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# Designing and Managing Infrastructure for Shared Connected Electric Vehicles

**July 2018**

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# Designing and Managing Infrastructure for Shared Connected Electric Vehicles

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# Disclaimer



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# Executive Summary

Electric vehicles (EVs) generally lead to a reduction in greenhouse gas emissions and have the potential to reduce our dependency on fossil fuels and increase the penetration of renewable sources of energy. Further, new mobility services, like carsharing in general and free-float carsharing (FFCS) in particular, have the potential to reduce the need for car ownership and complement transit, ultimately reducing vehicle miles traveled. Electric free-float carsharing (eFFCS) is the amalgamation of the two concepts, which promotes emission-free mobility, while providing the flexibility of owning and operating the vehicle only between and during the points of travel. The pay-per-minute-use subscription model and features like park anywhere within service area make FFCS quite attractive for the environmental and economically conscious, ever-mobile, smartphone-savvy population of the 21st century. Presently, due to slow recharging times of electric vehicles compared to gasoline-fueled vehicles, a charging event represents a constraint on trips and requires staff labor to relocate the free-floating vehicle to a charging station. This relocation leads to a high operational expenditure and unreliable downtimes. This study aims to develop a demand model for an eFFCS service in the City of Seattle. The model consists of a destination model predicting end location given the start location, and a duration model predicting the dwell time after a trip at a particular location. This model can increase the feasibility of eFFCS by reducing the cost of relocation by optimally locating the charging stations near the areas of heavy usage and real-time control to minimize manual relocation.

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# Introduction

Electric free-float carsharing (eFFCS) represents the convergence of two major trends: electrification and shared mobility. Electric vehicles (EVs) are increasingly attracting notice [1] from developed and densely populated countries of the world. The global stock of electric vehicles rose from around 1 million in 2015 to 2 million in 2016 and then to more than 3 million in 2017 [2]. While the lifecycle greenhouse gas emissions from electric vehicles may be at par with internal combustion engines for 2010 electricity mix, the emission reduction potential can increase with greater penetration of low-carbon electricity sources [3]. EVs already have zero tailpipe emissions, which can be beneficial particularly in urban areas. EV numbers are increasing in most parts of the USA as well [4].

Another trend that is gaining popularity [5] and poised to improve urban transportation is carsharing, which has been shown to motivate people to postpone car purchases [6] and reduce greenhouse gas emissions [7]. Carsharing can happen in many forms, namely: free-float carsharing (FFCS), which is the practice of using the car between any two points in the home area, whereas station-based carsharing refers to the practice of returning the car to a specific location, often the station where it was taken from. Carsharing is regarded as having a sizeable market opportunity, especially in Europe, which is estimated to have 200,000 cars and 15 million users by 2020 [8].

To operate a FFCS system efficiently, one needs to model the demand and usage of these vehicles. Jorge et al. [9] presented a review of various works done on modeling the demand for carsharing systems. Stillwater et al. [10] performed a GIS-based study to model the effects of built environment like street width etc. and show that carsharing can be complementary to public transit. Schmöller et al. [11] performed an empirical analysis on FFCS data for the City of Munich to find spatial and temporal variations of FFCS usage and further [12] analyzed the effect of external factors on demand to conclude that weather and the average age in the neighborhood did not play a major role in the use of FFCS. Ciari et al. [13] used MATsim to model the current station-based carsharing setup in Berlin and predict usage for two future scenarios: one with higher station-based carsharing and another with FFCS as well. Wagner et.al [14] used points of interest derived from Google Maps as a proxy for the attractiveness of an area to explain spatial variation, and used this to support expansion decisions.

Further, while eFFCS offers the benefits of both EVs and FFCS, it also suffers from the challenges of both – namely the need for rebalancing and recharging – creating several unique challenges. First, EVs often have a shorter range than conventional gasoline-fueled vehicles, meaning that they must be taken out of service for refueling more often. Second, the time to recharge an EV is 1-2 orders of magnitude longer than the time to refill a gasoline tank, meaning fewer revenue hours of operation. Third, EV charging infrastructure is sparser than the gasoline infrastructure, meaning more labor time is needed when taking the vehicles in for charging. The significant costs associated with recharging vehicles in an eFFCS system make it important to have a sound decision support system in place to minimize those costs and maximize revenue-producing operations. Weikl et al. [15] discussed commonly employed relocation strategies and proposed a two-step model for relocation of vehicles in a FFCS system that consists of an offline module that makes demand prediction and an online module tasked with finding the optimal relocation strategy. Brandstatter et al. [16] presented a comprehensive literature review on various problems around electric carsharing and [17] developed an algorithm for locating charging stations for electric carsharing systems with a focus on maximizing the expected profit or number of accepted trips while explicitly considering the charge state of the individual vehicles, i.e., ensuring that their batteries are never depleted when fulfilling the demand.

As can be seen from the brief literature review, while there have been several studies on understanding the travel behavior of carsharing users and use of carsharing vehicles, few have tried to model the demand for FFCS. Further, there has been little effort to develop a theoretical framework for describing eFFCS and determining locations of charging stations needed for these vehicles. No previous work, to our knowledge, has characterized the demand for eFFCS based on real data. Instead, most studies on the optimal design and control of FFCS systems simply assume that the demand patterns are known *a priori*. Further, while the theoretical framework developed for eFFCS by Brandstatter is certainly detailed, it relies on a stochastic forecast for demand and may be computationally intractable to be applied at the scale of an entire city in real-time.

In the current study, we develop a demand modeling framework for eFFCS based on historical trip data of an operator in the City of Seattle. The model consists of two parts: a destination model to probabilistically predict the destination of a trip based on the origin and time of day, and a duration model to predict how long a vehicle is expected to stay parked or "dwell" at a particular location. Together, these models allow us to simulate and map out trajectories of eFFCS vehicles throughout the city. The trips are first analyzed to extract any temporal patterns. Trip origins and destinations are then spatially clustered into zones and machine learning is used to predict the destination zone, given an origin zone and time of day. Further, a hazard model is used to predict the dwell duration, while adjusting for the number of other available cars in the vicinity. While the demand model presented in this study is specific to Seattle, the method used to arrive at the said model is generic and can be applied to other regions with minimal changes, once the historical trip data is known. Since eFFCS vehicles are used for similar distances as FFCS vehicles [18], FFCS historical data can also be used for arriving at the demand model for cities in which eFFCS is not yet available. The demand model can then be used for finding the optimal locations of charging stations and developing a cost-effective relocation/rebalancing strategy prior to market introduction of eFFCS.

# Data

For destination modeling, trip data was provided by ReachNow. The data consists of trips taken by electric vehicles in the ReachNow Seattle fleet from May 2016 to February 2017. The data consists of latitudes and longitudes of origin and destination, the distance traveled during the trip, booking start and trip end time. No information identifying and differentiating the vehicle (such as vehicle ID, state of charge, etc.) or the user (e.g. age or sex) was provided as part of the data.

For duration modeling, data captured from the car2go API [19], a competing FFCS service provider in Seattle, was used. The data captured the state of the system every 30 seconds, with the state here referring to the locations of all the vehicles parked within city limits. Data was mined from the public API [19], as has been done before [20], from August 2016 to December 2016. The continuous tracking of parked vehicles allowed us to find out the trips undertaken by the vehicles as their location information vanishes the moment they start the trip.

# Research Methodology

## Seattle – Transportation context

Seattle is one of the fastest growing large cities in the USA. During 2015-2016, Seattle had a net gain of 21000 people, which translates to 57 people per day on average. The rate of population growth is expected to continue at least for the next 20 years [(21)]. Seattle features a variety of transportation options including link light rail, King County Metro transit, streetcars, monorail, taxis, ridesharing, carsharing, bikesharing etc. [(22)]. While transit ridership in Seattle has increased by about 60% since 2002 [(23)], the travel times for the region have increased by 50% since 2014 [(24)]. Per-capita average daily VMT, though still above 20 miles [(25)], is gradually decreasing, mainly due to good quality transit and the proliferation of complementary services like ride-hailing, carsharing and bikesharing. **Error! Reference source not found.** (right) [(26)] shows the transit routes in the northwestern part of the city. Observe the high density in the lower central portion of the figure where the city is thinnest, the downtown Seattle area. This compares well with the map of population density of Seattle (Figure 1 (left)).

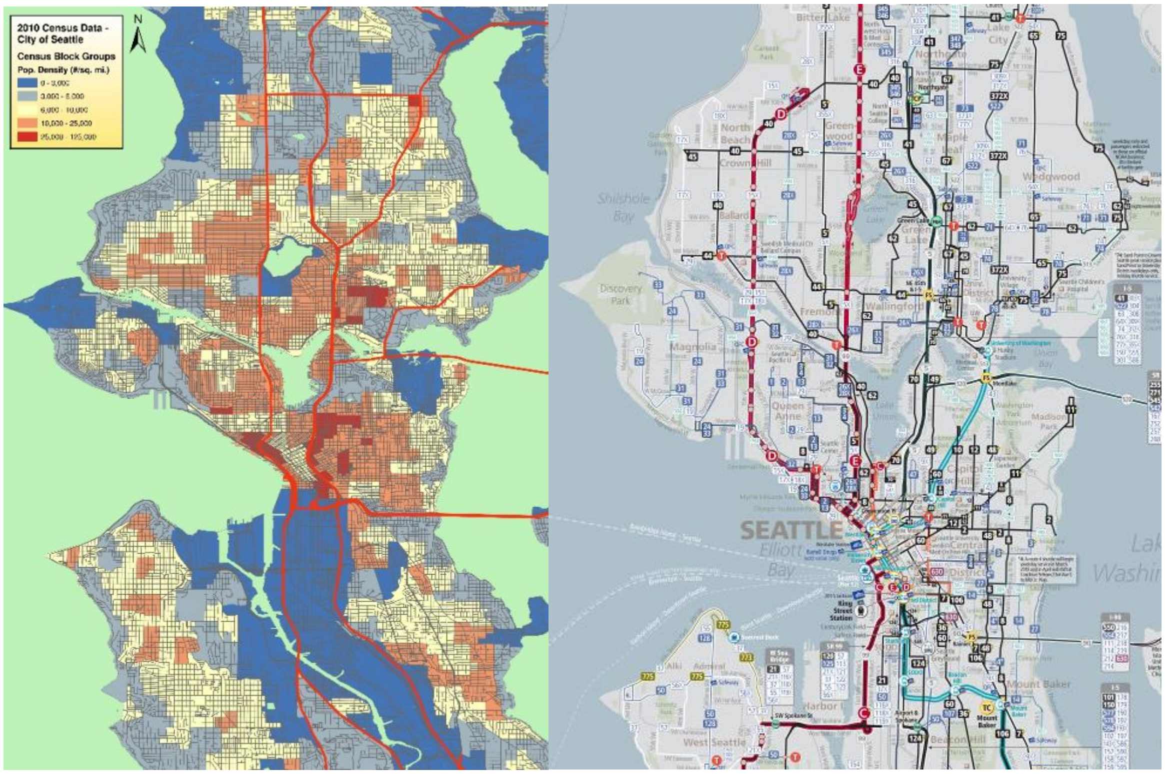


**Figure 1: (Left) Seattle Metro - Population Density (red is densest) and (right) Seattle Metro Transit Map - NW Region**

## ReachNow – Seattle

ReachNow in Seattle is a fleet of BMW cars, consisting of 3-series sedans, MINIs and i3 EVs. They operate within the home area defined by the map (Figure 2) in the ReachNow smartphone app [27], and are regulated by city bylaws [28]. ReachNow's Seattle home area is around 193 km$^2$ [27], which is around 90% of Seattle's land area. In addition to covering most of the City of Seattle proper, the ReachNow home area also includes a small area near the SeaTac airport. The ReachNow app shows the locations of vehicles nearby and the walking distance to a selected vehicle. Any vehicle can be reserved for up to half an hour before the start of a trip and can be unlocked through the app or using a key card. Customers are billed by the minute for the time the vehicle is in use, excluding any advance booking time. The booking can be ended only in the home area, on any legal street parking location. The vehicle then shows itself as available on the app for further booking/reservation. The trip fare is deducted from the linked credit/debit card and an email with the trip summary is sent to the registered email address.


**Figure 2: ReachNow in Seattle - Home Area**

## Temporal Analysis

To understand how Seattleites utilize FFCS, we began by looking at the variation of trip bookings over time.

### Daily Variation of Booking Frequency

Launched in April 2016 [29], ReachNow added more cars to its fleet and expanded its operating area in July 2016 [30]. Figure 3 shows the daily variation of booking frequency from May 2016 to Feb 2017, for only the i3 EVs in the ReachNow fleet. Overall, it can be said that the usage of the electric vehicles in the fleet has gone down slightly. Since the total number of EVs in the fleet during this period and the methods of rebalancing and recharging are not known, the exact reason for this variation cannot be determined.

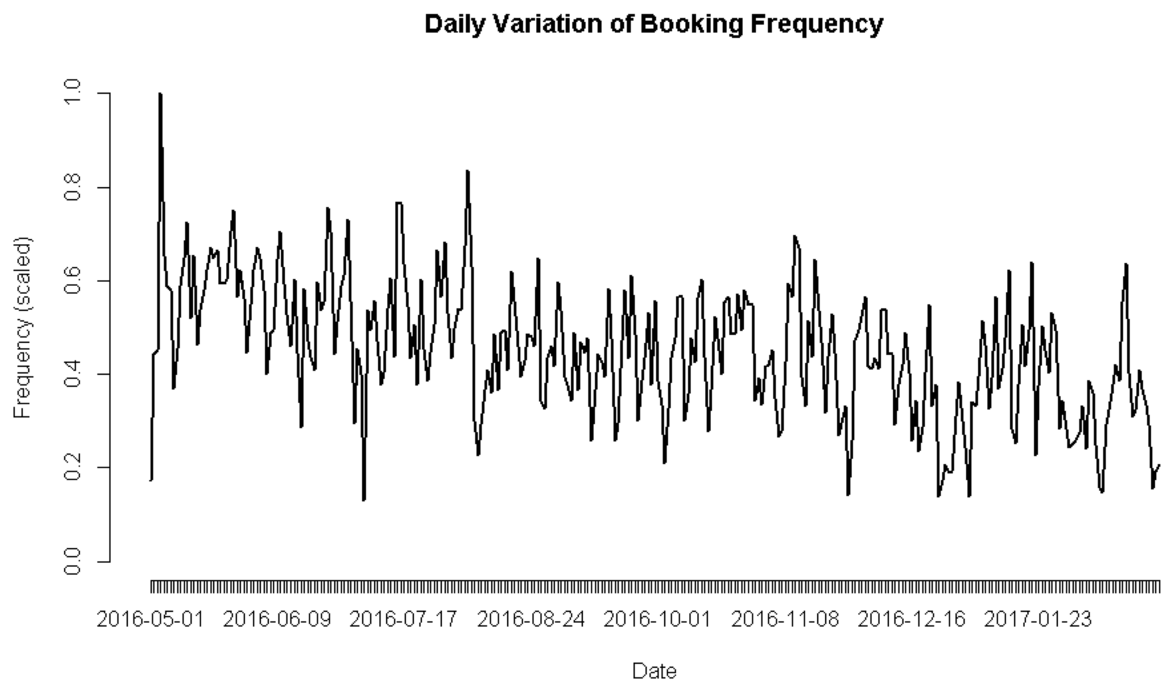


**Figure 3: Daily Variation of Booking Frequency**

## Day of Week Variation of Booking Frequency

Day of the week affects travel behavior, which is apparent from the plot shown in Figure 4. This trend is similar to other cities, as has been reported elsewhere [11]. The rate of bookings increases over the course of the work week, before declining on Saturday and Sunday.

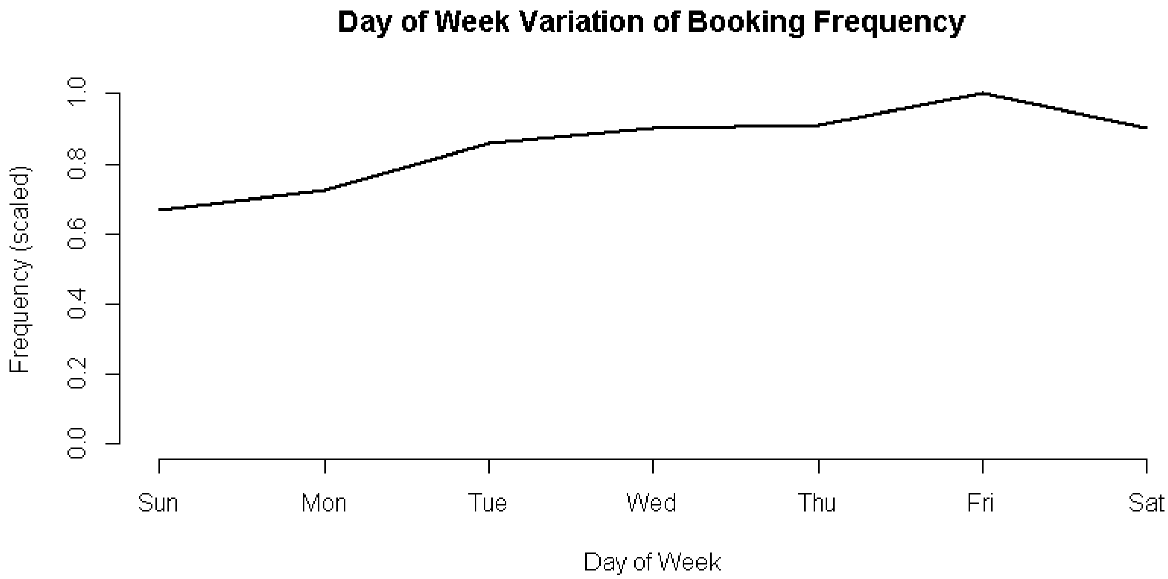


**Figure 4: Day of week variation of booking frequency**

## Hourly Variation of Booking Frequency

A plot of the frequency of bookings (scaled to the maximum number of bookings) is shown in Figure 5. This trend is expected and is similar to the reported trends from other cities [(11)] and for car2go in Seattle [(31)]. There is a first peak around 7-9 am showing trips possibly made for travel to work, where the flexible one-way nature of FFCS is ideal as it makes the vehicle available for re-use. Subsequently, a slight increase is seen around noon, building to an afternoon peak around 4-6 pm.

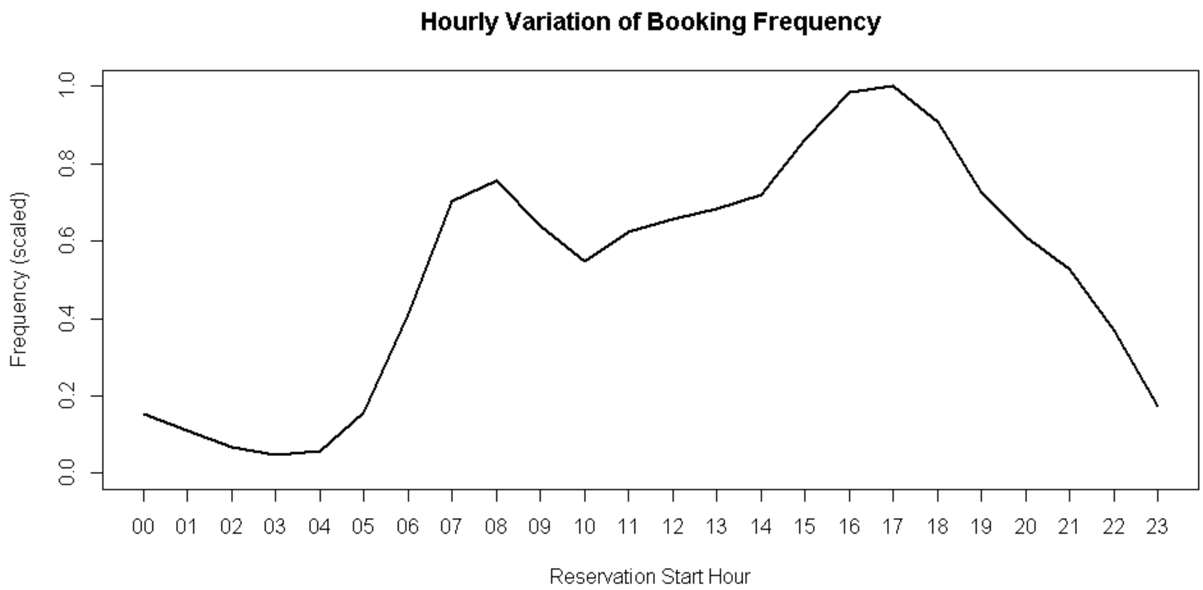


**Figure 5: Hourly variation of booking frequency**

### Drive Times

Drive Times reflect the time the vehicle was driven -- an indirect measure to capture the trip length and duration. **Error! Reference source not found.** shows the variation of drive time frequency. Only drive times up to 100 minutes are shown.

Together, **Error! Reference source not found.**, **Error! Reference source not found.**, **Error! Reference source not found.Error! Reference source not found.**, and**Error! Reference source not found. Error! Reference source not found.**6 tell us about the nature of FFCS trips in Seattle. Trips are usually around 20 minutes, occur on all days with frequency peaking on Friday and with higher frequency in early morning hours and evening hours. With the temporal analysis done, we can try to figure out where these trips are being made.

## Spatial Analysis

### Cluster Analysis

We began by using k-means clustering to define clusters of trip origins. Figure 7 shows the trip start points clustered using k-means into 20 clusters. We can see from Figure 7 that a high density of trips starts around the central area of the map, which is downtown, and fewer trips start near the periphery. The clusters align well with different Seattle neighborhoods [32].

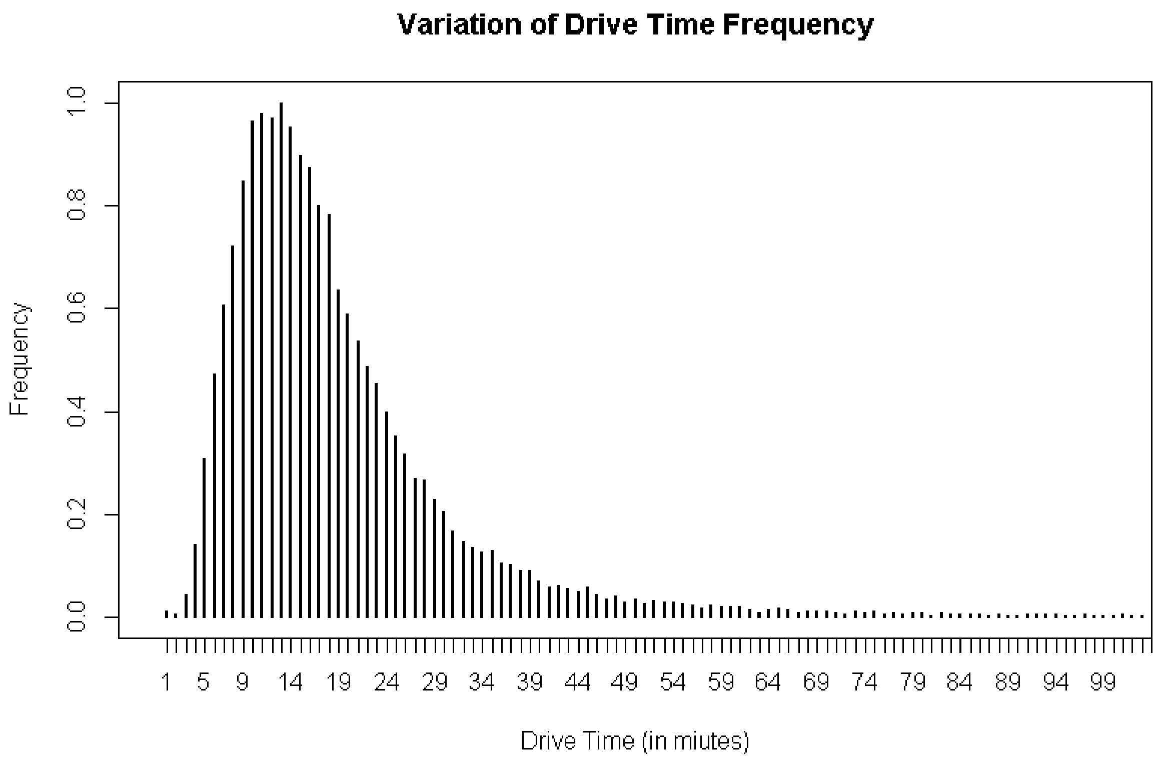


**Figure 6: Histogram showing the frequencies of drive time up to 100 minutes**

Figure 8 shows the frequency of trips (scaled to the maximum frequency) per cluster. Similarly, Figure 9 shows the frequency of trips (scaled to the maximum frequency) for four different time blocks. These figures indicate which clusters and time blocks are popular and which are not.

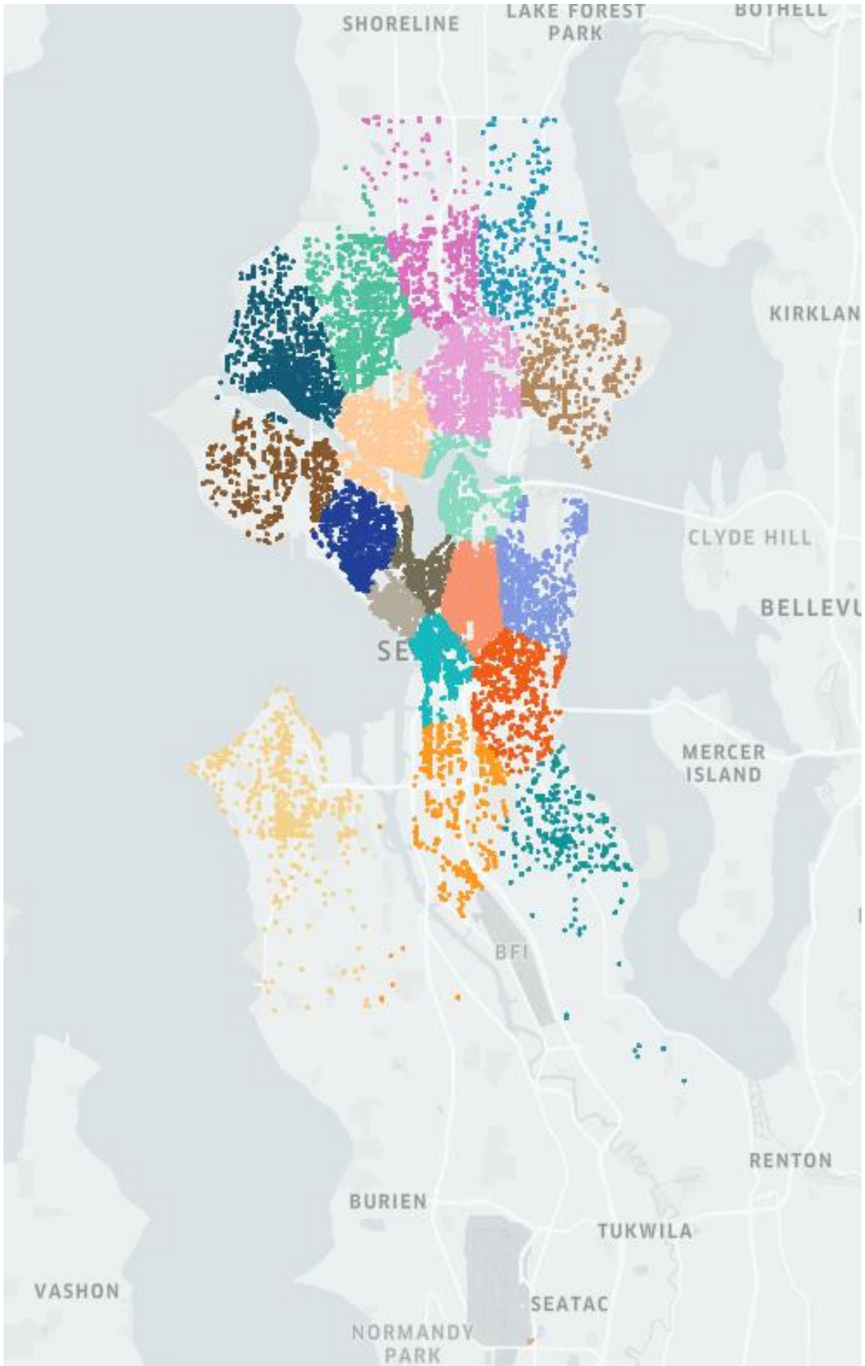


**Figure 7: ReachNow Trip StartPoints clustered using k-means**

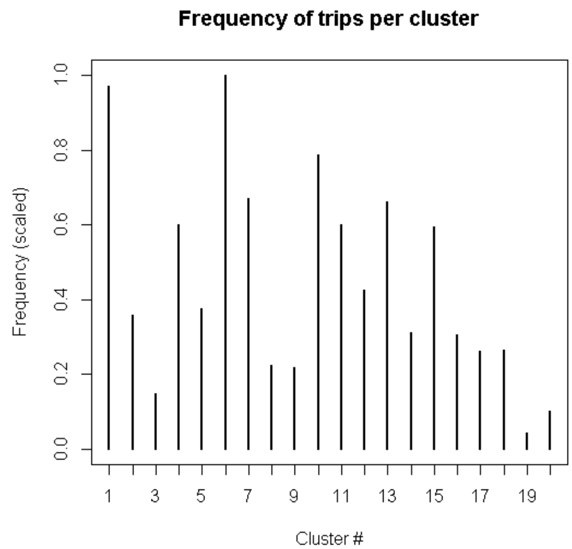


**Figure 8: Frequency of trips per cluster**

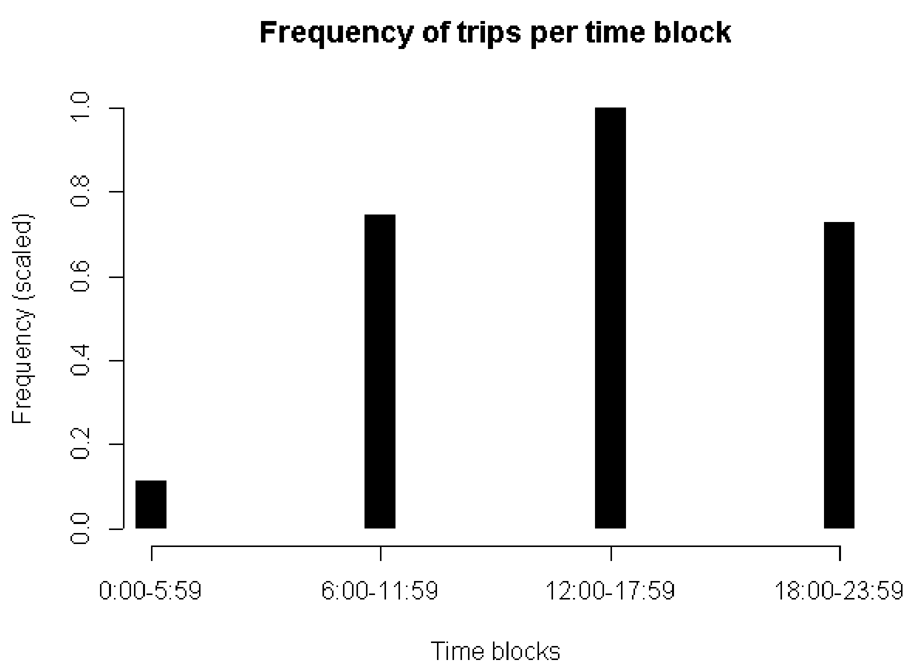


**Figure 9: Frequency of trips per time block**

## Destination Model

The destination model probabilistically predicts the destination of a trip given its origin and start time. The utility of the destination model increases with the resolution with which the “origin” and “destination” are defined. Similarly, the computational complexity of prediction also increases with an increase in resolution. For example, it is much easier to predict the destination if the city is divided into two zones, let’s say, north and south. However, such a distinction has limited practical utility. On the other hand, choosing a location resolution of one meter would result in 193 million possible locations, which becomes computationally intractable for any number of observations (besides which, most of these locations would have no trips starting or ending in them). Therefore, origin and destinations are divided into zones or clusters as obtained from k-means cluster analysis. Similarly, time of day can be considered every minute, resulting in a discrete variable with 24*60 = 1440 levels. Though from **Error! Reference source not found.**, we can ascertain that the variation in trip bookings doesn’t change so drastically (i.e. every minute). So, an aggregated time variable is justified to manage the computational complexity. Time of day is, therefore, divided into 4 bins throughout the day (0:00-5:59, 6:00-11:59, 12:00-17:59, 18:00-23:59). We compared the accuracy of destination zone predictions, given the origin zone and time of day as a categorical variable, using two approaches: multinomial logistic (MNL) regression and naïve Bayes (NB) classification. Figure 10 shows how the percentage of destinations correctly predicted declines with the number of clusters used, for both the MNL and NB approaches. We can see even if the city is divided into just 4 zones, we can only predict the destination correctly in approximately 55% of cases. This prediction accuracy gets progressively worse as the number of clusters is increased. With 20 clusters, we can correctly predict the destination about 20% of the time. For context, a random selection from 20 equally likely outcomes has an accuracy of 5%. Figure 11 shows the results of the destination model for a few cases. Top figures have the same origin cluster at two different time-blocks, while the bottom figures are for another origin cluster and same two time blocks.

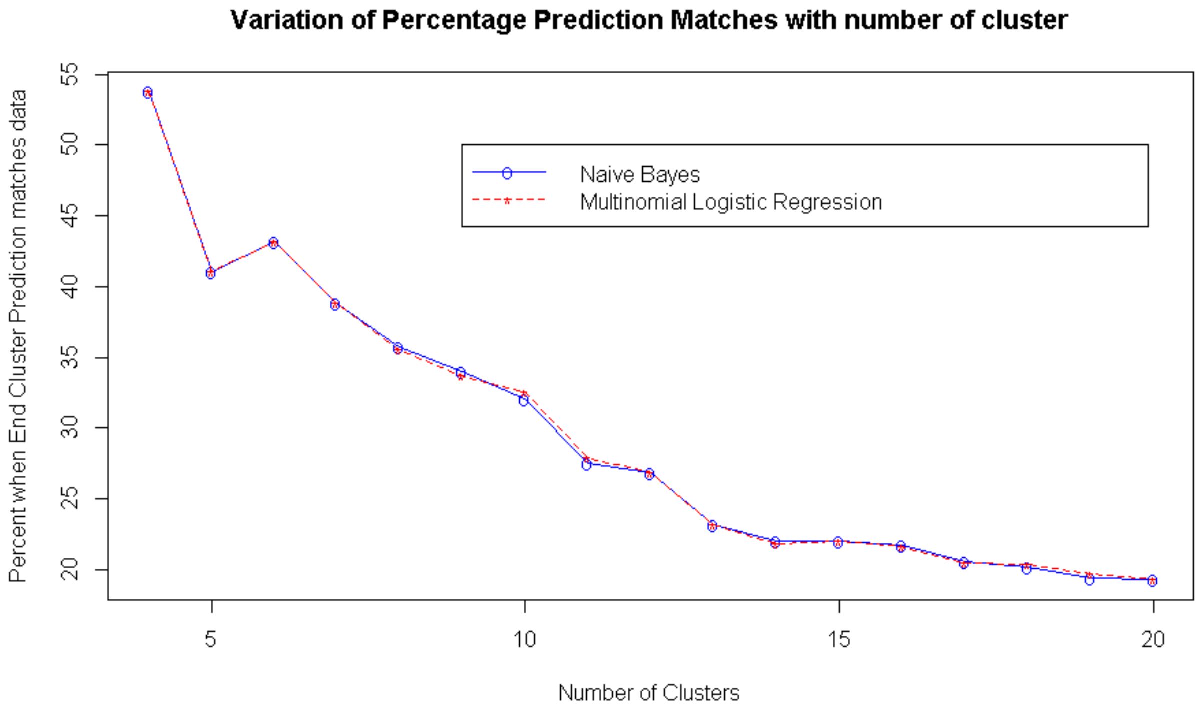


**Figure 10: Variation of percentage prediction match with number of clusters using Multinomial Logistic Regression and Naïve Bayes Classification**

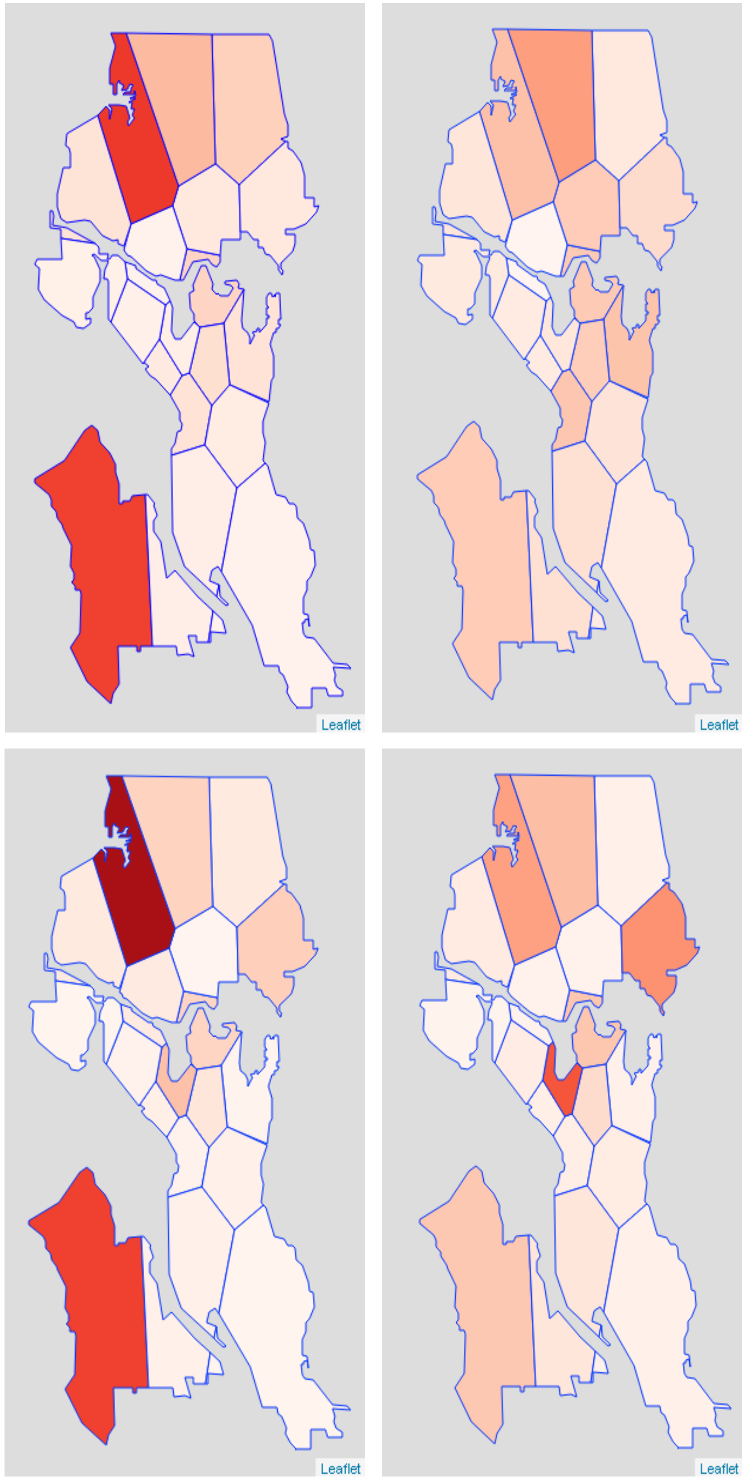


**Figure 11 Destination Model results, colored to show destination probability, top-left: origin cluster 10, time block 6:00-11:59, top-right: origin cluster 10, time block 18:00-23:59, bottom-left: origin cluster 18, time block 6:00-11:59, and bottom-right: origin cluster 18, time block 18:00-23:59**

## Duration Model

The destination model developed in the previous section can help us predict where a vehicle is likely to end up given the time of day and start cluster. However, to completely define a FFCS vehicle trajectory, we need to model the dwell times between trips as well, i.e. the time a vehicle is parked at a certain location before being taken on a trip. The available data from ReachNow does not contain dwell times, or vehicle IDs that would allow us to identify dwell times between consecutive trips by the same car. Therefore, we use data from a similar, competing service: car2go. Figure 12 shows the dwell times of car2go vehicles in various start clusters (The cluster boundaries are defined by ReachNow data). We see that some start clusters, like cluster numbers 1, 6, 10, and 15, have very low dwell times, indicating that a vehicle is less likely to be parked for long durations in these clusters compared to others, like cluster numbers 3, 9, and 20, which show longer dwell times.

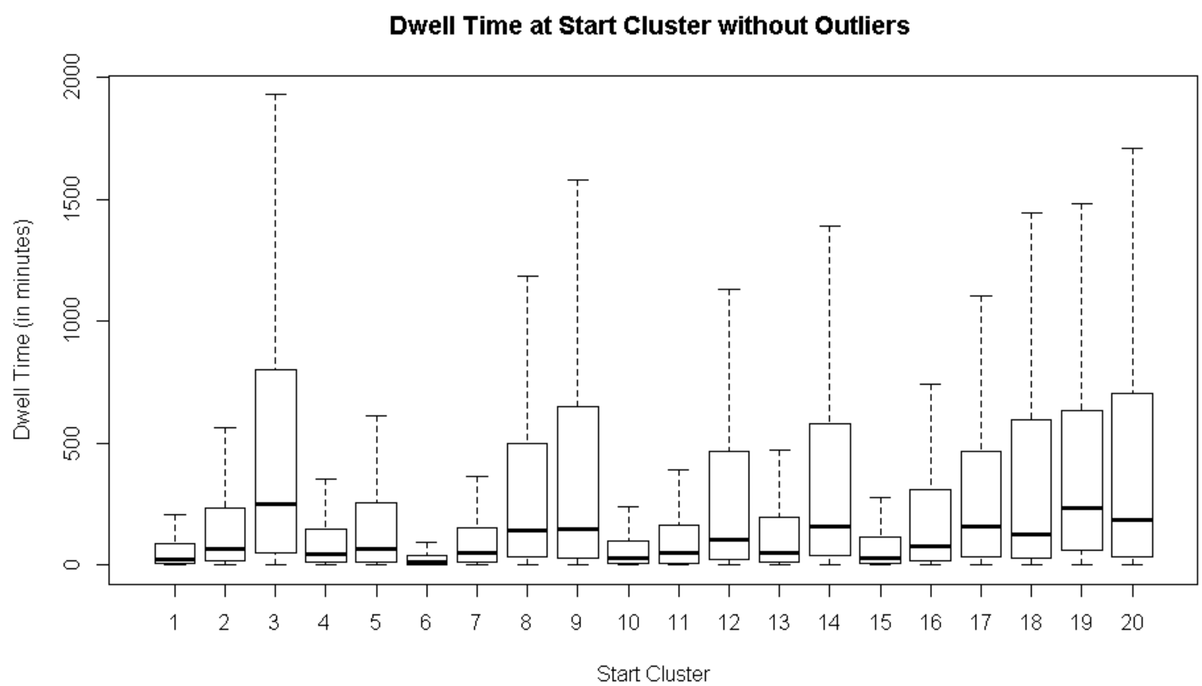


**Figure 12: Dwell times at Start Clusters without outliers**

Dwell times appear to follow a negative exponential distribution, as can be seen in Figure 13. This confirms our intuition about FFCS events, that FFCS trips are a memoryless process, with time until the next trip being conditionally independent of the time already spent at a given location.

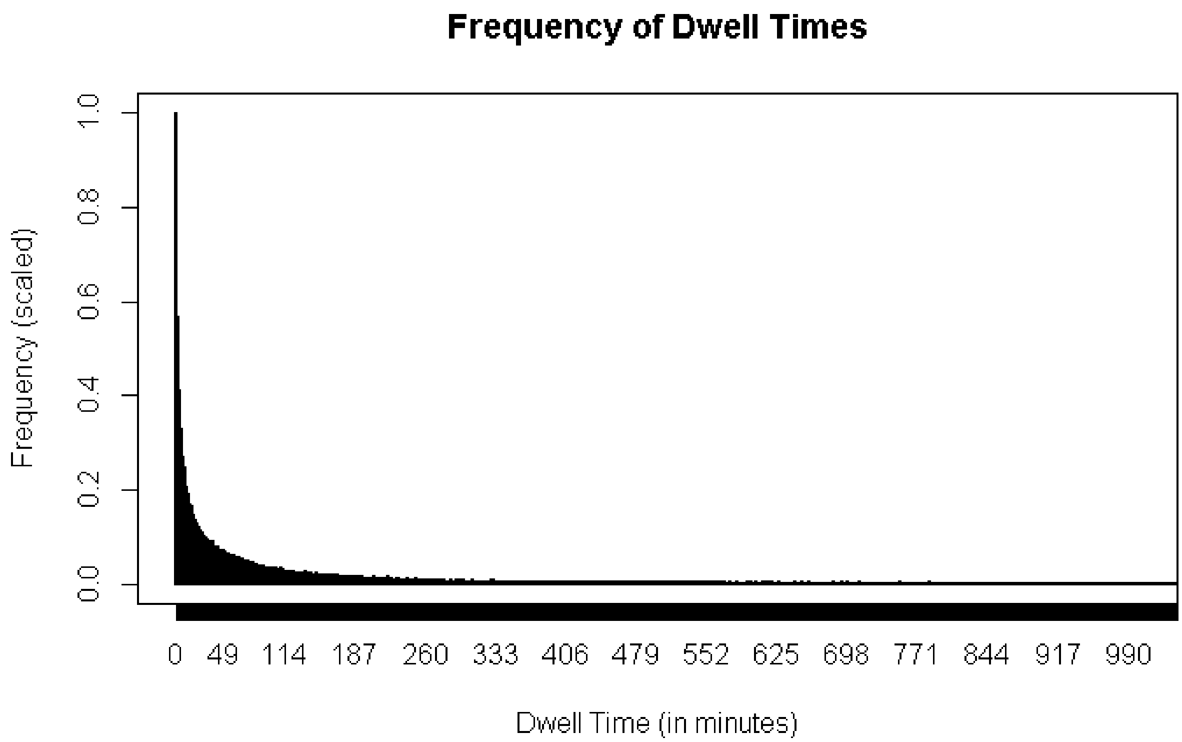


**Figure 13: Density of Dwell Times right-censored to 2000 minutes**

## Cox Proportional Hazard Model

A Cox proportional hazard model was applied to model the dwell time of vehicles using the location and time of day as covariates. In two variations (Model-II and Model-III in results), one covariate was added each time to reflect vehicles in the vicinity. “Cars_in_cluster” represents the number of cars present in the cluster when the trip started. “Cars_within_distance” captures the number of cars present within 500m of the vehicle starting the trip. **Error! Reference source not found.** shows the hazard ratios from Cox proportional hazard model.

The hazard ratios can be interpreted as multiplicative effects on the hazard. Therefore, a hazard ratio greater than 1 indicates a higher trip generation rate (thus a shorter expected dwell time) and a hazard ratio of less than 1 indicates a lower trip generation rate (thus a longer expected dwell time). So, from **Error! Reference source not found.**, row 5, we see that Cluster 6 has a hazard ratio greater than 1, which would mean that the dwell time would be low for this cluster. Similarly, dwell time is low when time block is 12:00-17:59 or 18:00 to 23:59, indicating that cars are likely to dwell less or get used more in the afternoon and evening times. Surprisingly, covariates “cars_in_cluster” and “cars_within_distance” do not have much impact on the dwell time as the hazard ratios of these two covariates are close to 1. Figure 14 shows that the hazard ratios follow very closely with the trip generation density, i.e. places that have high trip generation density are locations where the FFCS cars stay parked the least. Detailed statistics for the three models can be found in Appendix-A.

| | Hazard Ratio | | |
|---|---|---|---|
| | Model-I | Model-II | Model-III |
| Cluster 2 | 0.55 | 0.49 | 0.42 |
| Cluster 3 | 0.28 | 0.28 | 0.20 |
| Cluster 4 | 0.66 | 0.63 | 0.50 |
| Cluster 5 | 0.52 | 0.50 | 0.40 |
| Cluster 6 | 1.28 | 1.15 | 1.02 |
| Cluster 7 | 0.64 | 0.63 | 0.49 |
| Cluster 8 | 0.35 | 0.32 | 0.26 |
| Cluster 9 | 0.33 | 0.46 | 0.24 |
| Cluster 10 | 0.94 | 0.96 | 0.82 |
| Cluster 11 | 0.74 | 0.74 | 0.70 |
| Cluster 12 | 0.42 | 0.45 | 0.32 |
| Cluster 13 | 0.54 | 0.57 | 0.41 |
| Cluster 14 | 0.34 | 0.39 | 0.25 |
| Cluster 15 | 0.72 | 0.66 | 0.56 |
| Cluster 16 | 0.50 | 0.47 | 0.38 |
| Cluster 17 | 0.35 | 0.42 | 0.27 |
| Cluster 18 | 0.38 | 0.36 | 0.28 |
| Cluster 19 | 0.26 | 0.21 | 0.23 |
| Cluster 20 | 0.32 | 0.34 | 0.23 |
| Time Block 6:00 – 11:59 | 1.11 | 1.08 | 1.17 |

| | | | |
|---|---|---|---|
| **Time Block 12:00– 17:59** | 1.49 | 1.46 | 1.76 |
| **Time Block 18:00 – 23:59** | 1.93 | 1.90 | 2.17 |
| **Cars_in_cluster** | -NA- | 0.99 | -NA- |
| **Cars_within_distance (500m)** | -NA- | -NA- | 0.97 |

**Table 1: Hazard Ratios for three variations of the Cox Proportional Hazard Model**

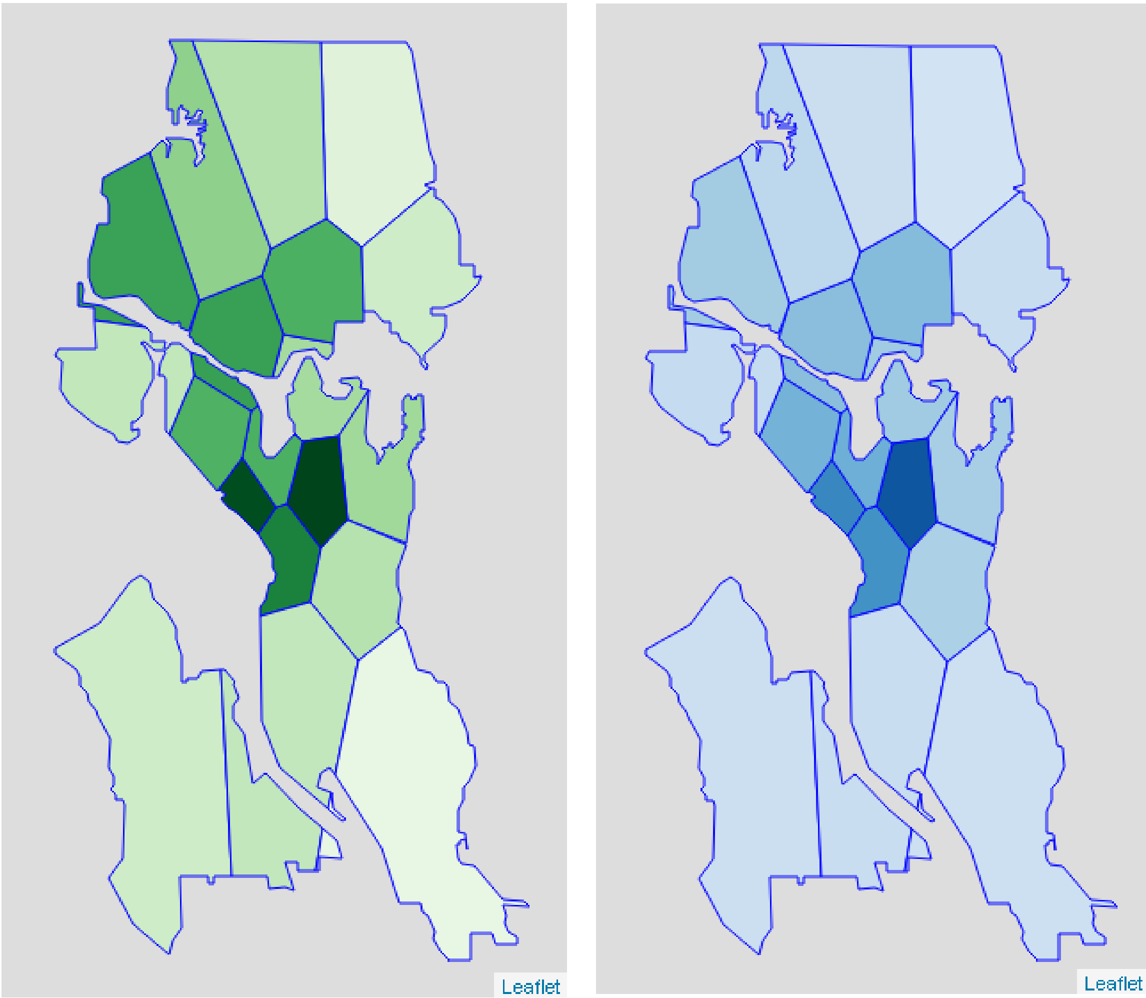


**Figure 14: ReachNow clusters showing trip generation density on the left in green vs the hazard ratios from the Cox proportional hazard model as for Model-I on the right in blues**

## Trajectory Synthesizer

A trajectory synthesizer combining the destination and duration model above has been created as an interactive web-app and hosted online [33]. The trajectory synthesizer allows a selection of number of trips and time block and predicts the trajectory based on the click position in the ReachNow Seattle home area.

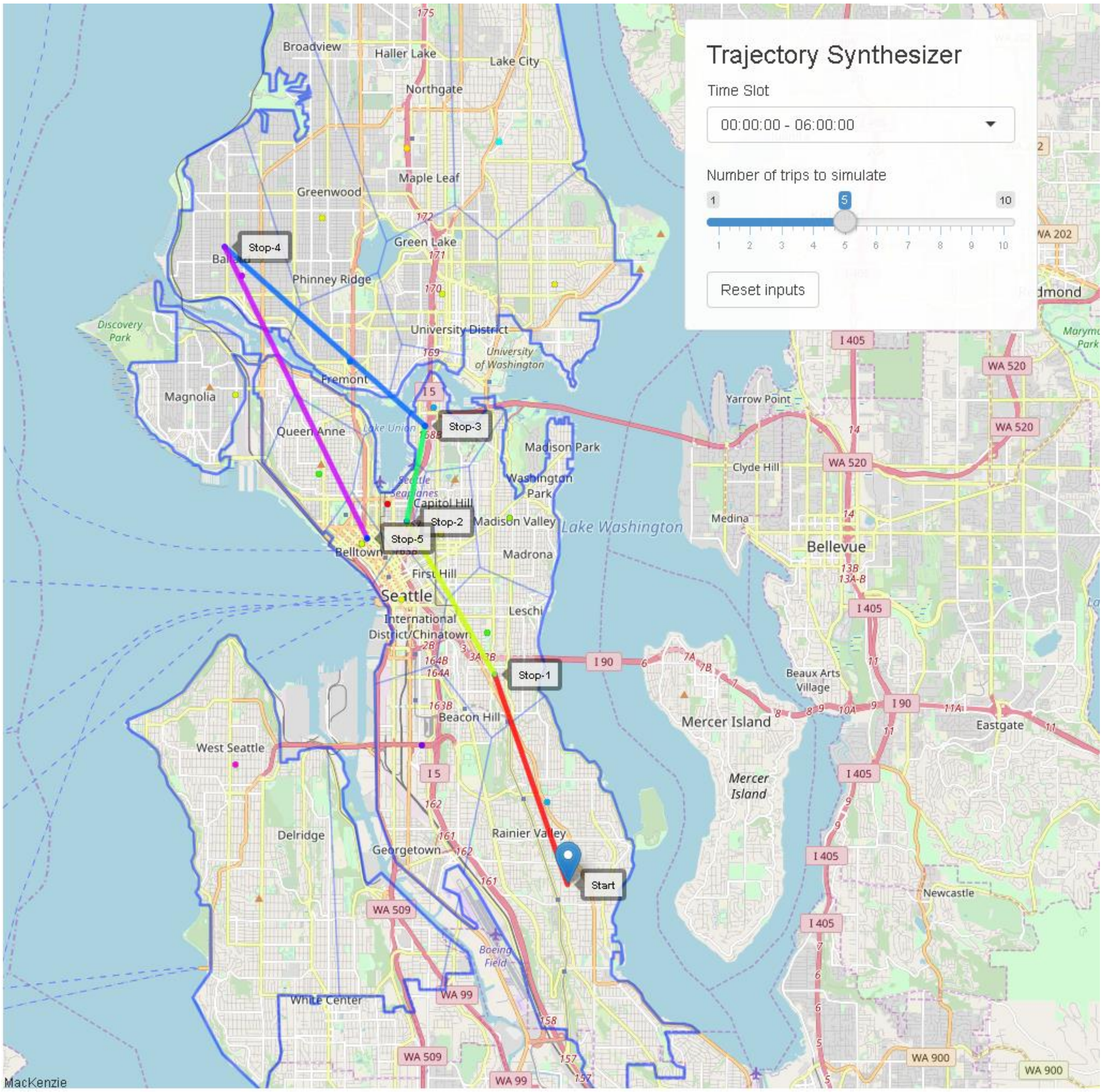


**Figure 15 Trajectory Synthesizer model run showing 5 trips**

# CONCLUSION

The paper analyzes FFCS in the context of Seattle. We propose a framework for modeling the usage patterns of FFCS, which comprises of a destination model that predicts the destination given the origin and the time of day; and a duration model that predicts the dwell time given the location, time of day and optional covariates capturing cars in the vicinity. Together, these two models can be used to probabilistically simulate trajectories for FFCS vehicles. Next, the modeling framework can be used to predict the optimal locations of charging stations by finding locations that are frequent destinations for cars with a low SOC and have longer dwell times. This would make sure that cars require a minimum amount of relocation effort and are out-of-service for charging where they are likely to stay parked longer.

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# APPENDICES

## Appendix – A: Details of the Duration Model

Columns labeled (1), (2), and (3) represent the Cox Proportional Hazard Model goodness of fit statistics, i.e. coefficients, standard errors, R2, Log-likelihood etc.

**Dependent Variable: Dwell Time**

| | **(1)** | **(2)** | **(3)** |
|---|---|---|---|
| **Cluster2** | -0.600*** | -0.707*** | -0.875*** |
| | (0.013) | (0.013) | (0.013) |
| **Cluster3** | -1.284*** | -1.267*** | -1.591*** |
| | (0.016) | (0.016) | (0.016) |
| **Cluster4** | -0.420*** | -0.469*** | -0.696*** |
| | (0.011) | (0.011) | (0.011) |
| **Cluster5** | -0.648*** | -0.701*** | -0.926*** |
| | (0.012) | (0.012) | (0.013) |
| **Cluster6** | 0.245*** | 0.143*** | 0.019** |
| | (0.009) | (0.010) | (0.010) |
| **Cluster7** | -0.449*** | -0.466*** | -0.705*** |
| | (0.011) | (0.011) | (0.011) |
| **Cluster8** | -1.057*** | -1.146*** | -1.362*** |
| | (0.016) | (0.016) | (0.016) |
| **Cluster9** | -1.115*** | -0.773*** | -1.425*** |
| | (0.012) | (0.013) | (0.012) |

| | | | |
|---|---|---|---|
| **Cluster10** | -0.064*** | -0.041*** | -0.195*** |
| | (0.010) | (0.010) | (0.010) |
| **Cluster11** | -0.306*** | -0.299*** | -0.354*** |
| | (0.011) | (0.011) | (0.011) |
| **Cluster12** | -0.867*** | -0.790*** | -1.150*** |
| | (0.012) | (0.012) | (0.012) |
| **Cluster13** | -0.615*** | -0.562*** | -0.895*** |
| | (0.011) | (0.011) | (0.011) |
| **Cluster14** | -1.069*** | -0.950*** | -1.368*** |
| | (0.013) | (0.013) | (0.013) |
| **Cluster15** | -0.330*** | -0.408*** | -0.587*** |
| | (0.011) | (0.011) | (0.012) |
| **Cluster16** | -0.684*** | -0.745*** | -0.973*** |
| | (0.013) | (0.013) | (0.013) |
| **Cluster17** | -1.052*** | -0.866*** | -1.320*** |
| | (0.013) | (0.013) | (0.013) |
| **Cluster18** | -0.960*** | -1.021*** | -1.261*** |
| | (0.015) | (0.015) | (0.015) |
| **Cluster19** | -1.345*** | -1.563*** | -1.461*** |
| | (0.034) | (0.034) | (0.034) |
| **Cluster20** | -1.149*** | -1.066*** | -1.469*** |
| | (0.014) | (0.014) | (0.014) |
| **Time Block 6:00 – 11:59** | 0.108*** | 0.075*** | 0.158*** |
| | (0.010) | (0.010) | (0.010) |

| | | | |
|---|---|---|---|
| **Time Block 12:00 – 17:59** | 0.401*** | 0.380*** | 0.566*** |
| | (0.010) | (0.010) | (0.010) |
| **Time Block 18:00 – 23:59** | 0.660*** | 0.642*** | 0.777*** |
| | (0.010) | (0.010) | (0.010) |
| **cars_in_cluster** | | -0.010*** | |
| | | (0.0001) | |
| **cars_within_distance(500m)** | | | -0.031*** |
| | | | (0.0004) |
| **Observations** | 246,237 | 246,237 | 246,237 |
| **R2** | 0.198 | 0.216 | 0.219 |
| **Max. Possible R2** | 1.000 | 1.000 | 1.000 |
| **Log Likelihood** | -2,783,352.076 | -2,780,540.549 | -2,780,141.010 |
| **Wald Test** | 54,387.040*** (df = 22) | 60,335.610*** (df = 23) | 61,291.850*** (df = 23) |
| **Note:** | *p<0.1; **p<0.05; ***p<0.01 | | |

**Table 2: Detailed statistics for three variations of the Cox Proportional Hazard Model**