Fast Charging Infrastructure for Electrifying Road Trips to and from National Parks in the Western United States

Dong-Yeon Lee, Kaylyn Bopp, Matthew Moniot, and Alicen Kandt

National Renewable Energy Laboratory

NREL is a national laboratory of the U.S. Department of Energy
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List of Acronyms

AADT	annual average daily traffic
ADOPT	Automotive Deployment Options Projection Tool
ATO	always topping off
BEV	battery electric vehicle
CARB	California Air Resources Board
CDF	cumulative distribution function
DCFC	direct current fast charging
DOT	U.S. Department of Transportation
ECR	energy consumption rate
EEI	Edison Electric Institute
EIA	U.S. Energy Information Administration
ESC	energy storage capacity
EVI-Equity	Electric Vehicle Infrastructure for Equity
EVI-RoadTrip	Electric Vehicle Infrastructure for Road Trips
FASTSim	Future Automotive Systems Technology Simulator
LR-Car	long-range car
NLUD	National Land Use Data
NPS	National Park System
NREL	National Renewable Energy Laboratory
O-D	origin-destination
OSM	OpenStreetMap
OSRM	Open Source Routing Machine
PDF	probability distribution function
PUT	pickup truck
SOC	state of charge
SR-Car	short-range car
SUV	sport utility vehicle
TPM	time penalty minimization
TSDC	Transportation Secure Data Center

Executive Summary

National parks in the western United States draw more than 80 million visitors every year, and most visitors rely on personal cars for their road trips (i.e., long-distance travel) to/from those parks. Travel to national parks represents distinct travel demand because the parks are typically located in remote areas necessitating long-distance trips. This study investigates the quantity and locations of on-route fast charging infrastructure needed by 2030 to enable seamless travel to/from national parks using electric vehicles in seven target states in the region by employing unprecedented high-resolution spatial and temporal analysis. We find that the required number of fast charging ports for on-route charging infrastructure ranges from 1,200 to 22,000, depending on different assumptions of key input parameters—vehicle electrification rate, charging behavior, average gap between charging stations, port utilization rate, and whether the vehicle is towing a trailer. Our analysis also indicates that electrical load for on-route fast charging infrastructure would peak in the afternoon, ranging from 70 MW–400 MW, varying with the key input parameters. This study illustrates how different input parameters result in different degrees of impact on various aspects of the charging infrastructure, illuminating the complexities that planners or decision makers would need to navigate when designing charging infrastructure for electrified road trips. We also examine the characteristics of the projected charging infrastructure in terms of land use type, relationship with traffic volume, the size of charging stations, and other variables.

Table of Contents

List of Figures

List of Tables

1 Introduction

1.1 Electrification of Long-Distance Travel

The rate of electric vehicle adoption in the United States is rapidly increasing. A decade ago, there were approximately 0.05 million plug-in electric vehicles in the United States (AFDC 2020; Bureau of Transportation Statistics 2022a), accounting for merely 0.02% of all light-duty vehicles (230 million) on the road (Bureau of Transportation Statistics 2022b). During the past 10 years, however, the sales share of plug-in electric vehicles in the United States has soared to 7% (Mock and Yang 2022; PwC 2023). Today, approximately 1% of all light-duty vehicles (250 million) (Bureau of Transportation Statistics 2022b) on U.S. roads are plug-in electric vehicles (Blanco 2022)—a 5,000% increase from 2012 to 2022. Looking forward, 30%–50% of new light-duty vehicle sales in the U.S. market are expected to be plug-in electric vehicles by 2030 (IHS Markit 2021; EEI 2022; Boudway 2022), which could translate into 20–40 million plug-in electric vehicles (approximately 10% of the entire stock of light-duty vehicles) on the road in 2030.

Currently, public charging infrastructure to support this rapidly growing fleet of electric vehicles in the United States tends to be concentrated in large cities (Desilver 2021). This is, in part, a result of electric vehicles also being concentrated in large cities or population centers; the supply of charging infrastructure might naturally follow the demand (for electric vehicles). This co-located adoption of electric vehicles and the deployment of charging infrastructure helps meet charging demand and mitigates range anxiety (the fear of being stranded due to insufficient battery capacity/size) for electric vehicle drivers in and around cities.

When people purchase vehicles (electric or nonelectric), however, most consumers/drivers expect their vehicles to perform not only their daily short-distance travel in and around cities or home locations but also on occasional road trips (long-distance travel of 100 miles or more) for family visits, business, recreation, weekend getaways, and so on. Further, according to a large-scale public survey conducted by Consumer Reports, the logistics of determining when and where to charge, combined with range anxiety, are the top barriers that would prevent consumers from adopting electric vehicles (Consumer Reports 2022). Therefore, a gap of charging infrastructure between cities (unlike the heavy concentration of public charging infrastructure in large cities or population centers) is likely to cause some concerns for road trips and thus discourage potential consumers from purchasing electric vehicles.

1.2 National Parks and Charging Infrastructure

The lack of sufficient charging infrastructure connecting U.S. cities and population centers becomes even more pronounced in the western part of the country, specifically along the roads to and from national parks, which are often located in remote or rural areas. The western United States (U.S. Census Bureau 2022), excluding Hawaii and Alaska, represents approximately 20% of the U.S. population (U.S. Census Bureau 2021) but is home to approximately 30% of the approximately 500 National Park System (NPS) units (National Park Service 2002) (e.g., national parks, national monuments) in the country. The NPS units in the West draw more than 80 million domestic and international visitors annually (National Park Service 2002), more than the total number of residents (76 million) in the region (U.S. Census Bureau 2021). Each month, the region has intra-regional and out-of-region visitors—equivalent to approximately 10% of the total number of residents—traveling to and from the NPS units in its territory. This highlights the significance of the NPS units in the region and the importance of developing proper and sufficient charging infrastructure to enable and support electrified road trips to and from those NPS units. More broadly, such an effort is critical to improve fuel diversity and reduce greenhouse gas emissions across the region (Campbell 2022).

When it comes to charging infrastructure for road trips (including those to and from NPS units), the most relevant charger type is direct current fast charging (DCFC) (Burnham et al 2017; Kampshoff et al. 2022). In the case of destination charging (e.g., overnight at home, workplace, parks, retail), electric vehicles are parked for a few to several hours in one location (for reasons other than refueling), and thus they can be charged during that window of opportunity. On the other hand, for road trips, vehicles are constantly on the move most of the time (except overnight stays at hotels), and drivers would generally want to keep moving/driving while avoiding or minimizing time spent for refueling. In other words, unlike "opportunity charging" at home or a destination, on-route (or waypoint) charging is a time-sensitive activity where drivers typically seek to charge as quickly as possible. Therefore, for road trips and associated on-route (or waypoint) charging, other than overnight (opportunity) charging at hotels where Level 2 charging would be most relevant, DCFC should comprise most of the charging infrastructure.

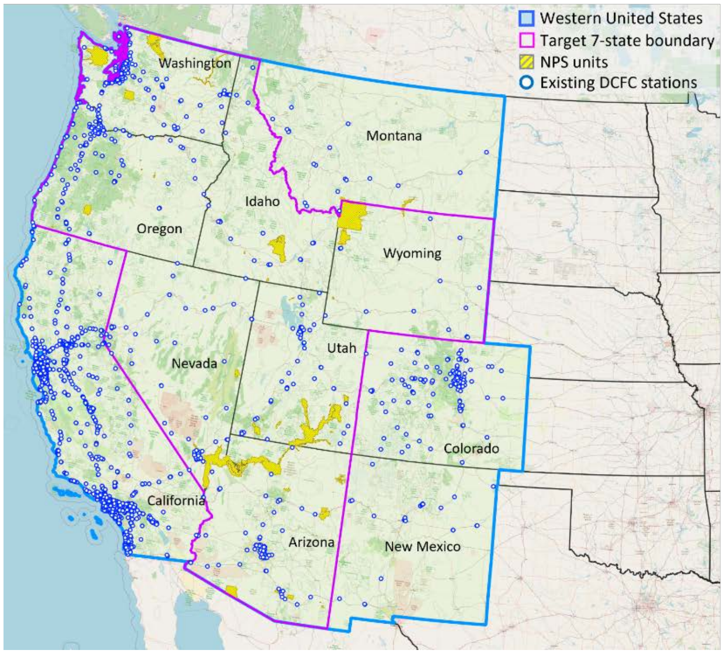
1.3 Research Objective

Given the significance of the NPS units in the western United States, as well as the importance of electric vehicles being capable of seamlessly traveling to and from the NPS units, it is crucial to develop and deploy sufficient charging infrastructure along the routes for those road trips. To that end, we investigate three key aspects of fast charging infrastructure that will enable electrified road trips to and from NPS units in the western United States.

First, we evaluate where and how many on-route DCFC ports would be needed to support electrified road trips to and from the NPS units, focusing on seven western U.S. states (Washington, Oregon, Idaho, Wyoming, Utah, Nevada, and Arizona) where NPS units are most concentrated. The seven target states (Figure 1) are home to 73 NPS units, hosting 41 million visitors annually (approximately 50% greater than the total population [28 million] in the region). NPS units in California are excluded from the analysis because multiple statewide analyses have already been conducted for the state's regulatory and planning purposes (Lee and Wood 2020; California Energy Commission 2021a, 2021b).

Second, we investigate how the on-route charging infrastructure projections might change with different assumptions around vehicle electrification rates, seasonal variations in the volume of the recreational road trips, and increased energy consumption for vehicles when towing trailers, among others.

Last, in addition to on-route DCFC infrastructure for waypoint charging, we examine how many Level 2 chargers would be needed for opportunity charging at NPS units and overnight stays at lodging locations (e.g., hotels).



State	Study Area	Human Population	NPS Units	NPS Unit Visitors (Annual)
Washington	Yes	7.7 million	15	7.3 million
Oregon		4.2 million	5	1 million
Idaho		1.8 million	7	0.7 million
Wyoming		0.6 million	7	7 million
Nevada		3.1 million	4	6 million
Utah		3.3 million	13	11 million
Arizona		7.2 million	22	7.7 million
California	No	40 million	28	28 million
Montana		1.1 million	8	4 million
Colorado		5.7 million	13	6 million
New Mexico		2.1 million	15	1.5 million

Figure 1. Target study area: (left) seven states in the western United States and (right) existing DCFC stations (AFDC 2023a), human population (U.S. Census Bureau 2021), and high-level NPS unit statistics (National Park Service 2002)

Several studies have shed light on the charging infrastructure for long-distance travel and/or highway corridors. Nie and Ghamami (2013) showed that DCFC is more relevant and cost-effective for long-distance travel and that longer range (per vehicle) reduces the required number of charging stations. Ghamami, Zockaie, and Nie (2016) highlighted the importance of minimizing queuing/congestion at charging stations and its cost implications (i.e., value of time) in addition to charging infrastructure cost. Xie et al. (2018) estimated the required number of fast chargers for electrified intercity travel in California based on 532 preselected nodes (potential sites for charging stations) across the state. He, Kockelman, and Perrine (2019) designed a network of fast charging stations along U.S. interstate highways and concluded that 250 stations can support more than 70% of long-distance travel demand when the range of electric vehicles is 100 miles, and almost 100% with a range of 150 miles. Breck et al. (2019) identified gaps in charging infrastructure coverage along highway corridors related to NPS units. Xie and Lin (2021) suggested that approximately 3,000 corridor charging stations would be needed along interstate highways across the United States by 2040, when 34% of cars on the road (approximately 95 million of 280 million) are projected to be battery electric vehicles (BEVs) (EIA 2022). Xie and Lin (2021) also showcased the importance of evaluating long-distance travel beyond the boundary of individual states or regions.

Previous studies have demonstrated that various methodologies can be applied to determine the necessary fast charging infrastructure for electrified long-distance travel. Some are based on optimization (e.g., flow-capturing location model), which is frequently adopted for the refueling infrastructure network design (Honma and Kuby 2019), whereas others use relatively simplistic approaches, including spatial gap analysis. Optimization-based methods have proven to be effective for evaluating the coverage (filling the gaps) and capacity (absorbing demands) of fast charging infrastructure for long-distance travel. The studies using optimization tend to rely on predefined nodes or points in the space domain in part due to the computational burden. The nodes/points for candidate station locations are often evenly distributed along the routes (e.g., interstate highways), and an optimal solution identifies a subset of those nodes/points for stations and determines the size of stations to absorb the refueling demands.

In this study, we approach the problem of fast charging infrastructure design for electrified long-distance travel from a slightly different angle. Rather than focusing on optimization, we employ a bottom-up and "brute force" approach by using the Electric Vehicle Infrastructure for Road Trips (EVI-RoadTrip™) tool (Lee and Wood 2020; California Energy Commission 2021b; NREL 2023a). EVI-RoadTrip, explained further in the following section, simulates individual road trips from origins to destinations at a high resolution in the space and time domain, identifies charging demands along the routes, and aggregates those charging demands within a certain radius for charging stations. By repeating this process for the entire study area, EVI-RoadTrip develops a network of fast charging stations that provide sufficient (100%) coverage and capacity. Unlike the optimization-based method, EVI-RoadTrip does not use predefined nodes/points but rather organically determines the locations and sizes of charging stations based on high-resolution trip and charging simulation as well as land use type. This allows for flexibility (e.g., exploring other types of roads, including state highways, beyond interstate highways) and improved realism (e.g., charging stations are more likely to be sited in retail and commercial areas rather than artificially predefined nodes/points that are sometimes used in optimization studies).

The contribution of our study is not methodological by any means because we do not attempt to advance methodology (e.g., optimization). Also, we do not claim that one methodology (e.g., our brute force approach) is better than others (e.g., optimization). Nonetheless, to our knowledge, no study has been performed with the level of detail and comprehensiveness present in this analysis with an emphasis on projecting infrastructure requirements to support long-distance recreational travel in electric vehicles. We also bring new data that have not been reported before for electrified long-distance travel, which will benefit future research in this space.

In summary, while using the rather simplistic brute force analysis approach using the EVI-RoadTrip tool, we evaluate the charging infrastructure needs for NPS units in the western United States by primarily focusing on three aspects: (1) the location and quantity of on-route DCFC ports needed to support electrified road trips to and from the NPS units in the western United States, (2) how on-route charging infrastructure projections change with different assumptions, and (3) the quantity of Level 2 chargers needed for opportunity charging at both NPS units and overnight stays at lodging locations (e.g., hotels).

2 Methods

2.1 EVI-RoadTrip

EVI-RoadTrip is an on-route charging infrastructure simulation tool with a particular focus on on-road long-distance travel (road trips) that was originally developed by the National Renewable Energy Laboratory (NREL) in 2020 for the California Energy Commission (Lee and Wood 2020; California Energy Commission 2021a, 2021b). The overall structure of the model is illustrated in Figure 2, and more details are provided in the following sections. Since its development, the model has been employed for regulatory analyses for California Assembly Bill 2127 (California Energy Commission 2021a; 2021b). EVI-RoadTrip is a four-step model (Lee and Wood 2020) consisting of (1) road trip volume and pattern estimation, (2) electric vehicle energy use and charging simulation, (3) charging station siting and sizing, and (4) electric grid capacity analysis. In the following sections, we explain each step, focusing on input parameters and assumptions used in this study. Note, however, that we use only the first three steps in this study, excluding electric grid capacity analysis (Step 4) due to the lack of data covering the entire western United States (our study area).

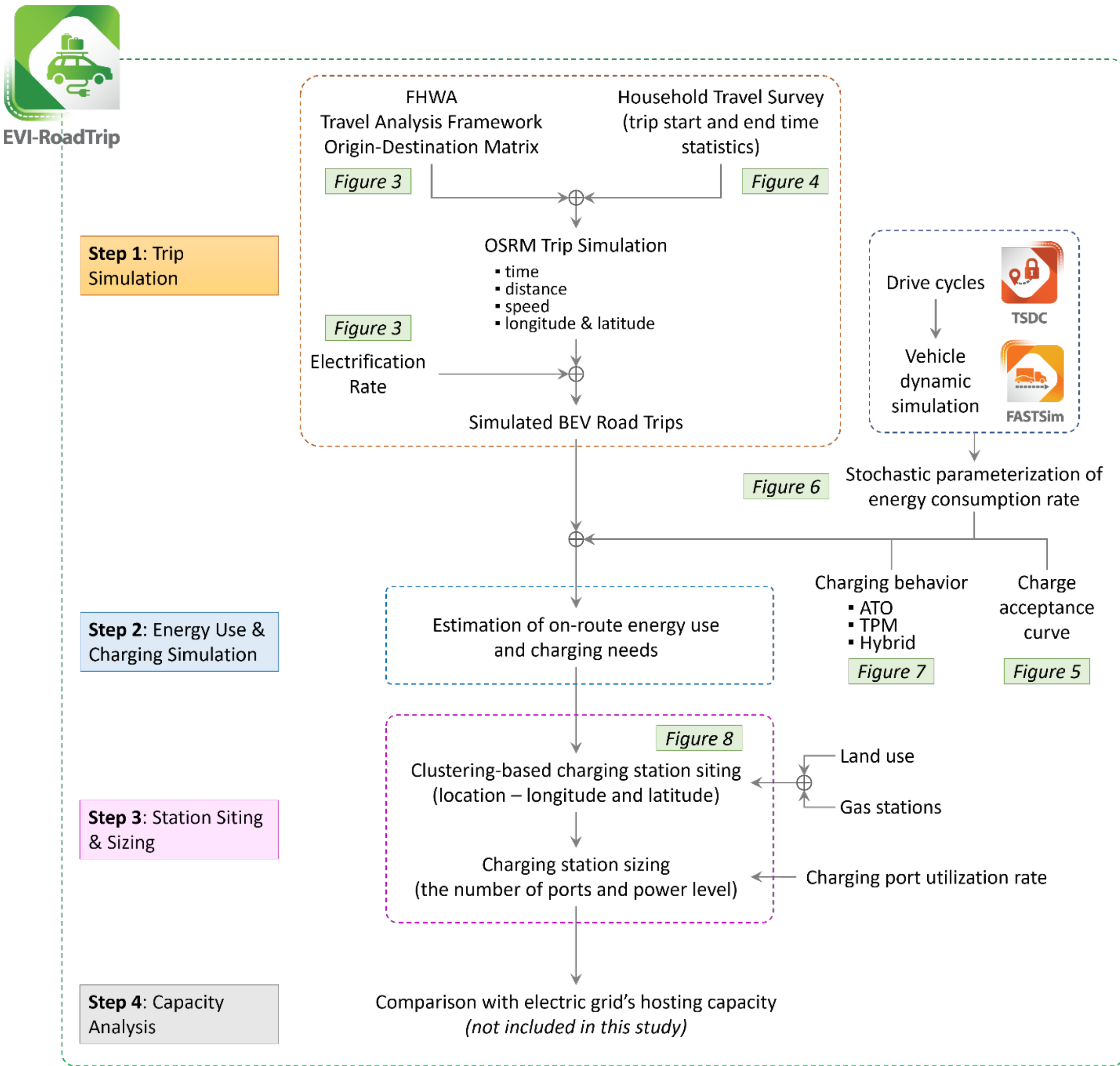
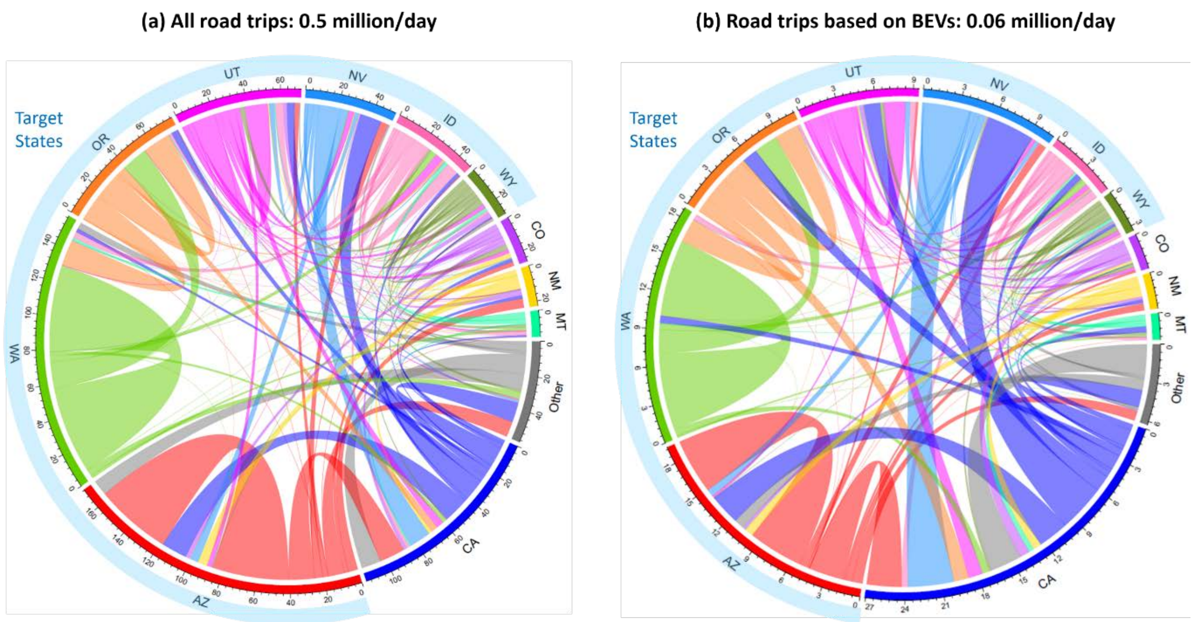


Figure 2. Schematic diagram of EVI-RoadTrip

2.2 Road Trip Volume and Pattern

For the volume and pattern of road trips, we use an origin-destination (O-D) matrix for passenger cars from the Federal Highway Administration's (FHWA's) "Traveler Analysis Framework" (2016). This includes road trips to, from, and through NPS units in addition to those that are not directly related to NPS units. Because the O-D matrix is for all types of road trips across the country, we selected O-D pairs that are only relevant to our study—those that originate from the study area of seven states (Figure 1), those for which the final destinations fall within the area, and those that pass through the area (e.g., from Los Angeles, California, to Houston, Texas). On a typical day, more than 30% of all road trips in the study area are directly associated with (i.e., originated from or destined to) NPS units (FHWA 2016). As such, the significance of NPS units in the overall road trip volume is rather unique in the western United States compared to other parts of the country.

Figure 3 illustrates the state-level characterization of the O-D pairs. We then convert the O-D pairs to those for BEVs; plug-in hybrid electric vehicles are not relevant for DCFC infrastructure as most plug-in hybrid electric vehicles on the market do not work with DCFC (DOT 2023). California is leading the country with the highest penetration of electric vehicles. Therefore, for California, we adopt a California-specific BEV penetration rate based on the California Assembly Bill 2127 analysis (California Energy Commission 2021b) and the California Air Resources Board's latest regulations (CARB 2022). For states other than California, we use the U.S. Energy Information Administration's "Annual Energy Outlook" High case (EIA 2022).



Vehicle Stock Penetration Rate (%) for BEVs by 2030	Low	High
California	10%	20%
Non-California	2%	4%

Figure 3. Road trip volume and pattern: (left) all electrified and nonelectrified and (right) electrified vehicles (based on BEVs)

We evaluate two BEV penetration scenarios (low vs. high), distinguishing between California and non-California. Although California is not part of the seven-state study area, it still has a very meaningful presence (approximately 20% of all BEV-based road trips in the seven states) for the overall analysis due to the significantly higher BEV penetration rate, as shown on the right. Arizona and Nevada have the greatest impact associated with California, which is not surprising given their physical proximity. This also illustrates why it is crucial to conduct regional/nationwide analysis—not only within the study area but also including all directly and indirectly related road trips (originating from, destined to, and passing through the study area)—when assessing the charging infrastructure for road trips.

2.3 Road Trip Simulation

Each O-D pair in the "Traveler Analysis Framework" data provides geospatial information for the start and end of the trip. We simulate the trip between origin and destination using the Open Source Routing Machine (OSRM),[1] generating the traces (longitudes and latitudes) of vehicle

[1] OSRM is free, open source, and available under the very permissive (simplified) two-clause BSD license. See https://project-osrm.org/.

movement from the origin to destination, which, in turn, translates into distance and speed for each time interval (1 minute is the default time interval in EVI-RoadTrip). Because the raw output of OSRM starts at time 0, we reset the trip start time (e.g., 10 a.m. rather than OSRM's absolute 0 in the time axis) using stochastic data for departure time based on travel surveys for long-distance travel (Lee and Wood 2020). Figure 4a illustrates the survey-based probability distribution function of the departure time for long-distance travel.

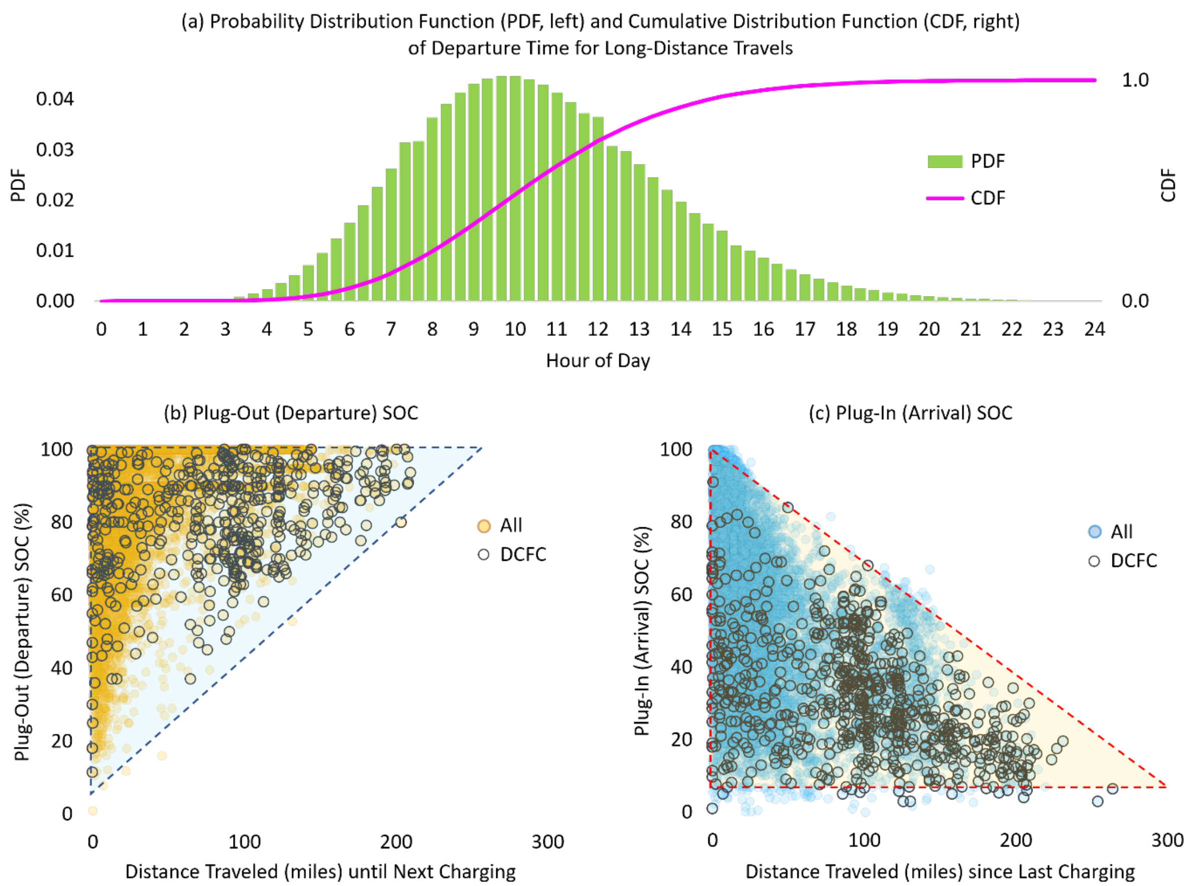


Figure 4. (Top) Probability distribution function (PDF) and cumulative distribution function (CDF) for departure time for road trips based on travel surveys on long-distance travelers. (Bottom) Empirical relationship between plug-in and plug-out SOC as a function of pre-/post-charging distance traveled/driven

The filled circles for "All" include both Level 2 and DCFC, whereas the empty circles are only for DCFC. Including Level 2 improves the sample size (particularly for ranges of 30 miles or less) but does not significantly affect the simulation because the overall pattern does not change, especially for long-distance travel (100 miles or more).

Once traces of vehicle movement in the space and time domain are set as such, we then pair each trip with one of the three types of BEVs used in the Assembly Bill 2127 analysis: short-range cars (SR-Car), long-range cars (LR-Car), and sport utility vehicles or pickup trucks (SUV/PUT)—see Table 1. SR-Car is assumed to have 150 miles (with a 40 kWh battery) of nominal range per full charge for current model years and 170 miles (45 kWh battery) for model year 2030. For LR-Car, these are 350 miles (with a 100 kWh battery) and 450 miles (125 kWh battery), respectively. For SUV/PUT, we used 300 miles (100 kWh battery) and 400 miles (125 kWh battery) as our respective assumptions. After pairing one trip (O-D) with one vehicle, we assign a unique vehicle identification to that pair and track each vehicle's minute-by-minute location (longitude and latitude), speed, energy consumption rate (ECR), charging demand, and charging power (when charging).

Table 1. Assumed BEV Characteristics by Vehicle Type and Model Year in 2030

Attribute	BEV Type	Model Year 2020 or Older	Model Year 2025	Model Year 2030
Vehicle fleet (or stock) share[a]	SR-Car	11%	7%	5%
	LR-Car	16%	21%	18%
	SUV/PUT	2%	10%	10%
Nominal ECR (kWh/mile)	SR-Car	0.27	0.26	0.26
	LR-Car	0.29	0.28	0.28
	SUV/PUT	0.41	0.4	0.4
Battery capacity (kWh)	SR-Car	40	45	45
	LR-Car	100	125	125
	SUV/PUT	130	160	160
Nominal range (miles)	SR-Car	150	170	170
	LR-Car	350	450	450
	SUV/PUT	320	400	400
DCFC peak power (kW) – see Figure 5	SR-Car	55	120	180
	LR-Car	100	220	320
	SUV/PUT	150	250	350

[a] The sum of all vehicle types (SR-Car, LR-Car, and SUV/PUT) and model years (2020 or older, 2025, and 2030) is 100% for calendar year 2030.

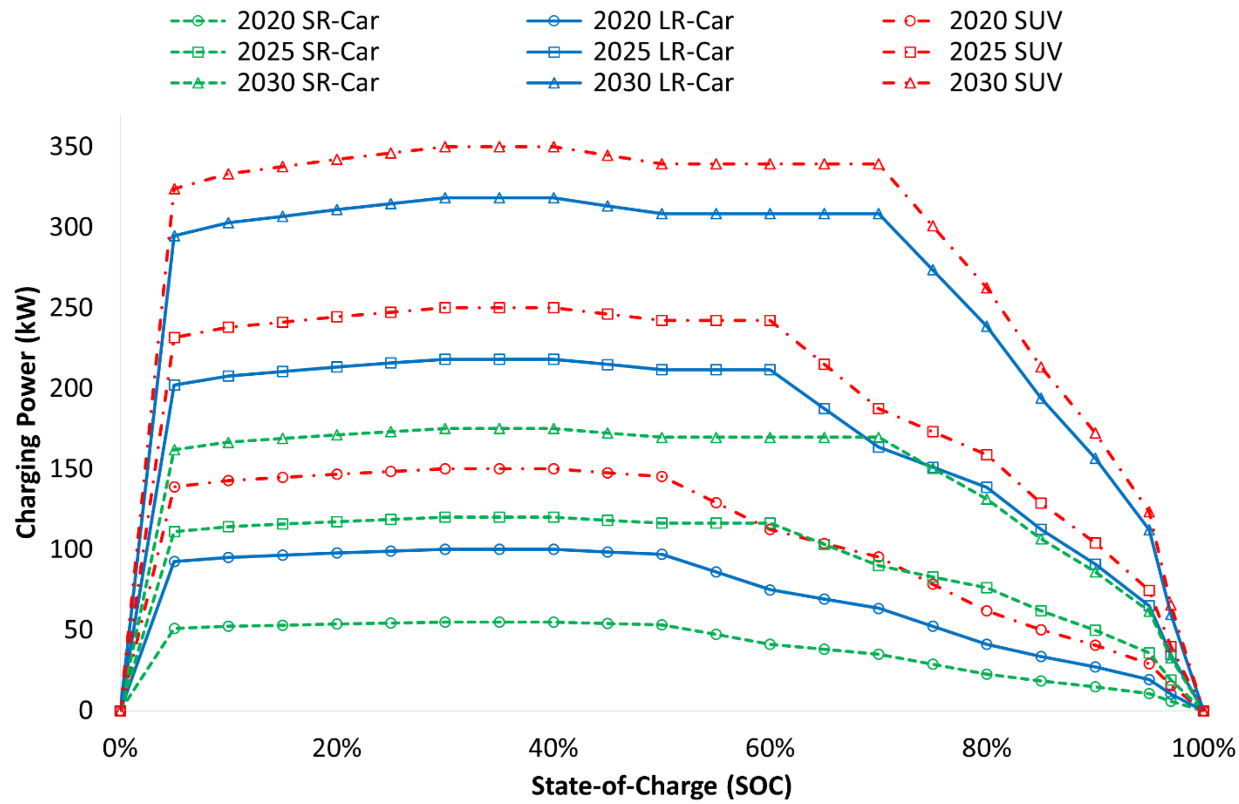


Figure 5. The level of DCFC power that BEVs can accept at charging stations varies with vehicle type (e.g., long-range SUV vs. short-range small car), model year (2020 vs. 2030), etc.

The charge curves shown here were developed with industry stakeholder input to capture the vehicle charging power (kW) as a function of battery SOC. Charging power (kW) varies with the level of SOC, BEV type, and model year. One of the most significant effects of the relationship between SOC and charging power is charging speed. For the same initial and final SOC, a higher charging power will result in a shorter charging session. Charge curves illustrate how the vehicle charging power (kW) changes as a function of battery SOC. These DCFC charge curves were developed for three classes of vehicles on 5-year intervals for the model years. In general, charging power significantly decreases around 80% to 85% SOC.

2.4 Energy Use and Charging Simulation

Charging demand along the route of road trips mainly depends on the preferred initial departure or final arrival state of charge (SOC) as well as the evolution of on-route SOC between the origin and destination. This is affected by on-route vehicle energy efficiency and driving conditions (e.g., speed, temperature, terrain), among others.

Initial departure and final arrival SOC values determine the boundary conditions in terms of energy consumption and corresponding charging needs for road trips. For the initial departure SOC, we use the empirical plug-out (departure) SOC data, shown in Figure 4b. Our empirical electric vehicle charging data (Lincoln Electric System 2020) indicate that plug-out (departure) SOC is a function of the total distance (miles) traveled after charging. In other words, the long-distance travelers know that they will drive hundreds of miles, so they tend to start their trips with higher SOCs to have sufficient driving range. A similar pattern is observed for plug-in (arrival) SOC—the longer the distance traveled since the last charging event, the lower the SOC when drivers plug in (Figure 4c). Therefore, employing the two-dimensional relationship (including the variation) between plug-in/plug-out SOC and between-charging travel distance, characterized in Figure 4b and Figure 4c, we perform two-dimensional random sampling based on a uniform distribution for plug-in/plug-out SOC.

With the boundary conditions for the initial and final SOC set as such, we then estimate on-route (between origin and destination) energy consumption and corresponding charging demands. For the on-route ECR (kWh/mile), we employ the Automotive Deployment Options Projection Tool (ADOPT) (NREL 2023b), real-world drive cycle data from the Transportation Secure Data Center (TSDC) (NREL 2023c), and the Future Automotive Systems Technology Simulator™ (FASTSim™) (NREL 2023d) model, as depicted in Figure 2. The ECR is fundamentally a function of vehicle attributes (e.g., vehicle weight, battery size) and driving conditions, which can be formulated using the vehicle dynamic equation:

$$ECR = \frac{\int_{T_0}^{T_0+\Delta T}\left[\left(m\times a+C_{RR}\times m\times g+\frac{1}{2}\times\rho_{air}\times A_f\times V^2\right)\times V\right]dt}{\int_{T_0}^{T_0+\Delta T} V dt} \quad (1)$$

where T_0 is the initial or reference point in time, ΔT is the elapsed time, m is the vehicle mass (kg), a is the acceleration (m/s^2), C_{RR} is the rolling resistance coefficient, g is the gravitational acceleration, ρ_{air} is the air density (kg/m^2), A_f is the frontal area (m^2) of the vehicle, and V is the vehicle speed (m/s). Acceleration (a) and speed (V) would be represented by drive cycles (speed–time trace), and the other variables would be associated with vehicle attributes.

Because EVI-RoadTrip is based on the time interval of 1 minute, instead of trying to solve the vehicle dynamic equation (Eq. 1), we take a parametric and stochastic approach. For this, first, we simulate the energy consumption of electric vehicles for thousands of real-world drive cycles available in TSDC, using FASTSim, a physics-based, high-fidelity, vehicle dynamic simulation model. The vehicle dynamic simulation results are then used to create a parameterized stochastic relationship between the ECR and the vehicle speed for the EVI-RoadTrip model, as illustrated in Figure 6. The overall process of the vehicle dynamic simulation and parameterization is based on the work by Lee and Thomas (2017). In addition to the ECR, which is attributable to vehicle characteristics and drive cycles, EVI-RoadTrip considers accessory load for heating, ventilating, and air conditioning based on Lee et al.'s (2018) method, which can be relatively significant for electric vehicles in extreme climate (hot/cold) conditions that are prevalent in the study area.

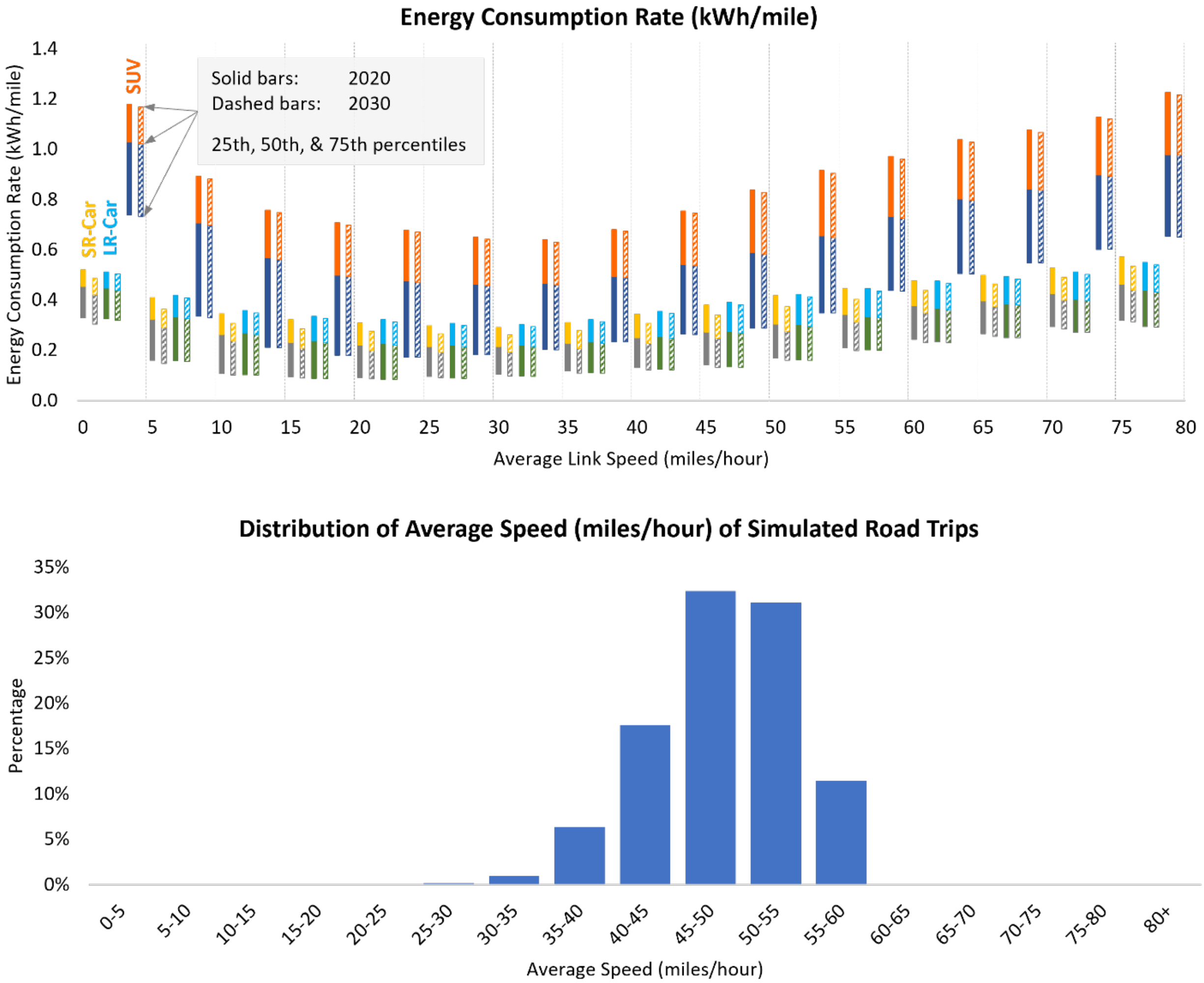


Figure 6. (Top) ECR (kWh/mile) for three different BEV types (SR-Car, LR-Car, and SUV/PUT) for different model years (2020 and 2030). (Bottom) Average speed (miles/hour) distribution for simulated road trips

The parameterized and stochastic approach converts Eq. 1 to the following discrete equation for the ECR estimation in EVI-RoadTrip:

$$ECR_k = \left\{[f(\bar{V}_k) \approx ECR] + \left[\frac{\bar{P}_{HVAC} \times \Delta T}{D_k}\right]\right\} = \left[f(\bar{V}_k) + \frac{\bar{P}_{HVAC}}{\bar{V}_k}\right] \quad (2)$$

$$D_k = \bar{V}_k \times \Delta T \quad (3)$$

where ECR_k, $\bar{V}_k$, and D_k are the ECR (kWh/mile), the average speed (miles/hour), and the distance traveled (miles) at the k-th moment, respectively. Recall that EVI-RoadTrip is based on minute-by-minute resolution; $f(\bar{V}_k)$ is a stochastic distribution of ECR corresponding to $\bar{V}_k$ (shown in Figure 6), and $\bar{P}_{HVAC}$ is the heating, ventilating, and air-conditioning load (kW)—see Lee et al.'s (2018) work. With Eq. 2, EVI-RoadTrip stochastically estimates the ECR at each time interval as a function of driving conditions (e.g., average vehicle speed) at that time interval, which is built upon sophisticated vehicle dynamic simulation and real-world drive cycles, as mentioned.

Figure 7 (left) shows the simulated trip-by-trip ECR (aggregated for the entire trip, $\frac{\sum ECR_k \times D_k}{\sum D_k}$, from the minute-by-minute ECR estimation) for three types of BEVs as a function of the overall average trip speed (miles/hour) as a simple proxy of driving conditions. It clearly shows why it is important to account for different vehicle types and driving conditions, especially for road trips that tend to have higher average speed when driving predominantly on highways rather than local/urban roads that have slower vehicle movement.

It is possible that some BEVs tow trailers, which can lead to increased energy consumption, shorter range, and thus more frequent charging. It is highly uncertain, however, how many or what percentage of BEVs will tow trailers, what types of BEVs are likely to tow trailers for road trips, and what types of trailers (shapes and weight) will be towed. Therefore, as a bounding sensitivity case, we consider a scenario in which all BEVs tow trailers, assuming a doubled ECR (kWh/mile), based on real-world BEV tests (Evans 2021; Vanderwerp 2022). Road trips will consist of a mix of BEVs that tow trailers and those that do not, but no empirical data are available to reasonably and accurately characterize that element. For that reason, we use two extreme scenarios: one in which all BEVs tow trailers and the other in which no BEVs tow trailers.

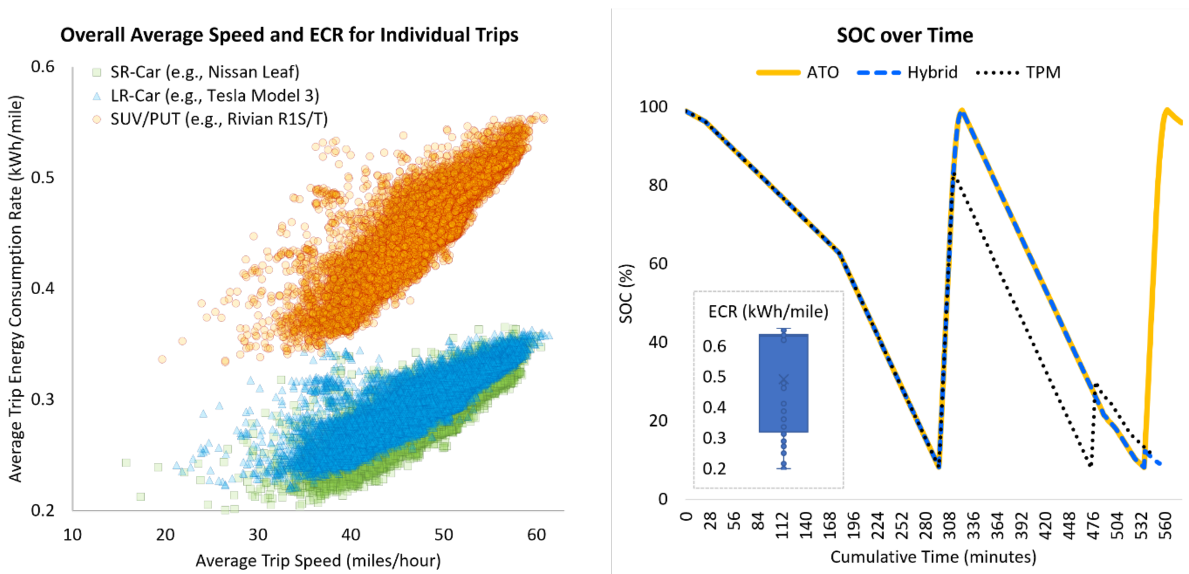


Figure 7. (Left) ECR (kWh/mile) for each trip simulated in the spectrum of average trip speed. (Right) Example of the evolution of SOC throughout the trip, illustrating the three different charging behaviors evaluated: always topping off (ATO), time penalty minimization (TPM), and hybrid

As shown in the scatter plot for ECR on the left, higher-speed driving, relevant for road trips, is more energy-intensive due to aerodynamic drag that increases with the square of vehicle speed. The box and whisker plot on the bottom left shows ECR evolution throughout the trip, which determines the SOC and thus charging demand (in addition to charging behavior, which is mainly associated with personal preferences or sensitivity to range and the value of time).

Given the doubly higher ECR, one might think that towing trailers could be equivalent to a scenario with doubly higher BEV penetration, but this is not the case. For example, if all BEVs were charging every 200 miles without towing trailers, they would now need to stop every 100 miles when towing trailers due to the doubly higher ECR (for the same battery capacity). On the other hand, all things equal, if we have double the number of BEVs on the road without towing trailers, we will only have double the charging demand every 200 miles. In other words, towing trailers and BEV penetration rate are expected to have different impacts on charging demands and infrastructure. That is why we consider two scenarios separately: towing trailers (leading to doubly higher ECR) and different BEV penetration rates (low vs. high in Figure 3).

ECR is one of the key contributing factors that influence SOC at the k-th moment of road trips (SOC_k), along with the distance traveled (D_k) and energy storage capacity (ESC), which can be summarized as follows:

$$SOC_k = \frac{\sum_0^k ECR_k \times D_k}{ESC} \tag{4}$$

Based on the evolution of SOC_k at each (k-th) moment between origins and destinations, we then determine whether to charge (or plug in) the vehicle, and if charging is already initiated, whether or when to terminate the charging (or plug out). For the plug-in, the decision ($S_{k_{plug-in}}$) is based on the minimum SOC, meaning that vehicles would continue to travel without stopping for charging as long as SOC_k is greater than the minimum threshold (SOC_{min}). This can be formulated as:

$$S_{k_{plug-in}} = \begin{cases} True & SOC_k \leq SOC_{min} \; (\neq SOC_{req}) \\ False & otherwise \end{cases} \tag{5}$$

Here, SOC_{min} is the sum of the 5% absolute minimum threshold (for the so-called “turtle” mode) and SOC that would allow the vehicle to travel to the nearest charging station. Once the charging event occurs (for $SOC_k \leq SOC_{min}$), we assume that the vehicle will remain plugged in until it reaches the plug-out SOC threshold (SOC_{req}), which varies with the charging behavior, which, in turn, might depend on the individual driver’s preferences, total travel distance, vehicle type, etc.:

$$S_{k_{plug-out}} = \begin{cases} True & SOC_k \geq SOC_{req} \; (\neq SOC_{min}) \\ False & otherwise \end{cases} \tag{6}$$

To account for potential heterogeneity in charging behavior, we incorporate three different scenarios (Lee and Wood 2020): always topping off (ATO), time penalty minimization (TPM), or hybrid (somewhere in between ATO and TPM). The three charging behavior scenarios are illustrated in Figure 7 (right).

In ATO, whenever a vehicle is charged, it is always fully charged (“topped off”). Related to Eq. 6 for the plug-out decision variable, this ATO charging behavior can be formulated as:

$$SOC_{req,ATO} \approx 100\% \tag{7}$$

For DCFC, however, the charging speed (or power) significantly drops at high SOC (e.g., 80% or higher). Stated differently, gaining an additional 1% SOC at 95% SOC could take exponentially longer than adding 1% SOC at 60% SOC (Petrovsky 2021). For that reason, some drivers might terminate their charging session around the optimal SOC that gives them the fastest charging speed for the overall charging session, which will then help reduce their overall travel time. We call this scenario time penalty minimization (TPM), which is very relevant for our analysis, given the fact that people tend to want to minimize the time they spend in refueling stations during road trips. Under this TPM scenario, drivers would terminate their on-route charging sessions once the SOC_k reaches 80%. Using the same logic (minimizing the time spent in refueling stations), however, it does not make sense for drivers to charge their vehicles to 80% when they know that they would need only an SOC of approximately 40% to get to their destination. Therefore, for the last charging event (near the destination), we assume that drivers will terminate their charging sessions once the SOC_k reaches the level ($SOC_{req,dest}$) that will allow them to get to the destination that is $D_{remaining}$ miles away. This charging behavior (TPM) can be formulated as:

$$SOC_{req,TPM} = \begin{cases} min\left(80\%,\ SOC_{req,dest}\right) & the\ last\ charging\ event\ in\ the\ trip \\ 80\% & otherwise \end{cases} \tag{8}$$

$$SOC_{req,dest} = \frac{\frac{\sum_0^k ECR_k}{k} \times D_{remaining}}{ESC} \tag{9}$$

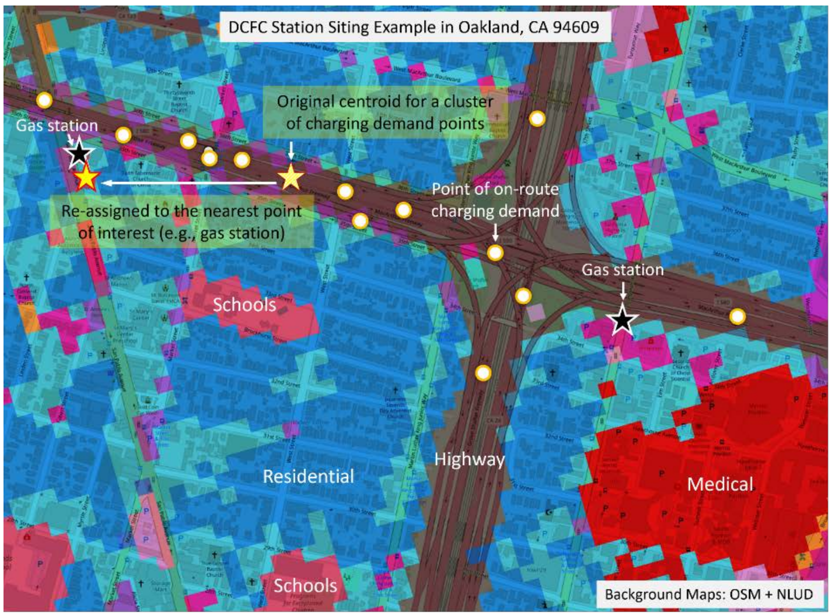
It is also possible that some people might choose to top off (ATO) in the middle of their trips, but as they near their destinations, they might choose to not spend too much time refueling and thus behave more like the TPM scenario because they know they would have more convenient charging opportunities at their destinations (e.g., home). We call this charging behavior scenario the hybrid, which can be formulated as:

$$SOC_{req,Hybrid} = \begin{cases} SOC_{req,TPM} & the\ last\ charging\ event\ in\ their\ trip \\ SOC_{req,ATO} & otherwise \end{cases} \tag{10}$$

2.5 Charging Station Siting and Sizing

Based on the trip and charging simulation in space (longitude and latitude) and time (minute-by-minute) domain described in the previous sections, we then aggregate the charging demands (points/locations where each vehicle requires charging, if any). For this, we employ the widely used k-means clustering method, which allows us to combine neighboring charging demand points within a certain radius that charging stations will serve. When combining charging demand in the proximity, we start with small clusters (e.g., groups of charging demand points within a 1-mile radius), and then we combine nearby smaller neighboring clusters (groups of charging demand points) to create larger clusters, depending on the desired cluster size (e.g., 5 miles). The final size of the clusters reflects the desired service area (e.g., 5 miles) in the analysis. This two-step clustering approach (starting with smaller clusters and aggregating them to build larger clusters as needed) provides flexibility in terms of evaluating different design values for a target service area of DCFC stations as well as the gaps between stations (e.g., 5 miles vs. 50 miles).

Once we generate the clusters (service areas of charging stations containing individual charging demands that those stations absorb), we reassign the centroid of each cluster to the nearest point of interest using National Land Use Data (NLUD) (Theobald 2014)—30-m by 30-m land use characteristics (e.g., retail, airport, highway). In addition, we use the location information for gas stations from OpenStreetMap (OSM) (2023). Figure 8 shows an example for a cluster of charging demand points along the road network in Oakland, California. The centroid of the cluster is snapped to the nearest point of interest—a gas station in this example. In general, based on the stakeholder input (Lee and Wood. 2020), we use prioritized land use or facility types, as summarized in the right side of Figure 8. Within each cluster or service area, first, we identify the nearest retail and commercial locations, including gas stations. If the search returns a useful candidate location, we reassign the center of the cluster to that point where we believe a DCFC station would be located. If the search fails to produce any candidate (meaning no retail/commercial spots), we move on to the second priority (e.g., airports, ports, rail stations) and repeat the whole process.



Priority	NLUD Code	Land Use Type
1	222	Retail or shopping centers
	224	Lodge
2	N/A	Gas stations (coordinates sourced from OSM)
3	251	Airports (developed)
	254	Port, train station
4	411	Urban park
	410	General park
5	421	Natural park
	414	Off-highway vehicle staging area or trailhead
	413	Motorized park
	223	Entertainment (stadiums)
	422	Designated recreation area
	417	Campground or ranger station
	416	Marina
	415	Resort or ski area
	418	Picnic or trailhead

Figure 8. (Left) An example of DCFC station siting—reassigning the centroid of a cluster of charging demand points along the road network to the nearest gas station (going with the second priority due to the lack of retail locations nearby). NLUD has a 30-m by 30-m resolution showing the representative land use type for each cell. (Right) List of ranked land use types and NLUD codes, including gas stations, based on OSM

After we determine the location of the station for each cluster containing a group of charging demand points for different vehicles/trips, we estimate the size of the station in terms of the number of charging ports. For this, we overlay all charging profiles (minute-by-minute charging events and power) for all charging demands within each cluster. We then determine the peak hour that has the most charging activities during the course of the day. Based on the number of simultaneous charging events during that peak hour in that station, we estimate the minimum required number of ports. In doing so, for simplicity, we do not account for queuing. In other words, we use a simplistic assumption that charging stations will meet 100% of demand, in which the utilization rate (during peak hour) of charging station/ports is 100%. That is our lower bound for the required number of charging ports. For the upper bound, we assume a scenario in which there will be excess charging ports based on a 50% utilization rate. Stated differently, when a station has 10 simultaneous charging events during the peak hour, our lower-bound estimate of station size is 10 charging ports (100% utilization rate), and the upper bound is 20 ports (50% utilization rate).

As for DCFC station sizing, note that EVI-RoadTrip estimates the number of stations and ports, as well as the power ratings of those ports. As illustrated in Figure 9, a station can have multiple ports, and a port can have multiple connectors (AFDC 2023b). As such, we distinguish between the station, the port, and the connector. Throughout this study and in EVI-RoadTrip, station size refers to the number of ports.

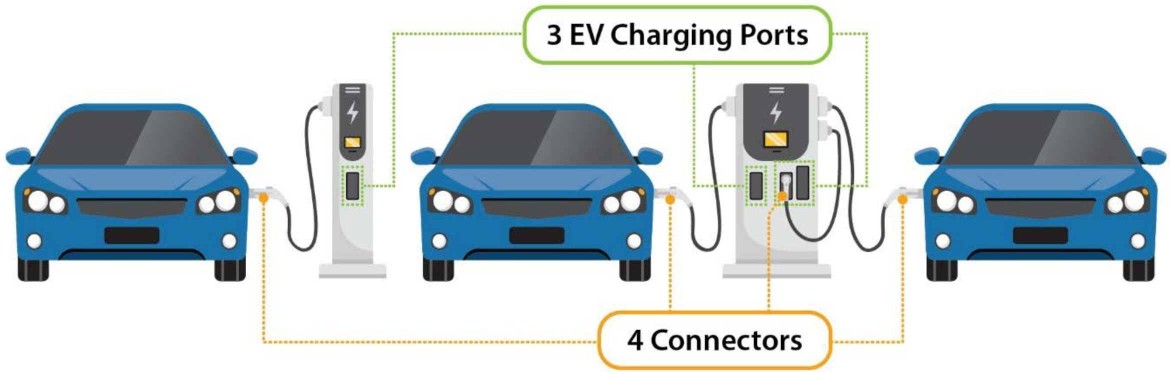


Figure 9. An illustration of a charging station that has three charging ports and four connectors

Illustration by Elizabeth Stone, NREL

When it comes to DCFC infrastructure design in EVI-RoadTrip, the results are twofold: station siting and sizing. For station siting, the results are the locations and the number of DCFC stations. For station sizing, the results refer to the number of ports for each station or the entire DCFC infrastructure network.

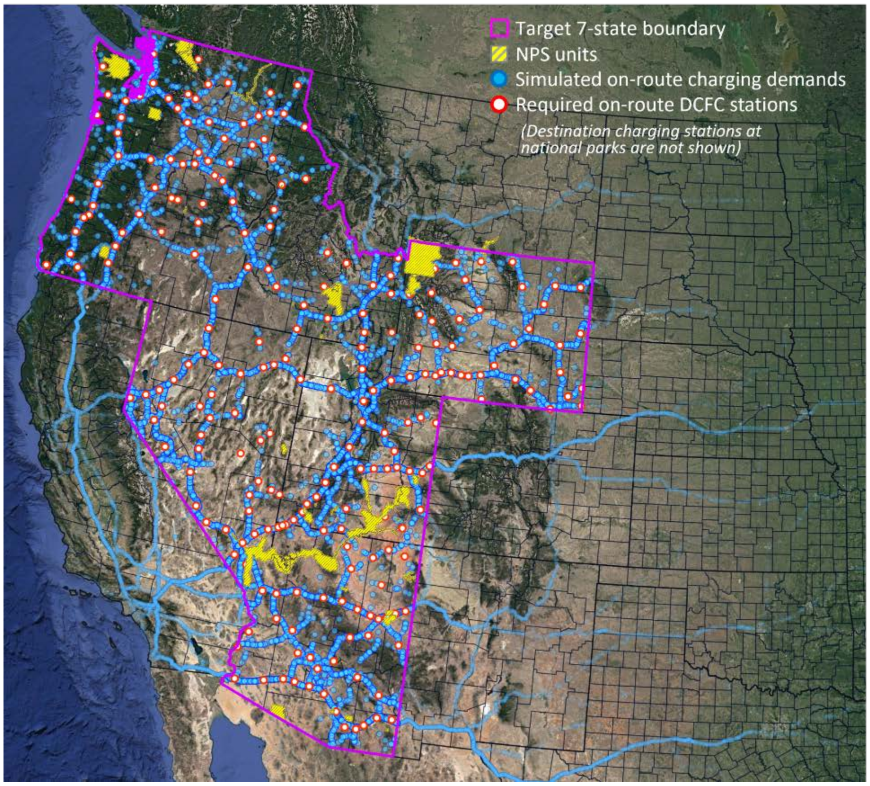
3 Results

3.1 Network of DCFC Stations

For the high BEV penetration scenario (20% in California and 4% elsewhere), we estimate that approximately 2,350–4,610 DCFC ports (depending on utilization rate—100% vs. 50%) would be needed to support the on-route charging of electrified road trips in the seven states by 2030, assuming hybrid charging behavior and 50-mile average gaps between stations. The spatial distribution of DCFC stations is shown in Figure 10, while Figure 11 illustrates the county-by-county DCFC port gap (surplus or deficit) between projected on-route DCFC ports vs. existing ones. Note that the charging demands (light blue circles) along the road network in and around the study area clearly illustrate the importance of considering inter-region road trips (in addition to intra-region) for charging infrastructure analysis. Although California is outside the study area (as indicated in Figure 1 and Figure 3), it has a significant influence in terms of charging needs in the study area. Similarly, those who travel to and from the eastern/southern United States also have a meaningful impact on the study area. The significance decreases farther from the seven states, which is reasonable.

Arizona and Utah represent the largest share of DCFC stations and ports in the study area, which is not surprising given that some of the most popular NPS units are in those two states (Figure 1); however, Arizona and Utah (as well as Nevada) tend to have a lot of through traffic, particularly between Texas and California (Figure 3). As discussed earlier, DCFC stations in our study area do not exclusively serve those traveling to, from, and through NPS units, but rather they serve both types of road trips—those that are directly related to NPS units and those that are not. That is exactly why we need to consider both types of road trips when designing a DCFC station network, especially in the western United States.

The DCFC network size varies with different assumptions around BEV penetration, charging behavior, station spacing, and utilization rate, among others. Table 2 summarizes the total area-wide number of DCFC ports required to support electrified road trips. The estimates in Table 2 significantly deviate from the 2,350–4,610 ports for one example scenario in Figure 10, which is based on the assumptions of high BEV penetration, hybrid charging behavior, and a 50-mile gap between stations. If we adopt a 5-mile gap between stations, the number of ports increases significantly (e.g., from 2,350–4,610 to 5,790–9,650). Charging behavior has a relatively smaller impact on the number of DCFC ports compared to the parameters considered for spacing between stations (i.e., 5 miles vs. 50 miles). Given the two utilization rates (100% [lower bound] vs. 50% [upper bound]) assumed in this study, one might suspect that the upper bounds would be simply twice the lower bounds, but that is not what Table 2 implies. The reason is that approximately 10% of DCFC stations simulated in this study have one port for the lower bound (100% utilization rate). For those stations, we assume that both the lower and upper bounds will have two ports rather than one for the lower bounds (100% utilization) and two for the upper bounds (50% utilization). In other words, regardless of the lower or upper bounds (tied to utilization rate), we assume that the minimum number of ports per DCFC station would be two.



Required Number of On-Route DCFC Ports in 2030
(Scenario: High BEV penetration; Hybrid charging behavior; 50-mile gap between stations)

	Lower	Upper
Total	2,350	4,620
Washington	140	270
Oregon	245	470
Idaho	140	290
Wyoming	205	400
Nevada	440	860
Utah	540	1,060
Arizona	640	1,270

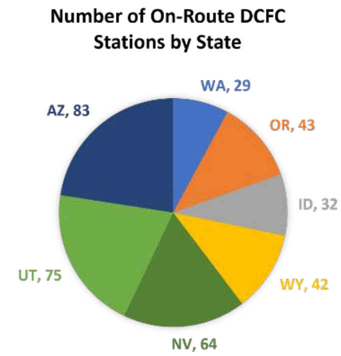


Figure 10. (Left) Simulated network of on-route DCFC stations in the seven states in 2030. (Right) The required number of DCFC ports (lower [100% utilization rate] and upper [50% utilization rate] estimates) and stations by state for one scenario (high BEV penetration, hybrid charging behavior, and 50-mile average gap between DCFC stations)

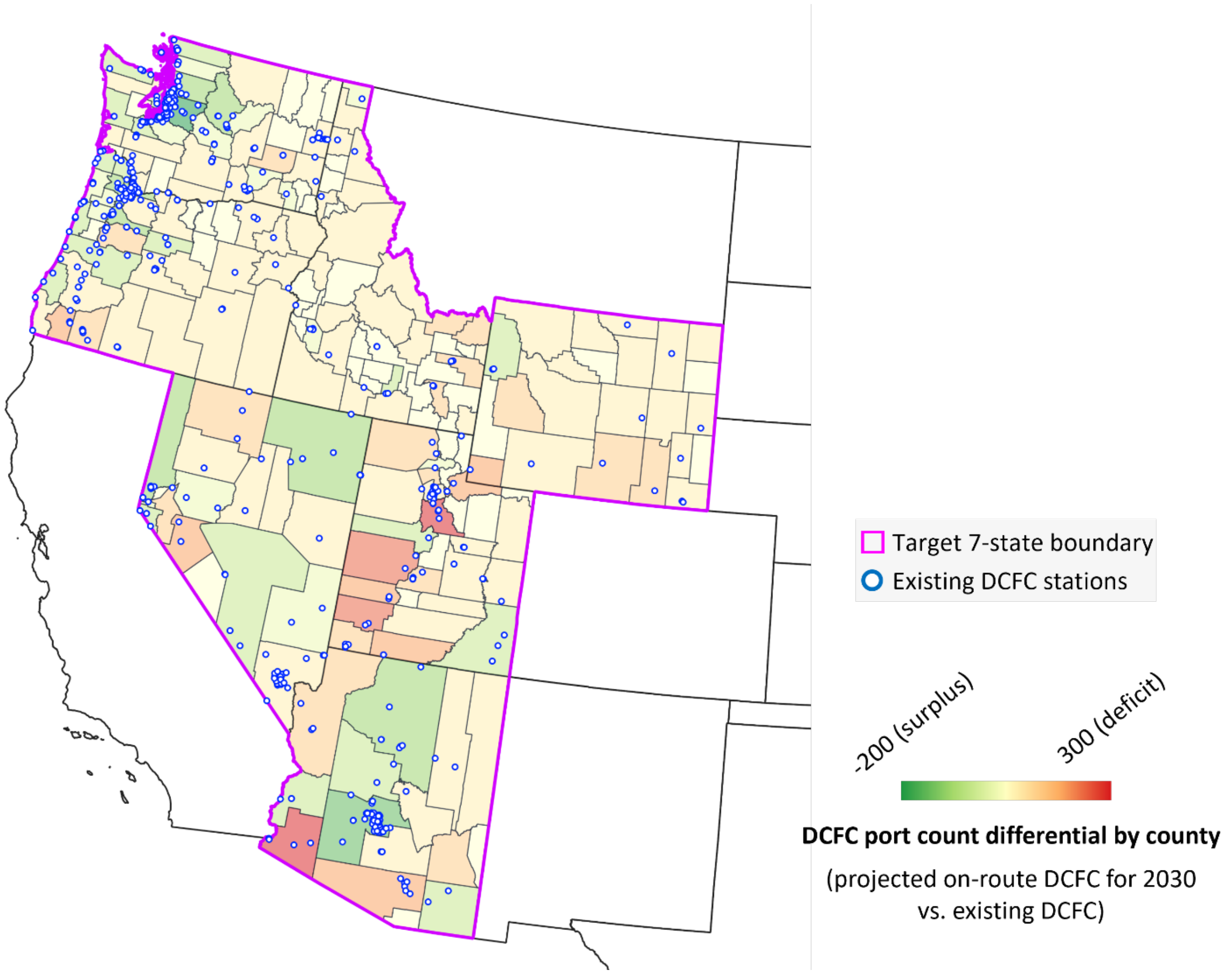


Figure 11. County-by-county DCFC port count differential (negative: surplus; positive: deficit) between projected on-route DCFC for 2030 vs. existing DCFC

Table 2. Total Number of On-Route DCFC Ports in the Study Area by Scenario

BEV Penetration	Charging Behavior	5-Mile Gap Between Stations		50-Mile Gap Between Stations	
		Lower	Upper	Lower	Upper
Low	ATO	4,290	7,110	1,850	3,650
	Hybrid	3,990	6,300	1,560	3,060
	TPM	3,750	5,790	1,230	2,400
High	ATO	6,450	11,220	2,980	5,900
	Hybrid	5,790	9,650	2,350	4,610
	TPM	5,440	8,850	1,970	3,870

Note: For the number of charging ports, the lower bound refers to an assumption of 100% port utilization rate (during peak hour), and upper bound 50% utilization rate.

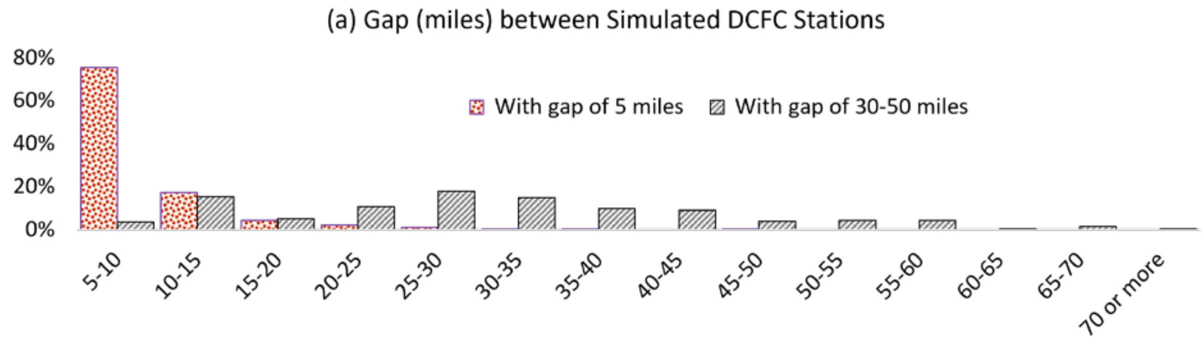
3.2 Charging Infrastructure Characteristics

We examine the characteristics of the simulated DCFC infrastructure network from several different angles, including the gaps (miles) between designed DCFC stations, the relationships between the refueling stations with the overall traffic volume around them, the land use types for the projected station locations, the size of the charging stations, and the types of BEVs that those stations serve.

Figure 12a shows the distribution of gaps for the projected DCFC station network. Each gap is a direct, unrouted distance between stations. For the 5-mile gap scenario, most stations are within 5 to 10 miles from each other. In some cases, larger gaps between stations are due to the lack of potential candidate sites (e.g., retail) nearby. In other cases, the spatial isolation of clusters also contributes to the distance being much larger than expected. For example, if a cluster is 100 miles away from the nearest cluster, and when 5 miles is the design value for the gap between stations, the model will place one station for each cluster but nothing in between the two. Although this means that the gap will exceed the design value (5 miles), it does not make sense to put stations in places that do not have nearby charging demands.

Figure 12a also shows that some stations will be within 30 miles of each other, even when the design value is 50 miles. The reason is that when there is too much charging demand nearby (within a cluster or design value for the gap), we split the station for that cluster into multiple stations so that each station does not end up with an unreasonably large number of ports (100+). This is mirrored for existing gas stations along interstate highways, in which multiple gas stations are located near the same highway exit. In general, on average, Figure 12a demonstrates the effect of design value for controlling the gaps between DCFC stations in EVI-RoadTrip.

Figure 12b depicts the relationship between the refueling infrastructure (projected and existing) and the traffic volume (annual average daily traffic [AADT]), based on the AFDC (2023a) for existing charging stations, the OSRM for gas stations, and the FHWA's Highway Performance Monitoring System (2022) for AADT. For context, I-70 in Moab, Utah, near Arches National Park, has approximately 15,000 AADT, and I-40 in Flagstaff, Arizona, near Grand Canyon National Park, has approximately 30,000 AADT, whereas I-5 in downtown Los Angeles, California, has approximately 250,000 or more AADT. In general, AADTs of 100,000 or more are typically for urban/suburban areas, and smaller AADTs are mostly associated with rural areas or parts of urban/suburban areas that have low traffic volume. In addition to the relationship between the fast charging infrastructure and AADT (Figure 12), Figure 13 shows refueling and energy infrastructure distribution by population density (Figure 14).



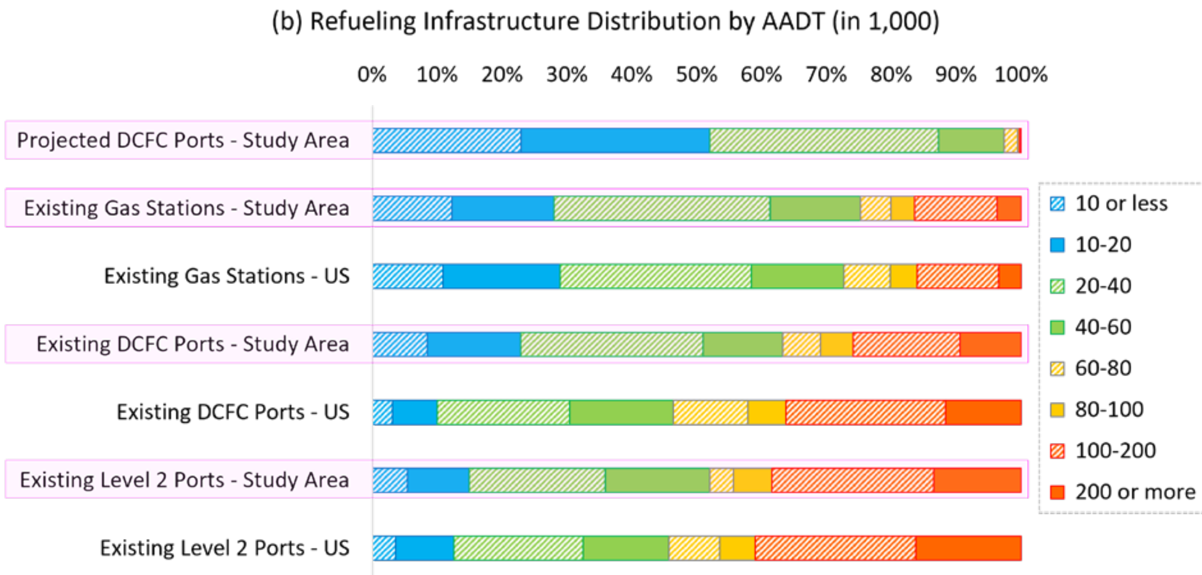


Figure 12. (a) Distribution of the gaps (miles) between DCFC stations for two different scenarios: 5 miles vs. 50 miles. (b) Relationship between the concentration of the refueling infrastructure (in the study area vs. the United States) and the AADT as a proxy of the level of vehicle activity

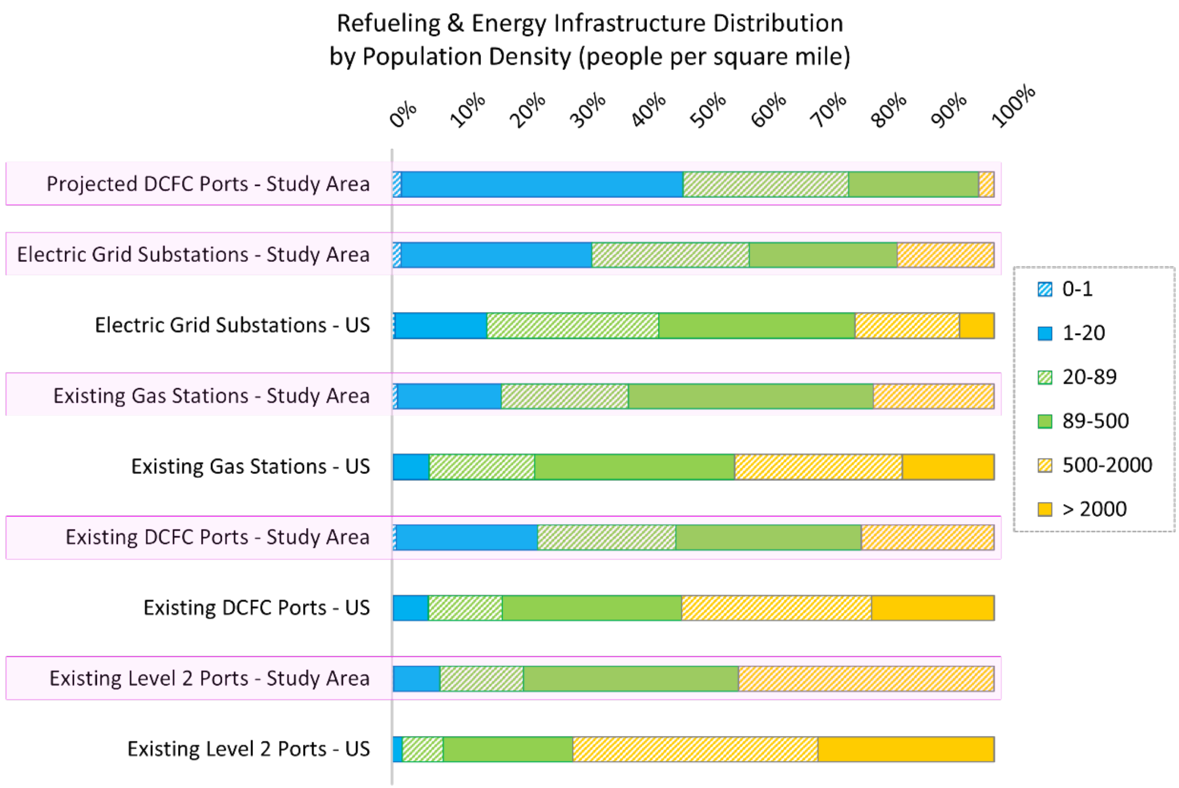


Figure 13. Relationship between the county-by-county concentration of refueling and energy infrastructure (in the study area vs. the United States) and population density (people per square mile)

County-by-County Population Density (people per square mile)

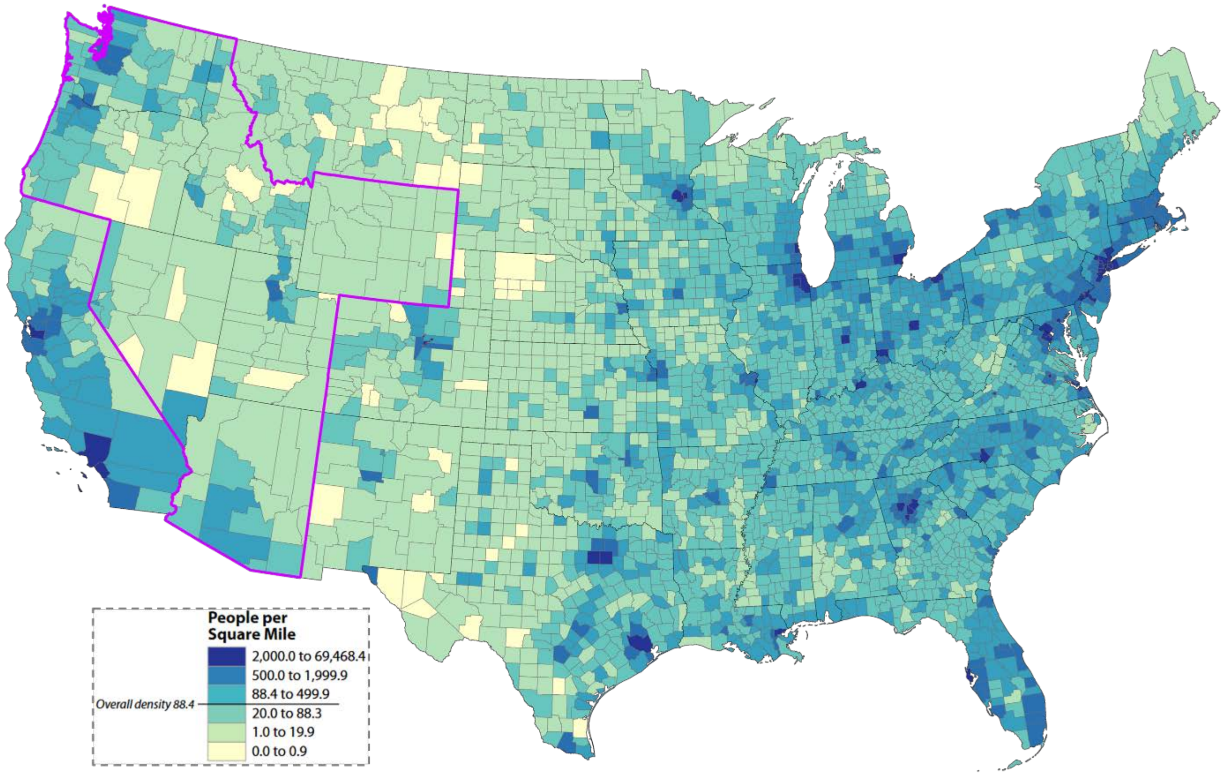


Figure 14. County-by-county population density

Data from U.S. Census (2022)

Our results indicate that projected DCFC stations in this study are predominantly located in rural areas (Figure 13 and Figure 14), which is reasonable because our study primarily focuses on on-route charging in seven states that are mostly rural. If existing gas stations are any reference point to compare, except for the highest AADT groups (e.g., 100,000 or greater, which might be more relevant for city dwellers and short-distance travelers), the relative ratio between AADT groups for our projected DCFC stations is generally similar to that for gas stations (Figure 12). This is also true for existing DCFC stations in the study area; however, the pattern significantly diverges, even for AADT groups that have 80,000 AADTs or less, for existing DCFC stations in the United States and existing Level 2 stations in the United States for our study area.

As described earlier, we identify preferred locations for DCFC stations based on land use type data (NLUD and OSM). We show the locations of simulated DCFC stations by land use type in Figure 15a and Figure 15d for 5-mile and 50-mile gaps between stations, respectively. As shown, when we use smaller (5-mile) gaps between stations, our results indicate that parks and recreational locations would be the most popular types of facilities that could be considered for siting DCFC stations for on-route charging, followed by retail and gas stations. On the other hand, when we use larger (50-mile) gaps, retail locations (followed by gas stations) would be the most preferred for DCFC stations. This might reflect the fact that having more options with greater radius (50-mile vs. 5-mile) to search the preferred facility types (listed in Figure 6) allows more flexibility for station siting.

The gap between stations affects not only the land use types that are likely to host DCFC stations for on-route charging but also the size of the stations (i.e., the number of ports). As depicted in Figure 15b and Figure 15e, the greater the gap between stations, the larger the stations become. When the gap is 5 miles on average, more than 70% of the stations are small (a few to several ports per station). On the other hand, for the average gap of 50 miles, small stations account for only 26%, and medium (several to 20 ports per station) or large (20 or more) stations comprise more than 70%. Interestingly, however, the average gap between stations does not affect the types of BEVs that the stations serve, as shown in Figure 15c and Figure 15f.

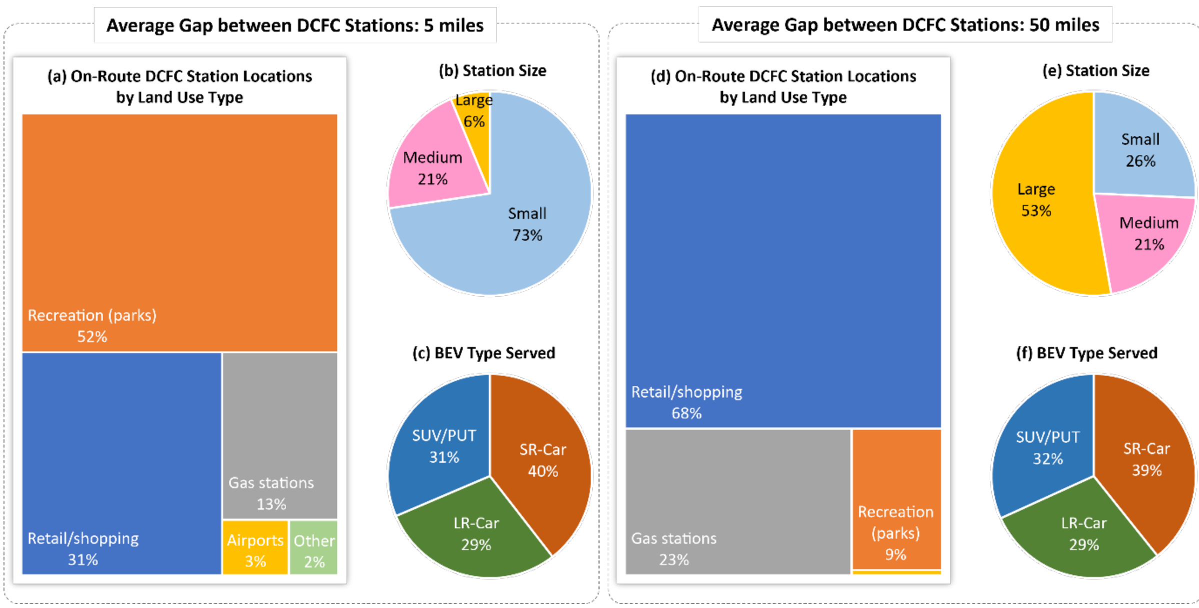


Figure 15. Land use type, station size, and BEV type served for two different settings for the average gap between stations—5 miles (left: a, b, and c) vs. 50 miles (right: d, e, and f)—for the simulated network of on-route DCFC stations in the seven states in 2030 (Figure 10)

In summary, the average gap between stations changes the dynamic for which facility types or locations are more likely to host DCFC stations for on-route charging. The gap also influences the size of the stations but not the types of BEVs that the stations collectively serve. This is reasonable considering that the design value for the gap between stations essentially determines the spatial distribution of the stations (land use type and concentration or density of ports) but not necessarily the fleet of BEVs that the network of stations serves (because the fleet will remain the same regardless of the gap between stations).

3.3 Load Profiles

In addition to the location and the size of the network of on-route DCFC stations, we estimate charging load profiles. Figure 16a shows a site-level charging load profile for one example station. As shown in Figure 16b, for this example station, most DCFC charging events occur in the afternoon, and the least occur between midnight and early morning. The station total charging load profile peaks at around 3 p.m., and the peak load is approximately 1.5 MW. We repeat the estimation of the load profile and charging events for each station in the study area by assembling individual vehicles' charging activities for the station. When we aggregate the values for all stations, we get area-wide load profiles (Figure 16c) and charging events (Figure 16d) that both peak at around 4 p.m. The peak network-wide on-route DCFC load is estimated to be approximately 140 MW, and the total number of charging events during the peak hour (4 p.m.) is approximately 800. The area-wide peak on-route DCFC load of 140 MW is roughly equivalent to 0.5% of the current electrical load for the entire northwest (35 GW on average) (EIA 2020). The results shown in Figure 16 are only for one particular scenario, and thus we explore different scenarios and the sensitivity of the results in the next section.

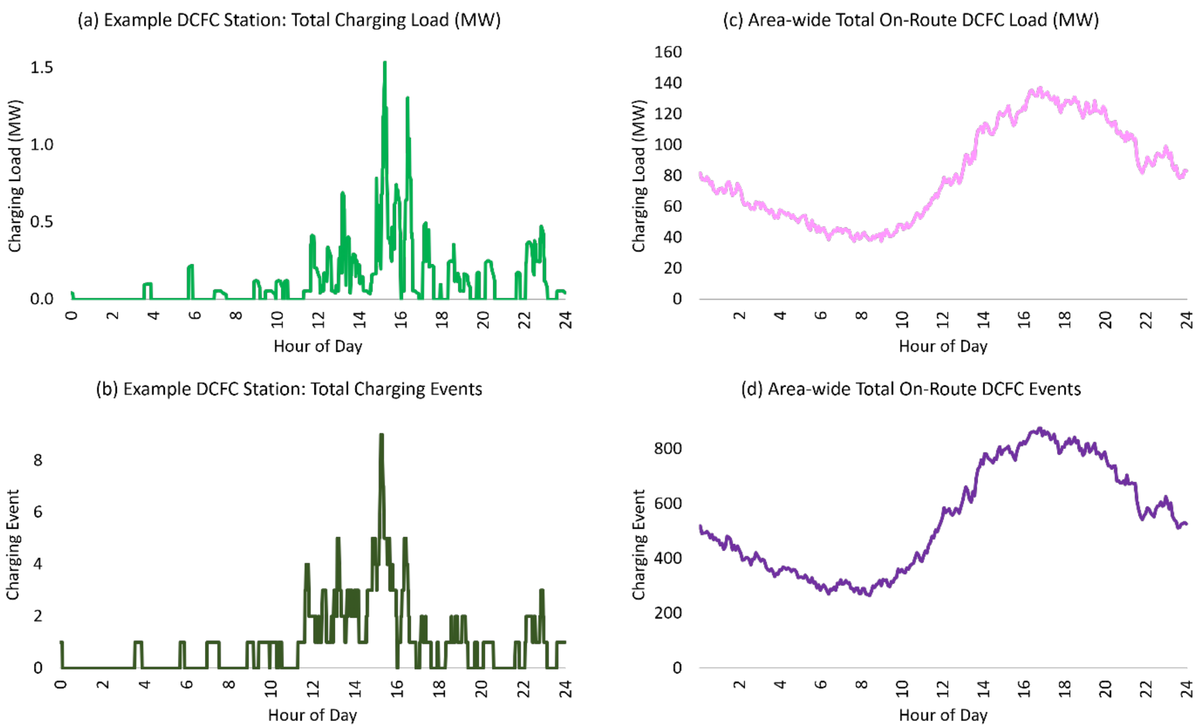


Figure 16. (a) Site-level on-route DCFC load profiles and (b) total charging events; (c) and area-wide charging load profiles and (d) total charging events for the scenario of high BEV penetration, TPM charging behavior, and 50-mile gaps between stations in 2030

3.4 Sensitivity Analysis

We assess the impact of different scenarios/assumptions around key parameters on the on-route DCFC station network in terms of the number of required ports (Figure 17a) and load profiles (Figure 17b). We compare the cases for BEV penetration rate (low vs. high), charging behavior (ATO vs. TPM), average gap between stations (5-mile vs. 50-mile), port utilization rate (100% vs. 50%), and towing trailers (doubly higher ECR).

As illustrated in Figure 17a, we estimate that we will require approximately 22,000 DCFC ports for on-route charging to support electrified road trips in 2030 if we have high BEV penetration, ATO charging behavior, a 5-mile average gap between stations, a 50% utilization rate, and all BEVs towing trailers. This is a rather extreme case (e.g., all BEVs towing trailers) for bounding analysis. All things equal, as we increase the utilization rate from 50% to 100%, the total area-wide required number of on-route DCFC ports decreases to approximately 12,000 (45% drop). Changing the charging behavior from ATO to TPM further reduces the required number of ports to a little less than 10,000. If we also assume that no BEVs tow trailers, the required number of ports diminishes by approximately 45%, similar to the magnitude of utilization rate (50% vs. 100%). As the gap between stations increases from 5 to 50 miles, the number of required ports decreases to approximately 2,000. Note that although the station gap distance has a larger impact on the number of DCFC ports required, it has a very small impact on the load profiles. This could imply that transportation system and power system managers might have some competing objectives when trying to plan for regional EV charging infrastructure. In addition, a lower BEV penetration rate leads to the smallest number of required DCFC ports (1,230), as shown in Table 2.

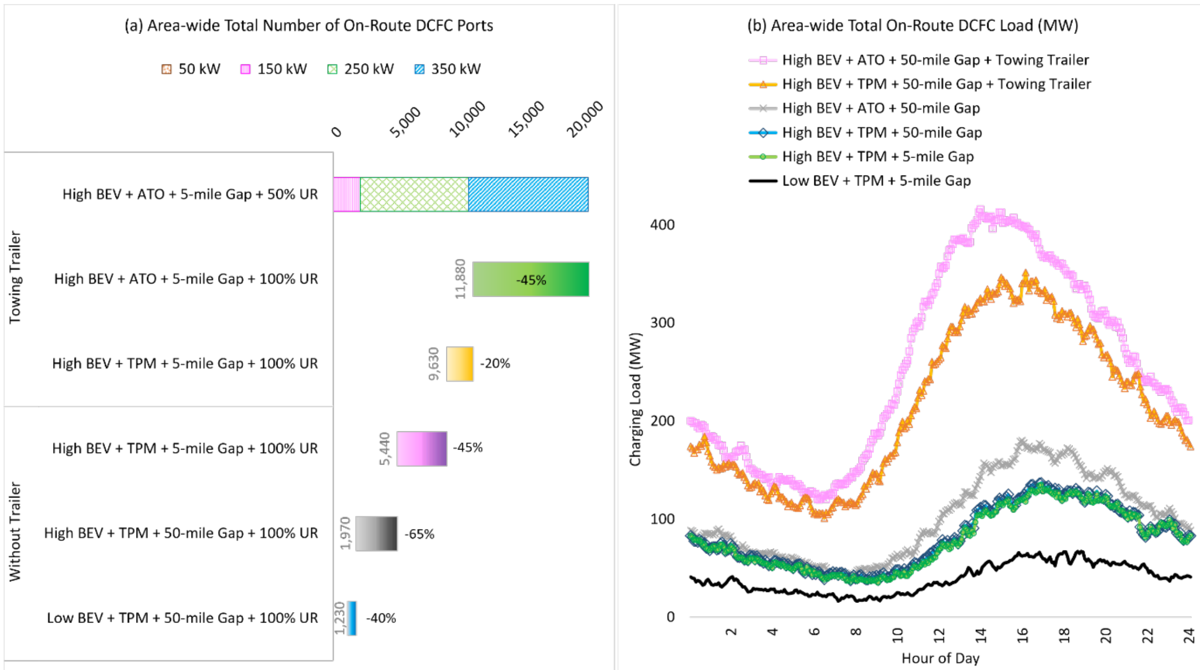


Figure 17. (a) The numbers of required on-route DCFC ports in 2030 and their variations according to different scenarios/assumptions. (b) Total on-route charging load profiles in the study area in 2030, depending on various scenarios/assumptions

Among the set of variables/parameters tested, Figure 17a indicates that the average gap between stations, all things equal, has the greatest impact (65% difference) on the number of required DCFC ports in the study area. The second most influential factor is the utilization rate of towing trailers, changing estimates for the number of ports by 45%. The third most significant parameter is BEV penetration rate (40%), and charging behavior is the least influential variable (changing the results by 20%).

Numerous on-route charging load profiles for the study area are shown in Figure 17b for different scenarios/assumptions around BEV penetration rate, charging behavior, and so on. By and large, the shape of the charging load profiles does not change much between different scenarios/assumptions; however, the scale drastically varies. A scenario with a low BEV penetration rate, TPM charging behavior, a 5-mile gap between stations, and no trailer towing results in approximately 70 MW of peak load in the afternoon. All things equal, the peak load almost doubles, increasing to 130 MW, as the BEV penetration rate changes from low to high. A change in charging behavior from TPM to ATO, all things equal, leads to an increase in peak load from 130 to 180 MW. Evidently, the largest impact on load profiles is associated with the scenario of towing trailers—all things equal, the charging load can increase from 180 MW to 410 MW. Although it is for an extreme case of all BEVs in road trips towing trailers, it is worth mentioning that 400 MW is equivalent to approximately 1% of total regional electrical load (35 GW) in the northwest (EIA 2020).

Overall, Figure 17 implies that different variables have different impacts on different aspects of on-route DCFC infrastructure. For example, all things equal, the gap between stations is one of the most influential parameters for the number of on-route charging ports (Figure 17a); however, that is not the case for charging load profiles. As illustrated in Figure 17b, the gap between stations has a very small impact on the load profiles. The spatial distribution of on-route DCFC stations can significantly affect the number of ports required to support the fleet of electrified road trips, but as the fleet size remains the same (for the same BEV penetration rate), the area-wide charging load profiles show more or less the same results. Note, however, that some parameters have significant influence on both the number of ports and the load profiles. For example, towing trailers can increase the number of required on-route charging ports by 1.8 times (e.g., from 5,400 to 9,600; see Figure 17a) and peak charging load by 2.5 times (e.g., from 135 MW to 340 MW; see Figure 17b).

3.5 Level 2 Charging in NPS Units and Hotels

In addition to on-route DCFC, we estimate the number of Level 2 ports for opportunity charging for electrified road trips, whether for on-site charging in NPS units or overnight charging in hotels/lodging. For opportunity charging in NPS units, the feasibility of on-site chargers can vary from one NPS unit to another. Some parks (e.g., Grand Canyon National Park) are more conducive to on-site charging because they have a hub-and-spoke style of vehicle movement in which vehicles could be left in a central parking lot for charging while visitors explore the area for a few hours. On the other hand, other parks (e.g., Arches National Park) are not very conducive to on-site charging because they have smaller parking lots spread across the property, and/or visitors tend to keep moving rather than staying or leaving their vehicles parked in one location for a few hours or longer. Given the significant heterogeneity of different NPS units, we do not attempt to estimate the study area-wide number of charging ports, which will require assessing on-site charging needs in each national park, which widely vary in terms of their characteristics.

The NPS units that are relatively conducive to on-site charging (e.g., Grand Canyon National Park) are estimated to have approximately 500 electric vehicles visiting the park, i.e., per park, on a typical summer day, when the travel volume is the greatest during the year. This estimate includes both battery electric and plug-in hybrid electric vehicles, both of which can use Level 2 chargers, unlike DCFC, which is only applicable for BEVs. To support charging for 25%–50% of approximately 500 electric vehicles per park per day, 50–100 Level 2 ports per park would be required. Not all electric vehicles will arrive at the parks with very low SOCs and require charging while they are parked at the parks, and thus they should be able to continue to travel and use on-route chargers outside the parks.

As for overnight chargers in hotels/lodging, our simulation indicates that there will be approximately 1,000–2,000 electric vehicles (including battery electric and plug-in hybrid electric) parked overnight in hotels/lodging during road trips in the study area in 2030. In other words, 1,000–2,000 Level 2 ports in hotels/lodging in the study area would be sufficient to support overnight charging for 100% of those electric vehicles. Note that not all road trips (100 miles or more per day) require overnight stays in hotels/lodging.

4 Conclusion

For seven states in the western United States, we estimated the quantity and location of on-route DCFC infrastructure needed to support electrified road trips by 2030, including those to and from NPS units (including national parks and national monuments) as well as intra-regional and interregional road trips outside the study area. Along with the location, size, and technological characteristics of the on-route DCFC infrastructure, we examined charging load profiles to inform electric grid operation and planning. We then evaluated how the infrastructure projections would change with different scenarios or assumptions, including BEV penetration rate, charging behavior, average gap between stations, charging port utilization rate, and towing trailers.

This study presents various valuable empirical data on long-distance travel (i.e., road trips of 100 miles or more per day), including departure time and charging behavior, whereby plug-in and plug-out SOC is a function of pre- and post-charging travel distance. Further, this analysis is based on an unprecedented level of spatial and temporal resolution when estimating vehicle movement in the space and time domain, energy consumption along the routes, charging simulation, and station siting and sizing.

Our work also clearly exemplifies the importance of comprehensively accounting for road trips that are directly and indirectly related to the study area when evaluating on-route charging infrastructure needs. On-route charging infrastructure does not exist in a vacuum but rather is co-used by all types of road trips that occur not only within the study area but also those that are inbound, outbound, and traveling through the boundary of the study area.

Despite the provision of novel empirical data, the unprecedented high-resolution analysis of charging infrastructure needs, and the comprehensive representation of a wide variety of road trips across the country, this work could benefit from future improvements. First, our study makes projections for 2030, but a longer-term analysis (e.g., up to 2050) would be helpful for multidecade infrastructure planning that requires long-term insights. Second, future work could consider equity elements and investigate how to ensure an equitable transition when building out charging infrastructure and supporting vehicle electrification. For this, energy justice/equity tools and models such as Electric Vehicle Infrastructure for Equity (EVI-Equity) (NREL 2023e) could be integrated with EVI-RoadTrip to holistically assess the equity implications of electrified road trips and the corresponding charging infrastructure. Last, a future study would need to be based on more detailed empirical data that can characterize people's behavior while on road trips for driving, taking breaks, refueling, and so on. Such data are currently scant in the field of long-distance travel research.

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