Simulation Environment to Optimize Public Investments in Electric Vehicle Charging Infrastructure

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SIMULATION ENVIRONMENT TO OPTIMIZE PUBLIC INVESTMENTS IN ELECTRIC VEHICLE CHARGING INFRASTRUCTURE

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16. ABSTRACT:

Electric vehicles (EVs) are a promising approach to reducing greenhouse gas emissions, but plug-in electric vehicles (PEVs) need charging stations, and charging stations can be costly. While much charging can be done at home for low cost, long-distance travel requires fast chargers that can deliver a charge while the driver takes a short break. Consumers would like chargers to be fast, reliable, and ubiquitous, while developers would like them to be highly utilized. Hence, public charging infrastructure siting is a complex problem requiring collaboration among several stakeholders and in many cases public investment. This report presents an agent-based model of long-distance EV travel in Washington state to support public and private sector decision-making. The framework integrates empirically grounded behavioral models of vehicle choice for a trip and charging choice during the trip with models of charging station operations. It improves upon previous fast-charging siting tools by incorporating greater behavioral realism while allowing the evaluation of specific candidate sites for charging stations.

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INTRODUCTION

Plug-in electric vehicle (PEV) registrations in Washington state increased by 19 percent between November 2018 and July 2019, bringing the state's total to more than 46,000 registered PEVs. While the state is on track to achieve the Governor's goal of 50,000 PEVs by 2020, the continued growth in PEV adoption will require continued growth in EV charging infrastructure. While Washington now hosts more than 400 public DC fast charging plugs at 120 stations, it has roughly half as many fast charging stations per capita as neighboring Oregon.

Washington is anticipating significant continued investment in direct current fast charging (DCFC) infrastructure over the next several years, including private funds as a part of the "dieselgate" emissions scandal settlement and the state's EV Infrastructure Pilot Program. Given that funding is finite and DCFC stations are expensive, public investments must be made where they can generate the biggest impact on EV adoption and travel. The motivation for this project is to help WSDOT staff to make tradeoffs and prioritize investments of funds in DCFC infrastructure.

When investing in EV charging stations, WSDOT is trying to accomplish multiple goals: encourage adoption of EVs by new customers, encourage existing EV owners to drive electric more often, and provide equitable opportunities for different groups and areas of the state. The central question addressed by this project was the following:

With limited funding available for electric vehicle charging stations, where should WSDOT invest in highway corridor DC fast charging?

GOALS AND OBJECTIVES

The objective of the proposed research was to develop a simulation model in which users can specify the locations and characteristics of charging stations along Washington's highway network (e.g., number of plugs, charging power, etc.), and which will then calculate key performance indicators (KPIs) for the resulting charging network. These KPIs will include, for example:

- Technical performance (e.g., utilization rate—vehicles served per day)
- Cost effectiveness (e.g., vehicles served per public dollar invested, operating costs and revenues at each charging station)
- Environmental sustainability (e.g., EV registrations in Washington, electric vehicle miles traveled (eVMT))
- Equity (e.g., percentage of state area served, public investment by county).

The modeling platform under development is modular, with different sub-models that can be refined over time. This will allow WSDOT to obtain useful results in the near term, while the model can also be improved as the market grows and the behavior of EV buyers and owners becomes more well understood. The primary sub-models are parameterized on the basis of previously published research and include the following:

- *EV ownership*: How many EVs are owned in a given zone (e.g., ZIP codes)?
- *Long distance trips*: How many trips are generated between each origin zone and destination zone in the state?
- *EV use*: Does an EV get used for a given long-distance trip?
- *Charging choices*: Does an EV driver charge at a given charging station?
- *Charging station operations*: Simulates how long a charge takes for a given vehicle and uses queuing models to determine the likelihood of drivers waiting to charge.
- *Charging station costs*: Capital and operating costs based on the number and type of chargers, level of demand, and local utility rate structure.

REVIEW OF PREVIOUS WORK

APPROACHES TO ALTERNATE FUELS INFRASTRUCTURE DESIGN

Infrastructure design can be treated as a facility location problem [1], and many studies have explored this. Optimal facility location involves minimizing transportation costs in the form of distance [2] and travel time [3] [4], often in a supply chain management context. Facility location planning can also be affected by other concerns such as integration of sustainability issues [5] and roadway capacity expansion planning [6]. Another approach for optimal facility location is to maximize customer flow, which involves placing facilities in the path of customer flow instead of at centers of population clusters [7]. Applied to the location of alternative fuel stations, flow capturing models also need to account for how vehicle range interacts with the length of the shortest path between origin and destination, allowing for multiple stops along the way [8]. Furthermore, the higher the deviation is from the shortest path to refuel, the lower is the captured flow at the refueling station [9], hence affecting location planning.

Electric vehicle infrastructure siting has more complexities than liquid refueling station planning. Because EV charging usually takes much longer than typical vehicle refueling, activity options during recharging also play a role in charging preferences [10]. Because of the high capital cost of charging stations, cost minimization is always a consideration to achieve profits in charger operation. Furthermore, any charging station is useful for passing traffic flow only up to a specific coverage distance, and not the range of the vehicle [11]. That is, a driver of 200-mile range EV will not want to travel 200 miles just 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 [12]. In addition, because of the long time it takes to charge an EV, even at a fast charging station, a station can serve only a limited number of users, and therefore capacity constraint should be considered during EV infrastructure planning [13]. Dong et al. [14] proposed an activity-based assessment method to evaluate battery electric vehicle (BEV) charging feasibility at a station on the basis of simulated travel and charging behavior. Their method also calculated the impact of increased EV infrastructure on electric vehicle miles travelled (eVMT).

MODELING ELECTRIC VEHICLE USE AND CHARGING

Electric Vehicle Use

Ideal siting for users means an available charging station whenever and wherever they need it, and ideal siting for electric vehicle supply equipment (EVSE) operators means maximum utilization at minimal cost. Therefore, to create an optimal network of EVSEs, one needs to understand the underlying motivations of all stakeholders. Once the decision to embark on a long distance trip has been made, the next decision is to choose the vehicle. This depends on various factors, of which EVSE infrastructure along the route is just one; trip distance and EV range are also important [15]. 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 [15].

Electric Vehicle Charging Choice

One way to model the charging choice decision is to perform survival analysis on times between charging events, which can be predicted by using charging-discharging time histories and vehicle use data, ultimately providing hazard ratios for various factors such as trip distance, range anxiety, speed etc. [16]. Consumer preference and interaction with the EV infrastructure is an important topic that has been the subject of some comprehensive studies [17]. Researchers have found that public and corridor charging stations are the least used infrastructure; with around 5 percent of charging events;, however, these charging stations can still be important for longer journeys and can be perceived as a safety net for other charging options [18] [14] [19] [20] [21]. 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 [22] and Norway [23], short-range BEVs are unlikely to undertake long distance travel, but long-range BEVs are. For short-range BEVs, DCFC points are used mostly at intra-urban locations, while for long-range BEVs the charge points tend to be used mostly at inter-urban locations [24] [25] [26]. A UK study analyzed data from EVSE and from GPS-tracked BEVs and found that fast charging infrastructure could increase the vehicle miles traveled (VMT) of BEVs. This was partly because the infrastructure helped drivers overcome actual range issues, allowing them 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 because of unforeseen circumstances [27] [28] [29] [30].

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 have focused on the technical feasibility of travel, rather than being based on models of actual behavior. There are a number of existing decision support tools for charging station siting, but they each have shortcomings. Agent-based models (ABMs) are a natural extension of the increased understanding of human behavior related to EV and EVSE usage, as they model the individual units—consumers, EVs, and EVSEs—as autonomous decision-making entities called agents and describe the system from the perspective of constituent units [31]. While ABMs are sometimes programmed from scratch, usually they are implemented in one of several commonly used ABM platforms, such as AnyLogic [32], Repast [33], GAMA [34], NetLogo [35], SUMO [36], JADEX [37], or MATSim [38]. Several studies have used ABMs for modeling EVs and related systems. For small regions such as a metropolitan area, travel diaries are used as the underlying basis for simulating trips [39]. The flexibility of ABMs allows the study of emergent phenomena such as the effects of changing certain parameters of the electric vehicle infrastructure (EVI), including charging power, charging type (conductive vs inductive) [40], and EV owner residences and demographics [41]. The effects on associated systems such as electric utilities [42] [43] [44] or greenhouse gas emissions [44] can be examined over short- to long-term scales [45]. Agent-based modeling 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 that satisfy multiple objectives simultaneously [46].

EXISTING DECISION SUPPORT TOOLS

M.J. Bradley & Associates (MJB&A) released an EVI location tool [47] that uses proximity to existing charging stations, commercial activity, population, and traffic density, and outputs scores for all freeway exits. On the basis of 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., whether vehicles starting from a certain location can they 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 total traffic density.

The National Renewable Energy Laboratory (NREL) developed a tool called EVI-Pro [48], which uses long distance travel data from the FHWA Traveler Analysis Framework to generate city-level charger counts and projected loads on charging stations by using the projected PEV sales for the target year. EVI-Pro considers the vehicle attributes of current EVs on the road and infrastructure attributes, i.e., the type of charging stations, and creates driving and charging simulations, which ultimately lead to target EVSE density and EVSE utilization. While EVI-Pro is quite exhaustive in its approach, it needs lot of travel data to generate driving/charging simulations. Furthermore, it does not take into account the driver's choice of vehicle for the trip. Finally, it gives city-level counts but does not tell where in the city, or along which route, the charging stations should be sited.

Lawrence Berkeley National Laboratory (LBNL) is developing an agent-based solution for EVSE siting, BEAM [49], that extends the Multi-Agent Transportation Simulation Framework (MATSim). Its approach is to model 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. Furthermore, it is overly complex for solely EVSE siting problems, as it also includes mobility services simulation.

RESEARCH APPROACH

INTRODUCTION

"Electric vehicle infrastructure" refers to the charging infrastructure needed to support the use of electric vehicles for short and long trips. Charging can be done at home overnight if a charging point or station is available at the owner's parking location. Home charging can be supplemented by workplace charging when charging stations are installed at workplaces. While most charging happens at home or at the workplace, the need remains 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 a 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, public charging stations should also support fast charging. Fast charging at a station allows customers to take shorter charging breaks and provides the charging station with the capability to serve more vehicles during a day. Fast charging stations, though preferred, are costlier in terms of both capital and operating costs. Therefore, it is vital to find locations for fast charging stations where they will be highly utilized.

The decision support system (EVI-DSS) described in this report uses a combination of models to estimate fast charger utilization. The utilization is dependent on several factors, including EV fleet size, driving patterns, and charging propensity. The utilization can be fed into an economic model for the charging station, which takes into account 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 could evaluate the feasibility of a set of charging station candidate sites and could compare multiple siting scenarios.

DECISION SUPPORT SYSTEM

Definition

A decision support system is a tool to help assess the outcome of a decision. Because the outcome is often stochastic and dependent on several extraneous factors, there is inherent uncertainty in the prediction of the outcome. To manage the uncertainty and validate the underlying models, the outcome of decision support systems should be validated against real-world data. Furthermore, even with or in the absence of validation, decision support systems should not be used to blindly to decide whether a decision makes sense. They should rather be used to compare the outcomes of two decisions.

Need

EV infrastructure siting is a facility location problem. Facility location problems are nondeterministic polynomial problems. There are multiple criteria for evaluating the feasibility of siting a fast charger. In the absence of a deterministic optimal solution for fast charger locations, those who build the infrastructure will need to manually evaluate which locations make more sense than others. The decision support system can provide the key performance indicators (KPIs) of metrics relevant to all stakeholders, so a sustainable solution to EV infrastructure development can be found.

Justification of Selected Framework

The available frameworks are either too simplistic, in that they do not capture local and regional travel models and propensities, or are so complex and time-consuming that their application for statewide EV infrastructure development would not warrant the cost and effort involved. The EVI-DSS framework reported here is modular, so that various sub-models can evolve over time. As we have better understanding of the dynamics of EV adoption or energy consumed during a trip, the underlying model for the system can be changed or updated to refine estimates of performance and test new hypotheses. Furthermore, none of the available decision support systems is available in an easy to deploy, open-source format. The open-source nature of the reported decision support system will allow 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.

EVI-DSS

The electric vehicle infrastructure decision support system (EVI-DSS) is a tool to guide decision makers in planning the deployment of EV infrastructure. Both public agencies and private companies can use the EVI-DSS because it predicts KPIs relevant to each domain. The EVI-DSS has been developed in collaboration with and with funding from the Washington State Department of Transportation. The results and scenarios presented in this paper are therefore for the Washington state region. However, the methodology described is general enough to be applied anywhere across the world.

Goals of the EVI-DSS

The EVI-DSS shows an infeasibility metric across the state, indicating where high volumes of traffic flow overlap with long distances between charging stations. These areas are good candidates for charging stations if the objective is to maximize the feasibility of EV travel throughout the state. Once the sites have been chosen, the EVI-DSS estimates the potential utilization for a chosen site. The utilization is output as energy and power. The total energy consumed per charging station in a month and the peak power draw in a month are important statistics that affect the economics of charging stations.

Components of the EVI-DSS

The various components of the EVI-DSS are described below. For an in-depth technical exposition refer to the corresponding paper or contact the authors.

Long Distance Travel Demand Model

The necessity for a charging station on a route depends on the number of EV trips passing through the route. Trip counts between origin-destinations (OD) were estimated by using INRIX data, as reported in previous work [50]. The OD matrix was composed of around 300k+ rows indicating trip counts from all origin ZIP codes to all destination ZIP codes within Washington. This count was lower than the total number of possible OD pairs in Washington (500k+), since only the ZIP codes with non-zero population were considered in the above modeling. The trip counts were dependent on several factors, such as the origin and destination population, respective counties, and distance between origin and destination. The total trip count between an OD pair was composed of two quantities: the traffic belonging to the O, going from the O to the D, and the traffic belonging to the D, returning to the D from the O. This is illustrated in Figure 1.

Figure 1: EV trip count calculation

The sequential process to obtain the EV trip counts is as summarized as follows:

1. On the basis of the gravity model presented by Jabbari et al [50], which predicts the monthly trip generation rate between an OD pair (separated into returning and departing trips), the average daily trip generation rate is calculated.
2. To simulate a typical travel day, a random draw is made from a Poisson distribution by using the average daily trip generation rate as the occurrence rate.
3. To determine the number of trips made by EV-owning households, a random draw from a binomial distribution is performed with the probability defined as the number of EVs in a ZIP code divided by the number of car-owning households in a ZIP code. This assumes that each household owns no more than one EV.
4. Finally, the number of EV trips between an OD pair is estimated on the basis of whether each household owning an EV decides to use the EV for the trip. A random draw from a binomial distribution with the probability derived from the vehicle choice decision model (detailed later) tells us whether an EV is used for the trip.

Vehicle Choice Decision Model

The vehicle choice decision model (VCDM) can tell us whether an EV is feasible for a trip depending on various trip and vehicle characteristics. Ge [51] estimated several discrete choice models generated through stated preference surveys. For the purposes of EVI-ABM, a latent class logistic regression model is used to make a vehicle selection among a household-owned internal combustion engine vehicle (ICEV), a rental vehicle, or a battery electric vehicle (BEV) and is described 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 particular 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 ($\frac{\mathrm{Max}_{\mathrm{Spacing}}}{r_{full}}$), largest spacing between restrooms along the route ($l_{restrooms}$), whether there is a restaurant near the charging station ($Restaurants$), whether the destination has a level-2 charger ($Des_{charger_{type(L2)}}$), and 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 1.

Table 1: Model coefficients for the vehicle choice decision model

Covariates	Est.	P-value
ICEV gas cost ($) $\boldsymbol{\theta_1}$	-0.040	0.000
RENT cost ($) $\boldsymbol{\theta_2}$	0.059	0.010
RENT gas cost ($) $\boldsymbol{\theta_3}$	-0.075	0.000
relative distance $(\frac{L}{r_{full}})$ $\boldsymbol{\theta_4}$	-1.659	0.002
relative max spacing $(\frac{\mathbf{Max_{Spacing}}}{r_{full}})$ $\boldsymbol{\theta_5}$	-9.342	0.000
furthest restroom break (miles) $\boldsymbol{l_{restrooms}}$ $\boldsymbol{\theta_6}$	0.002	0.271
Restaurants $\boldsymbol{\theta_7}$	0.197	0.688
Des charger (Level 2) $\boldsymbol{\theta_8}$	-0.748	0.141
Des charger (Level 3) $\boldsymbol{\theta_9}$	1.428	0.039
ASC_BEV	11.184	0.000

EV Infrastructure Agent-Based Model

The EV Infrastructure Agent-Based Model (EVI-ABM) is the agent-based model for estimating the utilization of EVSE in the state of Washington. It has the following attributes:

1. Agents:
    a. Electric vehicles in Washington: We consider all the electric vehicles registered in Washington as our EV agents. While some EVs may travel outside the state and some out of state vehicles may travel within Washington, for this study we ignored these vehicles. Data Source: Washington Department of Licensing [52]

b. Washington road network: The EVs move on roads, and travel is restricted to roads. For now, we ignored road elevation, but in the future, roadway elevation could be included, and the energy model can account for changes in elevation. Data Source: Washington State Department of Transportation [53]

c. Electric vehicle supply equipment (EVSE) / charging stations: The charging stations are where EVs charge when they are depleted. The instantaneous power drawn and total energy consumed are the EVSE utilization simulation outputs in which we are interested. Data Source: Alternative Fuels Data Center [54]

2. Environment: Currently, a 2D simulation is bounded by the state of Washington.
3. 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.

The ABM for this project was built in GAMA [34]. GAMA is a free and open-source modeling and simulation development environment for building spatially explicit, agent-based simulations and is used for multiple application domains, including transportation, urban growth, and epidemiology. It uses a high-level, intuitive, agent-based language, GAML, which facilitates quick and efficient coding of agent properties and behaviors. Furthermore, GAMA has built-in GIS capabilities and allows imports of several common file formats, including csv and shapefile. It also has the capability to connect to external databases such as MySQL and PostgreSQL, as well as tools such as R to allow data-driven modeling. It has a declarative user-interface that allows users to see the agents moving and interacting and to interact with the simulation by using mouse-clicks, sliders, etc.

EVI-ABM System Overview

The EVI-ABM system as it exists today is shown in Figure 2. 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 each agent's characteristics. Some of these are built-in, such as location and speed, while some user-defined attributes (e.g., veh_ID, capacity) define the particular agent's characteristics. Figure 2 shows the object-oriented nature of a GAMA model, which intuitively transfers to the real world. Depending on the problem at hand, agents can be defined in as much detail as users choose.

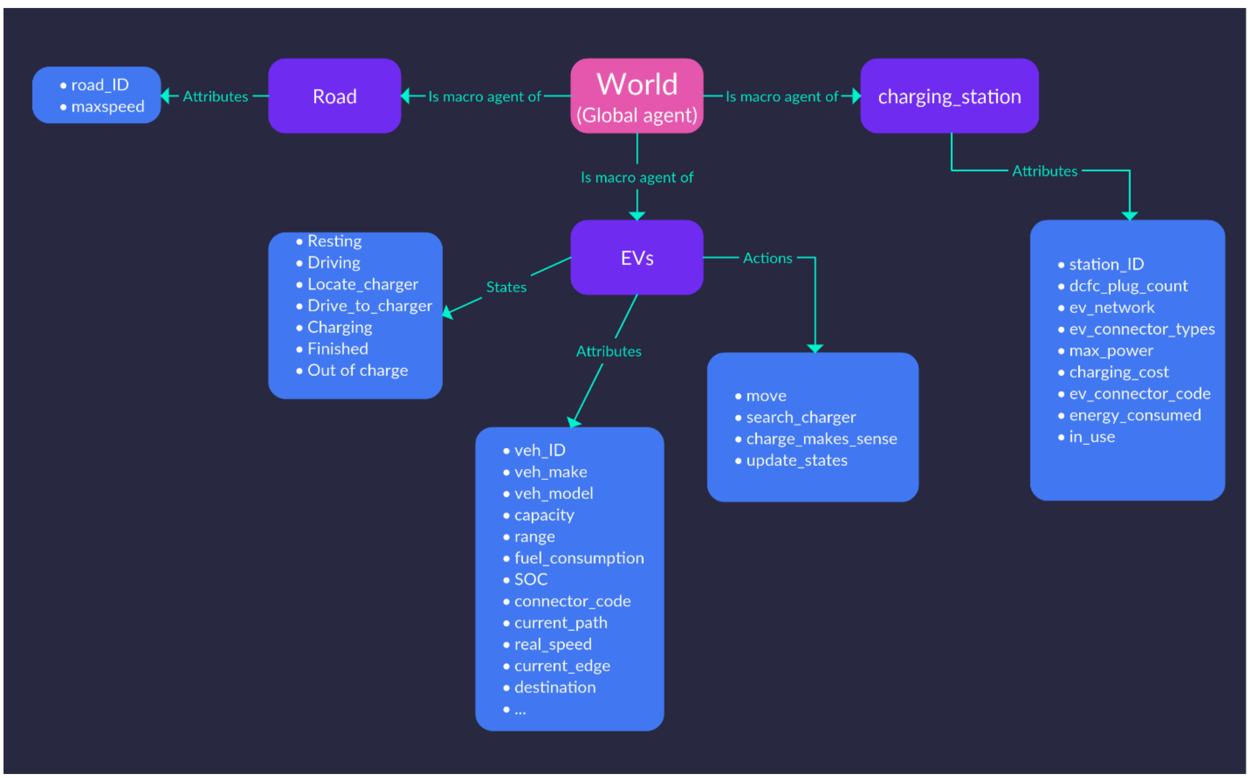

Figure 2: EVI-ABM system overview

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 for modeling EV operation, as the vehicle can be in deterministic and finite states (resting, driving, charging, etc.). The benefit of FSM control for this use case is that it helps in managing the complexity of operation and allows for easy testing. While the infrastructure and driver behavior are modeled, FSM control allows users to observe the state of agents at any time-step of the simulation, and provides greater observability to aid in debugging. FSM control is also flexible, e.g., if users decide to add more complexity to the operation by adding more states (e.g., waiting in a queue); users can do that by changing the transition conditions. The state diagram for the system is shown in Figure 3.

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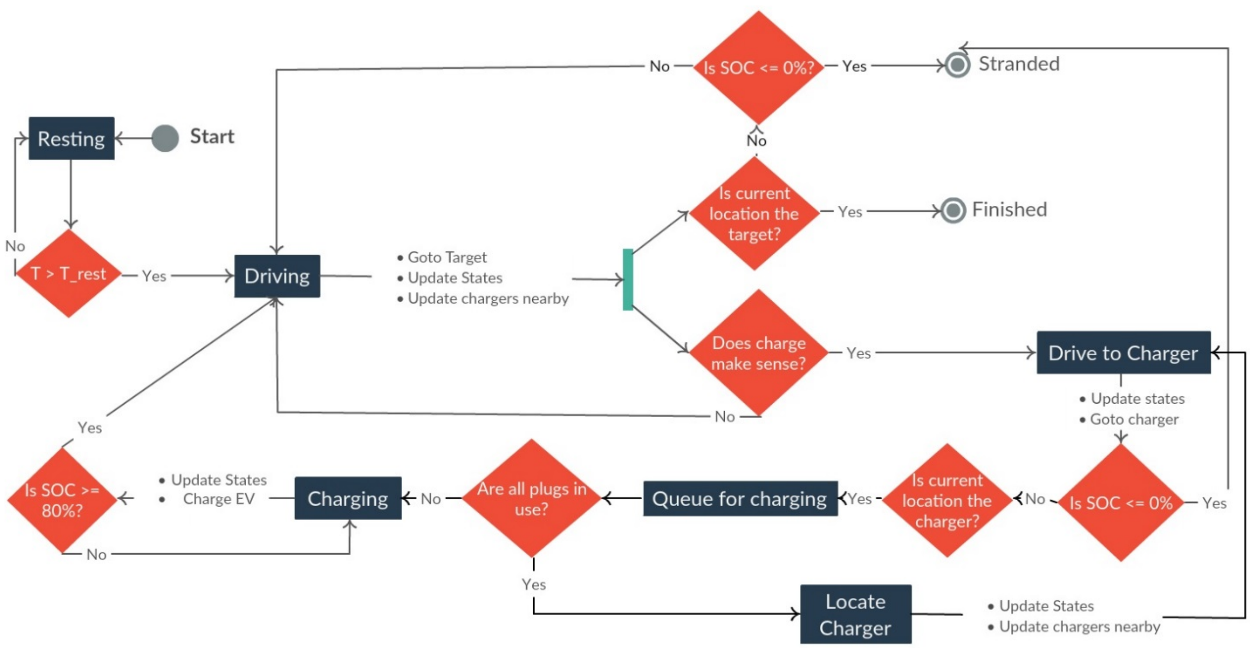

Figure 3: Finite state machine diagram for the EVI-ABM

To parse the state diagram, first observe the start and finished states. Other states in the system are indicated by dark rectangular blocks: “Resting,” “Driving,” “Locate Charger,” “Drive to Charger," and "Charging." These are connected to diamond-shaped decision boxes, which represent the transition conditions, and the statements above the connecting lines are actions, or behaviors that are undertaken by agents at every time-step, such as "Goto Target," "Update States," etc. Some decision questions, such as *"Is T >T_rest?",* or *"Is current location the target?",* are easily answered in the ABM framework, as time is a global attribute common across agents, and all agents have a built-in attribute of location. However, some other EVI-ABM specific decision questions, such as "Does charging make sense?", are not so directly answerable and will depend on the trip and car's related parameters. The linkages among these conditions and preferences are captured in the behavioral models.

Charging Choice Decision Model

While the vehicle is en route to its destination, it might need to charge along the way. The choice of charging at a charging station can be modeled by a discrete choice model. Among the various models developed by Ge [55], this project used the static choice decision model. The model equations are 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 a vehicle has enough range to reach the next charger if it 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 restrooms are an amenity at the location of the charging station, $Amenity_{more}$ represents whether there are more amenities such as restaurants or Wi-Fi at the charging station location, and $\varepsilon_{charging}$ represents the error. The coefficients used for the charging choice decision model are as presented in Table 2. The utility of choosing not to charge is assumed to be zero.

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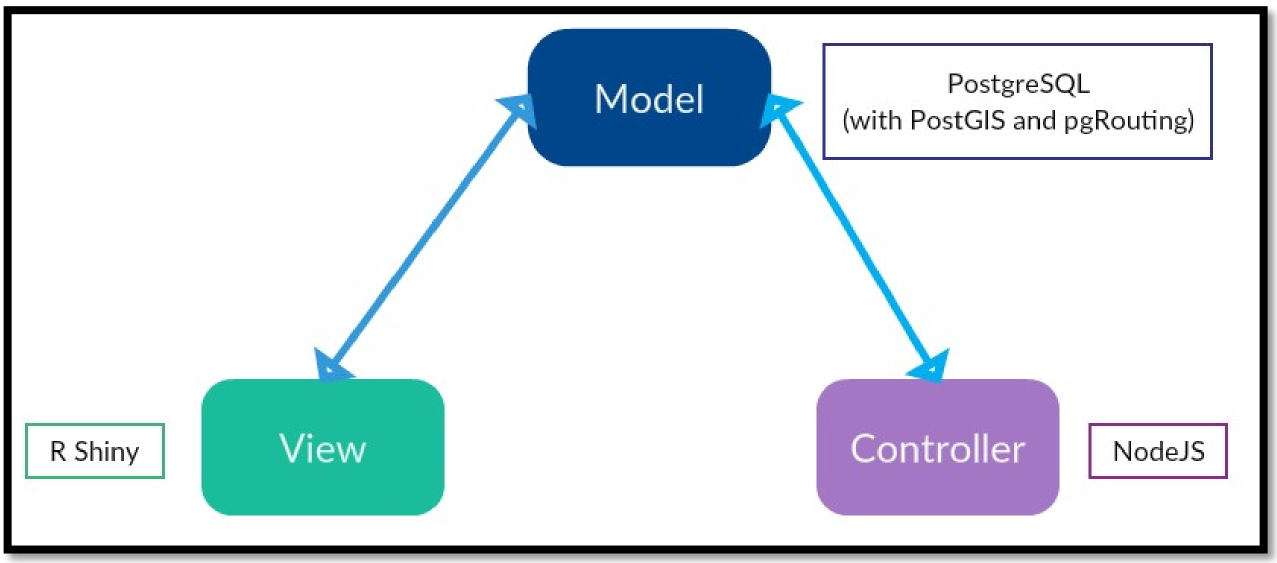
Table 2: Model coefficients for the charging choice decision model

Variables	SDCM4
(Intercept) $\boldsymbol{\theta_0}$	2.034***
SOC (%) $\boldsymbol{\theta_1}$	-4.584***
Deviation $\boldsymbol{\theta_2}$ *(DEV)*	2.440***
Time in car (h) $\boldsymbol{\theta_3}$ $(\boldsymbol{Hours})$	-0.069
Charging cost ($) $\boldsymbol{\theta_4}$ $(\boldsymbol{C_{charging}})$	-0.010***
Charging time (h) $\boldsymbol{\theta_5}$ $(\boldsymbol{T_{charging}})$	-0.242**
Access time (min) $\boldsymbol{\theta_6}$ $(\boldsymbol{T_{charging}})$	-0.025***
Amenity: restroom only $\boldsymbol{\theta_7}$ $(\boldsymbol{Amenity_{restroom}})$	0.049
Amenity: restroom, dining & WIFI $\boldsymbol{\theta_8}$ $(\boldsymbol{Amenity_{more}})$	0.213**

* p-value <0.1; ** p-value<0.05; *** p-value<0.01

EVI-DSS SYSTEM ARCHITECTURE

The EVI-DSS is based on the model-view-controller (MVC) architecture. In the MVC architecture, the model represents the data, the view refers to the interface(s) exposed to the user, and the controller handles the user requests. The architecture of the EVI-DSS is as shown in Figure 4



Model

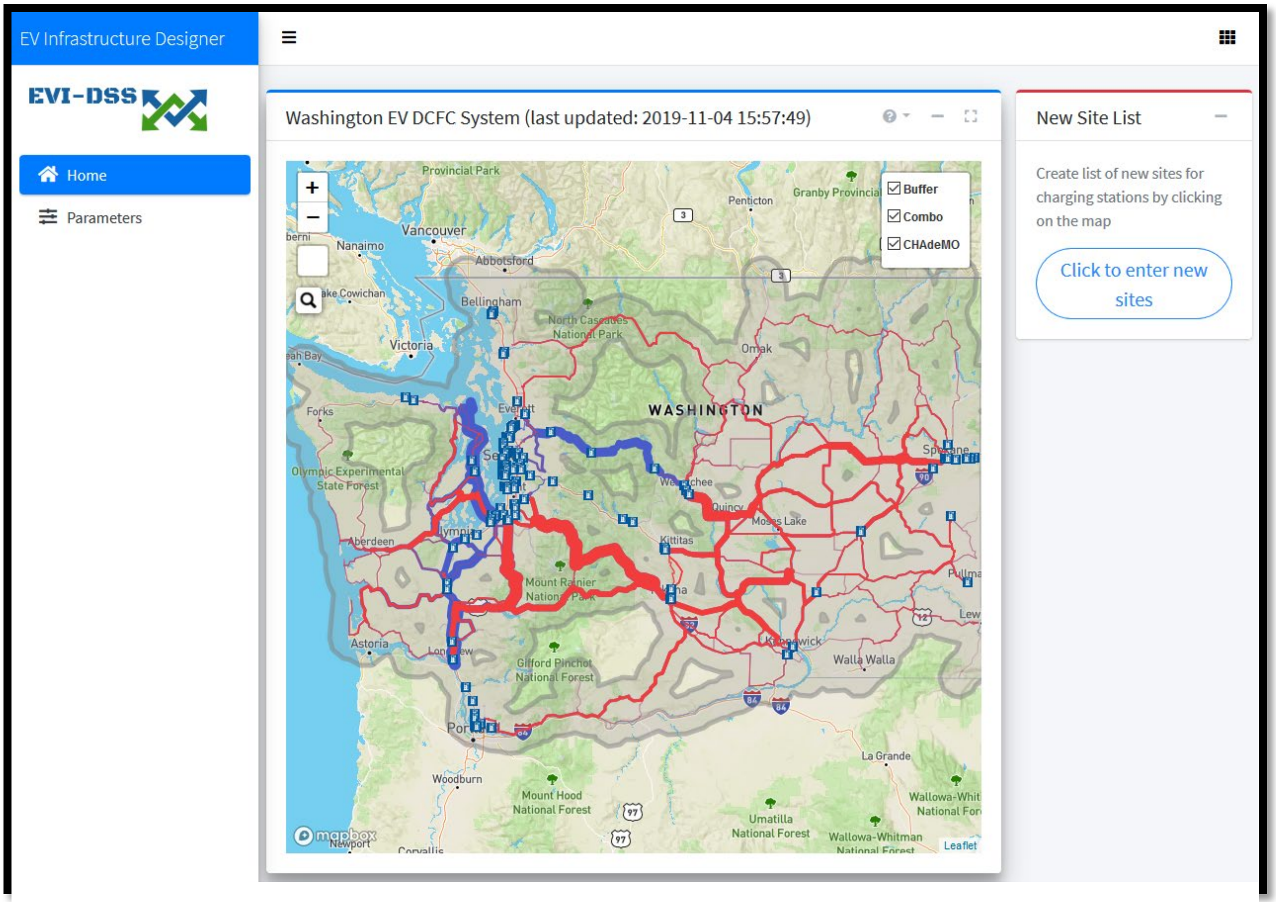
The model refers to the data in the application. A relational database management system, PostgreSQL (v12.0.0), was used as it provides geospatial capabilities through its extensions PostGIS (v3.0) and pgRouting (v3.0.0-alpha). The benefit of a database over files is that it enforces strict rules on data. This can help when the complexity of the application increases and several layers depend on the same data.

View

The view refers to the interface exposed to the users of the EVI-DSS. Users interact with the views. The EVI-DSS has two views: the "EV Infrastructure Designer" can be used to select the locations of prospective charging stations and configure the details for the charging stations placed; and the "EVI-ABM Results Viewer" can be used to view to the results of the simulation for the current EV infrastructure, which is the combination of built and proposed charging stations.

EV Infrastructure Designer

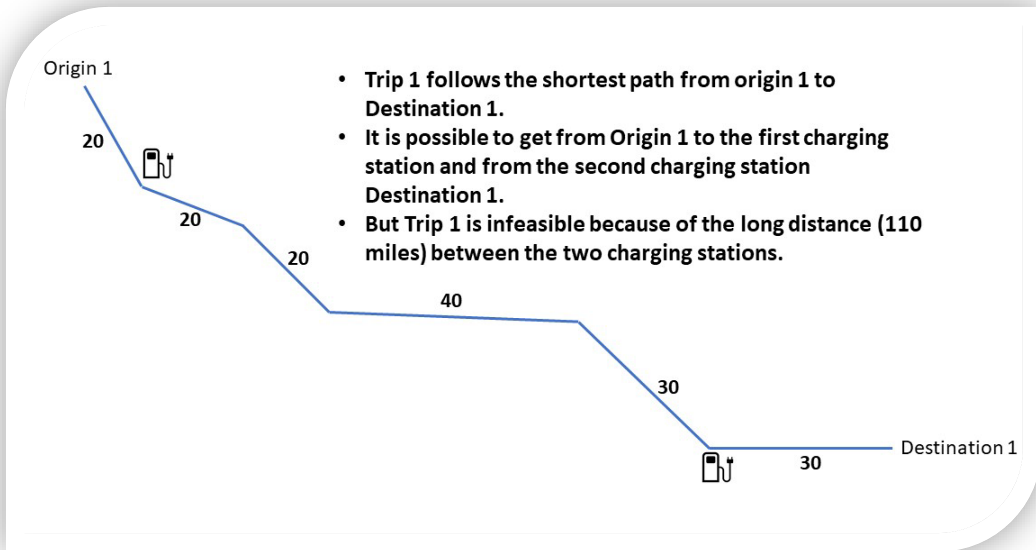
The EV Infrastructure Designer is the user interface (UI) for inputting the location, type, count, and other details about the prospective charging stations. After logging in by providing email-id and password, users are greeted with the interface shown in Figure 5.



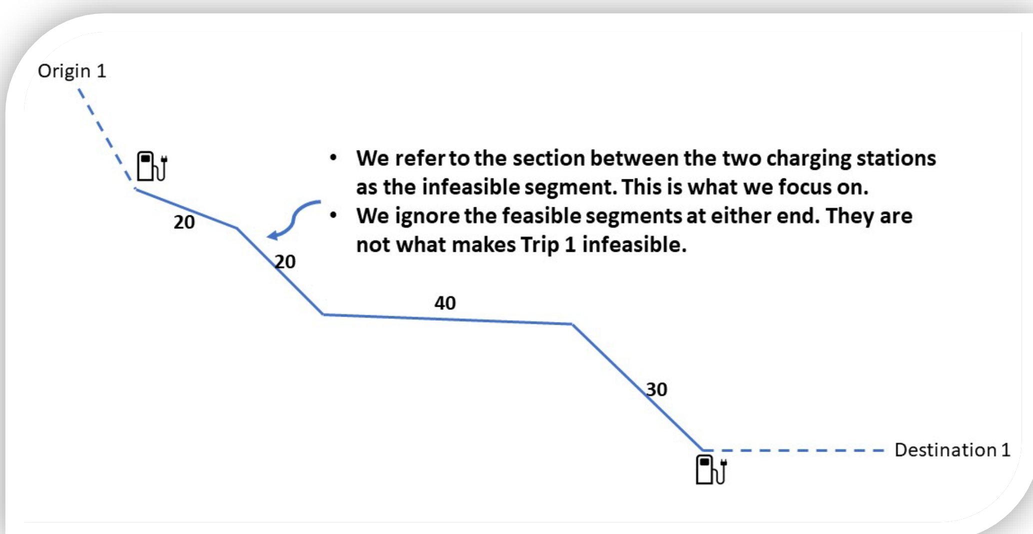
Washington EV DCFC System

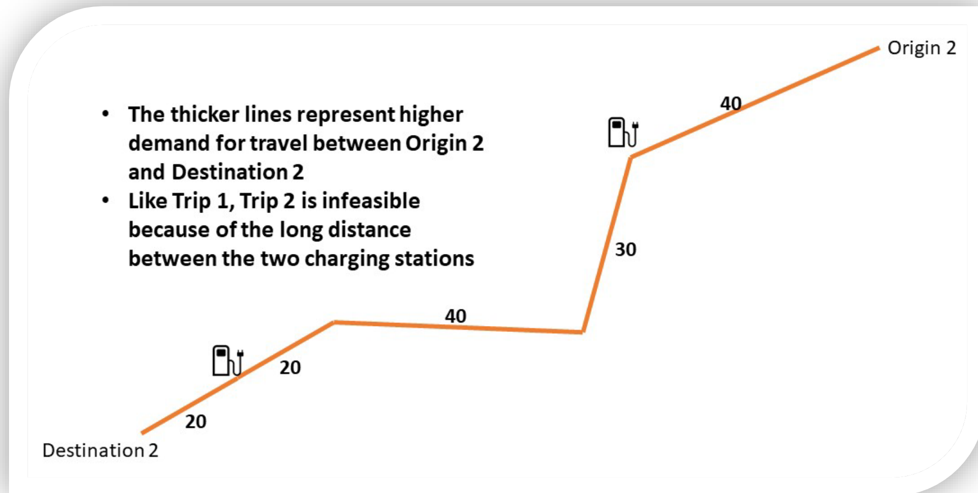
The “Washington EV DCFC System” page shows the WSDOT road network overlayed with the infeasibility metric for CHAdeMO and COMBO charging, along with the current as-built EV DCFC infrastructure—selectable from the radio buttons in the upper right corner, as in Figure 6. Besides the infeasibility overlay, the radio buttons also show the relevant type of charging stations on the road network.

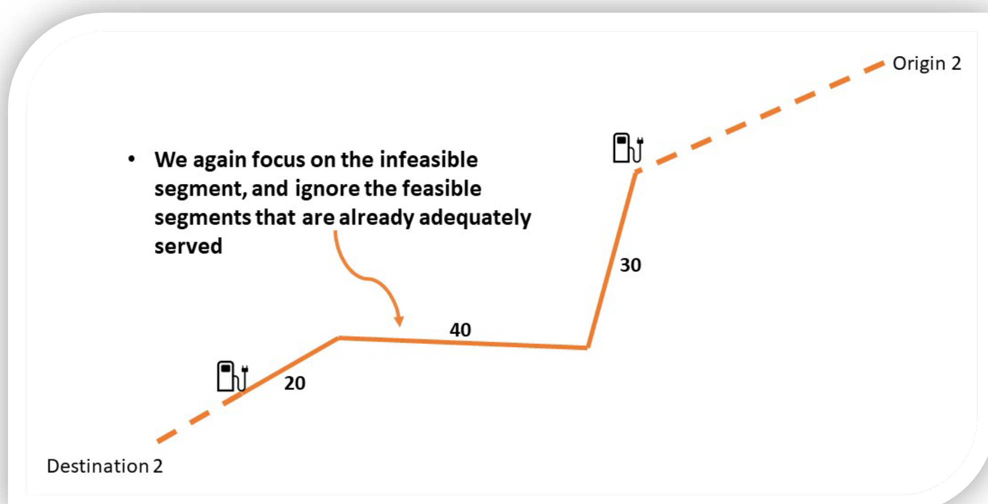
The infeasibility metric is an indication of the sparsity of EV infrastructure on a path. A count is calculated for the total number of vehicle trips passing over a road segment belonging to a shortest path between an OD pair if the spacing between charging stations on the segment is greater than 70 miles (the critical limit specified by WSDOT). The line weight of the overlay is directly proportional to the number of trips passing over a segment that are infeasible by EV. So, a thick overlay can mean that many trips pass over the segment that are infeasible by EV because of excessive distances between charging stations. A thin line indicates that few infeasible trips traverse the segment. No line weight on the roads means that the spacing between charging stations on the segment is less than 70 miles. There are separate overlays for CHAdeMO and COMBO charging stations, as not all charging stations feature both types of plugs. The illustration below explains the process of calculating the infeasibility metric.

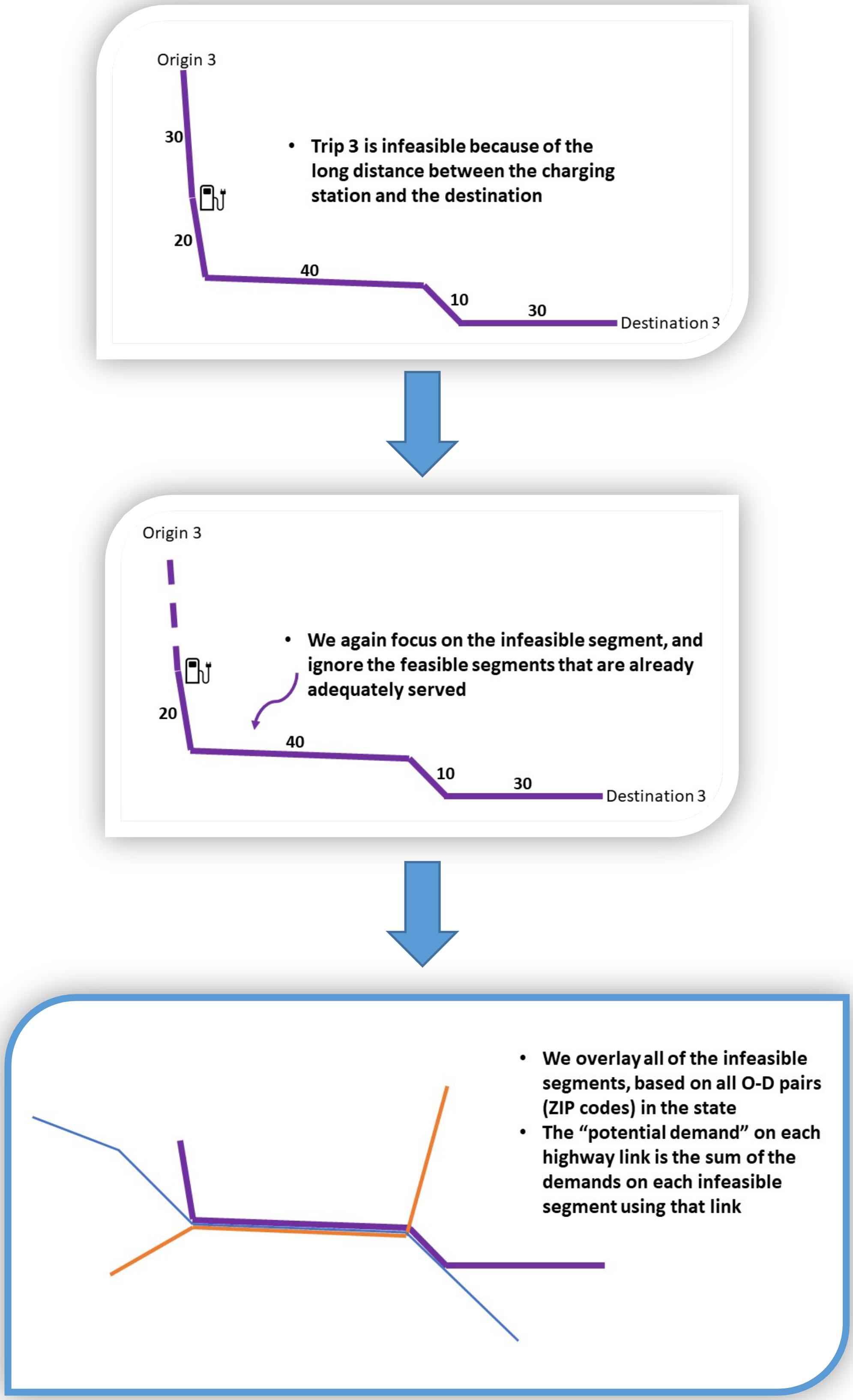


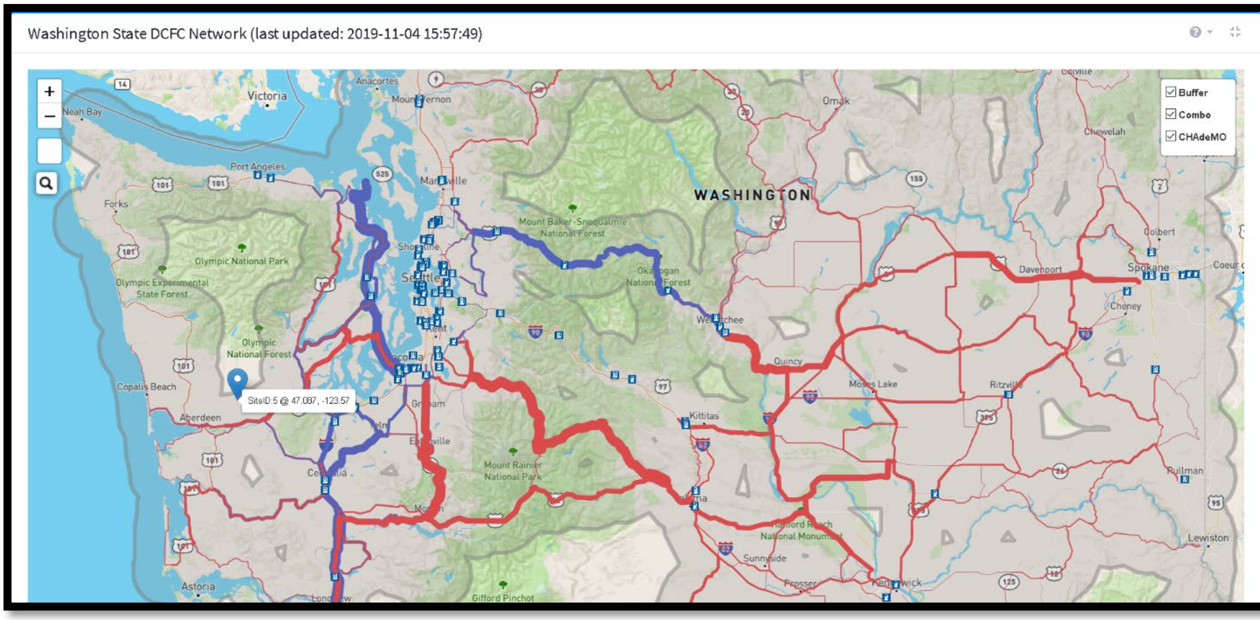
Visual explanation of trip infeasibility - 1




Origin 2
The thicker lines represent higher demand for travel between Origin 2 and Destination 2
Like Trip 1, Trip 2 is infeasible because of the long distance between the two charging stations
40
30
40
20
20
Destination 2


Origin 2
We again focus on the infeasible segment, and ignore the feasible segments that are already adequately served
30
40
20
Destination 2


Origin 3
30
20
40
10
30
Destination 3
• Trip 3 is infeasible because of the long distance between the charging station and the destination
Origin 3
20
40
10
30
Destination 3
• We again focus on the infeasible segment, and ignore the feasible segments that are already adequately served
• We overlay all of the infeasible segments, based on all O-D pairs (ZIP codes) in the state
• The "potential demand" on each highway link is the sum of the demands on each infeasible segment using that link

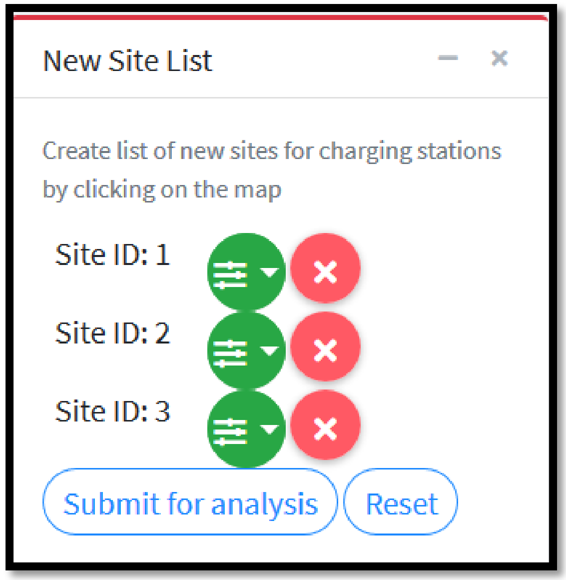


The checkbox under the radio buttons toggles the display of a buffer around the road network. This buffer, spanning a length of 10 miles around the roads, represents the area to consider for the location of prospective charging stations. The length of 10 miles is assumed to be the limit of the willingness of an EV driver to divert from the road to charge.

Figure 6 shows a selected charger location with a marker. The user interface will only allow charger placement in the buffer region around the roads, and a successful click results in a marker as shown. As many charging station locations can be picked as desired.

New Site List

The New Site List page lists all the chosen sites, with options to configure or cancel the selection, as shown in Figure 7.



For all the selected locations, configuration can be completed as shown in Figure 8.

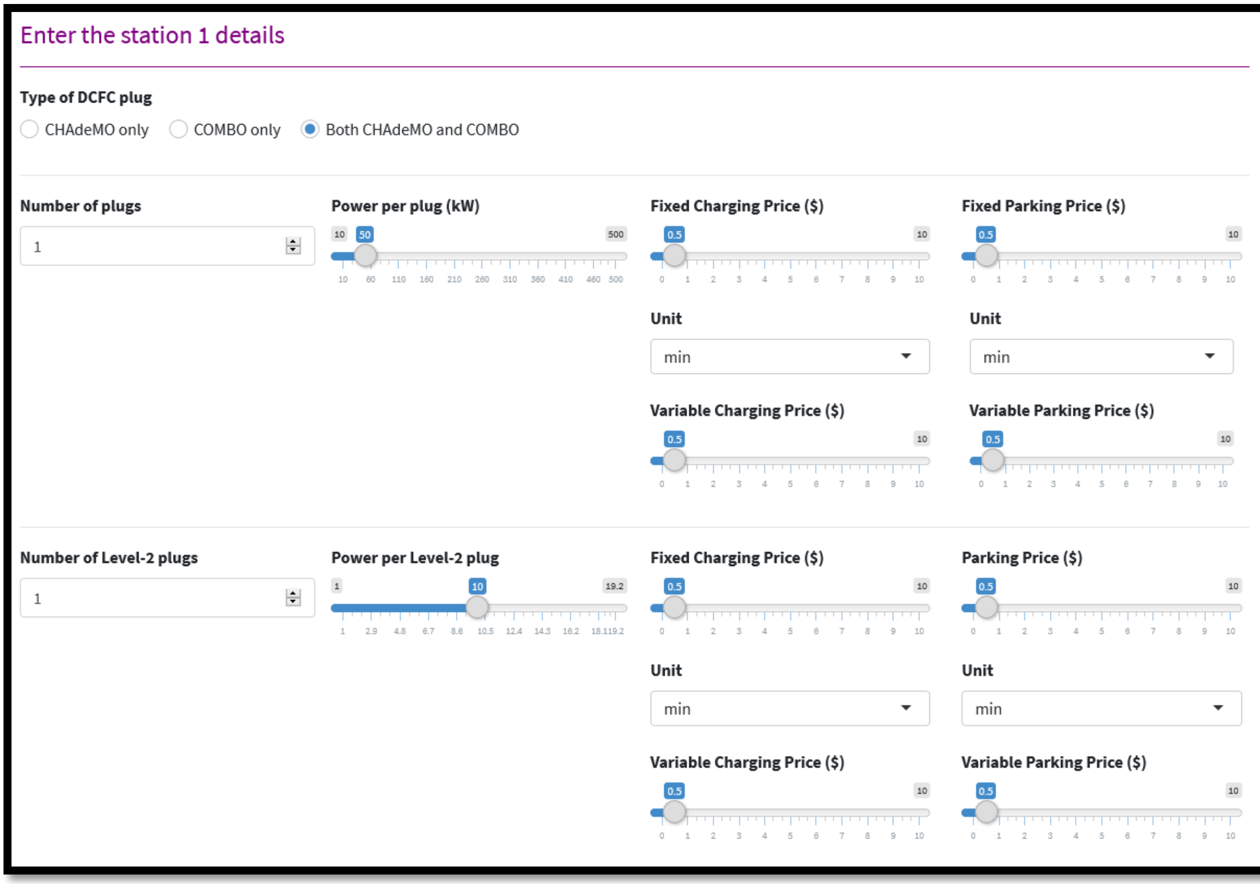


Figure 8: New station configuration

The station configuration model allows the of number of plugs to be set for DCFC and Level-2 stations, as well as the corresponding power per plug and pricing structure. Total price can include charging price and parking price. For both parking and charging, there could be a fixed (per session) and variable (per minute) component.

Once satisfactory counts of charging stations with appropriate configuration have been selected, the selection can be submitted for analysis by clicking the "Submit for analysis" button. The New Site List page then displays a successful analysis submission message with the submission date/time. Because the analysis process involves re-calculation of destination chargers, charging distances, EV trips, and subsequent agent-based simulation, it is computationally intensive and takes several hours to complete (at the time of this writing). When analysis has been completed, users are informed about the successful completion of analysis via an email at their registered email address. The results can then be viewed for the particular simulation date/time of interest.

<u>EVI-ABM Results Viewer</u>

Users receive an email at the registered email-id when a simulation has been successfully solved. The email contains the link to the Results Viewer. The Results Viewer allows users to browse through the results of all the simulations that they submitted and that have been solved. Being able to view the detailed output of several simulations allows users to compare the performance of charging station deployment scenarios. The Summary tab shown in Figure 9 is the first view to appear on a simulation run date/time selection from the dropdown list. This is the time when the simulation was submitted.

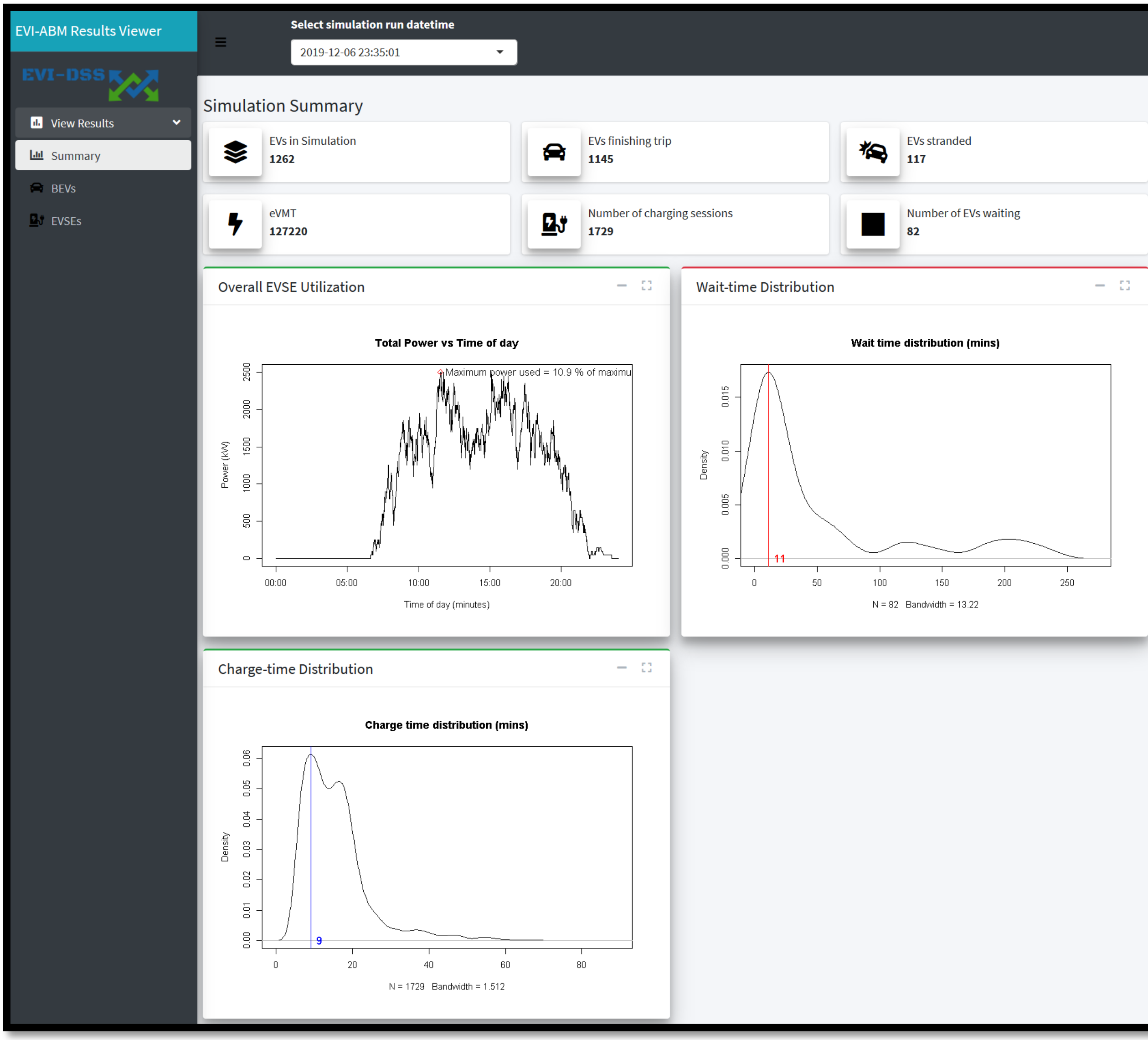


Figure 9: EVI-ABM Results Viewer – summary

Summary

The statistics presented on this page represent the key performance indicators for the simulated EV infrastructure (consisting of as-built + proposed).

- "EVs in Simulation" is the number of EVs that were simulated for travel on a typical day.

- "EVs finishing trip" represent the number of EVs that reached their destination, i.e., finished their trip.
- "EVs stranded" represents the number of EVs that were stranded during the trip, i.e., were out of charge because of a lack of charging infrastructure along their charging route.[1]
- "eVMT" refers to the electric vehicle miles travelled; this statistic does not include the added trip distance due to charging detours but counts only the shortest path lengths for EVs that finished their trips.
- "Number of charging sessions" represents the number of charging sessions predicted by the model.
- "Number of EVs waiting" represents the number of EVs that waited at a charging station because it was occupied when they needed to charge.

The graph "Overall EVSE Utilization" shows the variation of total charging power drawn by the EVSEs in Washington throughout the day at a 1-minute resolution. The graphs "Wait-time Distribution" and "Charge-time Distribution" show the probability density plots for waiting sessions and charging sessions, respectively.

[1] At present, the model likely over-estimates the number of EVs being stranded. One reason for this is that it allows for some agents to choose an EV for a long trip even if that trip involves long distances between charging stations. Second, agents in the simulation do not currently adapt their behaviors as they approach an empty battery, although real EV drivers can moderate their speed, wait in a queue, or use a level 2 charger if they are critically low on charge. Therefore, the number and locations of vehicles "stranded" is a proxy for locations that are underserved by charging stations, but should not be taken as an estimate of vehicles literally stranded.

BEVs

Figure 10 shows the trajectory of BEV agents through the simulation.

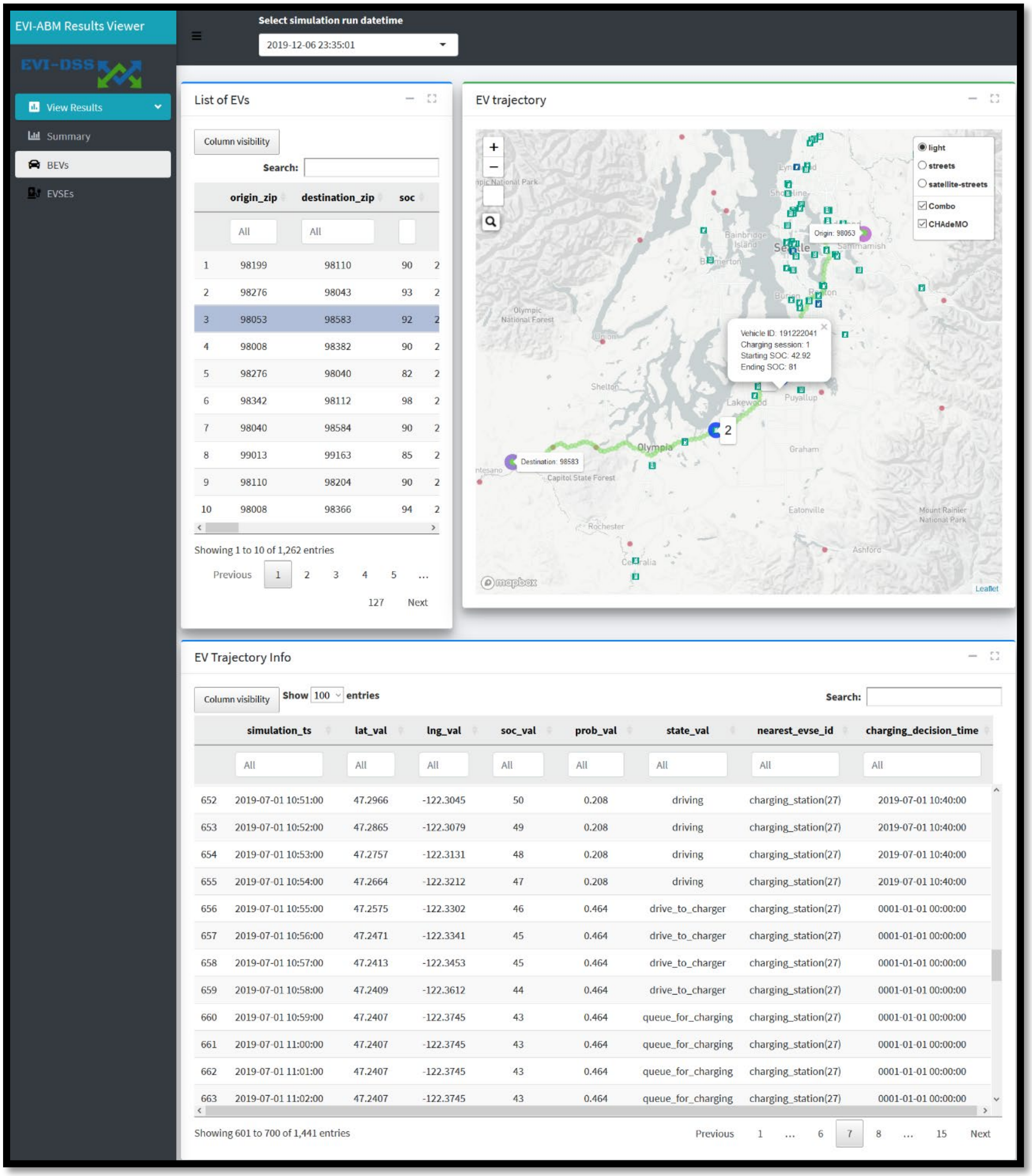


Figure 10: EVI-ABM Results Viewer - BEVs

Upon selection of a row in the "List of EVs" card, the trajectory for the EV through the simulation is plotted on the map. The trajectory also includes the charging sessions undertaken by the EV during the trip. The table "EV Trajectory Info" lists the various values during the simulation at 1-minute time-steps.

EVSEs

Figure 11 shows the details of the EVSE Utilization during a simulation. When an EVSE is selected from the "List of EVSEs," the tabs on the right, "Waiting" and "Serving," show the waiting and charging sessions, respectively, at the EVSE. The map shows the number of waiting and charging session counts as overlays, and clicking them shows the power profile on the EVSE throughout the day, as shown in Figure 12.

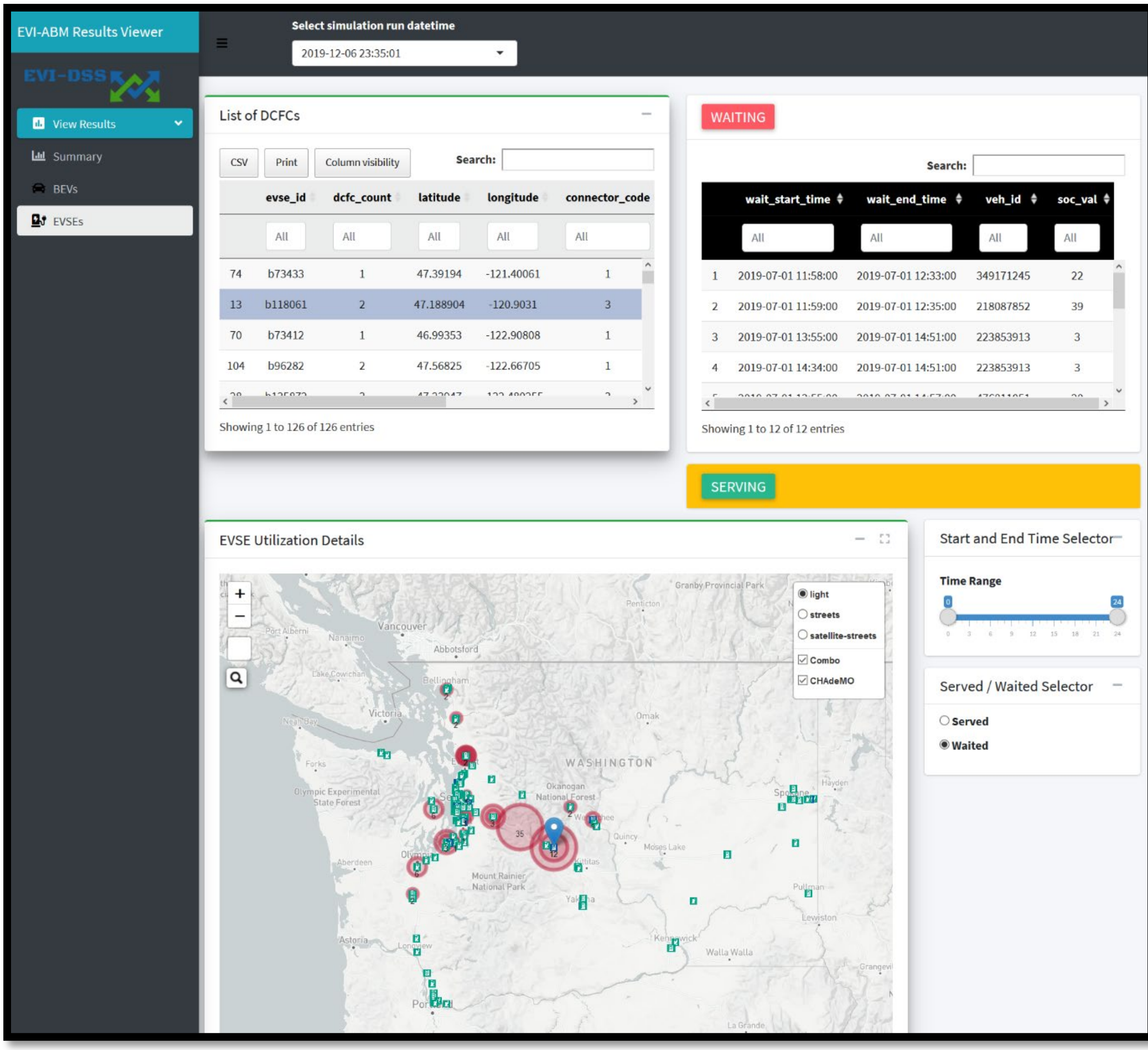
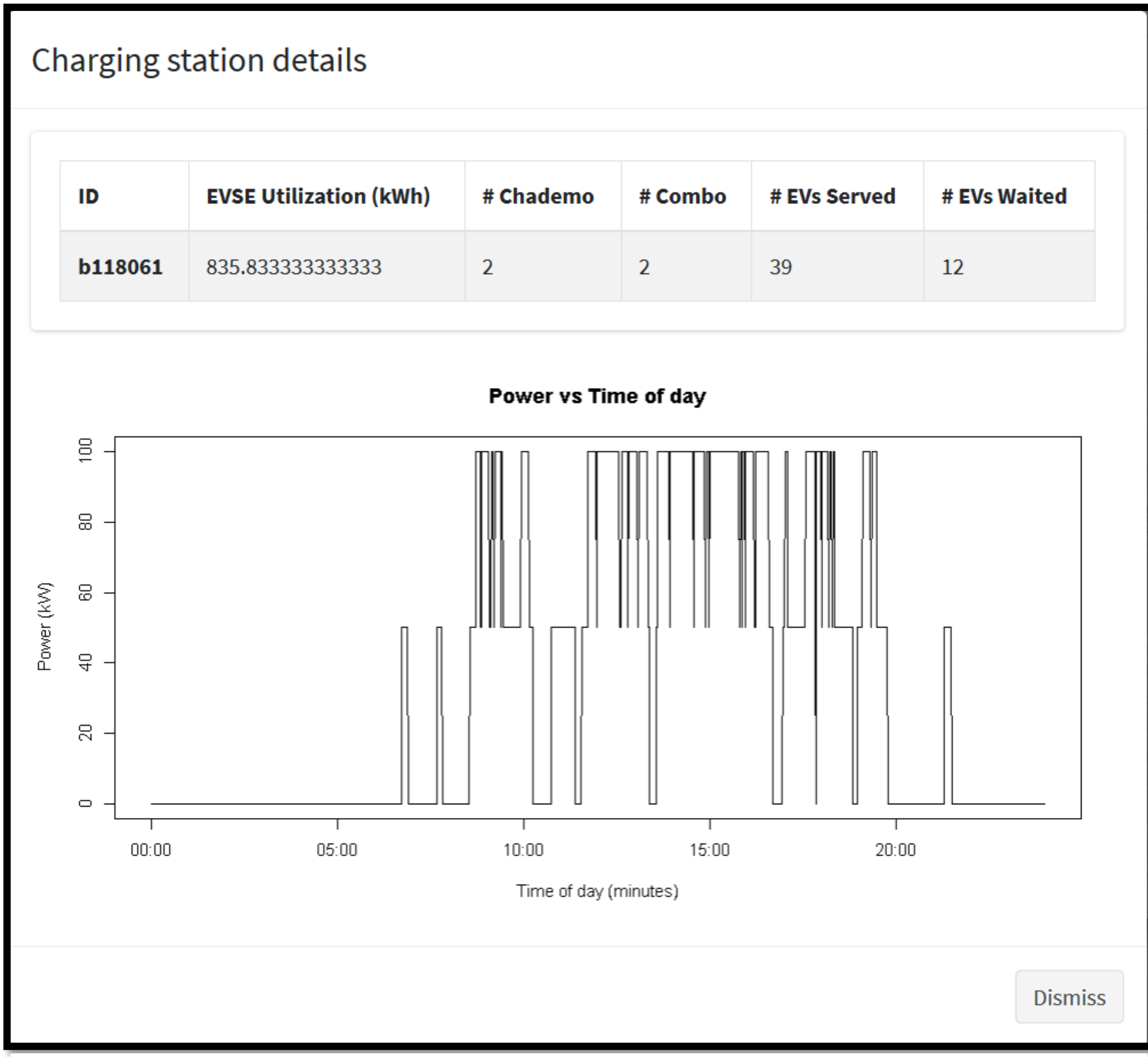


Figure 11: EVI-ABM Results Viewer - EVSEs



Charging station details

ID	EVSE Utilization (kWh)	# Chademo	# Combo	# EVs Served	# EVs Waited
b118061	835.833333333333	2	2	39	12

<u>Controller</u>

The controller is the application that manages the execution of a simulation process when a new analysis request is made. Because of the multi-user nature of EVI-DSS, many users may simultaneously submit analysis execution requests. The controller queues the analysis requests and allocates the available resources. The controller is called the "Simulation Manager," and workflow for it is described in Figure 13.

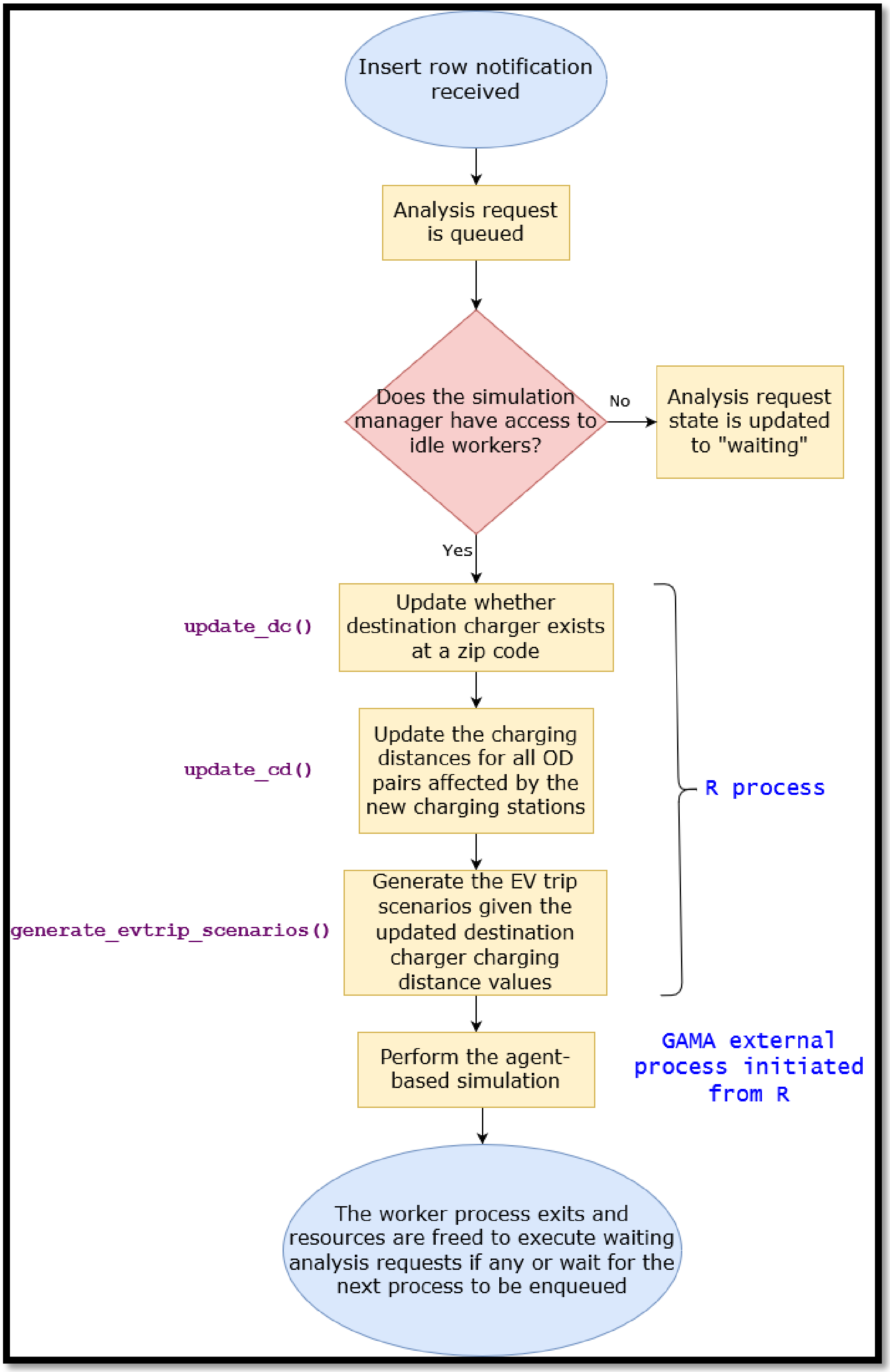


Figure 13: Simulation Manager workflow

Benefits of MVC Architecture

Model-view-controller (MVC) is a popular architecture for complex applications. The benefit in this case is that users can deploy all the component applications of EVI-DSS—namely the database, the EV Infrastructure Designer, the Results Viewer, and the Simulation Manager—on one machine, or they can deploy them across several machines, allowing the application to scale as needed. The modular nature of the EVI-DSS allows users to maintain the application with ease, and developers can work on one component without affecting the others. This also makes deployment easier, as the components can all be contained.

CONCLUSIONS

This report presents an agent-based framework for assisting in EV infrastructure siting. The aim of the EVI-ABM is to aid in investment decisions for EVSE siting. The EVI-ABM is programmed to output multiple system states, including EVSE power and energy utilization, long distance electric VMT, etc. The flexible nature of the ABM framework allows modelers to test multiple policy objectives, for example, how EVSE utilization changes when charging stations are placed at all locations so that all EV trips in Washington are feasible. Furthermore, the nature of the ABM allows for future integration of other models and systems that are related to EVs and EV infrastructure, for example, how the availability of EVI affects EV adoption and vice-versa, or how an increase in EVMT affects the electric grid load. The EVI-ABM does not come without limitations, though. The ABM and supporting models have significant computational requirements, making re-evaluation non-instantaneous. Also, while the EVI-ABM can compare multiple scenarios for EVI siting, an optimal solution for EVI siting is computationally intractable in the current formulation. Finally, any EVI siting solution will only suggest macro-level location, for example, a ZIP code or highway exit. The exact location and orientation of EVI sites are difficult to determine with certainty because of external factors such as the availability of land, power, and other factors.

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