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RESEARCH ARTICLE

Assessment of Factors in the Reduction of BEV Operational Inconvenience

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ABSTRACT As governments and the automotive industry push toward electrification, it becomes increasingly critical to address the broad set of factors 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 an empirical equation, derived using a novel data-based method, which relates operational inconvenience to a small number of housing and local Electric Vehicle Supply Equimpent (EVSE) infrastructure factors. The equation and method provided can be used to conduct quantitative analyses on the inconvenience impacts of current and proposed EVSE infrastructure. Ultimately such a quantitative approach is needed to understand and mitigate large inequities of BEV experience and adoption which might emerge from electrification.

INDEX TERMS Battery electric vehicle, BEV convenience, EV equity, EVSE infrastructure.

I. INTRODUCTION

Policy makers and industry have recently set ambitious goals for BEV market penetration [1]. These targeted efforts will help accelerate the growth of the BEV market share. The success or failure of these initiatives will depend on millions of individual decisions on whether or not to purchase or lease a BEV. Although economic factors are important in individual car buying decisions, evidence suggests that consumers also weigh perceived operational inconvenience in their decision making process [2], [3], [4].

Concerns about BEV operational inconvenience are founded in several realities related to vehicular energizing (charging or fueling) namely BEV range and charging times [5]. BEV ranges are limited by the capabilities of modern batteries. Current state-of-the-art Lithium-Ion (Li-Ion) batteries have a specific energy of around 1000 kJ/kg [6] whereas gasoline has a specific energy of 457,200 kJ/kg. The result of this disparity is that even though BEVs are more efficient than Internal Combustion Vehicles (ICVs) they often have less range than similarly sized ICVs. Comparing mid-size sedans, a 2022 Tesla 3 LR has a nominal range of 490 km and a curb weight of 1919 kg [7] while a 2022 Chevrolet Malibu has a nominal full-tank range of 915 km and a curb weight of 1422 kg [8]. Current BEV full-charge ranges are more than sufficient to meet daily driving requirements for most Americans [9], but their lesser range is perceived by consumers as an inconvenience.

The disparity in energizing times between BEVs and ICVs is also rooted in the fundamental characteristics of energizing. Gasoline contains 121.3 MJ per gallon [10]. At a fueling rate of 7 gallons per minute [11] an ICV is energizing at 14.15 MW. By comparison, modern DC Fast Charging (DCFC) occurs at 80-350 kW or roughly 40 - 180 times slower than fueling. In combined driving conditions, the 2022 Tesla 3 LR uses roughly 5 times less energy per km than the 2022 Chevrolet Malibu [7], [8] but would still expect to add range 8 times slower. If one were to charge a BEV in the same manner as one fuels an ICV, by going to a dedicated station every time, then the BEV would be much more inconvenient to operate.

Historically, BEV operational inconvenience has not been studied in depth as most BEV owners charge primarily at home [12]. The recent development of public and private

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charging networks have made long distance BEV travel increasingly feasible [13]. However, as adoption of BEVs increases, and as BEVs penetrate non-luxury auto markets, the assumption that all BEV operators have access to overnight charging will become invalid, and the role of public infrastructure may become more important still.

The importance of public infrastructure for various potential BEV market segments has already been recognized and funding for rapid development of public BEV infrastructure has been a key component of many national and regional BEV readiness plans. [14]. However several key questions remain to be answered:

- What are the ultimate relative operational inconveniences for BEVs vs ICVs for those who can charge at home and those who cannot?
- What are the relative merits of different types of EVSE infrastructure in the reduction of BEV operational inconvenience?
- What level of EVSE infrastructure rollout, if any, is sufficient to achieve convenience parity for BEV operators?

In order to answer these questions, a method of evaluating energizing inconvenience was developed and is the subject of this paper. Novel aspects of this paper are as follows: This paper presents a novel, flexible, and data-based method for evaluating energizing inconvenience which allows for direct comparisons between different vehicles and different conditions of operation. This method utilizes longitudinal itinerary data and optimal energization scheduling in order to produce least inconvenient energizing traces for vehicles following the itineraries. The objective function for the optimization is the novel metric Inconvenience Score (S_{IC}) which measures the distance-normalized sum of felt inconvenience for energizing events in an itinerary. The optimal energizing traces are influenced by vehicular and infrastructural parameters. Thus the results can be used to understand the relationships between vehicular and infrastructural parameters and operational inconvenience expressed as S_{IC}. Using the novel method, empirical equations relating S_{IC} to vehicular and infrastructural parameters are calculated using data from a proprietary, national, light-duty, longitudinal dataset. The empirical equations are generally applicable within the US and can be used to estimate felt inconvenience for light-duty BEVs and ICVs.

II. LITERATURE REVIEW

A. QUANTIFYING INCONVENIENCE

Quantifying the inconvenience experienced by users is a crucial step in the process of designing the BEV system to minimize inconvenience. In transportation literature, it is common to consider user inconvenience as a linear sum of separate factors which relate to time spent performing actions and to baseline inconveniences associated with performing certain actions. Examples of inconvenience being calculated as such a linear sum can be found in [15], [16], [17], [18], [19], and [20] which present a variety of linear sum cost functions. In [15], a train rescheduling algorithm is presented which calculates inconvenience as a weighted sum of time spent waiting, time spent in transit, and the number of transfers implicitly stating that the action of transferring trains has an inconvenience which is equivalent to a certain amount of waiting or transit time. A similar cost function for inconvenience can be found in [20] which also accounts for an equivalent inconvenience due to overcrowding of train cars. Some papers [17], [18] use cost functions which draw an equivalence between time and money in their cost functions. This allows for an implicit weighting of time-based inconvenience and cost of options. Researchers often represent inconvenience as being caused by actions happening outside of desired windows. Reference [19] proposes a compound cost function where early arrivals at destinations are explicitly penalized, while [16] proposes a variety of penalty functions which apply for deliveries that arrive either early or late compared to an expected delivery window.

A different approach sometimes taken is one which focuses on the users expectations as a source of inconvenience. In [21] time-based inconvenience is computed only for time spent in transit over an expected time in transit. An attempt was made in [22] to quantify the effects on perceived inconvenience due to expected waiting time of several factors including whether or not dynamic waiting times are displayed and found that displaying dynamic wait was most beneficial in reducing perceived inconvenience.

These two general approaches agree that inconvenience is fundamentally derived from delays and exertions. Any reduction in the underlying factors which cause inconvenience will almost certainly reduce perceived inconvenience. Thus for a high-sample-size study efforts are concentrated on modeling and quantifying the underlying factors that cause BEV inconvenience.

B. BEV OPERATIONAL INCONVENIENCE

The specific area of Electric Vehicle (EV) and Alternative Fuel Vehicle (AFV) operational inconvenience has been under-studied. Nevertheless several different approaches can be seen in literature. A fundamental difference between these methods is how they treat the issue of non-availability of home charging. Roughly 62% of Americans live in owner-occupied un-attached dwellings [23] leaving 38% who do not and, thus, are not well served by the "default" home charging model. Approaches to accounting for home charging availability or non-availability fall into three categories: assuming that only home charging will be available [24], [25], assuming that home charging will be available for all BEV operators but not sufficient to cover daily charging needs [26], and assuming that home charging will be available for some but not all BEV operators [27].

In [24] and [25], a study was conducted using surveyed itineraries and assuming that charging could only occur at home. the conclusion reached was that BEVs with a range of 120 miles would be acceptable as one-to-one replacements for 90% of US vehicles under home-only charging and 60 miles of range would be sufficient for 90% of US households to own at least one BEV. In [26] a dollar equivalence for time lost due to charging was used to determine the relative inconveniences of BEVs, AFVs, and ICVs using survey data and the locations of public EVSE infrastructure. The study found that significant inconvenience is encountered for daily itineraries of greater than 60 miles. In [27], a quantification of BEV inconvenience for users with limited charging options based on survey data, assumed EVSE infrastructure presence, and a charge scheduling heuristic is proposed. A key conclusion is that BEV operators may be able to charge their vehicles in the same amount of time as ICV operators would spend fueling or stopping for other purposes on a given long trip. The cited papers differ greatly in problem definition and methodology. What can be synthesized from the papers is that home charging is sufficient to complete a large portion of daily itineraries and that reliance on public EVSE infrastructure causes inconvenience for sufficiently long daily itineraries. It could be concluded, therefore, that complete reliance on public EVSE infrastructure would make all but the shortest daily itineraries inconvenient.

The different approaches seen in [24], [25], [26], and [27] reflect different assumptions regarding the nature of the problem. References [24] and [25] theorizes that BEV owners will predominantly charge at home and will not rely on public charging options to extend the range of their vehicles. Reference [26] assumes that BEV owners will be forced to rely on public charging frequently. In [27] whether or not a BEV operator has access to home charging will determine how much that operator will rely on public charging. The papers studied place limits on BEV charging which are not reflective of the current reality or a likely future reality. Both opportunity charging at destinations and fast charging en-route are increasingly available [13], [28], [29]. In the literature some itineraries are labeled as infeasible for BEVs when these trips are increasingly feasible with BEVs due to newer DCFC infrastructure. A further limitation of the reviewed literature is the data used. The state of publicly available vehicle itinerary data is quite poor and generally comes in the form of survey data rather than longitudinal tracking data. Presumably, it is due to lacking data that researchers have opted for methods which either generate itineraries synthetically or use a series of assumptions to adapt their models to the limitations in the available datasets.

In response to the state of the field, this paper presents a method which builds on and advances previous work by computing BEV operational inconvenience accounting for the availability of home charging, the state of EVSE infrastructure, and BEV ranges in a manner which is directly comparable to ICV operation for the same set of big-data derived itineraries.

III. DATA

The dataset used for this study was a proprietary long-term longitudinal dataset which tracked the movements of 2,177 vehicles across the continental US over the course of multiple years. The data was collected via an opt-in program which allowed the data collector to view CANbus data in real time. The raw data was processed into a longitudinal data format providing trip start and end locations, distances, and durations. Using this data the authors calculated dwell times for parking events and home locations for most of the vehicles based on location frequencies, dwell durations, and dwell times of day. The columns of the derived dataset are listed in Table 1.

The principle advantage of this dataset was the duration of the itineraries. Of the 2,177 itineraries in the dataset, 1,626 contained at least 1,000 entries. The distribution of itinerary lengths and mean driving distances are displayed in Figures 1 and 2.

TABLE 1. Dataset fields.

Field	Description
Park Location	Lat-Lon coordinates of present dwell
Park Start Time	UTC code for start of dwell
Park End Time	UTC code for end of dwell
Is Home	Boolean for dwell location being at home or not being at home
Trip Distance	Distance traveled in the trip immediately prior to dwelling
Trip Time	Time in travel in the trip immediately prior to dwelling

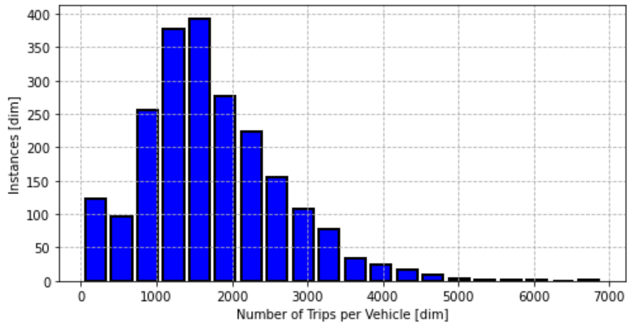


FIGURE 1. Distribution of itinerary lengths in the dataset.

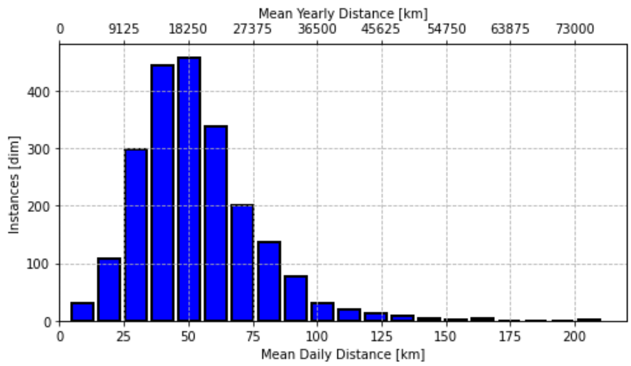


FIGURE 2. Distribution of daily and yearly mean driving distances in the dataset.

The proprietary dataset used in this study had the advantage of being primarily intended for use as a longitudinal dataset and it compares favorably to publicly available datasets for that purpose. Two commonly used, publicly available alternatives are the 2005 Puget Sound Regional Council (PSRC) study available via National Renewable Energy Laboratory (NREL)'s Transportation Secure Data Center (TSDC) and the 2009 or 2017 National Highway Transportation Survey (NHTS). The PSRC survey contains similar numbers of vehicle itineraries as this study's proprietary dataset but most PSRC itineraries contain missing entries which would have to be filled in order for the itineraries to be used. Other large datasets available from TSDC such as those used in [25] contain less data than the PSRC data and come with similar issues. The NHTS, collected most recently in 2017, provides a national dataset but is of limited use for longitudinal analysis as it is a manually filled survey for a single day of household activity. The proprietary dataset was, thus, the best alternative for use in this study.

On average, vehicles included in the dataset completed 1,445 trips per year for an average of 19,235.5 km traveled. For reference, the US Bureau of Transportation Statistics (BTS) calculated that the average American household completed 1,865 vehicle trips for 28,670.4 km based off of the 2017 NHTS [9]. Noting that the vehicles tracked in the proprietary dataset were not necessarily the only vehicle used by the households to which they belonged, these numbers are compatible with the available BTS data.

Although nominally a national dataset, the proprietary dataset showed a heavy bias towards large metropolitan areas in the south-western region of the continental US. Home locations were able to be estimated for 1,932 of the 2,177 vehicles in the dataset and these were located in a total of 127 counties. However, 30.1% of home locations were located in just Los Angeles County and San Diego County while the top ten most common counties accounted for 60.7% of home locations. The distribution of home locations is plotted in Figure 3.

Although the vehicles in the proprietary dataset were predominantly based in a small number of locations, the vehicles traveled considerably over the course of the tracking period and made frequent visits to a number of locations distant from their origins as plotted in Figure 4.

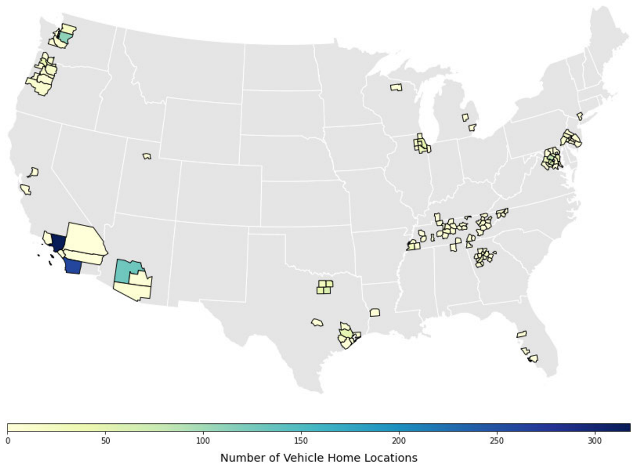


FIGURE 3. Home locations in dataset.

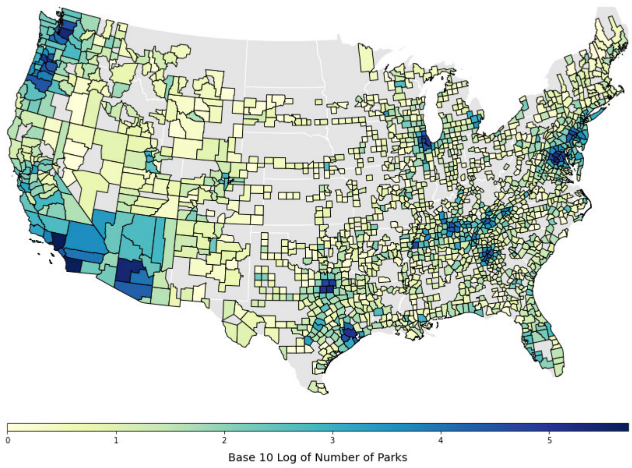


FIGURE 4. Parking event locations in dataset.

IV. METHODS

The overall objective of this study was to understand what combinations of vehicular characteristics and charging infrastructure characteristics allow for BEVs to attain convenience parity with ICVs. In order to accomplish this a metric of inconvenience was created which could be evaluated for any vehicle and Dynamic Programming (DP) was used to find the optimal energizing strategy for any vehicle on a given itinerary defined in terms of trip lengths, dwell times, and location types. This allowed for the direct comparison of BEVs and ICVs traveling on the same itineraries and, thus, the direct comparison of inconvenience between the two.

A. DEFINITION OF INCONVENIENCE

A fundamental insight in the study of vehicular operational inconvenience is that not all energizing events are the same. The authors contend that different types of energizing events inconvenience operators to vastly different degrees. The differences are rooted in the concept that energizing a vehicle is only inconvenient for the duration of time that it constrains an operator's actions. If one is able to energize a vehicle without having to add devoted energizing time to his or her daily itinerary then that person is not inconvenienced. If that same person has to spend significant time at locations that he or she would not otherwise visit in order to energize his or her vehicle then that person is inconvenienced. Thus charging at night and at home would be far less inconvenient than charging at a dedicated charging station during the day. Relative to inconvenience, charging events may be broken down into four categories as follows:

- Home energizing events: Energizing 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 energizing events, regardless of duration, do not force the operator to devote time out of his or her itinerary to energizing.

- Work energizing events: Energizing 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 energizing events, regardless of duration, do not force the operator to devote time out of his or her itinerary to energizing.
- Destination energizing events: Energizing 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 energizing. Thus, destination energizing events only inconvenience the operator for the amount of time that he or she would need to spend paying for the energizing event.
- En-route energizing events: Energizing events which take place at a location which the operator visits specifically to energize a vehicle. Locations such as petroleum stations or centralized DCFC charging stations (Tesla Supercharger stations for example [30], [31]) 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 energizing 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 energizing station. Because operators are only traveling to the station to energize their vehicles the travel time is also considered to be devoted energizing time. Thus operators are also inconvenienced for the travel time required to get to and from the energizing station.

Because the different types of energizing 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.

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

for an itinerary of N trips where D_E is the duration of the energizing event, D_T is the duration of travel to get to the energizing 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 energizing time per kilometer traveled in a given itinerary. The values of the multipliers based on the type of energizing event are shown in Table 2.

So defined, S_{IC} is able to account for the differences between energizing 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.

TABLE 2. Values of multipliers based on energizing 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

TABLE 3. 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]

B. MODELS

1) VEHICLES

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 3.

The vehicle model is of a rather standard type used in longitudinal analysis. The efficiencies for the three speed ranges reflect vehicular efficiency in different driving conditions. In the absence of second-by-second speed data an assumption is made that if a trip's average speed falls within a given range then that speed range will be most representative of the driving conditions of the trip. The energy storage parameter reflects the usable energy storage capacity of the vehicle. As batteries age usable storage capacity declines. This model also implicitly accounts for the effects of heating and cooling loads. On hot or cold days the auxiliary loads required to run the temperature control system for the vehicle will reduce the efficiency of the vehicle on an energy consumption per unit distance basis. Thus, one can account for battery degradation and significant auxiliary loads due to temperature control by changing the vehicle model parameters.

For this study two vehicles were used as representative models for BEVs and ICVs. These vehicles were based on the 2022 Tesla 3 LR and the 2022 Chevrolet Malibu. The Tesla 3 LR and Chevrolet Malibu were chosen as they are roughly equivalent in size, shape, storage, and seating, as well as both being mid-tier models in their ranges.

TABLE 4. Base vehicle energy consumption rates.

Vehicle	Parameter	Value
BEV	Energy Storage Capacity [kWh]	82
	City Consumption Rate [kJ/km]	385
	Mixed Consumption Rate [kJ/km]	479
	Highway Consumption Rate [kJ/km]	587
ICV	Energy Storage Capacity [kWh]	528
	City Consumption Rate [kJ/km]	2600
	Mixed Consumption Rate [kJ/km]	2356
	Highway Consumption Rate [kJ/km]	2094

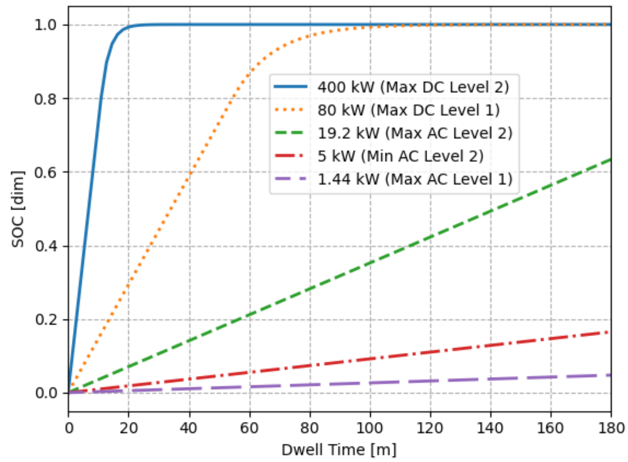


FIGURE 5. 3 hour SOE charging traces at various charging rates for a vehicle with an 80 kWh battery.

The consumption data for the base vehicles is listed in Table 4.

The representative BEV and ICV models most closely represent the vehicles they are based on but the differences between the models are representative of the differences between BEVs and ICVs more generally. The important differences are the greater efficiency of the BEV model and the efficiency trends for each model. Where BEVs are more efficient in urban conditions, ICVs are more efficient on highways. The difference is because BEVs are able to recover energy when decelerating where ICVs are not. Data for vehicle energy consumption rates was attained from [7] and [8] and verified with data from [32] with the city consumption rate calculated from US06 drive cycles, the highway consumption rate calculated from HWFET drive cycles, and the mixed consumption rate calculated from FTP drive cycles.

2) BEV CHARGING

It was also necessary to define models for EVSE infrastructure. BEV charging rates were based on the Society of Automotive Engineers (SAE) J1772 standard [33] and information from [7]. 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 [34]. The energy added, as a function of time is

$$dSOE = \frac{P_{DC}}{C_B} t_{cc} + (1 - e^{(\lambda_C t_{cv})}) \tag{2}$$

$$P_{DC} = P_{AC}\eta \tag{3}$$

$$\lambda = \frac{P_{DC}}{0.2C_B} \tag{4}$$

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 5.

3) ICV FUELING

ICV fueling events were treated as linear energization occurring at a rate of 7 gallons per minute [11]. Compared to charging, fueling times are relatively short and inconvenience is dominated by the time penalty for going out of one's way to get to the fueling station.

C. OPTIMAL CHARGE SCHEDULING

Inconvenience will be effected by when and where a user chooses to charge. In order to evaluate all scenarios on equal

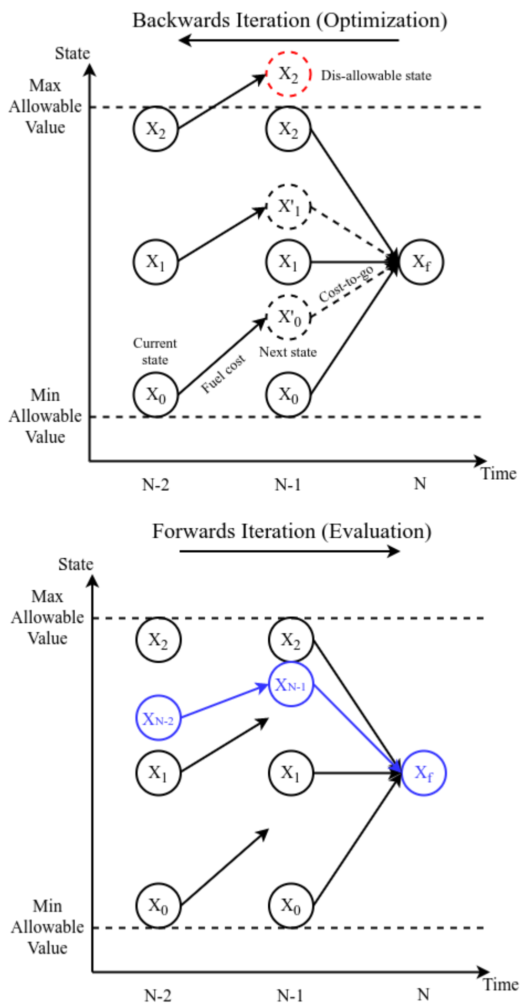


FIGURE 6. Top-down DP schematic.

footing, optimal charge scheduling was implemented. Optimal charge scheduling was conducted via Dynamic Programming (DP) [35], [36]. 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 implementation used here is the "top-down" implementation [36] which includes an "optimization" step wherein an optimal control matrix is generated via backwards integration and an "evaluation" step wherein an optimal control trace is generated via forwards integration as diagrammed in Figure 6.

The goal of the optimization was to find an optimal charging control such that the inconvenience of the itinerary would be minimized. This goal can be stated as

$$\min_{\overline{U}} J(S_0, \overline{U}) \tag{5}$$

where

$$J(S_0, \overline{U}) = \Phi(S_N) + \sum_{k=1}^{N} \Psi(S_k, U_k) \tag{6}$$

s.t.

$$S_{k+1} = f(S_k, U_k), \quad k = 0, \ldots, N-1 \tag{7}$$

$$S_{min} \leq S(t) \leq S_{max} \tag{8}$$

where $\Psi(\overline{S}, \overline{U})$ is the running cost (inconvenience), $\Phi(\overline{S})$ is the final state cost, $\overline{S} = [SOE]$ is the state vector containing the vehicle SOE, $\overline{U}$ is the control vector formulated as $\overline{U} = [D_{E,D}, D_{E,ER}]^{\top}$ containing charging durations at destination $D_{E,D}$ and en-route $D_{E,ER}$ for BEVs or $\overline{U} = [D_{E,ER}]$ containing en-route fueling durations for ICVs, 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 energizing time.

The BEV model is a 1-state, 2-control model where the one state is the vehicle's SOE and the controls are destination charging and en-route charging. Destination charging is available to BEVs at locations where destination chargers are present which may include the BEV's home location. BEVs are assumed to charge for the duration of a dwell at a destination or until they have reached full charge. En-route charging is available to BEVs during every trip but requires the BEV operators to drive to a dedicated charging station which will cause them to deviate from their itineraries.

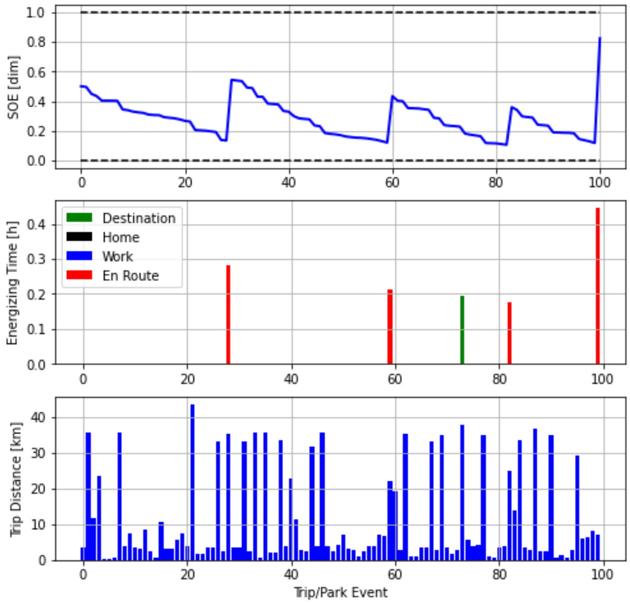
The ICV model is a 1-state, 1-control model where the one state is SOE which is the proportion of the fuel tank capacity which is fueled at any given moment and the control is en-route fueling. ICVs are not able to fuel at home or at destinations. En-route fueling is available to ICVs during every trip but requires the vehicle operators to drive to a dedicated fueling station which will cause them to deviate from their itineraries.

V. RESULTS

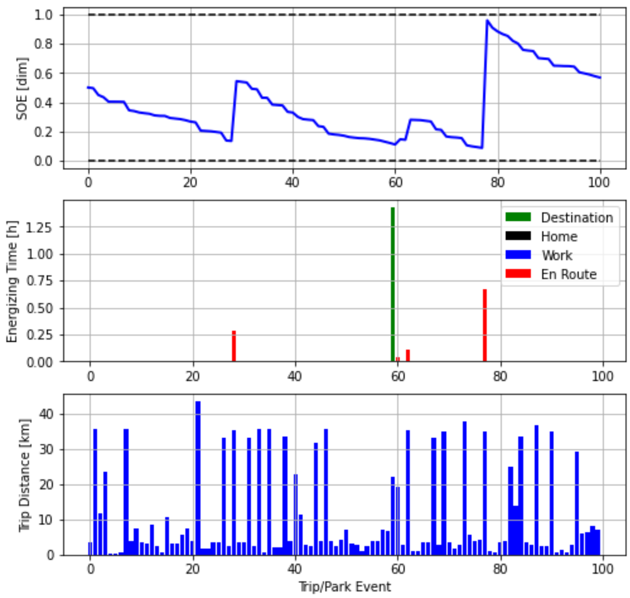
Because the assignment of destination chargers is probabilistic, the results for a given BEV and set of infrastructure parameters may be different from run to run. Figure 7 demonstrates this by showing two simulation runs of 100 trips where all vehicle and infrastructure parameters are the same between the simulations. In both cases, the vehicle did not have access to home or work charging.

Although all parameters were identical between the runs shown in Figure 7 the random assignment of chargers to destinations made the SOE traces visually different between the runs even if the S_{IC} values were within 10% of each-other.

Figure 8 illustrates a 100 trip trace for a BEV which is able to charge at home. The itinerary used in Figure 8 is the same as in Figure 7. The effects of being able to charge at home are visibly evident. Because home dwells are long and the operator does not suffer a payment or travel penalty



(a) Simulation #1



(b) Simulation #2

FIGURE 7. Optimal charging traces for BEVs with no home charging and identical vehicle and infrastructure parameters.

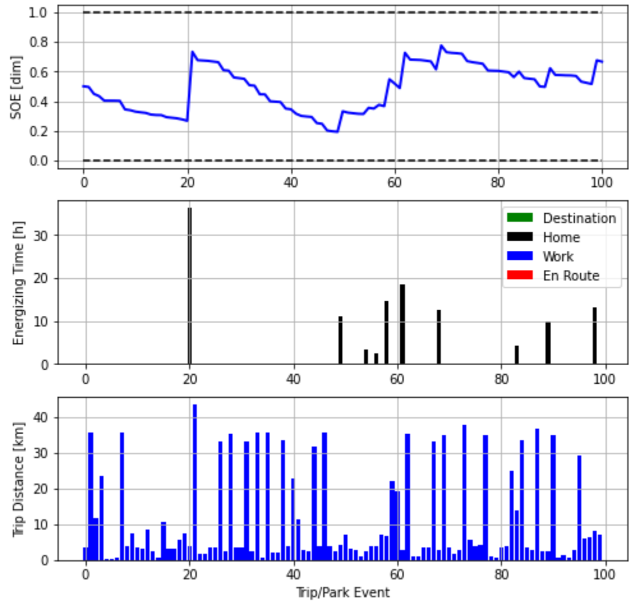


FIGURE 8. Optimal charging trace for BEV with home charging.

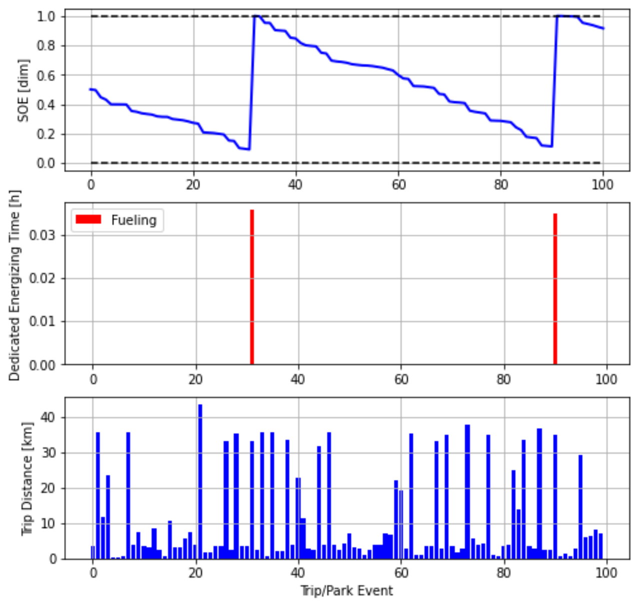


FIGURE 9. Optimal fueling trace for ICV.

associated with home charging events, these events tend to dominate.

The SOE traces presented are post-trip values. Those who can charge at home or during long dwells at destinations will be able to maintain acceptable SOE without needing to charge en-route in the course of normal operation but they will still need to do so for long trips. The pattern of frequent long duration and low rate charging events differs fundamentally from how ICV operators usually energize their vehicles and may even manifest a reduction in inconvenience compared to an ICV. For the purposes of this study ICVs may only charge en-route at a fueling station. An example of ICV operation is provided in Figure 9.

The typical ICV optimal fueling trace behavior is to let the SOE reduce until a safety margin is violated and then to completely refuel thus minimizing the number of fueling events. This type of charging behavior can be thought of as the "gas station" model. The type of behavior typical of optimal charging traces for BEVs where charging during dwells at home, work, or other destinations is most common can be thought of as the "dwell charging" model. The psychological effects of range anxiety are not addressed in this study but it

TABLE 5. 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, 7.5, 15]	%
En-Route Charging Rate (ERCR)	[50, 150, 250]	kW
En-Route Charging Penalty (ERCP)	[15, 30, 45]	min

TABLE 6. Model summary.

R	R-Squared	Adjusted R-Squared	Std. Error
0.986	0.972	0.965	0.000

is worth noting that BEV operators who follow the gas station model of charging may suffer from additional range anxiety in addition to whatever inconvenience they experience.

A. EXPERIMENT AND REGRESSION ANALYSIS

1) EV INCONVENIENCE ANALYSIS

Having derived a model for energizing inconvenience an experiment was run considering several vehicle and EVSE infrastructure parameters. The purpose of the experiment was to create regressed empirical equations relating vehicular and infrastructural parameters to inconvenience. The empirical equations can be used to evaluate expected inconvenience for individuals or groups based on their experimental parameter values. The experiment was a full-factorial design on the parameters listed in Table 5.

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 [37]. The range for ERCR was based on ranges identified in [7] and [38]. It would be quite difficult to find a true range of values for DCL or ERCP but these values were estimated by comparing the numbers of different types of chargers present at different types of locations identified in [38] with statistics about numbers and geographical distributions of petroleum fueling stations found in [11].

The electric vehicle models used in the experiment were those described in Table 4. For each of the 324 experimental cases, inconvenience scores were generated for all 1,626 vehicles with itineraries of at least 1000 trips. Each case was simulated 3 times and the mean inconvenience score was used as the result for the case. A linear regression was then performed on all min-max normalized terms and interactions. Minimums and maximum values for all terms can be found in Table 5. The output (S_{IC}) was not normalized. Significant results for this regression, including the terms of the empirical equation, are presented in Tables 6, 7, and 8.

TABLE 7. ANOVA.

Category	Sum of Squares	DOF	Mean Squares
Model	1.521	63	0.024
Error	0.044	260	0.000
Total	1.565	323	0.005
F		$P(>F)$	
143.798		$2.256\exp(-170)$	

TABLE 8. Significant terms in empirical equation ($\alpha = 0.01$).

Coefficient	Value	t-value	p-value
Intercept	0.242	26.910	0.000
HC	-0.186	-14.637	0.000
WC	-0.154	-12.110	0.000
BC	-0.056	-4.032	0.000
DCL	-0.092	-6.606	0.000
ERCR	-0.136	-9.785	0.000
ERCP	0.146	10.493	0.000
HC:WC	0.129	7.182	0.000
HC:DCL	0.073	3.725	0.000
WC:DCL	0.060	3.062	0.002
WC:ERCP	-0.089	-4.519	0.000
HC:ERCP	-0.109	-5.523	0.000
HC:ERCR	0.111	5.617	0.000
WC:ERCR	0.093	4.719	0.000
BC:ERCP	-0.081	-3.744	0.000
DCL:ERCR	0.063	2.904	0.004
HC:WC:ERCR	-0.079	-2.817	0.005
HC:WC:ERCP	0.075	2.678	0.008

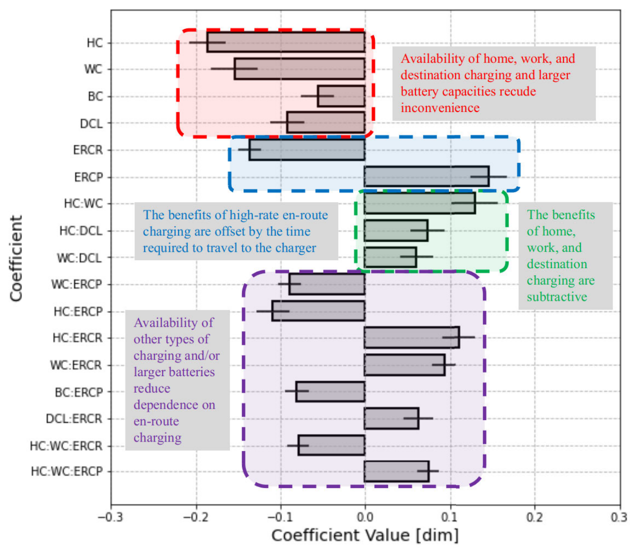


FIGURE 10. Significant ($\alpha = 0.01$) terms of empirical equation and standard error.

The significant coefficients from the regression are also shown visually in Figure 10.

The regression was performed with normalized regressor values in order to remove the impact of the scales of the

TABLE 9. Experiment Parameters and Levels.

Parameter	Levels	Unit
Fuel Tank Capacity (FTC)	[264, 528, 792]	kWh
Fuling Time Penalty (FTP)	[10, 15, 20]	min

TABLE 10. Model Summary.

R	R-Squared	Adjusted R-Squared	Std. Error
0.973	0.946	0.892	0.008

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, WC, DCL and ERCR were shown to contribute to decreasing inconvenience while ERCP was shown to contribute to decreasing inconvenience. A few key findings can be taken from the regression analysis. The variables HC and WC (home and work charging availability) play a major role in decreasing inconvenience as does DCL (the percentage of regular destinations where a charger might be available) but the interactions between the terms are positive. Home, work, and destination charging fill the same role in charging schedules. More charging availability at long dwell locations will not increase the need for charging and, as such, a saturation effect is seen. Generally the regression analysis indicates that those factors which contribute to lowering inconvenience work to mitigate the impacts of one-another in reducing inconvenience while also reducing the effects of ERCP in increasing inconvenience.

2) ICV INCONVENIENCE ANALYSIS

For ICVs, inconvenience derives from the need to refuel en-route. ICV operators, like BEV operators, will live at varying distances from fueling stations and ICVs, like BEVs, will have different energy capacities. A full-factorial designed experiment was run for ICVs on the previously mentioned parameters. The parameter levels for the ICV experiment are listed in Table 9.

The levels for FTC were set based on the capacity of the base ICV model seen in Table 4 ±50% and the levels for FTP were based on information from [11].

The experiment was conducted similarly to the BEV experiment with each case being evaluated using all 1,626 vehicles with itineraries of at least 1000 trips. Significant results for the ICV regression analysis, including the terms of the empirical equation, are presented in Tables 10, 11, and 12.

VI. DISCUSSION

The results of the regression analysis point to the overwhelming importance of home and work charging availability in determining the inconvenience experienced by BEV operators. Also shown to be very important were the infrastructure parameters DCL and ERCP. It should be noted that the effects of investing in destination and en-route charging infrastructure simultaneously were shown to be subtractive i.e. the impact of one reduces the impact of the other. Investment policies which seek to increase DCL by creating an ubiquity of low rate chargers are projected to be more effective than those which seek to promote high rate charging stations unless high rate charging stations become very common.

The empirical equations derived in this study can be used to project the experience of individuals who may be considering purchasing a BEV. Infrastructure and housing parameters for three example localities which are presented in Table 13.

The presented scenarios reflect an assumption that public charging infrastructure tends to be more prevalent in highly urbanized locations and that high volume residences also tend to be more common in highly urbanized locations. Everyone in a given locality will have access to the same public charging infrastructure but those who live in single unit residences and, more importantly, those who own their homes are more likely to be able to install charging stations at home. Projected operational inconvenience for the vehicle models from Table 4 and the localities listed in Table 13 are shown in Table 14.

TABLE 11. ANOVA.

Category	Sum of Squares	DOF	Mean Squares
Model	0.002	3	0.000
Error	0.000	5	0.000
total	0.002	8	0.000
F		$P(>F)$	
29.204		0.001	

TABLE 12. Significant terms in empirical equation.

Coefficient	Beta	t-value	p-value
Intercept	0.035	8.519	0.000
FTC	-0.020	-3.084	0.027
FTP	0.032	4.980	0.004

TABLE 13. Parameters for example localities.

Locality	DCL	ERCR	ERCP	FTP
Small Town	0%	50	45	20
Suburb	5%	150	25	15
Major City	10%	250	15	10

TABLE 14. S_{IC} [min/km] for ICV and BEV with and without home charging in example localities.

Locality	ICV	BEV			
		Home Charging	Work Charging	Both	Neither
Small Town	0.047	0.053	0.085	0.031	0.214
Suburb	0.036	0.047	0.076	0.029	0.188
Major City	0.025	0.042	0.067	0.028	0.164

For the given example localities three clear trends emerge: (1) Those EV operators who can charge at home, work, or both experience similar levels of inconvenience between the ICV and BEV but those who cannot charge at either can expect large increases in inconvenience, (2) those in highly urbanized localities experience less operational inconvenience than those in suburban or semi-rural localities, and (3) with home charging, BEV operational inconvenience can approach and surpass parity with ICV operational inconvenience. These trends underlie two forms of inequity in relation to BEV operation - economic and geographical. BEV ownership or usage will remain a much more desirable alternative for middle class to wealthy urbanites and suburbanites as long as home charging remains such an important determinant of BEV operational experience. If public EVSE infrastructure investment comes disproportionately into economically advantaged communities then the inequity of experience will grow and an inequity in BEV adoption may follow.

VII. CONCLUSION

As governments around the world attempt to reduce the climate impact of their transportation sectors while maintaining personal mobility for their citizens they will increasingly turn to the promotion of BEVs. While BEV technology has advanced significantly in recent years and is projected to continue to do so, BEVs will continue to be significantly slower to energize than ICVs for the foreseeable future. As a result of the energizing rate limitations inherent to BEVs, patterns of energizing behavior which allow for energizing to happen while the operator is otherwise occupied such as charging at home, at work, or at destinations are necessary in order for individuals to achieve convenience parity. Important specific conclusions from this study are:

- At present, BEV operational inconvenience is greatly different for those who can and cannot charge at home.
- BEV operational inconvenience for who can charge at home, work, or both approaches and even surpasses parity with ICV operational inconvenience for the same itineraries.
- For those who cannot charge at home, a ubiquity of AC Level 2 chargers at common destinations or easy access to DCFC charging stations can help to reduce the inconvenience disparity between BEVs and ICVs.

The state of public EVSE infrastructure will define the experience of BEV operators unable to charge at home or work. This dependence on public charging means that governments will play a major role in the ultimate course of BEV adoption. EVSE infrastructure investment must be implemented in a thoughtful and balanced manner or massive economic and geospatial inequities of BEV experience and adoption will emerge. Failure to equitably distribute EVSE investment will fundamentally limit the BEV market to those confident of the availability of home charging.

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