Electric Vehicle Infrastructure Decision Support System

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Abstract

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Electric vehicles (EVs) need DC fast-charging stations (DCFC) for long-distance trips. DCFCs are costly investments and so charging station companies want to install them in locations where they expect high utilization. Further, government agencies are usually interested in ensuring that DCFCs are available on all roads and adequately spaced so that residents do not feel anxious about EV ownership. DCFC deployment therefore must balance the private and public objectives. This thesis presents a framework, ChargEVal, for simulating charging station deployment scenarios using agent-based modeling (ABM). The ABM utilizes behavioral models for simulating vehicle choice for the trip and charging choice during a trip. ChargEVal supports multiple users to submit multiple simulations simultaneously. ChargEVal also has a dedicated results viewer for viewing the simulation summary statistics and agent state values facilitating detailed insight and simulation comparison. Results from a few sample runs, model verification, and sensitivity analysis are shown. We also answer the question of whether it is more cost-effective to create a new charging station vs upgrading an existing station with more plugs. While the current implementation of

ChargEVal is specific to the state of WA, USA; the underlying framework is generic enough to be applied to any geography at any scale.

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ACKNOWLEDGEMENTS

First and foremost, I would like to acknowledge the University of Washington and all our project sponsors for making the research presented in this thesis possible. Our project sponsors include the Connected Cities with Smart Transportation (C2SMART) that supported the work on electric free-float carsharing, Washington State Department of Transportation (WSDOT) for supporting the development and hosting of the tool ChargEVal, PacTrans for supporting tech-transfer and outreach related to ChargEVal and UWRCC for supporting the cloud expense during the ChargEVal development and testing.

I would be perpetually thankful to Prof. Don MacKenzie for choosing me to be their vehicle of novel and impactful research and for giving me a chance to collaborate with the Sustainable Transportation Lab and the UW family. I am also indebted to the members of my dissertation committee, namely Prof. Ed McCormack, Prof. Dave Beck, and Prof. Baosen Zhang for their continued support and motivation during my dissertation.

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Finally, I would like to thank my parents for supporting me every day of my life. It is through their hard work and sacrifices that I have been able to achieve what I have. I would have had a very hard time navigating the Ph.D. at UW without the inspiration and motivation from my brother.

Chapter 0. INTRODUCTION

"Experience without theory is blind, but theory without experience is mere intellectual play." – Immanuel Kant

The role of science is to aid in our understanding of nature, whereas the role of engineering is to use the advanced understanding for betterment of humanity. Specific to the case at hand, the science of sustainable transportation helps us to quantify and qualify existing and new modes of transportation from the perspective of equity, environmental impact and economy. With this advanced understanding an engineer is tasked to devise solutions that solve sustainable transportation problems around us.

This thesis presents some of sustainable transportation problems, specifically related to electric vehicle infrastructure and micro-mobility. The science of the subject helps to quantify and qualify the extent and impact of the problem, whereas the engineering aspect aims at developing tools that help the users in making informed decisions based on the science.

Chapter-1 of the thesis focuses on gaining understanding of and facilitating electric travel using free-float car share. A destination model is created that predicts the likely destination given an origin and time of day. Further, a duration model is proposed that predicts the length of time a vehicle is expected to stay at a given location. These models are made accessible to the end user in the form of a web-app called Trajectory Synthesizer, that can probabilistically simulate free-float car share trajectories. The vehicle trajectories can help us find the optimal locations of charging stations for free-float car share vehicles.

Chapter 2 of thesis presents the implementation details of a framework for simulating and analyzing charging station deployment scenarios using agent-based modeling, ChargEVal. As new charging stations are deployed, more electric vehicle trips become feasible. More trips will likely result in an increased charging station utilization. An estimation of the utilization helps us to determine if and when a charging station becomes economic. The framework leverages behavioral models of vehicle choice and charging choice and performs detailed minute-by-minute simulation of a typical travel day in the state of Washington to predict charging station utilization. Framework users can use a browser-based interface that allows point and click placement and configuration of chargers.

Chapter-3 delves deeper into the algorithmic aspects of ChargEVal, presents results from the sensitivity analysis and some example studies that demonstrate the strengths of the agent-based modeling framework.

Finally, chapter 4 presents the most recent work. One of the ways to maximize level of service of EV infrastructure is to ensure that a vehicle does not have to wait to charge at a charging station. Charging station investments can be either directed towards deploying a new station or upgrading an existing station by adding new plugs – both strategies will likely reduce the waiting times. Therefore, it is proposed to compare the cost-effectiveness of installing new chargers v/s upgrading existing chargers.

Chapter 1. A MODELING FRAMEWORK FOR FORECASTING DESTINATIONS AND DWELL TIMES IN A FREE-FLOAT ELECTRIC CARSHARING SYSTEM

1.1 ABSTRACT

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. 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, slow recharging times of electric vehicles compared to gasoline-fueled vehicles, a charging event represents trip bounds and further requires a manual relocation of the free-floating vehicle to a charging station. This relocation leads to a high operational expenditure and unreliable downtimes. This study aims to prepare 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 be used for increasing 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.

Keywords: Free-float car sharing, electric vehicles, demand models, new mobility services.

1.2 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] with major interest 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 emission due to 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 also 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 has been regarded as a sizeable market opportunity, especially in Europe, with an estimated 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 other 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 use 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 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 further [17] develop an algorithm for locating charging stations for electric carsharing systems with 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 that 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.

1.3 DATA

For destination modeling, trip data were 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, 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.

1.4 RESEARCH METHODOLOGY

This work takes a stochastic approach to modeling FFCS demand patterns. While global digitization and the Internet of things (IoT) now generate vast amounts of data, concerns around security and privacy of users often result in limited access to user travel data. Moreover, even with vast quantities of data, until a FFCS car is booked, it may be impossible to know exactly when it will get booked and the precise destination of the person booking it. Nevertheless, an eFFCS operator needs to understand the likelihoods of different booking times and destinations in order to intelligently manage vehicle availability and state of charge, in advance of future bookings. Before, we prepare the destination model, it is worthwhile to do some data exploration to first understand how Seattle moves around and then discern temporal variations of FFCS demand.

1.4.1 *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 1) in the ReachNow smartphone app [21], and are regulated by city bylaws [22]. ReachNow's Seattle home area is around 193 km^2 [21], 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 a using 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 1: ReachNow in Seattle - Home Area

1.4.2 *Temporal Analysis*

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

1.4.2.1 Daily Variation of Booking Frequency

Launched in April 2016 [23], ReachNow added more cars to its fleet and expanded its operating area in July 2016 [24]. Figure 2 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.

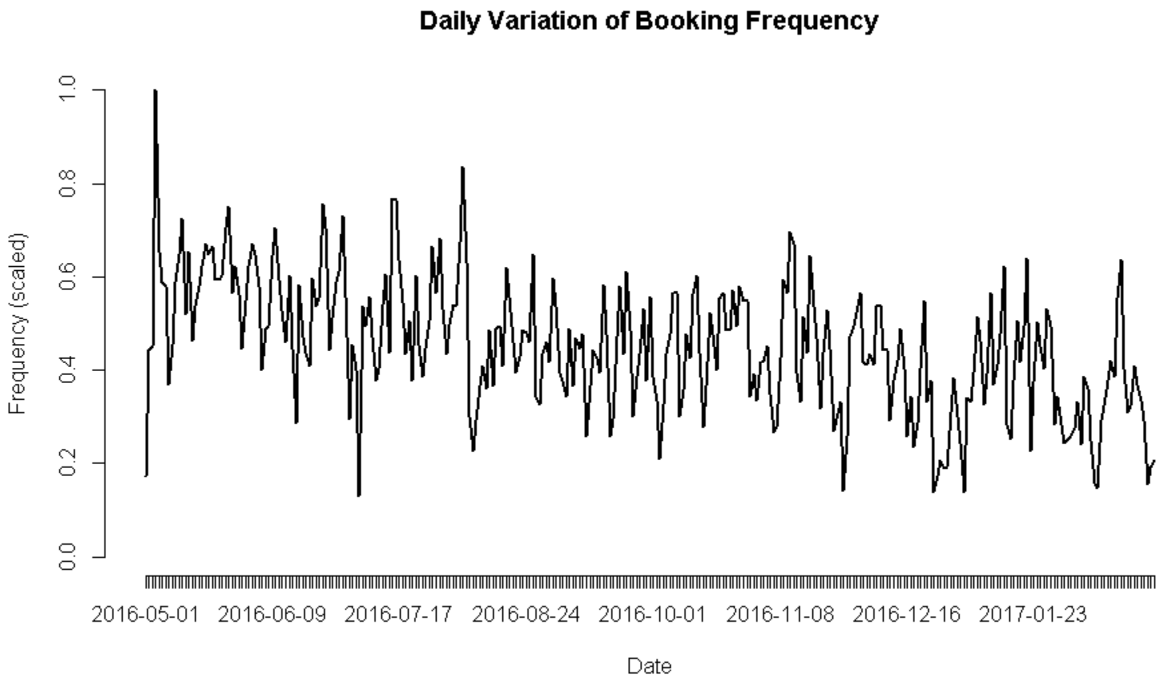


Figure 2: Daily Variation of Booking Frequency

1.4.2.2 Day of Week Variation of Booking Frequency

Day of the week affects travel behavior which is apparent from the plot shown in Figure 3. 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.

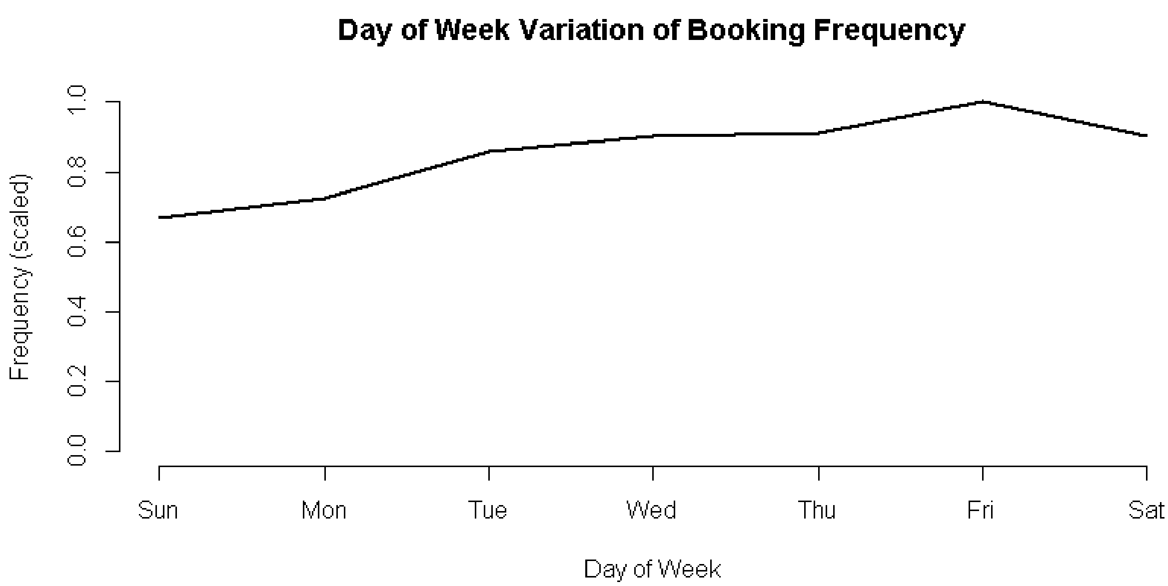


Figure 3: Day of week variation of booking frequency

1.4.2.3 Hourly Variation of Booking Frequency

A plot of the frequency of bookings (scaled to the maximum number of bookings) is shown in Figure 4. This trend is expected and is similar to the reported trends from other cities [11] and for car2go in Seattle [25]. 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.

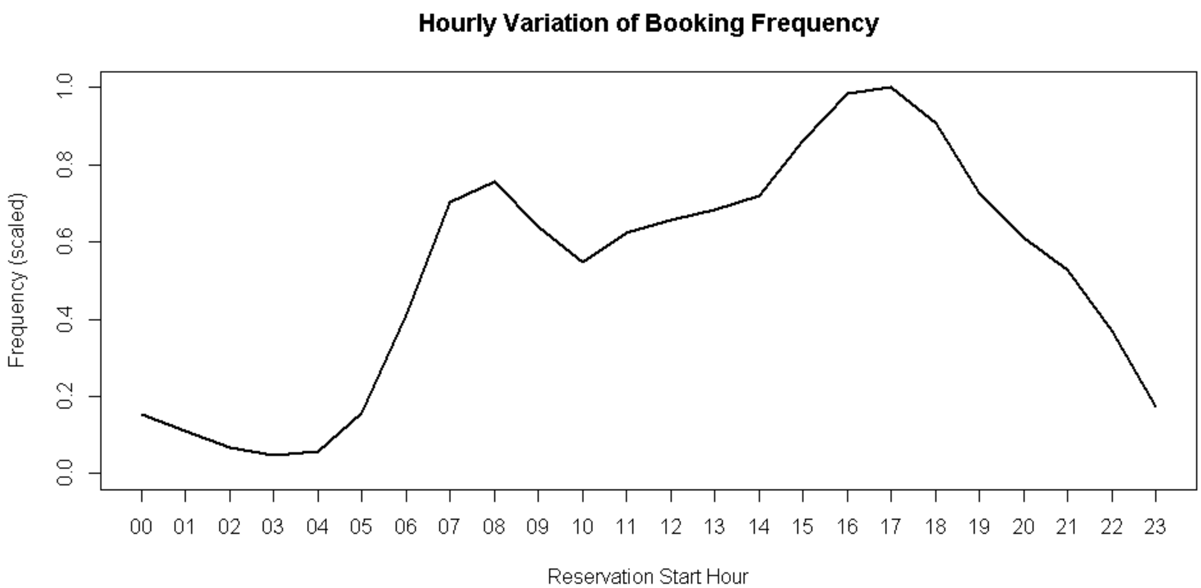


Figure 4: Hourly variation of booking frequency

1.4.2.4 Drive Times

Drive Times reflect the time the vehicle was driven -- an indirect measure to capture the trip length and duration. Together, the figures Figure 2, Figure 3, Figure 4, and Figure 5 tell us about the nature of FFCS trips in Seattle, i.e. trips are usually around 20 minutes, occur on all days with slightly higher frequency

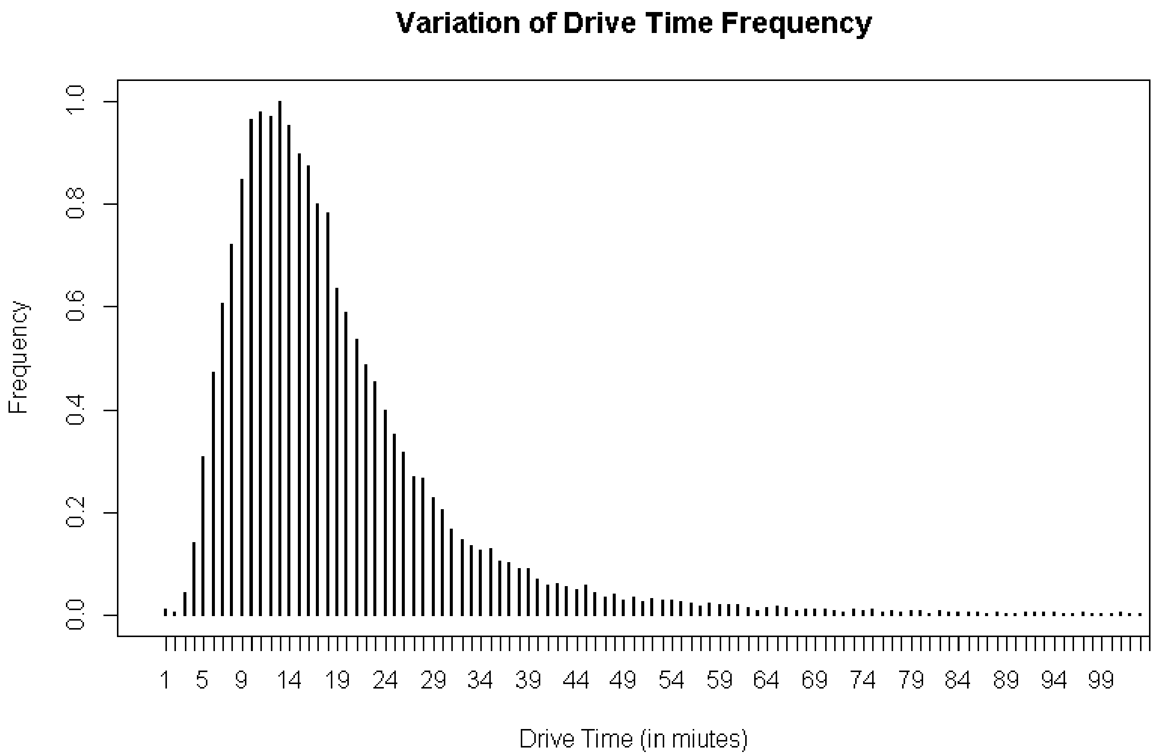


Figure 5: Histogram showing the frequencies of drive time up to 100 minutes

on weekends 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.

1.4.3 *Spatial Analysis*

1.4.3.1 Cluster Analysis

We began by using k-means clustering to define clusters of trip origins. Figure 6 shows the trip start points clustered using k-means into 20 clusters. We can see that from Figure 6 a high density of trips around the central area of the map, which is downtown, and fewer trips near the periphery. The clusters align well with different Seattle neighborhoods [26]. Figure 7 shows the frequency of trips (scaled to the maximum frequency) per cluster. Similarly, Figure 8 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.

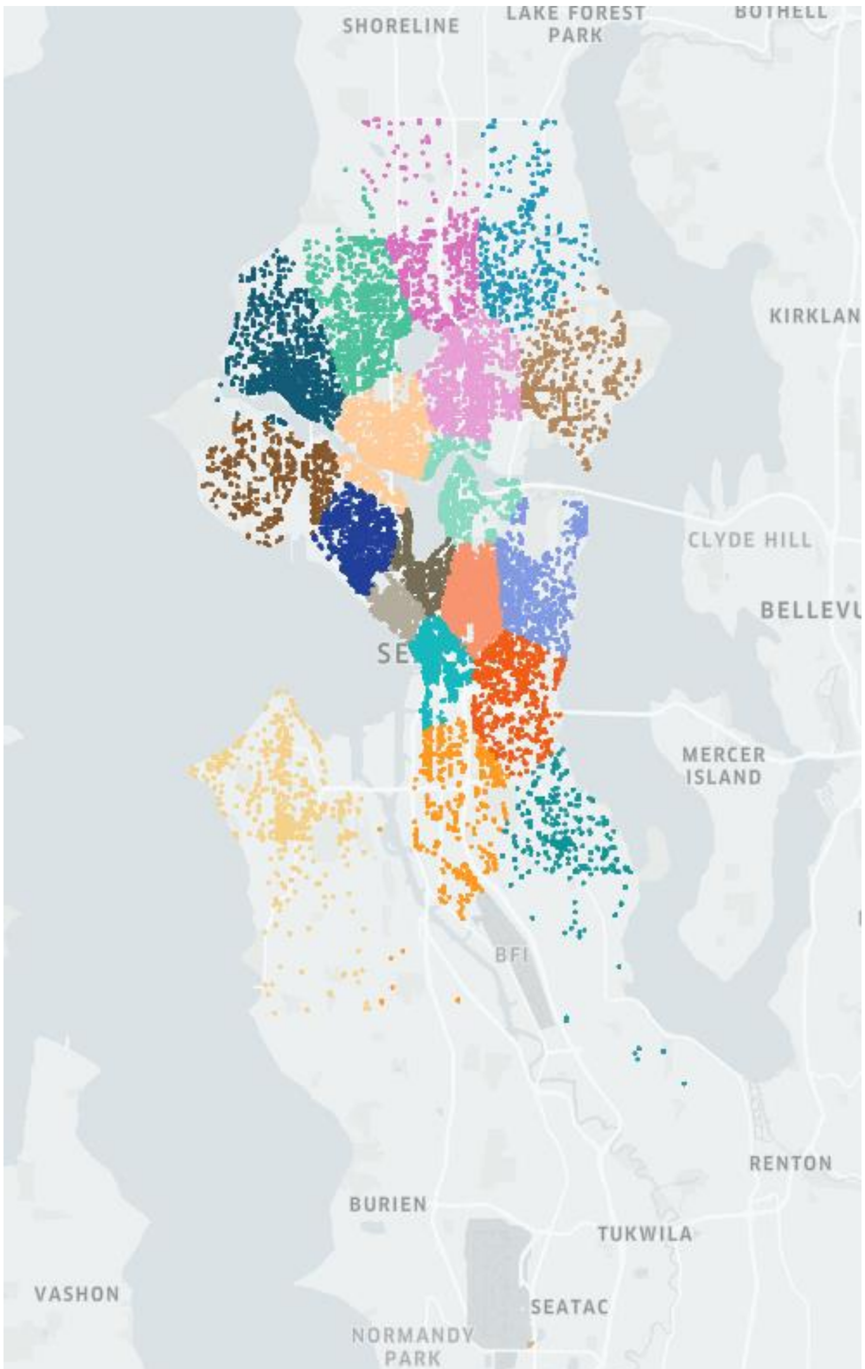


Figure 6: ReachNow Trip StartPoints clustered using k-means

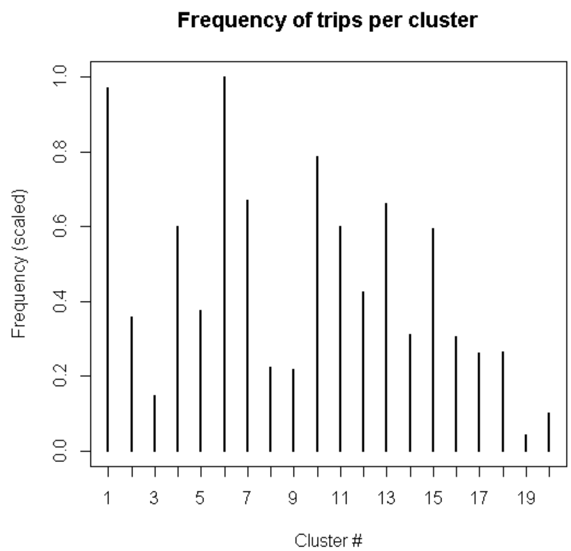


Figure 7: Frequency of trips per cluster

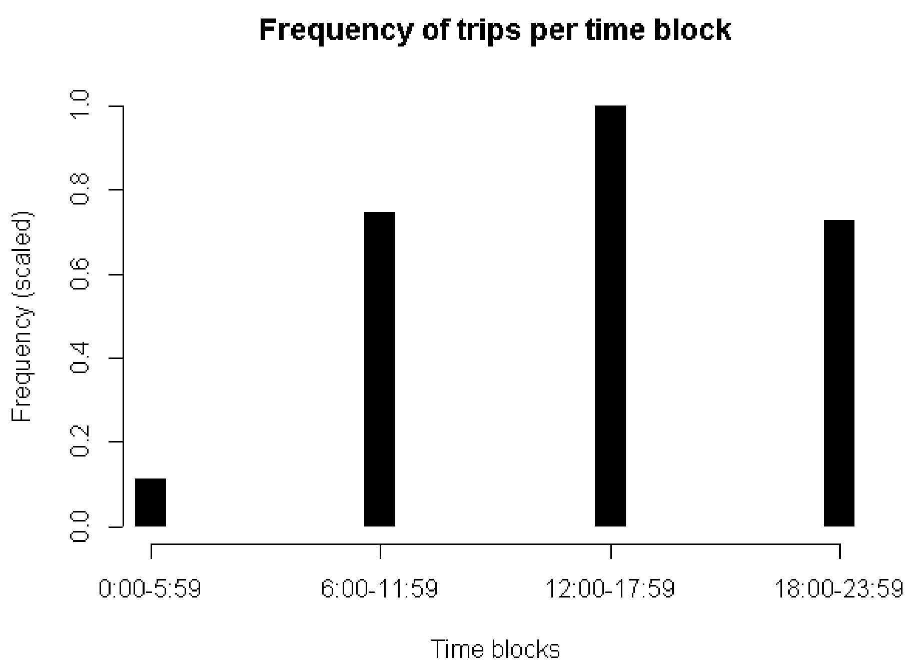


Figure 8: Frequency of trips per time block

1.4.4 *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. So, for example it is much easier to predict the destination if the city is divided into two zones, let us 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 Figure 4, we can ascertain that the variation in trip bookings does not 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 9 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 10 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.

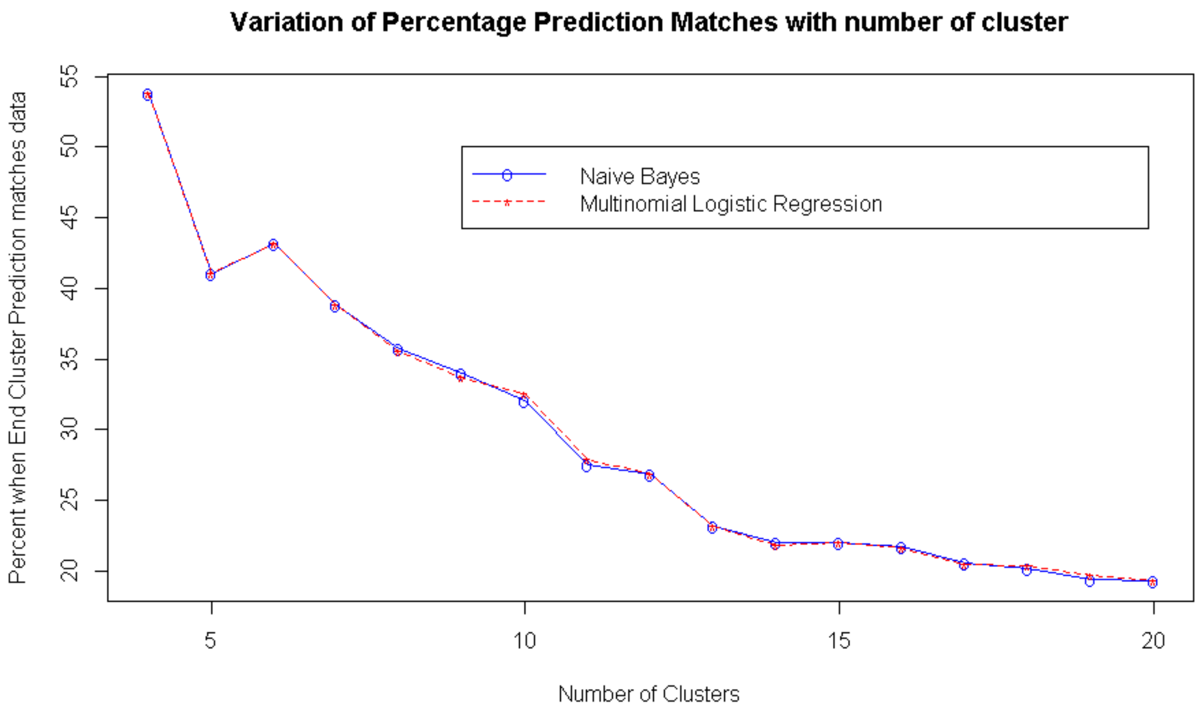


Figure 9: Variation of percentage prediction match with number of clusters using Multinomial Logistic Regression and Naïve Bayes Classification

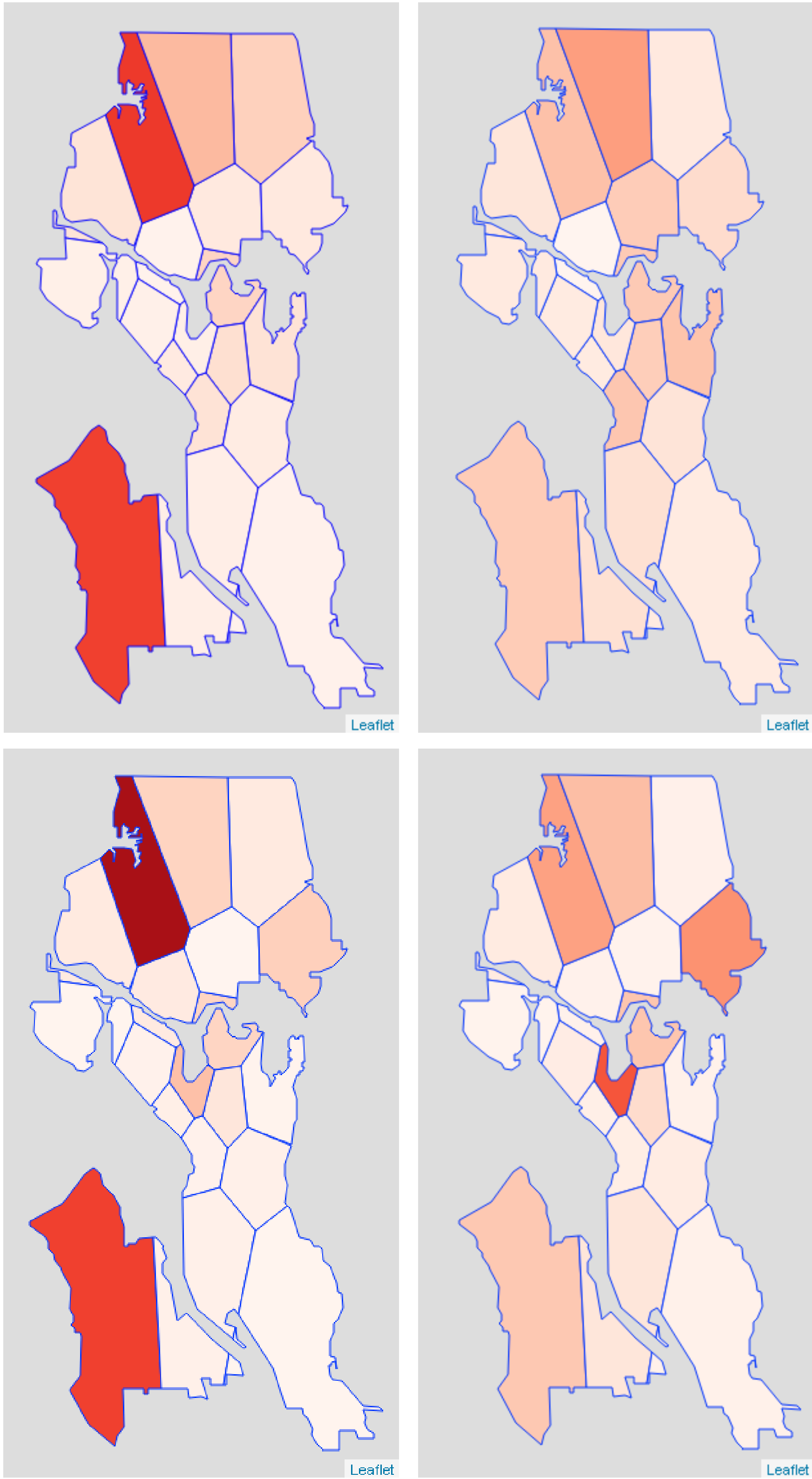


Figure 10: Destination Model results, colored to show destination probability, top-left: origin cluster 10, time block 6:00-11:59, top-right: origin cluster 10, time block 18:00-23:59, bottom-left: origin cluster 18, time block 6:00-11:59, and bottom-right: origin

1.4.5 *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 11 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 number 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 number 3, 9, and 20 which show longer dwell times.

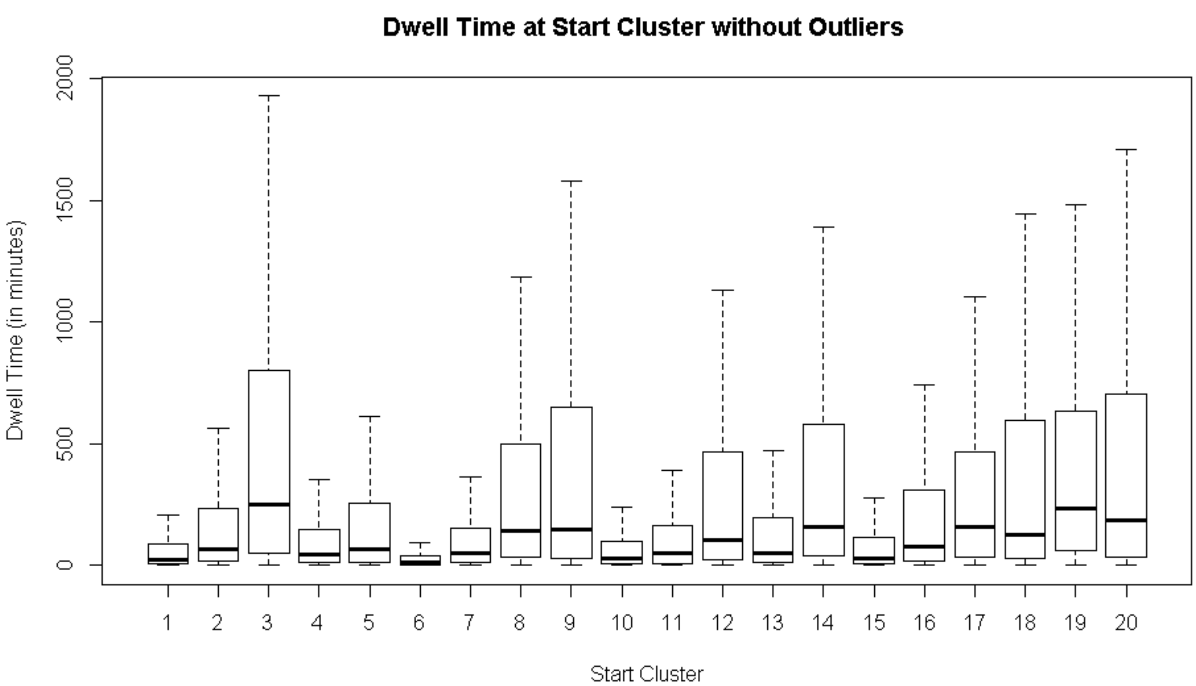


Figure 11: Dwell times at Start Clusters without outliers

Dwell times appear to follow a negative exponential distribution, as can be seen in Figure 12. 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.

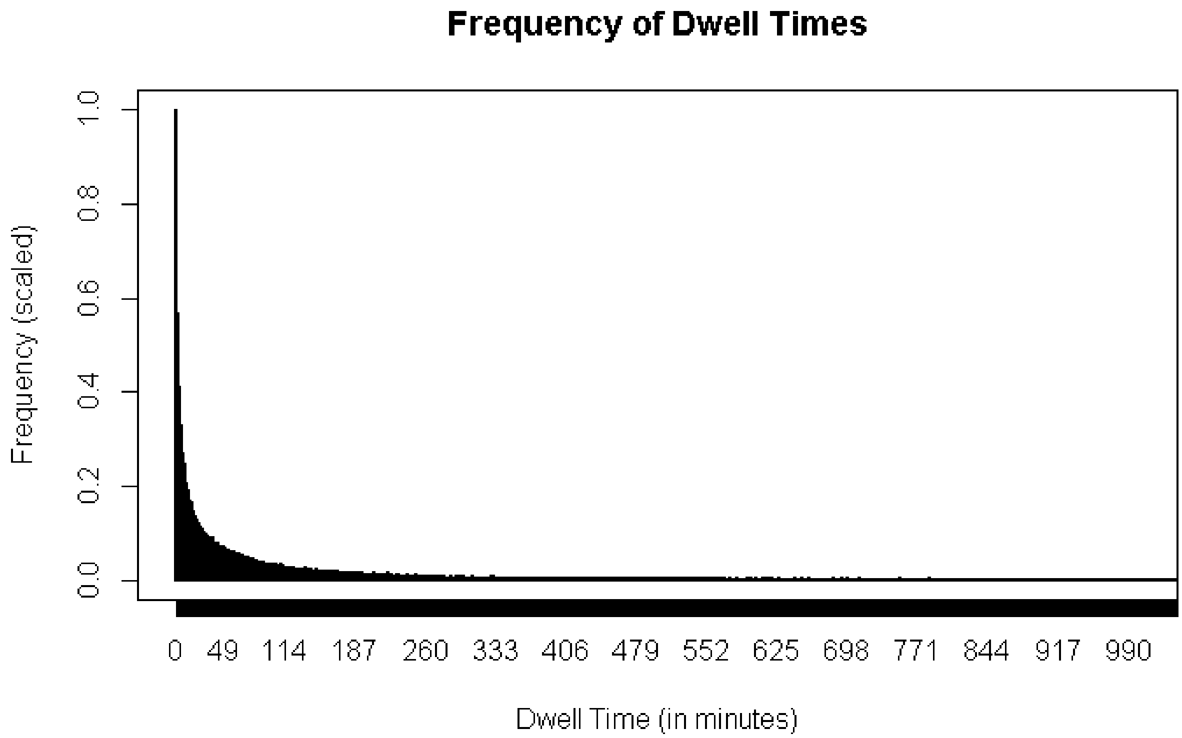


Figure 12: Density of Dwell Times right-censored to 2000 minutes

1.4.5.1 Cox Proportional Hazard Model

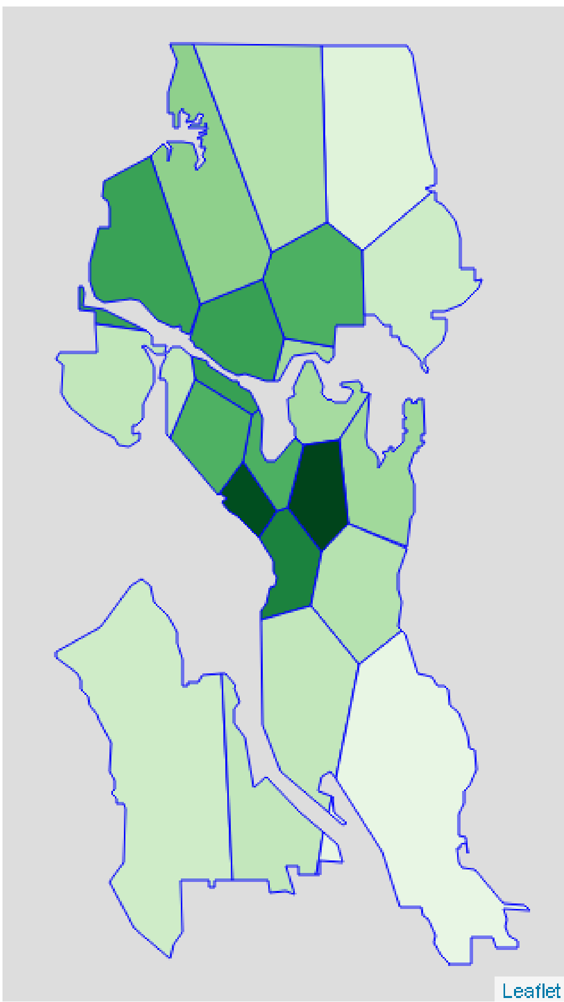
A Cox proportional hazard model was applied to model the dwell time of vehicles using the location and time of day as covariates. In two variations (Model-II and Model-III in results), one covariate was added each time to reflect vehicles in the vicinity. “Cars_in_cluster” represents the number of cars 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. Table 1 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 Table 1, 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 13 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. However, there are a few noticeable differences, places where these two factors are not entirely aligned. This can be interpreted as areas where rebalancing may be helpful: cars may not be dropped off very frequently, but when they are, they get used quickly; or lots of trips may start in that zone, but cars tend to wait longer there than elsewhere in the city before getting used.

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

Names	**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



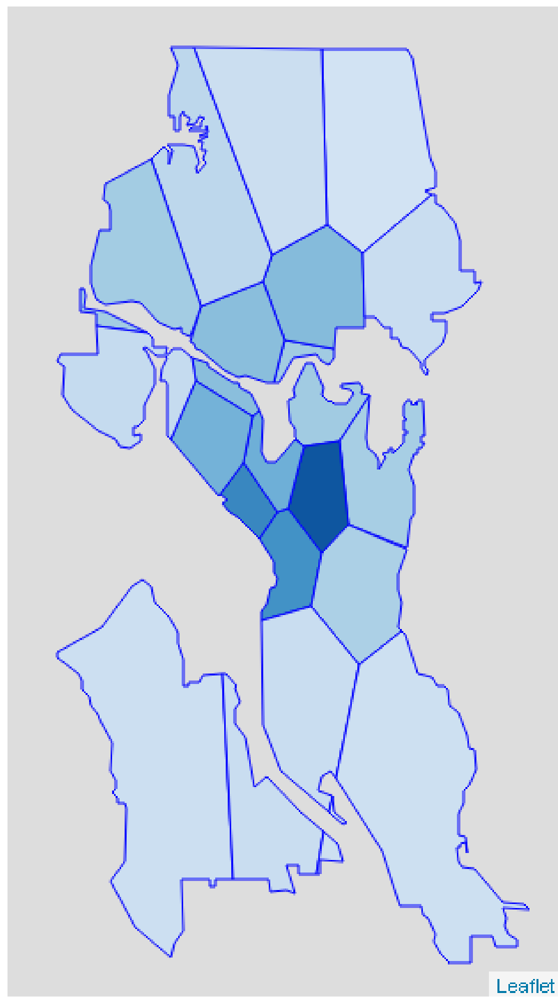


Figure 13: ReachNow clusters showing trip generation density on the left in green vs the hazard ratios from the cox proportional hazard model as for Model-I on the right in blues

1.4.6 *Trajectory Synthesizer*

A trajectory synthesizer combining the destination and duration model above has been created as an interactive web-app and hosted online [27]. The trajectory synthesizer allows a selection of number of trips and initial time block and predicts the trajectory based on the click position in the ReachNow Seattle home area.

1.5 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 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.

Chapter 2. CHARGEVAL - A MULTI-USER FRAMEWORK FOR SIMULATING AND ANALYZING CHARGING STATION DEPLOYMENT SCENARIOS USING AGENT-BASED MODELLING – IMPLEMENTATION DETAILS

2.1 ABSTRACT

ChargEVal is a framework for simulating charging station deployment scenarios using agent-based modelling (ABM). The ABM utilizes behavioral models for simulating vehicle choice for the trip and charging choice during a trip. ChargEVal supports several users to submit multiple simulations simultaneously, using the graphical user interface or programmatically. ChargEVal also has a dedicated results viewer for viewing the simulation summary statistics and agent state values facilitating detailed insight and simulation comparison. While the current implementation of ChargEVal is specific to the State of Washington, USA; the underlying framework is generic enough to be applied to any geography at any scale.

Keywords:
electric vehicles; fast-charging; electric vehicle supply equipment.

2.2 CODE METADATA

Table 2: Code metadata

Nr	**Code metadata description**	
C1	Current code version	*1.0.0*
C2	Permanent link to code/repository used of this code version	*https://github.com/s-t-lab/ChargEval* *https://github.com/s-t-lab/evi-abm*
C3	Legal Code License	*MIT License*
C4	Code versioning system used	*git*
C5	Software code languages, tools, and services used	*R, Shiny, PostgreSQL, NodeJS, Flyway, Docker, GAMA, Redis, Grafana, AWS EC2, AWS SDK, Read The Docs etc.*

C6	Compilation requirements, operating environments & dependencies	*Linux*
C7	If available Link to developer documentation/manual	*https://chargeval.readthedocs.io*
C8	Support email for questions	dwhm@uw.edu

2.3 MOTIVATION AND SIGNIFICANCE

While most electric vehicle (EV) charging happens at home or at the workplace, there is still a need for public charging stations for people taking long distance trips and for people who do not have access to home or workplace charging. Public charging infrastructure can also help with range anxiety, which is the fear of being stranded without charge. Evidence suggests that a network of charging stations available for public use can help in alleviating range anxiety and make more long-distance trips feasible.

To be useful in a long-distance trip, a public charging station should support fast charging. Fast charging from a station allows for shorter charging breaks for customers and provides the charging station a capability to serve more vehicles during a day. Fast charging stations, though preferred, are costlier in terms of the capital investment as well as operational cost. It is therefore vital to find locations for fast-charging stations such that they have high potential utilization.

This paper reports on the software architecture of ChargEVal - that combines empirically grounded models of travel demand and charging behaviour in an agent-based simulation framework to estimate fast charger utilization. The simulated utilization depends on factors including EV fleet size, charging propensity etc. The simulated charger utilization can be fed to an economic model of the charging station, that considers the fixed and variable costs of installing and operating a charging station. With the use of the proposed decision support system, public agencies and private companies can evaluate the feasibility of a set of charging station candidate sites and compare multiple siting scenarios.

2.4 COMPONENT MODELS IN CHARGEVAL

The various components of ChargEVal are described below.

2.4.1 *Long Distance Travel Demand Model*

The necessity of charging on a route is directly proportional to the number of EV trips passing through the route. The trip counts between origin-destination (OD) pairs were estimated using INRIX data, as reported in previous work by Jabbari et.al. [28]. The OD matrix is composed of around 300k+ rows for indicating trip counts from all origin zips ZIP codes to all destination zips ZIP codes within Washington.

2.4.2 *Vehicle Choice Decision Model*

The vehicle choice decision model (VCDM) provides the probability of a traveler using an EV for a long-distance trip, depending on various trip and vehicle characteristics. Ge [29] estimates several discrete choice models generated through stated preference surveys. For the purpose of implementation in ChargEVal, a latent choice logistic regression model is used that makes a vehicle selection between an internal combustion engine vehicle (ICEV), a rental vehicle or a battery electric vehicle (BEV).

2.4.3 *Charging Choice Decision Model*

While the vehicle is en-route its destination, it might need to charge along the way. The choice of charging at a charging station can modelled by a binary choice decision model. Among the various models developed by Ge [29], ChargEVal currently uses the static choice decision model.

2.4.4 *EV Infrastructure Agent-based Model (eviabm)*

The EV Infrastructure Agent-based Model (eviabm) is an agent-based model for modelling the utilization of EVSE in the state of Washington. As such, it has the following attributes:

- Agents:
  - **Electric vehicles in the state of Washington:** We consider all the electric vehicles registered in the state of WA as our EV agents. While some EVs maybe travelling outside

the state and some out of state vehicles maybe traveling within WA, for the present study, we ignore these vehicles.

    - **Washington road network:** The EVs move on roads and travel is restricted to state roads. Currently, we ignore the elevation of the roads, but in future, the roadway elevation can be included, and the energy model can account for the changes in elevation.
    - **Electric Vehicle Supply Equipment / Charging Stations:** The charging stations are the agents where the EVs charge when they are charge depleted. The instantaneous power drawn, and total energy consumed are the EVSE utilization outputs from the simulation that we are interested in.

- Environment: Currently, a two-dimensional simulation is bounded by the state of WA.
- Time: A single simulation runs for 24 hours in 1-minute time-steps. This means that we simulate EV travel around the state for a period of one day at a time and update the states of our agents each minute.

2.5 SOFTWARE DESCRIPTION

2.5.1 *System Architecture*

Figure 14 shows the ChargEVal system diagram. The arrows show a typical simulation request flow. It can be summarized as below (corresponding step numbers on the image):

0. The Nginx webserver serves the web UIs EV Infrastructure Designer (*evides*). A Grafana instance is used for centralized monitoring and logging of the system.
1. Upon authentication, a user can place and configure new charging stations via the *evides* and submit a simulation request.
2. The simulation request is written to the database.
3. The database generates an insert notification, which is picked up the Simulation Manager (*simman*)).
4. The *simman* queues the incoming simulation request and processes them in order.
5. A trip generation (*tripgen*) virtual machine is launched.
6. Upon completion of *tripgen*, the *tripgen* EC2 instance is terminated and an *eviabm* EC2 instance is launched.

7. Upon completion of the *eviabm*, the *eviabm* instance is terminated, and a success email is sent to the user with a link to the *resview*.

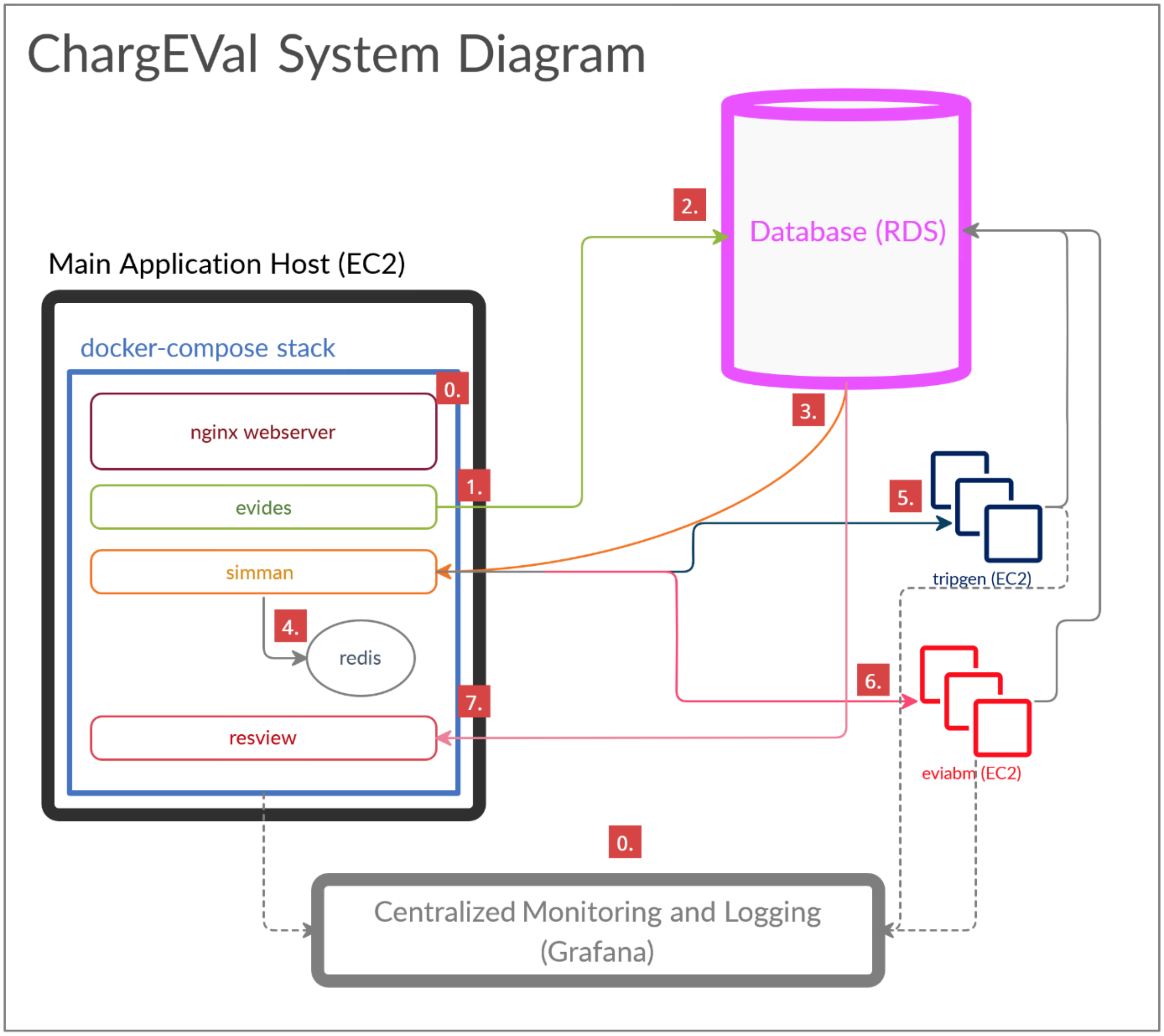


Figure 14: ChargEVal System Diagram

The distributed nature of the deployment makes it harder to debug and maintain. However, this design ensures (almost) infinite number of simulations can run in parallel with the only bottleneck being the database, which can be scaled up or down as demand varies. Another important consideration of the design is the high uncertainty in system demand. It might take time for the framework to be popular, and the programmatic control of infrastructure allows for provisioning only the necessary compute thereby minimizing the system cost.

2.5.1.1 Main Application Host

The ChargEVal application is hosted on a Linux machine, currently on an AWS EC2 instance. An instance of size *T3a.large* or higher is recommended for this setup. This machine uses a *Docker Compose* stack to host the component services.

2.5.1.1.1 Nginx

A Nginx container routes all the web-requests to the individual containers by reverse proxying the requests to the respective ports.

2.5.1.1.2 EV Infrastructure Designer (evides)

The *evides* (Figure 15) is the user-interface (UI) created using R Shiny for inputting the details (location, type, count etc.) of the prospective charging stations and then submitting a simulation

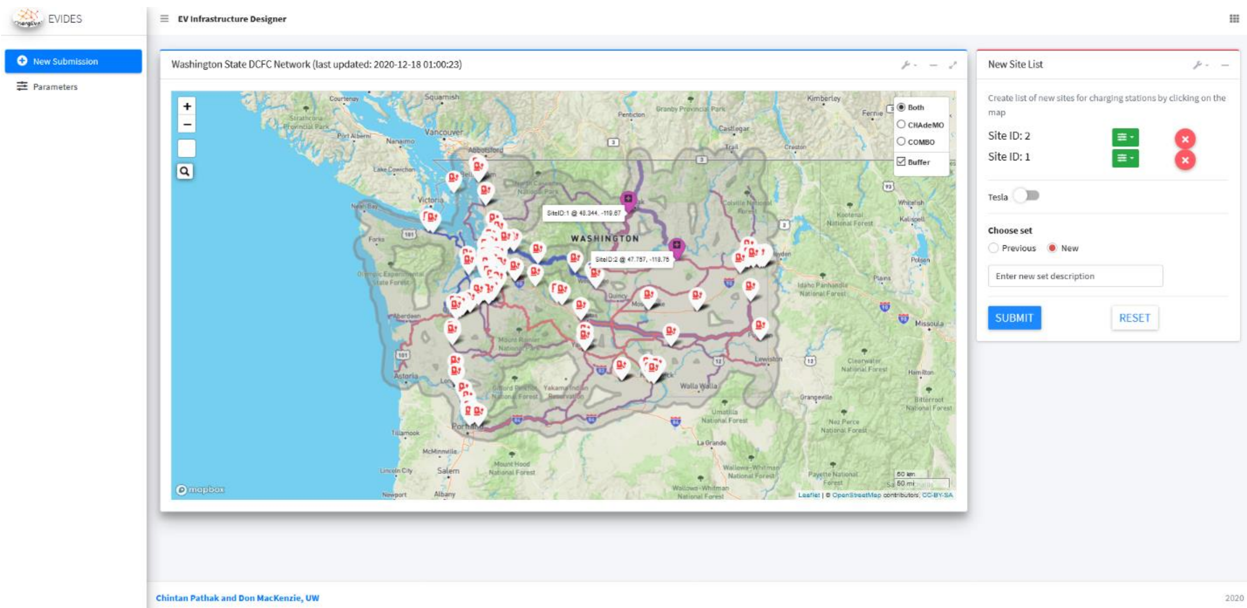


Figure 15: EV Infrastructure Designer (evides)

request.

2.5.1.1.3 Simulation Manager (simman)

The *simman* is the controller in ChargEval written in NodeJS. The purpose of the *simman* is to watch for inserts into the database. New simulation requests are queued and processed in order. Since the next steps in the simulation - namely trip generation and agent-based simulation are both long-running CPU intensive processes – they are run in dedicated virtual machines launched asynchronously, leaving *simman* available to process incoming requests. AWS SDK for JavaScript

[30] is used for launching and terminating AWS EC2 instances for *tripgen* and *eviabm* processes. The *simman* process is shown in Figure 16.

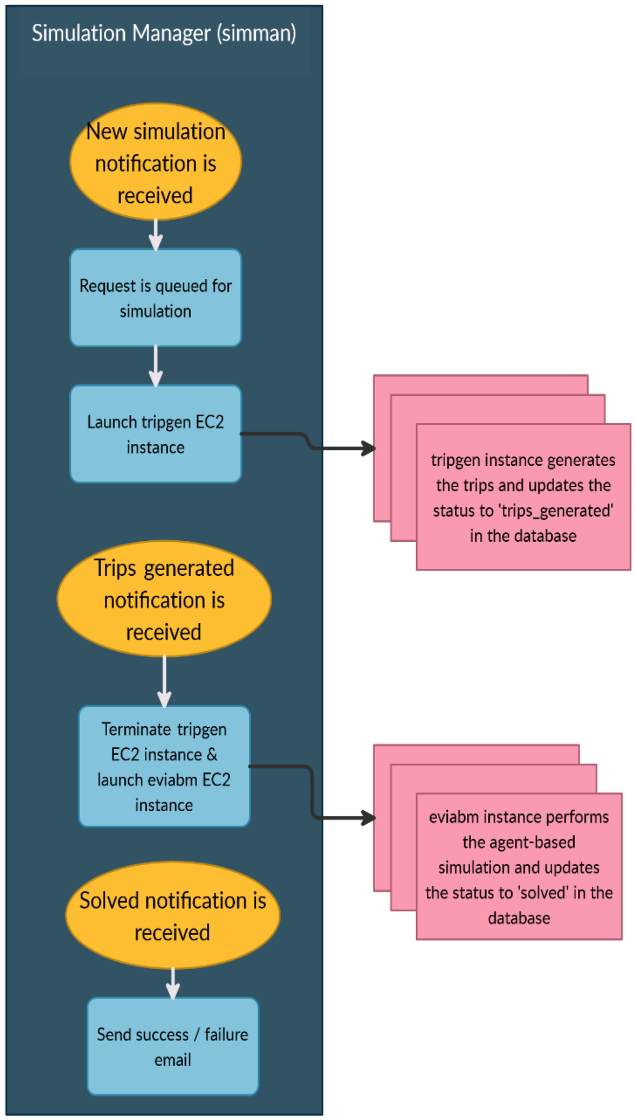


Figure 16: Simulation manager process

2.5.1.1.4 Redis

A Redis container is used to persist the state of the queue in simulation manager.

2.5.1.1.5 Results Viewer (resview)

The user gets an email at the registered email-id when a simulation has been successfully solved. The email contains the link to resview, a R Shiny web-app. resview allows the user to browse through the results of all the simulations that they submitted and have been solved. Being able to view the detailed output of several simulations allows the user to compare the performance of charging station deployment scenarios. The Summary Stats tab shown in Figure 17 is the first view to appear on a simulation run date-time selection from the dropdown. Tabs BEVs and EVSEs show the states of EV and charging station agents respectively, throughout the simulation.

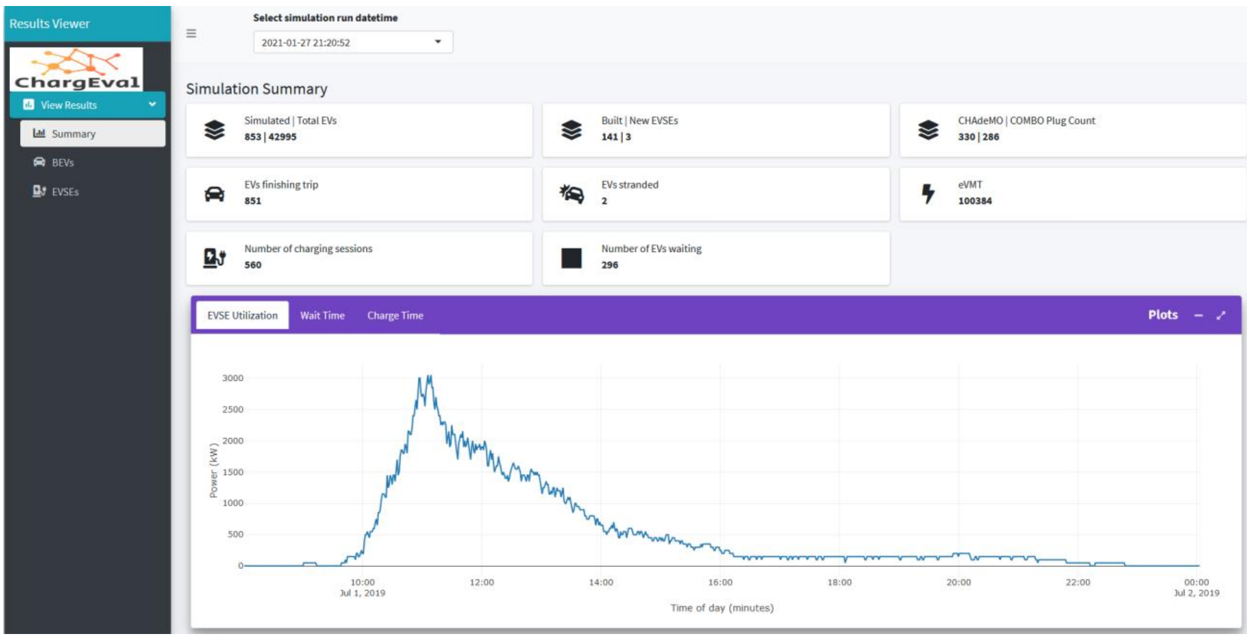


Figure 17: Results Viewer - Summary Stats tab

2.5.1.2 Database

A cloud-hosted PostgreSQL database with PostGIS and pgRouting extensions is used as the central data-store for ChargEVal due its best-in-class geospatial support. Database security is enforced using firewalls limiting access to trusted IP addresses and creating users with minimal permissions. Database triggers are used to generate notifications to signal external clients about the simulation status updates. The database migrations are applied using Flyway [31].

2.5.1.3 Trip Generation (tripgen)

The agent-based model simulates the long-distance EV trips happening in the state of WA Washington in a day. The long-distance travel demand model described in 2.4.1 is used along-with the vehicle choice decision model (2.4.2) to generate the EV trips on a typical day in the state of Washington. The trip generation process starts by estimating the number of EV trips between any given pair of origin and destination zip codes and then assigning an EV from the WA state EV pool to the respective trip. It then inserts the generated trip and associated vehicle information into the relevant database table, to be used later by *eviabm*.

2.5.1.4 EV Infrastructure Agent-based Model (eviabm)

The EV Infrastructure Agent-based Model *eviabm* is implemented in GAMA [32]. GAMA was considered suitable for this project as it supports spatially explicit agent-based models. The GAMA *eviabm* is run in a headless mode in a dedicated virtual machine. The agent definitions for the corresponding simulation are read from the database and simulation outputs are written back to the database.

2.5.1.5 Centralized Monitoring and Logging

Monitoring and logging are needed to ensure smooth and efficient operation of a software framework as well as during debugging and optimization. Dockprom [33] is used to capture detailed metrics like CPU, memory, and disk-space consumption over time for all the running services. Loki docker driver is used to ship the logs from the docker services to an instance of Loki. Metrics and logs are displayed in dashboards in Grafana [34] and updated every 5 seconds for fine-grained monitoring and logging of the application host resources. Other dashboards display live updates to the database as well as the metrics and logs from ephemeral *tripgen* and *eviabm* instances.

2.5.2 *Submitting new simulation requests*

New simulation requests can be generated either through the UI *evides* or programmatically. *evides* features a map that allows point and click placement and configuration of chargers suitable for first time users, or where geographical context is helpful. Programmatic submission is enabled by allowing the user to directly make the insertion into the database. This allows one to use any programming language, like say Python, to make the inserts. This mode is helpful when several simulations need to be submitted with minor changes. Another use-case for the programmatic approach, is when the candidate locations and configurations are chosen through some mechanism outside of ChargEVal. A few example scripts are provided in the repository to demonstrate how this can be achieved.

2.6 ILLUSTRATIVE EXAMPLE

2.6.1 *Problem description*

While the exact locations of charging stations to be deployed are determined with careful considerations of multiple criteria, as an example, consider the case of deploying 5 new charging stations. The two deployment scenarios (Figure 18) will both consider charging stations in charging station deserts, i.e., locations where there are no charging stations nearby. In scenario - 1 these charging stations will be deployed in far-off locations where there are no charging stations nearby, whereas in scenario - 2 they will be deployed in locations where there is high unserved traffic on the roads nearby. The two scenarios are then compared against the basecase scenario which is the situation as is, i.e., without the 5 new charging stations.

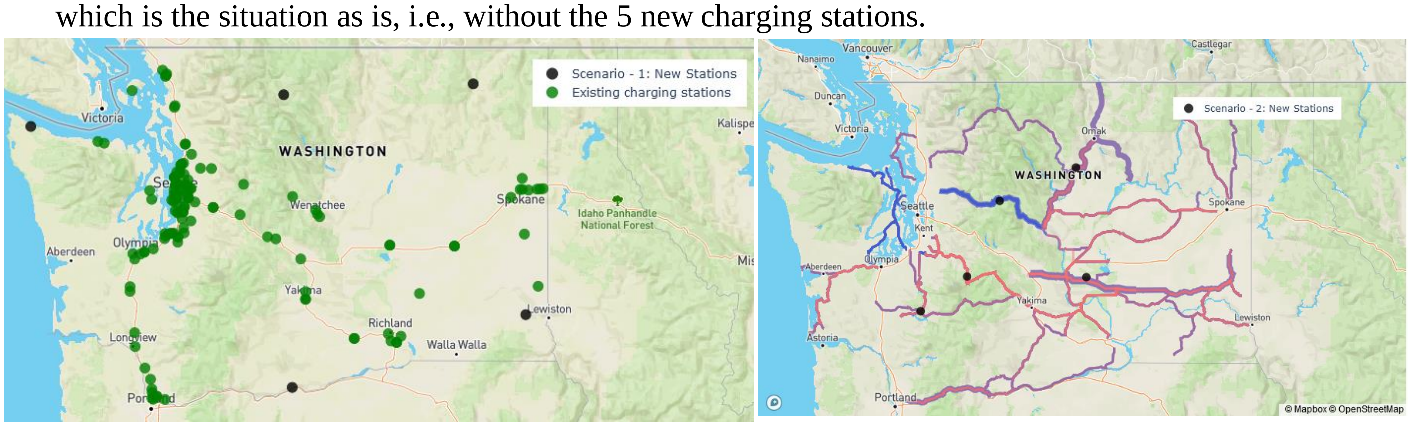


Figure 18: Locations of new charging stations for scenario – 1 (left) and scenario – 2 (right). The roads in the scenario - 2 are overlaid with unserved estimated traffic index. Thicker lines indicate higher unserved traffic.

2.6.2 *Comparison of results*

Comparison of the results between the basecase, scenario – 1, and 2 can be seen in Figure 19. The number of vehicles in the simulation and hence the electric vehicle miles travelled (eVMT) are higher for scenario 1 and 2 compared to basecase. This is because as more charging stations are added to the system, more trips are feasible as per the vehicle choice decision model (2.4.2). More trips also mean a greater count of charging sessions. The quantification of impact of charging station addition can help in comparing scenarios. For example, scenario – 2 has a more positive impact on vehicle counts, charging sessions, eVMT etc. and maybe more profitable in near-term than scenario – 1, as the charging stations in scenario – 2 are near areas of high-demand. However, this example demonstrates the dichotomy of motivations between public and private agencies. While the latter is merely concerned about profit-making, the former is more likely to also consider the long-term environmental impact and equity. While charging station deployments in far-off locations may appear less profitable with current vehicle population, charging station vicinity has an impact on people's vehicle ownership decision [35] and new purchases in the region will then have an impact on the EVSE utilization in the region. It should be also mentioned that the utilization in far-off locations maybe less accurate as currently, ChargEVal travel demand model does not consider inter-state travel.

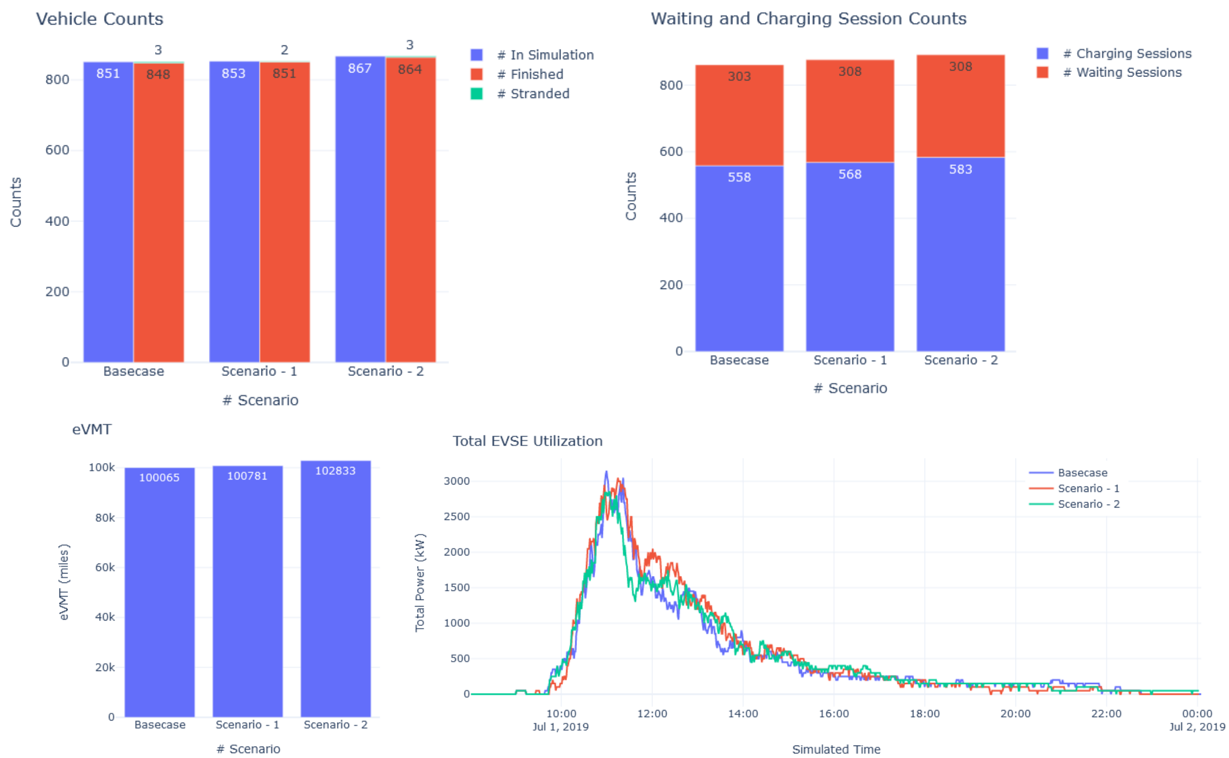


Figure 19: Comparison of EV counts (in simulation, finished and stranded) (top-left), charging session and waiting session counts (top-right), eVMT (bottom-left) and total EVSE utilization (bottom-right) for base-case, Scenario 1, and 2.

2.7 IMPACT

ChargEVal allows for agent-based simulation of EVs and EVSEs around the state of Washington and predicts the charging station utilization for existing as well as proposed stations. ChargEVal considers a data-based approach for travel demand prediction and incorporates behavioral models for vehicle choice and charging choice. The charging utilization prediction can be used to model the economics of the station as well as impact on associated system like the electric grid. The models are parameterized, and the parameters are customizable through the database, allowing for studies in variation of parameters with ease. Some common parameter variation studies include variations of the random number generator seed, critical distance, rental car cost, timestep etc. The software architecture of ChargEVal allows for several users to submit multiple simulation requests in parallel without having to worry about the underlying compute infrastructure or implementation making the research accessible to a wider audience. The open-source and well-documented nature of the software allows users around the world, in public or private agencies to deploy ChargEVal for their geography and vehicle system of choice. For example, while the current implementation focuses on passenger vehicles in the state of Washington, with minor tweaks in the database and local travel demand model estimations, ChargEVal can be used in a totally different geography and scale (city, county etc.) and vehicle systems like fleets, trucks, etc. Upgrades, outreach and commercial application of the framework are being actively pursued.

Chapter 3. CHARGEVAL - A MULTI-USER FRAMEWORK FOR SIMULATING AND ANALYZING CHARGING STATION DEPLOYMENT SCENARIOS USING AGENT-BASED MODELING – SENSITIVITY ANALYSIS AND EXAMPLE STUDIES

3.1 INTRODUCTION

While most electric vehicle (EV) charging happens at home or at the workplace, there is still a need for public charging stations for people taking long distance trips and for people who do not have access to home or workplace charging. Public charging infrastructure can also help with range anxiety, which is the fear of being stranded without charge. Evidence suggests that a network of charging stations available for public use can help in alleviating range anxiety and make more long-distance trips feasible.

To be useful in a long-distance trip, a public charging station should support fast charging. Fast charging from a station allows for shorter charging breaks for customers and provides the charging station a capability to serve more vehicles during a day. Fast charging stations, though preferred, are costlier in terms of the capital investment as well as operational cost. It is therefore vital to find locations for fast-charging stations such that they have high potential utilization.

This paper reports on the development of a simulation tool (ChargEVal) that combines empirically grounded models of travel demand and charging behavior in an agent-based simulation framework to estimate fast charger utilization. The simulated utilization depends on factors including EV fleet size, charging propensity etc. The simulated charger utilization can be fed to an economic model of the charging station, that considers the fixed and variable costs of installing and operating a charging station. With the use of the proposed tool, public agencies and private companies can evaluate the feasibility of a set of charging station candidate sites and compare multiple siting scenarios.

3.2 LITERATURE REVIEW

3.2.1 *Approaches to Alternate Fuels Infrastructure Design*

Infrastructure design can be treated as a facility location problem [36] and many studies have explored this. Optimal facility location involves minimization of transportation costs in the form of distance [37] and travel time [38] [39], often in a supply chain management context. Facility location planning can also be impacted by other concerns like integration of sustainability issues [40] and roadway capacity expansion planning [41]. Another approach for optimal facility location is to maximize customer flow, which involves placing the facilities in the path of customer flow instead of at centers of population clusters [42]. Applied to location allocation of alternative fuel stations, flow capturing models also need to account for how vehicle range interacts with the length of shortest path between origin and destination, allowing for multiple stops along the way [43]. Further, the higher the deviation from the shortest path to refuel, the lower is the captured flow at the refueling station [44], hence impacting location planning.

Electric vehicle infrastructure siting has additional complexities compared to liquid or gaseous refueling station planning. Since EV charging usually takes much longer than typical vehicle refueling, activity options during recharging also play a role in charging preferences [45]. Due to the high capital cost of charging stations, cost minimization is always a consideration to achieve profits in charger operation. Further, any charging station is useful for the passing traffic flow only up to a specific coverage distance, and not the range of the vehicle [46], i.e., a driver of an EV with a 200 mile range will not want to travel 200 miles just trying to charge the vehicle. Another way to reduce the EV infrastructure cost is to install mixed capacity charging stations, i.e., slow as well as fast, which has been shown to be an economical solution to increase coverage and make more EV trips feasible [47]. In addition, due to the long time it takes to charge an EV, even at a fast-charging station, a station can serve limited number of users and therefore the capacity constraint should be considered during EV infrastructure planning [48]. Dong et al. [49] proposed an activity-based assessment method to evaluate the BEV charging feasibility at a station based on simulated travel and charging behavior. Further, the impact of increased EV infrastructure on electric vehicle miles travelled (eVMT) is also calculated.

3.2.2 *Modeling Electric Vehicle Use and Charging*

3.2.3 *Electric Vehicle Use*

Ideal siting for users means an available charging station whenever and wherever they need it, and ideal siting for EVSE operators means maximum utilization at minimal cost. These goals can be in opposition, as increasing a station's utilization inherently reduces the probability that it will be available when a driver arrives [50]. Therefore, to evaluate a candidate set of EVSE locations, one needs to understand the underlying motivations of all stakeholders. This is especially important when dealing with DC fast charging stations, which have very high capital and fixed costs [50]. Once the decision to embark on a long-distance trip is made, a driver's next decision is to choose whether to use an EV or an ICE. This depends on various factors, of which EVSE infrastructure along the route is just one; trip distance and EV range are also important [51]. During the trip, the next decision is when to charge the vehicle. This decision depends on the distance to the next charging station, remaining range, and other amenities at the charging station [51].

3.2.4 *Electric Vehicle Charging Choice*

One way to model the charging choice decision is to perform survival analysis on times between the charging events, which can be predicted using the charging-discharging time histories and vehicle use data, ultimately giving us the hazard ratios for various factors like trip distance, range anxiety, speed etc. [52]. Consumer preference and interaction with the EV infrastructure is an important subject with some comprehensive studies [53]. It is found that public and corridor charging stations are the least used infrastructure; with around 5% charging events, however these charging events can still be important for longer journeys and can be perceived as a safety net for other charging options [54] [49] [55] [56] [57]. DC fast chargers are being rolled out in many regions as public charging stations and the placement of these chargers depends on which vehicles use the infrastructure. According to data from PEV drivers in the USA [58] and Norway [59], short range BEVs are unlikely to undertake long distance travel, but longer range BEVs are. For short range BEVs, DCFC points are used mostly at intra-urban locations, while for longer range BEVs the charge points may be used mostly at inter-urban locations [60] [61] [62]. A UK study analyzed data from EVSE and from GPS tracked BEVs, finding that fast charging infrastructure can increase the VMT in BEVs. This was partly because the infrastructure helped overcome actual range issues allowing drivers to complete more journeys beyond the range of their vehicles. Drivers were also more willing to travel longer distances within the driving range of their vehicles as the charging infrastructure acted as a safety net, they could use in the event they might need to charge due to unforeseen circumstances [63] [64] [65] [66].

3.2.5 *Agent-based models for EVs*

There is a good deal of academic literature on optimally siting charging stations and other alternative fueling stations. However, a common problem is that they are focused on technical feasibility of travel, rather than being built on models of actual behavior. There are a few existing decision support tools for charging station siting, but they each have shortcomings. A natural extension of the increased understanding of human behavior related to EV and EVSE usage, is agent-based modeling (ABM), which allows for modeling the individual units, consumers, EVs, EVSEs as autonomous decision-making entities called agents and describe the system from the perspective of constituent units [67]. While ABMs are sometimes programmed from scratch, usually they are implemented in one of the commonly used ABM platforms like AnyLogic [68], Repast [69], GAMA [32], NetLogo [70], SUMO [71], JADEX [72], or MATSim [73]. Several studies have used ABMs for modeling EVs and related systems. For small regions like a metropolitan area, travel diaries are used as the underlying basis for simulating trips [74]. The flexibility of ABMs allows the study of emergent phenomena like effects of changing certain parameters of the EVI like charging power, charging type (conductive vs inductive) [75], EV owner residences and demographics [76] on associated systems like the electric utility [77] [78] [79] or greenhouse gas emissions [79] over small to long time scales [80]. It can also be used as a decision support tool, by comparing the output of different input scenarios in simulation and can therefore provide near optimal solutions satisfying multiple objectives simultaneously [81].

3.2.6 *Why did we choose our approach?*

Optimization tools work well if you are designing a system from the ground up, or have a single entity planning an expansion, and the objective is well defined. However, there is a need for a decision support tool in real-world situations where these assumptions do not hold. For example, Washington states takes proposals from bidders and weighs them against one another, rather than prescribing specific station locations. And the state has many criteria of interest, including coverage of larger areas of the state, supporting future EV adoption in new areas, reliability of access, along with charger utilization and eVMT.

3.2.7 *Other decision support tools*

There are several decision support tools currently available to inform EV infrastructure planning efforts. These vary in their analytical approaches, requirements for data, and outputs.

M.J. Bradley & Associates (MJB&A) released an EVI location tool [82] that uses proximity to existing charging stations, commercial activity, population, and traffic density, and outputs scores for all interstate exits and other key intersections. Based on these scores, they generate a prioritized list of exits suitable for charging station siting. While the tool does use a combined metric of charging stations, population, and activity density, it fails to account for trip feasibility, i.e., when vehicles start from a certain location, whether they can actually reach another location in the region. While the MJB&A tool accounts for traffic density, it does not account for car traffic density, which may be different from the total traffic density.

NREL developed a tool called EVI-Pro [83], which uses the long-distance travel data from the FHWA Traveler Analysis Framework and generates city level charger counts and projected loads on these charging stations using the projected PEV sales for the target year. EVI-Pro considers the vehicle attributes of the current EVs on the road, the infrastructure attributes, that is the type of charging stations and creates driving and charging simulations, which ultimately lead to the target EVSE density and EVSE utilization. While EVI-Pro is quite exhaustive in its approach, it needs lot of travel data to generate the driving/charging simulations. Further, it does not take in to account the driver's choice of vehicle for the trip. Finally, it only gives the city level counts, but does not tell us where in the city, or along which route the charging stations should be sited.

An agent-based solution for EVSE siting is being developed by LBNL, BEAM [84], that extends the Multi-Agent Transportation Simulation Framework (MATSim). It is an approach to modeling the resource markets in the transportation sector. While it is open-source and quite detailed in its treatment of the problem, the PEV-only version of the solution is not supported anymore. Further, it is overly complex for the just the EVSE siting problem, as it also includes mobility services simulation.

Another tool being developed by ORNL, called the Regional Electric Vehicle Infrastructure Strategic Evolution (REVISE) [85] uses a multistage mixed integer model for long-term strategic planning of charging infrastructure. A planning horizon is divided into multiple stages and the objective is to minimize the total system cost of charging infrastructure. REVISE outputs the impact of adding charging stations on trip coverage. However, it does not consider the difference in charging standards (CHAdeMO vs COMBO), vehicle choice for trip, charging choice during the trip etc.

3.2.8 *How is our approach different?*

The ChargEVal tool seeks to fill a different niche than existing EV infrastructure decision support tools. It is intended to provide more behavioral realism than MJ Bradley or REVISE, more spatial sensitivity than EVI-Pro, with less computational burden and data requirements than BEAM. The proposed framework is modular, so that as various sub-models can evolve over time. As we have better understanding of the dynamics of a system like EV adoption or energy consumed during a trip, the underlying model for the system can be switched or updated to test for the new hypothesis. The well-documented and open-source nature of the proposed decision support system allows others to use the system in the same or other geographical areas. Support, feedback, and scrutiny from other users is another avenue for system advancement.

3.3 CHARGEVAL

ChargEVal is a tool for simulating long-distance EV travel in the state of WA to aid in decision making related to charging station deployment [86].

3.3.1 *Goals of ChargEVal*

ChargEVal allows the user to specify new charging stations, estimate the EV trips happening on a given day and predict various KPIs like eVMT, charging and waiting session count, individual EVSE utilization etc.

3.3.2 *Component models*

The various components of the ChargEval are described below.

3.3.2.1 Long Distance Travel Demand Model

The necessity of charging on a route is directly proportional to the number of EV trips passing through the route. The trip counts between origin-destination (OD) pairs were estimated using INRIX data, as reported by Jabbari et.al. [28]. The OD matrix is composed of around 300k+ rows for indicating trip counts from all origin ZIP codes to all destination ZIP codes within Washington. The trip counts are dependent on several factors like the origin and destination population, respective counties, and driving time between origin and destination. The total trip count between an OD pair is composed of two quantities, the traffic belonging to O, departing from O to D, and the traffic belonging to D, returning to D from O. It is imperative to separate the total traffic volume between an OD pair into returning and departing sub-volumes since EV ownership rates vary significantly across ZIP codes within Washington.

3.3.2.2 Vehicle Choice Decision Model¶

The vehicle choice decision model (VCDM) provides the probability of a traveler using an EV for a long-distance trip, depending on various trip and vehicle characteristics. Ge [87] estimates several discrete choice models generated through stated preference surveys. For the purpose of EVI-ABM a latent choice logit model is used that makes a vehicle selection between an internal combustion engine vehicle (ICEV), a rental vehicle or a battery electric vehicle (BEV), and is specified as follows:

$$u_{icev_i} = \theta_1 * gas\ cost_{i,icev} + \ \varepsilon_{icev_i} \tag{1}$$

$$u_{rent_i} = \theta_2 * C_{rental_i} + \theta_3 * gas\ cost_{i,rent} + \ \ \varepsilon_{rent_i} \tag{2}$$

$$u_{bev_i} = \theta_4 * \frac{L}{r_{full}} + \theta_5 * \frac{\mathrm{Max}_{\mathrm{Spacing}}}{r_{full}} + \theta_6 * l_{restrooms} + \theta_7 * Restaurants + $$

$$\theta_8 * Des_{charger_{type(L2)}} + \theta_9 * Des_{charger_{type(L3)}} + ASC\_BEV + \ \ \varepsilon_{rent_i} \tag{3}$$

In the above equations, u represents the utility of the vehicle choice. θ_i are the model coefficients for the covariates: cost of gas for ICEV during the trip ($gas\ cost_{i,icev}$), cost of a rental car (C_{rental_i}), gas cost for a rental car ($gas\ cost_{i,rent}$), ratio of trip length and full range of BEV

($\frac{L}{r_{full}}$), ratio of maximum spacing between chargers along the trip route and full range of a BEV ($\frac{\text{Max}_{\text{Spacing}}}{r_{full}}$), largest spacing between restrooms along the route ($l_{restrooms}$), whether there is a restroom near the charging station ($Restaurants$), whether the destination has a level-2 charger ($Des_{charger_{type(L2)}}$), whether the destination has a fast charger ($\theta_9 * Des_{charger_{type(L3)}}$). ASC_BEV is the alternative specific constant for BEV and ε are the error terms. The coefficients for the variables used in this study are presented in Table 3 .

Table 3 Model Coefficients for the Vehicle Choice Decision Model

Covariates	**Est.**
ICEV gas cost (\$) $\boldsymbol{\theta_1}$	-0.040
RENT cost (\$) $\boldsymbol{\theta_2}$	0.059
RENT gas cost (\$) $\boldsymbol{\theta_3}$	-0.075
relative distance ($\frac{L}{r_{full}}$) $\boldsymbol{\theta_4}$	-1.659
relative max spacing ($\frac{\text{Max}_{\text{Spacing}}}{r_{full}}$) $\boldsymbol{\theta_5}$	-9.342
furthest restroom break (miles) $\boldsymbol{l_{restrooms}}$ $\boldsymbol{\theta_6}$	0.002
Restaurants $\boldsymbol{\theta_7}$	0.197
Des charger (Level 2) $\boldsymbol{\theta_8}$	-0.748
Des charger (Level 3) $\boldsymbol{\theta_9}$	1.428
ASC_BEV	11.184

3.3.2.3 Charging Choice Decision Model

While the vehicle is en route its destination, it might need to charge along the way. The choice of charging at a charging station can modeled by a binary choice model. Among the various models developed by Ge [29], we use the static choice decision model. The utility function is as follows:

$$u_{charging_{it}} = \theta_0 + \theta_1 * SOC_{it} + \theta_2 * DEV_{it} + \theta_3 * Hours + \theta_4 * C_{charging_{it}} + \theta_5 * T_{charging_{it}} + \theta_6 * T_{access_{it}} + \theta_7 * Amenity_{restroom_{it}} + \theta_8 * Amenity_{more_{it}} + \varepsilon_{charging_{it}} \quad (4)$$

In Equation 4, u represents the utility of charging, θ_i are the model coefficients, SOC represents the state of charge of the BEV, DEV is a Boolean denoting whether vehicle has enough range to reach the next charger if chooses to not charge at this charger, $Hours$ represents the hours the driver has been driving the vehicle, $C_{charging}$ represents the cost of charging the vehicle, $T_{charging}$ refers to time taken to charge the vehicle, T_{access} represents the time taken to access the charging station from the current route, $Amenity_{restroom}$ represents whether we have restroom as an amenity at the location of charging station, $Amenity_{more}$ represents whether we have more amenities (specifically, restaurants and Wi-Fi) at the charging station location, and $\varepsilon_{charging}$ represents the unobserved component of utility, assumed to be independently and identically Gumble distributed. The coefficients for the charging choice decision model used are as presented in Table 4.

Table 4: Model Coefficients for the Charging Choice Decision Model

Variables	**SDCM4**
(Intercept) $\boldsymbol{\theta_0}$	2.034
SOC (%) $\boldsymbol{\theta_1}$	-4.584
Deviation $\boldsymbol{\theta}_2$	2.440

(DEV)	
Time in car (h) $\boldsymbol{\theta_3}$ $(Hours)$	-0.069
Charging cost ($) $\boldsymbol{\theta_4}$ $(C_{charging})$	-0.010
Charging time (h) $\boldsymbol{\theta_5}$ $(T_{charging})$	-0.242
Access time (min) $\boldsymbol{\theta_6}$ $(T_{charging})$	-0.025
Amenity: restroom only $\boldsymbol{\theta_7}$ $(Amenity_{restroom})$	0.049
Amenity: restroom, dining & WIFI $\boldsymbol{\theta_8}$ $(Amenity_{more})$	0.213

3.3.2.4 EV Infrastructure Agent-based Model (EVIABM)

EVIABM, is an agent-based model for modeling the utilization of EVSE in the state of Washington. As such, it has the following attributes:

- Agents:
  - Electric vehicles in the state of WA: We consider all the electric vehicles registered in the state of WA as our EV agents. While some EVs maybe travelling outside the state and some out of state vehicles maybe traveling within WA, for the present study, we ignore these vehicles. Data on EV registrations come from the Washington State Department of Licensing [88].
  - Washington road network: The EVs move on roads and travel is restricted to roads. Currently, we ignore the elevation of the roads, but in future, the roadway elevation can be

included, and the energy model can account for the changes in elevation. Data come from the Washington State Department of Transportation [89].

    - Electric Vehicle Supply Equipment / Charging Stations: The charging stations are the agents where the EVs charge when they are charge depleted. The instantaneous power drawn, and total energy consumed are the EVSE utilization outputs from the simulation that we are interested in. The source of data is the Alternative Fuels Data Center [90]. The price of charging was found manually, and assumptions are made for price for parking.

- Environment: Currently, a two-dimensional simulation is bounded by the state of WA.
- Time: A single simulation runs for 24 hours in 1-minute time-steps. This means that we simulate EV travel around the state for a period of one day at a time and update the states of our agents each minute.

3.3.2.4.1 EVIABM System Overview

The EVIABM system overview is shown in Figure 20. We see that all agents, EVs, charging stations, and roads are children of the global agent "World". All agents have attributes and possibly actions and states, which together define the agent's characteristics. Some of these are built-in like location and speed, while some are user-defined like vehicle ID, capacity etc. Figure 20 shows the object-oriented nature of a GAMA model, and intuitively transfers to the real world. Depending on the problem at hand, we can define agents in as much detail as we choose.

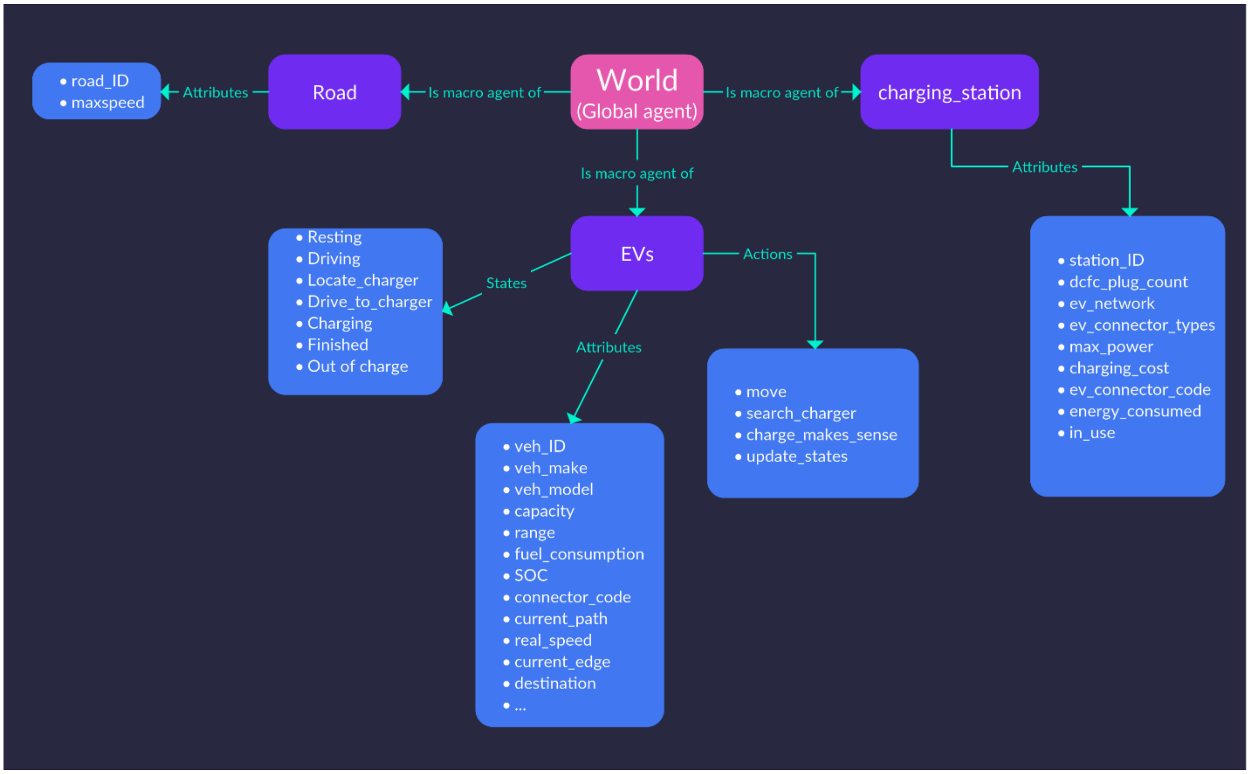


Figure 20: EVIABM System Diagram

3.3.2.4.2 Finite State Machine Control

Finite state machine (FSM) is a commonly used control paradigm and divides the system into several states and transitions. Agents begin the simulation in a certain state and transition into any (one of the) other states when a certain condition is fulfilled. It is important to note that, at any time-step agents can be in only one state.

FSM control is suitable to model the EV operation as we have deterministic and finite states the vehicle can be in (resting, driving, charging). The benefit of FSM control for our use case is that it helps in managing the complexity of operation and allows for easy testing. While modeling the infrastructure and driver behavior, FSM control allows us to observe in which state our agents are at any time step of the simulation and hence, we can get greater observability aiding in debugging. FSM control is also flexible, i.e., if we decide to add more complexity to the operation by adding more states (e.g., waiting in queue); we can do that by changing the transition conditions. The state diagram for our system is shown in Figure 21.

To parse the state diagram, first observe the start and finished states. Other states in the system are “Resting”, “Driving”, “Locate Charger”, “Drive to Charger”, “Queue for Charging” and

"Charging", dark rectangular blocks. These are connected to diamond shaped decision boxes, that are the transition conditions, and the statements above the connecting lines are actions, or behaviors that are undertaken by agents at every time step, like "Go to Target", "Update States" etc. While some decision questions like "Is T > T_rest?", or "Is current location the target?" are easily answered in the ABM framework; some other EVIABM specific decision questions like "Does charging make sense?" are not so directly answerable and will depend on the trip and car related conditions as well as individual preferences. The linkages between these conditions and preferences are captured in behavioral models.

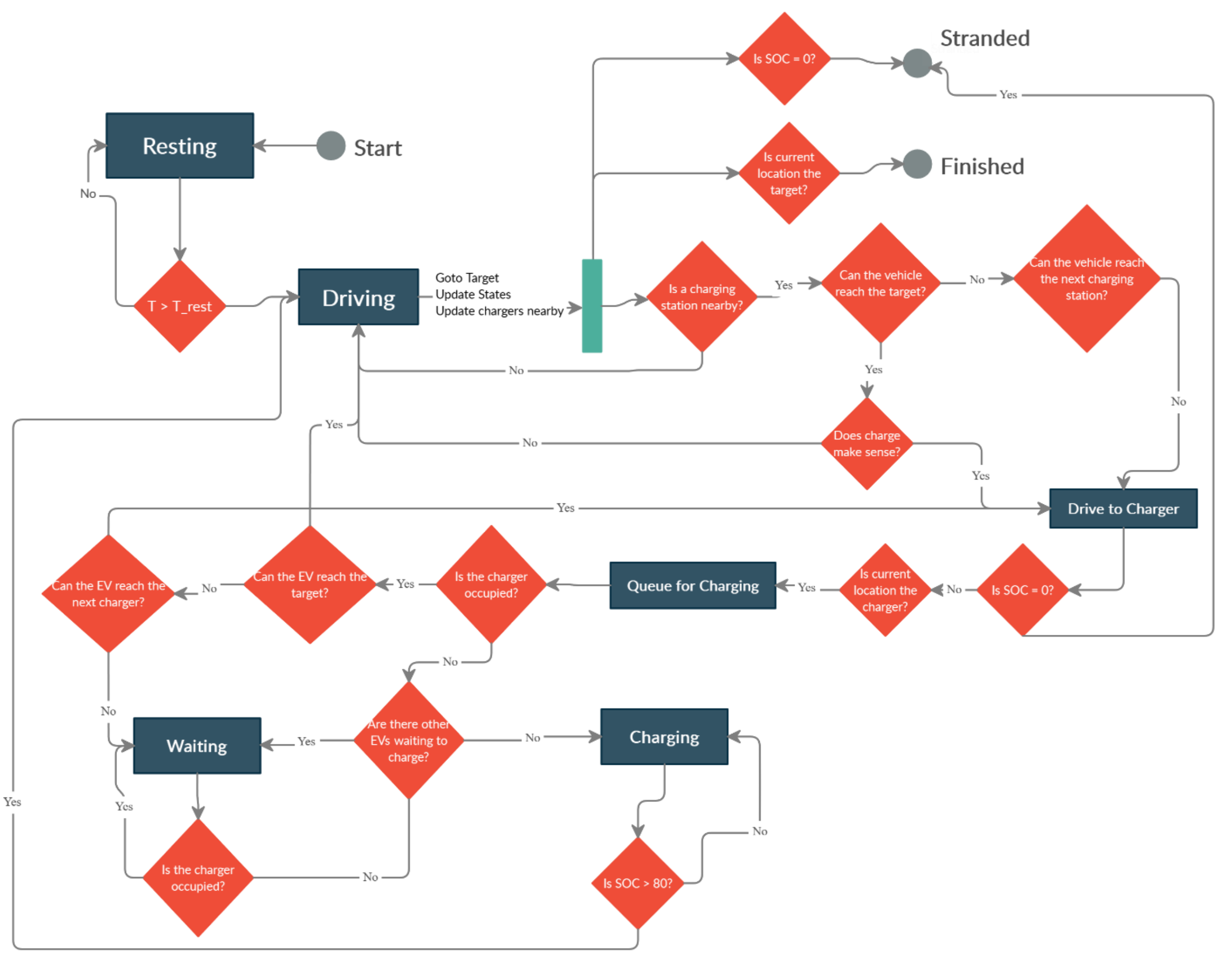


Figure 21: Finite state machine diagram for EVIABM

3.3.3 *Assumptions*

Several assumptions have been made to keep the model estimations tractable and computationally feasible. Key assumptions are described below.

- **Energy Consumption**: The energy consumption during travel is assumed to be a constant currently. It is chosen as the capacity divided by the range. In reality, the energy consumption is dependent on the vehicle speed, road gradient, ambient temperature etc.
- **Charging Rate**: The agent-based model (eviabm) only considers a constant charging rate of 50kW for each EV - since the *fueleconomy.gov* website used for collecting vehicle information does not contain information about maximum charge power for an EV. It also considers all chargers to be charging at 50 kW too, since AFDC does not maintain charging station maximum charging power information. This was not much of an issue when most vehicles allowed only 50 kW and most CHAdeMO and COMBO chargers allowed 50 kW too. With Electrify America charging stations, however, and advent of ultra-fast charging - the model will have to be updated to consider vehicle / charger specific charging rates. In reality, EVs rarely fast charge using the constant power profile. Charging profiles are proprietary and dynamic.
- **Charging Choice**: While the charging choice at a charging station is being governed by the Charging Choice Decision Model, a few additional constraints are imposed on the charging choice:
  - Vehicle will not charge if the SOC is above the value `MIN_SOC_CHARGING` (currently set at 60%) and will always charge if the SOC is at or below the `MAX_SOC_CHARGING` (currently set at 20%).
  - Vehicle will only consider charging when it is in vicinity of a charging station. This means that a vehicle will consider charging at the station nearest to it when it is within 1 timestep from the station.
  - The vehicle will only reconsider charging after `reconsider_charging_time` (currently 10 minutes) has elapsed in simulation. This means that if a vehicle has considered to charge (using the CCDM), then it will do so again only after 10 minutes, even if it is in vicinity of other charging stations.

    - A vehicle must charge at a charging station if it cannot make it to the next charging station or its destination with the amount of charge currently in the vehicle.
- **Queueing and Waiting**: A vehicle will queue for charging at the charging station when it reaches there. The following assumptions are made around queueing and waiting at the charging stations:
    - If the charging station is completely occupied on arrival, and if the vehicle has enough charge to go to the next station, then it will proceed to do so.
    - If the charging station is full and distance to the next station is greater than `BLOCK_SIZE` (currently 200 meters), or the distance of the next station is greater than the range left, then the vehicle will wait at the current charging station.
    - If vehicle charging station is occupied and the next charging station is not too far (less than 200 meters), then the vehicle will relocate to the next charging station.
    - Waiting EVs will be served on a first come, first-serve basis.
- **Trip Start Time:** The trip start time for simulated trips is assumed to lie between 6 am and the time such that the trip ends by 10 pm. Trip start times are then randomly generated as per a uniform distribution to lie within the time interval [6 am, 10pm – trip driving time].
- **State of Charge (SOC):**
    - Trip start SOC: Trip start SOC is the SOC of a vehicle before it starts a trip. Trip start SOC is assumed to be uniformly distributed between 80% and 100%, since the vehicle may not be fully charged at the time of travel. Both these limits are settable parameters.
    - Charge end SOC: Charge end SOC is the SOC of a vehicle at the when it stops charging. Charge end SOC is assumed as 80% since most vehicles are known to switch to a slower charging rate above this value. This value is also a settable model parameter.

3.3.4 *Simulation Process*

The simulation process in ChargEVal consists of two steps, trip generation followed by agent simulation. Since, EV agents in EVIABM need vehicle specific data like range, charging connector type etc. and trip level data like origin, destination, trip start time, etc., the role of trip generation is to first determine the number of EV trips between any origin-destination pair and then to assign a specific vehicle to the trip from the vehicle inventory in the zip code. The agent-based simulation then simulates the travel for each vehicle that results from the trip generation process. It is during this simulation that the interplay of agents, i.e., charging, congestion and waiting at charging stations, give us an insight into a *possible state of the system* grounded in models based on data and stated human behavior. To facilitate submitting new simulation requests, a GUI has been created where new charging station deployments can be configured including locations, charging price, charging power etc. and submitted for analysis. The submission then serially triggers the trip generation and agent-based simulation. Upon successful completion of the simulation, an email is sent to the submitter and the results from the simulation can be viewed in another GUI - the Results Viewer. More details about the GUI features can be found in the documentation [86]

3.4 SIMULATION OF DAY-TO-DAY VARIATION

Keeping the seed steady allows us to make sure our model is reproducible and ensure the various model components are wired appropriately. Varying the seed can help us quantify the inherent stochasticity and when the results of model are to be fed to other systems for longer period say a week or a month, each day in the period should be generated using a different seed. Figure 22 shows the effect of variation of seed on the summary statistics like the vehicles in simulation (finished and stranded), waiting and charging session counts, eVMT and total EVSE utilization.

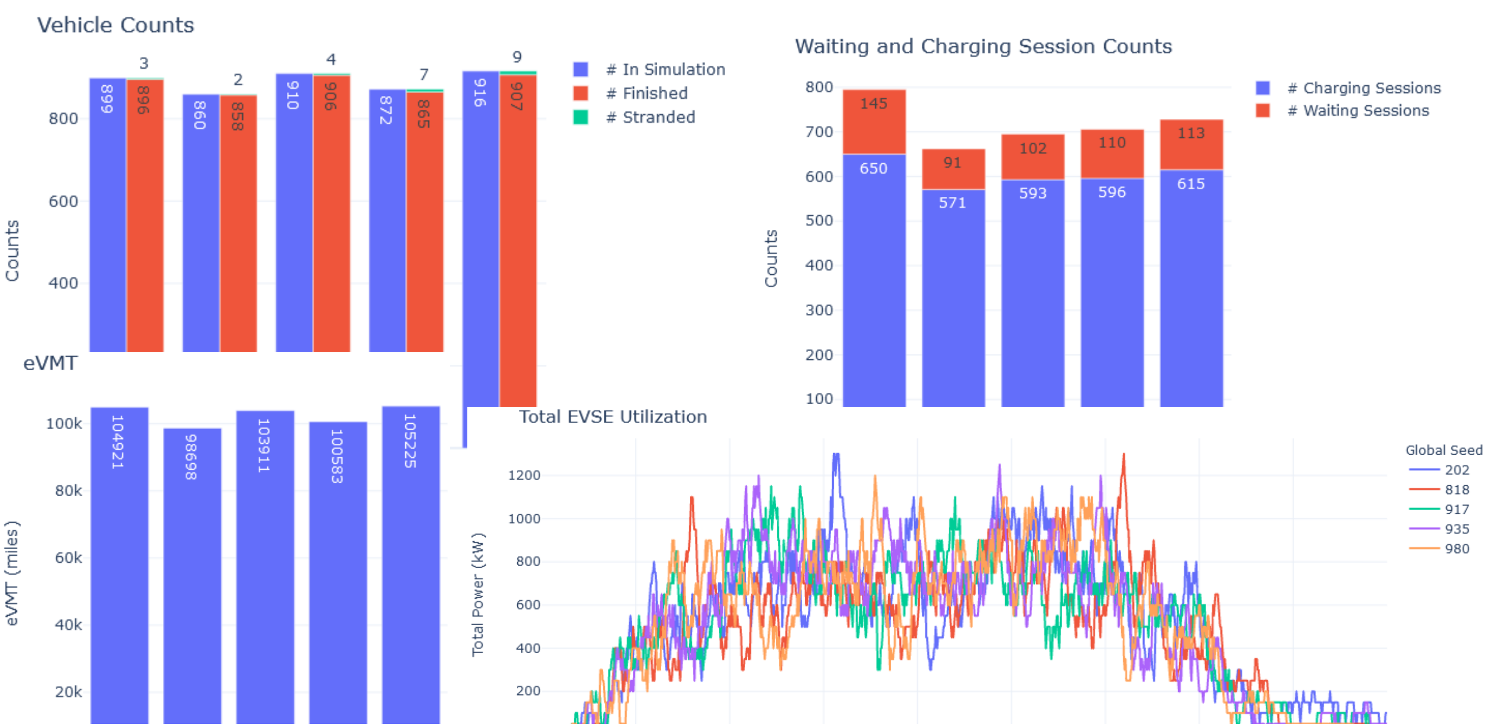


Figure 22: Effect of variation of seed on vehicle counts (in simulation, finished and stranded), waiting and charging session counts, electric vehicle miles travelled (eVMT) and total EVSE utilization.

3.5 Sensitivity Analysis

3.5.1 *Effect of varying the critical distance*

Only trips with trip length greater than the critical distance are considered as long-distance trips for simulation in ChargEVal. Reducing the critical distance, would increase the number of simulated trips and vice-versa. A higher EV count during simulation can impact EVSE utilization, waiting counts etc. Figure 23 shows the effect of variation of critical distance on the key summary stats, namely, vehicle counts (in simulation, finished and stranded), waiting and charging session counts, eVMT and total EVSE utilization. As expected, the effect of increased count of vehicles

Figure 23: Effect of variation of critical distance on vehicle counts (in simulation, finished and stranded), waiting and charging session counts, electric vehicle miles travelled (eVMT) and total EVSE utilization.

on fast charging session counts is minimal, as short trips do not need charging.

3.5.2 *Effect of variation of count of new EVSEs*

New charging stations can be placed using the EV Infrastructure Designer (EVIDES) and configured as needed or they can be placed programmatically. New charging stations affect the variable tracking the maximum spacing between charging stations along a vehicle trajectory. Therefore, adding new stations should generate different EV trips. Further, new chargers also affect the charging choice, hence, we are likely to observe changes in EVIABM results as well. Figure 24 shows the effect of variation of number of new EVSEs on the key summary stats.

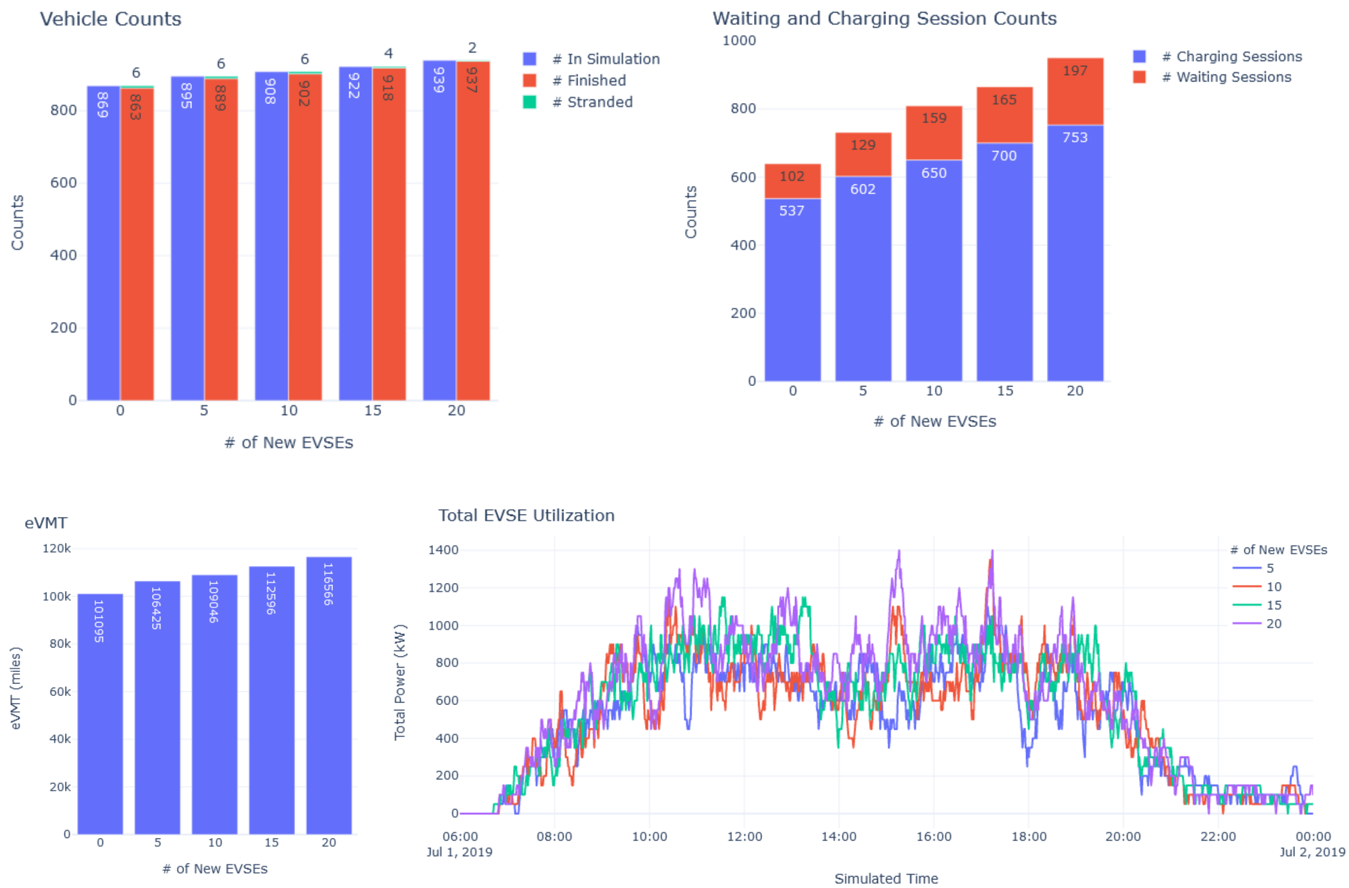


Figure 24: Effect of variation of number of new EVSEs on vehicle counts (in simulation, finished and stranded), waiting and charging session counts, electric vehicle miles travelled (eVMT) and total EVSE utilization.

3.6 Computation Time

ChargEVal's design ensures that one analysis request does not impact another request. So, several simulation requests can be executed in parallel. The simulation time, however, is impacted by the number of EVs in simulation, and to a lesser extent by the number of EVSEs. Figure 25 shows the effect of varying the seed and critical distance on the time taken for tripgen and eviabm. The times are almost similar when only the seed is varied since the number of EVs in simulation do not change significantly. However, when the critical distance is the changed, the number of EVs change inversely with respect to the critical distance, and hence the computational time is also inversely related to the critical distance.

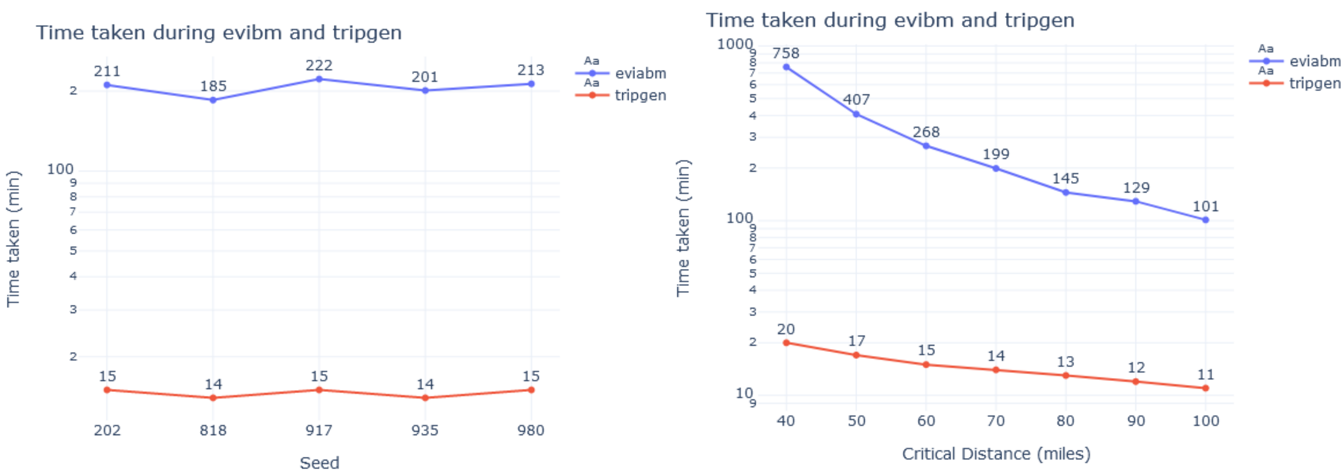


Figure 25: Effect of varying seed and critical distance on tripgen and eviabm computation time

3.7 Case Studies

3.7.1 *New stations to reduce congestion at charging stations or new stations in charging deserts*

ChargEVal is a framework for evaluation of impact of charging station deployments. Depending on the whether the user has an environmental concern or a profit concern, they might choose different criteria for placing new charging stations in the network. As an example, let us consider a constraint that a total of 10 new charging stations are to be deployed. To compare the charging station deployment strategies, the basecase is defined as the system with the current charging station deployment and travel as per the Long Distance Travel Demand Model. Given a fixed number of new charging stations, the following two strategies are tested in this example study:

3.7.1.1 Scenario – 1: New stations to reduce congestion at charging stations

Congestion is likely at charging stations with high demand for charging. For this scenario, we choose top 10 charging stations by the count of charging sessions in the basecase, and new stations were placed intersecting the roadway to the next nearest charging station (Figure 26).

3.7.1.2 Scenario – 2: New stations in charging deserts

Trips are *considered* infeasible if maximum distance between charging stations along a route is greater than 70 miles. All the infeasible sections that have trips passing through them have shaded lines on them (Figure 26). So, the stations in this scenario are placed in locations where the trip infeasibility lines are thickest indicating a heavy traffic flow of traffic between infeasible origin-destination pairs, as can be seen in (Figure 26).

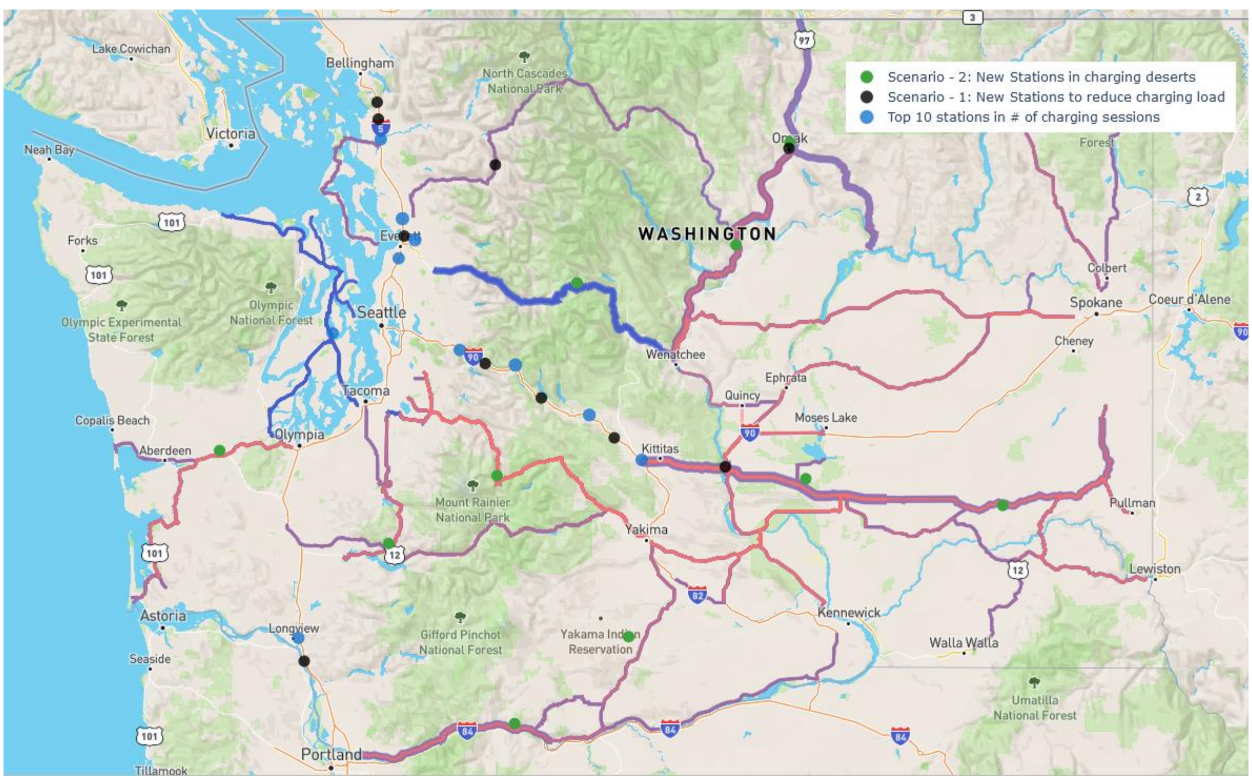


Figure 26: Location of charging stations for Scenario-1 and Scenario-2

3.7.1.3 Comparison of Results

The summary statistics from Scenario - 1 and Scenario - 2 are compared against the basecase and presented in Figure 27. As expected, addition of new chargers makes more trips feasible as per the Vehicle Choice Decision Model and we see an increase in number of vehicles in simulation and correspondingly the charging session counts, and eVMT compared to the basecase. While the increase in vehicle count is similar in both cases, new stations in Scenario - 1 take up bulk of added charging sessions compared to new stations in Scenario - 2. This indicates that the charging station deployment strategy depends on the motivation (profit or improving charging station access) and as a result may impact different statistics.

Figure 27: Comparison of EV counts (in simulation, finished and stranded), charging session and waiting session counts, eVMT and total EVSE utilization for base-case, Scenario 1, and Scenario - 2.

3.7.2 *Effect of charging station failure on system performance*

In an extreme event, a section of charging infrastructure may be down, and the vehicles will have to adapt to the new charging station deployment, since it may take a significant amount of time before they are restored. It is observed that a few charging stations are out of order from time to time. It is also possible that a charging station operator is not in business anymore and a set of charging stations are suddenly not available anymore. This study simulates the base-case when say, 30 charging stations, selected at random, are out of operation. The simulations are launched programmatically 5 times, with 30 different random charging stations (locations in Figure 28) each time. The results are presented in Figure 29. It is interesting to note that some disabled charging stations can have more impact on summary statistics than others. Since the charging stations are chosen at random, nearby charging stations take the slack and make up for it. More drastic results are expected when charging stations on a whole corridor or county are disabled. The study demonstrates the capability of the ChargEVal framework that even existing agent properties can be modified for running the simulations. Another use-case for this capability is comparing the impact of adding more plugs or more power at existing charging stations versus constructing new charging stations. The results from this simulation can help the stakeholders to plan for mitigation scenarios.

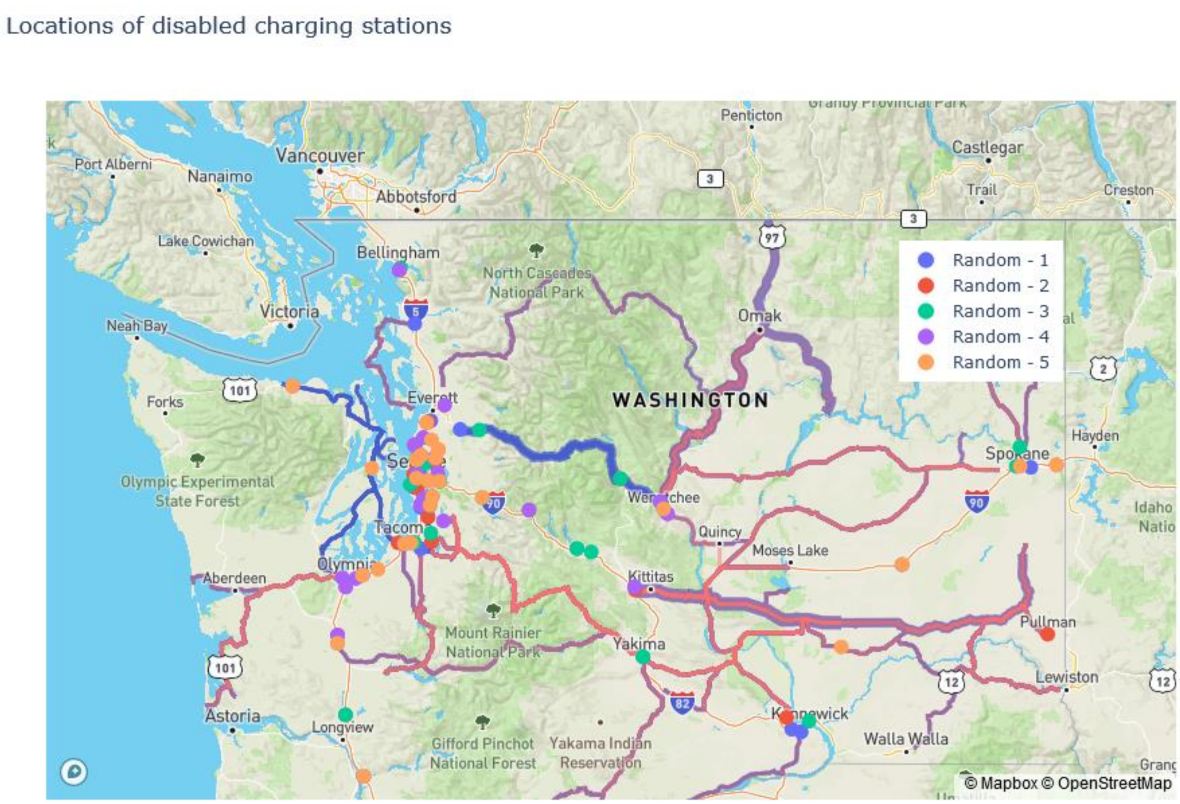


Figure 28: Locations of disabled charging stations for 5 random samples of 30 charging stations each

Figure 29: Comparison of EV counts (in simulation, finished and stranded), charging session and waiting session counts, eVMT and total EVSE utilization for base-case, and the 5 random samples with 30 disabled charging stations each.

3.8 Ongoing and Future Work

ChargEVal project is under active development and new features are being added as the requirements arise to solve practical problems. In the current round of development, the planned capabilities include the ability to provide a forecasted EV population and ferry links on the road network. Further, easing the deployment process, ability to switch underlying geography and component models, and additional monitoring capabilities are also being worked on. Another ongoing research effort is to validate the model against real EVSE utilization across the state.

As part of future work, it would be interesting to provide the capability to upload the charging station locations and forecasted EV population from EVIDES. Another interesting feature would be to use a cost-based routing scheme to find the shortest path that is season-aware, since there are several major roads in Washington state that are closed during winter months. This can also be helpful when studying road closures due to maintenance or congestion. Further, it could also be interesting to be able to provide updates to the charging station network while the simulation is running to the study the effect of real-time pricing on overall EVSE utilization. It is also planned to integrate the ChargEVal framework with the EV adoption model to simulate effect of charging infrastructure on EV adoption and vice-versa. Another planned integration is the long-term financial model for EVSE operation. Other goals for the project include reducing the simulation time and making the framework cloud agnostic to remove a hard dependency on one cloud provider.

3.9 Conclusion

ChargEVal is a decision support system for predicting EVSE utilization and can be a valuable tool to aid in comparing various charging station location scenarios. It can also help in short-term and long-term planning and analysis related to charging infrastructure.

Chapter 4. COMPARING THE COST-EFFECTIVENESS OF INSTALLING NEW CHARGER STATIONS V/S UPGRADING EXISTING CHARGER STATIONS USING CHARGEVAL

4.1 RESEARCH QUESTION

Which charging station deployment strategy is likely to be more profitable in near-term if the state wishes to provide a high level of service – new chargers or upgrading existing chargers?

The question above is different from discussion in section 3.7.1 as here we discuss the effect of upgrading charging stations and compare that to new charging station creation strategies. Since, we identify locations of upgrade first, we use these locations to guide the location decisions for creating new stations.

4.2 DEFINITIONS

The definitions relevant to the current discussion are as follows:

1. **Cost-effectiveness:** Cost-effectiveness can be defined as an increase in eVMT per dollar invested from the basecase.
2. **Upgrading charging stations:** Charging station upgrades can be of two types – increasing the charging power to a higher value or increasing the number of plugs. For the current study, only the upgrade strategy of increasing the number of plugs will be investigated, as currently there are not many EVs in market that can use a charging power higher than 50 kW. Further, it should be established that upgrading stations to increase plugs will require erection of a charging pedestal (which would also be done when adding a new station). The only difference in cost then between the case of creating a new station vs upgrading to add more plugs is due to the cost of the surrounding power electronics like inverter, transformer etc. which might have been over-sized during the original station creation. The exact information about the existing infrastructure capacity is however not currently available.

4.3 STUDY – 1: DETERMINE CANDIDATE LOCATIONS

To answer the question of whether it makes sense to install the new stations or upgrade existing stations, it is important to first determine what these candidate locations are. Following criteria are used to determine the candidate sites for creating new station or upgrade existing stations:

1. **High utilization:** Sites with high utilization have a high number of charging sessions predicted by ChargEVal. We will use the results from a basecase (charging stations as built) simulation to determine these sites. The Results Viewer reports the number of charging sessions happening at each station. After a basecase simulation, sites with top 5 counts of charging sessions are determined. 5 stations are chosen to be compared so that geographical and traffic characteristics of one station do not bias the results. Highly utilized charging stations are likely to have a high demand for charging.
2. **High congestion:** Sites with high congestion have a high number of waiting sessions predicted by ChargEVal. Like finding the sites for the case of high utilization, using the same basecase simulation results, the sites with top 5 count of waiting sessions are chosen. Highly congested charging stations are likely a result of either a high demand or a moderate demand with inadequate number of plugs. As such, the candidate sites from the case of high congestion may or may not be the same as the candidate sites from the case of high utilization.

The goal of study-1 is to determine which of the above two criteria result in a more cost-effective deployment strategy.

4.3.1 *Locations of charging stations to be upgraded*

Locations found in the previous step, i.e., for the case of high utilization and high congestion are the charging stations to be considered for upgradation.

4.3.2 *Locations of new charging stations*

To keep the new stations comparable to the upgraded stations, they should be placed in the general vicinity of the chosen candidate sites. However, it may not make *practical* sense to have them very near to the existing stations. So, the new stations have been chosen to be approximately bisecting the gap between the candidate site and the nearest charging station on both sides of the roadway on which the candidate charging station is located. So, for each case of charging station upgrade, we compare it against two cases of new charging station location. These are referred to as New-1 and New-2 in the current discussion. There is no pattern intended with these assignments, i.e., New-1 and New-2 are stations on either side of the upgraded stations. Depending on the orientation of the road, this can be to the left and right of the station, or above and below the station. The locations of stations for the two cases – high utilization and high congestion are shown in Figure 30 and Figure 31 respectively.

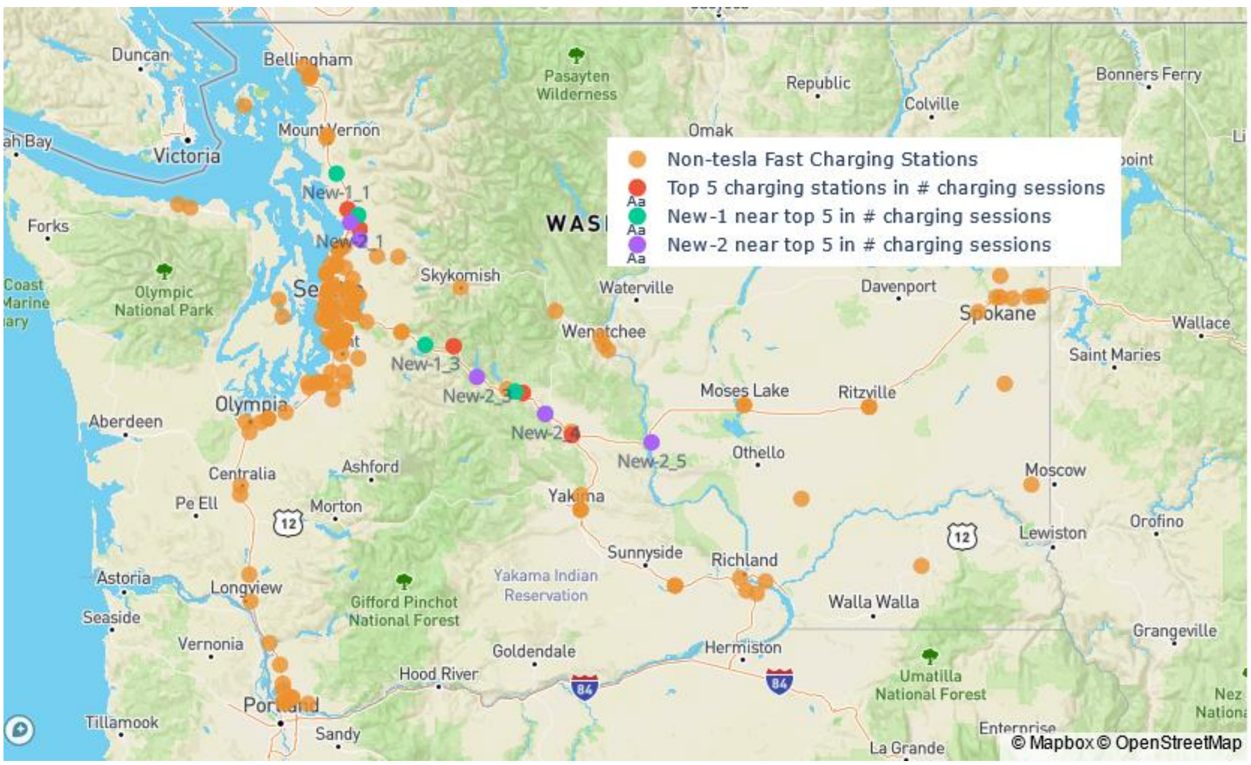


Figure 30: Locations of charging stations for the high utilization case.

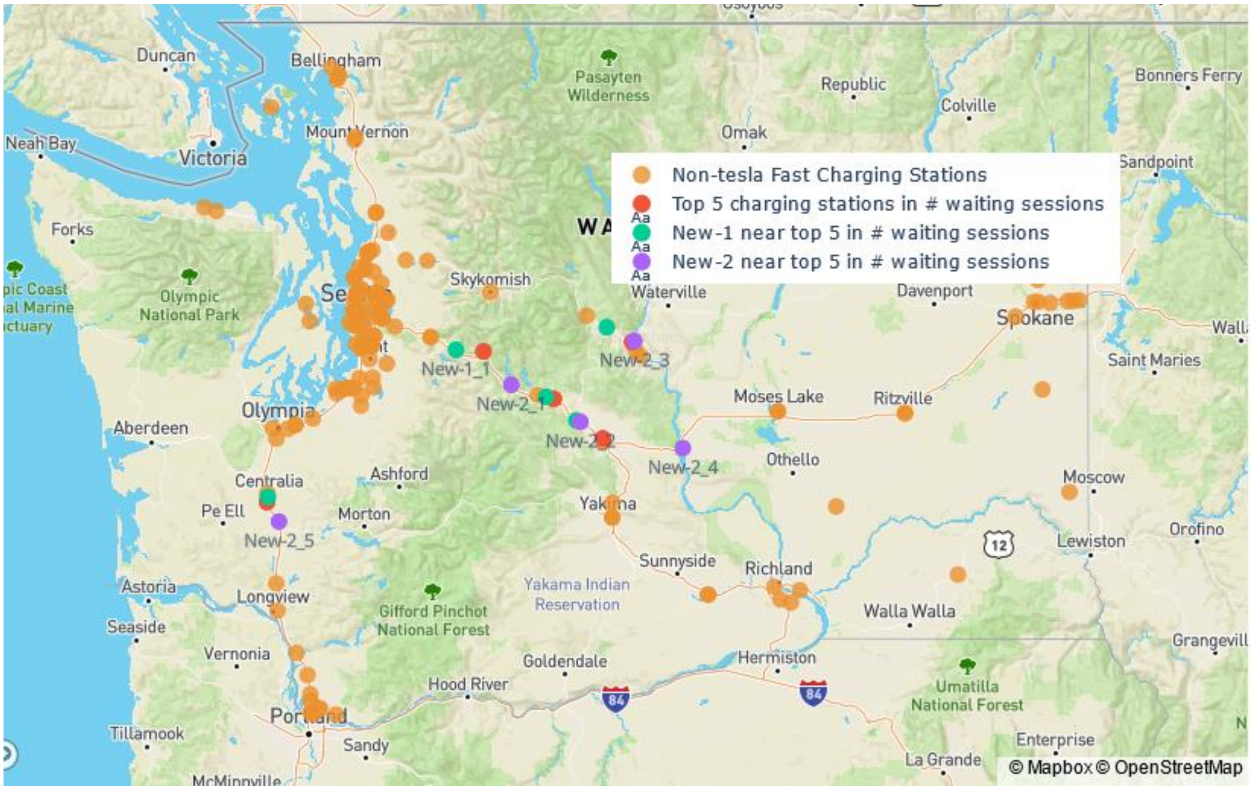


Figure 31: Locations of charging stations for the high congestion case.

4.3.3 *Number of plugs at new/upgrade stations*

To make the case of new station vs station upgrade to be similar, the number of plugs is kept same for the two cases, i.e., the number of plugs added during the station upgrade is same as the plugs added at the new stations (New-1 and New-2). Simulations and analyses are performed for plug count of 5 and plug count of 10 to test the effect of variation of plug count on summary statistics of interest.

4.3.4 *Variation of simulation seed*

5 random but same seeds are chosen for all simulations. Simulations are performed with different values of seed to simulate the effect of daily variation. For this study, therefore, we end up comparing the results of {3 (upgrade, new-1, new-2) * 2 (cases of varying plug count) * 5 (number of seeds) } = 30 cases against the basecase.

4.3.5 *Charging station cost*

Charging station at a site requires several electrical equipment to deliver the power at the right voltage. A typical site or charging station complex includes a connection from a substation which feeds to a step-down transformer, and an AC-DC inverter, which may then feed to DCFC units, each delivering a maximum of 50 kW of power during charging [91]. If the surrounding equipment are installed with a higher capacity, then adding further DCFC units may be cheaper than installing everything on a new site. However, in the absence of the information regarding the exact infrastructure at each site, it is not possible predict with certainty what the cost of upgrade would be. Therefore, for the purpose of this study a cost step function is used based on some of the published cost numbers for 50kW DCFC chargers [92]. The cost numbers in the table below do not include the cost of the charging station hardware unit itself. A cost of $28,401 is considered towards the charging station hardware [92].

Table 5: Cost of 50 kW charging stations

# Chargers per site	**1**	**2**	**3-5**	**6-50**
Total Cost	$45,506	$36,235	$26,964	$ 22,470*

* Cost number modified to ensure that the cost of creating 6 chargers is equal to the cost of creating 5 chargers.

These cost numbers agree with cost estimates for 50 kW DCFC stations from other sources [93], [94] as well as were corroborated by industry professionals associated with the charging station installation process.

4.3.6 *Results and Discussions*

4.3.6.1 EVs in simulation

EVs in simulation refers to the number of vehicles in simulation after the trip generation. The trip generation process is affected by the maximum spacing of charging stations along the vehicle route. So, we see that new stations are likely going to have more impact in reducing the maximum spacing for trips, making them feasible. Figure 32 and Figure 33 show the results for the vehicles in simulation for the case of high utilization and high congestion, respectively. Principally, upgrading stations should not affect the vehicles in simulation. However, for one or more of candidate stations, the upgrade meant adding plugs supporting both CHAdeMO and COMBO where previously it supported only one of those charging standards. New-2 seems to have more impact on vehicles in simulation compared to New-1 and this just coincidental with the fact that the chosen sites in New-2 happened to be in locations of greater traffic than New-1. The number of plugs does not affect the number of EVs in simulation.

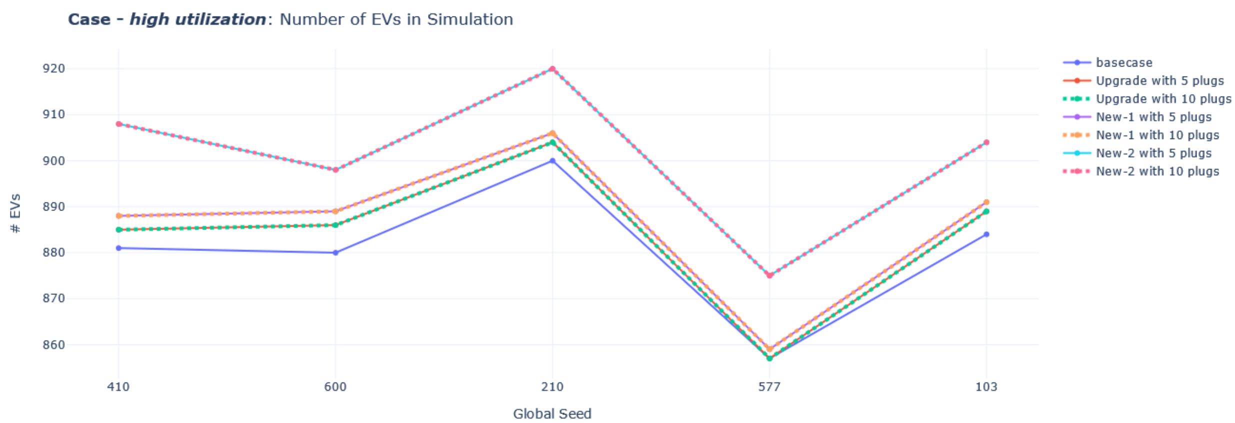


Figure 32: Variation in number of EVs in simulation for sites in high utilization case.

Figure 33: Variation in number of EVs in simulation for sites in high congestion case.

4.3.6.2 EVs finished

EVs finished refers to the number of EVs that reach their destination during the agent-based simulation. As we see from Figure 34 and Figure 35, for the case of high utilization and high congestion respectively, that the EVs finished follow the same trend as EVs in simulation. The simulations can have minor differences in counts, due to the variation in sequence of random number generation which can lead to a different number with the same probability.

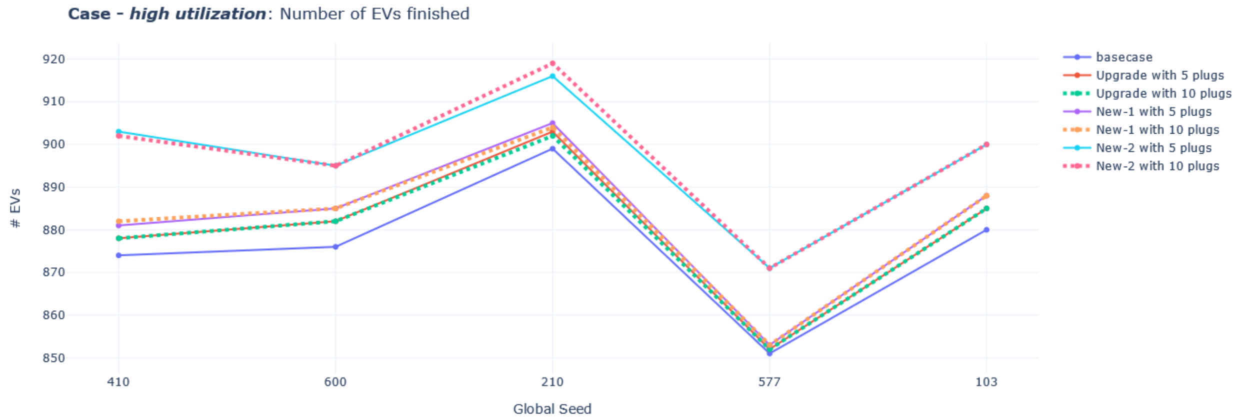


Figure 34: Variation of number of EVs finished when sites in high utilization case.

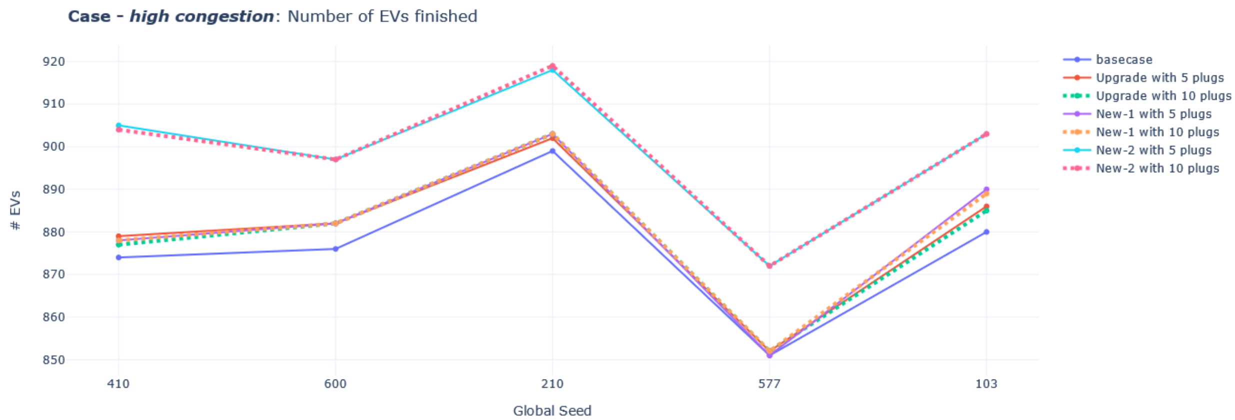


Figure 35: Variation of number of EVs finished when sites in high congestion case.

4.3.6.3 eVMT

eVMT refers to the electric vehicle miles travelled. The eVMT also follows the same trend as the EVs in simulation and EVs finished as can be seen in Figure 36 and Figure 37.

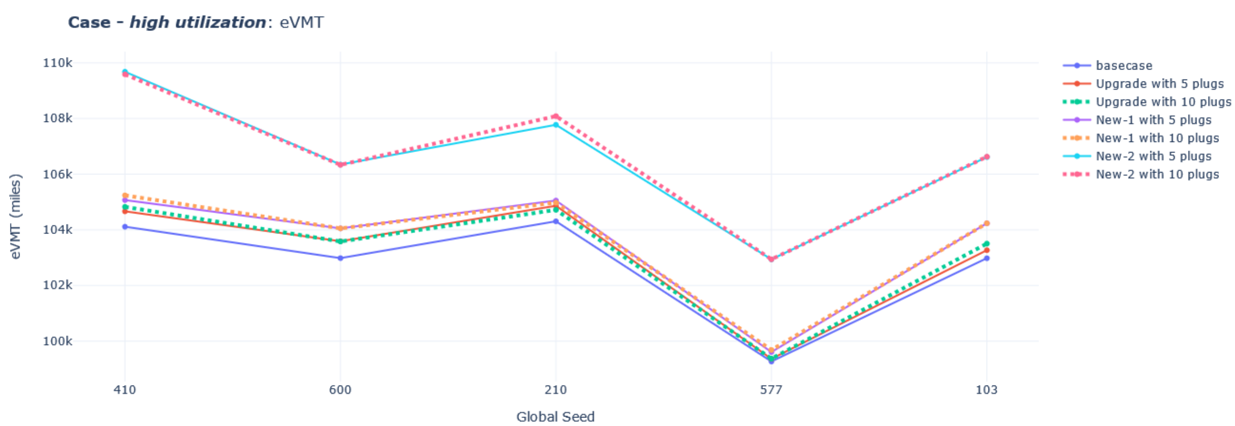


Figure 36: Variation in cumulative eVMT when sites in high utilization case.

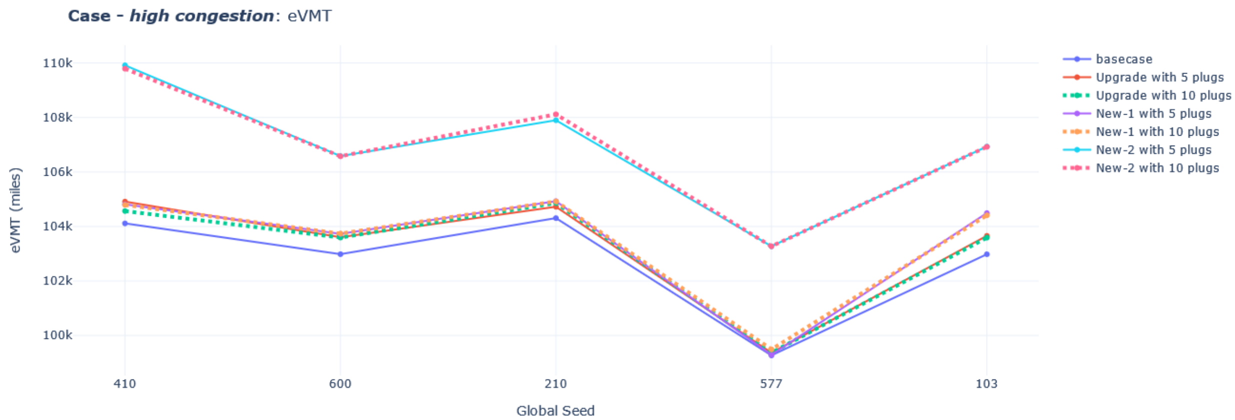


Figure 37: Variation in eVMT when sites in high congestion case.

4.3.6.4 Charging Sessions

The total number of charging sessions are for the case of high utilization and high congestion are shown in Figure 38 and Figure 39. Both cases show similar trends, but the noteworthy aspect here is that new stations (both New-1 and New-2) have a greater positive impact on charging session counts compared to the upgrade case. Further adding more plugs (10 instead of 5) has a small but positive impact on the charging session counts.

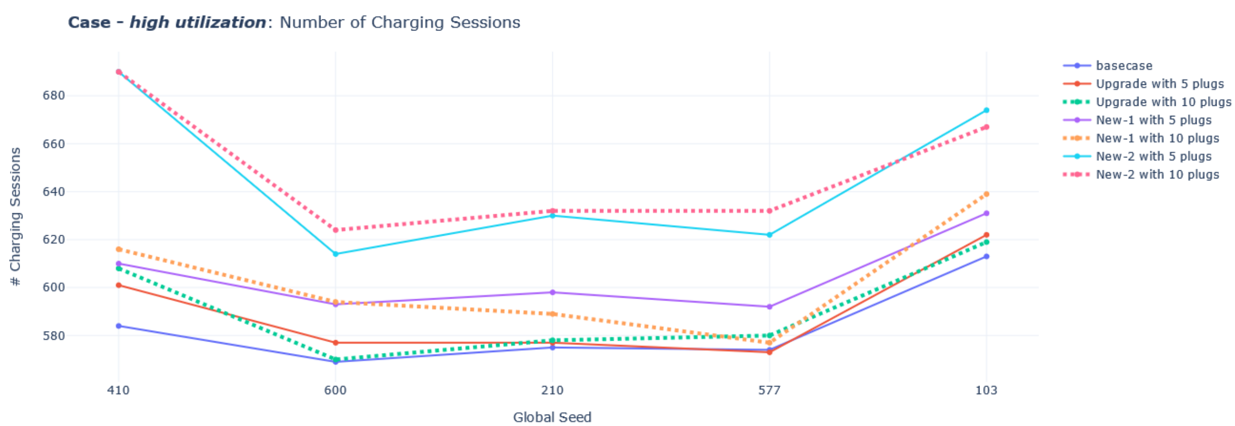


Figure 38: Variation in the count of charging sessions when sites in high utilization case.

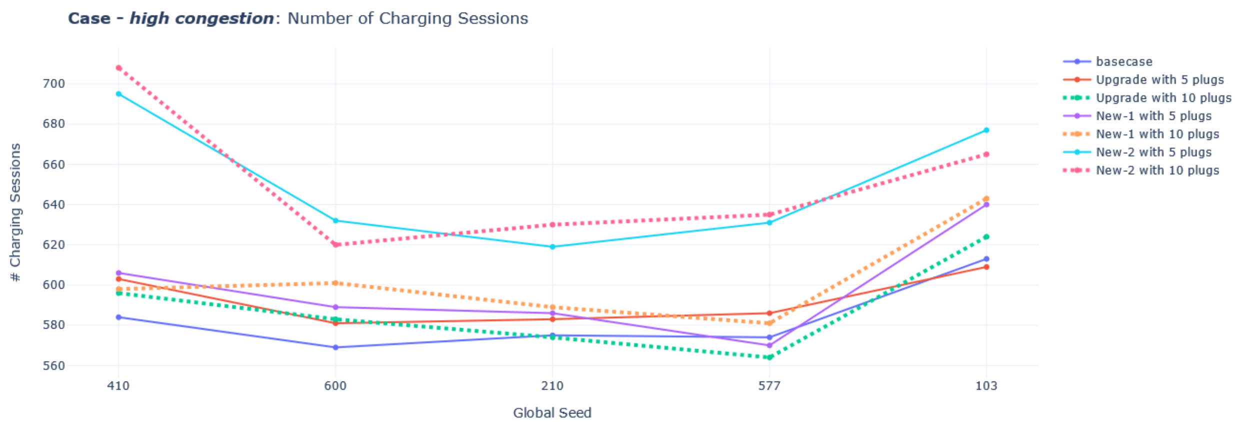


Figure 39: Variation in the count of charging sessions when sites in high congestion case.

4.3.6.5 Waiting Sessions

Figure 40 and Figure 41 show the variation in waiting session counts for the case of high utilization and high congestion, respectively. Here we see the impact of upgrade is more than the impact of adding new stations. New stations bring in more vehicles in simulation and more charging sessions, but they may not help in alleviating waiting sessions. It is not definitive that adding more plugs (10 instead of 5) has necessarily a proportional influence on the waiting session counts. This probably means that 5 additional plugs are enough for most purposes and the returns are diminishing in these *modeled outcomes*.

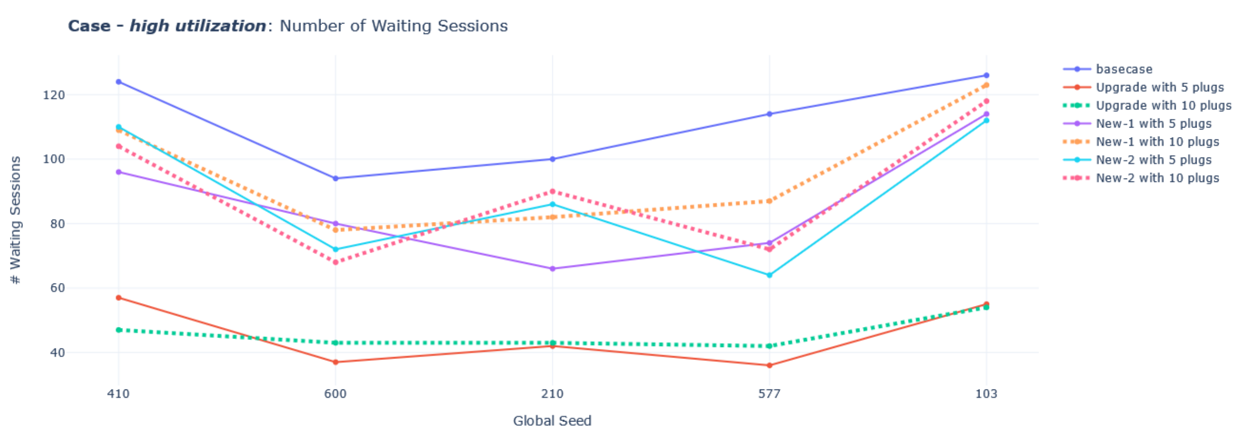


Figure 40: Variation in count of waiting sessions when sites in high utilization case.

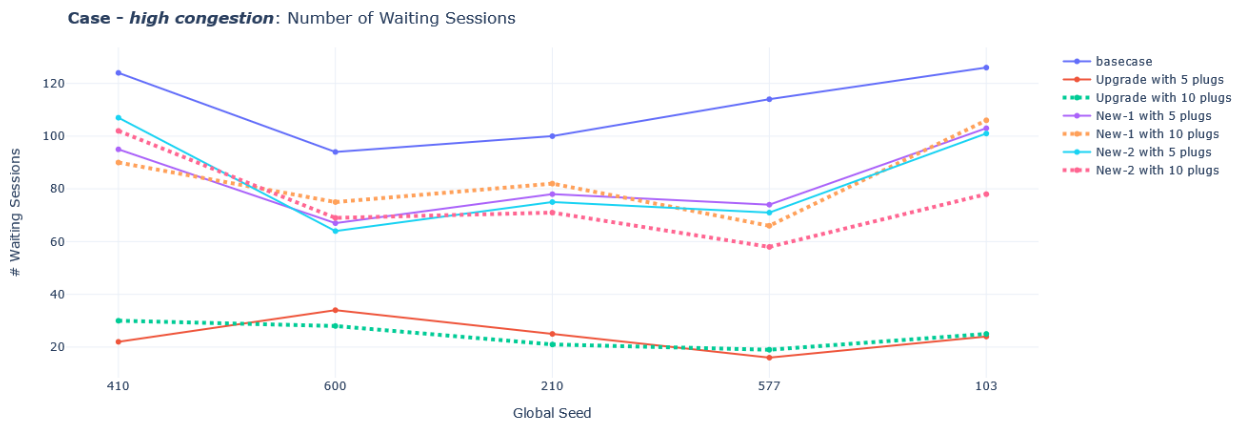


Figure 41: Variation in count of waiting sessions when sites in high congestion case.

4.3.6.6 Cost effectiveness

Table 6 and Table 7 summarize the cost-effectiveness calculations for the case of high utilization and high congestion, respectively. Mean eVMT is calculated by averaging the eVMT for 5 different seed values. Delta eVMT is then the difference between the mean eVMT and the basecase mean eVMT. Lifetime delta eVMT is calculated assuming a lifetime of 10 years for a charging station and that it eVMT impact happens every day during the period. The charging station cost is calculated as per the cost function in section 4.3.5. Figure 42 shows the line plot of the variation of cost effectiveness for the case of high utilization and high congestion.

Table 6: Cost effectiveness calculations for the case of high utilization.

#	Mean eVMT	Delta eVMT	Type	DCFC plug count	Total cost (USD)	Cost Effectiveness (Delta lifetime eVMT / $)
1	102731	0	basecase	0	0	NA
2	103150.4	419.4	upgrade	5	1271775	1.20
3	103200.6	469.6	upgrade	10	2543550	0.67
4	103604	873	New - 1	5	1384125	2.30
5	103639	908	New - 1	10	2543550	1.30
6	106671.8	3940.8	New - 2	5	1384125	10.39
7	106717	3986	New - 2	10	2543550	5.71

Table 7: Cost effectiveness calculations for the case of high congestion.

#	Mean eVMT	Delta eVMT	Type	DCFC plug count	Total cost (USD)	Cost Effectiveness (Delta lifetime eVMT / $)
1	102731	0	basecase	0	0	NA
2	103252.6	521.6	upgrade	5	1271775	1.50
3	103197	466	upgrade	10	2543550	0.67
4	103450.2	719.2	New - 1	5	1384125	1.90
5	103470.6	739.6	New - 1	10	2543550	1.06
6	106920	4189	New - 2	5	1384125	11.05
7	106936.2	4205.2	New - 2	10	2543550	6.03

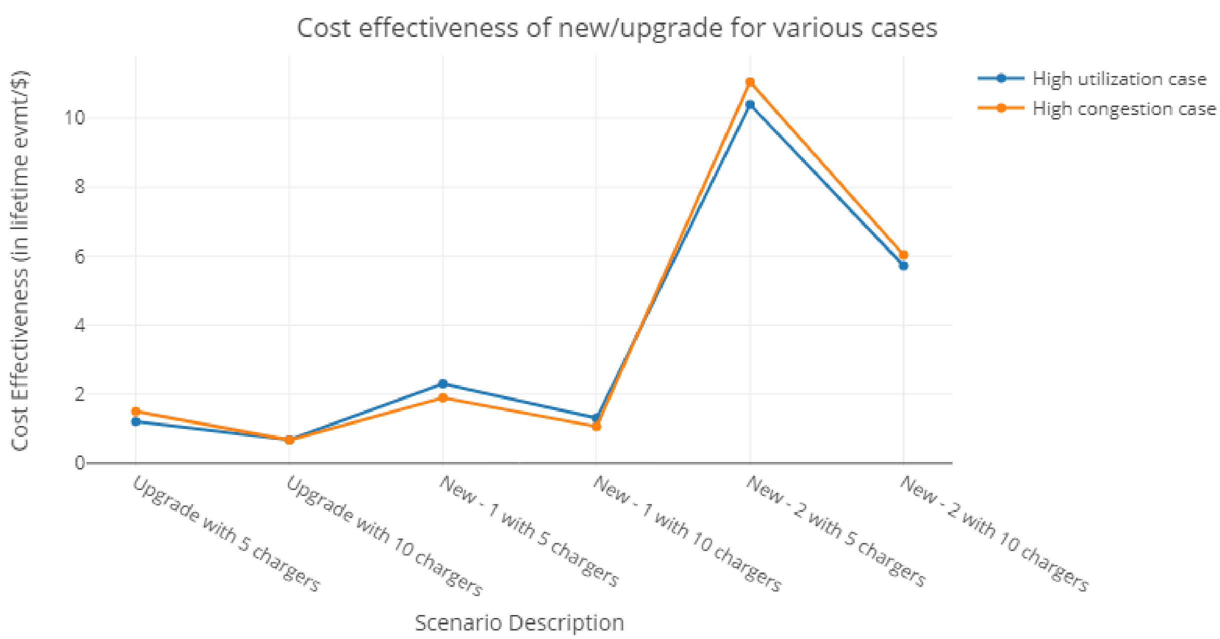


Figure 42: Variation of cost-effectiveness for high utilization and high congestion case

4.3.6.7 Conclusion

Based on the results presented in section 4.3.6.1-4.3.6.6, we can draw the following conclusions:

1. **Not all new stations are alike:** Cost-effectiveness depends on the *where* the new stations are created. Some locations may fare better than others. In general, the farther they are from existing stations and located in areas of high demand, the more positive will be their impact on EVs in simulation and therefore, other summary statistics.
2. **High utilization and high congestion are very similar:** The case of high utilization and high congestion seem very similar in terms of the effect of adding new stations or upgrading existing stations.
3. **Upgrading has impact on number of waiting sessions:** The number of waiting sessions has a significant impact when stations were upgraded, rather than when new stations were created.
4. **Adding more plugs is less cost-effective:** For the current set of selected chargers, adding more plugs beyond a certain number did not affect summary statistics. Hence, it was less cost-effective to add more plugs.

4.4 STUDY – 2: DETERMINE OPTIMAL PLUG COUNT

From the Study-1 described previously we can conclude that the case of high utilization is similar to the case of high congestion. Also, 10 plugs were found to be less cost effective 5 plugs for all cases. So, next we investigate if there is an optimal number of plugs that we can upgrade the stations with or create new stations with. In this study, for the same basecase, and locations of new/upgrade stations, seeds, locations with high congestion are chosen with varying number of plugs from 1 to 10 for the case of new and upgrade as before. So, in total we compare a total of {3 (New-1, New-2, upgrade) * 5 (number of seeds) *10 (number of plugs cases)} = 150 cases to determine the optimal number of plugs that maximize the cost effectiveness. To make the results easy to interpret, the variations in seeds can eb considered as day-to-day variation and therefore they are averaged to report the 5-day averages of summary stats.

4.4.1 *Results and Discussions*

4.4.1.1 EVs in simulation

We see from Figure 43 that the number of EVs in simulation are not affected by the number of plugs. This is a limitation of the Vehicle Choice Decision Model, which does not account for the expected congestion at the stations along the route, and only accounts for where the charging station exists. New-1 case is like the upgrade, whereas New-2 has the maximum positive impact on the EVs in simulation compared to the basecase.

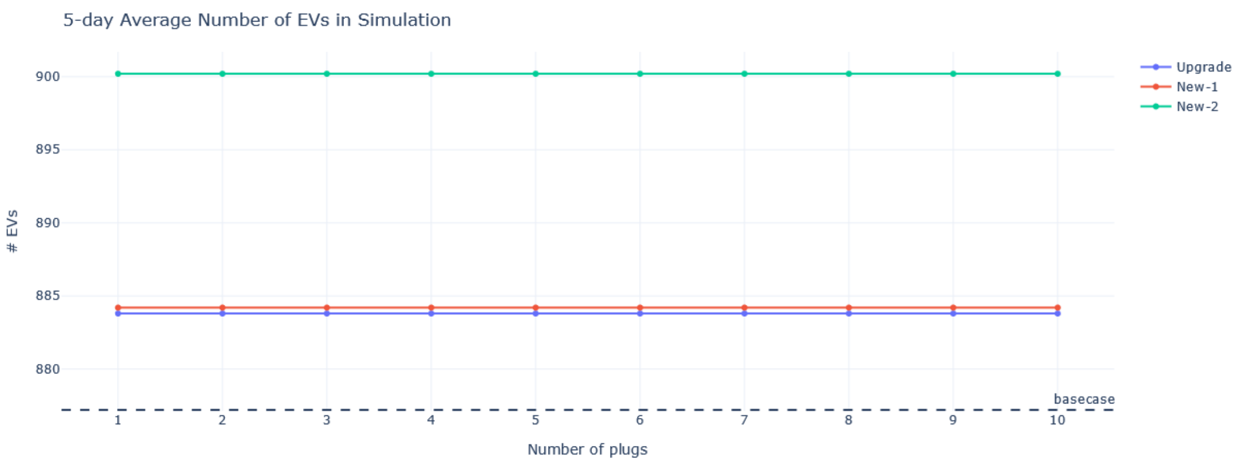


Figure 43: Variation in number of EVs in simulation as number of plugs are varied.

4.4.1.2 EVs finished

Figure 44 shows the variation in the number of EVs finished with change in number of plugs. Number of plugs does not affect the finished count as well.

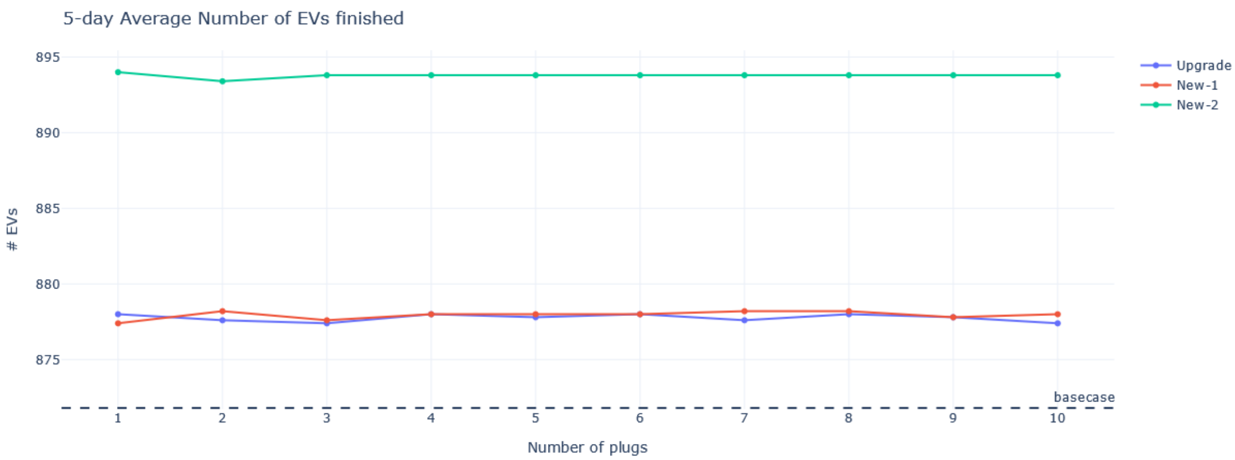


Figure 44: Variation in number of EVs finished as number of plugs are varied.

4.4.1.3 eVMT

eVMT variation with the number of plugs can be seen in Figure 45. This follows the same trend as before and number of plugs does not have any noticeable impact on eVMT.

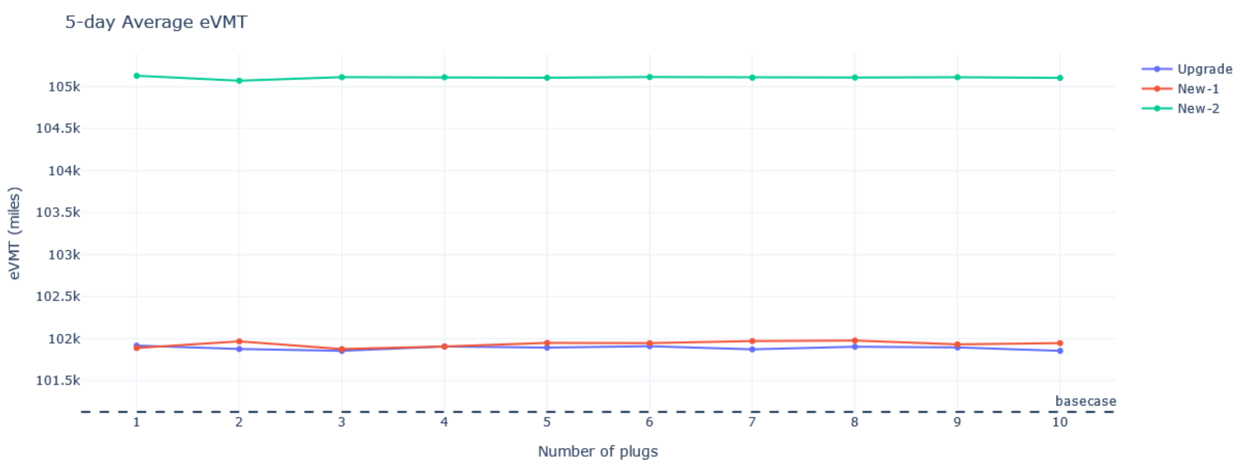


Figure 45: Variation in eVMT as number of plugs are varied.

4.4.1.4 Charging sessions

Figure 46 shows the variation in charging sessions count as the number of plugs are varied and there is no definitive advantage here as well as more plugs are added.

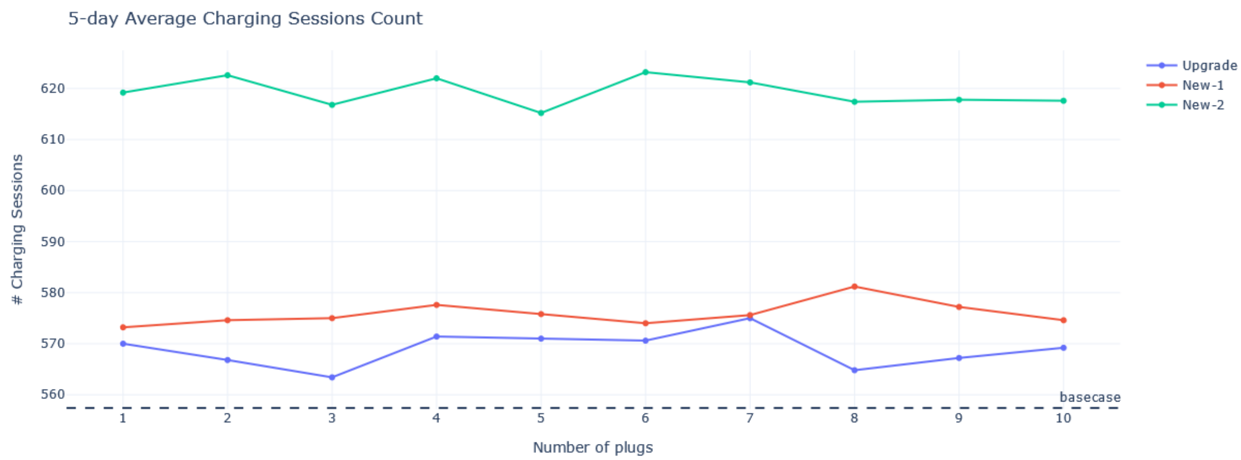


Figure 46: Variation in charging sessions count as number of plugs are varied.

4.4.1.5 Waiting sessions

Figure 47 shows the waiting sessions count and here we see a marked variation as plug count is increased. Charger upgrades cause a greater reduction in waiting sessions count, though the effect flattens out beyond a plug count of 3 or 4. Similarly, for the case of New-1 and New-2, the returns are diminishing beyond a plug count of 3.

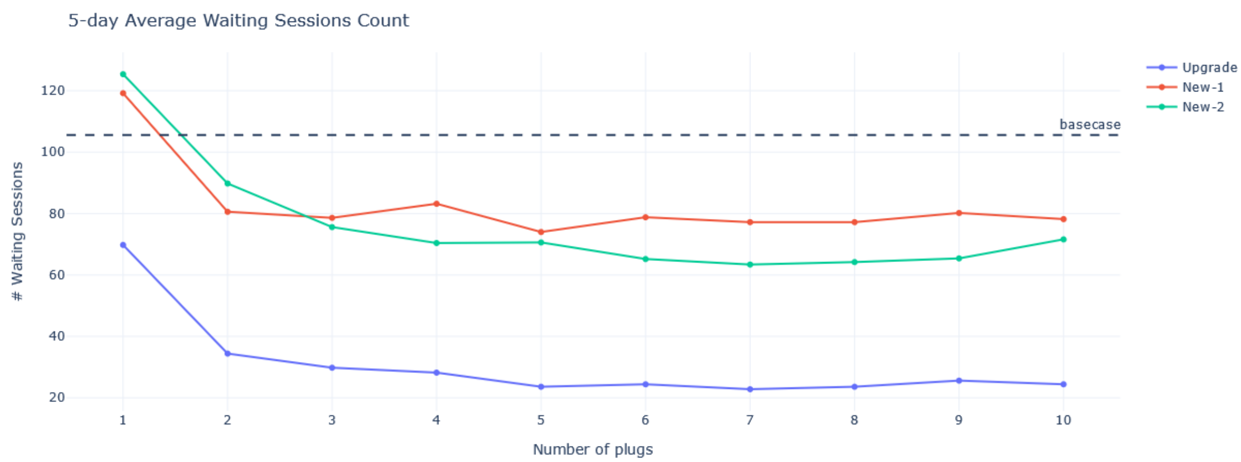


Figure 47: Variation in waiting sessions count as number of plugs are varied.

4.4.1.6 Cost effectiveness

Figure 48 shows the variation in cost-effectiveness as number of plugs are varied and we see that the cost-effectiveness tapers as more plugs are added.

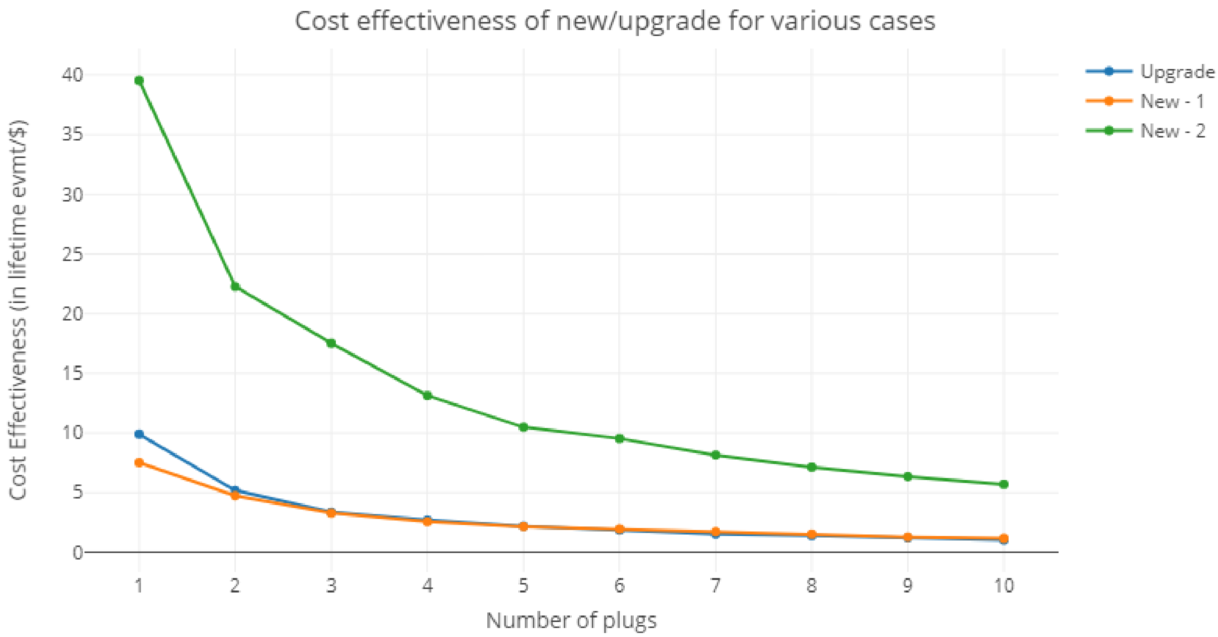


Figure 48: Variation in cost-effectiveness as number of plugs are varied.

4.4.1.7 Waiting duration

Figure 49 shows the variation of cumulative wait duration as the number of plugs are varied and is generated by adding the time spent during the individual waiting sessions.

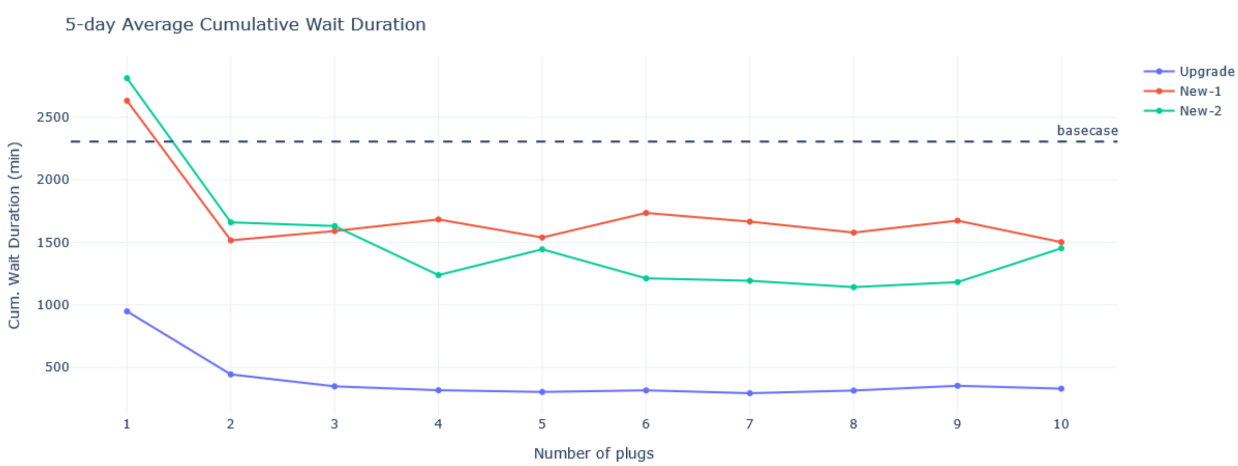


Figure 49: Variation in cumulative wait duration as number of plugs are varied.

4.4.1.8 Conclusion

The objective of Study-1 presented in section 4.3 was to determine whether it is more cost-effective to create new charging stations or upgrade existing charging stations. From the perspective of electric vehicle miles travelled (eVMT) alone, it can be concluded that new stations are likely to be more cost-effective if they are created in locations farther from existing stations and in areas of high demand. The infeasibility metric [95], an overlay on the EV Infrastructure Designer described in section 2.5.1.1.2 helps in determining areas of high travel demand and charging station scarcity. Study-2 then takes the learnings from Study-1 and tries to arrive at an optimal count of charging plugs that maximizes the cost-effectiveness. The conclusion here is that the maximum cost-effectiveness occurs at a plug count of 1 and adding plugs beyond 3 has diminishing returns for the case investigated.

Another criterion that is interesting to look at is the effect of the said charging station deployments on the waiting sessions and ultimately the cumulative waiting time. We see station upgrades as a clear winner here. Reduction in waiting times will likely improve the quality of service for the charging station network users.

As such, this study brings the dichotomy to the forefront, the challenge whether to create the charging station network to appease the new users or existing users. New stations will likely bring more users to the road, whereas station upgrades improve the quality of service for people already on the road. Also, this study was done considering a random count of 5 stations to be created/upgraded.

It is to be kept in mind while looking at the results that these may not apply to all geographies or all choices of new/upgrade. The intent of presenting these studies is to showcase the power of the tool – ChargEVal, and to show how it *can be* used to answer questions of this nature.

4.5 IMPACT

Optimal location of charging stations is important to ensure high utilization and a high level of service for EV users. Since, the station development currently requires government support to break-even, it is important for the investing agencies to get the maximum bang for their buck, i.e., they need to make sure their decisions are cost-effective. Further, charging station deployment is a multi-criteria decision and an algorithmic solution that results in coordinates on a map may not produce a feasible candidate for locating a site. Often the candidate sites are chosen from a list of possible sites, the problem then is to identify which of these site selections is likely to be cost-effective. As several charging stations already exist in the State of Washington, another option to improve the level of service and reduce waiting times, is to increase the capacity at existing charging stations. A detailed evaluative tool like ChargEVal can be used to answer these questions, as it predicts the EVSE utilization based on empirical models of travel demand, vehicle choice and charging choice. With cost-effective charging station deployments, the state will be able to achieve its climate goals faster with the same amount of money as well as have a better chance of getting follow-on funding. The end goal is to setup a charging station system that is self-sufficient as well as ubiquitous such that EV range anxiety is no longer a concern during purchase or travel decisions.

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VITA

Chintan Pathak is a sustainable transportation researcher interested in supporting new *electric* mobility services. This includes, but is not limited to, personally owned electric vehicles, electric car-sharing, electric micro-mobility (bike-share, and scooter-share), electric buses, electric fleets, etc. His research projects in this space include:

1. Designing and managing infrastructure for shared connected electric vehicles (details).
2. An agent-based modeling framework to simulate electric vehicle infrastructure utilization and planning (details).
3. Crowdsourcing parking data for micromobility vehicles (details).

More about Chintan.