A Geo-Spatial Method for Calculating BEV Charging Inconvenience Using Publicly Available Data

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Abstract. As governments and the automotive industry push towards electrification, it becomes increasingly critical to address the factors which influence individual car buying decisions. Evidence suggests that operational inconvenience or the perception thereof plays a large role in consumer decisions concerning Battery Electric Vehicles (BEVs). BEV ownership inconvenience and its causal factors have been relatively understudied, rendering efforts to mitigate the issues insufficiently informed. This paper presents a method of producing an empirical equation which relates operational inconvenience to a small number of housing and local Electric Vehicle Supply Equipment (EVSE) infrastructure factors. The paper then further provides a method of applying the equation in a geo-spatial context allowing for the evaluation of the effects of policies in a geographical manner. this method enables future quantitative analyses concerning investment in EVSE infrastructure to be directly sensitive to BEV operational inconvenience due to charging.

Introduction

The wide-spread adoption of BEVs for personal use is imperative in the realization of a green transportation future in the US. In order to achieve high rates of adoption in the near and medium-term future, policy makers and industry have recently set ambitious goals for BEV market penetration (Person and Mason 2021). The degree to which BEV adoption will mitigate the environmental impact of the transportation sector is the subject of extensive and accelerating academic debate (Dolganova et al. 2020) and is contingent on related developments in the power generation sector. The trend in the power generation sector is towards decreased carbon intensity (US Environmental Protection Agency 2023b) implying that even current production BEVs will see reduced per-mile emissions within their terms-of-use. Ultimately, the success of BEV adoption initiatives will be the result of many millions of decisions made by individual consumers with different priorities. While much attention has been paid to the economic aspects of the decision to purchase a BEV evidence suggests that consumers also strongly weight perceived operational convenience in their decision making process (Kwon, Son, and Jang 2020; Neaimeh et al. 2017; Vassileva and Campillo 2017).

It is entirely rational to assume that operating a BEV will be more inconvenient than operating an Internal Combustion Vehicle (ICV) due to the time required to charge. BEV charging adds range at a much lower rate than ICV fueling even at the highest charging rates currently available (US Department of Transportation 2022). Thus BEVs should spend more time charging than ICVs spend fueling for an equivalent distance driven. This reality will effect BEV operators unevenly. Those with higher energy usage will need to charge their vehicles for longer and/or more often. Inequity will also result from different levels of access to EVSE.

A common model for BEV charging is the "Charging Pyramid" model as shown in Figure 1. In essence, the Charging Pyramid model states that the frequency of charge events will be inversely proportional to the rate at which the events occur. Explicitly, the Charging Pyramid model views home and work charging as fundamental as evidenced by their presence at the base of the pyramid.

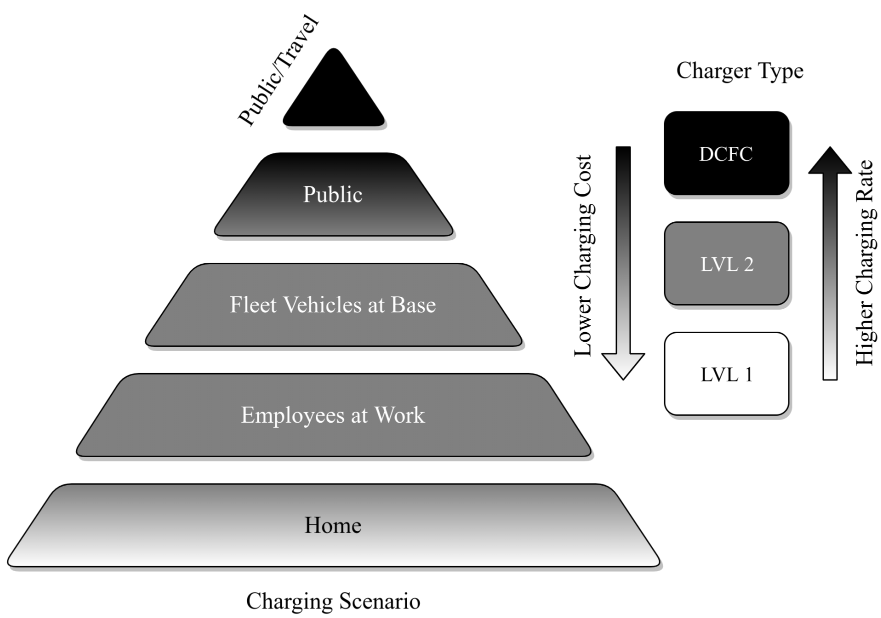


Figure 1. Charging activity pyramid. Modified composite of original graphic by T. Bohn, Argonne National Laboratory. From (Rabinowitz et al. 2023b)

As recently as 2021 Electric Vehicle (EV) sales constituted less than 4% of new car sales (EVAdoption 2022). With such a low volume of sales it would be safe to assume that the majority of BEV buyers are in relatively favorable BEV ownership situations. In order for BEVs to achieve a dominant market share in the US, they must be an attractive proposition for most of the market. Residents of owner-occupied single-unit dwellings make up about 62% of Americans per the 2021 American Community Survey (ACS) (US Census Bureau 2021) while residents of owner-occupied dwellings of all types make up roughly 68%. People who either do not own their residences or live in high density housing may not be able to install EV chargers for a variety of reasons. there are also a large number of Americans for whom work charging is not an option. As of 2021, just fewer than 10,000 workplace EVSE ports existed in the entire US (Brown, Schayowitz, and Klotz 2021). Thus, an important fraction of the population will not have access to home or work charging. It is worth considering what charging options are available to the portion of the market unable to charge at home or at work. The authors propose that charge events can be categorized by rate and deliberateness as in Figure 2.

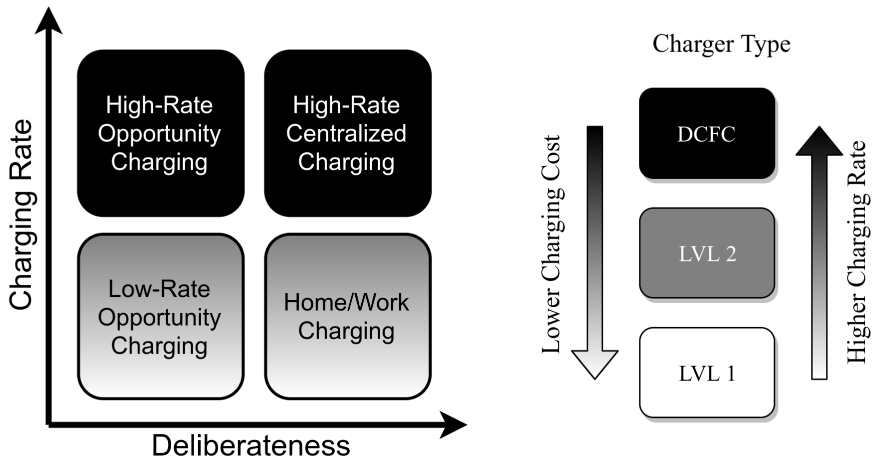


Figure 2. Dual-axis charging activity model. High-rate opportunity charging is rarely available.

As can be seen in Figure 2, the proposed model characterizes charging events by rate and deliberateness. In this case, deliberateness is the degree to which the charging event requires the operator to plan around it. In order to charge at home, work, or a centralized charging station, the operator must travel to a specific destination. This is opposed to opportunity charging wherein the operator travels to a given location (gym, retail, entertainment) for another purpose and charges at an available charger near the location.

Opportunity charging is most commonly low rate while high-rate charging is most commonly available in centralized locations such as dedicated stations on interstate highways (Trinko et al. 2021). High-rate opportunity charging is rarely available and thus not usually an option for EV operators. Thus, those who cannot charge at home or work are reliant on public infrastructure which is often limited to high-rate centralized charging and low-rate opportunity charging. The experiences of this demographic will depend heavily on the characteristics of local EVSE infrastructure. In order to evaluate the effectiveness of EVSE infrastructure investment in terms of its effect on those who rely upon it a new under-standing must be attained. In this paper a novel, quantitative, and geographical method for evaluating the inconvenience of BEV ownership for all demographics of potential BEV operators is presented. This metric and method provide the foundation for future inconvenience-sensitive EVSE infrastructure analysis.

Energizing Inconvenience

In a previous paper (Rabinowitz et al. 2023a), the authors proposed a metric (S_{IC}) which reflects this understanding of inconvenience. A BEV operator is only inconvenienced by charging their vehicle if they must devote time to doing so in which they are unable to, or have a limited ability to, perform other activities. For example, if a BEV owner parks at home and immediately begins charging his or her car then the amount of time dedicated to charging is only the time required to plug the car in and to un-plug it later. The inconvenience is minimal regardless of the duration of the charging event. Conversely, if one charges at a public charging station then he or she must remain at that location for the duration of the charge and is inconvenienced for the entire duration of the charge as well as the time required to travel to and back from the station. Relative to inconvenience, charging events may be broken down into four categories as follows:

- Home charging events: Charging events which take place at the operator's home location. The operator's vehicle will normally dwell at home for long periods on a daily basis. Thus, home charging events, regardless of duration, do not force the operator to devote time out of his or her itinerary to charging.

- Work charging events: Charging events which take place at the operator's work location. The operator's vehicle will normally dwell at work for long periods on workdays. Thus, work charging events, regardless of duration, do not force the operator to devote time out of his or her itinerary to charging.

- Destination charging events: Charging events which take place at long dwell destinations such as supermarkets, retail centers, gyms, etc. Because the operator would visit these locations regardless of whether or not he or she intended to energize a vehicle, these events do not force the operator to devote time out of his or her itinerary to charging. Thus, destination charging events only inconvenience the operator for the amount of time that he or she would need to spend paying for the charging event.

- En-route charging events: Charging events which take place at a location which the operator visits specifically to energize a vehicle. Locations such as petroleum stations or centralized DC Fast Charging (DCFC) charging stations may be located near amenities but operators will generally be constrained to stay within a small area adjacent to the station for the duration of the charging event. Thus operators are inconvenienced for the duration of the event and payment process. An assumption is also made that operators will have to travel a non-negligible distance to the charging station. Because operators are only traveling to the station to energize their vehicles the travel time is also considered to be devoted charging time. Thus operators are also inconvenienced for the travel time required to get to and from the charging station.

Because the different types of charging events effect the operator differently it is important to define a metric of inconvenience which can account for all four. To this end the authors propose a flexible metric, Inconvenience Score (S_{IC}) defined as

$$S_{IC} = \frac{\sum_{k=0}^{N}[D_{E,k}M_{E,k} + D_{T,k}M_{T,k} + D_{P,k}M_{P,k}]}{\sum_{k=0}^{N} L_k} \tag{1}$$

for an itinerary of N trips where D_E is the duration of the charging event, D_T is the duration of travel to get to the charging location, D_P is the duration of the payment process, $M_{E,k}$, $M_{T,k}$, and $M_{P,k}$ are integer multipliers which respectively define whether or not to count the various durations for trip k, and L_k is the length of trip k in kilometers. S_{IC}, thus, is the average dedicated charging time per kilometer traveled in a given itinerary. The values of the multipliers based on the type of charging event are shown in Table 1.

Table 1. Values of multipliers based on charging event type

Energizing Event Type	M_E	M_T	M_P
Home	0	0	0
Work	0	0	0
Destination	0	0	1
En-route	1	1	1

So defined, S_{IC} is able to account for the differences between charging event types and to account for differences in total travel distance between itineraries. The flexibility of the S_{IC} metric thus allows for the direct comparison of inconvenience between disparate itineraries.

Itinerary Data

Itinerary data for this study was based on the 2017 National Highway Transportation Survey (NHTS) (US Department of Transportation 2017). The decision to use NHTS data was taken due to the scope and information content of the survey when compared to other publicly available data-sets.

The NHTS is a comprehensive non-commercial travel survey conducted by the US FHA which serves as an authoritative source on travel behavior in the US. The most recent NHTS was conducted in 2017. The NHTS collects, by survey, travel activities for selected households for a single day. The surveyed households are located in all 50 US states and the District of Columbia. Data collected includes demographic data for the household as well as travel itineraries for each person and vehicle within the household. The publicly available version of the 2017 NHTS contains single day itinerary data for 117,222 households containing 219,194 persons and 153,351 vehicles. Because the daily itinerary distances for vehicles in the 2017 NHTS are more varied than trip counts, the decision was made to scale by distance in this paper.

The format of the NHTS is not ideal for use in longitudinal analysis due to the single day itineraries. Using NHTS data for longitudinal analysis requires one to derive long term itineraries from single day itineraries. Additionally because NHTS offers neither precise home locations nor precise destination locations, it is not possible to construct Household Activity Pattern Problems (HAPPs) (Recker 1995) as was done in (Kang and Recker 2014) using California Houslehold Travel Survey (CHTS) data. However, NHTS data does enable more demographic selection than any other comparable study and thus enables the most specific results to be attained. In order to use NHTS data for long term itineraries, the single day itineraries were simply tiled for a given number of repetitions.

Calculating Inconvenience Score

For any given itinerary, operators will experience different levels of inconvenience based on how they choose to schedule charging events. The authors contend that the fundamental inconvenience for a given itinerary is the minimum inconvenience for said itinerary. In order to calculate the minimum inconvenience for a given itinerary optimal charge scheduling was used.

Optimal charge scheduling was conducted via Dynamic Programming (DP) (Bellman 1956; Kirk 1970). DP is a commonly used technique in optimal control which is guaranteed to find a globally optimal solution subject to the chosen discretization of the problem.

The goal of the optimization was

$$\min_{\overline{U}} J(S_0, \overline{U}) \tag{2}$$

where

$$J(S_0, \overline{U}) = \Phi(S_N) + \sum_{k=1}^{N} \Psi(S_k, U_k) \tag{3}$$

s.t.

$$S_{k+1} = f(S_k, U_k), \quad k = 0, \ldots, N-1 \tag{4}$$

$$S_{min} \leq S(t) \leq S_{max} \tag{5}$$

where $\Psi(\overline{S}, \overline{U})$ is the running cost (charging inconvenience), $\Phi(\overline{S})$ is the final state cost, $\overline{S} = [SOC]$ is the state vector containing the battery State of Charge (SOC) for the vehicle, $\overline{U}$ is the control vector formulated as $\overline{U} = [D_D, D_{ER}]^\top$ containing durations of opportunity charging events at destinations C_D and durations of en-route charging events at centralized high-rate charging stations C_{ER}, J is the cost for S and U, and S_{min} and S_{max} are lower and upper limits for the state vector and are constant in time. The overline indicates an array containing values at multiple discrete time intervals. The goal of the optimization is to find the optimal charging schedule ($\overline{U}^*$) such that J^* is equal to the global minimum value for J. J is the inconvenience score (S_{IC}) as defined in equation (1) which accounts for total dedicated charging time.

Vehicle Model

For evaluation purposes, a vehicle model was defined which simulates the amount of energy consumed by the vehicle on a given trip based on the trip length and mean speed. The vehicle model is defined by the parameters listed in Table 2.

Table 2. Vehicle Parameters

Parameter	Description
Energy Storage Capacity [kWh]	Maximum amount of energy that can be stored on vehicle [J]
City Consumption Rate [kJ/km]	Amount of energy consumed per unit distance [J/m] in urban driving conditions [less than 15.6 m/s]
Mixed Consumption Rate [kJ/km]	Amount of energy consumed per unit distance [J/m] in mixed urban and highway driving conditions [15.6 m/s – 29 m/s]
Highway Consumption Rate [kJ/km]	Amount of energy consumed per unit distance [J/m] in highway driving conditions [greater than 29 m/s]

For this study the 2021 Tesla 3 LR was chosen as the baseline vehicle. The consumption data for the 2021 Tesla 3 LR is listed in Table 3.

Table 3. Base vehicle energy consumption rates

Parameter	Value
Energy Storage Capacity [kWh]	82
City Consumption Rate [kJ/km]	385.2
Mixed Consumption Rate [kJ/km]	478.8
Highway Consumption Rate [kJ/km]	586.8

This is, necessarily, an approximate measure. Data for vehicle energy consumption rates was attained from (Cars.com 2022; EV-Database 2021) and verified with data from (US Environmental Protection Agency 2023a) with the city consumption rate calculated from US06 drive cycles, the highway consumption rate calculated from HWFET drive cycles, and the highway consumption rate calculated from FTP drive cycles.

EVSE Infrastructure Model

It was also necessary to define models for EVSE infrastructure. BEV charging rates were based on the Society of Automotive Engineers (SAE) J1772 standard (Society of Automotive Engineers n.d.) and information from (EV-Database 2021). The following assumptions were made about charging infrastructure:

1. If a home charger is available then it will be an AC Level 2 charger
2. If a destination charger is available it will be an AC Level 2 charger
3. All DC Level 2 (LVL 2) charging will be done at 12.1 kW which is the middle of the AC Level 2 range
4. All en-route charging will be done at dedicated DCFC stations with DC Level 1 or 2 chargers
5. At all times, all vehicles are within a certain travel time to the nearest DCFC station regardless of their location.

The infrastructure model assigns chargers to destinations based on the stated assumptions. The assignment of AC Level 2 chargers to home locations is based on a Boolean which determines if there will be chargers at home locations or not. The assignment of chargers to destinations is done by assigning chargers, randomly, to a certain percentage of the locations visited by the vehicles. Because this randomness can have an effect on inconvenience score for a configuration, all configurations are run multiple times and the inconvenience scores for the runs are averaged.

DC charging was modeled on the CC-CV curve model for lithium-ion batteries (Marra et al. 2012). The energy added, as a function of time is

$$dSOE = \frac{P_{DC}}{C_B} t_{cc} + (1 - e^{(\lambda_C t_{cv})}) \tag{6}$$

$$P_{DC} = P_{AC}\eta \tag{7}$$

$$\lambda = \frac{P_{DC}}{0.2C_B} \tag{8}$$

where $dSOE$ is the change in State of Energy (SOE) over the course of the charge event, P_{AC} is the nominal AC power level of the charge event, η is the efficiency of the conversion between AC and DC, P_{DC} is the DC power of the charge event, t_{cc} is the time spent in the constant current portion of the charge event, t_{cv} is the time spend in the constant voltage portion of the charge event, and C_B is the vehicle's battery capacity. This model defines a relationship wherein charging is linear below 80% SOE and inverse-exponential after as it approaches 100% SOE. For AC charging the model used was a pure linear charging model which cuts off at 100% SOE. These charging traces are illustrated in Figure 3.

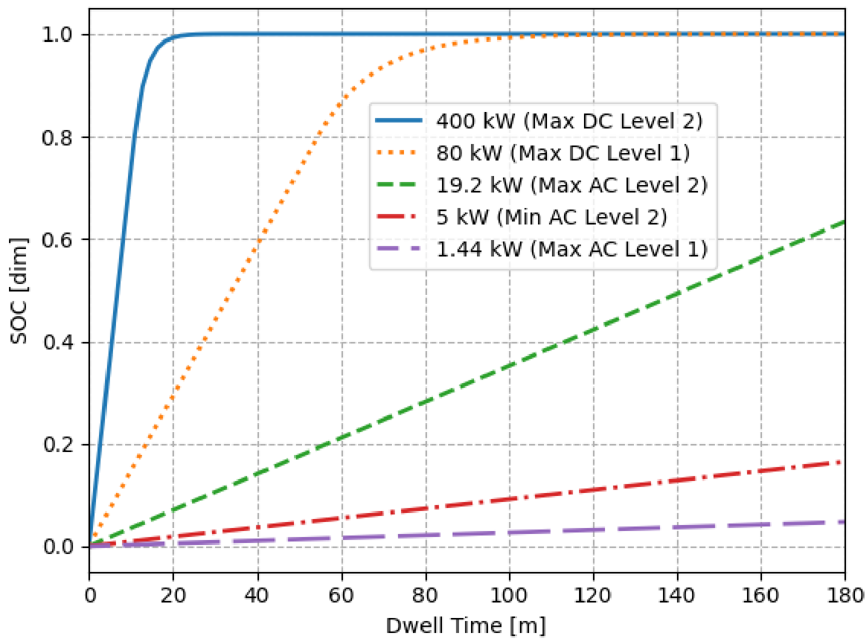
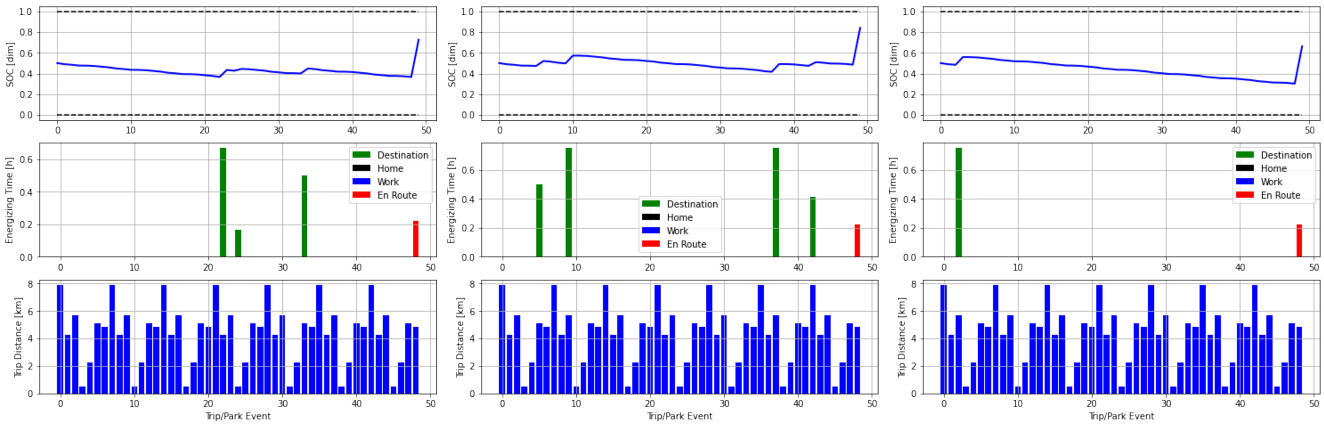


Figure 3. Three hour charging traces at various charging rates for a vehicle with an 80 kWh battery

As seen in Figure 3, charging rate has a significant effect on the amount of time required to charge. At 250 kW, a vehicle with an 80 kWh battery can charge to 80% SOC in about 15 minutes where the same vehicle would require 384 minutes to complete the same charge at 10 kW.

Individual Trace Results

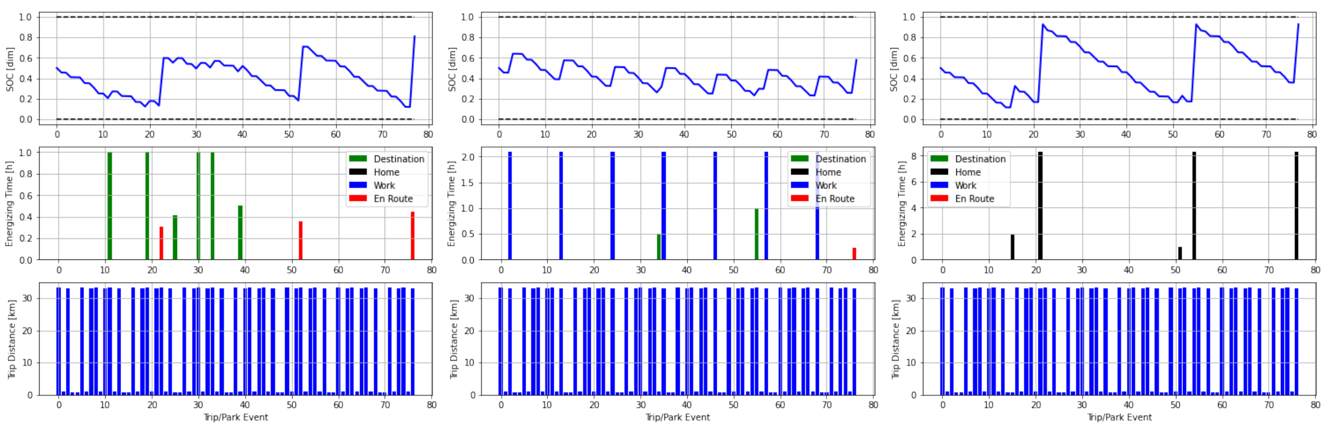
Because the assignment of destination chargers is probabilistic, the results for a given BEV and set of infrastructure parameters may be different from run to run. Figure 4 demonstrates this by showing three simulation runs of 7 tiled day long itineraries where all vehicle and infrastructure parameters are the same between the simulations.



(a) Simulation #1 of Vehicle #105 (b) Simulation #2 of Vehicle #105 (c) Simulation #3 of Vehicle #105

Figure 4. Traces for BEVs with no home or work charging and identical vehicle and infrastructure parameters

In Figure 4 the vehicle, in all cases, was neither able to charge at home nor at work. The effects of being able to charge at home or work are often visually striking. Because home dwells are long and the operator does not suffer a payment or travel penalty associated with home or work charging events, these events tend to dominate. An example of the effects of home and work charging over a 7 day trace is shown in Figure 5.



(a) Vehicle #48 without home or work charging (b) Vehicle #48 with work charging (c) Vehicle #48 with home and work charging

Figure 5. Traces for BEVs with no home or work charging and identical vehicle and infrastructure parameters

Vehicle #48, as shown in Figure 5, had a typical commuter itinerary which was dominated by two long daily trips. For this type of itinerary charging at home and work is particularly important as the vehicle uses a significant amount of its range over a given day. Having the ability to charge at work allows for a much smaller reliance on public charging but the operator will still have to occasionally charge at a destination or centralized charging station. Charging at home has a higher impact as it removes the need to charge anywhere else for normal daily driving as seen in panel (c).

Inconvenience Formulae

Having derived a model for energizing inconvenience an experiment was run concerning several vehicle and EVSE infrastructure parameters. The purpose of this experiment was to derive an empirical formula for Inconvenience Score based on vehicular and infrastructural parameters. The experiment was a full-factorial design on the parameters listed in Table 4.

Table 4. Experiment Parameters and Levels

Parameter	Levels	Unit
Home Charging (HC)	[False, True]	Boolean
Work Charging (WC)	[False, True]	Boolean
Battery Capacity (BC)	[40, 80, 120]	kWh
Destination Charger Likelihood (DCL)	[0, 4.5, 15]	%
DCFC Rate (DCFCR)	[50, 150, 250]	kW
DCFC Penalty (DCFCP)	[0, 25, 50]	min

The rationale for these levels was to capture the realistic range of values for each parameter in the present and near future. The range of battery capacities was based on the values of usable battery capacity found in (EV-Database 2023). The range for DCFCR was based on ranges identified in (EV-Database 2021; Trinko et al. 2021). It would be quite difficult to find a true range of values for DCL or DCFCP but these values were estimated by comparing the numbers of different types of chargers present at different types of locations identified in (Trinko et al. 2021) with statistics about numbers and geographical distributions of petroleum fueling stations found in (American Petroleum Institute 2023). The ranges of values used for DCL and DCFCP were also in line with calculated values for the Denver Colorado urbanized area as discussed later.

The electric vehicle model used for energy consumption was the Tesla 3 LR model described in Tables 2 and 3 with BC being the only parameter modified during the experiment. For each of the 324 experimental cases, inconvenience scores were generated for all 61,039 itineraries from vehicles in the 2017 NHTS containing more than 3 trips. A linear regression was then performed on all min-max normalized terms and interactions. Significant results for this regression ($\alpha = 0.05$) are presented in Tables 5, 6, and 7.

Table 5. Model Summary

R	R-Squared	Adjusted R-Squared	Std. Error
0.991	0.982	0.978	0.000

Table 6. ANOVA

Category	Sum of Squares	DOF	Mean Squares
Model	10.100	63	0.160
Error	0.181	260	0.001
total	10.281	323	0.032
F Statistic		$P(>F)$	
290.509		$3.504\exp(-200)$	

Table 7. Significant Coefficients

Coefficient	Value	F Statistic	$P(>F)$
Intercept	0.317	17.297	0.000
HC	-0.291	-11.234	0.000
WC	-0.119	-4.578	0.000
DCL	-0.136	-4.784	0.000
HC:WC	0.117	3.183	0.002
DCFCR	-0.222	-7.805	0.000
DCFCP	0.629	22.126	0.000
HC:DCL	0.134	3.327	0.001
HC:DCFCR	0.206	5.139	0.000
WC:DCFCR	0.089	2.208	0.028
BC:DCFCP	-0.261	-5.934	0.000
HC:DCFCP	-0.566	-14.074	0.000
WC:DCFCP	-0.235	-5.859	0.000
DCL:DCFCR	0.107	2.441	0.015
DCL:DCFCP	-0.297	-6.751	0.000
HC:BC:DCFCP	0.208	3.349	0.001
HC:WC:DCFCP	0.221	3.893	0.000
HC:DCL:DCFCP	0.293	4.712	0.000

The significant coefficients from the regression are also shown visually in Figure 6.

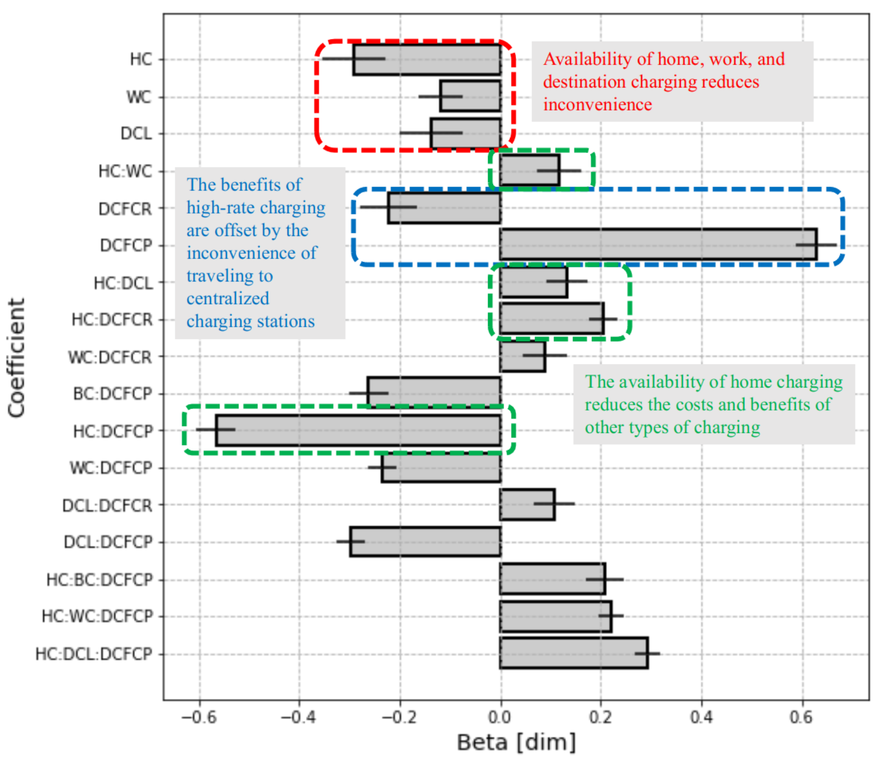


Figure 6. Significant Regression Coefficients and Error Bars

The regression was performed with normalized regressor values in order to remove the impact of the scales of the regressors. Thus normalized, it is possible to make a comparative analysis of the importance of the parameters and their interactions. Of the parameters BC, HC, DCL and DCFCR were shown to contribute to decreasing inconvenience while DCFCP was shown to contribute to decreasing inconvenience. Of the parameters, the most important for reducing inconvenience was HC. As discussed previously, BEV operators who are able to charge at home rarely need to charge anywhere else to complete their daily driving. The dominance of home charging is further borne out in the primary interaction terms where all interactions with HC strongly counteract the impacts of the primary terms. It is also worth noting that, while the rate of high-rate charging matters in reducing inconvenience, the penalty for having to travel to a fast charging center is quite large and thus, for many BEV operators, traveling to a fast charging station will not be an attractive option.

One advantage of using NHTS data for itinerary analysis is the degree to which the data can be down-selected to increase specificity. In order to increase the relevance of the empirical formula for the Denver CO case study, the same experiment was run for only Colorado itineraries and for only Denver Metropolitan Statistical Area (MSA) itineraries. The differences in values for the significant terms from these itinerary subsets and from the national set were minor. A comparison between the values of the significant parameters of the empirical equations from the mentioned itinerary subsets is provided in Figure 7.

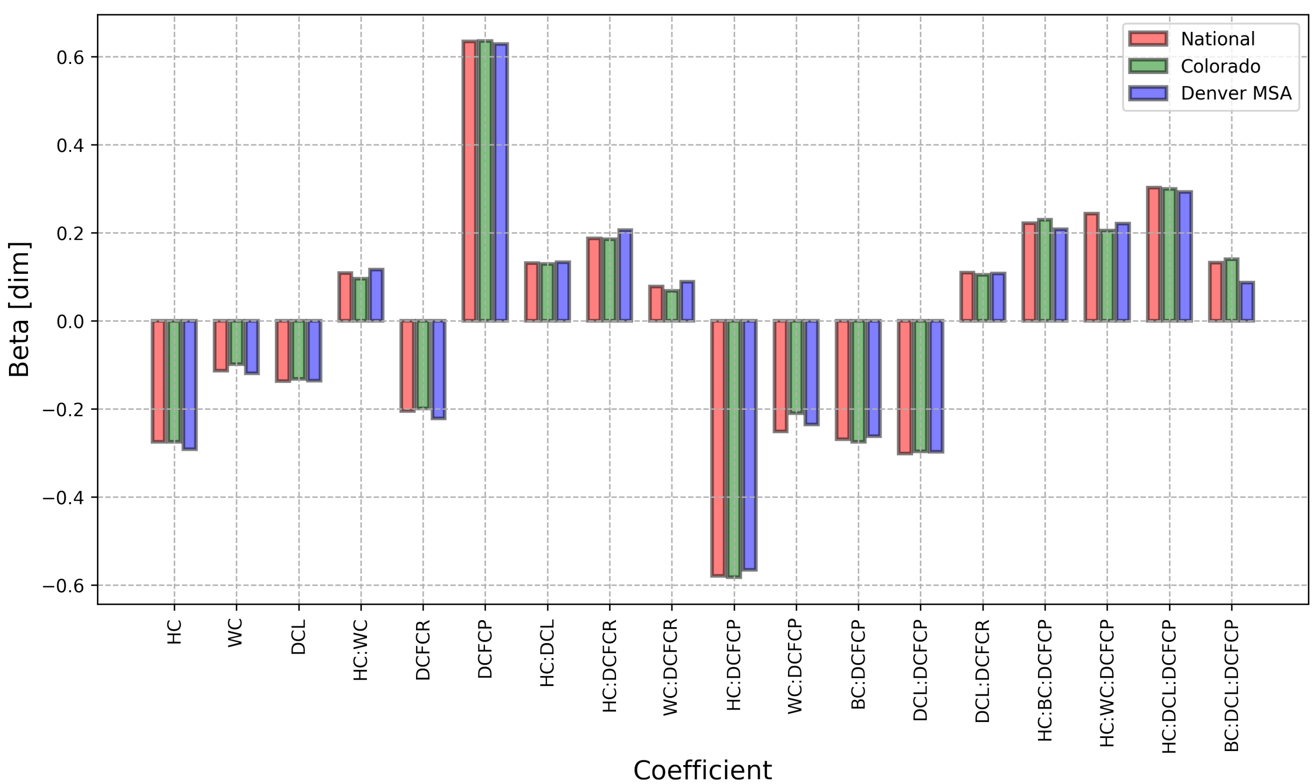


Figure 7. Significant Regression Coefficients and Error Bars for national, Colorado, and Denver MSA itinerary subsets

Geographical Calculation

One promising application for the Inconvenience Score is the direct evaluation of expected inconvenience on a geographical basis. Using any desired subset of NHTS data, an empirical formula for inconvenience based on the parameters in table 4 can be derived. Values for the coefficients can be calculated for a given geographical area using publicly available data and from this an Inconvenience Score can be assigned to the area. This geographical analysis allows for the visualization of location based inequity of experience due to BEV charging inconvenience and for the direct evaluation of proposed future EVSE infrastructure in terms of its effects on BEV charging inconvenience. In this section, the methods for computing Inconvenience Score at a census tract level are presented using the Denver Colorado urban area as an example.

ACS census tracts

The census tracts used for the geographical calculation of inconvenience were taken from the 2019 ACS. The 2019 ACS was chosen as the ACS contains a great variety of demographic data on a census tract level and the 2019 version is the most recent complete version of the survey. In this paper, the authors defined the urbanized area surrounding Denver Colorado to be the area within 25 km of the center of the city as plotted in Figure 8.

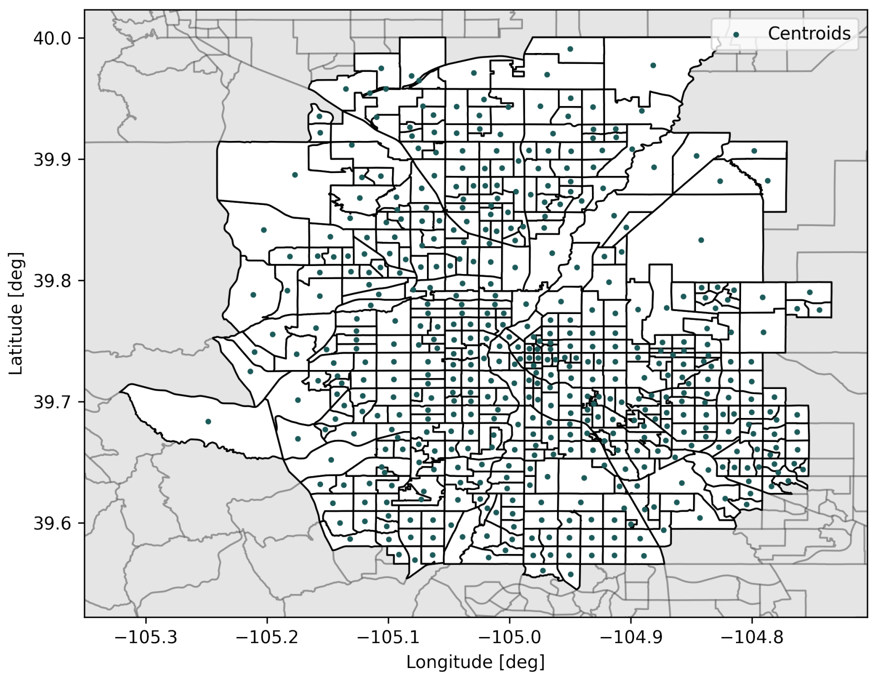
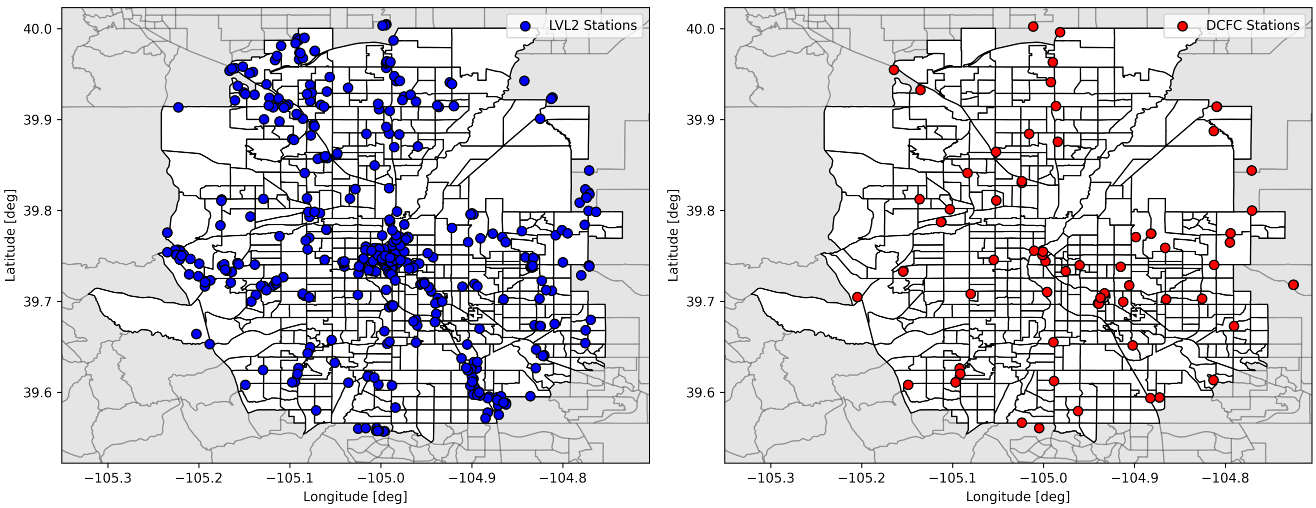


Figure 8. Denver Colorado urbanized area census tracts form 2019 ACS

Locations of EVSE Infrastructure

The locations of existing chargers were pulled from National Renewable Energy Laboratory (NREL)'s Alternative Fuels Data Center (ADFC) (Alternative Fuels Data Center 2023). The data provided by ADFC lists the locations of publicly available as well as private chargers along with the charger category (AC level 1, AC level 2, DCFC) and other information. For this study only publicly available level 2 and DCFC chargers were considered. Maps of the locations of level 2 and DCFC chargers in the Denver Colorado urbanized area are provided in Figure 9.



(a) AC Level 2 charging stations

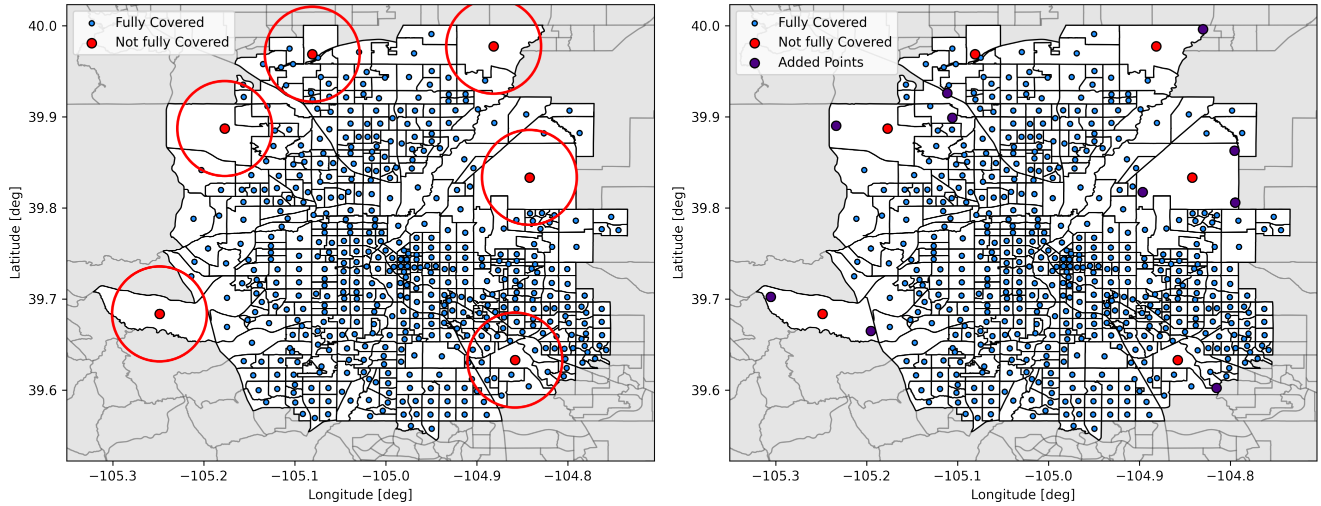
(b) DCFC stations

Figure 9. Locations of Charging stations in Denver Colorado urbanized area

Computing DCL

DCL is defined as the likelihood of finding a Level 2 charger at or sufficiently close to a given destination. Thus, to compute DCL requires knowledge of the locations of all likely destinations for a given person or geographical area. While there are a huge number of possible destinations that a person could visit in a given area, the authors propose that the only destinations that are relevant are popular long-dwell locations. The locations of popular long-dwell locations can be pulled from various mapping services such as Open Street Map (OSM) (OpenStreetMap 2023), Google Maps (Google 2023), Bing Maps (Microsoft 2022; Microsoft 2023), and others. The authors chose to use Bing Maps due to a combination of factors including the ease-of-use of the API, the quality of documentation, and pricing.

Using Bing Maps API, it is possible to pull the 25 most relevant destinations in a given category for a 5 kilometer area around a given point. The categories selected were the "Shop" category which includes the locations of major retailers, the "EatDrink" category which includes the locations of bars, restaurants, and grocery stores, and the "SeeDo" category which includes the locations of entertainment venues and local attractions. therefore, For a given census tract up to 75 popular, long-dwell destinations could be pulled based on the census tract centroid. For certain census tracts, the area covered by the centroid-based search did not contain the entire tract area so additional points were added in the centroids of the non-covered areas until the whole area was covered as shown in Figure 10.



(a) Covered and non-covered tracts

(b) Added points for destinations search

Figure 10. Census tract centroids and added search points

Finally, the locations of the destinations could be compared to the locations of Level 2 charging stations and those within a given distance (in this case 50 m) would be considered to have a nearby charger. Thus, for a given census tract the value for DCL would be the ratio of destinations with nearby chargers to total destinations. The locations of relevant destinations in the Denver Colorado urbanized area and the census tract level DCL for the same area are presented in Figures 11 and 12.

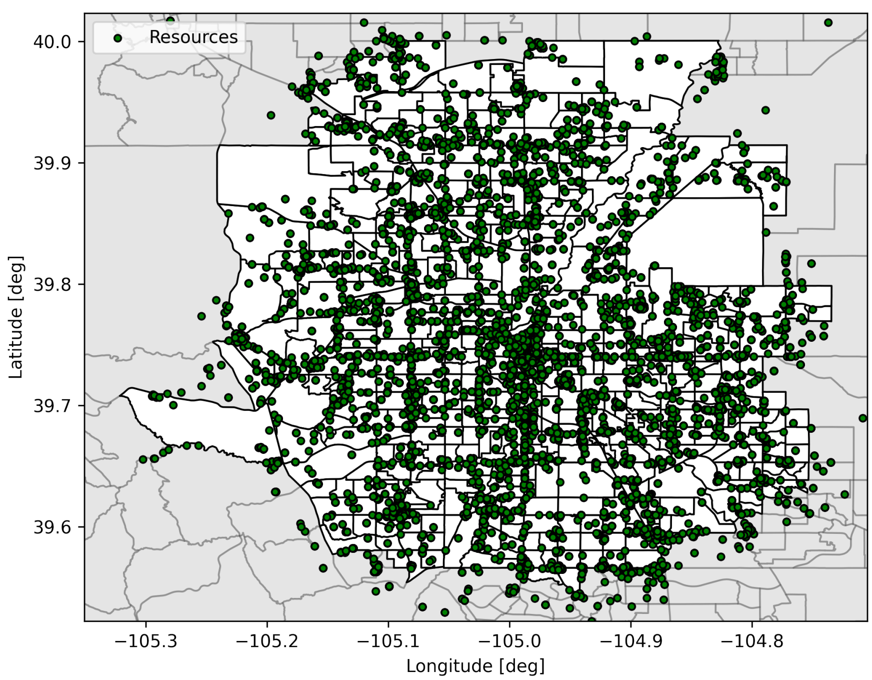


Figure 11. Locations of relevant destinations

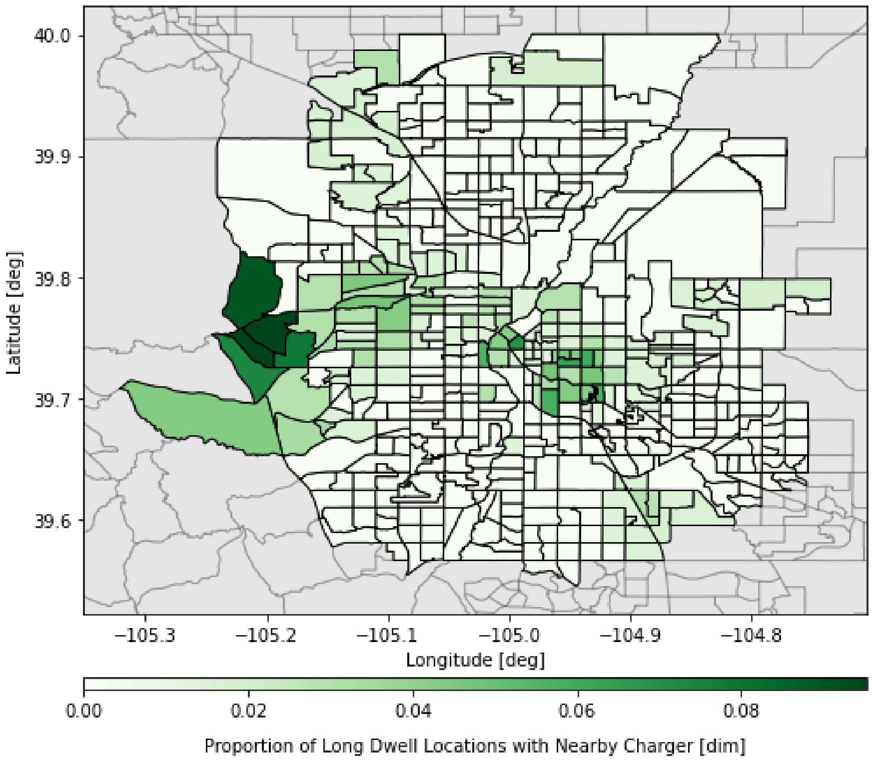


Figure 12. census tract level DCL

Computing DCFCP

DCFCP is the round-trip travel time, in minutes, to the nearest DCFC station. For a census tract this can be approximated by calculating the time required to travel from the tract centroid to the nearest DCFC station. for larger tracts this value is the average of travel times originating from added points as discussed previously. To calculate the expected travel time from a given tract centroid to the nearest DCFC station the authors used Mapbox routing (Mapbox 2023) with the trip duration being used as the travel time multiplied by two to reflect the round trip duration. DCFCP values for the selected census tracts are given in Figure 13.

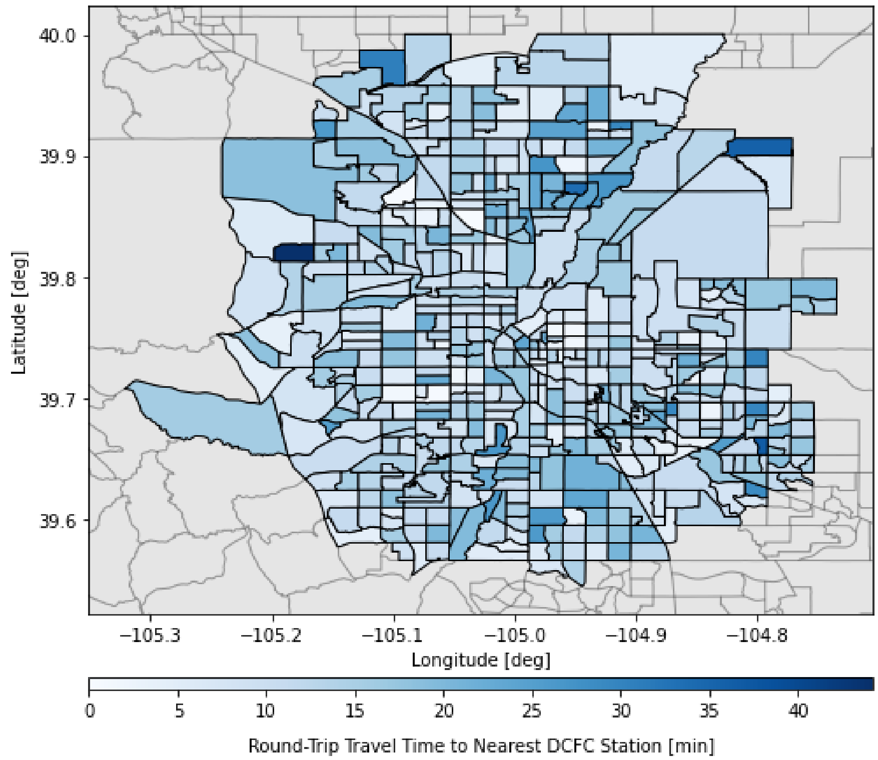


Figure 13. census tract level DCFCP

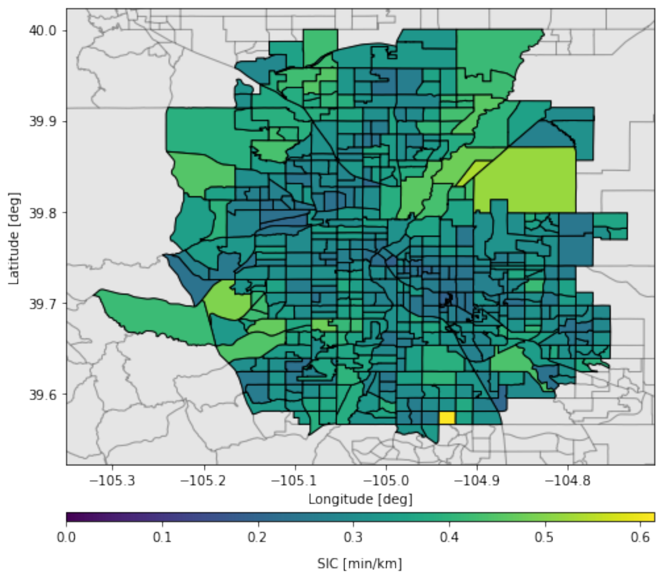
Results

With census tract level DCL and DCFCP computed, S_{IC} can be plotted on a census tract level. Calculating S_{IC} or a given census tract does require assuming values for HC, WC, BC, and DCFCR. DCFCR must be assumed because charging rate information is not provided by ADFC. census tract level values for HC, WC, BC, and DCFCR could possibly be estimated from census and other data in the future but for the purposes of this paper the same values will be assigned to all census tracts to show the impacts of the infrastructure parameters DCL and DCFCP. Unless otherwise specified the values used are those seen in Table 8.

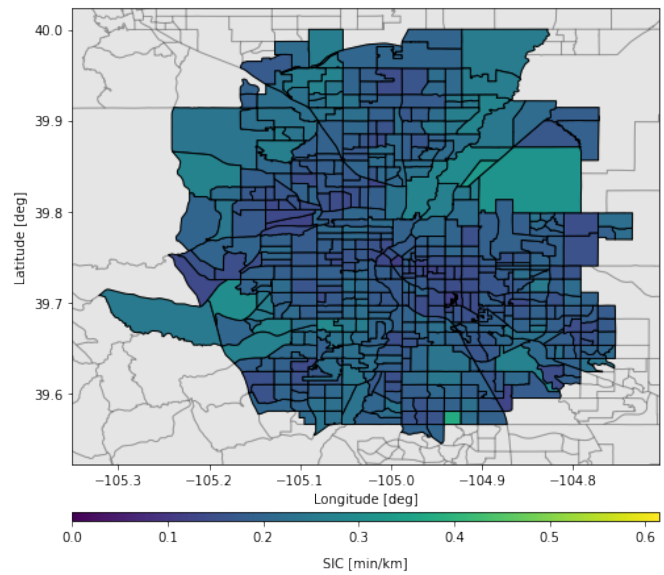
Table 8. Default Values for Parameters

Parameter	Levels	Unit
HC	0	dim
WC	0	dim
BC	80	kWh
DCFCR	150	kW

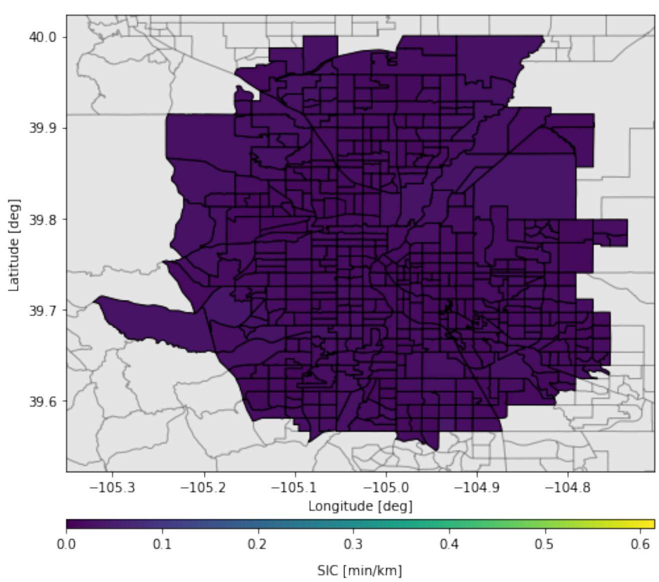
A comparison of census tract level S_{IC} relative to assumptions about the availability of home and work charging is shown in Figure 14.



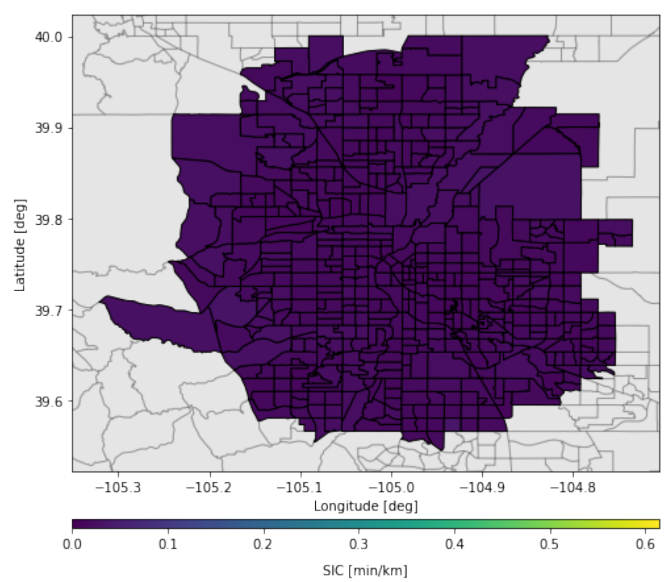
(a) HC = 0, WC = 0, $\mu_{S_{IC}} = 0.317315$ min/km, $\sigma_{S_{IC,D}} = 0.056954$ min/km



(b) HC = 0, WC = 1, $\mu_{S_{IC}} = 0.193744$ min/km, $\sigma_{S_{IC,D}} = 0.03496$ min/km



(c) HC = 1, WC = 0, $\mu_{S_{IC}} = 0.020381$ min/km, $\sigma_{S_{IC,D}} = 0.003683$ min/km



(d) HC = 1, WC = 1, $\mu_{S_{IC}} = 0.017014$ min/km, $\sigma_{S_{IC,D}} = 0.003269$ min/km

Figure 14. Comparison of S_{IC} for those with home and work charging available and those without

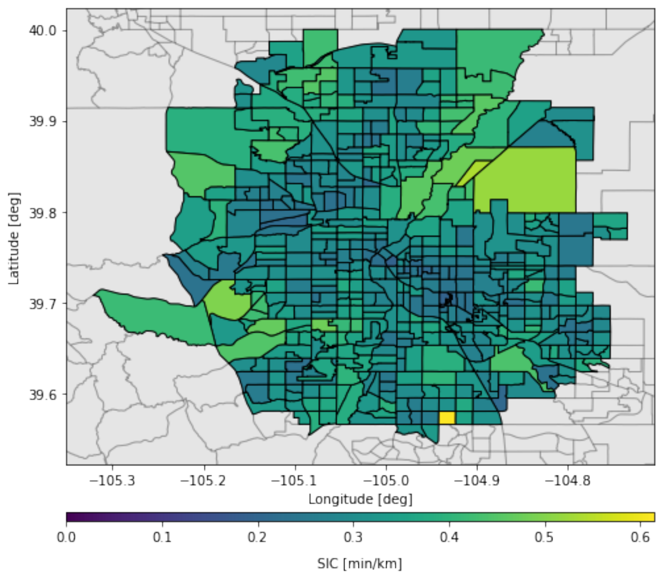
The resulting choropleths seen in Figure 14 provide real context to the empirical formulae presented earlier in this paper. What is plain is how much a BEV operator's experience will be effected by whether or not he or she can charge at home and/or work. Although disparities between the census tracts still exist, having the ability to charge at home decreases both the mean value and the standard deviation of inconvenience. Thus, those with the ability to charge at home are both better off and less susceptible to infrastructure parameters than those unable to. For those reliant on public infrastructure location plays an important role in determining experience. Even within the urbanized area surrounding Denver Colorado, the amount of inconvenience experienced on a per kilometer basis can vary significantly. The distribution of EVSE infrastructure in the Denver Colorado urbanized area is rather unequal with Level 2 chargers clustered towards the city center and in the western areas of the city and DCFC stations located close to the highways. Therefore one should not be surprised to find a resulting geographic inequity of experience due to inconvenience.

Discussion

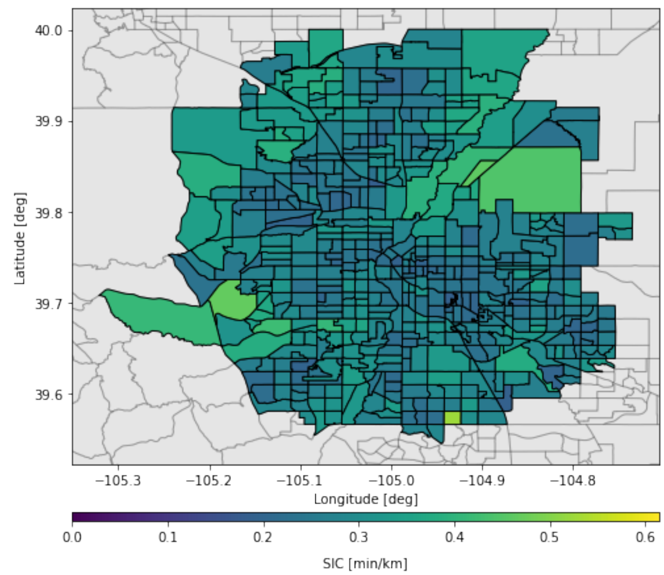
It should be no surprise that home and work charging are such powerful factors in determining BEV operational inconvenience. The importance of home charging was identified by the authors in a previous study (Rabinowitz et al. 2023a) which used a different dataset and slightly different methodology but came to roughly the same answers. Home charging is the foundational element in the Charging Pyramid model that has dominated thought on BEV charging in the past with work charging being the next element. The results of this paper more or less validate the descriptive quality of the Charging Pyramid model for the current state of EVSE infrastructure in a typical US city. If one cannot charge at home or at work the Charging Pyramid model is invalid for him or her.

Those most able to charge at home, and thus most able to operate a BEV, are also likely to be among the richest of Americans. Poorer demographics will probably not simply accept a massive time burden as an inevitable cost of BEV ownership. There is the possibility that, independent of economic incentives, poorer Americans will continue to buy new or used ICVs and run their vehicles for longer as a result of the inconvenience associated with BEVs. In addition to the moral issues inherent in any large inequity, the inequity in BEV operational experience due to charging may very well delay or limit BEV adoption and thus threaten emissions goals in the future. With this in mind, it is worth asking how infrastructure could be developed in order to minimize the inequity of experience between those who can charge at home and those who cannot.

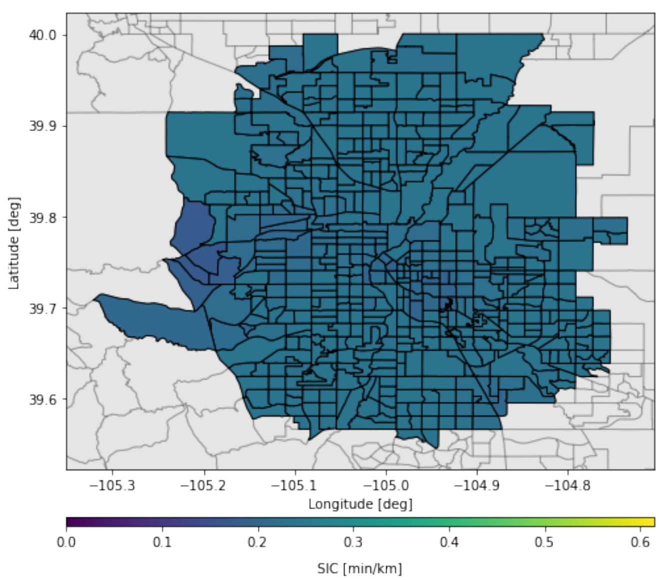
Policy makers looking to address the inequity in BEV operational experience should consider what are the relative merits of investment in high-rate charging vs low-rate charging. As a point of discussion, suppose that an investment could be made such that the DCL for all census tracts were raised to be at least half of the current maximum value. Alternately an investment could be made which would reduce the DCFCP of each tract to no higher than twice that of the current minimum value. Figure 15 shows how the S_{IC} maps change due to these investments.



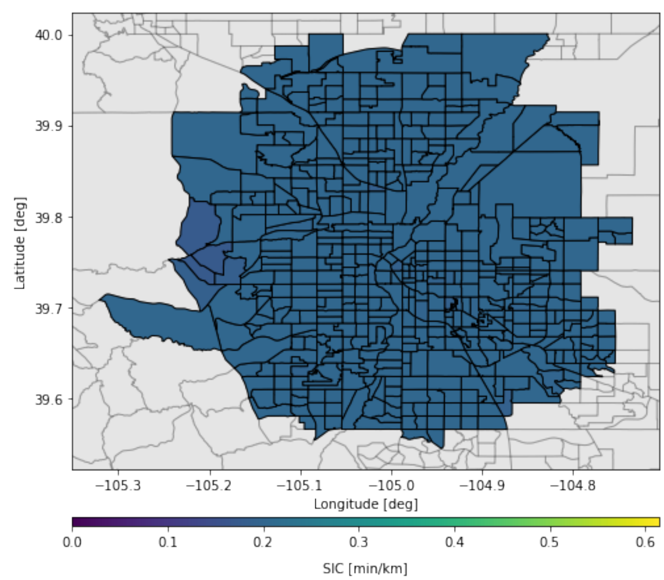
(a) Baseline (Neither Investment),
$\mu_{S_{IC}} = 0.317315$ min/km,
$\sigma_{S_{IC,D}} = 0.056954$ min/km



(b) Increasing minimum DCL,
$\mu_{S_{IC}} = 0.278611$ min/km,
$\sigma_{S_{IC,D}} = 0.047382$ min/km



(c) Decreasing maximum DCFCP,
$\mu_{S_{IC}} = 0.230185$ min/km,
$\sigma_{S_{IC,D}} = 0.010399$ min/km



(d) Both investments DCFCP,
$\mu_{S_{IC}} = 0.20293$ min/km,
$\sigma_{S_{IC,D}} = 0.003237$ min/km

Figure 15. Effects of doubling DCL and/or halving DCFCP for no home or work charging

Although likely expensive, both investments should be feasible as, inherently, as the required minimum and maximum levels are already achieved in many census tracts. Of the two investments, reducing the maximum DCFCP is clearly the more impactful. The combination of both investments would bring the mean and standard deviation of inconvenience down into the range seen for the work charging enabled scenario in Figure 14. More investment would be needed in order to get into the range of the home charging enabled scenario.

Conclusions

In order for a successful green transition to take place in the American transportation sector, the majority of Americans must decide to purchase or lease BEVs for personal transportation. Operating a BEV will always be easier for those with the ability to charge at home and/or work; currently, under-developed EVSE infrastructure exacerbates this inequity of experience. In order to effectively solve the issues with current EVSE infrastructure a quantitative understanding of charging inconvenience and the factors which underlie it must attained. In this paper a novel method for computing expected BEV operational inconvenience due to charging on a geographical basis is presented. This method allows for quantitative assessments of the impacts of potential EVSE infrastructure investment based on locations and types of chargers. The quantitative metric, Inconvenience Score (S_{IC}), which can be computed for specified demographics and geographical regions using only publicly available data should be considered as a performance metric in future EVSE infrastructure analyses.

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Biography

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