Impact of EVSE Deployment on Electrified Road Transportation Access for Long Trips

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Abstract

A well designed transportation system provides sufficient access from origins to destinations to accommodate household and business demand in an economy. Increasingly, climate action goals require that more transportation load be shifted to less Green-House Gas (GHG) intensive modes among which are Battery Electric Vehicles (BEVs). While BEVs use the same roads as Internal Combustion Engine Vehicles (ICEVs) they draw energy from a separate network of stations which neither as robust as nor coincident to the ICEV fueling network, a consequence of the different current and historical economics of both. Insufficiency and unreliability of public DC Electric Vehicle Supply Equipment (EVSE) which is primarily used for charging on long itineraries mean that BEV drivers, depending on vehicle range and risk attitude, may opt for less direct paths with lower charging risk, opt for a more GHG intensive mode, or abandon an itinerary. Holistically, the transportation system provides less access to BEVs for distant pairs. This project develops methods and tools to optimize deployment of future EVSE to mitigate the issue. Methods herein are based on range and charging risk sensitive optimal routing between O/D pairs subject to the locations and usability rates of EVSE. These methods and tools may be used by policy makers to directly evaluate the impact of proposed stations on BEV transportation access.

Introduction

Developed economies rely on their transportation sectors to move persons and goods in astounding volumes underpinning multi-trillion dollar yearly outputs and setting the conditions for households and individuals. The concept of transportation access can roughly be considered as the inverse of the difficulty of reaching selected destinations from selected origins. More efficient transportation allows for individuals and businesses to access more opportunities for the same expenditure in time and/or money. Transportation access is, thus, a nuanced and multi-dimensional concept which must vary, at least, by location, entity, and scope. Further complexity is added by the reality that all elements of the global transportation system are, to a greater or lesser degree, connected. How one selects Origin-Destination (O/D) pairs and the entities which must transit them will color one's analysis. It is, thus, important to carefully define the scope of analysis.

Transportation researchers and planners have introduced the concept of transportation accessibility primarily as it applies to routine household behavior. From the personal transportation perspective, access is defined as the ease with which individuals can reach the destinations they need or desire, considering both the distribution of destinations and the various transportation options available [1]. Accessibility is influenced by several key factors. Land-use dynamics determine the distribution and demand for amenities like jobs and services across different locations, while transportation factors such as travel time, costs, and infrastructure availability also play a significant role [2]. Temporal considerations reflect the availability of opportunities throughout the day, and individual characteristics such as age, income, and education predict access to transportation modes and opportunities [3].

The access provided by a road transportation system for BEVs is different than that for ICEVs due to vehicular and supply network characteristics as well as individual and household characteristics. Modern BEVs possess sufficient practical ranges to accomplish much daily travel [SOURCE - or maybe derive this from NHTS]. However, for long itineraries ICEVs offer greater accessibility compared to BEVs due to the extensive availability of fueling stations in contrast to charging stations. Fueling stations are widely distributed across urban, suburban, and rural areas, ensuring that drivers have convenient access to refueling points wherever they travel. In contrast, the EVSE network is less developed and distributed. This infrastructure gap poses challenges for BEV drivers, especially in remote or less densely populated areas, leading to concerns about range anxiety and limitations on travel options. Inadequate access for BEV may result in trip cancellations or mode switches, often favoring ICEV or air travel.

While incentives for EVSE deployment can help mitigate this issue, it may not fully resolve the disparities which result from the different economic models. Gas pumping equipment requires lower up-front costs than DC EVSE and is cheaper to operate [4]. It is, nevertheless, the case that gas is often sold at low markup or a slight loss with stations making most profit on convenience items [SOURCE]. Nearly all light-duty ICEV drivers source all of their fuel from public fueling stations regardless of travel behavior [SOURCE]. BEV drivers are expected to, and currently do, source much of their electricity from AC supply equipment during long dwells, often at private chargers [5]. Thus DC EVSE is subject to higher capital expenditure and lower revenue potential while simultaneously benefiting less from historical investment. Public investments in EV supply infrastructure, thus, must be made judiciously. Evaluation methods for potential charging stations should consider their network-wide impact on accessibility, considering vehicle types, charging outcomes, and driver risk attitudes.

This study introduces a novel methodology to assess the impacts of vehicle electrification on the accessibility of road transportation systems subject to supply networks. The methodology will measure ICEV and BEV accessibility by computing optimal-feasible travel routes of O/D pairs using a Monte-Carlo Dijkstra routing algorithm subject to vehicle range limitations, infrastructure constraints and driver risk attitudes. Additionally, a case study is presented for the state of California showing a comparison between ICEVs and BEVs access for important O/D pairs. The methodology introduced, as well as the open-source code provided in the supplemental information will be an invaluable tool for planners and policymakers in originating and evaluating EVSE deployment policies.

Transportation Accessibility

Transportation access has been studied as a tool for urban and regional planners since the middle of the 20th century with theoretical origins in the theory of population migration proposed by Ravenstein in 1885 [6]. The movement of people over a given time-scale can be analogized to an electrical circuit. In this analogy push and pull factors determine are the "voltage" separation, traversal difficulty is the "resistance" and the resulting flow is the "current". The field of transportation accessibility uses this framework to study the efficiency of a region. The accepted definition of transportation access is the ease with which individuals can access opportunities subject to the transportation system in the relevant area. Thus, accessibility is a framework which encompasses voltage factors such as land use and temporal availability, resistance factors such as transportation system design, and universal factors such as personal preference [2]. Literature provides four essential frameworks for computing access as surveyed in [1–3, 7, 8] and discussed below.

It is not necessarily apparent what voltages occur where in a region. Individuals are assumed to need or desire location specified opportunities such as grocery shopping. However, there may be several near-equivalents for a given opportunity type. The simplest methods for quantifying voltage are based on proximity to an opportunity type [9, 10]. Proximity methods consider that a person has a level of access to a given need determined by that person's proximity to the closest equivalent opportunity. These methods do not account for heterogeneity within an opportunity category nor for the benefits of redundancy within an opportunity category. The inverse are isocost methods wherein a person is said to have access to determined by the number of opportunities available within a given isocost polygon. This method has the drawback of not considering the differences in traversal cost for O/D pairs within the iso-cost region. These methods have been used widely [11] due to their computational lightness and form the basis for modern big-data methods such as th US DOE's Mobility Energy Productivity metric [12].

Proximity and isocost methods are easy to compute because they treat redundancy arbitrarily respectively by neglecting it and by defining a region of consideration. Equivalent and near-equivalent opportunities compete with one-another if sufficiently proximate or if the paths required to reach them overlap [13]. Gravity/entropy methods [14, 15] address this shortcoming. These methods are so called as they concern the cumulative effect of opportunities for a given origin on the basis of demand over proximity (gravity) or information content (entropy). Such methods were first formalized into a quantitative framework in 1959 [16] as a generalization of previous methodology for quantifying the efficiency of urban land use. Gravity/entropy methods define accessibility as the intensity of the possibility for interaction thus focusing on the voltage separation (demand for opportunities) and the resistance (difficulty of traversal for O/D pairs). Gravity/entropy methods consider the cumulative effect of equivalent opportunities at different locations for each origin with their impact weighed by their proximity. Implicit in the formulation of gravity/entropy methods is that every opportunity has some effect on every individual even if this is, often, negligible and the effect of any one opportunity is determined by its individual proximity and those of all others.

Proximity and gravity/entropy methods rely on the assumption that traversal cost is the primary factor determining individuals decision to select one opportunity from among a set of similar entities. While this is certainly true if the difference in traversal cost is large enough it is not, altogether, obvious what the threshold of disambiguation is or if this is similar among the population. Thus, researchers have proposed to use Discreet Choice Modeling [17] to explain revealed choices wherein ease-of-access is one of several possible factors in determining the utility of a given opportunity for an individual [18–20].

There are, thus, a variety of methods which can be used to quantify the accessibility of a given region with varying computational and data requirements. The relationship between land-use, transportation, and demography is circular rather than linear. Which method one chooses for an analysis reflects the scope and purpose of that analysis. Definition of scope can be difficult and can lead to self-defeating policies [21]. This study is concerned with the effects of electrification on accessibility for users of road vehicles. This very specific scope neglects to specify the demand element. Rather, for a given set of demand locations, the methodology introduced quantifies the difference in access for a driver by vehicle powertrain type as a function of the vehicle and the supply network. This paper is focused on regional travel rather than local travel as this is where public DC EVSE infrastructure becomes important but, it should be noted, that the method is valid for all travel scales. Methodology is developed in the following section.

Methods

Vehicle Reduced Sub-Network Graph

Critical to this analysis is the definition of the Reduced Sub-Network Graph (RSNG) for a given vehicle. Powered vehicles are range-limited due to the finite capacity of their energy Storage Systems (ESSs). In order to traverse an O/D pair whose energy requirement is greater than the capacity of the ESS a vehicle must stop at a supply station. The above applies equally to road vehicles of all powertrain types, the difference being the qualities of the respective supply networks which are neither equivalent nor isomorphic.

For a network $G = \{V, E\}$ where V is the set of nodes and E is the set of edges, a reduced sub-network $\hat{G} = \{\hat{V}, \hat{E}\}$ can be computed where $\hat{V} \subseteq V$ and $\hat{E}$ is the set of paths between all nodes in $\hat{V}$. In other words, the cardinality of V is reduced but the relationships between the nodes in $\hat{V}$ are maintained by considering multi-edge paths which contained nodes not in $\hat{V}$ as single edges. For a road vehicle with ESS capacity C located at an origin node $v_i \in O \subseteq V$ $\hat{V}$ contains O and opportunity nodes $D \subseteq V$ where the edge traversal cost $f((o,d)) \leq C$. The set of origins O consists of the vehicle's current location and locations where the vehicle may be supplied energy. Where a destination is in range from the vehicle starting position a direct path will be seen on the RSNG and will be the shortest path. Otherwise, an indirect path utilizing at least one supply station may be the shortest path. Finally no feasible path will exist where the destination cannot be reached. An example source and equivalent sub-network are shown in Figure 1.

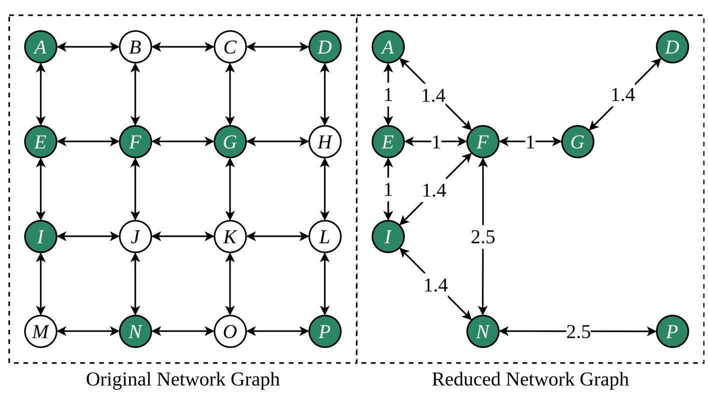


Figure 1: Example original and reduced sub-network graphs. The original graph is a lattice where all edges are valued at 1. The reduced network contains all paths less than or equal to 2.5 between selected nodes as edges.

Models

The method requires several models which serve to inform optimal routing. Vehicular, infrastructural, and individual parameters effect the ultimate solution.

Vehicles

Vehicles contribute to routing parameters related to their ESSs as listed in Table 1.

Table 1: Vehicle Parameters for Routing

Parameter	Description	Unit
ESS Capacity	Accessible energy storage capacity for vehicle	[kWh]
Energy Consumption	Energy required to move the vehicle a given unit of distance	[kJ/km]
Energizing Rate	Rate at which energy can be added to the ESS at a supply location	[kW]
DC Charge Limits	Lower and upper State of Charge (SOC) bounds for DC charging	[-]

Supply Stations

Supply infrastructure impacts routing by providing the ability for trips greater than a vehicle's usable range to be completed. Utilizing a supply station resets the vehicle's SOC to a set level but costs money and time. The cost of the energy supplied is a station level parameter and may vary by location and time. The time added due to energizing is a function of the vehicle and supply equipment maximum energizing rate, the total energy added, and the time spent prior to energizing due to queuing if no equipment is immediately available. The amount of time that a vehicle can expect to queue is a function of the arrival rate of vehicles at a given station, the time taken to energize by those vehicles, the number of supply equipment at the station, and the probability of usability for said equipment. Expected queuing time distributions for different arrival rates and numbers of equipment for DC Electric Vehicle (EV) chargers are shown in Figure 2.

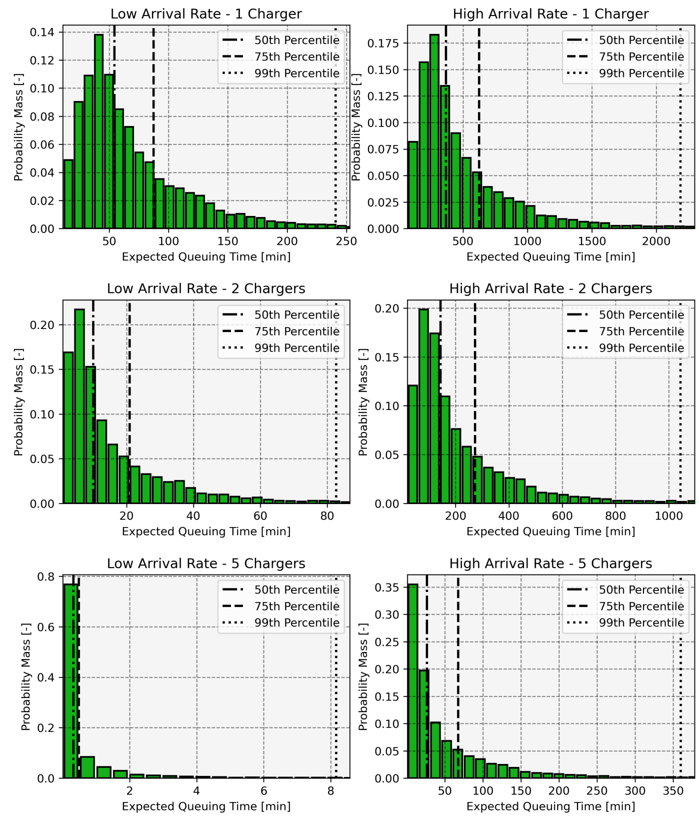


Figure 2: Expected queuing time at charging stations. Low arrival rate is 10 - 60 minutes between arrivals. High arrival rate is 1 - 10 minutes between arrivals. All charge rates are 80 kW and charge events are 60 $\pm$ 15 kWh.

Expected queuing time is highly determined by variable factors like arrival rate, which must be estimated, and numbers of usable equipment, which is a function of installed equipment and reliability. The amounts of energy purchased are less variable station-to-station for the same powertrain type. The queuing times shown in Figure 2 were computed using the expected waiting time formula for a M/M/c queue. This approximation is reflective of reality as long trips will begin well before there can be certainty about queues at distant stations. Supply station parameters are listed in Table 2.

Table 2: Supply Station Parameters for Routing

Parameter	Description	Unit
Inter-Arrival Time	Time between arrivals at the station	[s]
Service Time	Time taken to supply energy to vehicles	[s]
Servicers	Number of vehicles which can be simultanously serviced	[-]
Usability	Percentage of the time that a given servicer will be usable (accessible and functional)	[-]

Drivers

Given the same physical circumstances, different drivers will evaluate route costs differently. In a basic sense, drivers will weight several factors such as time, money cost, distance, and complexity. Where any important factor is not known precisely drivers will consider a range of outcomes and decide based on an expectation. Driver risk attitude concerns what range of outcomes will be used to compute expected cost. Risk attitude is modeled using a superquantile risk function defined as

$$S(D, p_0, p_1) = \frac{1}{p_1 - p_0} \int_{p_0}^{p_1} Q(D, \alpha)\, d\alpha \tag{1}$$

where D is a distribution, p_0 and p_1 are the boundaries of the range of probabilities considered in the expectation, and Q is the quantile function of D. The superquantile is, thus, the mean value of a distributed quantity within a range of probability. Drivers with an aggressive risk attitude will consider a low range of probabilities, drivers with a neutral attitude will consider a central range, and drivers with a cautious attitude will consider a high range. Thus, a driver's perceived route cost is computed via taking the superquantile of a weighted sum of route costs. Driver parameters are listed in Table 3.

Table 3: Supply Station Parameters for Routing

Parameter	Description	Unit
Route Cost Weights W	Set of multipliers for route costs to be used in computation of weighted sum	[-]
Probability Range (p_0, p_1)	Range of probabilities for superquantile function	[-]

Routing

The purpose of optimal routing is to find the "shortest-paths" from a given origin $o \in V$ to a set of destinations $D \in V$ on a graph $G = \{V, E\}$. The output of the routing algorithm is tree R containing the shortest feasible paths from the origin to all destinations as edges. The objective of routing between i and j is

$$\min_{U \in \bar{(U_{i,j})}} \quad \mathbb{E}[J(S_0, U)] \tag{2}$$

where

$$J(U) = \sum_{k=0}^{M} w_k \phi_k(s_{0,k}, U) \tag{3}$$

s.t.

$$b_l^w \leq \mathbb{E}\left[\int_0^t \Phi_w(S_0, U)dt\right] \leq b_u^w \quad \forall t \in T \tag{4}$$

where S_0 is the vector of route states, U is a control (route) between i and j, $\overline{U}_{i,j}$ is the set of possible routes between i, and j, Φ_w is the cost function for route weight $w \in W$, and $\mathbb{E}$ denotes an expectation and is computed as in (1). The optimal routes may be found using a stochastic implementation of the Dijkstra or Bellman-Ford algorithms. In either case route states S are initialized and stored as vectors containing N discreet variables. An empirical distribution D for a state vector can be computed from a histogram of the values. States can be changed at nodes and edges. Routes are considered feasible if the expectations of all states remain within set bounds. Comparison between routes is performed using expectation of cost.

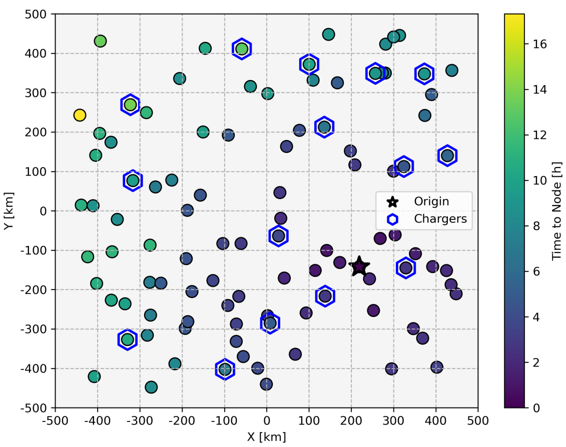
Random Graph Example

The optimal routing method in this study accounts for factors which influence road vehicle accessibility and derive from vehicular, infrastructural, and behavioral parameters. Important vehicular parameter for accessibility is range which determines which locations can be reached with and without charging. Important infrastructural parameters such as the number and locations of charging stations, usability rates, and expected delay times. Important behavioral parameters include risk attitude parameters as in (1). These factors influence routing individually and via interactions as demonstrated on a randomly generated graph.

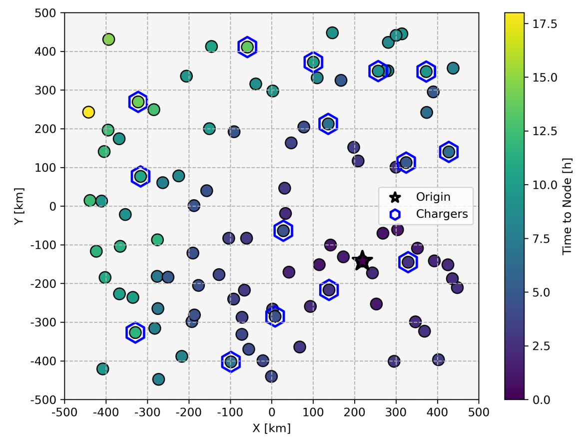
A random graph of 100 nodes, 15 containing charging stations within a 100 km by 100 km square was generated with a random node selected as the origin. Edge probabilities were defined relative to a characteristic distance using

$$P(e) = \exp(-L(e)/d) \tag{5}$$

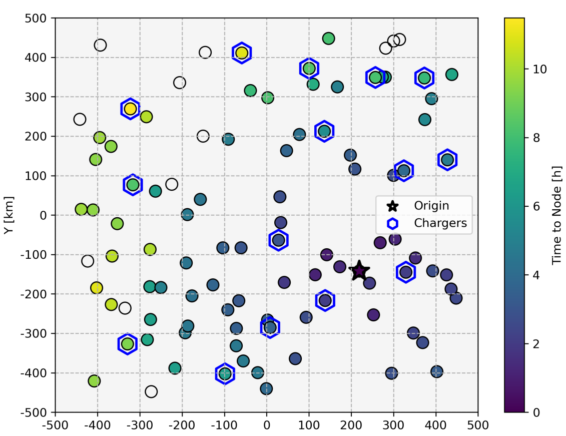
where e is an edge, $L(e)$ is the distance of edge e, and d is a characteristic distance set to 200 km for this example. In this example the vehicle has a range of 460 km and each charging station has one charger and a low vehicle arrival rate. Figure 3 show how R is effected by different usability rates and risk attitudes.



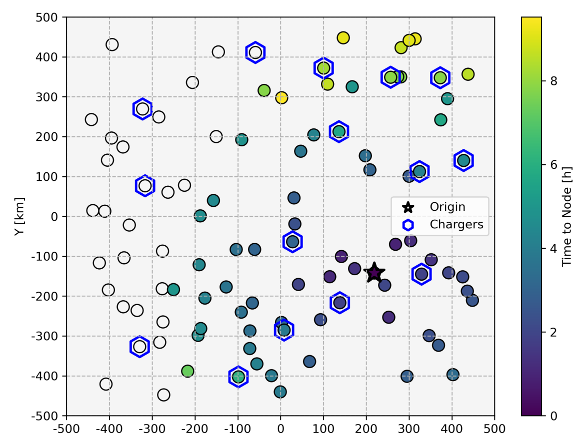
(a) High charger usability and aggressive risk attitude



(b) High charger usability and cautious risk attitude



(c) Low charger usability and aggressive risk attitude



(d) Low charger usability and cautious risk attitude

Figure 3: Single-origin expected travel time trees with varying charger reliability and driver risk tolerance

As the example shows, it is possible for the impact of several factors to be additive when made disadvantageous simultaneously. Where the driver has an aggressive risk attitude, chargers are reliable, or both, accessibility is high. Where neither is the case accessibility is low. The differential can be dramatic and this highlights the importance of considering vehicular, infrastructural, and behavioral factors simultaneously to get a complete picture.

California Case Study

The state of California contains several large population centers distributed across the state and several important transportation corridors connecting said population centers and population centers in neighboring states. In this case study the accessibility of the road transportation system for light duty vehicles will be considered in terms of accessibility to 15 important locations. These locations are enumerated in Table 4.

Table 4: Locations Considered for Long Trip Accessibility

Index	Location
0	Crescent City
1	Yreka
2	Redding
3	Chico
4	I-80 to Reno (State Line)
5	Sacramento
6	Stockton
7	San Francisco
8	San Jose
9	Fresno
10	I-15 to Las Vegas (State Line)
11	Bakersfield
12	Los Angeles
13	I-10 to Phoenix (State Line)
14	San Diego

These locations were chosen either because they are, themselves, important destinations in California or because they are the closest points in California to important destinations in neighboring states. The selected locations as well as the 1906 DC charging stations scraped form Alternative Fuels Data Center (AFDC) [22] are mapped in Figure 4.

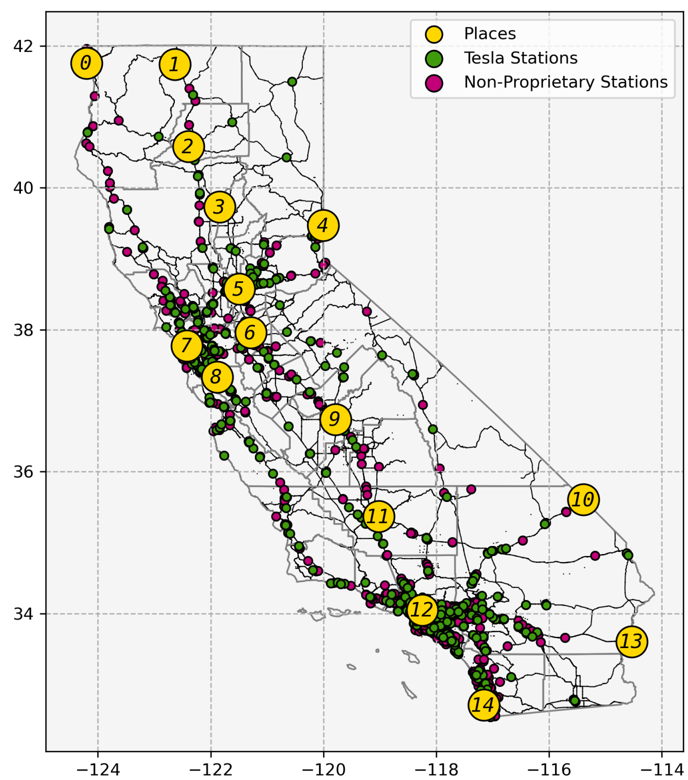


Figure 4: Selected locations and charging stations for California case study

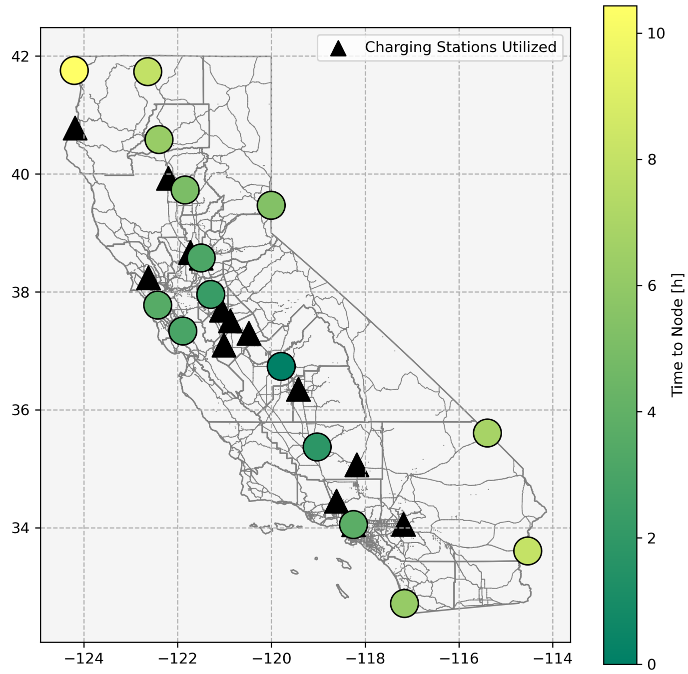


Figure 5: Selected locations and charging stations for California case study

Table 5: Neutral expectation of hours to locations from Fresno for example scenarios

Index	SC 1	SC 2	SC 3	SC 4
0	9.73	10.44		
1	7.51	7.95		
2	5.92	6.21		
3	4.91	5.04		
4	5.19	5.34		
5	3.13	3.13		
6	2.32	2.32		
7	3.41	3.54		
8	3.01	3.01		
9	0.00	0.00		
10	6.55	6.81		
11	1.82	1.82		
12	3.69	3.75		
13	7.56	8.00		
14	5.87	6.15		

SC 1 Generic ICEV

SC 2 Tesla Model 3 with high charger usability (97%), low arrival rate (10 - 60 min), and neutral risk attitude.

SC 3 Chevrolet Bolt EV with high charger usability (75%), low arrival rate (10 - 60 min), and aggressive risk attitude.

SC 4 Chevrolet Bolt EV with high charger usability (75%), low arrival rate (10 - 60 min), and cautious risk attitude.

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