A Quantitative Framework for Assessing Long-Trip Transportation Accessibility for Road Vehicles

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Abstract

Battery Electric Vehicles (BEVs) are an important part of transportation de-carbonization goals globally and especially in car dependent countries such as the US. While BEVs provide a nearly equivalent experience to Internal Combustion Engine Vehicles (ICEVs) for routine and short-trip travel, their limited ranges and long recharge times make the less well-suited to long-trip travel. Long-trip travel has repeatedly been shown to be an important consideration in individual and household vehicle purchasing decisions. In order to better enable long-trip travel, public money has been invested into the public DC charging network. In order to enable the assessment of network performance in providing long-trip access, this paper proposed a novel and quantitative framework. This framework accounts for network, vehicle and individual characteristics allowing for holistic and extensible assessments. The framework is demonstrated using the State of California as a case study. Results show the importance of improved ranges and charge rates as well as the differences in outcome based on individual risk attitude and charger network availability.

Introduction

Transportation accessibility is the study of two related phenomena. (1) how structural and individual factors create latent flows or demand. (2) how efficiently transportation systems accommodate said flows. An effective transportation system is an economic and social asset of tremendous value and one which justifies continual investment. Investments in transportation are inherently long-horizon and come with considerable uncertainty. Changes in social, technical, environmental, and other factors can lead to poor returns on investments.

The US and similarly wealthy anglophone nations are unusually car-centric by global standards [1]. In retrospect, it is apparent that urban development in wealthy nations in the second half of he 20$^{\text{th}}$ century led to a self-reinforcing car-dependence. Fully meeting climate goals will necessitate lowering car travel [2] but this is necessarily a long-term project. The Green-House Gas (GHG) impacts of car travel can be substantially mitigated by large scale vehicle electrification [3]. Whether or not, and to what extent, such a transition happens in democratic countries will hinge on the fundamentals. Even supply-side policies, such as California's Advanced Clean Cars II, are unlikely to succeed ultimately if it becomes apparent to voters that BEVs result in dramatically worse access.

Evidence suggests that long itinerary performance is a persistent and important factor in individual car buying decisions. Negative perceptions of BEV long trip utility on consumer stated preference were found to be impactful in the late 2010s [41–44]. In the intervening time period BEV ranges and maximum charge rates have markedly increased. Nevertheless, negative perceptions related to long itinerary utility persist for purchasers [45–48] and BEV range is a significant factor in determining usage share of BEVs in multi-vehicle household fleets [49].

For long itineraries ICEVs offer greater accessibility compared to BEVs due to greater maximum ranges and the ubiquitous availability of fueling stations. Fueling stations are widely distributed across urban, suburban, and rural areas, ensuring that drivers have convenient access to refueling points wherever they travel. The charging network is considerably less developed. Disparities between the fueling and DC charging networks result from differences in their underlying economic fundamentals. Gas pumping equipment requires lower up-front costs than DC Electric

Vehicle Supply Equipment (EVSE), is cheaper to operate [4], and has been deployed for far longer. Nearly all light-duty ICEV drivers source all of their fuel from public fueling stations regardless of travel behavior. BEV drivers are expected to, and currently do, source much of their electricity from private AC supply equipment during long dwells [5].

The fundamental disparities between ICEVs and BEVs are well known and well studied. How these manifest as differentials in access is important to understand. This study introduces a novel framework for the assessment of transportation accessibility for long vehicular trips. The methodology measures accessibility by computing optimal-feasible travel routes for Origin-Destination (O/D) pairs using a stochastic routing algorithm subject to vehicle range limitations, supply infrastructure, and driver risk attitudes. This methodology is powertrain agnostic and can be used to directly compare accessibility for different types of vehicles. A case study is presented for the state of California showing a comparison between ICEVs and BEVs accessibility. The methodology introduced, as well as the open-source code provided in the supplemental information is a valuable tool for planners and policymakers in originating and evaluating EVSE deployment policies.

Transportation Accessibility

Transportation accessibility is a framework which encompasses demand factors such as land use and temporal availability, impedance factors such as transportation system design, and universal factors such as personal preference [7]. Literature provides four essential frameworks for computing access as surveyed in [7–11]. Much of the variance between analyses is on the demand side. There will usually be several near-equivalents for any given opportunity type and computing a single-number metric of access requires a model.

The simplest methods for selecting opportunities are Proximity methods [12, 13]. Proximity methods determine access by proximity to the closest relevant opportunity. Proximity 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 which determine access by the number of opportunities available within a given isocost polygon. Isocost methods do not consider the differences in travel costs within the isocost region. Isocost methods have been used widely due to their transparency and computational lightness [14], and form the basis for modern big-data methods such as the US DOE's Mobility Energy Productivity metric [15].

Proximity and Isocost methods are easy to compute because they handle redundancy with arbitrary rules. In practice, equivalent and near-equivalent opportunities compete with one-another if sufficiently proximate or if the paths required to reach them overlap [16]. Gravity and Entropy methods [17, 18] address this shortcoming by computing the cumulative effect of multiple opportunities on access for a given origin. Gravity/Entropy methods define accessibility as the intensity of the possibility for interaction [19]. Implicit in the formulation of Gravity/Entropy methods is that every opportunity has some effect on every individual, even if negligible, and the effect of any one opportunity is determined by its network position. Discrete Choice Modeling [20] is often used to explain revealed choices from traffic measurements and travel surveys [21–23] in order to fit Gravity/Entropy models allowing for generalization and the evaluation of hypothetical scenarios. Human decision making is complex and it is common for such models to have large error terms.

Which method one chooses for an analysis should reflect the scope and purpose of that analysis. Definition of scope can be difficult and arbitrary and can lead to self-defeating policies in the worst cases [24]. This study is concerned with the effects of electrification on regional accessibility for road vehicle users. This scope simplifies opportunity selection. It is necessary that a transportation system provide for access between population centers within a region of interest. This study is focused on non-routine regional travel rather than routine local travel as this is where supply infrastructure becomes important. It should be noted that the method is, nevertheless, valid for all travel scales. Said methodology is developed in the following section.

Methods

The focus of this study is regional accessibility for road vehicles. The metric developed reflects the time-cost for drivers in a region to access population centers within the region from one-another. It is important to consider total trip time. A sufficiently long trip will require at least one re-supply (refuel or recharge) event which adds to total trip time. In addition to the time required to re-supply the vehicle, there will be the time required to deviate from the shortest path to the supply station and time spend waiting for an available port, time spent setting up the supply event. Before setting out for a trip, a driver will have limited and approximate information with which to plan a route. Drivers are faced with two related informational problems:

Uncertainty The driver may not know the instantaneous status of a given supply port.

Latency The status of a supply port may change before the driver arrives.

Informational issues are particularly relevant for BEV drivers because of the relatively long duration of charging sessions compared to fueling sessions and the relative immaturity of the DC charging network as compared to the petroleum fueling network. For BEV drivers the variance in possible trip total time can be meaningful necessitating an earlier departure or other adjustment. As the journey progresses variance decreases. The routing methodology developed in this section reflects the informational difficulties facing BEV drivers. These are not helped by the fragmentary charging information space where network operators often guard status information and reservation capability within their proprietary apps if these are provided at all.

Regional characteristics determine how important the differences between vehicles and supply networks are. The land-use within a region has two principle effects. First, for a multi-city region, peripheral cities should experience worse regional access than central cities. Second, geographically large and/or sparse regions should experience worse overall accessibility than compact regions. Non-vehicular travel modes will vary by region and may take load away from the vehicular transportation system. Where only vehicular travel is concerned, mode choice is reduced to vehicle choice.

Metric Definition

Regional travel is often modeled using gravity models. Gravity models theorize that the degree of connectivity between two entities is in proportion to the attractiveness of each and the difficulty-of-travel or impedance between them. Fitting such a model requires substantial and granular observed trip data not often available to the public. Impedance modeling (the denominator) is a key element of transportation demand modeling and is the focus of this study.

Being concerned with regional performance, this study proposes the regional impedance metric Z_R which is a weighted mean of impedance. For region R of N nodes $O = \{O_1, O_2, \ldots, O_N\}$ and a corresponding set of weights $W = \{W_0, W_1, \ldots, W_N\}$, G_R is computed as

$$Z_R = \frac{1}{N^2} \sum_{i=0}^{N} \sum_{j=0}^{N} Z_{ij} \tag{1}$$

for region R. Regional impedance as experienced at a specific origin $Z_{R,i}$ is defined as

$$Z_{R,i} = \frac{1}{N} \sum_{j=0}^{N} Z_{ij} \tag{2}$$

for origin i. Z_R is a useful single-number metric for comparing the experience of travel in a region for different people living in different places and with different modes available to them. The variation within a region can be expressed using any metric of statistical dispersion such as standard deviation, Gini coefficient of inequality, etc.

Metric Computation

In order to traverse an O/D arc whose energy requirement is greater than a vehicle's energy Storage System (ESS) capacity, the vehicle must be re-supplied. Drivers will hold energy in reserve limiting a vehicles practical range in most cases. Because supply events add time to a trip, they will be minimized where possible [25]. For ICEVs, supply events are brief and supply stations are ubiquitous in most areas. Routing services often neglect refueling events. For BEVs, supply events are lengthy and DC charging stations are not ubiquitous in most areas. For this reason, dedicated BEV routing services such as A Better Route Planner and Tesla's UI compute routes which include supply events.

All drivers deal with uncertainty and latency issues when computing an optimal route. Rational drivers will plan a route based on some expectation of the many outcomes which contribute to travel cost. Traffic, availability of re-supply, and vehicle range are important factors as is the risk attitude of the driver. This mental process is modeled via stochastic optimization.

Stochastic Optimal Routing

The purpose of stochastic optimal routing is to find lowest-expected-cost paths from origin $i \in V$ to a set of destinations $D \in V$ on graph $G = \{V, E\}$. The output is tree P containing the optimal-feasible paths from the origin to the selected destinations. The objective of routing on arc (i, j) $i, j \in V$ is

$$\min_{U \in \overline{U}_{i,j}} \mathbb{E}[J(S_0, U)] \quad (3)$$

where

$$J(U) = \sum_{k=0}^{M} \Phi_k(S_0, U) \quad (4)$$

s.t.

$$b_l^k \leq \mathbb{E}\left[\int_0^t \Phi_k(S_0, U)dt\right] \leq b_u^k \quad (5)$$

$$\mathbb{E}\left[\int_0^T \Phi_k(S_0, U)dt\right] \geq b_f^k \quad (6)$$

$$t \in [0, T] \quad k = 1, 2, \ldots, M \quad (7)$$

where T is the final value of time for a route, S is the state vector of M states, S_0 is the initial values of the states, U is a path between i and j, $\overline{U}_{i,j}$ is the set of possible paths between i, and j, Φ is the set of cost functions, b_l^k and b_u^k are the upper and lower bounds for state k respectively, and b_f^k is the final state minimum value for state k. $\mathbb{E}$ denotes an expectation. State vector S is initialized and stored as vectors containing N discreet variables. A distribution D for a the state vector at any node and time-step can be computed from a histogram of the values. Routes are considered feasible if state expectations remain within set bounds. Comparison between routes is performed using cost expectation. the goal of the optimization is to find the optimal path U_{ij}^* such that $J(U_{ij}^*)$ is equal to the global minimum cost J_{ij}^* for each arc (i, j) $i, j \in V$.

Th study assumes that drivers will attempt to minimize total trip time while maintaining a level of reserve energy determined by their risk tolerance. In theory, it is possible to traverse all O/D arcs where both are connected to the road network. In practice certain arcs will be infeasible with this subset varying by driver. The structure of the optimization process is as follows. First, a graph is created to represent the supply network and its interactions among itself and with origins and destinations of interest. This graph is referred to as the Supply Network Graph (SNG) herein. All arcs which are feasible should be included as edges in the SNG, including those directly between origins and destinations. Second, edge costs in terms of total-time are assigned, using the driver, vehicle, and supply station models as described in the following subsections. Third, stochastic optimization is performed using an optimal routing algorithm based on the expectation of edge cost. Because this study concerns finding optimal paths for all pairs in a large set of locations, the Floyd-Warshall algorithm is used [26, 27].

Driver Model

Different drivers will have different perceptions of cost for the same information based on their priorities and risk attitudes. Drivers will prioritize factors such as time, money, distance, and complexity differently. In this study, drivers are assumed to only consider total trip time. Where any important factor is not known precisely drivers will consider a range of outcomes and decide based on an expectation. The result will be cost distribution D. 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

$$S(D, p_0, p_1) = \frac{1}{p_1 - p_0} \int_{p_0}^{p_1} Q(D, \alpha)\, d\alpha \quad (8)$$

where 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 the mean value of a distributed quantity within a range of probability. $S(D, 0, 1)$ reduces to the mean of D. Drivers with an aggressive risk attitude will consider the least costly outcomes. Drivers with a neutral attitude will consider central outcomes. Drivers with a cautious attitude will consider the most costly outcomes.

Drivers will desire to keep a minimum amount of range in reserve in any circumstance. This value is referred to as SOC_{min}. In practice, drivers may want to increase SOC_{min} when operating in areas where supply infrastructure is sparsely distributed such that a backup station can be reached should the intended station not be usable. This behavior is modeled as the driver should arriving at a given station with enough remaining range to make it to at least three alternate stations. Thus, SOC_{min} at each station is increased by the distance from the station to the third closest adjacent station. Driver parameters are listed in Table 1.

Table 1: Driver Parameters for Routing

Parameter	Description	Unit
Risk Attitude (p_0, p_1)	Range of probabilities for superquantile function	[-]
State of Charge (SOC) Reserve SOC_{min}	The lowest point of SOC that the driver will accept before re-supplying	[-]

Vehicle Model

Vehicles effect routing due to their range limits and supply methods. The vehicle model used herein is highly simplified due to the inexact nature of the problem. Vehicles are modeled as storing energy and consuming energy at a constant rate per unit distance driven. More exact information on road conditions, traffic conditions, and atmospheric conditions among others can be used to compute edge-specific efficiencies. Vehicular parameters are listed in Table 2.

Table 2: Vehicle Parameters for Routing

Parameter	Description	Unit
ESS Capacity	Accessible energy storage capacity	[kWh]
Energy Consumption	Energy required to move the vehicle	[kJ/km]
Maximum Supply Rate	ESS maximum energy addition rate	[kW]
Linear Charging Fraction	Percentage of the battery capacity which can be charged in the linear (constant current) range	[kW]

DC charging is modeled using a CC-CV relationship where the first part of charging is linear and the second part follows exponential decay [28]. The inflection point which separates the linear and exponential decay sections is the Linear Charging Fraction η. The time required for a given charge event is

$$\Delta T = \Delta T_l + \Delta T_e \tag{9}$$

$$\Delta T_l = \begin{cases} \frac{(SOC_f - SOC_i)C}{v} & SOC_i \leq SOC_f \leq \eta \\ \frac{(\eta - SOC_i)C}{v} & SOC_i \leq \eta \leq SOC_f \\ 0 & \eta \leq SOC_i \leq SOC_f \end{cases} \tag{10}$$

$$\Delta T_e = \begin{cases} 0 & SOC_i \leq SOC_f \leq \eta \\ -\frac{1}{\alpha} \ln\left(1 - \frac{SOC_f - \eta}{1-\eta}\right) & SOC_i \leq \eta \leq SOC_f \\ -\frac{1}{\alpha} \ln\left(1 - \frac{SOC_f - SOC_i}{1-\eta}\right) & \eta \leq SOC_i \leq SOC_f \end{cases} \tag{11}$$

$$\alpha = \frac{v}{\eta C} \tag{12}$$

Where C is the vehicle ESS capacity, v is the actual power of the charge event, ΔT_l and ΔT_e are the time spent in the linear and exponential decay portions of the charge event, and SOC_i and SOC_f are the initial and final values of SOC for the charge event. Charge events are modeled to occur at the minimum of the maximum powers for the vehicle and charger. A typical value for η will be in the range of 0.7 to 0.8. DC charging for a given quantity of energy past η will take substantially longer than the same quantity below η. The difference in effective charging rate may serve to favor more DC charge events each terminating at a lower SOC.

Supply Station Model

Supply station parameters are number of ports, reliability of ports, and the maximum supply rate of ports. The probability of port availability at a station is determined by the rate at which vehicles arrive at the station and how long they spend at the station. In combination, these factors determine the likelihood of a port being usable and available as well as the likely duration of queue if no port is usable and available. Supply station parameters are listed in Table 3.

Table 3: Supply Station Parameters

Parameter	Description	Unit
Supply Rate	Maximum rate of energy supply	[kW]
Ports	Number of chargers/pumps at a station which can be used simultaneously	[-]
Reliability	Percentage of the time that a given pump will be usable	[-]
Demand Level ξ	Non-dimensional parameter for station demand distribution.	[-]

Information on ports is taken from Alternative Fuels Data Center (AFDC) [29], information on equipment reliability is taken from [30], and information on port supply rates is taken from Google Maps.

Queue waiting time is computed using the M/M/c queuing formula with parametric uncertainty. The expected waiting time in an M/M/c queue is computed as

$$W_q = \pi_0 \frac{\rho (c\rho)^c}{\lambda (1-\rho)^2 c!} \tag{13}$$

$$\pi_0 = \left[\left(\sum_{k=0}^{c-1} \frac{(c\rho)^k}{k!} \right) + \frac{(c\rho)^c}{c!\,(1-\rho)} \right] \tag{14}$$

$$\rho = \frac{\lambda}{c\mu} \tag{15}$$

where λ is the arrival frequency, μ is the service completion frequency, c is the number of homogeneous servers, ρ is the ratio of arrival frequency to composite maximum service completion frequency, and π_0 is the probability of an empty system. One can think of ρ as equivalent to "utilization". Where ρ is low the station has excess capacity and where high the station is saturated. The expected waiting time in a M/M/c queue can be mapped for values of ρ and c as in Figure 1.

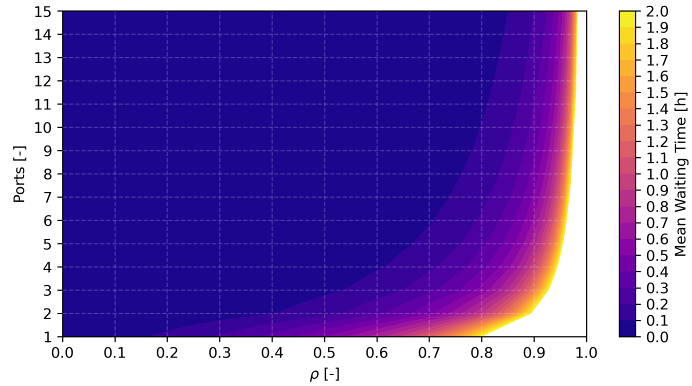


Figure 1: Effects of in-station redundancy and ρ on expected waiting time. Projected times of greater than 2 hours omitted in order to preserve scale.

The main implication of queue dynamics is that stations with more chargers will handle equivalent levels of utilization with shorted queues. The reason for this is that not all sessions will be of the same length and more chargers allows for further de-coordination of session start and end times.

Having a good idea of values for μ and c, the remaining parameter to estimate is the arrival rate λ. The driver will be aware that demand for transportation is likely to change with time-of-day, day-of-week, season, and on special occasions. An experienced driver should have some idea of how busy stations are likely to be based on experience and on road traffic volumes. In this study driver estimates of ρ are sampled from Beta distribution where $2 \leq \alpha \leq 4$ and $\alpha + \beta = 6$. PDFs for the distribution are shown in figure 2. The distirbution is parameterized by a singe variable $\xi \in [0,1]$ where $\xi = .5(\alpha - 2)$.

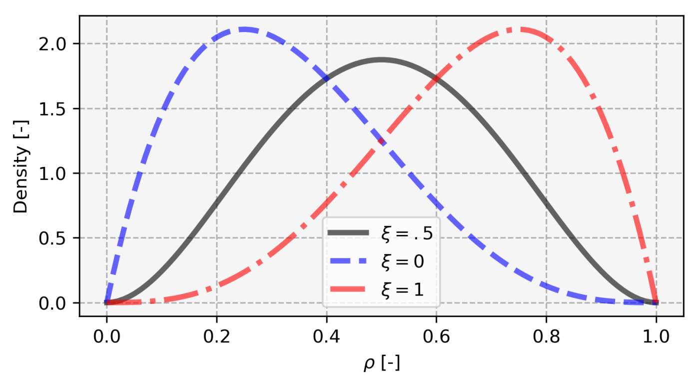


Figure 2: PDFs for ρ Beta distributions reflecting low, medium, and high demand conditions.

Thus, based on informed but imprecise knowledge, the driver can plan a time-minimal route accounting for likely queuing times.

California Case Study

Background

The state of California is geographically large and diverse in demography and land use. Per 2022 US census bureau annual estimates, California's population numbers over 39 million persons with around 32.5 million living in 482 Incorporated Places including cities and towns. These Places range from Los Angeles with a population of 3.8 million located near the coast to Amador City with a population of 201 located in the Sierra foothills. Connecting these disparate locations are a collection of major road transit corridors. Running roughly north-south are S-1/101, I-5/S-99, and U-395. Running roughly east-west are I-8, I-10, I-15, I-40, and I-80. Much of the traffic on the east-west corridors represents interactions with adjoining states. Incorporated Places in California are shown in Figure 3.

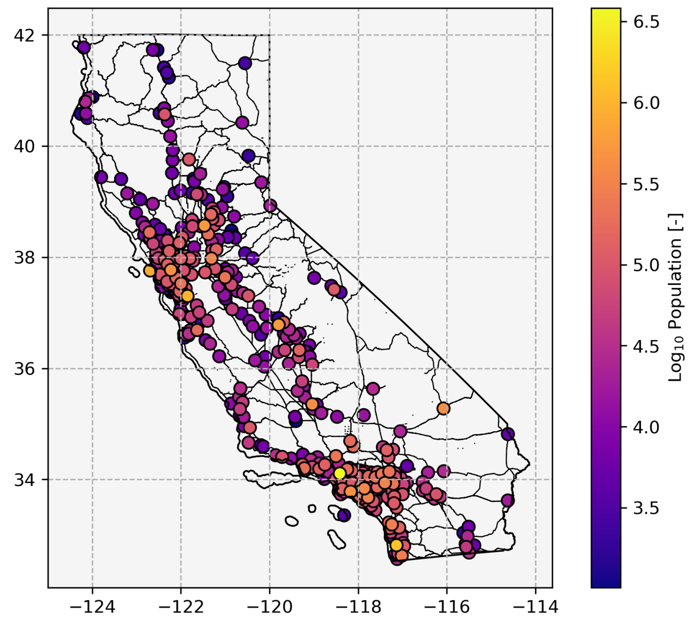
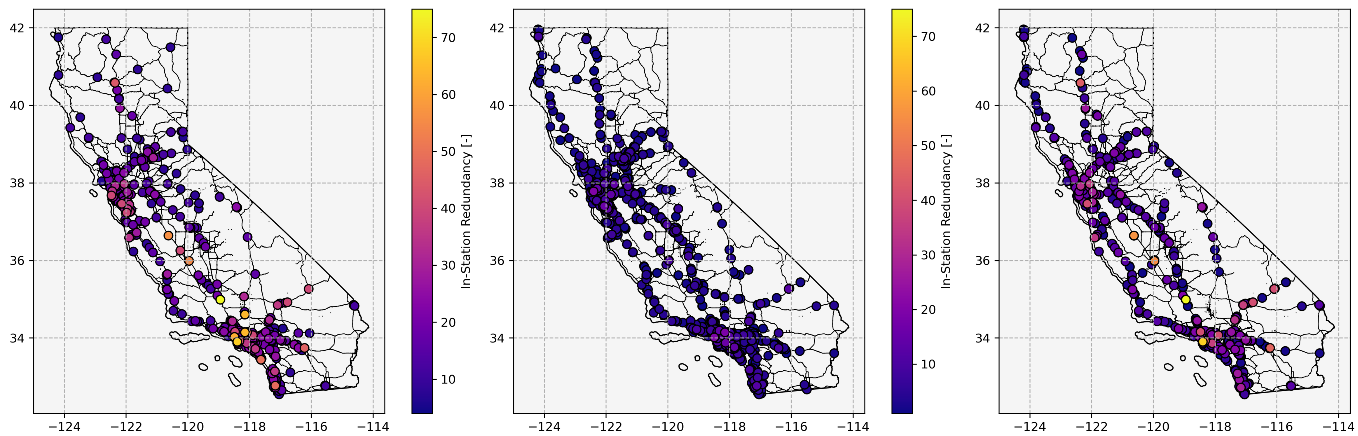


Figure 3: Base 10 logarithm of population for incorporated Places in California

For long trips, BEVs will rely on DC charging stations. The locations of all DC charging stations in California are available from AFDC [29]. AFDC is a reasonable but imperfect source for Dc chargers [31]. In may 2024 AFDC listed 2,149 active stations with at least 1 DC charger. This number is somewhat misleading as certain networks report each charger as an individual station even if within line-of-sight of one-another. After merging all stations of the same network which are within 100 meters direct distance of each other the number of stations becomes 1,689. California's DC charging stations include proprietary (vehicle Original Equipment Manufacturer (OEM) owned and operated) stations such as Tesla Superchargers and the Rivian Adventure network as well as non-proprietary stations such as those operated by ChargePoint, Electrify America, eVgo, and others. The selected locations and DC charging stations are mapped in Figure 4.



(a) Tesla Stations (b) Non-Tesla Stations (c) Corridor Stations

Figure 4: California DC charging stations from AFDC (May 2024)

There are 419 Tesla and 16 Rivian DC charging stations in the state as compared to 1,254 non-proprietary DC charging stations. In practice, many of these stations will be of little use for long distance travel being located far away from primary and secondary roads. Considering only those stations within 1 km of a highway as "corridor" chargers, there are a total of 500 corridor DC charging stations. Of the corridor stations, 156 are Tesla stations, 7 are Rivian stations, and 344 are non-Proprietary stations.

The non-Tesla networks overwhelmingly use CCS or combination CCS/ChaDeMo chargers which reflect the ports on the overwhelming number of non-Tesla BEVs. By contrast, Tesla chargers and vehicles use the NACS standard. The Tesla and non-Tesla systems are historically separate but increasingly interoperable with the aid of adapters. Tesla drivers use Tesla DC chargers almost exclusively [32]. The Rivian Adventure network is technically interoperable with other J1772 vehicles but is set aside for the exclusive use of Rivian vehicles. The purpose of the Rivian Adventure network serves to allow for Rivian vehicles to charge in remote locations and is not intended to be relied upon exclusively.

The difference between the Tesla DC charging network and the non-Tesla networks extends from function to form. Built out as an investment to entice sales of Tesla vehicles and, until recently, exclusive to them, the Tesla network is technically superior with high maximum charging rates and more greater port usability rates [30, 33]. The Tesla network is mainly composed of high redundancy stations. Non-proprietary networks have, so far, been utilization and subsidy driven [4] and are widely distributed with low redundancy stations. A stark contrast is seen when examining the ratios of chargers to stations. In California there are 403 Tesla DC charging stations with a total of 7,101 DC chargers for an average of 16.9 chargers per station. Among non-proprietary networks there are a total of 1,254 stations with 4,129 chargers for an average of 3.3 per station. Redundancies for Tesla and non-proprietary networks are shown in Figure 5.

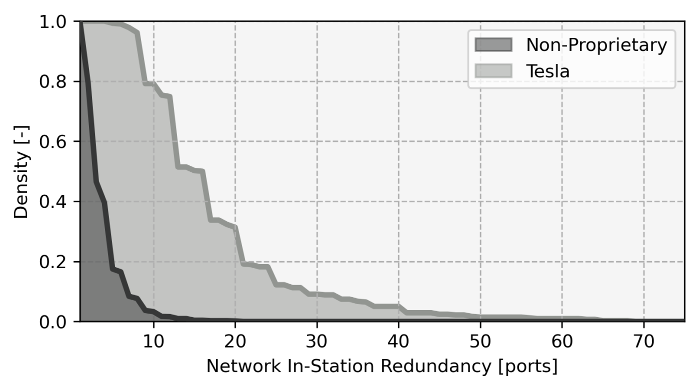


Figure 5: Survival functions for in-station redundancy for Tesla and other DC charger networks in California

The Tesla DC charging network develops redundancy primarily in-station where the non-proprietary networks develop redundancy primarily between stations. Non-Tesla chargers are also more likely to be sighted in urban areas suggesting a desire to capture local as well as corridor travel demand. Tesla stations are more often sighted along travel corridors suggesting a focus on enabling long distance travel. In more remote parts of California the proprietary networks nearly match the non-proprietary networks in station numbers. In-station redundancies for DC charging networks in California can be found in Figures in the DC Charger Network Details section of the Appendix. Summary statistics for DC charging networks in California can be found in the DC Charger Network Details section of the appendix.

California ICEVs utilize a third and completely separate network of supply stations. There are estimated to be over 8,000 gasoline stations in California [34] and these are widely and proportionally distributed. Because no public database for the locations of gasoline stations in the state exists, and due to their ubiquity it is assumed in this study that ICEV driver optimal paths will not be effected by fueling station availability. For this reason, ICEVs are, herein, assumed to take the "direct" path between cities where BEVs need to find optimal paths on their SNGs.

Experiment

In order to understand the effects of vehicular, infrastructural, and behavioral parameters on road-trip accessibility an experiment was carried out on randomly generated combinations. As a baseline, three ICEVs were also modeled. These ICEVs represent different levels of efficiency present in the ICEV fleet. The ICEV models use ESS capacity numbers are pulled from manufacturer websites and energy consumption rates from [35]. Although substantially less efficient than equivalent BEVs the comparatively high specific energy of liquid petroleum allows for ICEVs to have high full-tank ranges. ICEV supply infrastructure is modeled to dispense fuel at the normal US rate of 7 gallons per minute which is an equivalent energy supply rate of 14.15 MW. When refueling, the Prius. Golf, and Pacifica, add highway range at rates of 631, 462, and 282 km per minute respectively. The ICEV models are shown in Table 4.

Table 4: ICEV models

Vehicle Model	Parameter	Value
2024 Toyota Prius	ESS Capacity	381 [kWh]
	Energy Consumption	1,346 [kJ/km]
	Full-Tank Range	1,018 [km]
2024 Volkswagen Golf	ESS Capacity	445 [kWh]
	Energy Consumption	1,839 [kJ/km]
	Full-Tank Range	871 [km]
2024 Chrysler Pacifica	ESS Capacity	640 [kWh]
	Energy Consumption	3,015 [kJ/kM]
	Full-Tank Range	764 [km]

ICEVs were given the "direct" path between locations with stop times added where additional range was needed. For each necessary stop, time was added for refueling to full as well as 10 minutes to divert from the road and handle the transaction prior to refueling. Additionally, drivers of the ICEVs were assumed to keep a 10% buffer of remaining range. The ICEVs each had similar road-trip accessibility scores of roughly 5.5 hours. The longest arc considered in Crescent City (Location 0) to Phoenix - State Line (Location 13) which is roughly 1,530 km just exceeding double the usable range of the Pacifica.

500 random scenarios were generated by uniform random sampling of the parameters listed in Table 5 and run on three SNGs as described in 6. All randomly sampled BEVs in this study are assumed to have an energy consumption rate of 608 kJ/km this being the EPA energy consumption rate of a Tesla Model 3 in highway operation [35]. Highway operation is assumed herein due to the focus on long trips. Thus BEV full-charge ranges will be between 237 and 711 km. When charging, sampled BEVs add highway range at a rate between 4.9 and 19.7 km per minute. Risk attitude is modeled as in (8) with the range centered around the mean parameter $\overline{p}$ where $p_0 = \overline{p} - .1$ and $p_1 = \overline{p} + .1$.

Table 5: Parameters and ranges for experiment.

Parameter	Range
ESS Capacity	[40 kWh, 120 kWh]
ESS Max Charge Rate	[50 kW, 200 kW]
Driver Risk-Attitude Mean	[.1, .9]
EVSE Reliability	[.5, 1]
Demand Level	[0, 1]

Table 6: SNGs used in experiment.

Label	Networks Included
Combined	All stations
Tesla	Only Tesla stations
Non-Tesla	All non-Tesla stations

Outputs were processed to compute neutral expectations of Regional Gravity and Regional Impedance as in (**??**) and (1) respectively. Boxplots of Regional Gravity and Regional Impedance by SNG are presented in Figures 6 and 7.

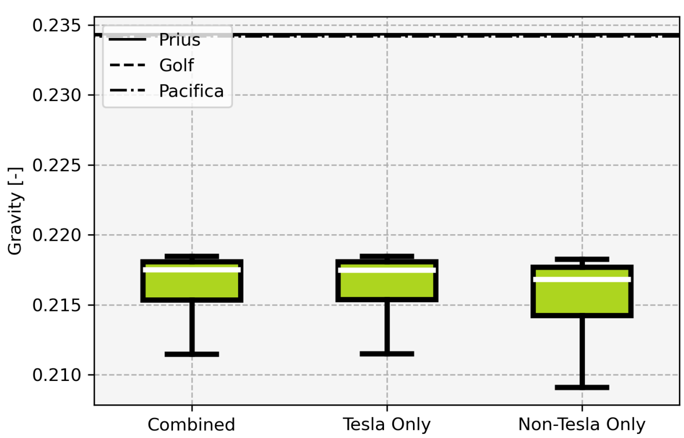


Figure 6: Boxplots of Regional Gravity (G_R) outputs by SNG

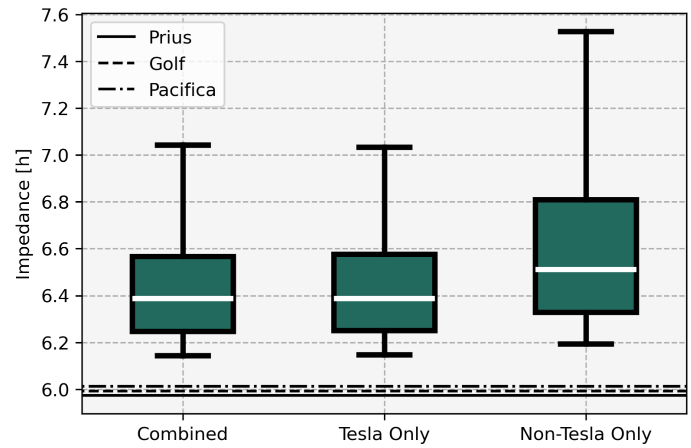


Figure 7: Boxplots of Regional Impedance (Z_R) outputs by SNG

An immediate takeaway is the value of access to Tesla stations. The median performance of the Tesla SNG is only very slightly worse than that of the complete SNG while the performance of the non-Tesla SNG is notably worse than either. The outcome spread among the sampled cases is substantial ranging from marginally worse than the ICEVs to markedly worse. As gravity scales with the inverse of the square of impedance it follows that, purely from a road transportation perspective, the current BEV infrastructure would result in a noticeably less connected region. The bulk of the increase in impedance occurs at-station whether due to queuing or charging times. Although statistically significant, the time lost due to path deviations is minimal as seen in Figure 8.

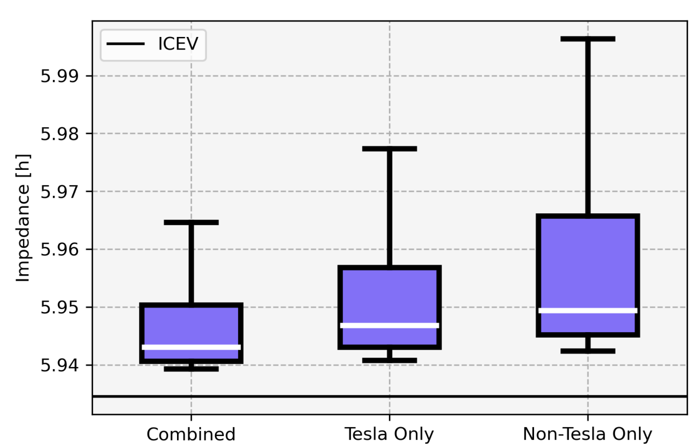
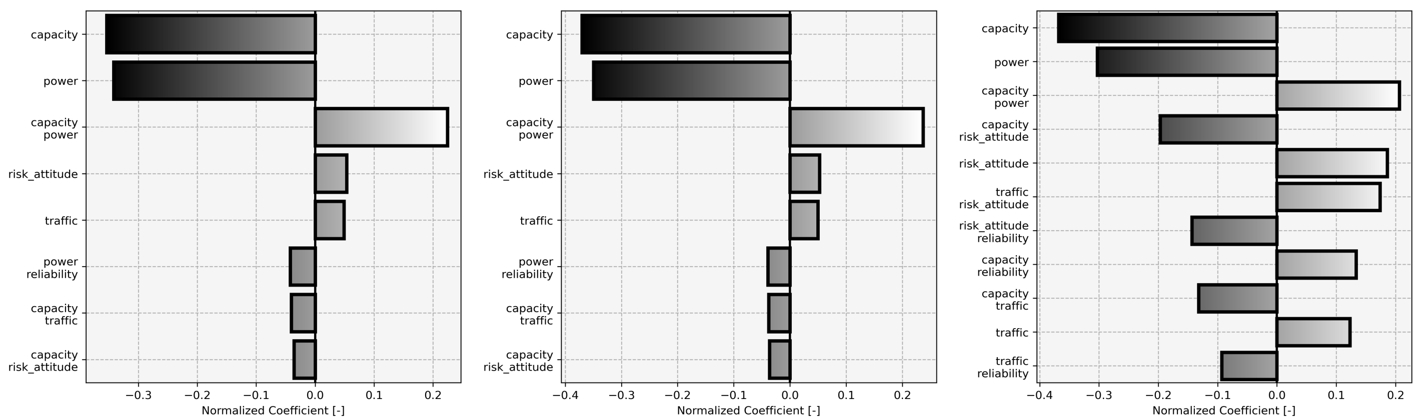


Figure 8: Boxplots of Regional Impedance (Z_R) outputs by SNG neglecting supply time

Having identified the effects of SNG, the effects of vehicular and behavioral parameters on experience for the given SNGs can be identified. Linear regression was performed on the Regional Impedance results of the random experiment and the experimental parameters for each SNG. Significant parameters from the regression are shown in Figure 9. Regression details are tabulated in the Regression Details section of the Appendix.



(a) Complete network

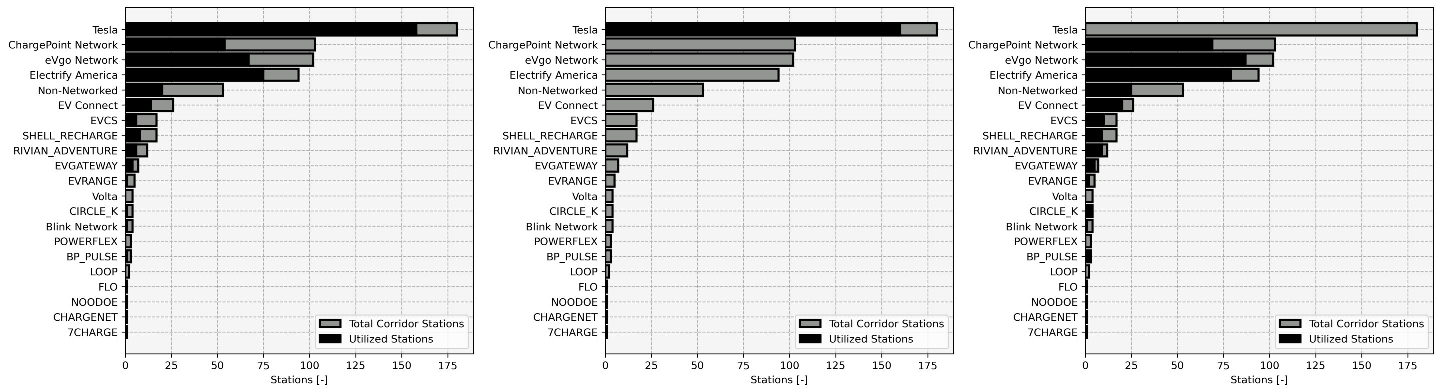
(b) Tesla stations only

(c) Non-Tesla stations only

Figure 9: Coefficients for significant parameters from linear regression

Regardless of SNG, ESS capacity and charging power were shown to be significant and important in reducing Z_R. The interaction between the two was shown to be subtractive indicating that vehicles with longer ranges benefit less from low recharge times and *vice versa*. Vehicles with high maximum charging speeds can only utilize this advantage at a subset of stations which boast maximum charging speeds equal to or in excess of their own. Vehicles with high ranges have more freedom to choose which stations to utilize on a given route. Past a point, however, these beneficial effects will be saturated. The role of equipment reliability is more complicated. In the model developed herein, poor equipment reliability may cause drivers to opt for paths which appear optimal but are worse in fact due to non-functional equipment. Reliability interacts heavily with risk attitude and in-station redundancy. Where the highly redundant Tesla stations are available the role of reliability in anticipated queuing time is low as, even in the worst case, there is a good chance that the queue will be dissipated. Where these stations are not available, the perceptions of the drivers matter much more in determining expected queuing time. In general, the more and higher quality the stations within a SNG the less important risk attitude becomes as the fundamental drivers of queuing are lessened.

Some insight into the utility provided by each network can be gained by looking into utilization rates for networks and stations. Ratios of stations utilized at least once to total corridor stations are shown in Figure 10. Most of the utilized chargers belong to the top four networks. Where Tesla stations are available most were utilized at least once with those not utilized being remote locations. Where Tesla stations are not available, load is shifted towards the other top four networks. This observation indicates that as more vehicles are able to use Tesla stations, traffic will shift towards these stations or other stations which provide similar benefits.



(a) Complete network

(b) Tesla stations only

(c) Non-Tesla stations only

Figure 10: Ratios of corridor stations utilized at least once to total corridor stations by network for each SNG.

One important parameter for station utilization is location. Those stations which are most central to the network should see the highest rate of vehicles undertaking long trips passing by. In order to understand the relative value of location as compared to station design, the betweenness centralty for each station, in terms of driving time was computed. Betweenness centrality is the ratio of optimal paths which include a given node to the total number of optimal paths. A second regression analysis was performed on station utilization for the complete SNG. In this case, the output used was log of utilization (number of times a station appears on an optimal route). Regressors were in-station redundancy and station betweenness centrality using driving time as the cost. Regression results are shown in Tables 7 and 8.

Table 7: Combined Network Linear Regression Analysis ANOVA

R	R-Squared	Adjusted R-Squared	Std. Error
0.614	0.377	0.371	0.005
Category	Sum of Squares	DOF	Mean Squares
Model	1135.565	3	378.522
Error	1873.617	414	4.526
Total	3009.182	417	7.216
F		$P(>F)$	
83.639		0.000	

Table 8: Combined Network Linear Regression Analysis Coefficients

Parameter	Coefficient	P-Value
Intercept	1.919	0.000
redundancy	1.518	0.000
centrality	1.181	0.330
redundancy:centrality	0.987	0.098

The two factors can only partially explain the results due to the differences in vehicles and individuals. It is notable that redundancy and interaction terms are significant at $\alpha = 0.1$ while centrality, on its own, is not. A possible interpretation is that the redundancy has a more determinant effect and that drivers are sometimes willing to sacrifice route directness in favor of more redundant stations.

Discussion

Results of this study suggest that BEVs drivers experience increased Regional Impedance within California. The expeced difference between a given ICEV and BEV is roughly 5%-10% of total travel time for long trips. A large part of this delta is the unavoidable difference in charging times vs. fueling times. Should BEV ranges or charging speeds substantially increase the delta will substantially decrease. The rest of the delta is due to the differences between the SNGs used by BEVs and ICEVs. the differences within the DC charging SNG are worth examining in light of continued and future public investment in its build-out.

Because of the structure of the network, Tesla stations are well positioned to absorb traffic should they become fully open to the general light duty Electric Vehicle (EV) fleet. This may have the result of worsening the user experience at Tesla stations and improving it at other stations until a new equilibrium is reached. The results would also suggest that a second Tesla-style network could enjoy a competitive advantage over the existing non-Tesla networks. It is worth theorizing why such a network has not yet developed. When one single entity has control over all stations in a network and has a captive customer base that network can optimize its expansion. Tesla has, in the past, been able to concentrate chargers to maximize in-station redundancy and minimize between-station redundancy. Simultaneously, Tesla has been able to subsidize overbuilt remote stations with the revenues generated from highly utilized central stations and from car sales. When each network is developed by an independent actor game theoretical considerations come into play. The independent actors must build out their networks under the fear that a competitor could build a competing station near any of their stations at any time. The risk of building station only to lose business to a nearby competitor combined with the opportunity cost of not doing the same results in an inefficient combined network. As Tesla integrates into the wider DC charging network it may begin to behave more like the current non-Tesla companies rather than the other way around.

What makes the distributed network inefficient are the twin issues of uncertainty and latency. These issues can be mitigated by an integrated status reporting and reservation system. Some information is available to drivers. Crowd sourcing applications such as PlugShare have been available for years allowing drivers to get a better idea of the overall reliability and utilization of stations on the basis of user reviews. Google Maps has recently implemented active plug-level availability monitoring with some, but not all, networks. Finally the private applications of the various networks provide different degrees of information and reservation capability. Future work will investigate the impacts of these systems.

Often, the case for BEVs is made on an economic basis as BEV may have lower levelized costs of driving. This study focuses on travel times and routing did not optimize for cost. Partly, this is because at present there is no publicly available data on energy costs at a granular station-level for either gasoline or DC fast charging stations. Nevertheless, some sense of the relative economics of long-trip travel can be attained by examining energy costs per km. Energy costs vary substantially by region in the US with California being the most expensive. Energy costs around the time of writing are shown in Table 9.

Table 9: Residential electricity and petroleum average prices USD

Source	US	California
Petroleum [gallon]	3.609	5.138
Residential Electricity [kWh]	0.1668	0.3247
Transportation Electricity [kWh]	0.1520	0.1191
DC Fast Charging (Estimated) [kWh]	0.35 - 0.50	0.35 - 0.60

Petroleum prices are from AAA [36] and electricity prices are from EIA [37]. DC fast charging pricing schemes display much heterogeneity and may not be as easily accounted as metered electricity prices. An Ad-Hoc Text Mining study performed on over 90,000 recorded PlugShare events from 2019 and 2021 found the mode of DC fast charging prices to be in the range of 0.3 and 0.4 USD per kWh [38]. Prices did not significantly correlate with local energy prices. In the same time period California residential electricity increased from 0.1995 USD per kWh to 0.2282 USD per kWh and transportation electricity increased from 0.0891 to 0.1179 USD per kWh. By comparison with 2024 electricity prices, one would expect prices in the range of 0.35 and 0.60 USD per kWh for DC fast charging in California and 0.35 to 0.5 in the US, ranges backed by informal reporting [39, 40]. Thus, expected energy costs per highway km traveled can be computed and are shown in Table 10.

Table 10: Expected energy costs per highway km traveled in US cents.

Vehicle	Source	US Price	CA Price
Prius	Petroleum	4.00	5.70
Golf	Petroleum	5.47	7.78
Pacifica	Petroleum	8.97	12.77
BEV	Residential Electricity	2.82	5.48
BEV	DC Fast Charging	5.91 - 8.44	5.91 - 10.13

In the US, DC fast charging a BEV presents no appreciable economic benefit over fueling an efficient ICEV. In much of the US, home-charging a BEV provides cost savings for daily travel and the initial part of a long trip. This is not the case in California where residential electricity is, on average, nearly twice as expensive as in the US as a whole.

If BEVs are a worse option than efficient ICEVs for long trips on a time basis and no better on an energy cost basis this will make them less appealing to customers who value the ability to make long road trips. That customers seem to so highly value these uncommon events is a continuing source of frustration for BEV advocates. Negative perceptions of BEV long trip utility on consumer stated preference were found to be quite important in the late 2010s [41–44]. In the intervening time period BEV ranges and maximum charge rates have markedly increased. Nevertheless, negative perceptions related to long trip utility persist for purchasers [45–48] and BEV range is a significant factor in determining usage share of BEVs in multi-vehicle household fleets [49]. In the same time period, a massive build-out of DC charging infrastructure has taken place yet is not evident that the increased presence of DC charging infrastructure changes perceptions [50]. It is, sometimes, argued that the time added to a trip due to DC charging is not relevant as breaks are needed regardless. This argument has been used to support the idea that time parity is relatively attainable [51]. While possibly true for a subset of drivers, in order to take advantage of natural breaks to charge a vehicle, the driver must time these breaks to coincide with good charging intervals. The loss of optionality is an inconvenience in this case even if total trip time parity is achieved.

Most travel is not long trip travel. As shown in Figure **??**, a BEV with 300 km of range can accomplish 80% of US daily itineraries on a single charge. Fundamentally, home nd work charging lead to operational costs that are often cheaper and rarely more expensive than petroleum. Similarly, home and work charging can lead to convenience benefits for BEVs as compared to ICEVs [52] as ICEVs require trips and trip deviations to reach supply stations. In theory, the trade-off of lower cost routine travel for higher cost long-distance travel is one which works in favor of BEVs. This is the logic which underpins the "charging pyramid" model which places long dwell charging events at its base and corridor DC fast charging events at its peak. This model is also, to some degree, self-reinforcing. If BEV drivers prefer AC charging, DC charging infrastructure will have limited revenue potential leading to lower network capacity. Lower network capacity, in turn, leads to the perception that the network is inadequate and should be avoided.

The charging pyramid implies a different way of thinking about the role of car travel as a subset an individual's travel needs. Personal travel is inherently multi-modal and, for many O/D arcs and many individuals, the cost differential between different modes is within the threshold of disambiguation. The strengths and weaknesses of BEVs as compared to ICEVs may shift more short trips away from local transit and towards cars while shifting more long trips away from cars to air travel and inter-city transit. BEVs will only be one part of future mobility, unable to meet transportation needs or environmental goals on their own. Investments in BEV corridor infrastructure should be considered alongside investments into other low carbon inter-city transit modes.

Conclusions

Personal vehicles play a major role in the transportation systems of all major developed economies globally. The role of personal vehicles is particularly pronounced in the US. As the transition to BEVs continues, BEVs will be pressed into more unsuitable roles and less forgiving drivers. Where BEVs provide advantages for routing travel where long dwells enable slow charging events to suffice, they are disadvantageous for long-trip travel. As many customers disproportionately weight long trips in purchase decisions, public money has been poured into subsidy programs to build out a national DC charging network in the US. This paper provides a framework for the quantitative analysis of the performance of said network from the point of view of transportation accessibility. The framework proposed accounts for the effects of vehicle and behavioral parameters as well as the precise structure of the network. The current DC charging network in California is analyzed and shown to enable BEV travel reasonably well. Outcomes are found to be also dependent on vehicle range and maximum charge rate and individual risk attitude. If vehicles can charge at existing Tesla stations then the time difference between BEV and ICEV is found to be mostly due to unavoidable differences in range-addition rates. Where Tesla chargers are not accessible, drivers can expect substantial additional time due to route deviations and queuing. The structure of the Tesla network with relatively few stations and relatively many ports per station is particularly conducive to long-trip travel. Current market dynamics have pushed the non-Tesla networks towards the opposite structure. Public investment may be more productively used to encourage more Tesla-like networks. However, even with a substantially improved DC charging network, BEV travel will not achieve total-time parity with ICEVs unless charging speeds are massively increased. thus investments in enabling inter-city vehicle travel should be considered alongside investments inn other low-carbon inter-city travel modes.

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Appendix

DC Charger Network Details

Network characteristics for DC charging networks in California are shown in Figure 11 and in Table 11. Data pulled from AFDC in May 2024.

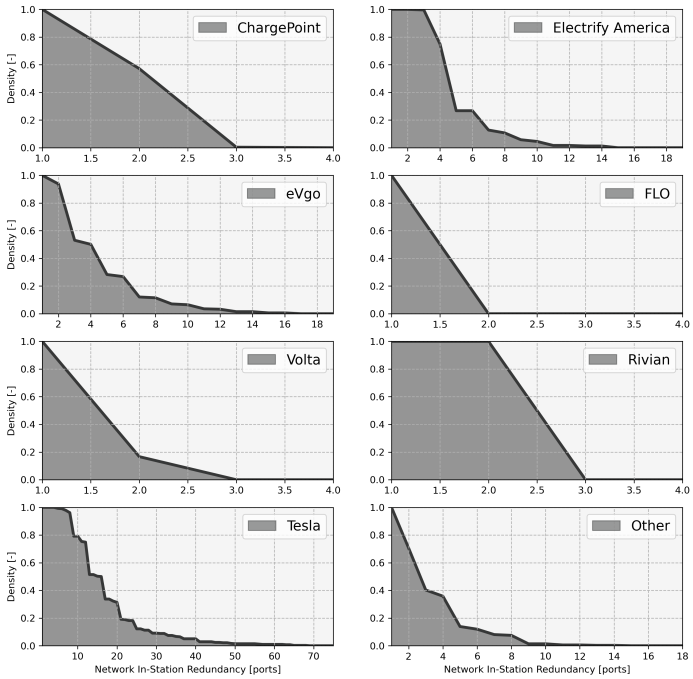

Figure 11: In-station redundancy for DC Charging networks in California

Table 11: Summary statistics for California DC charging networks from AFDC

Network	Chargers	Stations	Chargers per Station
Non-Networked	288	51	5.6
Tesla	2753	156	17.6
Electrify America	526	77	6.8
EV Connect	59	19	3.1
ChargePoint Network	186	79	2.4
Volta	2	2	1.0
EVCS	41	11	3.7
SHELL_RECHARGE	39	11	3.5
EVGATEWAY	21	5	4.2
eVgo Network	332	63	5.3
BP_PULSE	3	2	1.5
POWERFLEX	12	3	4.0
FLO	1	1	1.0
EVRANGE	11	3	3.7
RIVIAN_ADVENTURE	14	7	2.0
CIRCLE_K	16	3	5.3
CHARGENET	7	1	7.0
Blink Network	2	2	1.0
NOODOE	2	1	2.0
LOOP	6	2	3.0
7CHARGE	4	1	4.0

Network characteristics for DC charging networks in California, conunting only corridor chargers, are shown in Figure 11 and in Table 11. Data pulled from AFDC in May 2024.

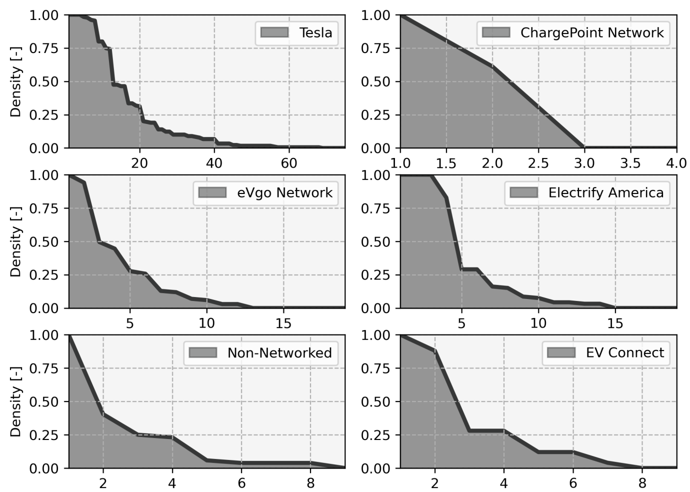

Figure 12: In-station redundancy for DC Charging networks in California

Table 12: Summary statistics for California DC charging networks from AFDC (corridor stations)

Network	Chargers	Stations	Chargers per Station
Non-Networked	274	50	5.5
Tesla	2745	155	17.7
Electrify America	518	76	6.8
EV Connect	58	18	3.2
ChargePoint Network	184	78	2.4
Volta	1	1	1.0
EVCS	35	10	3.5
SHELL_RECHARGE	37	10	3.7
EVGATEWAY	19	4	4.8
eVgo Network	329	62	5.3
BP_PULSE	1	1	1.0
POWERFLEX	10	2	5.0
EVRANGE	5	2	2.5
RIVIAN_ADVENTURE	12	6	2.0
CIRCLE_K	12	2	6.0
Blink Network	1	1	1.0
LOOP	2	1	2.0

Regression Details

Details of linear regression on random experiment results are displayed in the following tables. Tables 13 and 14 concern the combined network, Tables 15 and 16 concern the Tela network, and Tables 17 and **??** concern the non-Tesla network.

Table 13: Combined Network Linear Regression Analysis ANOVA

R	R-Squared	Adjusted R-Squared	Std. Error
0.926	0.858	0.853	0.000
Category	Sum of Squares	DOF	Mean Squares
Model	28.706	15	1.914
Error	4.754	484	0.010
Total	33.460	499	0.067
F		$P(>F)$	
194.848		0.000	

Table 14: Combined Network Linear Regression Analysis Significant Coefficients ($\alpha = 0.5$)

Parameter	Coefficient	P-Value
Intercept	7.121	0.000
power	-1.009	0.000
capacity	-1.031	0.000
reliability	-0.227	0.040
capacity:power	0.984	0.000
capacity:reliability	0.422	0.036

Table 15: Tesla Network Linear Regression Analysis ANOVA

R	R-Squared	Adjusted R-Squared	Std. Error
0.926	0.857	0.852	0.000
Category	Sum of Squares	DOF	Mean Squares
Model	27.188	15	1.813
Error	4.541	480	0.009
Total	31.728	495	0.064
F		$P(>F)$	
191.609		0.000	

Table 16: Tesla Network Linear Regression Analysis Significant Coefficients ($\alpha = 0.5$)

Parameter	Coefficient	P-Value
Intercept	7.218	0.000
power	-1.099	0.000
capacity	-1.179	0.000
reliability	-0.220	0.047
capacity:power	1.130	0.000
power:risk_attitude	0.479	0.035
capacity:reliability	0.481	0.016
capacity:power:risk_attitude	-0.879	0.028

Table 17: Non-Tesla Network Linear Regression Analysis ANOVA

R	R-Squared	Adjusted R-Squared	Std. Error
0.866	0.750	0.742	0.000
Category	Sum of Squares	DOF	Mean Squares
Model	72.583	15	4.839
Error	24.215	484	0.050
Total	96.798	499	0.194
F		$P(>F)$	
96.720		0.000	

Table 18: Non-Tesla Network Linear Regression Analysis Coefficients

Parameter	Coefficient	P-Value
Intercept	7.095	0.000
power	-1.373	0.000
capacity	-1.130	0.000
risk_attitude	0.954	0.001
capacity:power	1.505	0.004
power:risk_attitude	1.429	0.006
capacity:power:risk_attitude	-1.915	0.037
power:reliability:risk_attitude	-1.744	0.047