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Quantifying the Costs of Charger Availability Uncertainty for Residents of Multi-Unit Dwellings

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ABSTRACT

Even when charging at the highest rates currently available, Electric Vehicles (EVs) add range at substantially lower rates than Internal Combustion Engine Vehicles (ICVs) do while fueling. In addition, DC charging comes at a cost premium and leads to accelerated battery degradation. EV users able to rely on AC charging during long dwells at home or work may experience cost and time savings relative to ICV users with similar driving patterns. However, EV users unable to charge during long dwells will face higher charging costs and higher dedicated charging time. An important question is how occupants of Multi-Unit Dwellings (MUDs), which provide some AC Electric Vehicle Supply Infrastructure (EVSE) but not enough for all cars to charge at once, will be effected. In this paper the authors' previously published method for quantifying EV user inconvenience due to charging is extended to deal with stochastic charger availability. Stochastic Mixed Integer Linear Programming (S-MILP) is used to determine optimal charging behavior for EV users based on itineraries and the likelihood of availability of charging. Expected inconveniences for levels of charger availability and the quantitative value of additional EVSE and of charger scheduling schemes are presented.

INTRODUCTION

Mass Battery Electric Vehicle (BEV) adoption is a necessary, but not independently sufficient [1, 2], step towards meeting transportation de-carbonization goals set out by the US and EU [3, 4]. Currently, BEV adoption is continually increasing year-over-year indicating the success of present policy. Present policy levers utilized by governments to push BEV purchases largely consist of various demand and supply side subsidies which span from direct and indirect purchase subsidies to grants for EVSE installation. These subsidies help to overcome manifest cost and operational disadvantages inherent to BEVs compared to ICVs under the theory that mass adoption will bring economies of scale which remove these disadvantages before the subsidy programs become infeasible. There is considerable evidence to support this approach. Increased investment in BEV production, and particularly EV battery production, has resulted in substantial reductions in prices in the previous decade [5] which are expected continue to a lesser degree in the coming decade [6] allowing BEVs to approach cost parity with equivalent ICVs [7]. Simultaneously, the numbers of private and public EVSE operating in the US have grown tremendously in recent years [8].

Although adoption numbers indicate successful policies to date, there is reason to question the long-term viability of these policies. Current BEV purchasers and lessees still fit within the paradigm of technological early adopters being generally older, wealthier, male-skewed, highly educated, and having positive views of technology [9, 10, 11, 12, 13]. BEVs appear most commonly in larger, single-family, suburban households with larger vehicle fleets [14, 15, 16, 17]. The demographics most likely to adopt BEVs to date are, unsurprisingly, those most able to deal with the pitfalls of BEVs and most able to utilize the incentives provided. The most effective incentives for driving BEV adoption have been direct purchase subsidies [18, 19, 20, 21, 22, 23] and access subsidies such as used of carpool lanes and preferential parking [24, 25, 26, 27]. Direct purchase subsidies are often reserved for purchasers of new cars and will become unsustainable with high adoption while access subsidies will become meaningless with high adoption due to saturation effects. For as long as the fundamentals of BEVs are a disadvantage and sales are incentive driven there will be an upper limit on market penetration.

Enthusiastic early adoption does not guarantee eventual mass adoption and, often, new policy approaches are required to continue the trend. BEV sales have increased year-over-year in recent years on net but there has been notable discontinuance. Surveys conducted between 2015 and 2019 on California EV buyers who applied for a California Clean Vehicle Rebate showed a discontinuance rate of roughly 18% for BEVs [28]. Significant factors leading to discontinuance were dissatisfaction with reliability, range, and charging experience. The availability of AC Level 2 charging at home is critical in determining BEV charging experience [29, 30]. The importance of home charging is due to clear and present public EVSE reliability and availability issues [31, 32, 33] which require costly solutions [34, 35] as well as the inherent convenience of being able to "plug-in and ignore" at home. Modeling efforts suggest that the availability of home charging may lead to a ten-fold decrease in expected dedicated charging time for otherwise identical BEV users [36, 37]. Home AC level 2 is considerably more likely to be available for residents of Single-Unit Dwellings (SUDs) than residents of MUDs [38], with a similar disparity existing between home owners and renters. A common situation for residents fo MUDs is that the parking lot will have some chargers installed but this number will not be nearly equal to the total number of parking spaces. Thus, residents of MUDs are left in a situation wherein sufficient charging for all residents may be available but with uncertainty on when said charging will be available for any individual resident. For the duration of time that a significant disparity in user experience exists between residents of SUDs and MUDs disontinuance will be high and market penetration will be limited.

A critical question is what is required in order to address the SUD/MUD disparity. Matching the volume of AC Level 2 EVSE with he volume of BEVs in MUD parking lots is an un-economical solution. Generally, travel behavior dynamics dictate that demand will be temporally clustered at a given location. Providing sufficient capacity to match peak demand will require very high costs to be passed on to customers for profitable operation. The objective of EVSE installation incentives is to allocate EVSE resources in order to minimize BEV user inconvenience subject to limited resources. This objective requires not merely comparing supply to demand but understanding how the supply/demand relationship effects user experience.

The central question in this study is what effect uncertainty of charger availability will have on BEV user experience. Long dwell charging is fundamental to BEV user behavior due to the relatively slow charging speeds of BEVs [39]. As a result, users formulate charging plans and routines rather than charging ad-hoc [40, 41, 42]. Formulating charging plans and routines is a simpler task with better future information. With imperfect future information, rational agents will sacrifice optimality in order to reduce risk, especially if the downside is substantial. For BEV users, the ultimate downside risk is an extremely inconvenient event such as having insufficient range to complete an intended trip. For drivers engaged in long trips or trip chains, a stranding event can sometimes be triggered by one or several failed charge events [31]. For drivers completing routine travel in a populated environment, the downside is being forced to delay for significant time and/or travel out of the way to charge. Desire to avoid downside risk can lead BEV drivers to elect for less convenient charge events as part of their regular behavior. By this theory, one would expect that the inconvenience cost of charging a BEV due to scarce and uncertain charging opportunities will be non-negligibly greater than that which arises from scarce but predictable charging opportunities. In this paper, the value of information associated with charger availability uncertainty is assessed quantitatively and results are presented along with ensuing operational and policy implications.

METHODS

This study serves to test the hypothesis that there is an inconvenience cost-of-uncertainty associated with reliance on public and shared EVSE. This hypothesis is evaluated by comparing how theoretical BEV users would charge their vehicles with perfect and imperfect information about charger availability in the future. The scope of this analysis is limited to routine commuter travel behavior. Drivers with unpredictable driving routines and/or very high daily travel distances such as ride-sharing and delivery drivers or very low daily travel requirements such as home-workers will naturally have to rely more on ad-hoc charging. Routine commuter driving constitutes the bulk of light-duty driving [43] and is the focus herein. The method of evaluation in this study is to compare the dedicated charging time required for the exact same itineraries with perfect and imperfect future information. This is accomplished via comparing the optimal charging schedules generated for a given itinerary using MILP with perfect information and S-MILP with imperfect information. The method relies in the following assumptions:

- A.1: Charging a vehicle is only inconvenient for the amount of time that a user has to devote to charging said vehicle.
- A.2: BEV users will attempt to schedule charging events in a manner which minimizes inconvenience.
- A.3: For a given vehicle and itinerary the characteristic inconvenience cost is the minimum inconvenience cost.

A possible shortcoming of this method is that BEV users may optimize for charging cost as well as charging inconvenience. Some evidence exists that BEV users will opt to charge away from home if doing so is cheaper [29]. However, charging costs are difficult to model and vary considerably due to factors such as charger network, time-of-day, location, incentives, and others making precise integration of financial charging costs into the optimization imprecise. Furthermore, it is largely true that high-rate charging typical of dedicated charging stations is more expensive on a per-kWh basis than the low-rate charging typical of long-dwell charging at home, work, or retail locations [44]. Thus the type of charge events selected by an inconvenience minimization strategy should be the same as those selected by a financial cost minimization strategy.

METRIC OF OPTIMIZATION In order to assess inconvenience cost-of-uncertainty, a metric of inconvenience must be defined. In this study the Inconvenience Score (S_{IC}) metric from [36] is used. The S_{IC} metric is an implementation of the logic of assumption A.1. 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

S_{IC} reflects the differences in dedicated time spent by charging event type with charging events that fit into dwells in an existing itinerary being substantially less inconvenient than those which require alterations to an existing itinerary.

OPTIMIZATION The objective of the optimization is to find the charge schedule which minimizes S_{IC} for a given itinerary and given charger availability at all dwells along said itinerary. As seen in (1), much of S_{IC} accrued during a given charge event arises from the travel and payment penalties. Thus, S_{IC} is discontinuous around zero. In order to make the problem solvable with integer-linear solvers the decision variables are split into Booleans which represent the decision to charge during a given dwell or trip and durations which represent the duration of the charge event. Each potential charge event has a charging rate known a priori. This combination of variables allows for the problem to be solved as a MILP. In order to evaluate the cost-of-uncertainty the problem must be formulated in both a deterministic and a stochastic manner. The deterministic formulation allows for optimization to take place for one defined itinerary with known charger rates and availability and reflects optimization with perfect future knowledge. The stochastic formulation allows for an optimal solution to be computed for all scenarios (same itinerary but different charger availabilities) within a set sensitive to all others within the set. This is accomplished by separating decision variables into first-stage decision variables which influence all scenarios and second-stage decision variables which influence only the specific scenario. In this case the Booleans are first-stage and the durations are second-stage. In other words, the theory is that BEV users will have to plan when to charge but may alter durations to suit their needs. The stochastic formulation reflects optimization with imperfect future knowledge.

<u>Deterministic Formulation</u> To minimize the number of decision variables, and thus solver run-time, the objective is formulated differently than in (1). For the deterministic optimization the objective function is

$$\min_{u \in U} \quad \sum_{e \in E} [u_e^{db} c_e^{db} + u_e^{ab} c^{ab} + u_e^{ad} c^{ad}] \tag{2}$$

where E is the set of itinerary events (trip then dwell), $U = [u^{dd}, u^{db}, u^{ad}, u^{ab}]$ is the set of decision variables including, in order, dwell charge event duration, dwell charge event Boolean, ad-hoc charge event duration, ad-hoc charge event Boolean, and $C = [c^{dd}, c^{db}, c^{ad}, c^{ab}]$ is the set of constant cost multipliers corresponding to U. The variables are bounded as follows

$$\begin{gathered} lb^{dd} u_e^{db} - u_e^{dd} \leq 0 \\ ub^{dd} u_e^{db} - u_e^{dd} \geq 0 \\ lb^{ad} u^{ab} - u_e^{ad} \leq 0 \\ ub^{ad} u^{ab} - u_e^{ad} \geq 0 \\ s.t. \\ u^{db}, u^{ab} \in \mathbb{B} \qquad \forall e \in E \end{gathered} \tag{3}$$

The problem is subject to several constraints which serve the purpose of maintaining the vehicle's State of Charge (SOC) within allowed limits and returning the vehicle's SOC to a given final value. these constraints are

$$s_i + \sum_{k=0}^{K} [u_{e_k}^{dd} r_{e_k}^{d} + u_{e_k}^{ad} r_{e_k}^{a} - d_{e_k}] \geq s_{lb} \quad \forall K \in E \tag{4}$$

$$s_i + \sum_{k=0}^{K} [u_{e_k}^{dd} r_{e_k}^{d} + u_{e_k}^{ad} r_{e_k}^{a} - d_{e_k}] \leq s_{ub} \quad \forall K \in E \tag{5}$$

$$s_i + \sum_{e \in E} [u_e^{dd} r_e^d + u_e^{ad} r_e^a - d_e] = s_f \quad (6)$$

where s_i is the initial vehicle charge level, s_f is the final vehicle charge level, s_{lb} is the lower bound for vehicle charge level, s_{ub} is the upper bound for vehicle charge level, r^d and r^a are the dwell and ad-hoc charging rates respectively available for each event, and $D = \{d_0, d_1, \ldots, d_n\}$ is the set of discharges corresponding to the events in E.

Stochastic Formulation For the stochastic optimization the objective function is

$$\min_{u \in U} \quad \sum_{\phi \in \Phi} \sum_{e \in E} [u_{\phi,e}^{db} c_e^{db} + u_e^{ab} c^{ab} + u_{\phi,e}^{ad} c^{ad}] \quad (7)$$

where Φ is the set of scenarios, E is the set of itinerary events (trip then dwell), $U = [u^{dd}, u^{db}, u^{ad}, u^{ab}]$ is the set of decision variables including, in order, dwell charge event duration, dwell charge event boolean, ad-hoc charge event duration, ad-hoc charge event boolean, and $C = [c^{dd}, c^{db}, c^{ad}, c^{ab}]$ is the set of constant cost multipliers corresponding to U. The variables are bounded as follows

$$\begin{gathered} lb^{dd} u_{\phi,e}^{db} - u_{\phi,e}^{dd} \leq 0 \\ ub^{dd} u_{\phi,e}^{db} - u_{\phi,e}^{dd} \geq 0 \\ lb^{ad} u^{ab} - u_{\phi,e}^{ad} \leq 0 \\ ub^{ad} u^{ab} - u_{\phi,e}^{ad} \geq 0 \\ s.t. \\ u^{db}, u^{ab} \in \mathbb{B} \quad \forall \phi \in \Phi, \quad \forall e \in E \end{gathered} \quad (8)$$

The problem is subject to several constraints which serve the purpose of maintaining the vehicle's SOC within allowed limits and returning the vehicle's SOC to a given final value. these constraints are

$$s_i + \sum_{k=0}^{K} [u_{\phi,e_k}^{dd} r_{e_k}^d + u_{\phi,e_k}^{ad} r_{e_k}^a - d_{e_k}] \geq s_{lb} \quad \forall \phi \in \Phi \quad \forall K \in E \quad (9)$$

$$s_i + \sum_{k=0}^{K} [u_{\phi,e_k}^{dd} r_{e_k}^d + u_{\phi,e_k}^{ad} r_{e_k}^a - d_{e_k}] \leq s_{ub} \quad \forall \phi \in \Phi \quad \forall K \in E \quad (10)$$

$$s_i + \sum_{e \in E} [u_{\phi,e}^{dd} r_e^d + u_{\phi,e}^{ad} r_e^a - d_e] = s_f \quad \forall \phi \in \Phi \quad (11)$$

where s_i is the initial vehicle charge level, s_f is the final vehicle charge level, s_{lb} is the lower bound for vehicle charge level, s_{ub} is the upper bound for vehicle charge level, r^d and r^a are the dwell and ad-hoc charging rates respectively available for each event, and $D = \{d_0, d_1, \ldots, d_n\}$ is the set of discharges corresponding to the events in E.

DATA Itineraries used for analysis were taken from the 2017 National Highway Transportation Survey (NHTS) [45]. Itineraries were composed from trips for each unique vehicle in the dataset with each trip only counted once regardless of number of passengers (PERSONID = WHODROVE). Itineraries were down-selected to primary household vehicles (VEHID $\leq$ 2 & TRPHHVEH = 1). Itineraries were down-selected for commuters by keeping only those containing at least one trip to work (WHYTO = 3). Finally, itineraries were down-selected to those originating from households in densely populated areas with high rentership (at least one trip with WHYFROM = 1 & OTRESDN $\geq$ 7000 & OBHTNRNT $\geq$ 70) as these households are most likely to be in MUDs.

EXPERIMENTAL DESIGN In order to gain an understanding of the cost-of-uncertainty over charger availability a full-factorial designed experiment was conducted on the parameters listed in Table 2.

Table 2: Designed Experiment Parameters

Parameter	Levels
S	[False, True]
Home Charger Likelihood (HCL)	[0, 0.125, 0.25, 0.375, 0.5]
Work Charger Likelihood (WCL)	[0, 0.125, 0.25, 0.375, 0.5]
Destination Charger Likelihood (DCL)	[0, 0.125, 0.25, 0.375, 0.5]

S is a Boolean representing whether stochastic (S-MILP) or deterministic (MILP) optimization was used. HCL, WCL, and DCL are likelihoods that chargers will be usable during a given itinerary dwell if it is at the user's home location, the user's work location, or another location respectively. The BEV model used is the same as in the previous paper [36] with a battery capacity of 80 kWh. The charging model used was a linearized version of the model in the previous paper with AC charging assumed to occur at 12 kW and DC charging at 120 kW. These values were selected to be in line with middle ranges from the previous paper.

Each case in the design was evaluated for each itinerary as described in the Data Section. For each case and itinerary 5 possible scenarios were created by randomly assigning charger availability to dwells in the itinerary with respect to the likelihoods for each type of dwell specified in the case. The 5 scenarios were then optimized simultaneously using S-MILP and individually using MILP as detailed in the Optimization Subsection of the Methods Section. The mean of the S_{IC} scores of the simultaneous optimization can be considered as the expected S_{IC} and the mean of the S_{IC} scores of the individual optimizations can be considered as the average S_{IC}. Thus, for each case a cost-of-uncertainty can be calculated by subtracting the average S_{IC} from the expected S_{IC}. Each optimization was prepared using the

Pyomo Python package [46] and solved using the COIN-OR CBC open-source solver [47].

RESULTS

Linear regression was applied to the results from the designed experiment in order to identify significant . Mean S_{IC} results for all cases were regressed onto the parameters in Table 2 and all interactions. The significant terms from the regression are displayed in Figure 1 and regression details are provided in Tables 3, 4, and 5.

Table 3: Summary for S_{IC} Regression

R	R-Squared	Adjusted R-Squared	Std. Error
0.974	0.948	0.944	0.000

Table 4: ANOVA for S_{IC} Regression

Category	Sum of Squares	DOF	Mean Squares
Model	0.287	15	0.019
Error	0.016	234	0.000
Total	0.303	249	0.001
F		$P(>F)$	
283.015		0.000	

Table 5: Significant Factors from S_{IC} Regression

Intercept	0.043	11.322	0.000
S	0.142	26.289	0.000
HCL	-0.092	-7.389	0.000
WCL	-0.092	-7.376	0.000
DCL	-0.049	-3.931	0.000
S:HCL	-0.235	-13.339	0.000
S:WCL	-0.226	-12.796	0.000
S:DCL	-0.144	-8.151	0.000
HCL:WCL	0.197	4.840	0.000
HCL:DCL	0.106	2.595	0.010
WCL:DCL	0.105	2.575	0.011
S:HCL:WCL	0.351	6.092	0.000
S:HCL:DCL	0.225	3.900	0.000
S:WCL:DCL	0.246	4.274	0.000
S:HCL:WCL:DCL	-0.380	-2.018	0.045

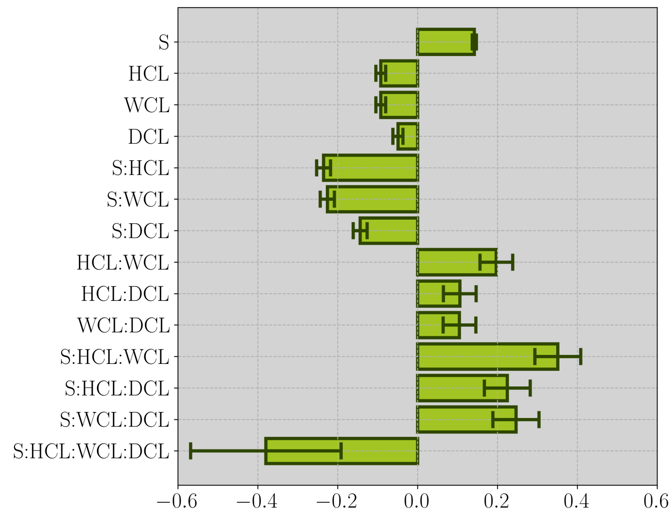

Figure 1: Significant factors from S_{IC} regression

All regression terms except HCL:WCL:DCL were significant at 95% confidence. Regression terms indicate that increasing charger usability likelihood results in a reduction in inconvenience and that home and work charging are more important than destination charging in achieving this. These takeaways are intuitive and in line with the findings in [36]. S and S-interaction terms indicate that cost-of-uncertainty is substantial and statistically significant, proving the hypothesis of this study.

Focusing on cost-of-uncertainty, Figure 2 shows the ignificant factors resulting from regressing cost-of-uncertainty upon HCL, WCL, and DCL (regression details provided in Tables 6, 7, and 8).

Table 6: Summary for S_{IC} Difference Regression

R	R-Squared	Adjusted R-Squared	Std. Error
0.924	0.853	0.843	0.000

Table 7: ANOVA for S_{IC} Difference Regression

Category	Sum of Squares	DOF	Mean Squares
Model	0.120	7	0.017
Error	0.030	117	0.000
Total	0.207	124	0.002
F		$P(>F)$	
65.816		0.000	

Table 8: Significant Factors from S_{IC} Difference Regression

Intercept	0.142	26.709	0.000
HCL	-0.235	-13.552	0.000
WCL	-0.226	-13.001	0.000
DCL	-0.144	-8.281	0.000
HCL:WCL	0.351	6.190	0.000
HCL:DCL	0.225	3.963	0.000
WCL:DCL	0.246	4.342	0.000
HCL:WCL:DCL	-0.380	-2.050	0.043

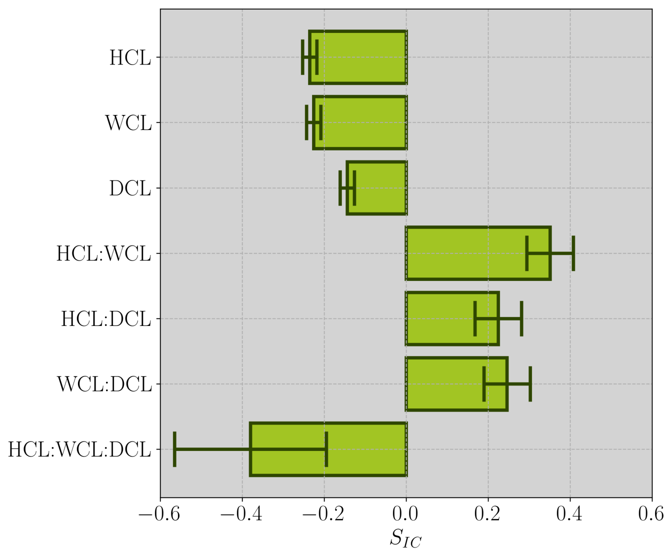

Figure 2: Significant factors from cost-of-uncertainty regression

HCL, WCL, and DCL and all interaction terms are significant in determining cost-of-uncertainty. Increasingly reliable access to chargers at home, work, and other destinations contribute to lowering cost-of-uncertainty with home and work having more impact. The positive first order interaction terms indicate a non-additive relationship wherein BEV users with high levels of access at one location type benefit less from increasing access at others.

DISCUSSION

Based on the experimental results presented in this study one can confidently accept the hypothesis that there is a non-negligible cost-of-uncertainty associated with unreliable dwell charging. The situation which inspired this study is that of MUD residents where the building provides some EVSE but fewer charge points than parking spaces. If such individuals work away from home then they may experience similar situations at work and all will experience similar situations at public locations such as retail centers. The cost of installing and operating chargers is considerable, especially for chargers in close proximity, due to the probable need for grid enhancement [34]. Because EVSE only generates revenue while in use it is economically infeasible to maintain a saturation of chargers wherein everyone can charge whenever desired whether in public or private spaces. It follows that EVSE will not always be available when desired unless the BEV user has exclusive use of EVSE as is the case for residents of SUDs. The lack of guaranteed, or even likely, charger availability will result in users being more opportunistic in selecting charge events and more conservative in maintaining SOC leading to more inconvenient charge events. As a result, charging inconvenience for MUD residents can be expected to scale at a rate in excess of the ratio of EVs to charge points in their buildings.

As recently as 2021 89% of respondents to a survey conducted by NREL who were owners of single-unit-detached dwellings claimed possible access to home charging while this number was only 29% for renters in high-capacity MUDs. The latter number does not account for the number of BEVs per charger. In the past it might be safe to assume that the number of electric vehicles in a given MUD will be fairly small. Since 2021, EV sales have risen rapidly in the US and globally [48, 49] and such assumptions will break down shortly if they have not already. It is, thus, imperative that EVSE subsidy programs begin to place high emphasis on MUDs and workplaces. While not equivalent to adding more chargers certain policies can mitigate the cost-of-uncertainty associated with shared charging resources. These policies include pricing schemes which discourage over-long charge events for public spaces [50] and scheduled charging sessions for private spaces. Such policies can help to maintain rational behavior and efficient allocation of shared charging resources allowing for fewer resources to be sufficient for a larger user base.

CONCLUSIONS

Continued BEV market penetration depends on a growing stream of new adopters and low discontinuance rates among current adopters. To a point, new adopters can be enticed with incentives but, ultimately, BEVs must win out on the strength of their fundamentals. As BEV purchase prices come down, BEVs become strong options for more and more of the market. However, there is a distinct and enduring difference in the value proposition for two groups of vehicle users, those with access to exclusive home AC level 2 charging and those without. The difference manifests as both a financial and time cost as the latter group are forced to select costly and inconvenient charging events more often than the former. Addressing this inequity requires understanding how reliance on shared community EVSE effects user behavior. With insufficient resources and governance users of shared resources will see limited benefits. In this paper, a quantitative method is provided which extends on the authors' previous charging inconvenience work to account for the cost-of-uncertainty associated with uncertain EVSE availability. Results of a designed computational experiment using real driving data show a statistically significant and substantial cost-of-uncertainty for BEV users reliant on public and shared EVSE. The experience of said users may be improved via investments in additional EVSE and by the implementation of governance policies such as financial disincentives for prolonged charge events and scheduled access. The relationship between EVSE expansion and reduction of uncertainty is additive and future EVSE subsidy programs which include governance requirements may be more successful than those which do not.

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