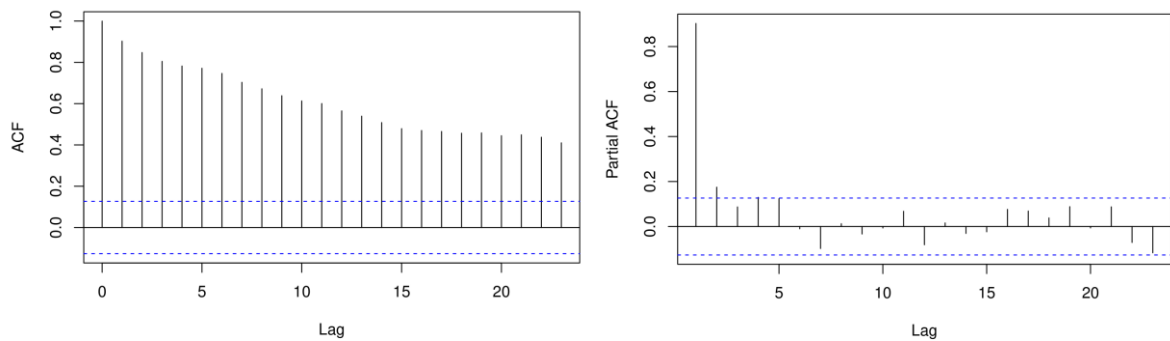
Figure 41: ACF and PACF of timeseries data of charging events per week

The fit with the chosen model with drift is checked visually in Figure 42. The Figure 42a plot shows standardized residuals, they look like white noise; the ACF of residuals (Figure 42b) shows no value over the blue dotted line after lag 0; all the p-values for Ljung-Box statistics (Figure 42c) are over the blue line. All these conditions speak for a good fit for this model.
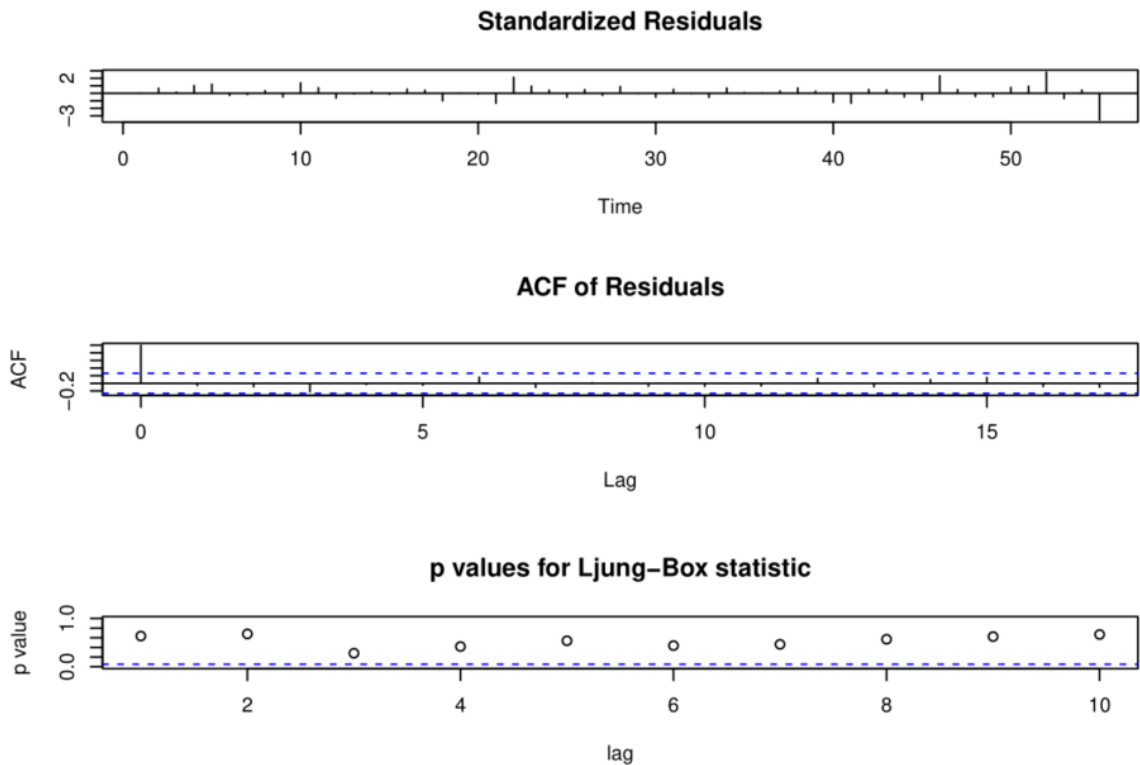
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Standardized Residuals

ACF of Residuals

p values for Ljung−Box statistic
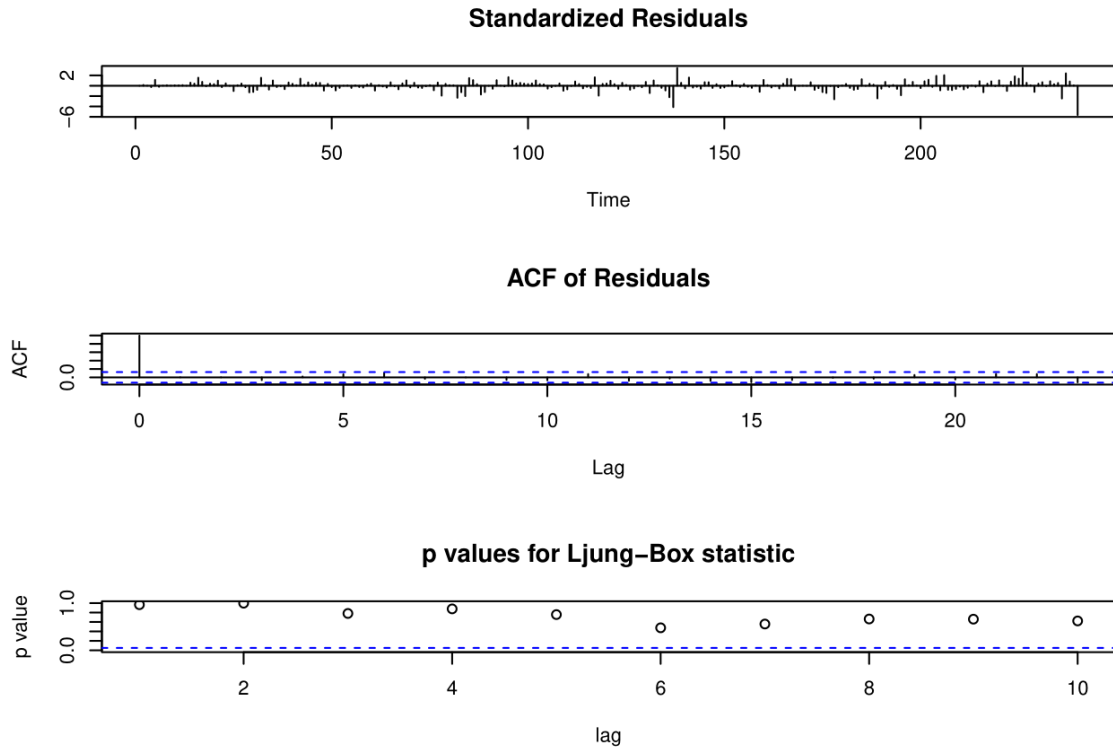
Figure 42: Test functions to proof a good fit for ARIMA (1,1,1) model (a: top)

Standardized Residuals (b: middle) ACF of Residuals (c: bottom) p-values for Ljung-

Box statistics

In the next step the ARIMA function is ran with a period of 156 weeks to predict

ahead until 2020. The forecasted model is plotted in Figure 43. There is a strong

upwards trend noticeable in the beginning of 2018, followed by a slighter upwards trend,

visualized with upper and lower prediction limits. The last week of the year 2020 could

have 462 charging events (lower limit: 80%: 327, 95%: 256; upper limit: 80%: 597,

95%: 688). The growth is less than in the previous models with 16,823 in 2020 (ARIMA

with month (Figure 40): 17,956 in 2020). The ARIMA (1,1,1) model with weekly data

should give the most accurate predictions out of this three, because it has the most data

points and the lowest prediction limits.

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Forecasts from ARIMA(1,1,1) with drift
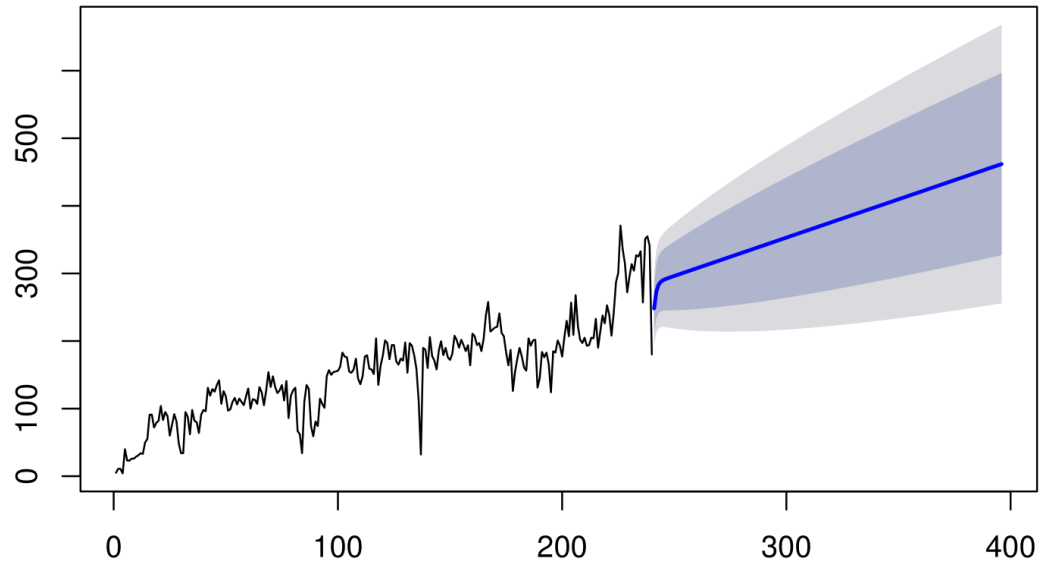
Figure 43: 156 weeks timeseries forecasting for charging events per week

The assumption that charging behavior is strongly dependent on the functional area has been further affirmed, regarding the timeseries data for charging behavior per weekday and daytime. The geographical influence on the charging behavior seems to be less, seemingly more like a mixture of functional areas. Predictions and forecasting of further demand on charging stations could be made. Still, future trends on charging behavior are strongly influenced by several factors. This is the reason why the predictions can only be seen as approximate trends.

CHAPTER 5 – Conclusion

The purpose of this research was to gain valuable insight into the usage of charging stations using Rhode Island as a case study. Each research question was intended to give special insight into different aspects of how EV drivers use public charging stations.

The first research question explored the overall use associated with these RI public charging stations. Based on the data, there is a strong connection between the total duration of charging events, actual charging time, and the amount of charging events, that implies by analyzing one, conclusions about the others can be drawn. As it turns out, RI EV charging station users come from many different places around the U.S., but most of the frequent users are from RI or within New England. Additionally, single charging stations are used very differently in the case of frequency and in charging behavior. The median utilization of the investigated stations is 6.4%, the mean 15.57% (Standard Deviation 17.89%). Not only are chargers utilized differently based on frequency and location, many users using charging stations as parking spots, this pattern exists regardless of charging fees. Further examination of fee or free based charging should be explored in future work.

Expansion of how charging stations differ with respect to use based on type of area was the purpose of the second research question. What has shown in the investigation of RI counties is that the EV adoption from county to county varies and possibly a connection to the median household income. The charging behavior varies greatly between the different functional areas: industrial areas do have the highest median amount of charges, whereas open space areas are the less frequently used charging

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stations. Also, the habit of using charging stations as parking spots is different between functional areas. Geographical areas seem to have less influence on charging behavior, they behave more like a mixture of functional areas. There is mainly a decreasing median amount of charges per user, which speaks for either more home charging or larger battery capacity.

Lastly, the final research question was with respect to how patterns exist in the data, such as seasonality and calendar dependence. The amount of charging events is clearly calendar dependent, the usage per day of the week is different between functional areas. Areas in which people are working (i.e., industrial, downtown, institutional) have less charging events on weekends, commercial and open space areas on the other hand have the same amount of charges on weekends or even more. Similar patterns exist during the charging behavior at daytime. The areas where people are working (downtown, industrial, institutional) have a strong peak in the morning, whereas other functional areas are more evenly distributed throughout the day. Yet, a pattern of seasonal changes are not recognizable, in none of the functional or geographical areas. Future trends could be drawn with linear regression models. It has been found that only about one third of the RI EV drivers are using RI charging stations. Additionally, timeseries forecasting models were performed with the data and found that currently there are enough charging stations in RI. Currently, RI is in the 'utilization gap' with respect to number of charging stations and usage, however the data was limited in terms of volume. As years pass and EVs become more ubiquitous, more data is required for a more accurate prediction.

This research has given an overview about the charging behavior in Rhode Island. The outcomes of this work can help the RI Office of Energy Resources and the RI

Department of Transportation to plan further action on EV infrastructure. This research could also be the corner stone of many following research projects in this field as it is the first of its kind. The research outcome can be compared to other states in the U.S., where nationwide trends could be analyzed and maybe even predicted. Knowing how people charge their EVs is vital to understanding and implementing a new sustainable transportation infrastructure at a critical time when the monumental paradigm shift has relatively, just begun.

5.1 LIMITATIONS

The given data set has a high potential for being utilized in future research. The scope of this particular research was to give an overview about the data and initial trends found within the dataset.

The first limitation to this work is that it is highly location based; implying that all charging stations are within the state of Rhode Island. It is unclear at this time if how people utilized charging stations in Rhode Island is similar or different to Florida, Missouri, California, or even Washington. Additional studies should expand the scope of this work toward understanding both nationally and internationally the differences in charging behavior.

The second limitation is the dataset itself. The data is public, government sponsored charging stations. How this data and conclusions interact with private charging stations and residential charging stations is still an area for opportunity in researching for human variability in transportation.

Another limitation is that this work is single-user based. There were assumptions that the person charging at the station was the same person and that the vehicles charged at that station were the same throughout time. Further expansions of this research can exist where clarifications of this can be used to explore in depth the variability in charging behavior based on vehicle type, person driving, and even links to driving behavior. Along with being a single-user based focused study, the limitations in this area is that it is not a closed-system. The fleet EV research was very specific to medium duty vehicles, but the system remained the same with just the drivers being the variable. In this study, all these facets in the system were not controlled and explored assuming all with equal value and weight. Future work can surely expand upon this work with additional data for a more comprehensive understanding at the individual user-level.

5.2 FUTURE WORK

This analysis is the cornerstone for the following, planned research projects.

Seasonality could be investigated more in depth. Potential questions are, but not limited to: How are charging stations used during the week versus weekend? Are there seasonal trends at single stations? The populations in the summer month is different to the rest of the year, does this has impact on charging behavior?

A series of new questions revolve around how to improve the utilization and user behavior at specific stations? How could users be motivated to park less at the stations? How could RI, specifically, make their charging stations with lower utilization be used more? Would guidelines based on location of the charging stations help to improve the utilization time on charging stations?

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Further data collection is being designed that surveys user behavior and preferences at kiosks located at various charging stations in different functional and geographical areas. An alternative could be a survey in collaboration with the Division of Motor Vehicles (DMV).

Also, there is the possibility to identify which EV the users are actually driving. The ChargePoint app reveals the latest vehicles at each charging station with a timestamp. If this data could be collected in an automated process or shared directly from ChargePoint it could be merged with the current dataset. This new data opens the way for a variety of research projects. With the EV information per user a vast amount of research could be considered, such as: How much is the charging process different? How fast is the charging process per vehicle? On which factor does the charging speed depend?

The primary expansion of this research currently planned starts in September 2018. It will investigate if the Deadline Rush Model applies to the charging habits of RI users. The hypothesis is, that many RI users wait until a critically low state of charge (SOC) before they decide to actually charge their vehicle. If a significant number of public users do this, it can cause a different kind of demand and directly influence future decision-making criteria in terms of infrastructure planning.

Collaborations with other faculty at distributed universities from other states could bring the topic to the next level. If there would be the possibility to compare the Rhode Island users' charging behavior to other states, conclusions on nationwide trends can be drawn. Deeper knowledge about charging behavior and infrastructure could improve the EV transportation system significantly.

Another research project could focus on single users. Do behavioral patterns of single users illustrate the Pareto model, meaning 80% of their charges are at their 20% favorite charging stations? What distances do user drive from home to the charging stations? Do they also commute longer distances? How much variability exists in the charging time per day per user? Can there be found certain groups of users which show similar behavior?

To make future predictions for EV charging station needs is difficult, there are many potential influencing factors, such as EV charging and its infrastructure. The new projection tool EVI-Pro from the U.S. DOE EERE projects how many charging plugs of which kind are needed for a specific number of BEVs and PHEVs (U.S. Department of Energy, 2018). The proportions of BEVs and PHEVs in RI differ from year to year: in 2014, there were 20% BEVs and 80% PHEV; in 2015 and 2016, it was 30% BEV and 70% PHEV, and in 2017, 32% BEV and 68% PHEV (Auto Alliance, 2016; EVAdoption, 2017; Office of Energy Efficiency & Renewable Energy, 2015; Office of Energy Resources, 2016). Regarding the nationwide trend it should already be 50% BEV, 50% PHEV, so it is assumed that RI will get to this number by 2020 (ChargePoint, 2017). Another study says that PHEVs will only play a role in EV adoption until 2025 and thus, after 2030 they will almost be gone. As the battery capacity grows, so does the range, resulting in a higher amount of higher range vehicles estimate over the next few years (Howell et al., 2017). With this information the EVI-Pro tool calculates that RI provides a lot more charging plugs than needed currently and in the near future as RI is still in the utilization gap. Also, the electric driving range influences the results significantly; out of the EVI-Pro tool the number of needed charging plugs does not

increase a lot despite a growing number of users due to the higher electric drive range (U.S. Department of Energy, 2018).

More research on potential influencing factors needs to be explored (e.g., battery evolution and electric driving range, user expectations, linkage between charging time and hour of the day, vehicle type). Especially the linkage between home charging and battery capacity needs to be invested; a vital question is, "Do EV drivers charge more at home if the driving range is larger?". Typically, Level-1 charging is used at home, do people decide to switch to Level-2 charging at home instead if the batteries have more capacity and take longer to charge? How do patterns of human behavior change these factors? These factors could be further investigated and input into a model in order to predict charging behavior. The outcomes of these studies could all be implemented into projection tools like EVI-Pro.

These are just a few ideas of projects that could be done with this data; embrace the possibilities.

APPENDIX 1: R-Markdown Code

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title: "Data Analysis Master Thesis in R"
author: "Roxana Voss"
date: "June 2018"
output:
  word_document: default
  pdf_document: default
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```{r setup, include=FALSE}
knitr::opts_chunk$set(echo = TRUE)
rm(list = ls()) #the whole environment

#install.packages("plyr")
#install.packages("maptools")
#install.packages("ddply")
#install.packages("tidyverse")
#install.packages("maps")
#install.packages("viridis")
#install.packages("ggplot2")
#install.packages("ggmap")
#install.packages("zipcode")
#install.packages("ddply")
#install.packages("ggplot2")
#install.packages("hrbrmstr")
#install.packages("scales")
#install.packages("RColorBrewer")
#install.packages("stats")
#install.packages("forecast")

library(plyr)
library(ggplot2)
library(maptools)
library(zipcode)
library(tidyverse)
library(maps)
library(viridis)
library(ggthemes)
library(readr)
library(mapdata)
library(gridExtra)
library(grid)
library(cumplyr)
library(RColorBrewer)
library(ggpubr)
library(stats)
library(forecast)
library(colorspace)
library(tseries)
library(survival)
library(coin)
```

```
#my data
Clean_Data <- read_delim("~/Desktop/Big Data Analysis/R/Final Project/Clean_Data_6.csv",
                ";", escape_double = FALSE, col_types = cols(`Charging Time (hh:mm:ss)` =
col_time(format = "%H:%M:%S"),
                                        Date = col_date(format = "%d.%m.%Y"),
                                        Date_1 = col_date(format = "%d.%m.%Y"),
                                        `End Date` = col_datetime(format = "%d.%m.%Y
%H:%M:%S"),
                                        `Energy (kWh)` = col_double(), `Start Date` =
col_datetime(format = "%d.%m.%Y %H:%M:%S"),
                                        Time = col_time(format = "%H:%M:%S"),
                                        `Time no charge` = col_time(format = "%H:%M:%S"),
                                        Time_1 = col_time(format = "%H:%M:%S"),
                                        `Total Duration (hh:mm:ss)` = col_time(format =
"%H:%M:%S"),
                                        `Transaction Date (Pacific Time)` = col_datetime(format =
"%d.%m.%Y %H:%M:%S")),
                locale = locale(decimal_mark = ","),
                trim_ws = TRUE)

Clean_Data <- Clean_Data %>% filter(`Station Name` != "RI OER / FRANCIS ST1") %>%
filter(`Station Name` != "RI OER / FRANCIS ST2") %>% filter(`Station Name` != "RI OER /
STATION#1") %>% filter(`Station Name` != "RI OER / STATION#2") %>% filter(`Station Name` !=
"RI OER / STATION#3")

```
```

Electric Vehicle (EV) Charging Behavior in existing Infrastructures

This is an R Markdown document to understand the processed statistics of the data.
It is a trial version, which keeps record of possibly usable statistics for the research.
Updated Data can easily be read in and the same analysis can be performed automatically.

Descriptive Statistics

Energy used in kWh: Mean, Standard Deviation, Minimum, Maximum and Sum of all the charging
events

```{r Energy}
mean(Clean_Data$`Energy (kWh)`, na.rm=TRUE)
sd(Clean_Data$`Energy (kWh)`, na.rm=TRUE)
min(Clean_Data$`Energy (kWh)`, na.rm=TRUE)
max(Clean_Data$`Energy (kWh)`, na.rm=TRUE)
sum(Clean_Data$`Energy (kWh)`, na.rm=TRUE)
```

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GHG Savings in kg: Mean, Standard Deviation, Minimum, Maximum and Sum of all the charging
events

```{r GHG}
mean(Clean_Data$`GHG Savings (kg)`, na.rm=TRUE)
sd(Clean_Data$`GHG Savings (kg)`, na.rm=TRUE)
min(Clean_Data$`GHG Savings (kg)`, na.rm=TRUE)
max(Clean_Data$`GHG Savings (kg)`, na.rm=TRUE)
sum(Clean_Data$`GHG Savings (kg)`, na.rm=TRUE)
```

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Gasoline Savings in Gallons: Mean, Standard Deviation, Minimum, Maximum and Sum of all the
charging events

```{r Gas}
mean(Clean_Data$`Gasoline Savings (gallons)`, na.rm=TRUE,)
sd(Clean_Data$`Gasoline Savings (gallons)`, na.rm=TRUE)
min(Clean_Data$`Gasoline Savings (gallons)`, na.rm=TRUE)
max(Clean_Data$`Gasoline Savings (gallons)`, na.rm=TRUE)
sum(Clean_Data$`Gasoline Savings (gallons)`, na.rm=TRUE)
```
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Total Plugged in Time in sec: Mean, Standard Deviation, Minimum, Maximum and Sum of all the
charging events
If further needed, it can be converted in a common time format.

```{r TT, echo=FALSE}
 ds1 <- Clean_Data %>%   filter(!is.na(`Time no charge`)) %>%
  filter(!is.na(`Total Duration (hh:mm:ss)`)) %>%  filter(!is.na(`Charging Time (hh:mm:ss)`))


print("Mean total duration pluged in")
ds1$`Total Duration (hh:mm:ss)` <- difftime(strptime(ds1$`Total Duration
(hh:mm:ss)`,"%H:%M:%S"),
              strptime("00:00:00","%H:%M:%S"),
              units="secs")
ds1.means <- mean(ds1$`Total Duration (hh:mm:ss)`)
ds1.means$Time <- format(.POSIXct(ds1.means,tz="GMT"), "%H:%M:%S")
ds1.means

print("SD total duration pluged in")
ds1.sd <- sd(ds1$`Total Duration (hh:mm:ss)`)
ds1.sd$Time <- format(.POSIXct(ds1.sd,tz="GMT"), "%H:%M:%S")
ds1.sd

print("Min total duration pluged in")
ds1.min <- min(ds1$`Total Duration (hh:mm:ss)`)
ds1.min$Time <- format(.POSIXct(ds1.min,tz="GMT"), "%H:%M:%S")
ds1.min

print("Max total duration pluged in")
ds1.max <- max(ds1$`Total Duration (hh:mm:ss)`)
ds1.max$Time <- format(.POSIXct(ds1.max,tz="GMT"), "%H:%M:%S")
ds1.max
```

```
print("Sum total duration pluged in")
ds1.sum <- sum(ds1$`Total Duration (hh:mm:ss)`)
ds1.sum

#print("Sum total duration pluged in")
#ds1.sum <- sum(ds1$`Total Duration (hh:mm:ss)`)
#ds1.sum$Time <- format(.POSIXct(ds1.sum,tz="GMT"), "%d 'Days' ,%H:%M:%S")
#ds1.sum

```
```

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Total Charging Time in sec: Mean, Standard Deviation, Minimum, Maximum and Sum of all the charging events
If further needed, it can be converted in a common time format.

```{r CT, echo=FALSE}
print("Mean charging time")
ds1$`Charging Time (hh:mm:ss)` <- difftime(strptime(ds1$`Charging Time
(hh:mm:ss)`,"%H:%M:%S"),
              strptime("00:00:00","%H:%M:%S"),
              units="secs")
ds1.means <- mean(ds1$`Charging Time (hh:mm:ss)`)
ds1.means$Time <- format(.POSIXct(ds1.means,tz="GMT"), "%H:%M:%S")
ds1.means

print("SD charging time")
ds1.sd <- sd(ds1$`Charging Time (hh:mm:ss)`)
ds1.sd$Time <- format(.POSIXct(ds1.sd,tz="GMT"), "%H:%M:%S")
ds1.sd

print("Min charging time")
ds1.min <- min(ds1$`Charging Time (hh:mm:ss)`)
ds1.min$Time <- format(.POSIXct(ds1.min,tz="GMT"), "%H:%M:%S")
ds1.min

print("Max charging time")
ds1.max <- max(ds1$`Charging Time (hh:mm:ss)`)
ds1.max$Time <- format(.POSIXct(ds1.max,tz="GMT"), "%H:%M:%S")
ds1.max

#print("Sum charging time")
ds1.sum <- sum(ds1$`Charging Time (hh:mm:ss)`)
#ds1.sum$Time <- format(.POSIXct(ds1.sum,tz="GMT"), "%d 'Days' ,%H:%M:%S")
ds1.sum
```
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```

Time the EV is plugged in after it has been fully charged in sec: Mean, Standard Deviation, Minimum, Maximum and Sum of all the charging events
If further needed, it can be converted in a common time format.

```{r NC, echo=FALSE}
print("Mean time plugged in after being fully charged")
ds1$`Time no charge` <- difftime(strptime(ds1$`Time no charge`,"%H:%M:%S"),
             strptime("00:00:00","%H:%M:%S"),
             units="secs")
ds1.means <- mean(ds1$`Time no charge`)
ds1.means$Time <- format(.POSIXct(ds1.means,tz="GMT"), "%H:%M:%S")
ds1.means

print("SD plugged in after being fully charged")
ds1.sd <- sd(ds1$`Time no charge`)
ds1.sd$Time <- format(.POSIXct(ds1.sd,tz="GMT"), "%H:%M:%S")
ds1.sd

print("Min plugged in after being fully charged")
ds1.min <- min(ds1$`Time no charge`)
ds1.min$Time <- format(.POSIXct(ds1.min,tz="GMT"), "%H:%M:%S")
ds1.min

print("Max plugged in after being fully charged")
ds1.max <- max(ds1$`Time no charge`)
ds1.max$Time <- format(.POSIXct(ds1.max,tz="GMT"), "%H:%M:%S")
ds1.max

ds1.sum <- sum(ds1$`Time no charge`)
#ds1.sum$Time <- format(.POSIXct(ds1.sum,tz="GMT"), "%d 'Days' ,%H:%M:%S")
ds1.sum

```
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Descriptive Statistics

Two Versions of bar charts about the usage of single Stations.
In the next step clustered in areas which show the range of the usage of the single stations in this region.

```{r Stationss, echo=FALSE}
st0 <- Clean_Data  %>% filter(Year == 2017)
st <- st0 %>% group_by(Area, `Station Name`) %>% tally() %>% filter(!is.na(Area))
barplot(st$n, main = "Charging events per station", xlab="Different Stations", ylab= "Amount of
charging events", col = "royalblue2")
stcounty <- st0 %>% group_by(County, `Station Name`) %>% tally() %>% filter(!is.na(County))
barplot(st$n, main = "Charging events per station", xlab="Different Stations", ylab= "Amount of
charging events", col = "royalblue2")

st$`Station Name` <- factor(st$`Station Name`, levels = st$`Station Name`[order(-st$n)])
ggplot(st, aes(x=`Station Name`, y=n, fill = Area))+ geom_col()

stcounty$`Station Name` <- factor(stcounty$`Station Name`, levels = stcounty$`Station Name`[order(-
stcounty$n)])
ggplot(stcounty, aes(x=`Station Name`, y=n, fill = County))+ geom_col()

#barplot(ds822$x, main = "Charging events per station", xlab="Different Stations", ylab= "Amount of
charging events", col = "royalblue2")
```

```
#ggplot(ds822, aes((color = count), x=`Station Name`, y=x))+ geom_col()
```


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Descriptive Statistics

Are 80 percent of the charges done at 20 percent of the stations?
No, at the 20% most popular stations are done 47 % of the charges.
Same with total Ddration:
No, at the 20% most popular stations are done 54 % of the total duration
Same with charging time:
No, at the 20% most popular stations are done 53 % of the chargintime


```{r 8020, echo=FALSE}
st1 <- Clean_Data %>% group_by(Area, `Station Name`) %>% tally() %>% filter(!is.na(Area))

print("Amount of Charges")
st8020 <- st1[order(st1$n),]
st80 <- sum(st8020[1:39,3])
st20 <- sum(st8020[40:50,3])
stsum <- sum(st8020[,3])

st80/stsum
st20/stsum


ds1 <- Clean_Data %>%   filter(!is.na(`Time no charge`)) %>%
  filter(!is.na(`Total Duration (hh:mm:ss)`)) %>%  filter(!is.na(`Charging Time (hh:mm:ss)`))


print("Total Duration")
ds1$`Total Duration (hh:mm:ss)` <- difftime(strptime(ds1$`Total Duration
(hh:mm:ss)`,"%H:%M:%S"),
            strptime("00:00:00","%H:%M:%S"),
            units="secs")
ds82 <- ds1 %>% group_by(`Station Name`) %>% summarise(x = sum(`Total Duration (hh:mm:ss)`))
%>% filter(!is.na(`Station Name`))

td8020 <- ds82[order(ds82$x),]

td80 <- sum(td8020$x[1:39])
td20 <- sum(td8020$x[40:50])
tdsum <- sum(td8020$x)

#td80/tdsum
214146099/489813848
#td20/tdsum
275667749/489813848

print("Charge Time")
ds1$`Charging Time (hh:mm:ss)` <- difftime(strptime(ds1$`Charging Time
(hh:mm:ss)`,"%H:%M:%S"),
            strptime("00:00:00","%H:%M:%S"),
```

```
                    units="secs")
ds822 <- ds1 %>% group_by(`Station Name`) %>% summarise(x = sum(`Charging Time (hh:mm:ss)`))
%>% filter(!is.na(`Station Name`))

ct8020 <- ds822[order(ds822$x),]

ct80 <- sum(ct8020$x[1:39])
ct20 <- sum(ct8020$x[40:50])
ctsum <- sum(ct8020$x)

#ct80/ctsum
113034756/252159542
#ct20/ctsum
139124786/252159542
```
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Descriptive Charts
Map of User Distribution

You can see 3 versions of a map of the United States which show the distribution of charging station
users using RI charging stations.
```{r map, echo=FALSE}
data(zipcode)
us<-map_data('state')
usa<-map_data("usa")
states <- map_data("state")

ri<-states %>% filter(region == "rhode island")
DZ <- Clean_Data
DZ.zip <- aggregate(data.frame(count=DZ$`User ID`), list(zip=DZ$`Driver Postal Code`, Area=
DZ$Area), length)
DZ2 <- merge(DZ.zip, zipcode, by='zip')

DZRI <- DZ2 %>% filter(state == "RI")

#works better
ggplot(DZ2, aes(longitude,latitude)) +
    geom_polygon(data=us,aes(x=long,y=lat,group=group),color='black',fill=NA,alpha=.35)+
    geom_point(aes(color = Area), size= 2,alpha=.45) +
    xlim(-125,-65)+ylim(20,50) +
    theme(panel.background = element_blank())
us_area <- ggplot(DZ2, aes(longitude,latitude)) +
    geom_polygon(data=us,aes(x=long,y=lat,group=group),color='black',fill=NA,alpha=.35)+
    geom_point(aes(color = Area), size= 2,alpha=.45) +
    xlim(-125,-65)+ylim(20,50) +
    theme(panel.background = element_blank())

us_area + coord_quickmap(xlim = c(-75,-68),  ylim = c(40,45))

#trial
ggplot(DZ2, aes(longitude,latitude)) +
  geom_polygon(data=us,aes(x=long,y=lat,group=group),color='black',fill=NA,alpha=.35)+
  geom_point(aes(color = count), size = 2, alpha=0.5) +
```

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```
    scale_colour_gradient(low= "blue", high = "red") + xlim(-125,-65)+ylim(20,50) +
    theme(panel.background = element_blank())

us_user <- ggplot(DZ2, aes(longitude,latitude)) +
    geom_polygon(data=us,aes(x=long,y=lat,group=group),color='black',fill=NA,alpha=.35)+
    geom_point(aes(color = count), size = 2, alpha=0.5) +
    scale_colour_gradient(low= "blue", high = "red") +
    xlim(-125,-65)+ylim(20,50) +
    theme(panel.background = element_blank())

us_user + coord_quickmap(xlim = c(-75,-68),  ylim = c(40,45))
```

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Descriptive Charts
Map of User Distribution

Map of RI with User Origin and amounts of charges

```{r map12, echo=FALSE}

#ri map with user zip distribution
ggplot(DZRI, aes(longitude,latitude)) +
    geom_polygon(data=ri,aes(x=long,y=lat,group=group),color='black',fill=NA,alpha=.35)+
    geom_point(aes(color = count), size = 5, alpha=0.5) +
    scale_colour_gradient(low= "blue", high = "red") +
    xlim(-71.9,-71.1)+ylim(41.3,42.1) +
    theme(panel.background = element_blank()) + coord_quickmap()
```

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Descriptive Charts
Map of User Distribution

Map of RI with Chargig Stations and amounts of charges

```{r map13, echo=FALSE}
#ri map amount of charging events per zip
DZ2017 <- Clean_Data %>% filter(Year == 2017)
DZ.sub <- aggregate(data.frame(count=DZ2017$`Station Name`), list(Station= DZ2017$`Station
Name`, latitude=DZ2017$Latitude, longitude=DZ2017$Longitude, Area=DZ2017$Area), length)

ggplot(DZ.sub, aes(longitude,latitude)) +
    geom_polygon(data=ri,aes(x=long,y=lat,group=group),color='black',fill=NA,alpha=.35)+
    geom_point(aes(color = count), size = 5, alpha=0.5) +
    scale_colour_gradient(low= "blue", high = "red", breaks = c(0,200,400,600,800,1000), limits=c(1,
1000)) +
    xlim(-71.9,-71.1)+ylim(41.3,42.1) +
    theme(panel.background = element_blank()) + coord_quickmap()


```
```

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Locations
Pie Chart about Areas and the Amount of Charging Stations in the zone.

```{r sz, echo=FALSE}
st1 <- Clean_Data %>% group_by(Area, `Station Name`) %>% tally() %>% filter(!is.na(Area))
st3 <- st1 %>% select(Area, `Station Name`) %>% group_by(Area) %>% count(Area) %>%
filter(!is.na(Area))
pie(st3$n, labels = st3$Area, main="Amount of Charging Stations by Area", col=rainbow_hcl(7))
```

Pie Chart about Areas and the Amount of Charging Events.

```{r Area, echo=FALSE}
ag <- Clean_Data %>% count(Area) %>%  filter(!is.na(Area))
pie(ag$n, labels = ag$Area, main="Amount of Charging Events by Area",col=rainbow_hcl(7))
```

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Pie Chart about Counties and the Amount of Charging Stations in the zone.

```{r sz2, echo=FALSE}
css1 <- Clean_Data %>% group_by(County, `Station Name`, Area) %>% tally() %>%
filter(!is.na(County))
st3 <- css1 %>% select(County, `Station Name`) %>% group_by(County) %>% count(County) %>%
filter(!is.na(County))
pie(st3$n, labels = st3$County, main="Amount of Charging Stations by County", col=rainbow_hcl(5))
```
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Pie Chart about Areas and the Amount of Charging Events.

```{r Area2, echo=FALSE}
ag <- Clean_Data %>% count(County) %>%  filter(!is.na(County))
pie(ag$n, labels = ag$County, main="Amount of Charging Events by County", col=rainbow_hcl(5))
```

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Locations

Boxplots about the Usage in the diffrent Areas and Counties

```{r Stations, echo=FALSE}

st1 <- Clean_Data %>% group_by(Area, `Station Name`) %>% tally() %>%  filter(!is.na(Area))

ggplot(data = st1, aes(x = Area, y = n, fill = Area)) + geom_boxplot() + theme(legend.position="none")
st11 <- Clean_Data %>% group_by(County, `Station Name`) %>% tally() %>%  filter(!is.na(County))
```

```
ggplot(data = st11, aes(x = County, y = n, fill= County)) + geom_boxplot() +
theme(legend.position="none")
```
```
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## Locations

Kruskal-Wallis Test

```{r wallisarea, echo=FALSE}

st1$Area <- as.factor(st1$Area)
kruskal_test(n~Area, data = st1)
print("Functional areas are not signifficantly different")

st11$County <- as.factor(st11$County)
print("Geographical areas are not signifficantly different")
kruskal_test(n~County, data = st11)
```
```
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## Locations

RI map with the diffrent stations in colors of the Area and size per Amount of usage

```{r newmap, echo=FALSE}

ggplot(DZ.sub, aes(longitude,latitude)) +
    geom_polygon(data=ri,aes(x=long,y=lat,group=group),color='black',fill=NA,alpha=.5)+
    geom_point(aes(color = factor(Area),size = count, alpha=0.1)) + xlim(-71.9,-
71.1)+ylim(41.3,42.1) +
    theme(panel.background = element_blank()) + coord_quickmap()
```
```
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## Locations


Amount of Charging Events in each County

```{r map2, echo=FALSE}

#ri map with counties
counties <- map_data("county")
ri<-states %>% filter(region == "rhode island")
ri_county <- counties %>% filter(region == "rhode island")
ri_c <- ggplot(data = ri, mapping = aes(x = long, y = lat, group = group)) +
 coord_quickmap() + geom_polygon(color = "black", fill = "gray") + geom_polygon(data = ri_county,
fill = NA, color = "white") + geom_polygon(color = "black", fill = NA) + theme_void()
```

```
#ri map amount of charging stations per county
DZ.sub2 <- aggregate(data.frame(count=DZ$`Station Name`), list(subregion=DZ$`County`), length)

county_data <- data.frame(subregion = c("bristol", "kent", "newport", "providence","washington"),
count = DZ.sub2$count/5)

ricopa <- left_join(ri_county, county_data, by = "subregion")

c_all <- ri_c + geom_polygon(data = ricopa, aes(fill = count), color = "white") + geom_polygon(color =
"black", fill = NA) + scale_fill_viridis(
                breaks = c(1, 10, 100, 1000, 10000),
                trans = "log10", limits=c(1, 10000))

#ri map amount of charging stations per county per year 2013
DZ13 <- DZ %>% filter(Year == 2013)
DZ.sub3 <- aggregate(data.frame(count=DZ13$`Station Name`), list(subregion=DZ13$`County`),
length)

county_data3 <- data.frame(subregion = c("bristol", "kent", "newport", "providence","washington"),
count = DZ.sub3$count)

ricopa3 <- left_join(ri_county, county_data3, by = "subregion")

c13 <- ri_c + geom_polygon(data = ricopa3, aes(fill = count), color = "white") + geom_polygon(color =
"black", fill = NA) +
  scale_fill_viridis(breaks = c(1, 10, 100, 1000, 10000),
                trans = "log10", limits=c(1, 10000)) + ggtitle("2013")

#ri map amount of charging stations per county per year 2014
DZ14 <- DZ %>% filter(Year == 2014)
DZ.sub4 <- aggregate(data.frame(count=DZ14$`Station Name`), list(subregion=DZ14$`County`),
length)

county_data4 <- data.frame(subregion = c("bristol", "kent", "newport", "providence","washington"),
count = DZ.sub4$count)

ricopa4 <- left_join(ri_county, county_data4, by = "subregion")

c14 <- ri_c + geom_polygon(data = ricopa4, aes(fill = count), color = "white") + geom_polygon(color =
"black", fill = NA) +
  scale_fill_viridis(breaks = c(1, 10, 100, 1000, 10000),
                trans = "log10", limits=c(1, 10000)) + ggtitle("2014")

#ri map amount of charging stations per county per year 2015
DZ15 <- DZ %>% filter(Year == 2015)
DZ.sub5 <- aggregate(data.frame(count=DZ15$`Station Name`), list(subregion=DZ15$`County`),
length)

county_data5 <- data.frame(subregion = c("bristol", "kent", "newport", "providence","washington"),
count = DZ.sub5$count)

ricopa5 <- left_join(ri_county, county_data5, by = "subregion")
```

```
c15 <- ri_c + geom_polygon(data = ricopa5, aes(fill = count), color = "white") + geom_polygon(color =
"black", fill = NA) +
  scale_fill_viridis(breaks = c(1, 10, 100, 1000, 10000),
               trans = "log10", limits=c(1, 10000)) + ggtitle("2015")

#ri map amount of charging stations per county per year 2016
DZ16 <- DZ %>% filter(Year == 2016)
DZ.sub6 <- aggregate(data.frame(count=DZ16$`Station Name`), list(subregion=DZ16$`County`),
length)

county_data6 <- data.frame(subregion = c("bristol", "kent", "newport", "providence","washington"),
count = DZ.sub6$count)

ricopa6 <- left_join(ri_county, county_data6, by = "subregion")

c16 <- ri_c + geom_polygon(data = ricopa5, aes(fill = count), color = "white") + geom_polygon(color =
"black", fill = NA) +
  scale_fill_viridis(breaks = c(1, 10, 100, 1000, 10000),
               trans = "log10", limits=c(1, 10000)) + ggtitle("2016")

#ri map amount of charging stations per county per year 2017
DZ17 <- DZ %>% filter(Year == 2017)
DZ.sub7 <- aggregate(data.frame(count=DZ17$`Station Name`), list(subregion=DZ17$`County`),
length)

county_data7 <- data.frame(subregion = c("bristol", "kent", "newport", "providence","washington"),
count = DZ.sub7$count)

ricopa7 <- left_join(ri_county, county_data7, by = "subregion")

c17 <- ri_c + geom_polygon(data = ricopa7, aes(fill = count), color = "white") + geom_polygon(color =
"black", fill = NA) +
  scale_fill_viridis(breaks = c(1, 10, 100, 1000, 10000),trans = "log10",
               limits=c(1, 10000)) + ggtitle("2017")

ri_c + geom_polygon(data = ricopa7, aes(fill = count), color = "white") + geom_polygon(color =
"black", fill = NA) +
  scale_fill_viridis(breaks = c(100, 1000, 10000),trans = "log10",
               limits=c(100, 10000)) + ggtitle("2017")

#All together
c_all
ggarrange(c13, c14, c15,
        c16, c17, ncol= 5, nrow = 1, common.legend = TRUE, legend="right")
```

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Locations

Amount of Charging Events done by User from each County

```{r map3, echo=FALSE}
```

```
#ri map amount of by user per county


zipcounty <- read_delim("~/Dropbox/Masterthesis/zipcounty.csv",
                ";", escape_double = FALSE,locale = locale(decimal_mark = ","), trim_ws = TRUE)

DZs <- Clean_Data[c("Year", "Driver Postal Code")]
DZs <- DZs %>% filter(!is.na(`Driver Postal Code`))
DZURI <- merge(zipcounty, DZs, by.x = "zip", by.y = "Driver Postal Code") %>%
filter(!is.na(subregion))

DZ.subu <- aggregate(data.frame(count=DZURI$`subregion`), list(subregion=DZURI$`subregion`),
length)

ricopau <- left_join(ri_county, DZ.subu, by = "subregion")

ri_c + geom_polygon(data = ricopau, aes(fill = count), color = "white") + geom_polygon(color =
"black", fill = NA) + scale_fill_viridis(
                breaks = c(1, 10, 100, 1000, 10000),
                trans = "log10", limits=c(1, 27000))

#ri map amount of charging stations per county per year 2013

DZs3 <- DZ13[c("Year", "Driver Postal Code")]
DZURI3 <- merge(zipcounty, DZs3, by.x = "zip", by.y = "Driver Postal Code") %>%
filter(!is.na(subregion))

DZ.subu3 <- aggregate(data.frame(count=DZURI3$`subregion`),
list(subregion=DZURI3$`subregion`), length)

ricopau3 <- left_join(ri_county, DZ.subu3, by = "subregion")


u3 <- ri_c + geom_polygon(data = ricopau3, aes(fill = count), color = "white") + geom_polygon(color =
"black", fill = NA) +
  scale_fill_viridis(breaks = c(1, 10, 100, 1000, 10000),
                trans = "log10", limits=c(1, 10000)) + ggtitle("2013")

#ri map amount of charging stations per county per year 2014
DZs4 <- DZ14[c("Year", "Driver Postal Code")]
DZURI4 <- merge(zipcounty, DZs4, by.x = "zip", by.y = "Driver Postal Code") %>%
filter(!is.na(subregion))

DZ.subu4 <- aggregate(data.frame(count=DZURI4$`subregion`),
list(subregion=DZURI4$`subregion`), length)

ricopau4 <- left_join(ri_county, DZ.subu4, by = "subregion")


u4 <- ri_c + geom_polygon(data = ricopau4, aes(fill = count), color = "white") + geom_polygon(color =
"black", fill = NA) +
  scale_fill_viridis(breaks = c(1, 10, 100, 1000, 10000),
                trans = "log10", limits=c(1, 10000)) + ggtitle("2014")
```

```
#ri map amount of charging stations per county per year 2015
DZs5 <- DZ15[c("Year", "Driver Postal Code")]
DZURI5 <- merge(zipcounty, DZs5, by.x = "zip", by.y = "Driver Postal Code") %>%
filter(!is.na(subregion))

DZ.subu5 <- aggregate(data.frame(count=DZURI5$`subregion`),
list(subregion=DZURI5$`subregion`), length)

ricopau5 <- left_join(ri_county, DZ.subu5, by = "subregion")


u5 <- ri_c + geom_polygon(data = ricopau5, aes(fill = count), color = "white") + geom_polygon(color =
"black", fill = NA) +
  scale_fill_viridis(breaks = c(1, 10, 100, 1000, 10000),
                trans = "log10", limits=c(1, 10000)) + ggtitle("2015")

#ri map amount of charging stations per county per year 2016
DZs6 <- DZ16[c("Year", "Driver Postal Code")]
DZURI6 <- merge(zipcounty, DZs6, by.x = "zip", by.y = "Driver Postal Code") %>%
filter(!is.na(subregion))

DZ.subu6 <- aggregate(data.frame(count=DZURI6$`subregion`),
list(subregion=DZURI6$`subregion`), length)

ricopau6 <- left_join(ri_county, DZ.subu6, by = "subregion")


u6 <- ri_c + geom_polygon(data = ricopau6, aes(fill = count), color = "white") + geom_polygon(color =
"black", fill = NA) +
  scale_fill_viridis(breaks = c(1, 10, 100, 1000, 10000),
                trans = "log10", limits=c(1, 10000)) + ggtitle("2016")

#ri map amount of charging stations per county per year 2017
DZs7 <- DZ17[c("Year", "Driver Postal Code")]
DZURI7 <- merge(zipcounty, DZs7, by.x = "zip", by.y = "Driver Postal Code") %>%
filter(!is.na(subregion))

DZ.subu7 <- aggregate(data.frame(count=DZURI7$`subregion`),
list(subregion=DZURI7$`subregion`), length)

ricopau7 <- left_join(ri_county, DZ.subu7, by = "subregion")


u7 <- ri_c + geom_polygon(data = ricopau4, aes(fill = count), color = "white") + geom_polygon(color =
"black", fill = NA) +
  scale_fill_viridis(breaks = c(1, 10, 100, 1000, 10000),
                trans = "log10", limits=c(1, 10000)) + ggtitle("2017")

#All together

ggarrange(u3,u4,u5,u6,u7, ncol= 5, nrow = 1, common.legend = TRUE, legend="right")

```
```

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Locations

Amount of User from each County

```{r map4, echo=FALSE}

#numer of User from RI


#zipcounty <- read_delim("~/Dropbox/Masterthesis/zipcounty.csv", ";", escape_double = FALSE,locale = locale(decimal_mark = ","), trim_ws = TRUE)


DZsi <- Clean_Data[c("Year", "User ID", "Driver Postal Code")] %>% filter(!is.na('User ID'))

DZii <- DZsi %>% group_by(`User ID`, Year, `Driver Postal Code`) %>% tally()

DZURIi1 <- merge(zipcounty, DZii, by.x = "zip", by.y = "Driver Postal Code") %>% filter(!is.na(subregion))

DZ.subi1 <- aggregate(data.frame(count=DZURIi1$`subregion`), list(subregion=DZURIi1$`subregion`), length)

ricopai11 <- left_join(ri_county, DZ.subi1, by = "subregion")

ri_c + geom_polygon(data = ricopai11, aes(fill = count), color = "white") + geom_polygon(color = "black", fill = NA) +
  scale_fill_viridis(breaks = c(5, 50, 500),
                trans = "log10", limits=c(1, 600)) + ggtitle("All User from each County")

#ri map amount of charging stations per county per year 2013

DZsi3 <- DZii %>% filter(Year == 2013)
DZURIi3 <- merge(zipcounty, DZsi3, by.x = "zip", by.y = "Driver Postal Code") %>% filter(!is.na(subregion))

DZ.subi3 <- aggregate(data.frame(count=DZURIi3$`subregion`), list(subregion=DZURIi3$`subregion`), length)

ricopai3 <- left_join(ri_county, DZ.subi3, by = "subregion")

uc3 <- ri_c + geom_polygon(data = ricopai3, aes(fill = count), color = "white") + geom_polygon(color = "black", fill = NA) +
  scale_fill_viridis(breaks = c(5, 50, 500),
                trans = "log10", limits=c(1, 500)) + ggtitle("2013")

#ri map amount of charging stations per county per year 2014
DZsi4 <- DZii %>% filter(Year == 2014)
DZURIi4 <- merge(zipcounty, DZsi4, by.x = "zip", by.y = "Driver Postal Code") %>% filter(!is.na(subregion))
```

```
DZ.subi4 <- aggregate(data.frame(count=DZURIi4$`subregion`),
list(subregion=DZURIi4$`subregion`), length)

ricopai4 <- left_join(ri_county, DZ.subi4, by = "subregion")

uc4 <- ri_c + geom_polygon(data = ricopai4, aes(fill = count), color = "white") + geom_polygon(color
= "black", fill = NA) +
  scale_fill_viridis(breaks = c(5, 50, 500),
                   trans = "log10", limits=c(1, 500)) + ggtitle("2014")

#ri map amount of charging stations per county per year 2015
DZsi5 <- DZii %>% filter(Year == 2015)
DZURIi5 <- merge(zipcounty, DZsi5, by.x = "zip", by.y = "Driver Postal Code") %>%
filter(!is.na(subregion))

DZ.subi5 <- aggregate(data.frame(count=DZURIi5$`subregion`),
list(subregion=DZURIi5$`subregion`), length)

ricopai5 <- left_join(ri_county, DZ.subi5, by = "subregion")

uc5 <- ri_c + geom_polygon(data = ricopai5, aes(fill = count), color = "white") + geom_polygon(color
= "black", fill = NA) +
  scale_fill_viridis(breaks = c(5, 50, 500),
                   trans = "log10", limits=c(1, 500)) + ggtitle("2015")

#ri map amount of charging stations per county per year 2016
DZsi6 <- DZii %>% filter(Year == 2016)
DZURIi6 <- merge(zipcounty, DZsi6, by.x = "zip", by.y = "Driver Postal Code") %>%
filter(!is.na(subregion))

DZ.subi6 <- aggregate(data.frame(count=DZURIi6$`subregion`),
list(subregion=DZURIi6$`subregion`), length)

ricopai6 <- left_join(ri_county, DZ.subi6, by = "subregion")

uc6 <- ri_c + geom_polygon(data = ricopai6, aes(fill = count), color = "white") + geom_polygon(color
= "black", fill = NA) +
  scale_fill_viridis(breaks = c(5, 50, 500),
                   trans = "log10", limits=c(1, 500)) + ggtitle("2016")

#ri map amount of charging stations per county per year 2017
DZsi7 <- DZii %>% filter(Year == 2017)
DZURIi7 <- merge(zipcounty, DZsi7, by.x = "zip", by.y = "Driver Postal Code") %>%
filter(!is.na(subregion))

DZ.subi7 <- aggregate(data.frame(count=DZURIi7$`subregion`),
list(subregion=DZURIi7$`subregion`), length)

ricopai7 <- left_join(ri_county, DZ.subi7, by = "subregion")

uc7 <- ri_c + geom_polygon(data = ricopai7, aes(fill = count), color = "white") + geom_polygon(color
= "black", fill = NA) +
  scale_fill_viridis(breaks = c(5, 50, 500),
```

```
                              trans = "log10", limits=c(1, 500)) + ggtitle("2017")

#All together

ggarrange(uc3,uc4,uc5,uc6,uc7, ncol= 5, nrow = 1, common.legend = TRUE, legend="right")
```
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Locations

Amount of User from each County devided by population

````{r map4new, echo=FALSE}
#numer of User from RI


#zipcounty <- read_delim("~/Dropbox/Masterthesis/zipcounty.csv", ";", escape_double = FALSE,locale
= locale(decimal_mark = ","), trim_ws = TRUE)


DZsi <- Clean_Data[c("Year", "User ID", "Driver Postal Code")] %>% filter(!is.na('User ID'))

DZii <- DZsi %>% group_by(`User ID`, Year, `Driver Postal Code`) %>% tally()

DZURIi1 <- merge(zipcounty, DZii, by.x = "zip", by.y = "Driver Postal Code") %>%
filter(!is.na(subregion))

DZ.subi1 <- aggregate(data.frame(count=DZURIi1$`subregion`),
list(subregion=DZURIi1$`subregion`), length)

ricopai11 <- left_join(ri_county, DZ.subi1, by = "subregion")

ri_c + geom_polygon(data = ricopai11, aes(fill = count), color = "white") + geom_polygon(color =
"black", fill = NA) +
  scale_fill_viridis(breaks = c(5, 50, 500),
                 trans = "log10", limits=c(1, 600)) + ggtitle("All User from each County")

#ri map amount of charging stations per county per year 2013

DZsi3 <- DZii %>% filter(Year == 2013)
DZURIi3 <- merge(zipcounty, DZsi3, by.x = "zip", by.y = "Driver Postal Code") %>%
filter(!is.na(subregion))

DZ.subi3 <- aggregate(data.frame(count=DZURIi3$`subregion`),
list(subregion=DZURIi3$`subregion`), length)

pop2013 <- c(49207,164356,82824,630033,126223)
pop2013 <- as.integer(pop2013)
pop2014 <- c(49047,164513,82822,632087,126313)
pop2014 <- as.integer(pop2014)
```

```
pop2015 <- c(49096,163740,83419,633519,126142)
pop2015 <- as.integer(pop2015)
pop2016 <- c(48878,163690,83495,635522,125981)
pop2016 <- as.integer(pop2016)
pop2017 <- c(48912,163760,83460,637357,126150)
pop2017 <- as.integer(pop2017)


DZ.subi3$count = DZ.subi3$count/pop2013


ricopai3 <- left_join(ri_county, DZ.subi3, by = "subregion")

uc3 <- ri_c + geom_polygon(data = ricopai3, aes(fill = count), color = "white") + geom_polygon(color
= "black", fill = NA) +
  scale_fill_viridis(breaks = c(0,0.0005,0.001), limits=c(0, 0.001)) + ggtitle("2013")

#ri map amount of charging stations per county per year 2014
DZsi4 <- DZii %>% filter(Year == 2014)
DZURIi4 <- merge(zipcounty, DZsi4, by.x = "zip", by.y = "Driver Postal Code") %>%
filter(!is.na(subregion))

DZ.subi4 <- aggregate(data.frame(count=DZURIi4$`subregion`),
list(subregion=DZURIi4$`subregion`), length)
DZ.subi4$count = DZ.subi4$count/pop2014
ricopai4 <- left_join(ri_county, DZ.subi4, by = "subregion")

uc4 <- ri_c + geom_polygon(data = ricopai4, aes(fill = count), color = "white") + geom_polygon(color
= "black", fill = NA) +
  scale_fill_viridis(breaks = c(0,0.0005,0.001), limits=c(0, 0.001)) + ggtitle("2014")

#ri map amount of charging stations per county per year 2015
DZsi5 <- DZii %>% filter(Year == 2015)
DZURIi5 <- merge(zipcounty, DZsi5, by.x = "zip", by.y = "Driver Postal Code") %>%
filter(!is.na(subregion))

DZ.subi5 <- aggregate(data.frame(count=DZURIi5$`subregion`),
list(subregion=DZURIi5$`subregion`), length)
DZ.subi5$count = DZ.subi5$count/pop2015
ricopai5 <- left_join(ri_county, DZ.subi5, by = "subregion")

uc5 <- ri_c + geom_polygon(data = ricopai5, aes(fill = count), color = "white") + geom_polygon(color
= "black", fill = NA) +
  scale_fill_viridis(breaks = c(0,0.0005,0.001), limits=c(0, 0.001)) + ggtitle("2015")

#ri map amount of charging stations per county per year 2016
DZsi6 <- DZii %>% filter(Year == 2016)
DZURIi6 <- merge(zipcounty, DZsi6, by.x = "zip", by.y = "Driver Postal Code") %>%
filter(!is.na(subregion))

DZ.subi6 <- aggregate(data.frame(count=DZURIi6$`subregion`),
list(subregion=DZURIi6$`subregion`), length)
DZ.subi6$count = DZ.subi6$count/pop2016
ricopai6 <- left_join(ri_county, DZ.subi6, by = "subregion")
```

```
uc6 <- ri_c + geom_polygon(data = ricopai6, aes(fill = count), color = "white") + geom_polygon(color
= "black", fill = NA) +
  scale_fill_viridis(breaks = c(0,0.0005,0.001), limits=c(0, 0.001)) + ggtitle("2016")

#ri map amount of charging stations per county per year 2017
DZsi7 <- DZii %>% filter(Year == 2017)
DZURIi7 <- merge(zipcounty, DZsi7, by.x = "zip", by.y = "Driver Postal Code") %>%
filter(!is.na(subregion))

DZ.subi7 <- aggregate(data.frame(count=DZURIi7$`subregion`),
list(subregion=DZURIi7$`subregion`), length)
DZ.subi7$count = DZ.subi7$count/pop2017
ricopai7 <- left_join(ri_county, DZ.subi7, by = "subregion")

uc7 <- ri_c + geom_polygon(data = ricopai7, aes(fill = count), color = "white") + geom_polygon(color
= "black", fill = NA) +
  scale_fill_viridis(breaks = c(0,0.0005,0.001), limits=c(0, 0.001)) + ggtitle("2017")

#All together

ggarrange(uc3,uc4,uc5,uc6,uc7, ncol= 5, nrow = 1, common.legend = TRUE, legend="right")

```

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## Locations

Median Amount of Charging Events done per User from each County
Is there more home charging?


```{r map5, echo=FALSE}
DZsi3 <- DZii %>% filter(Year == 2013)
DZURIi3 <- merge(zipcounty, DZsi3, by.x = "zip", by.y = "Driver Postal Code") %>%
filter(!is.na(subregion))

DZ.subi3 <- aggregate(data.frame(count=DZURIi3$`subregion`),
list(subregion=DZURIi3$`subregion`), length)

ricopai3 <- left_join(ri_county, DZ.subi3, by = "subregion")

#ri map amount of charging stations per county per year 2014
DZsi4 <- DZii %>% filter(Year == 2014)
DZURIi4 <- merge(zipcounty, DZsi4, by.x = "zip", by.y = "Driver Postal Code") %>%
filter(!is.na(subregion))

DZ.subi4 <- aggregate(data.frame(count=DZURIi4$`subregion`),
list(subregion=DZURIi4$`subregion`), length)

ricopai4 <- left_join(ri_county, DZ.subi4, by = "subregion")

#ri map amount of charging stations per county per year 2015
DZsi5 <- DZii %>% filter(Year == 2015)
```

```
DZURIi5 <- merge(zipcounty, DZsi5, by.x = "zip", by.y = "Driver Postal Code") %>%
filter(!is.na(subregion))

DZ.subi5 <- aggregate(data.frame(count=DZURIi5$`subregion`),
list(subregion=DZURIi5$`subregion`), length)

ricopai5 <- left_join(ri_county, DZ.subi5, by = "subregion")

#ri map amount of charging stations per county per year 2016
DZsi6 <- DZii %>% filter(Year == 2016)
DZURIi6 <- merge(zipcounty, DZsi6, by.x = "zip", by.y = "Driver Postal Code") %>%
filter(!is.na(subregion))

DZ.subi6 <- aggregate(data.frame(count=DZURIi6$`subregion`),
list(subregion=DZURIi6$`subregion`), length)

ricopai6 <- left_join(ri_county, DZ.subi6, by = "subregion")

#ri map amount of charging stations per county per year 2017
DZsi7 <- DZii %>% filter(Year == 2017)
DZURIi7 <- merge(zipcounty, DZsi7, by.x = "zip", by.y = "Driver Postal Code") %>%
filter(!is.na(subregion))

DZ.subi7 <- aggregate(data.frame(count=DZURIi7$`subregion`),
list(subregion=DZURIi7$`subregion`), length)

ricopai7 <- left_join(ri_county, DZ.subi7, by = "subregion")

#####

#numer of User from RI and their median events per year

DZ.subui <- data.frame(subregion = c("bristol", "kent", "newport", "providence","washington"), count
= c(DZ.subu[,2]/DZ.subi1[,2]))

ribui <- left_join(ri_county, DZ.subui, by = "subregion")

bui <- ri_c + geom_polygon(data = ribui, aes(fill = count), color = "white") + geom_polygon(color =
"black", fill = NA) +
  scale_fill_viridis(breaks = c(10,20,30,40,50), limits=c(5, 50)) + ggtitle("Me an Charging Events in RI
by RI User")

#Mean Charging Events in RI by RI User 2013

DZ.subui3 <- data.frame(subregion = c("bristol", "kent", "newport", "providence","washington"), count
= c(DZ.subu3[,2]/DZ.subi3[,2]))

ribui3 <- left_join(ri_county, DZ.subui3, by = "subregion")

bui3 <-  ri_c + geom_polygon(data = ribui3, aes(fill = count), color = "white") + geom_polygon(color =
"black", fill = NA) +
  scale_fill_viridis(breaks = c(10,20,30,40,50), limits=c(5, 50)) + ggtitle("2013")

#Mean Charging Events in RI by RI User 2014
```

```
DZ.subui4 <- data.frame(subregion = c("bristol", "kent", "newport", "providence","washington"), count
= c(DZ.subu4[,2]/DZ.subi4[,2]))

ribui4 <- left_join(ri_county, DZ.subui4, by = "subregion")

bui4 <-  ri_c + geom_polygon(data = ribui4, aes(fill = count), color = "white") + geom_polygon(color =
"black", fill = NA) +
  scale_fill_viridis(breaks = c(10,20,30,40,50), limits=c(5, 50)) + ggtitle("2014")

#Mean Charging Events in RI by RI User 2015

DZ.subui5 <- data.frame(subregion = c("bristol", "kent", "newport", "providence","washington"), count
= c(DZ.subu5[,2]/DZ.subi5[,2]))

ribui5 <- left_join(ri_county, DZ.subui5, by = "subregion")

bui5 <-  ri_c + geom_polygon(data = ribui5, aes(fill = count), color = "white") + geom_polygon(color =
"black", fill = NA) +
  scale_fill_viridis(breaks = c(10,20,30,40,50), limits=c(5, 50)) + ggtitle("2015")

#Mean Charging Events in RI by RI User 2016

DZ.subui6 <- data.frame(subregion = c("bristol", "kent", "newport", "providence","washington"), count
= c(DZ.subu6[,2]/DZ.subi6[,2]))

ribui6 <- left_join(ri_county, DZ.subui6, by = "subregion")

bui6 <-  ri_c + geom_polygon(data = ribui6, aes(fill = count), color = "white") + geom_polygon(color =
"black", fill = NA) +
  scale_fill_viridis(breaks = c(10,20,30,40,50), limits=c(5, 50)) + ggtitle("2016")

#Mean Charging Events in RI by RI User 2017

DZ.subui7 <- data.frame(subregion = c("bristol", "kent", "newport", "providence","washington"), count
= c(DZ.subu7[,2]/DZ.subi7[,2]))

ribui7 <- left_join(ri_county, DZ.subui7, by = "subregion")

bui7 <-  ri_c + geom_polygon(data = ribui7, aes(fill = count), color = "white") + geom_polygon(color =
"black", fill = NA) +
  scale_fill_viridis(breaks = c(10,20,30,40,50), limits=c(5, 50)) + ggtitle("2017")

#All together
bui
ggarrange(bui3,bui4,bui5,bui6,bui7, ncol= 5, nrow = 1, common.legend = TRUE, legend="right")
```

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## Time Dependence

Barchart about the usage of all stations per year.

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In the next step clustered in areas/counties which show the growth of charging events over the years in certain areas.

```{r Yearly, echo=FALSE}


am <- Clean_Data %>% group_by(Date) %>% tally()
am1 <- am %>% mutate(ym = format(Date, "%Y-%m"))%>%  group_by(ym) %>% filter(!is.na(ym)) %>%  tally()
ay1 <- Clean_Data %>% group_by(Year) %>% tally() %>% filter(!is.na(Year))
barplot(ay1$n, main = "Charging events per year", xlab="Years 2013 to 2017")
ay <- Clean_Data %>% group_by(Year, Area) %>% tally() %>%  filter(!is.na(Area))

Box.test(ay1[,2], lag=1, type='Ljung-Box')
Box.test(ay1[,2], lag=1, type='Box-Pierce')
print("p-values were not significant. independent observations possible")

RIuser <- as.vector(c(59,146,204,295,429))

Box.test(RIuser, lag=1, type='Ljung-Box')
Box.test(RIuser, lag=1, type='Box-Pierce')
print("for User in RI -> independent")

alluser <- as.vector(c(122,317,485,661,974))

Box.test(alluser, lag=1, type='Ljung-Box')
Box.test(alluser, lag=1, type='Box-Pierce')
print("for all User -> independent")


ggplot(data = ay, aes(x=Year, y=n))+ geom_col() + facet_wrap(~ Area) + theme_bw()
ggplot(data = ay, aes(x=Area, y=n))+ geom_col() + facet_wrap(~ Year) + theme_bw()

ay2 <- Clean_Data %>% group_by(Year, County) %>% tally() %>%  filter(!is.na(County))

ggplot(data = ay2, aes(x=Year, y=n))+ geom_col() + facet_wrap(~ County) + theme_bw()
ggplot(data = ay2, aes(x=County, y=n))+ geom_col() + facet_wrap(~ Year) + theme_bw()

```
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## Time Dependence

Barchart about the usage of all stations per weekday.
In the next step clustered in areas which show the usage of charging stations per weekday in certain areas.

```{r wdd2, echo=FALSE}
ad <- Clean_Data %>% group_by(Day, Area) %>% tally() %>%  filter(!is.na(Area))
ad2 <- Clean_Data %>% group_by(Day) %>% tally() %>%  filter(!is.na(Day))
ad3 <- Clean_Data %>% group_by(Day, County) %>% tally() %>%  filter(!is.na(County))
ad2$Day <- ordered(ad2$Day, levels = c("Sun", "Mon", "Tue", "Wed", "Thu", "Fri", "Sat"))
ad$Day <- ordered(ad$Day, levels = c("Sun", "Mon", "Tue", "Wed", "Thu", "Fri", "Sat"))
```

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ad3$Day <- ordered(ad3$Day, levels = c("Sun", "Mon", "Tue", "Wed", "Thu", "Fri", "Sat"))
ggplot(data = ad2, aes(x=Day, y=n))+ geom_col()
ggplot(data = ad, aes(x=Day, y=n))+ geom_col() + facet_wrap(~ Area) + theme_bw()
ggplot(data = ad3, aes(x=Day, y=n))+ geom_col() + facet_wrap(~ County) + theme_bw()

```

\newpage

##Time Dependence
As mentioned before, the charging events over time, are not dependent on time as a sum of years. But they are time series as a sum of month or days.

Here are the charging events per month as a line-plot, also divided into Areas and Counties.

```{r am, echo=FALSE}
am <- Clean_Data %>% group_by(Date) %>% tally() %>% filter(!is.na(Date))
am2 <- Clean_Data %>% group_by(Date, Area) %>% tally() %>% filter(!is.na(Area))
am3 <- Clean_Data %>% group_by(Date, County) %>% tally() %>% filter(!is.na(County))

########## for comparison of single stations
#am17 <- Clean_Data %>% filter(`Station Name`== 'RI OER / STATION#3') %>% filter(Year ==
2017) %>% group_by(Date) %>% tally() %>% filter(!is.na(Date))
#stationdata <- am17 %>% mutate(ym = format(Date, "%Y-%m"))%>%  group_by(ym) %>%
filter(!is.na(ym)) %>%  tally()
#########

Box.test(am1$nn, lag=12, type='Ljung-Box')
Box.test(am1$nn, lag=12, type='Box-Pierce')
print(" -> timeseries")

#same thing monthly
am1 <- am %>% mutate(ym = format(Date, "%Y-%m"))%>%  group_by(ym) %>% filter(!is.na(ym))
%>%  tally()

am12 <- am2 %>% mutate(ym = format(Date, "%Y-%m")) %>% group_by(ym,Area) %>% tally()
am13 <- am3 %>% mutate(ym = format(Date, "%Y-%m")) %>% group_by(ym, County) %>% tally()

ggplot(data = am1, aes(x=ym,y= nn, group=1))+ geom_line() + xlab("Month & Year")+ ylab("Number
of Charging Events") + theme_bw()  +
  theme(axis.text.x = element_text(angle=90))
ggplot(data = am12, aes(x=ym, y=nn, group=1))+ geom_line() + facet_wrap(~ Area) + xlab("Month &
Year")+ ylab("Number of Charging Events") + theme_bw()+
  theme(axis.text.x = element_text(angle=90))
ggplot(data = am13, aes(x=ym, y=nn, group=1))+ geom_line() + facet_wrap(~ County) + xlab("Month
& Year")+ ylab("Number of Charging Events") + theme_bw()+
  theme(axis.text.x = element_text(angle=90))
```

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##Time Dependence

This is now a Forecasting of the charging events per month performed with Arima

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````
```{r am12, echo=FALSE}

#forecasting month

am1.v <- as.vector(am1$nn)
adf.test(am1.v, alternative = "stationary")
print("fail to reject H0: it is non-stationary")
am1.d <- diff(am1.v)
adf.test(am1.d, alternative = "stationary")
print("reject H0: it is stationary")
acf(am1.d)
pacf(am1.d)

auto.arima(am1.v)

acf(am1.v)
pacf(am1.v)
fit <- Arima(am1.v, order=c(0,1,0), include.drift = T)
fit
tsdiag(fit)

plot(forecast(fit, h=36))

fcm <- forecast(fit, h = 36)
fcm2020 <- data.frame(x=fcm$mean)
tail(fcm$mean)
tail(fcm$lower)
tail(fcm$upper)
#options(od)
```
````

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Time Dependence

This is now a Forecasting of the charging events per week performed with Arima

````
```{r amcw, echo=FALSE}

#forecasting week

cw <- Clean_Data %>% group_by(Year, weeknumber) %>% tally() %>% filter(!is.na(Year))

Box.test(cw$n, lag=52, type='Ljung-Box')
Box.test(cw$n, lag=52, type='Box-Pierce')
print(" -> timeseries")

cw.v <- as.vector(cw$n)
adf.test(cw.v, alternative = "stationary")
print("reject H0: it is stationary")

acf(cw.v)
pacf(cw.v)
````

```
auto.arima(cw.v)

fit <- Arima(cw.v, order=c(1,1,1), include.drift = T)
fit
tsdiag(fit)

plot(forecast(fit, h=156))

fcw <- forecast(fit, h = 156)
fcw2020 <- data.frame(x=fcw$mean)
tail(fcw$mean)
tail(fcw$lower)
tail(fcw$upper)

#options(od)
```

\newpage

##Time Dependence

Here are the charging events per day as a line-plot, also divided into Areas and Counties.

```{r am13, echo=FALSE}

ggplot(data = am, aes(x=Date, y=n))+ geom_line() + theme_bw()
qplot(am$Date, am$n, geom='smooth', span =0.5)
ggplot(data = am2, aes(x=Date, y=n))+ geom_line() + facet_wrap(~ Area) + theme_bw()
ggplot(data = am3, aes(x=Date, y=n))+ geom_line() + facet_wrap(~ County) + theme_bw()

```
\newpage

##Time Dependence

This is now a Forecasting of the charging events per day performed with Arima, which is not accurate

```{r am14, echo=FALSE}

auto.arima(am[,2])
fit <- arima(am[,2], order=c(3,1,2))

fit
tsdiag(fit)

plot(forecast(fit, h=100))

predict(fit, n.ahead = 6)

print("This model is not accurate")

#predict(fit, n.ahead = 200)
#options(od)
```

```
 \newpage
```

Charging or Parking?

Descriptive Statistics

```{r cop, echo=FALSE}
cpc <- Clean_Data %>%  filter(!is.na(Area)) %>%  filter(!is.na(`Time no charge`)) %>%
  filter(!is.na(`Total Duration (hh:mm:ss)`)) %>%  filter(!is.na(`Charging Time (hh:mm:ss)`))


print("Mean total duration pluged in")
cpc$`Total Duration (hh:mm:ss)` <- difftime(strptime(cpc$`Total Duration
(hh:mm:ss)`,"%H:%M:%S"),
              strptime("00:00:00","%H:%M:%S"),
              units="secs")
cpt.means <- aggregate(cpc$`Total Duration (hh:mm:ss)`,by=list(cpc$Area),mean)
cpt.means$Time <- format(.POSIXct(cpt.means$x,tz="GMT"), "%H:%M:%S")
cpt.means

print("SD total duration pluged in")
cpt.sd <- aggregate(cpc$`Total Duration (hh:mm:ss)`,by=list(cpc$Area),sd)
cpt.sd$Time <- format(.POSIXct(cpt.sd$x,tz="GMT"), "%H:%M:%S")
cpt.sd

print("Max total duration pluged in")
cpt.max <- aggregate(cpc$`Total Duration (hh:mm:ss)`,by=list(cpc$Area),max)
cpt.max$Time <- format(.POSIXct(cpt.max$x,tz="GMT"), "%H:%M:%S")
cpt.max


print("Mean charge time")
cpc$`Charging Time (hh:mm:ss)` <- difftime(strptime(cpc$`Charging Time
(hh:mm:ss)`,"%H:%M:%S"),
              strptime("00:00:00","%H:%M:%S"),
              units="secs")
cpct.means <- aggregate(cpc$`Charging Time (hh:mm:ss)`,by=list(cpc$Area),mean)
cpct.means$Time <- format(.POSIXct(cpct.means$x,tz="GMT"), "%H:%M:%S")
cpct.means

print("SD charge time")
cpct.sd <- aggregate(cpc$`Charging Time (hh:mm:ss)`,by=list(cpc$Area),sd)
cpct.sd$Time <- format(.POSIXct(cpct.sd$x,tz="GMT"), "%H:%M:%S")
cpct.sd

print("Max charge time")
cpct.max <- aggregate(cpc$`Charging Time (hh:mm:ss)`,by=list(cpc$Area),max)
cpct.max$Time <- format(.POSIXct(cpct.max$x,tz="GMT"), "%H:%M:%S")
cpct.max

print("Mean time parking at the station after being fully charged")
cpc$`Time no charge` <- difftime(strptime(cpc$`Time no charge`,"%H:%M:%S"),
```

```
                strptime("00:00:00","%H:%M:%S"),
                units="secs")


cpc.means <- aggregate(cpc$`Time no charge`,by=list(cpc$Area),mean)
cpc.means$Time <- format(.POSIXct(cpc.means$x,tz="GMT"), "%H:%M:%S")
cpc.means

print("SD time parking at the station after being fully charged")
cpc.sd <- aggregate(cpc$`Time no charge`,by=list(cpc$Area),sd)
cpc.sd$Time <- format(.POSIXct(cpc.sd$x,tz="GMT"), "%H:%M:%S")
cpc.sd

print("Max time parking at the station after being fully charged")
cpc.max <- aggregate(cpc$`Time no charge`,by=list(cpc$Area),max)
cpc.max$Time <- format(.POSIXct(cpc.max$x,tz="GMT"), "%H:%M:%S")
cpc.max

print("Mean amount of charging events")
aggregate(st$n,by=list(st$Area),mean)
print("SD amount of charging events")
aggregate(st$n,by=list(st$Area),sd)
print("Min amount of charging events")
aggregate(st$n,by=list(st$Area),min)
print("Max amount of charging events")
aggregate(st$n,by=list(st$Area),max)

```
```

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##Charging or Parking?

Percentages of People Charging (gone within 30min after being fully charged) and people how stay
longer (staying over 30min after being fully charged)

```{r cop2, echo=FALSE}

cop2 <- cpc %>% select(Area,`Time no charge`)
copc <- cop2 %>% filter(`Time no charge`< 1801) %>% count(Area)
copp <- cop2 %>% filter(`Time no charge`> 1800) %>% count(Area)


copc1 <- data.frame(Area = c(copc[,1]), Charging = c(copc[,2]/(copc[,2]+copp[,2])), Parking =
c(copp[,2]/(copc[,2]+copp[,2])))
print("Percentage Cases Used as a charging spot(n) and parking spot(n.1) in each Area")
copc1

clustering1_dist <- dist(copc1[,2:3])
clustering1 <- hclust(clustering1_dist, method = "complete")
plot(clustering1)

cpca <- cpc %>% select(`Time no charge`) %>% tally()
copca <- cpc %>% select(`Time no charge`) %>% filter(`Time no charge`< 1801) %>% tally()
```

```
coppa <- cpc %>% select(`Time no charge`) %>% filter(`Time no charge`> 1800) %>% tally()
print("Charging all")
copca/cpca
print("Parking all")
coppa/cpca

cpcap1 <- cpc %>% filter(`Station Name` == 'NATIONAL GRID / TRUTH BOX') %>% select(`Time
no charge`) %>% tally()
copcap1 <- cpc %>% filter(`Station Name` == 'NATIONAL GRID / TRUTH BOX') %>% select(`Time
no charge`) %>% filter(`Time no charge`< 1801) %>% tally()
coppap1 <- cpc %>% filter(`Station Name` == 'NATIONAL GRID / TRUTH BOX') %>% select(`Time
no charge`) %>% filter(`Time no charge`> 1800) %>% tally()

print("Charging Truthbox")
copcap1/cpcap1
print("Parking Truthbox")
coppap1/cpcap1

cpcap2 <- cpc %>% filter(`Station Name` == 'NATIONAL GRID / GARDEN CITY#1') %>%
select(`Time no charge`) %>% tally()
copcap2 <- cpc %>% filter(`Station Name` == 'NATIONAL GRID / GARDEN CITY#1') %>%
select(`Time no charge`) %>% filter(`Time no charge`< 1801) %>% tally()
coppap2 <- cpc %>% filter(`Station Name` == 'NATIONAL GRID / GARDEN CITY#1') %>%
select(`Time no charge`) %>% filter(`Time no charge`> 1800) %>% tally()

print("Charging Garden City1")
copcap2/cpcap2
print("Parking Garden City1")
coppap2/cpcap2

cpcap3 <- cpc %>% filter(`Station Name` == 'NATIONAL GRID / GARDEN CITY#2') %>%
select(`Time no charge`) %>% tally()
copcap3 <- cpc %>% filter(`Station Name` == 'NATIONAL GRID / GARDEN CITY#2') %>%
select(`Time no charge`) %>% filter(`Time no charge`< 1801) %>% tally()
coppap3 <- cpc %>% filter(`Station Name` == 'NATIONAL GRID / GARDEN CITY#2') %>%
select(`Time no charge`) %>% filter(`Time no charge`> 1800) %>% tally()

print("Charging Garden City2")
copcap3/cpcap3
print("Parking Garden City2")
coppap3/cpcap3

```
```

APPENDIX 2: R-Markdown PDF Version

Data Analysis Master Thesis in R
Roxana Voss

June 2018

<u>Electric Vehicle (EV) Charging Behavior in existing Infrastructures</u>

This is an R Markdown document to understand the processed statistics of the data. It is a trial version, which keeps record of possibly usable statistics for the research. Updated Data can easily be read in and the same analysis can be performed automatically.

Descriptive Statistics

Energy used in kWh: Mean, Standard Deviation, Minimum, Maximum and Sum of all the charging events

```
mean(Clean_Data$`Energy (kWh)`, na.rm=TRUE)
```

[1] 7.125073

```
sd(Clean_Data$`Energy (kWh)`, na.rm=TRUE)
```

[1] 7.380458

```
min(Clean_Data$`Energy (kWh)`, na.rm=TRUE)
```

[1] -2.022

```
max(Clean_Data$`Energy (kWh)`, na.rm=TRUE)
```

[1] 99.843

```
sum(Clean_Data$`Energy (kWh)`, na.rm=TRUE)
```

[1] 268045.2

GHG Savings in kg: Mean, Standard Deviation, Minimum, Maximum and Sum of all the charging events

```
mean(Clean_Data$`GHG Savings (kg)`, na.rm=TRUE)
```

[1] 2.992569

```
sd(Clean_Data$`GHG Savings (kg)`, na.rm=TRUE)
```

[1] 3.099754

```
min(Clean_Data$`GHG Savings (kg)`, na.rm=TRUE)
```

[1] 0

```
max(Clean_Data$`GHG Savings (kg)`, na.rm=TRUE)
```

[1] 41.934

```
sum(Clean_Data$`GHG Savings (kg)`, na.rm=TRUE)
```

```
## [1] 112580.5
```

Gasoline Savings in Gallons: Mean, Standard Deviation, Minimum, Maximum and Sum of all the charging events

```
mean(Clean_Data$`Gasoline Savings (gallons)`, na.rm=TRUE,)
```

```
## [1] 0.8941957
```

```
sd(Clean_Data$`Gasoline Savings (gallons)`, na.rm=TRUE)
```

```
## [1] 0.9262491
```

```
min(Clean_Data$`Gasoline Savings (gallons)`, na.rm=TRUE)
```

```
## [1] -0.254
```

```
max(Clean_Data$`Gasoline Savings (gallons)`, na.rm=TRUE)
```

```
## [1] 12.53
```

```
sum(Clean_Data$`Gasoline Savings (gallons)`, na.rm=TRUE)
```

```
## [1] 33639.64
```

Total Plugged in Time in sec: Mean, Standard Deviation, Minimum, Maximum and Sum of all the charging events If further needed, it can be converted in a common time format.

```
## [1] "Mean total duration pluged in"
```

```
## Warning in ds1.means$Time <- format(.POSIXct(ds1.means, tz = "GMT"), "%H:
## %M:%S"): Wandle linke Seite in eine Liste um
```

```
## [[1]]
## [1] 13286.69
##
## $Time
## [1] "03:41:26"
```

```
## [1] "SD total duration pluged in"
```

```
## Warning in ds1.sd$Time <- format(.POSIXct(ds1.sd, tz = "GMT"), "%H:%M:%S"):
## Wandle linke Seite in eine Liste um
```

```
## [[1]]
## [1] 13097.33
##
## $Time
## [1] "03:38:17"
```

```
## [1] "Min total duration pluged in"
```

```
## Warning in ds1.min$Time <- format(.POSIXct(ds1.min, tz = "GMT"), "%H:%M:
## %S"): Wandle linke Seite in eine Liste um
```

```
## [[1]]
## [1] 0
##
## $Time
## [1] "00:00:00"
```

```
## [1] "Max total duration pluged in"

## Warning in ds1.max$Time <- format(.POSIXct(ds1.max, tz = "GMT"), "%H:%M:
## %S"): Wandle linke Seite in eine Liste um

## [[1]]
## [1] 86335
##
## $Time
## [1] "23:58:55"

## [1] "Sum total duration pluged in"

## Time difference of 489813848 secs
```

Total Charging Time in sec: Mean, Standard Deviation, Minimum, Maximum and Sum of all the charging events If further needed, it can be converted in a common time format.

```
## [1] "Mean charging time"

## Warning in ds1.means$Time <- format(.POSIXct(ds1.means, tz = "GMT"), "%H:
## %M:%S"): Wandle linke Seite in eine Liste um

## [[1]]
## [1] 6840.08
##
## $Time
## [1] "01:54:00"

## [1] "SD charging time"

## Warning in ds1.sd$Time <- format(.POSIXct(ds1.sd, tz = "GMT"), "%H:%M:%S"):
## Wandle linke Seite in eine Liste um

## [[1]]
## [1] 5367.777
##
## $Time
## [1] "01:29:27"

## [1] "Min charging time"

## Warning in ds1.min$Time <- format(.POSIXct(ds1.min, tz = "GMT"), "%H:%M:
## %S"): Wandle linke Seite in eine Liste um

## [[1]]
## [1] 0
##
## $Time
## [1] "00:00:00"

## [1] "Max charging time"

## Warning in ds1.max$Time <- format(.POSIXct(ds1.max, tz = "GMT"), "%H:%M:
## %S"): Wandle linke Seite in eine Liste um

## [[1]]
## [1] 53462
##
## $Time
## [1] "14:51:02"
```

```
## Time difference of 252159542 secs
```

Time the EV is plugged in after it has been fully charged in sec: Mean, Standard Deviation, Minimum, Maximum and Sum of all the charging events If further needed, it can be converted in a common time format.

```
## [1] "Mean time plugged in after being fully charged"
```

```
## Warning in ds1.means$Time <- format(.POSIXct(ds1.means, tz = "GMT"), "%H:
## %M:%S"): Wandle linke Seite in eine Liste um
```

```
## [[1]]
## [1] 6446.611
##
## $Time
## [1] "01:47:26"
```

```
## [1] "SD plugged in after being fully charged"
```

```
## Warning in ds1.sd$Time <- format(.POSIXct(ds1.sd, tz = "GMT"), "%H:%M:%S"):
## Wandle linke Seite in eine Liste um
```

```
## [[1]]
## [1] 10857.59
##
## $Time
## [1] "03:00:57"
```

```
## [1] "Min plugged in after being fully charged"
```

```
## Warning in ds1.min$Time <- format(.POSIXct(ds1.min, tz = "GMT"), "%H:%M:
## %S"): Wandle linke Seite in eine Liste um
```

```
## [[1]]
## [1] 0
##
## $Time
## [1] "00:00:00"
```

```
## [1] "Max plugged in after being fully charged"
```

```
## Warning in ds1.max$Time <- format(.POSIXct(ds1.max, tz = "GMT"), "%H:%M:
## %S"): Wandle linke Seite in eine Liste um
```

```
## [[1]]
## [1] 83507
##
## $Time
## [1] "23:11:47"
```

```
## Time difference of 237654306 secs
```

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Descriptive Statistics

Two Versions of bar charts about the usage of single Stations. In the next step clustered in areas which show the range of the usage of the single stations in this region.

Charging events per station

Descriptive Statistics

Are 80 percent of the charges done at 20 percent of the stations? No, at the 20% most popular stations are done 47 % of the charges. Same with total Ddration: No, at the 20% most popular stations are done 54 % of the total duration Same with charging time: No, at the 20% most popular stations are done 53 % of the charing time

```
## [1] "Amount of Charges"
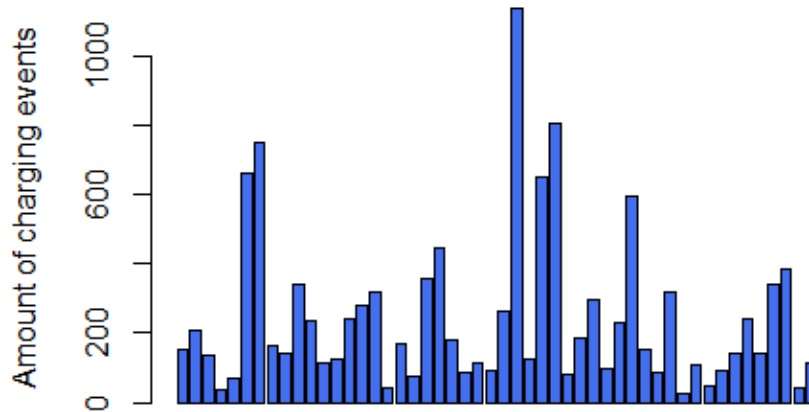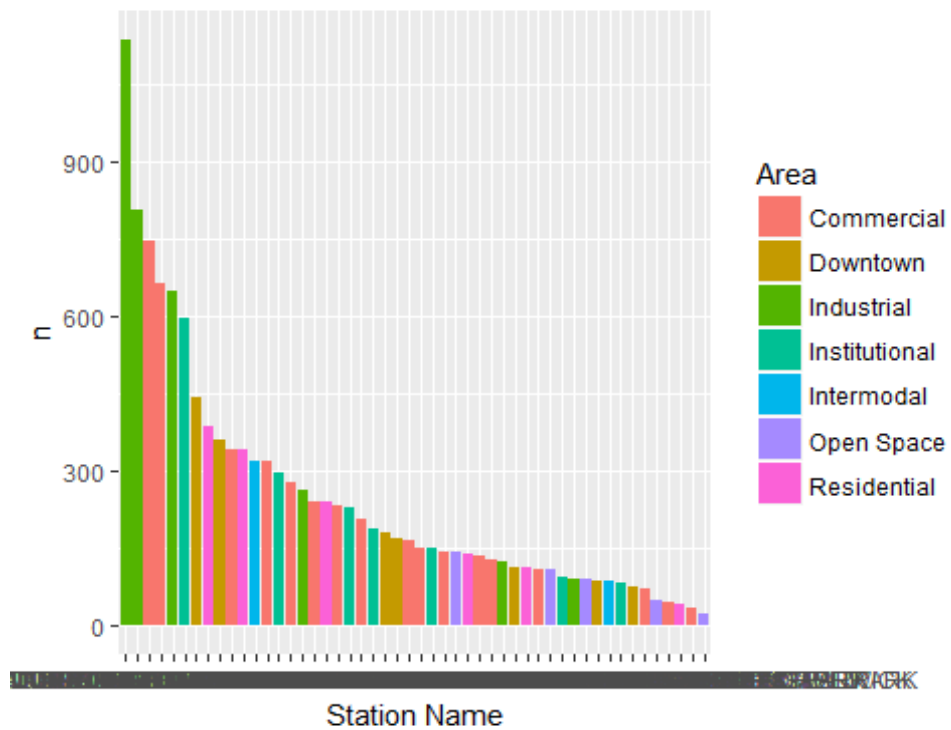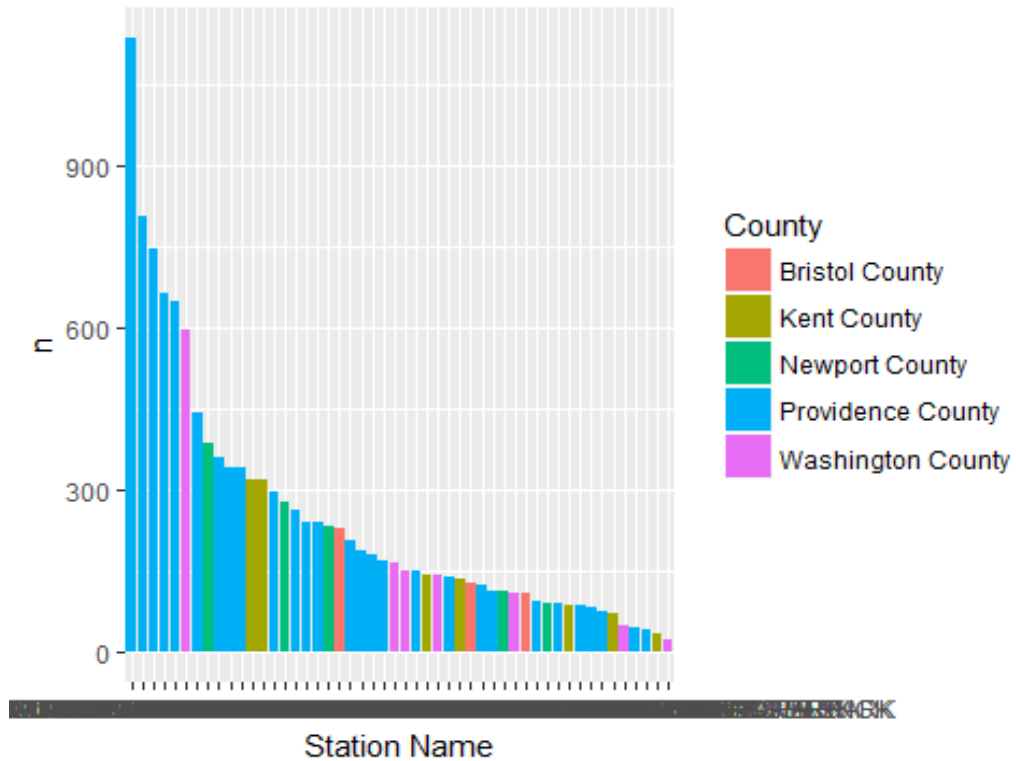
## [1] 0.5196704

## [1] 0.4803296

## [1] "Total Duration"

## [1] 0.4371989

## [1] 0.5628011

## [1] "Charge Time"

## [1] 0.4482668
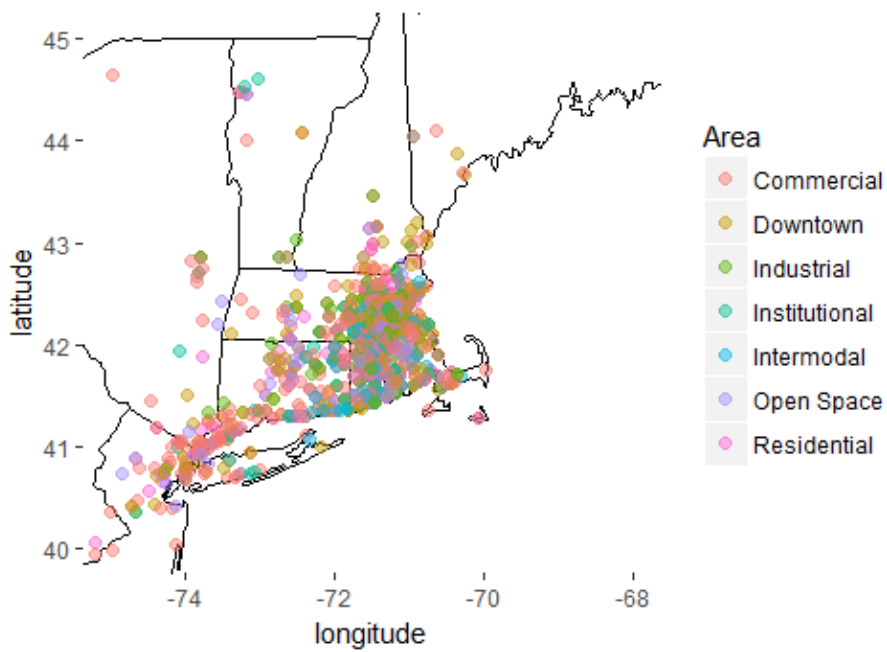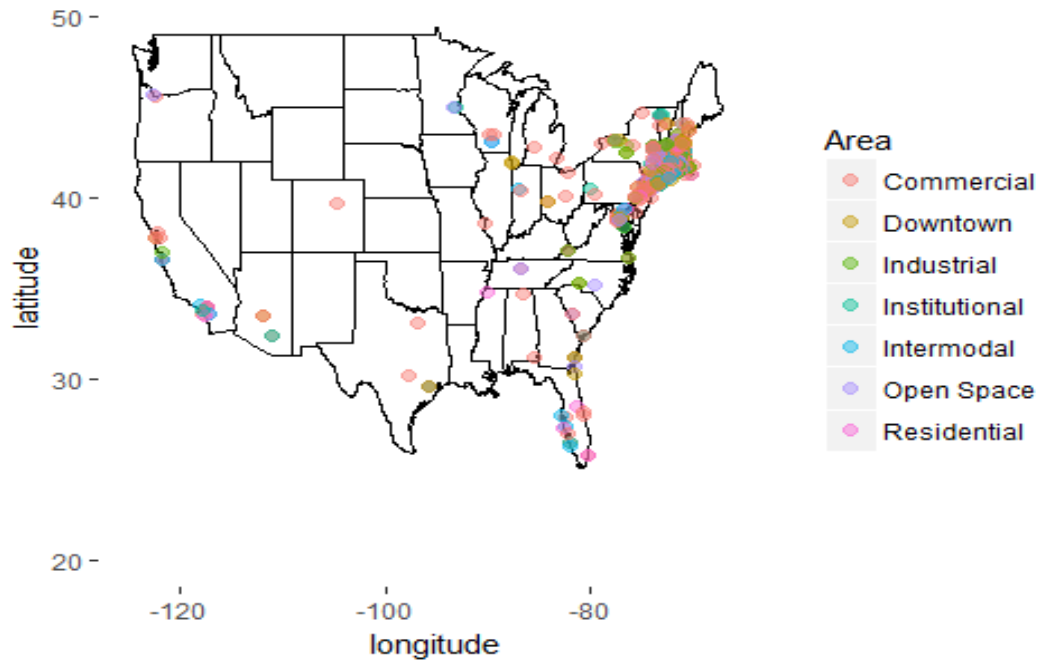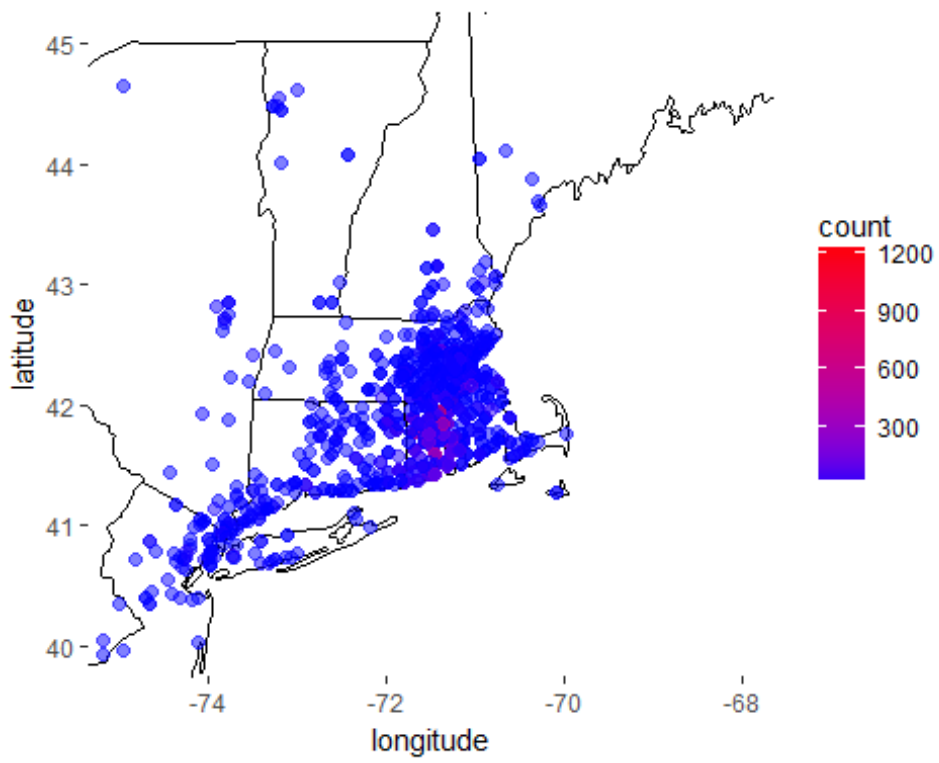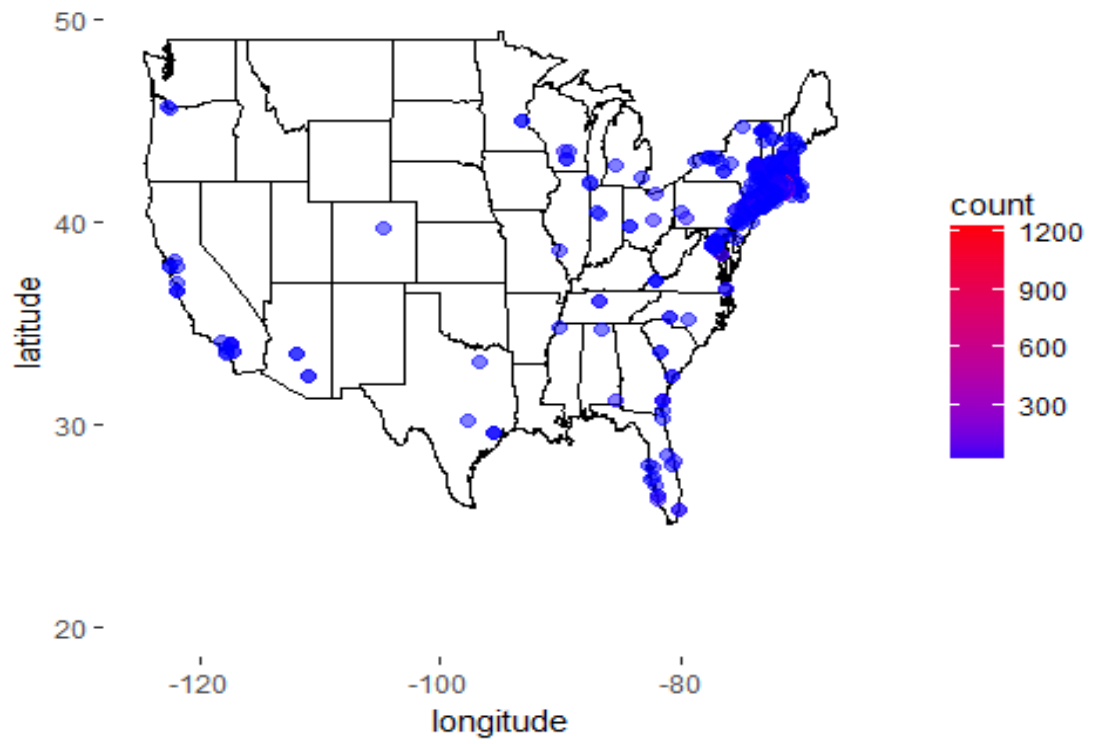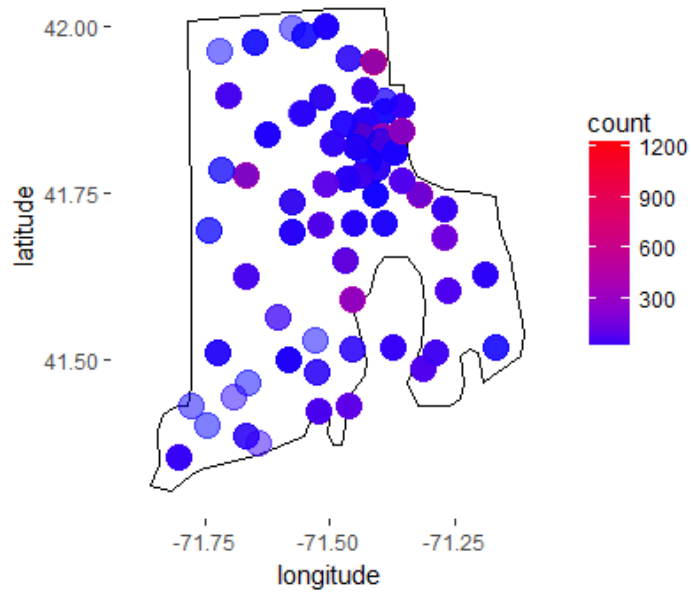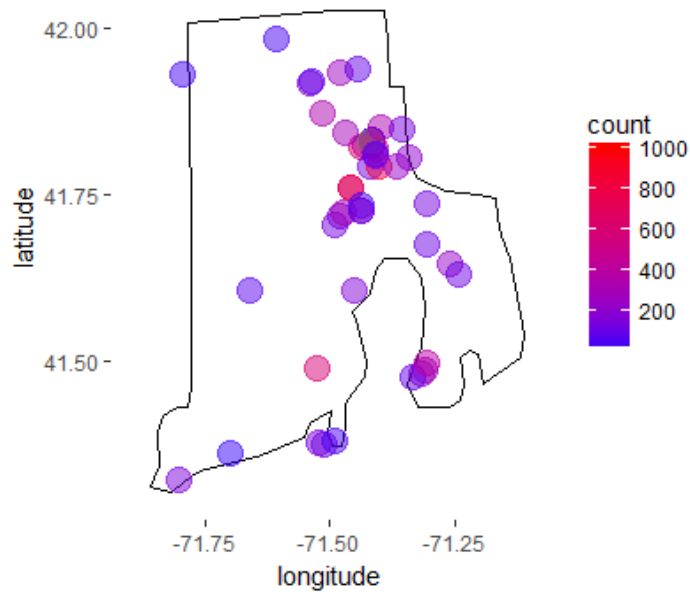
## [1] 0.5517332
```

You can see 3 versions of a map of the United States which show the distribution of charging station users using RI charging stations.

Map of RI with User Origin and amounts of charges

Map of RI with Chargig Stations and amounts of charges

Locations

Pie Chart about Areas and the Amount of Charging Stations in the zone.

Pie Chart about Areas and the Amount of Charging Events.

Amount of Charging Events by Area

Commercial

Downtown

Residential

Industrial

Open Space

Intermodal

Institutional

Pie Chart about Counties and the Amount of Charging Stations in the zone.

Amount of Charging Stations by County

Pie Chart about Areas and the Amount of Charging Events.

Amount of Charging Events by County

Locations

Boxplots about the Usage in the different Areas and Counties

Locations

Kruskal-Wallis Test

```
##
## Asymptotic Kruskal-Wallis Test
##
## data:  n by
##   Area (Commercial, Downtown, Industrial, Institutional, Intermodal, Open Space, Residential)
## chi-squared = 8.2494, df = 6, p-value = 0.2204
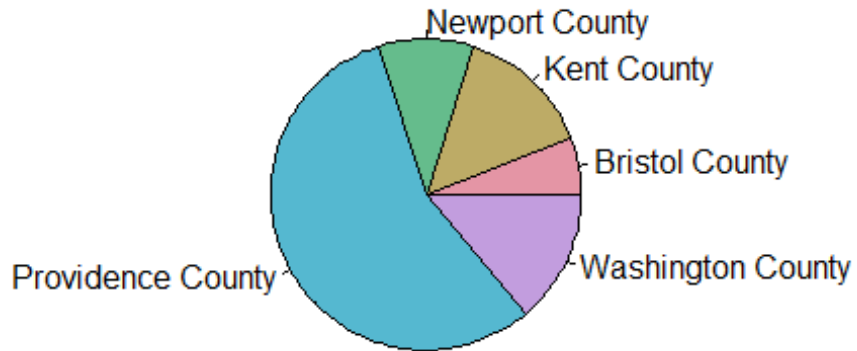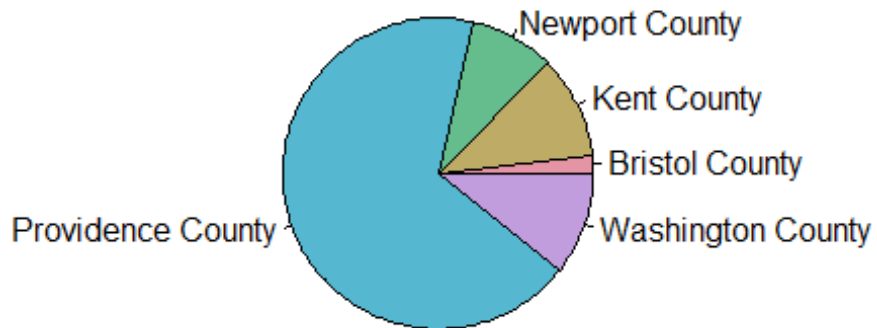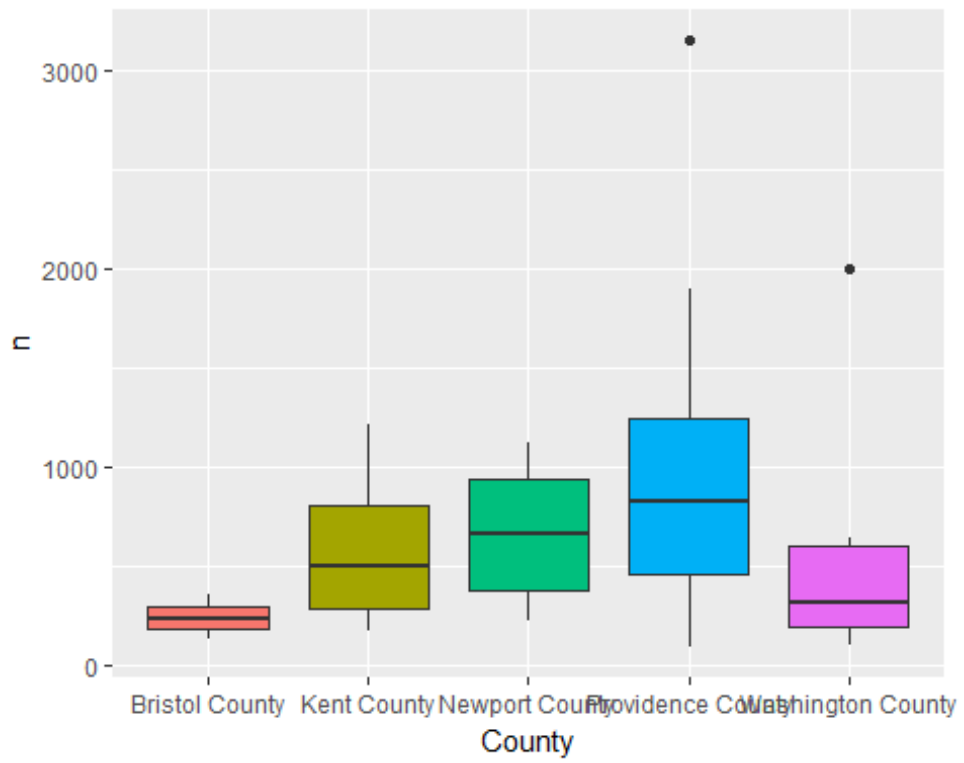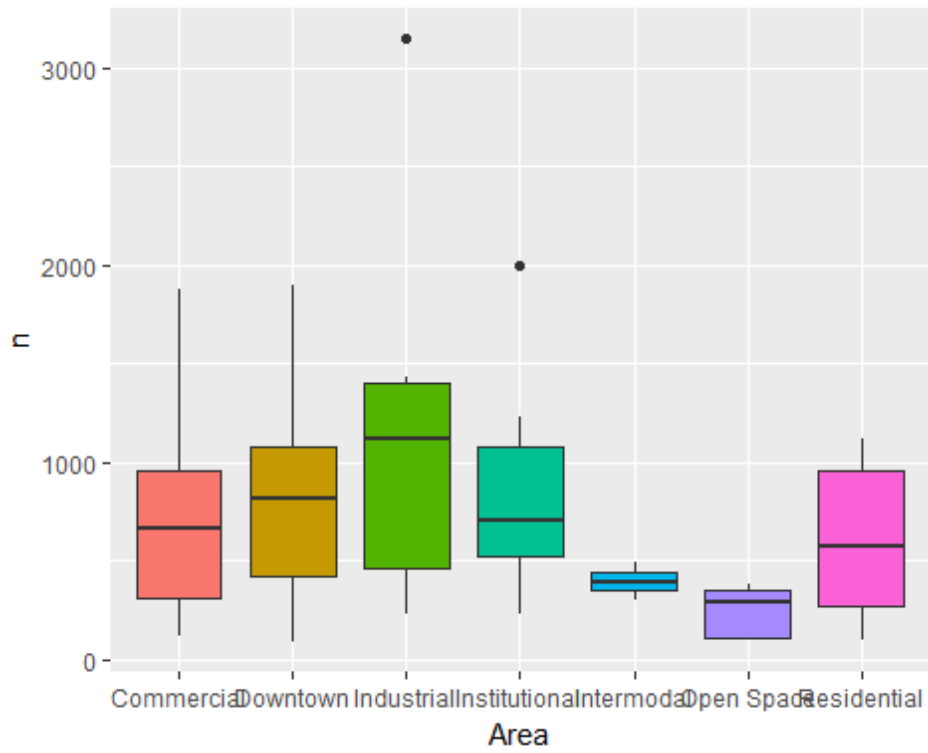
## [1] "Functional areas are not significantly different"

##
## Asymptotic Kruskal-Wallis Test
##
## data:  n by
##   County (Bristol County, Kent County, Newport County, Providence County, Washington County)
## chi-squared = 6.6665, df = 4, p-value = 0.1546

## [1] "Geographical areas are not significantly different"
```

Locations

RI map with the diffrent stations in colors of the Area and size per Amount of usage

Locations
Amount of Charging Events in each County

2017

Amount of Charging Events done by User from each County

Locations

Amount of User from each County

All User from each County

Amount of User from each County devided by population

Locations

Median Amount of Charging Events done per User from each County Is there more home charging?

Me an Charging Events in RI by RI User

Time Dependence

Barchart about the usage of all stations per year. In the next step clustered in areas/counties which show the growth of charging events over the years in certain areas.

Charging events per year

Years 2013 to 2017

```
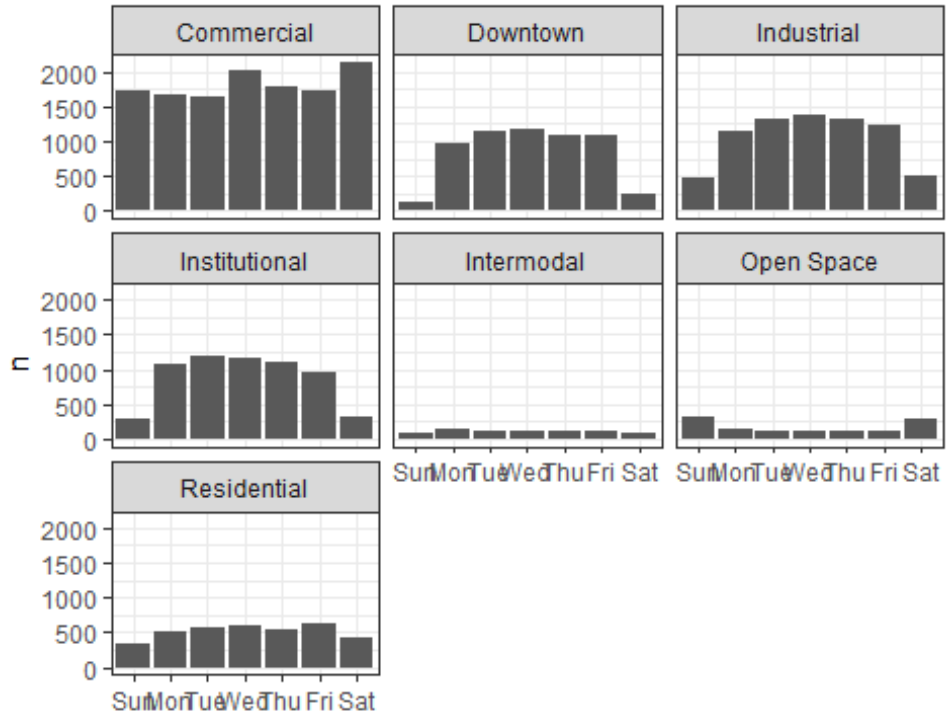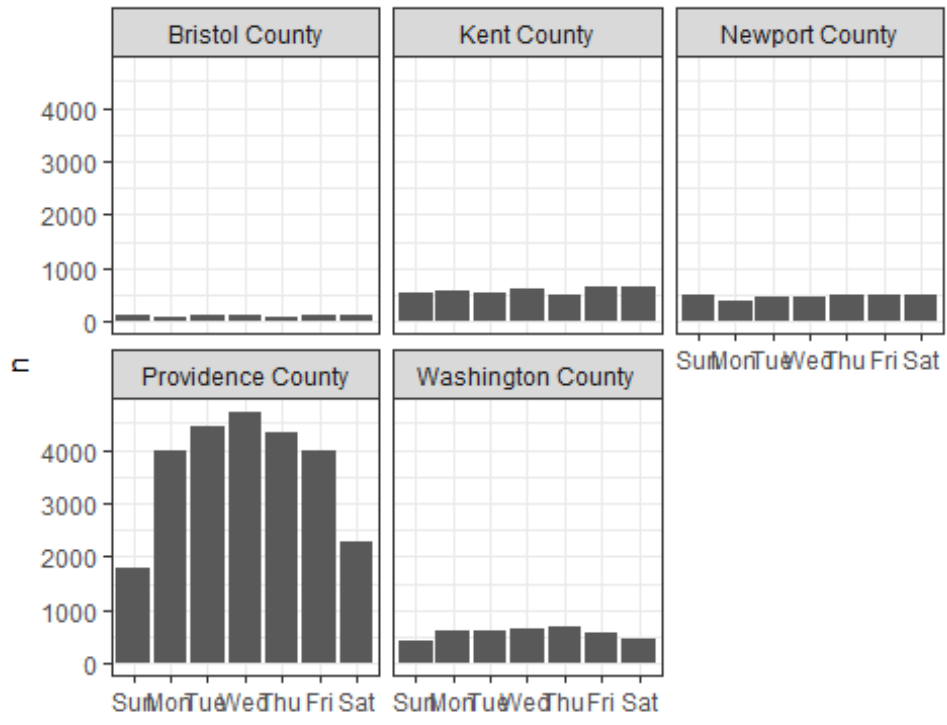##
##  Box-Ljung test
##
## data:  ay1[, 2]
## X-squared = 0.93609, df = 1, p-value = 0.3333
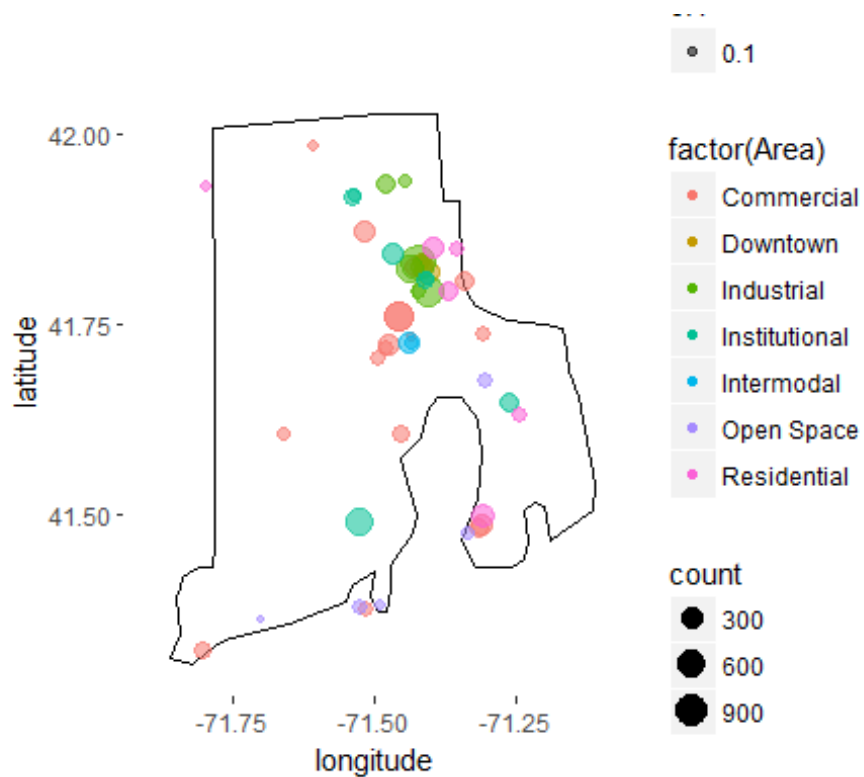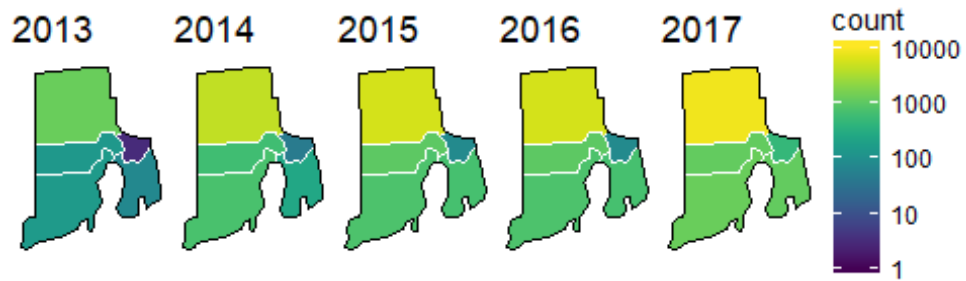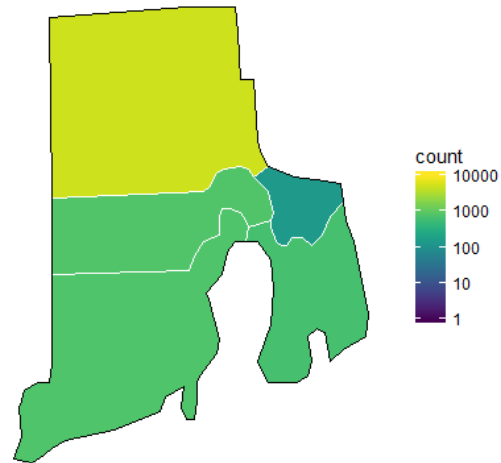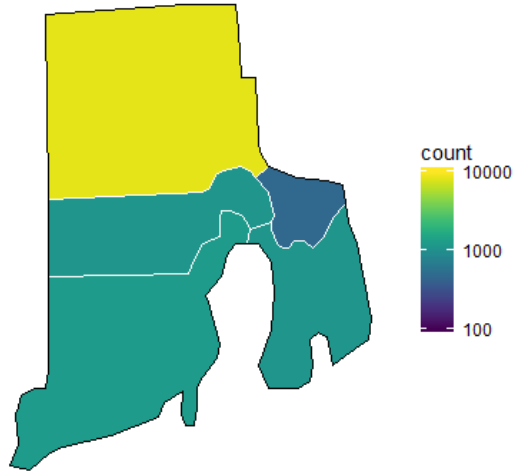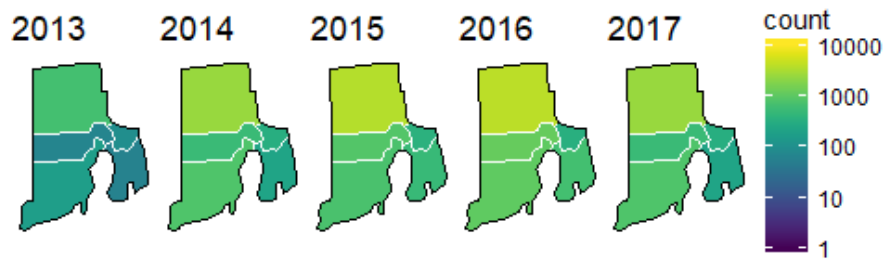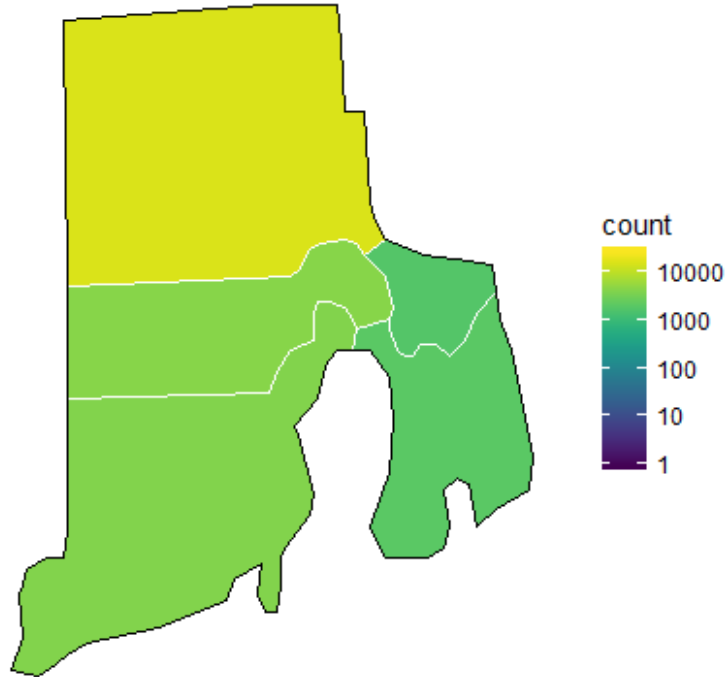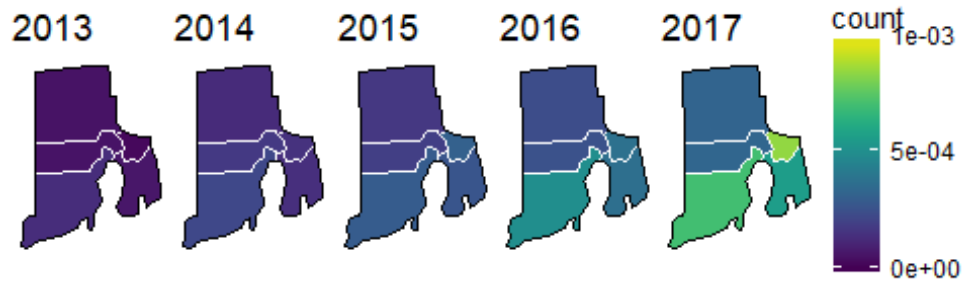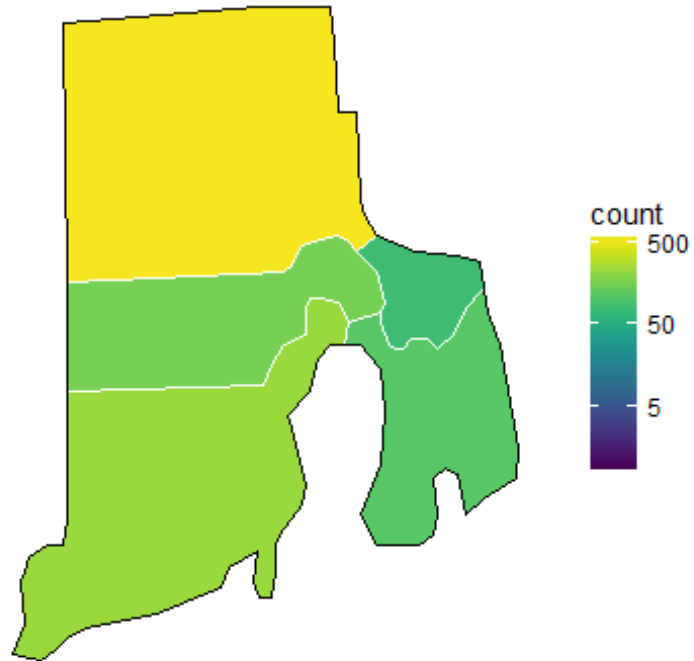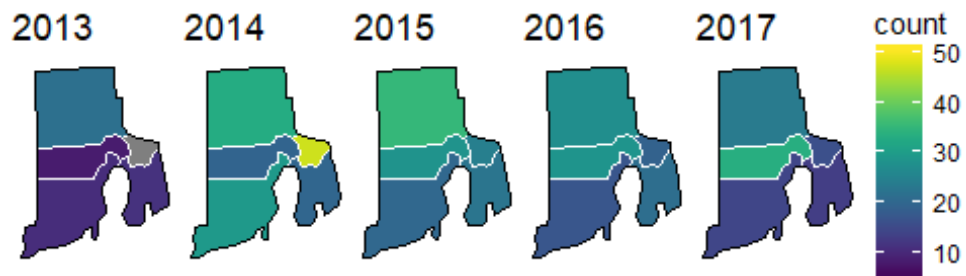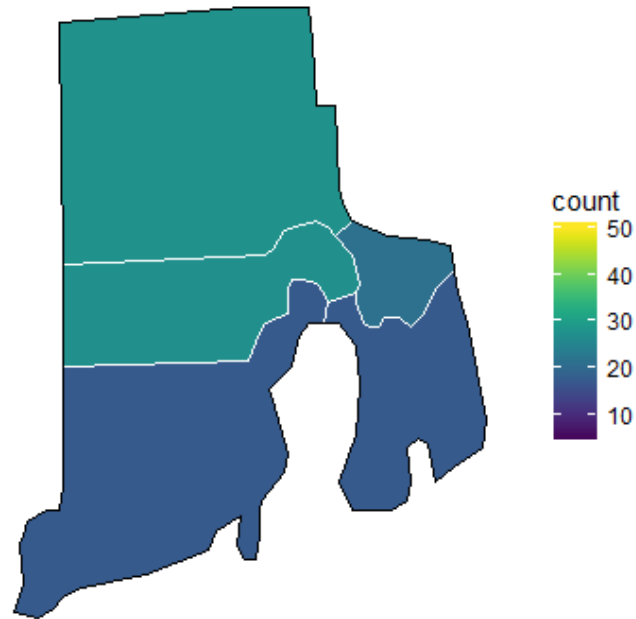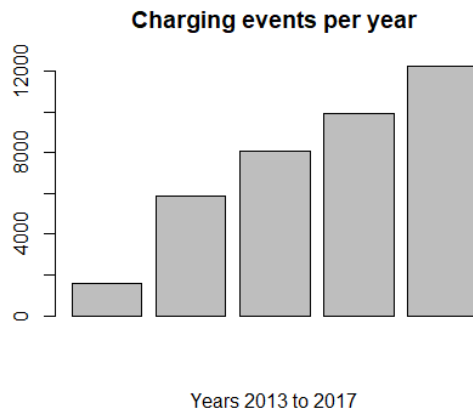

##
##  Box-Pierce test
##
## data:  ay1[, 2]
## X-squared = 0.53491, df = 1, p-value = 0.4646

## [1] "p-values were not significant. independent observations possible"


##
##  Box-Ljung test
##
## data:  RIuser
## X-squared = 1.0245, df = 1, p-value = 0.3114


##
##  Box-Pierce test
##
## data:  RIuser
## X-squared = 0.58545, df = 1, p-value = 0.4442

## [1] "for User in RI -> independent"


##
##  Box-Ljung test
##
## data:  alluser
## X-squared = 1.027, df = 1, p-value = 0.3109


##
##  Box-Pierce test
##
## data:  alluser
## X-squared = 0.58685, df = 1, p-value = 0.4436
```

[1] "for all User -> independent"

Time Dependence

Barchart about the usage of all stations per weekday. In the next step clustered in areas which show the usage of charging stations per weekday in certain areas.

Time Dependence

As mentioned before, the charging events over time, are not dependent on time as a sum of years. But they are time series as a sum of month or days.

Here are the charging events per month as a line-plot, also divided into Areas and Counties.

```
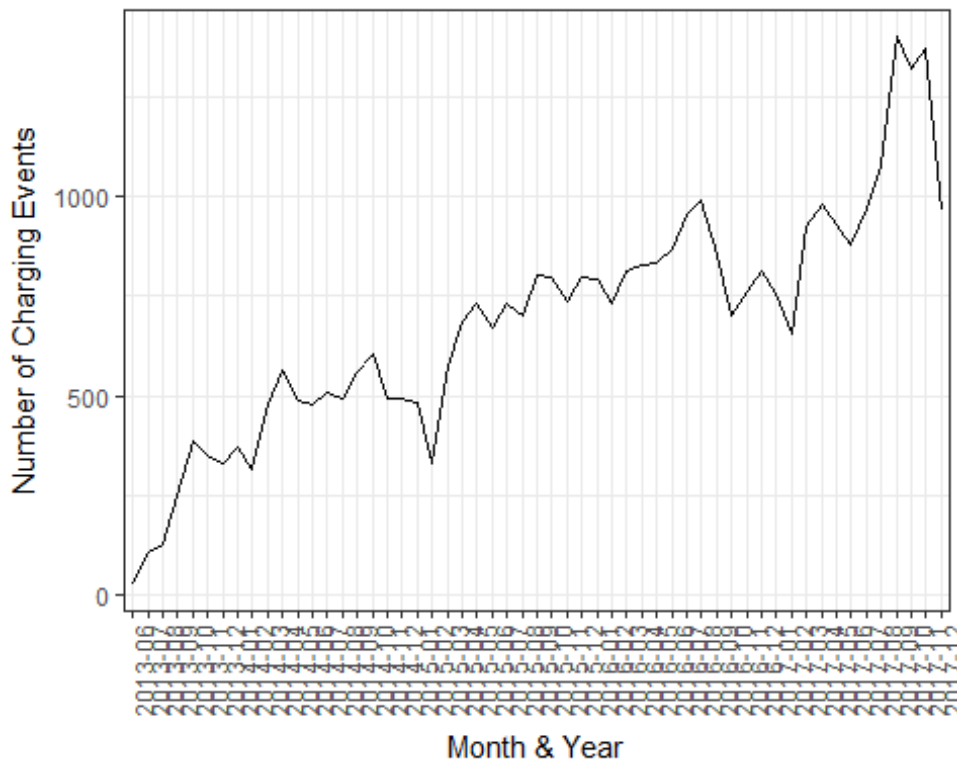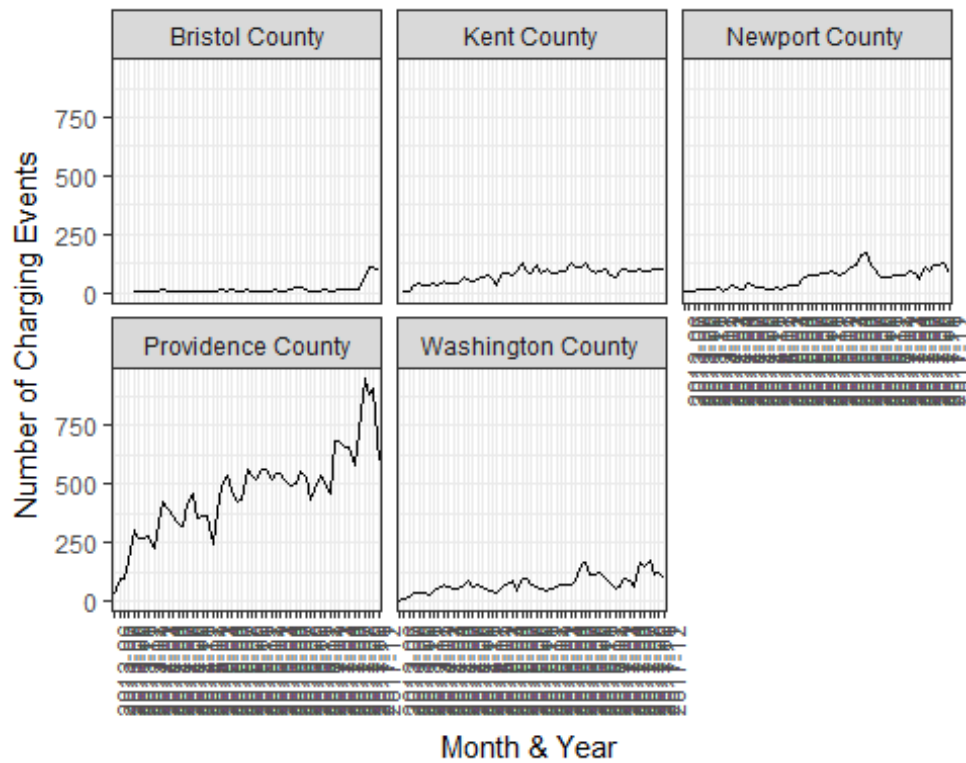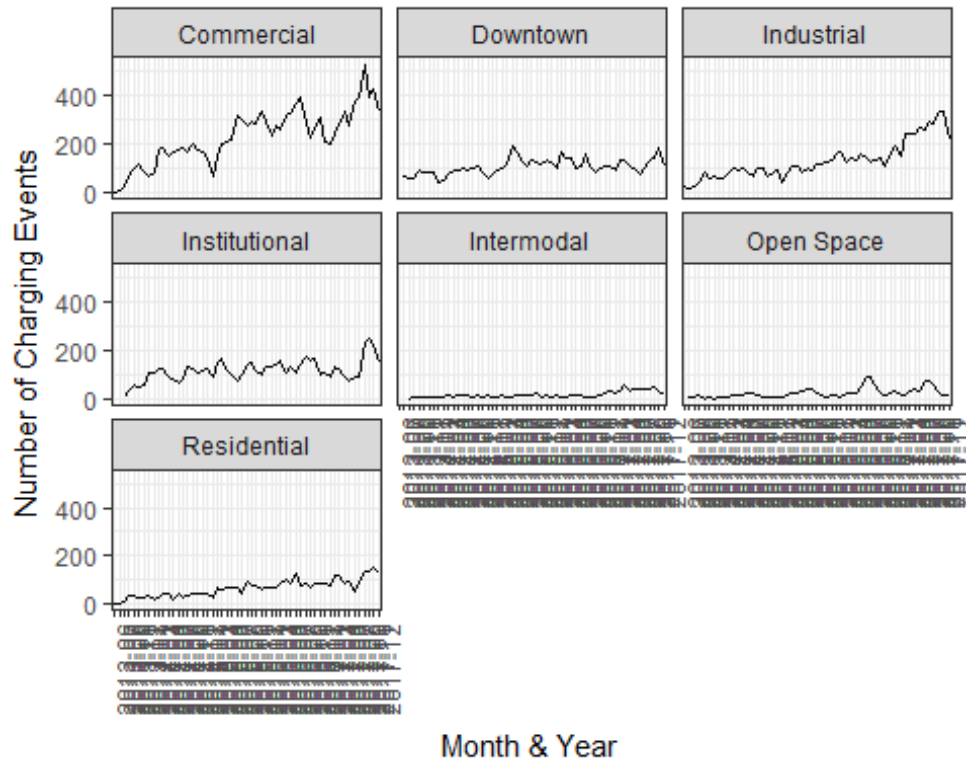##
## 	Box-Ljung test
##
## data:  am1$nn
## X-squared = 180.26, df = 12, p-value < 2.2e-16
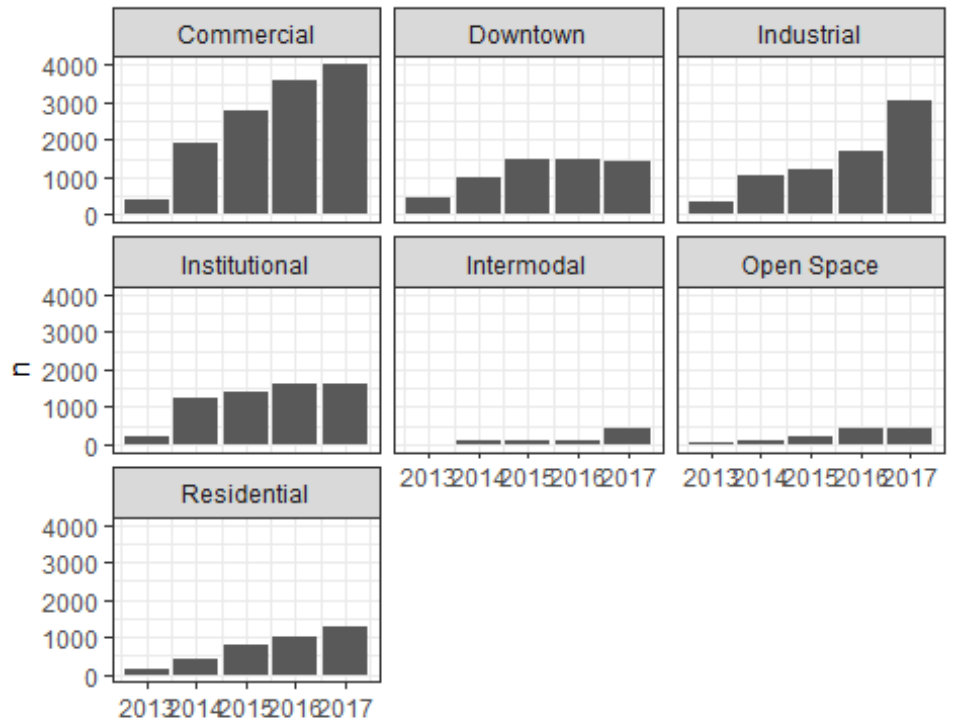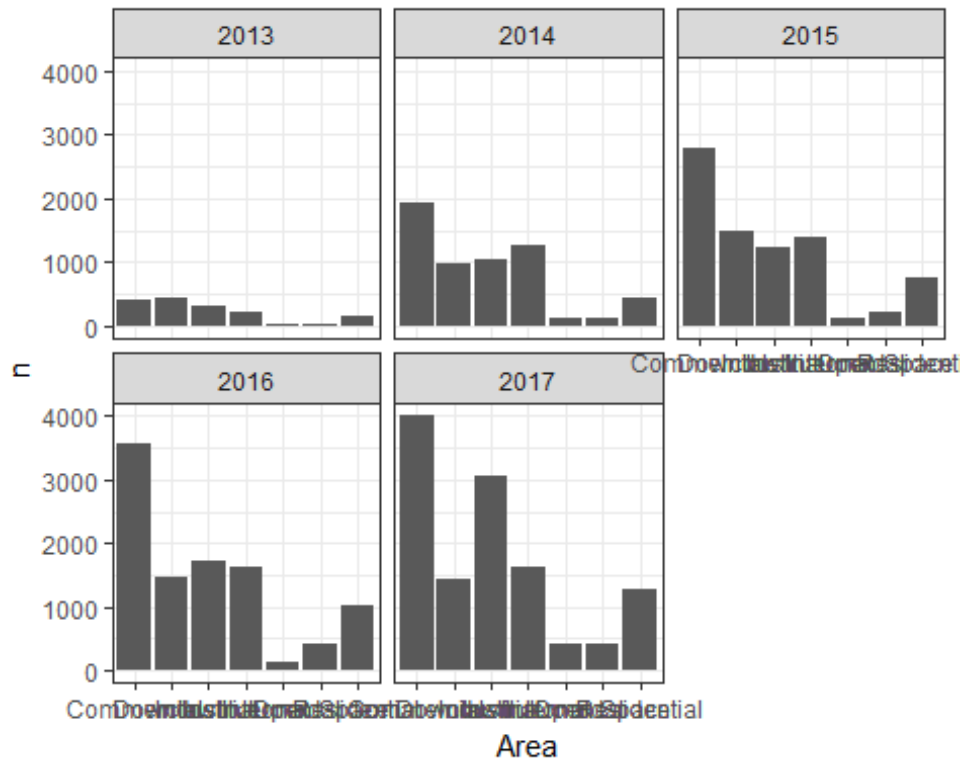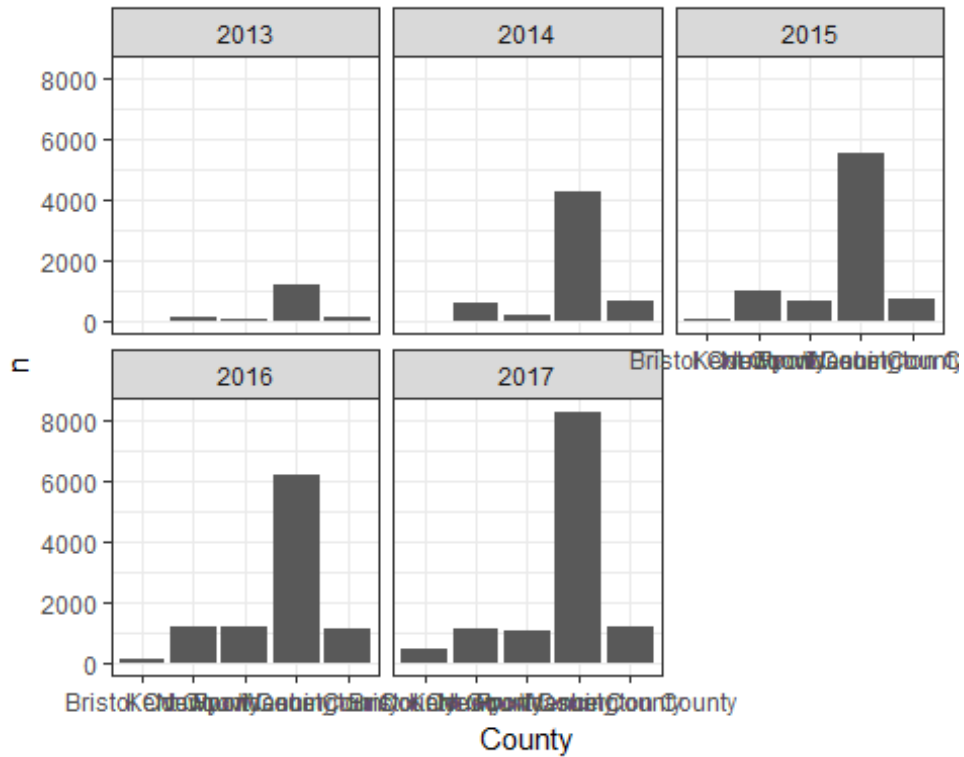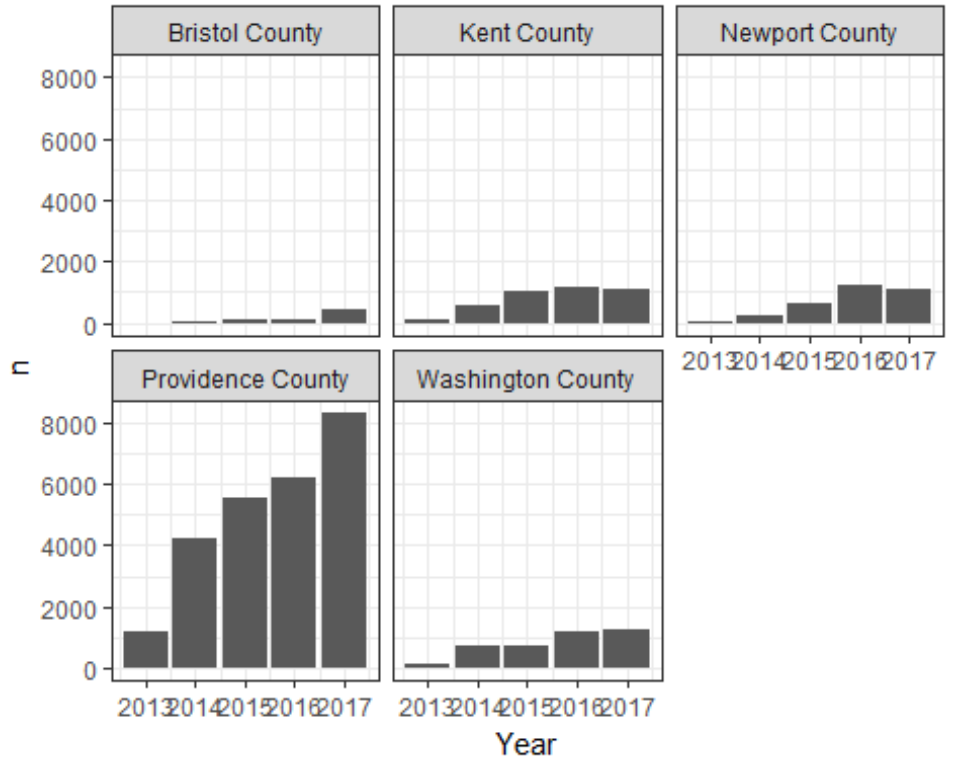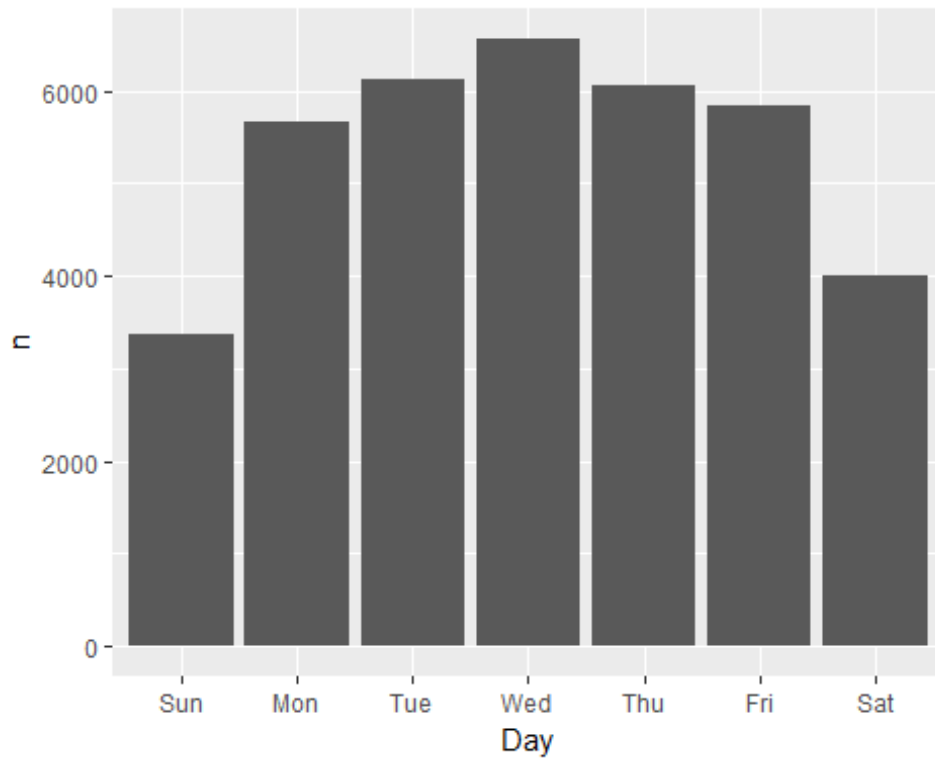

##
## 	Box-Pierce test
##
## data:  am1$nn
## X-squared = 160.97, df = 12, p-value < 2.2e-16
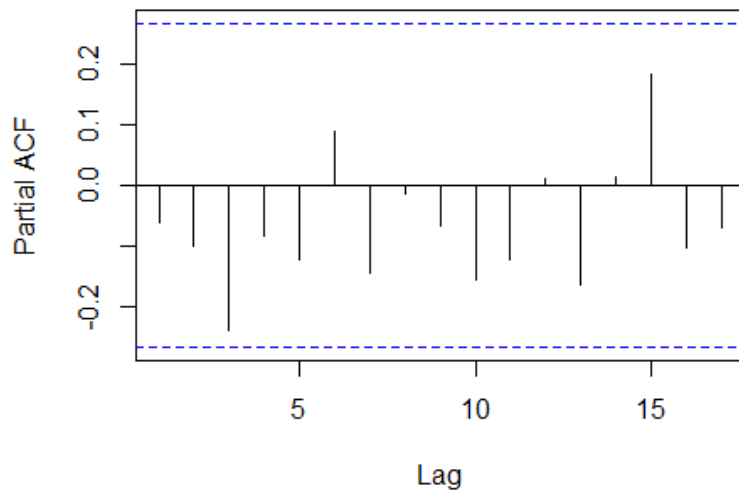
## [1] " -> timeseries"
```

Figure showing Number of Charging Events by land use type (Commercial, Downtown, Industrial, Institutional, Intermodal, Open Space, Residential) over Month & Year.

Figure showing Number of Charging Events by county (Bristol County, Kent County, Newport County, Providence County, Washington County) over Month & Year.

Time Dependence

This is now a Forecasting of the charging events per month performed with Arima

```
##
##  Augmented Dickey-Fuller Test
##
## data:  am1.v
## Dickey-Fuller = -3.2427, Lag order = 3, p-value = 0.08977
## alternative hypothesis: stationary

## [1] "fail to reject H0: it is non-stationary"

## Warning in adf.test(am1.d, alternative = "stationary"): p-value smaller
## than printed p-value

##
##  Augmented Dickey-Fuller Test
##
## data:  am1.d
## Dickey-Fuller = -4.7462, Lag order = 3, p-value = 0.01
## alternative hypothesis: stationary
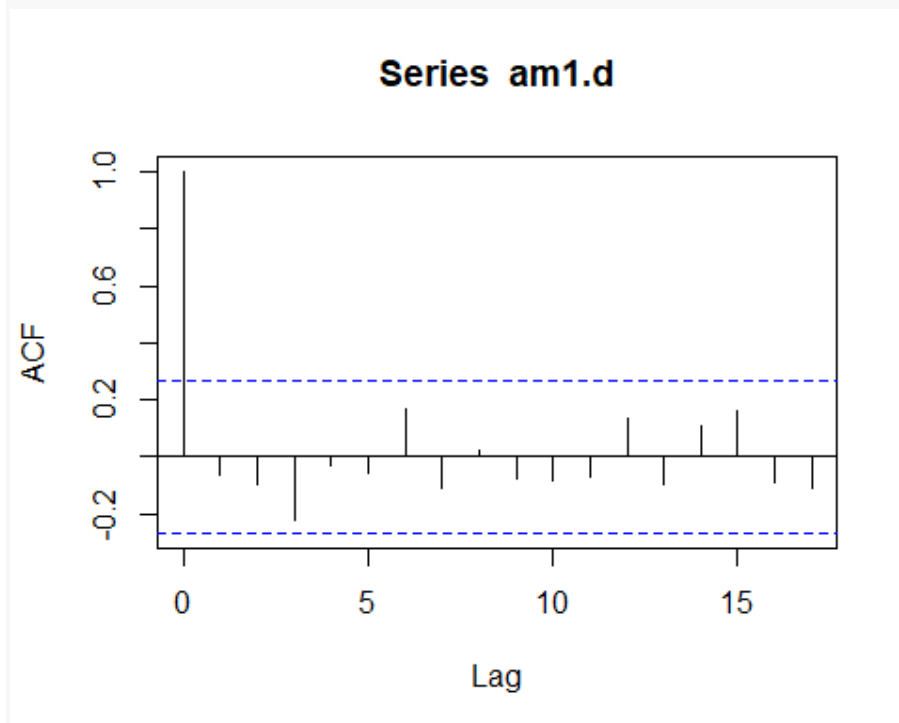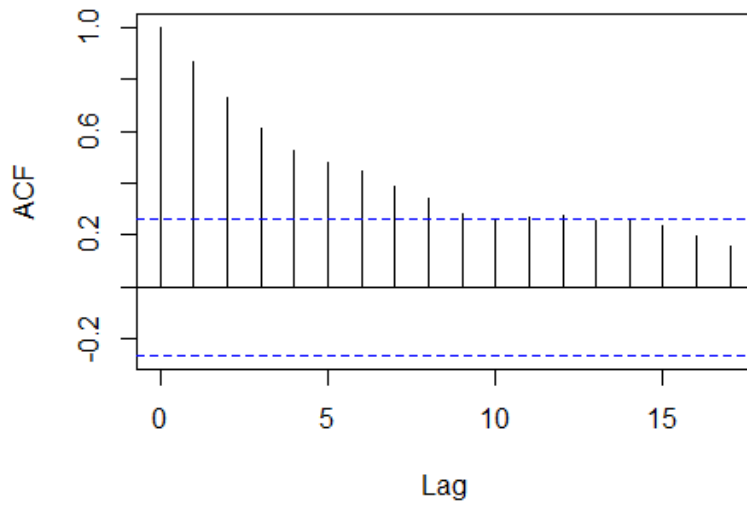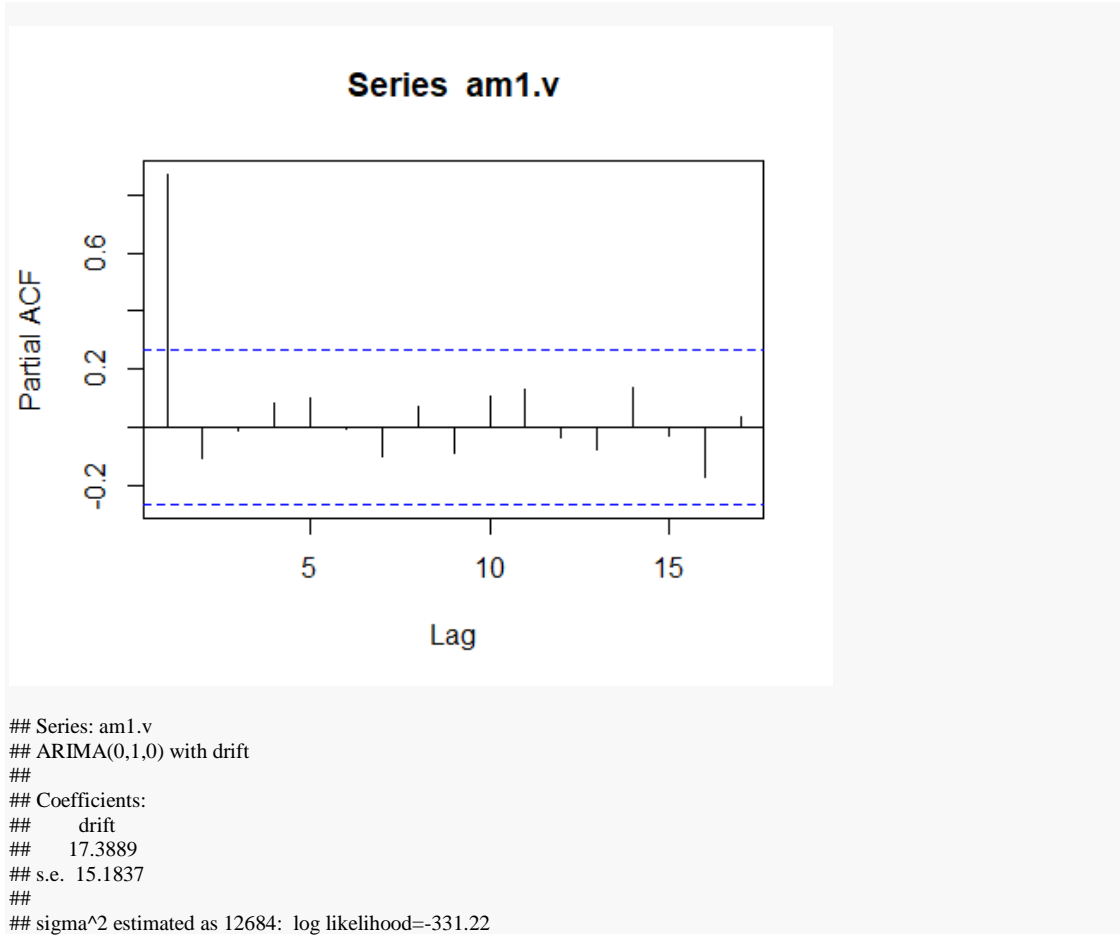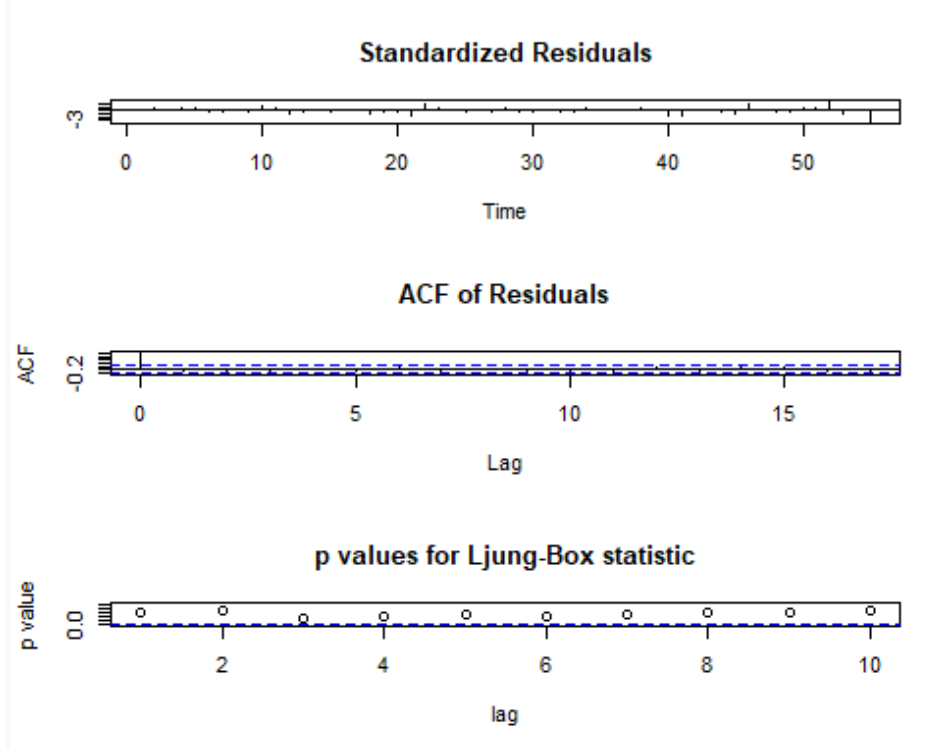
## [1] "reject H0: it is stationary"
```


Series am1.d

Series am1.d


```
## Series: am1.v
## ARIMA(0,1,0)
##
## sigma^2 estimated as 12752:  log likelihood=-331.87

## AIC=665.73   AICc=665.81   BIC=667.72
```

Series am1.v

Series am1.v


```
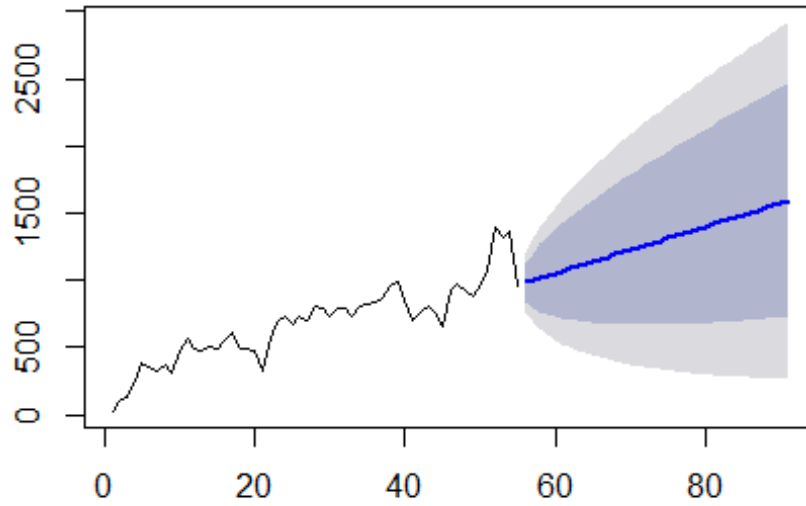## Series: am1.v
## ARIMA(0,1,0) with drift
##
## Coefficients:
##         drift
##       17.3889
## s.e.  15.1837
##
## sigma^2 estimated as 12684:  log likelihood=-331.22
```

AIC=666.43   AICc=666.67   BIC=670.41

Standardized Residuals

ACF of Residuals

p values for Ljung-Box statistic

Forecasts from ARIMA(0,1,0) with drift

Time Series:
Start = 86

```
## End = 91
## Frequency = 1
## [1] 1505.056 1522.444 1539.833 1557.222 1574.611 1592.000

## Time Series:
## Start = 86
## End = 91
## Frequency = 1
##        80%      95%
## 86 701.4360 276.0255
## 87 705.9662 273.7487
## 88 710.6957 271.7768
## 89 715.6157 270.0961
## 90 720.7177 268.6938
## 91 725.9940 267.5581

## Time Series:
## Start = 86
## End = 91
## Frequency = 1
##        80%      95%
## 86 2308.675 2734.086
## 87 2338.923 2771.140
## 88 2368.971 2807.890
## 89 2398.829 2844.348
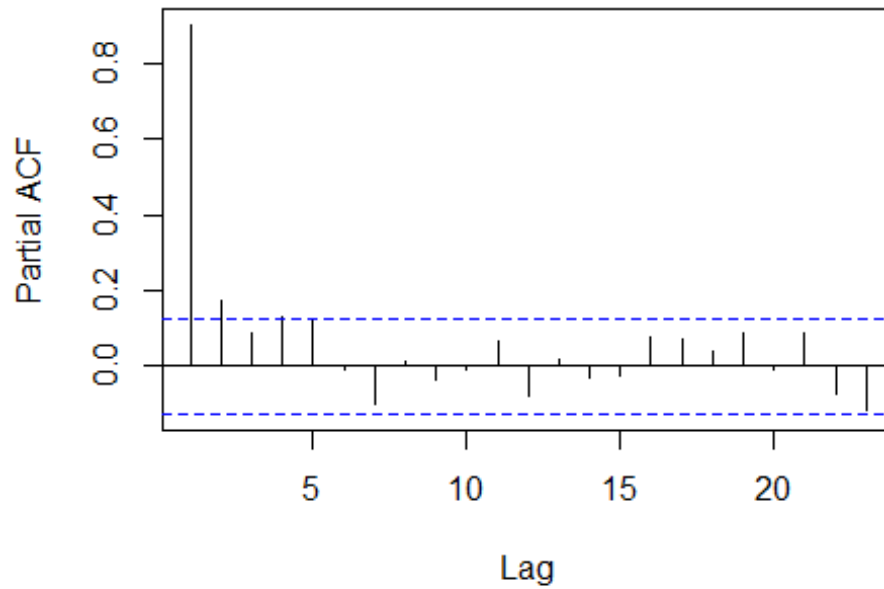## 90 2428.505 2880.528
## 91 2458.006 2916.442
```

Time Dependence

This is now a Forecasting of the charging events per week performed with Arima

```
##
##  Box-Ljung test
##
## data:  cw$n
## X-squared = 2945.8, df = 52, p-value < 2.2e-16

##
##  Box-Pierce test
##
## data:  cw$n
## X-squared = 2731.3, df = 52, p-value < 2.2e-16

## [1] " -> timeseries"

##
##  Augmented Dickey-Fuller Test
##
## data:  cw.v
## Dickey-Fuller = -3.5698, Lag order = 6, p-value = 0.03678
## alternative hypothesis: stationary
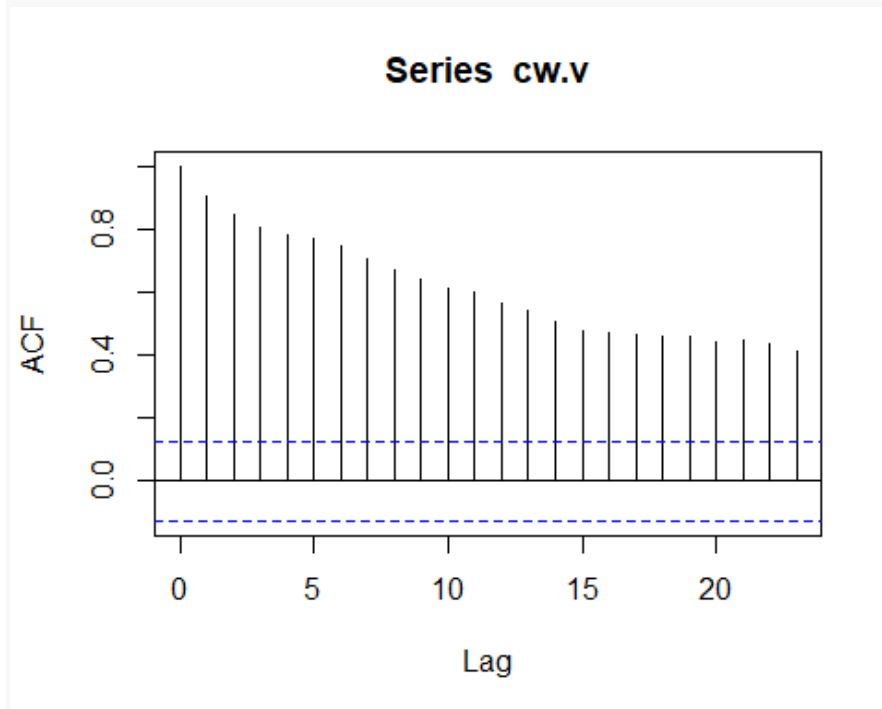
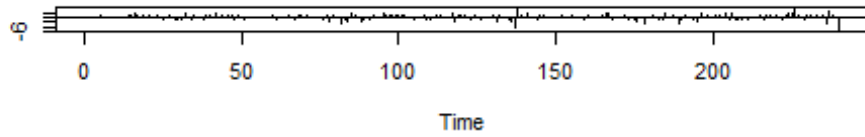## [1] "reject H0: it is stationary"
```

Series cw.v

Series cw.v


```
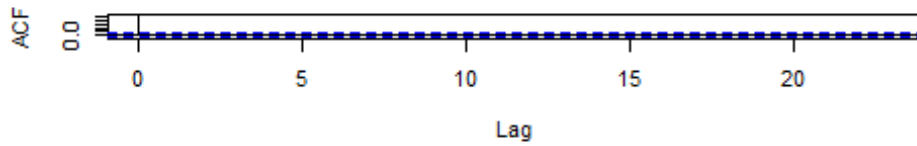## Series: cw.v
## ARIMA(1,1,1) with drift
##
## Coefficients:
##         ar1     ma1   drift
##      0.3615  -0.8119  1.1343
## s.e. 0.1233   0.0830  0.5269
##
## sigma^2 estimated as 748.8:  log likelihood=-1128.78
## AIC=2265.56   AICc=2265.73   BIC=2279.46

## Series: cw.v
## ARIMA(1,1,1) with drift
##
## Coefficients:
##         ar1     ma1   drift
##      0.3615  -0.8119  1.1343
## s.e. 0.1233   0.0830  0.5269
##
## sigma^2 estimated as 748.8:  log likelihood=-1128.78
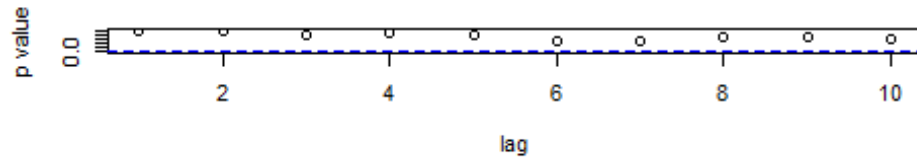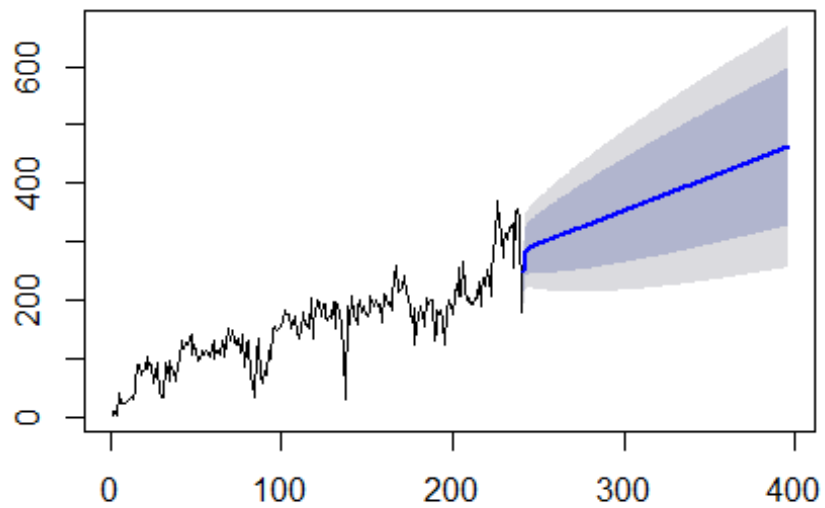## AIC=2265.56   AICc=2265.73   BIC=2279.46
```

Standardized Residuals

ACF of Residuals

p values for Ljung-Box statistic

Forecasts from ARIMA(1,1,1) with drift


```
## Time Series:
## Start = 391
## End = 396
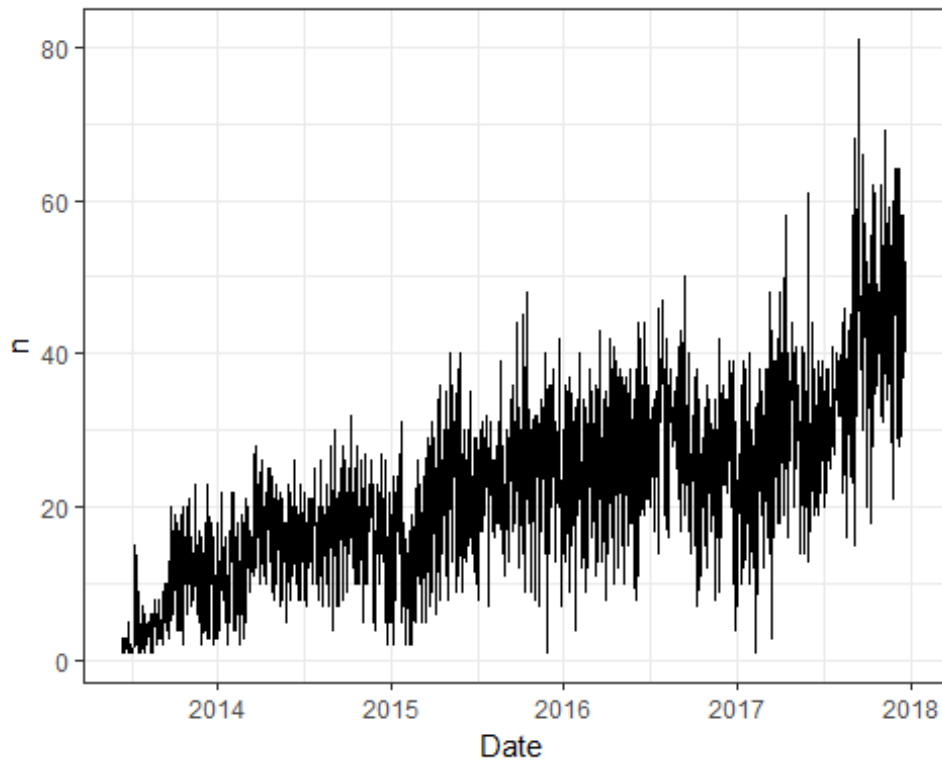```

```
## Frequency = 1
## [1] 456.2466 457.3810 458.5153 459.6497 460.7840 461.9184
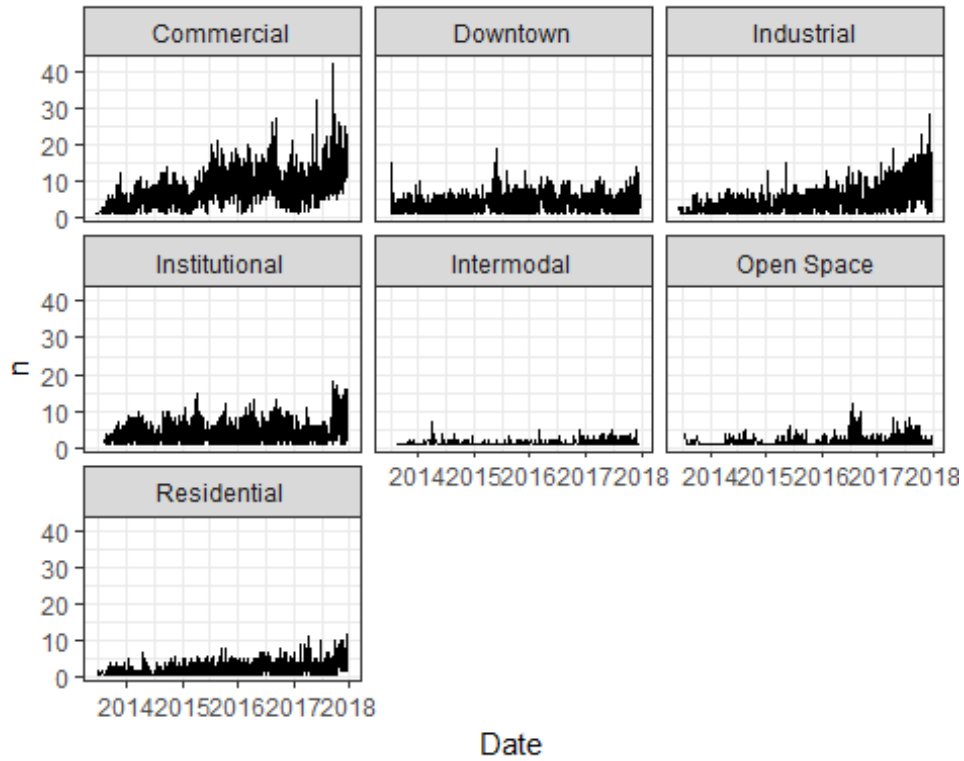
## Time Series:
## Start = 391
## End = 396
## Frequency = 1
##        80%     95%
## 391 323.4858 253.2065
## 392 324.2187 253.7268
## 393 324.9528 254.2490
## 394 325.6880 254.7730
## 395 326.4245 255.2988
## 396 327.1621 255.8264
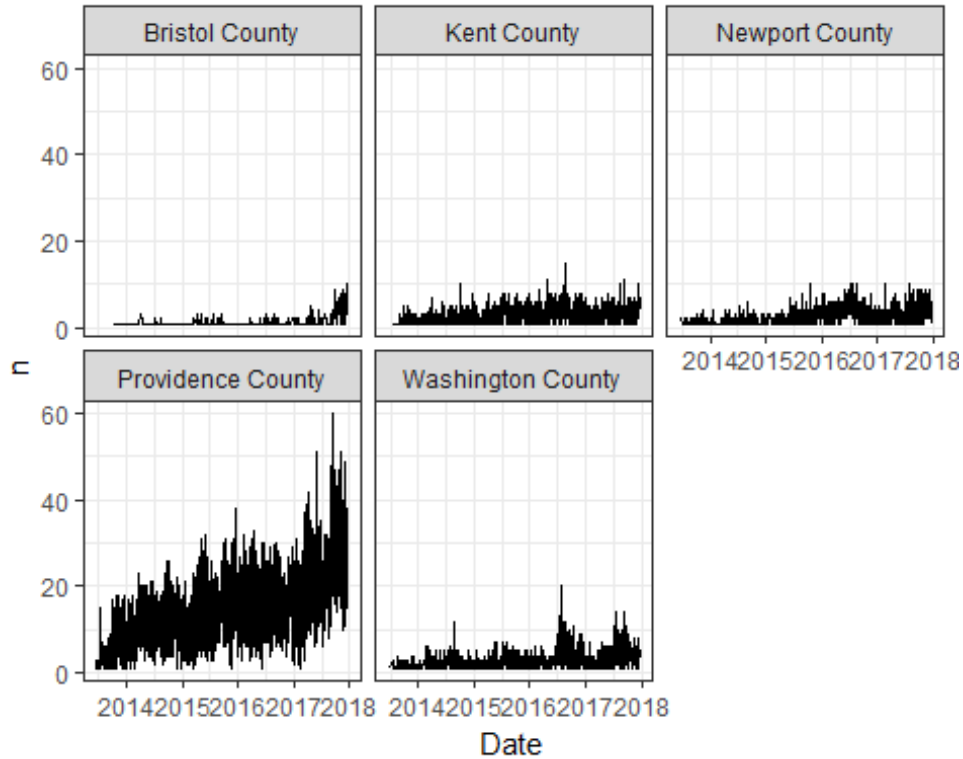
## Time Series:
## Start = 391
## End = 396
## Frequency = 1
##        80%     95%
## 391 589.0075 659.2868
## 392 590.5433 661.0352
## 393 592.0779 662.7817
## 394 593.6113 664.5264
## 395 595.1436 666.2692
## 396 596.6746 668.0103
```

Time Dependence

Here are the charging events per day as a line-plot, also divided into Areas and Counties.

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Time Dependence

This is now a Forecasting of the charging events per day performed with Arima, which is not accurate

```
## Series: am[, 2]
## ARIMA(3,1,2)
##
## Coefficients:
##          ar1      ar2      ar3      ma1     ma2
##       0.7265  -0.3059  -0.2133  -1.3695  0.4951
## s.e.  0.0428   0.0335   0.0299   0.0373  0.0396
##
## sigma^2 estimated as 50.73:  log likelihood=-5538.46
## AIC=11088.91   AICc=11088.96   BIC=11121.32
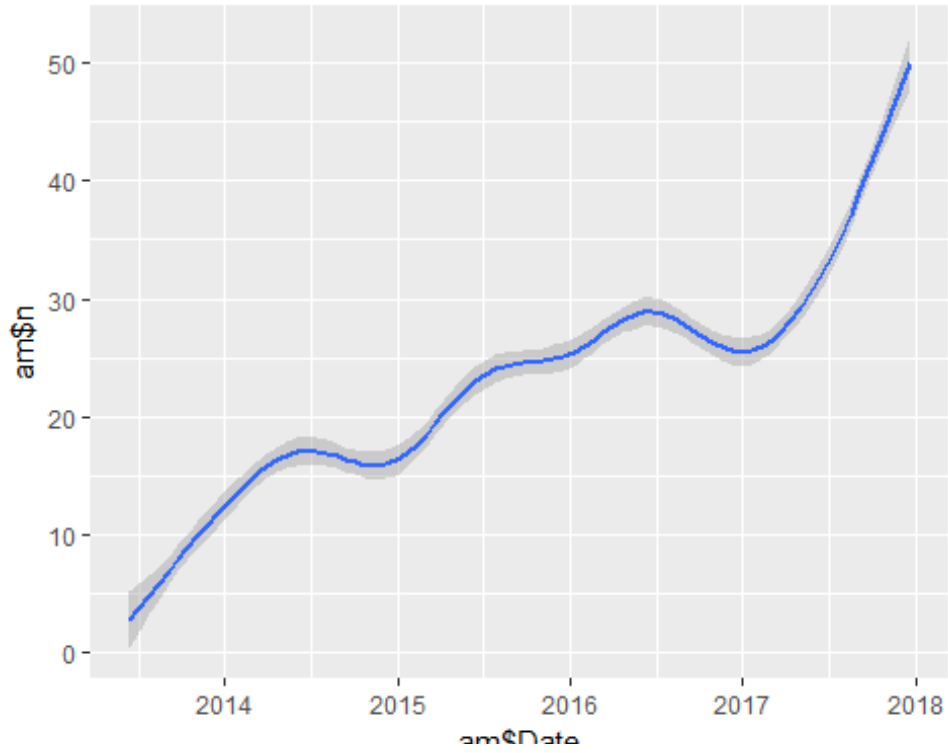

##
## Call:
## arima(x = am[, 2], order = c(3, 1, 2))
##
## Coefficients:
##          ar1      ar2      ar3      ma1     ma2
##       0.7265  -0.3059  -0.2133  -1.3695  0.4951
## s.e.  0.0428   0.0335   0.0299   0.0373  0.0396
##
## sigma^2 estimated as 50.57:  log likelihood = -5538.46,  aic = 11088.91
```

Standardized Residuals

ACF of Residuals

p values for Ljung-Box statistic

Forecasts from ARIMA(3,1,2)


```
## $pred
## Time Series:
## Start = 1640
## End = 1645
```

```
## Frequency = 1
## [1] 45.58813 46.78493 48.50447 48.19590 47.19050 46.18768
##
## $se
## Time Series:
## Start = 1640
## End = 1645
## Frequency = 1
## [1] 7.111325 7.551076 7.572057 7.636565 7.655625 7.686140
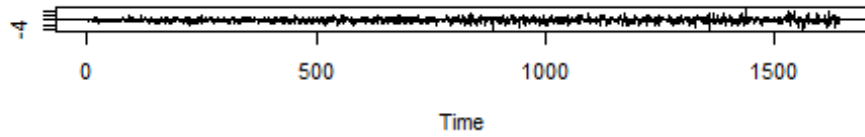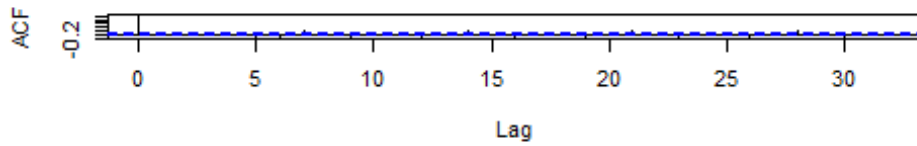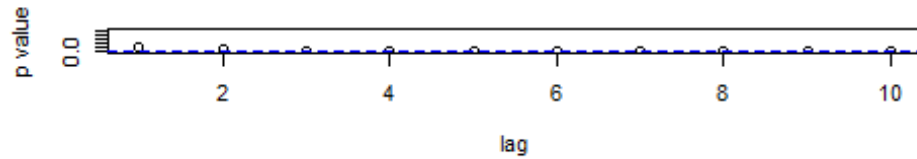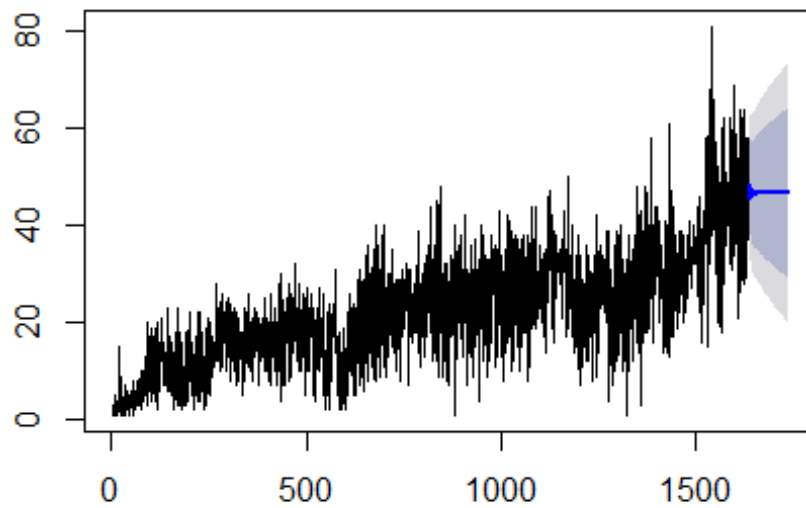

## [1] "This model is not accurate"
```

Charging or Parking?

Descriptive Statistics

```
## [1] "Mean total duration pluged in"

##       Group.1        x    Time
## 1    Commercial  8797.441  02:26:37
## 2      Downtown 22139.487  06:08:59
## 3    Industrial 12423.702  03:27:03
## 4 Institutional 15124.251  04:12:04
## 5     Intermodal 16005.934  04:26:45
## 6    Open Space  7505.444  02:05:05
## 7   Residential 16080.815  04:28:00

## [1] "SD total duration pluged in"

##       Group.1        x    Time
## 1    Commercial 10592.29 02:56:32
## 2      Downtown 16140.41 04:29:00
## 3    Industrial 11690.48 03:14:50
## 4 Institutional 11140.38 03:05:40
## 5     Intermodal 16315.36 04:31:55
## 6    Open Space 10365.91 02:52:45
## 7   Residential 13836.78 03:50:36

## [1] "Max total duration pluged in"

##       Group.1     x    Time
## 1    Commercial 86008  23:53:28
## 2      Downtown 86099  23:54:59
## 3    Industrial 86335  23:58:55
## 4 Institutional 72644  20:10:44
## 5     Intermodal 83034  23:03:54
## 6    Open Space 72201  20:03:21
## 7   Residential 85902  23:51:42

## [1] "Mean charge time"

##       Group.1        x    Time
## 1    Commercial 5875.599  01:37:55
## 2      Downtown 8130.098  02:15:30
## 3    Industrial 7567.202  02:06:07
## 4 Institutional 7092.694  01:58:12
## 5     Intermodal 6845.455  01:54:05
## 6    Open Space 5322.342  01:28:42
## 7   Residential 6921.705  01:55:21

## [1] "SD charge time"

##       Group.1        x    Time
## 1    Commercial 5083.195 01:24:43
```

```
## 2     Downtown 6217.221 01:43:37
## 3     Industrial 5311.221 01:28:31
## 4 Institutional 4422.938 01:13:42
## 5   Intermodal 6404.512 01:46:44
## 6   Open Space 5941.148 01:39:01
## 7  Residential 5459.783 01:30:59

## [1] "Max charge time"

##        Group.1     x    Time
## 1   Commercial 53462  14:51:02
## 2     Downtown 52587  14:36:27
## 3    Industrial 51555  14:19:15
## 4 Institutional 42010  11:40:10
## 5   Intermodal 50186  13:56:26
## 6   Open Space 49154  13:39:14
## 7  Residential 44845  12:27:25

## [1] "Mean time parking at the station after being fully charged"

##        Group.1       x    Time
## 1   Commercial  2921.842 00:48:41
## 2     Downtown 14009.389 03:53:29
## 3    Industrial  4856.500 01:20:56
## 4 Institutional  8031.558 02:13:51
## 5   Intermodal  9160.480 02:32:40
## 6   Open Space  2183.102 00:36:23
## 7  Residential  9159.110 02:32:39

## [1] "SD time parking at the station after being fully charged"

##        Group.1        x    Time
## 1   Commercial  7925.105 02:12:05
## 2     Downtown 14939.023 04:08:59
## 3    Industrial  8888.614 02:28:08
## 4 Institutional  9779.795 02:42:59
## 5   Intermodal 12558.373 03:29:18
## 6   Open Space  6619.294 01:50:19
## 7  Residential 11742.517 03:15:42

## [1] "Max time parking at the station after being fully charged"

##        Group.1     x    Time
## 1   Commercial 78622  21:50:22
## 2     Downtown 83507  23:11:47
## 3    Industrial 69494  19:18:14
## 4 Institutional 66244  18:24:04
## 5   Intermodal 72526  20:08:46
## 6   Open Space 57779  16:02:59
## 7  Residential 78917  21:55:17

## [1] "Mean amount of charging events"

##        Group.1       x
## 1   Commercial 235.8824
## 2     Downtown 204.0000
## 3    Industrial 511.6667
## 4 Institutional 233.8571
## 5   Intermodal 202.5000
## 6   Open Space  82.6000
## 7  Residential 210.0000

## [1] "SD amount of charging events"

##        Group.1        x
## 1   Commercial 197.77035
## 2     Downtown 142.17946
```

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```
## 3    Industrial 420.45674
## 4 Institutional 175.79669
## 5    Intermodal 166.17009
## 6    Open Space  46.83802
## 7   Residential 135.93822

## [1] "Min amount of charging events"

##       Group.1  x
## 1    Commercial 35
## 2      Downtown 77
## 3    Industrial 92
## 4 Institutional 82
## 5    Intermodal 85
## 6    Open Space 24
## 7   Residential 41

## [1] "Max amount of charging events"

##       Group.1   x
## 1    Commercial  747
## 2      Downtown  443
## 3    Industrial 1135
## 4 Institutional  595
## 5    Intermodal  320
## 6    Open Space  141
## 7   Residential  387
```

Charging or Parking?

Percentages of People Charging (gone within 30min after being fully charged) and people how stay longer (staying over 30min after being fully charged)

```
## [1] "Percentage Cases Used as a charging spot(n) and parking spot(n.1) in each Area"

##        Area        n       n.1
## 1    Commercial 0.7645576 0.2354424
## 2      Downtown 0.2930103 0.7069897
## 3    Industrial 0.5820467 0.4179533
## 4 Institutional 0.4170074 0.5829926
## 5    Intermodal 0.5401070 0.4598930
## 6    Open Space 0.8139918 0.1860082
## 7   Residential 0.4848569 0.5151431
```

Cluster Dendrogram

clustering1_dist
hclust (*, "complete")

```
## [1] "Charging all"
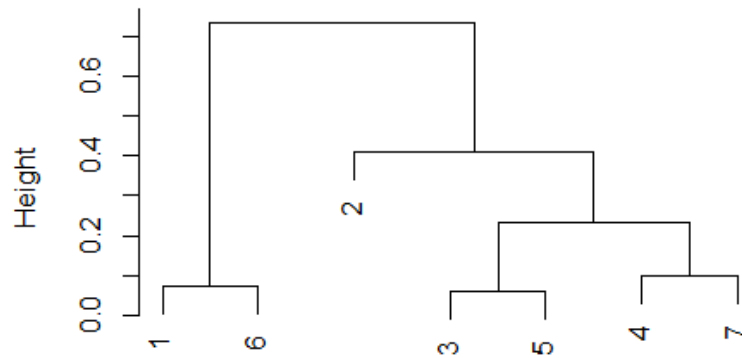
##         n
## 1 0.5729554

## [1] "Parking all"

##         n
## 1 0.4270446

## [1] "Charging Truthbox"

##         n
## 1 0.5824176

## [1] "Parking Truthbox"

##         n
## 1 0.4175824

## [1] "Charging Garden City1"

##         n
## 1 0.7041199

## [1] "Parking Garden City1"

##         n
## 1 0.2958801

## [1] "Charging Garden City2"

##         n
## 1 0.7133878

## [1] "Parking Garden City2"

##         n
## 1 0.2866122
```

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