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Agent-based modeling of electric vehicles with time-of-use electricity rates

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Summary

In this study we design and simulate scenarios in which battery-electric vehicle (BEV) drivers respond to the implementation of time-of-use (TOU) pricing schemes in the Chicago area. The evolving BEV unmet charging demand pinpoints locations for the future development of charging infrastructure. The simulation is designed as an agent-based-model (ABM), and a behavioral heuristic is formulated for drivers to dictate charging behavior in response to changing charging prices. We find that, when drivers obey this heuristic, it generally results in lower rates of unmet charging demand for drivers below their comfortable battery state-of-charge. However, the use of public chargers increases dramatically in this scenario. Despite the lower unmet demand, such higher public charging station utilization can cause congestion, indicating a need for more investment in charging infrastructure.

Keywords: electric vehicle (EV), infrastructure, modeling, simulation, utility

1 Introduction

1.1 Background

Many nations have highlighted the adoption of plug-in electric vehicles (PEVs), including BEVs and plug-in hybrids (PHEVs), as a significant step towards reducing greenhouse gas (GHG) emissions [1, 2], which contribute significantly to climate change and global warming [3]. In the United States, the PEV market share remains relatively low, but is steadily increasing. In December 2019, PEVs accounted for 5.40% of all car sales [4]. With that number continuing to rise, more and more drivers will be charging their PEVs, both at home and in public. As of yet, the most comprehensive study of PEV charging and infrastructure in the United States was the EV Project, which ran from October 2009 to December 2013, where they found that Nissan Leaf drivers during that time period performed 84% of their charging at home [5]. While the percentage of charging done at public locations is low, public charging infrastructure remains an important factor in the adoption of BEVs going forward for many reasons, including reducing so-called “range anxiety”. Additionally, there is an increasing popularity of ride-sourcing services (e.g. Uber, Lyft), where drivers accrue high levels of daily vehicle miles travelled (VMT) [6]. Such services also call for focus on the impact of public charging infrastructure.

Many studies have pointed out that higher amounts of PEV charging could have a significant impact on the electric grid [7, 8]. Peak grid demand is already becoming a significant problem in some areas [9], especially during the summer months when residents frequently use air conditioning units. As more people move to urban areas, average temperatures continue to rise, and PEV adoption grows, utility companies must come up with ways to shift demand away from peak hours in order to avoid blackouts and brownouts. This becomes especially important when renewables such as wind and solar make up a greater share of the energy mix since they cannot be “turned on” as readily as other traditional non-renewable sources.

In response to the potential for increased grid load during peak hours, utilities have incentivized off-peak electricity use by lowering prices during those times [10]. These dynamic pricing schemes range from a simple, two-tiered (on- or off-peak) system to a less predictable hourly schedule. These schemes that charge different rates based on what time of the day it is known as time-of-use (TOU). PEV drivers can take advantage of these rates by charging at home overnight (instead of upon returning from work, for example) and in public earlier in the day before rates rise for peak hours. Commonwealth Edison, the primary electricity provider for our case study region of the greater Chicago area, offers one of these TOU rates to its residential customers [11]. TOU and similar schemes will alter the charging behavior of PEV drivers. In this paper, we consider BEVs only, since they have no choice but to charge when the battery gets low. PHEVs, on the other hand, can continue operating in hybrid mode once their battery is depleted.

In this scenario analysis, we seek to understand how BEV charging behavior might change when there are TOU rates and the resulting evolution of spatially-distributed unmet charging demand. The findings can inform potential charging infrastructure investors, such as property owners and utility companies, in making decisions about where and when to build new charging stations. This type of spatial-temporal investigation can be approached using an agent-based model (ABM). An ABM is a model in which unique, autonomous agents interact with each other and their environment, resulting in emergent phenomena from the "bottom-up" [12]. The advantage of an ABM approach, in this case, is that it allows for a scenario analysis where mobility and inter-agent interaction across space and time lead to macroscopic trends in charging demand.

1.2 Literature Review

There is a substantial body of literature investigating ways in which peak grid load can be mitigated. A popular research area serving this purpose is developing "smart charging" algorithms that make use of vehicle-to-grid (V2G) electricity flow [13, 14]. These optimization models necessarily draw from many different disciplines, including economics, battery degradation models, control theory, and more [15, 16].

An emerging body of work focuses more specifically on TOU rates. Faruqui and Sergici found that peak demand could drop 23-30% in a TOU scenario if smart charging controllers are installed [17]. Similarly, Newsham and Bowker took for granted the installation of smart meters and estimated a significant decrease in peak demand [10]. On the other hand, Herter and Wayland found less substantial peak demand reduction with a more temporary critical peak pricing scheme [18]. They suggest that less demand reduction in this scenario may be due to greater inelasticity once prices are high enough. Schey, Scoffiled, and Smart [19] surveyed charging data from home charging stations among states and cities that participated in the EV Project. They found that nearly all PEV owners who used Pacific Gas & Electric's TOU plan would schedule their car to start charging at midnight, well after arriving back at home, in order to save money with lower night-time rates.

While the above studies measured consumer response to the implementation of TOU rates, many more have applied optimization models to the rate structures themselves. Cao et al. created a heuristic optimization algorithm that BEVs would use to charge at the best times to shave grid load peaks and fill the "valleys." This algorithm was developed within the framework of a TOU pricing scheme set by the utility company [20]. Yang et al. also used an optimization model to develop a TOU rate structure, while considering how consumers would respond. They concluded that if consumers either fully or partially shift their electricity usage based on different tiers of pricing, it would create a win-win scenario for consumers and utility companies alike [21].

Evidently, optimal TOU pricing is an important objective for peak demand shifting moving forward. However, a more complete TOU analysis requires consideration of evolving driver charging behavior within these schemes in conjunction with the infrastructure changes required to support growing BEV adoption. Baouche, Billot, Trigui et al. developed an optimization model for charging infrastructure placement in a dense urban network. They used integer linear programming (ILP) to minimize the total travel costs from demand zones to the location of the charger as well as the costs of charging [22]. Outside of optimization, the correlations between charging network coverage, charging cost, and utilization in public locations have been the subject of some recent studies. Kontou et al. investigated how charging opportunity is connected to charging network coverage using GPS data [23]. Boston and Werthman found that electric VMT and public charging events increase when there is a greater price difference between gasoline and the equivalent amount of electricity [24]. Tal et al. showed that BEV drivers alter their driving and charging behavior based on how the cost of charging compares to the price of gasoline at the time. For example, the Prius Plug-in had such a small range of electricity for which it would be worth it to charge (compared to filling the gas tank) that many didn't even charge at all [25].

Agent-based modeling is growing in popularity across many disciplines [12], including transportation studies. For example, MATSim is a robust ABM framework geared towards transportation [26], which can be used in many mobility studies that employ ABM techniques [27]. Recently, there has been a focus on using ABM for modeling BEV behavior as well as BEV adoption. Silvia and Krause implemented an ABM using the NetLogo software package [28] to simulate BEV adoption [29]. In their model, consumer agents respond to various policy scenarios based on their income, environmental attitudes, and vehicle range preferences to make BEV purchasing decisions. Investors, on the other hand, might provide subsidies or deploy some BEV fleets to increase BEV visibility. Adepetu, Keshav, and Arya used an ABM to simulate EV adoption as well, using a sophisticated scheme of individual consumer traits, vehicle usage, social networks, and more [30].

In terms of BEV driving and charging behavior, Dong implemented activity schedules based on a large swath of travel survey data to simulate BEVs in the greater Seattle metropolitan area [31]. Sheppard, Harris, and Gopal created an ABM for BEV mobility using Delhi as a case study [32]. In their model, drivers go about their day according to some pre-defined activity schedule while attempting to minimize their charging cost, which varies based on the charger level--level 1, level 2, or direct current fast charging (DCFC). They also include charging infrastructure adoption in their model, using a heuristic optimization approach to site new charging stations.

1.2.1 Contributions of this paper

While the above studies show consumer response to TOU pricing, optimization of dynamic rate structures, BEV adoption and charging infrastructure evolution, few studies consider all of these factors to show how BEV drivers behave in a TOU scenario and the resulting unmet charging demand, nor do they consider the infrastructure necessary to accommodate new demand associated with TOU-adjusted behavior. We use an ABM to simulate the everyday mobility and charging patterns of BEV drivers, as well as the long-term effects of these patterns on unmet demand, station utilization, and new infrastructure locations. The ABM approach allows us to gain insights into future behavior given a range of possible scenarios. Additionally, we develop a utility function to model drivers' decisions throughout their day on when and where to charge.

2 Methodology

2.1 The ATEAM model

We address the research gap using an ABM known as ATEAM [33], which was developed using the Repast Simphony modeling toolkit [34] at Argonne National Laboratory under a cooperative research and development agreement (CRADA) with Exelon. By modeling decisions of key stakeholders or agents, ABM captures their behavior as well as the complex interactions between them. Because agents are the key units for such models, agent-based models can evolve in complexity and robustness as additional agents and their capacity for making increasingly complex decisions are added to the underlying structure.

In ATEAM, the agents are BEV drivers, households, utility companies, and infrastructure investors. In our study, we apply the model to the greater Chicago area, including Cook, DuPage, Kane, Kendall, Lake, McHenry, and Will counties. Further details about the scenario are discussed in the "Data and Inputs" section. The model runs on two concurrent timescales to capture both the daily charging behavior and the long term co-evolution of charging infrastructure, BEV adoption, electricity rates, and charging demand.

When the model is initialized, the simulation environment is first established by integrating various datasets into a common geographical space. This includes locations of charging stations, initial locations of BEVs, and household characteristics such as income. In our analysis, an additional *utility agent* implements a TOU pricing scheme while drivers monitor the electricity prices, altering their charging behavior based on the current price per kilowatt-hour (kWh) of electricity.

2.1.1 Daily timescale

In the daily simulation, BEVs travel based on their unique activity schedules, charging in public, at home, or both. These activity schedules are assigned at the beginning of the day based on data from the Chicago Metropolitan Agency for Planning (CMAP) 2007-2008 Travel Survey [35] and are assumed to start the day with a full charge. We set the simulation time step to be 15 minutes, so there are 96 steps over 24 hours (3:00 am to 3:00 am). As BEVs proceed with each time step, their battery level decreases (if they are traveling). We assume that BEVs operate with "destination" charging in mind, rather than the "en-route" philosophy of a conventional ICE vehicle. This is due to the relatively long re-charging time compared to refueling with gasoline, even for DCFCs, which still take upwards of 30 minutes for a full charge [36]. When BEVs are at their destinations, they compare their current state of charge (SOC) to some pre-defined tolerance threshold (e.g. 50% of battery capacity). This threshold can be uniformly assigned to all drivers ("un-calibrated") or assigned according to a distribution taken from ChargePoint SOC data of over 300 instances of plugging in ("calibrated"). If their current SOC falls below this threshold, they check if there are any chargers nearby. If so, they go charge. If not, it is counted as an instance of "unmet demand," which the investor agent keeps track of at the tract level. This is the charging behavior assumed in the **base scenario**.

In addition to this basic method for choosing whether or not to charge while in public, we develop a behavioral heuristic for drivers to follow. The heuristic takes the form of a utility function with two components: the cost of traveling to a charging station, C_{tr}, and the cost of charging itself, C_{ch}. First, the cost to travel to a station is given below:

$$C_{tr}(d,t) = d * r(t) * E, \tag{1}$$

where d is the Euclidean distance to the given station, *r(t)* is the price of electricity at discrete time step t (in $\frac{¢}{kWh}$), and E is the energy efficiency of the BEV (in $\frac{kWh}{m}$). The other piece of the utility function is the cost to charge the BEV:

$$C_{ch}(t) = B * r(t). \tag{2}$$

Here, we call B the SOC "buffer", defined as the difference between the current SOC and the driver's comfortable SOC threshold, and *r(t)* is the same as in (1). B is a function of many variables, including various specific characteristics of the individual vehicle, which we have chosen not to write out for the sake of simplicity. The total cost function is a weighted sum of (1) and (2):

$$C(d,t) = \beta * C_{tr}(d,t) + \gamma * C_{ch}(t). \tag{3}$$

Since (2) tends to dominate (1), we use constants β and γ to scale the two cost functions to be relatively equal in magnitude. This re-scaling captures factors that affect the utility of traveling to charge, such as the inconvenience of walking back to your intended destination after plugging in. Finally, we define the overall utility function as

$$U = -C(d,t). \tag{4}$$

The behavioral heuristic for the BEV drivers, then, is to survey the area once at their destination and pick the station which maximizes their utility (i.e. the closest station, if there is one within a one-mile radius). If the utility is above some pre-defined threshold, P, they will want to charge, even if $B > 0$. If $B \leq 0$, the drivers will want to charge no matter what, which is the same behavior as in the base case. In **TOU scenarios**, we replace the old charging choice method with this utility function and vary the value of $\boldsymbol{P}$. A flowchart of BEV behavior is shown in Fig. 1. The pink "Want to charge?" diamond is where the charging behavioral heuristic goes in the TOU scenarios. This is the logic that each BEV agent follows in the model.

When the BEV arrives at home, what they do depends on which scenario is being run. In the base scenario, drivers who have chargers at home will immediately plug in to charge for the remainder of the day. In the TOU scenario, drivers who have home charging will wait until the price of electricity drops below a certain threshold, after which they will plug in, taking advantage of low overnight rates. This behavior has the added benefit of reducing the load on the grid at peak times (i.e. when drivers arrive home in the afternoon). We analyze the CMAP household data from the Travel Survey to determine the percentage of homes in each tract that have a place to charge their BEV at home, whether it be a garage or some other forms of off-street parking [35]. Homes that had a garage or had off-street parking and were either detached, single-family units or attached, single-family units were assumed to have at-home charging. All other cases were assumed to not have at-home charging available.

2.1.2 Yearly timescale

Due to computational constraints and lack of more descriptive data (e.g. across seasons or weekday versus weekend), one representative day is simulated for each year. At the end of the "year", the model is updated by the *households*, *investors*, and the *utility agent*. Households in each tract purchase new BEVs according to the projected number of BEVs for the next year. The new BEVs are distributed among the tracts based on the tract median incomes. Investors then build new charging stations throughout the study region. Again, the total number of new charging stations for the study area at the given year is predetermined according to a BEV adoption forecast (see "Data and Inputs"). In the case of investors, however, the new stations are assigned to the tracts according to the amount of unmet demand in each tract. Finally, the *utility agent* updates the hourly electricity prices. The price growth rates follow the 2019 EIA Energy Outlook projections for the East North Central region (converted to percent change from the previous year) [37]. Because TOU prices rely on several economic factors and are generally difficult to predict, we assume that each representative day simulated will come on a similar day of the week and time of year, thereby minimizing the potential price variation.

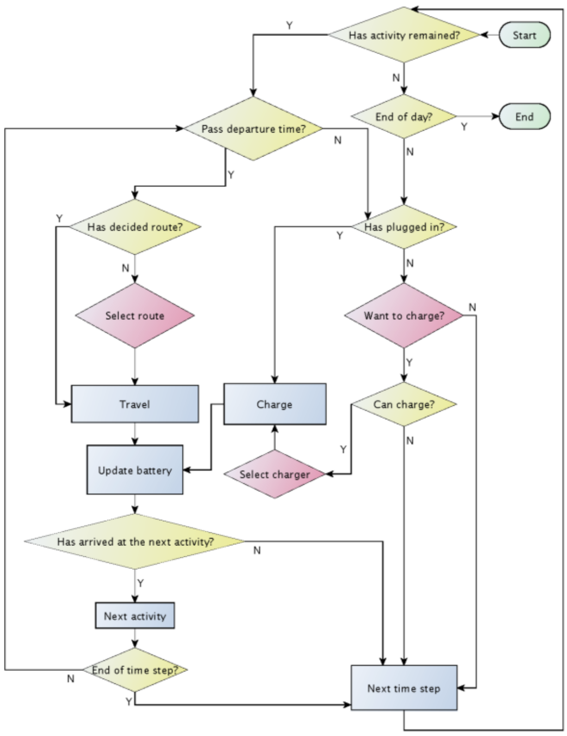

Figure 1: BEV logic flowchart

3 Data and Inputs

We use extensive data from the CMAP 2007-2008 travel survey [35] to generate daily activity schedules for the BEV driver agents. We also use the travel survey for data on household income, household charging availability, and household locations. IHSMarket data from 2017 provides the number of BEVs in Chicago at the zip code level [38], and data from fueleconomy.gov is used for market shares and car specifications of BEVs in the model [39]. The Chicago area transportation network and tract, county, and zip code boundary shapefiles were obtained from OpenStreetMap [40] and census.gov [41], respectively.

To project the number of BEVs in the study area each year, we utilize the EIA forecast of national BEV sales [42]. Chicagoland sales were assumed to represent a constant share of national BEV sales based on current adoption. The annual sales were then converted to vehicles in use (i.e., vehicle stocks) using the vehicle survival function from Argonne National Laboratory's VISION model [43]. For charging infrastructure projections, we turn to empirical data which show an inverse relationship between the density of charging stations and vehicle stocks (i.e., charging stations per 1000 vehicles) [38, 44]. We use this relationship at the state level to develop a regression curve ($R^2 = 0.94$) which provides the number of charging stations for each year of the simulation (given the projected BEV stock). These are both projections of the total number of BEVs and charging stations in the entire region, not where they are sited. The siting happens during the simulation as described in the "Yearly timescale" section. Original station locations are taken from the Alternate Fuels Data Center [44]. Level 1, level 2, and DC-fast chargers are assumed to deliver 1.4 kW, 7.7 kW, and 43.0 kW, respectively. For the ten years of the simulation, the numbers of charging stations in the study area are 391, 452, 549, 681, 847, 1046, 1278, 1531, 1806, and 2063.

In the simplest, un-calibrated version of the model, we uniformly assign drivers a SOC threshold (20%, 50%, or 80%), below which they will want to charge if given the opportunity. We obtained data from ChargePoint, whose network makes up about 70% of all Chicago area charging stations, which included the SOC of BEVs at plug-in time. Using this data, we calibrate the driver SOC thresholds by randomly assigning a plug-in SOC from the ChargePoint dataset to each driver. The distribution of SOC thresholds derived from ChargePoint data is shown in Fig. 2. SOC thresholds further to the right signify high levels of range anxiety for the BEV drivers.

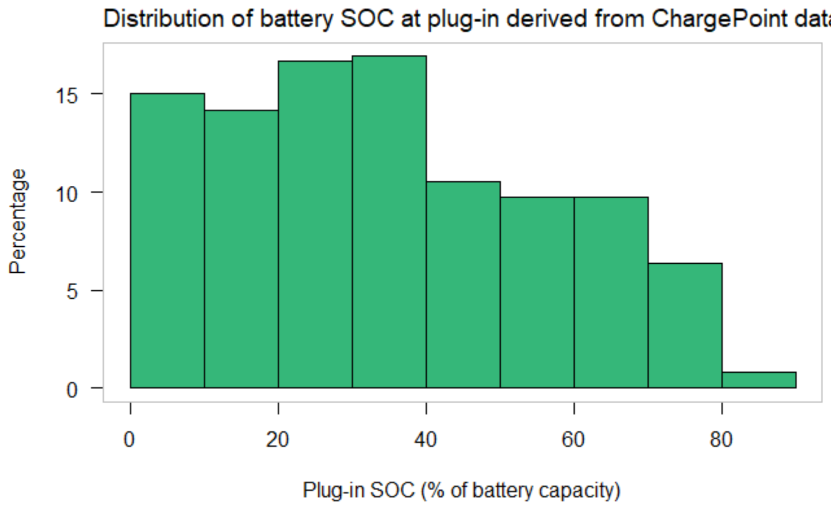

Figure 2: Distribution of SOC thresholds derived from ChargePoint data

ComEd, the primary power supplier in the Chicago area, offers a residential TOU-type rate to its customers [45]. We use one day of their pricing, from September 25th, 2019, for our study, and assume that the residential rate is applied to all public chargers. The EIA's 2019 Energy Outlook projects average electricity prices for the North Central region [37]. When converted to percent change from the previous year, these projections are used to update the ComEd TOU prices each year of the simulation.

4 Results

For all scenarios, we run 10-year simulations of the co-evolution of BEV adoption and charging infrastructure deployment, as well as the charging demand, and average the outputs. All runs are calibrated, i.e., the comfortable SOC thresholds are taken from the distribution derived from the real-world observation, rather than assigned uniformly. Apart from the base scenario, we simulate three different TOU scenarios by changing the value of P for sensitivity analysis. Recall that P represents the minimum utility required for a driver to choose to charge when they are still above their comfortable SOC threshold. In 2 of our TOU scenarios, P takes on the values -2.0 and -1.0, and is uniform across all BEV drivers. In the third TOU scenario, P is a normally distributed random variable with a mean of -1.5 and a standard deviation of 0.5. A P value of 0 is the same as the base scenario since the costs associated with traveling and public charging cannot be negative. We run 30 simulations for each of the four scenarios and average the outputs.

First, we examine the impact a TOU rate has on the overall unmet charging demand. An "instance of unmet demand" is registered when a BEV driver is under their SOC threshold, wants to charge, but cannot find a nearby available charger. Each year, all instances of unmet demand are aggregated by the *investor agent*. The yearly aggregated instances of unmet demand are shown in Fig. 3. All of the scenarios, both base and TOU, have the same general upward trend. With a lower value of *P*, more drivers will achieve the minimum charging utility, leading to more frequent public charging. As such, there are fewer cases where the BEVs fall below their comfortable SOC. We call this "proactive" charging.

However, as we see in Fig. 4, this "proactive" behavior results in much higher utilization of the existing charging stations. In the base case, stations get on average up to only 1.58 sessions per day in the first five years of the simulation, and their utilization only marginally increases in later years to 2.49 sessions per day. In the TOU scenarios, station utilization starts higher than the base scenario, and rises steadily every year, reaching 91.42 sessions per day when P = -2.0.

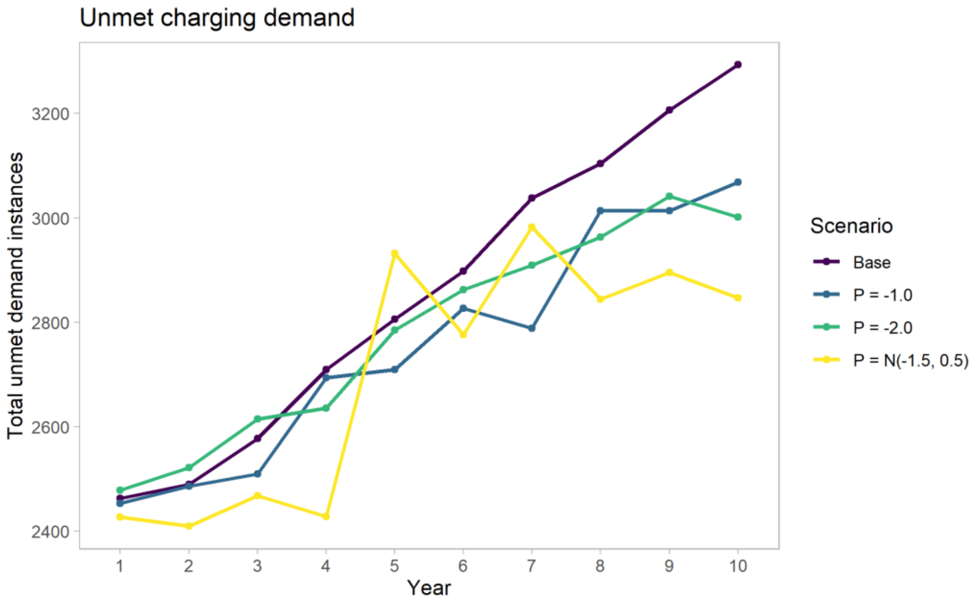

Figure 3: Unmet demand growth

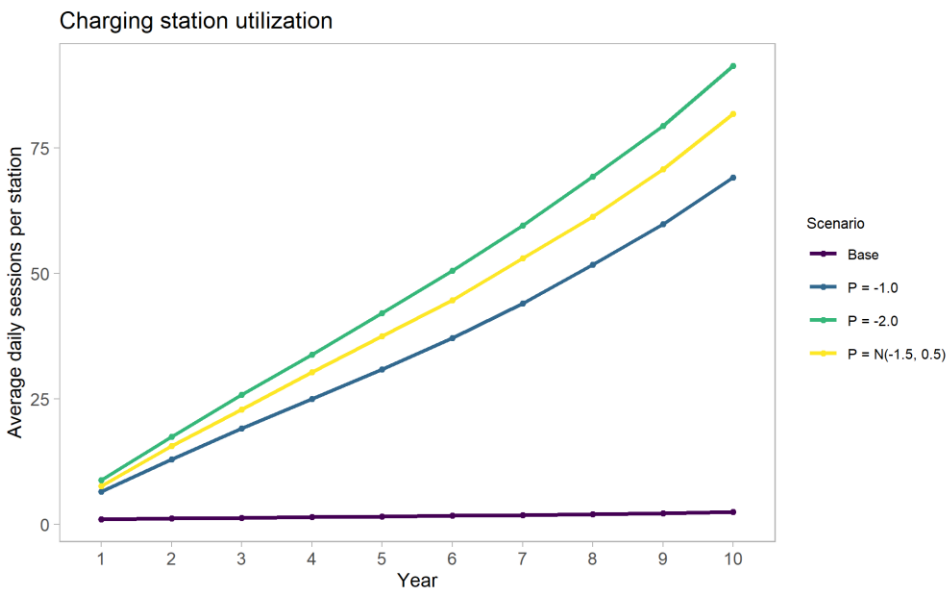

Figure 4: Higher station utilization in TOU scenarios

Station utilization shows higher sensitivity to *P* than unmet demand does. As *P* decreases, it is more likely that drivers' utilities will be high enough, triggering a desire to charge. With such high station utilization, there is a substantial opportunity for the development of more charging stations should BEV drivers pay attention to changing charging prices throughout the day.

Fig. 5 further illustrates this finding. The snapshots were both taken at 1:15 pm in the first year of their respective simulations. There are far more completely occupied stations in the TOU scenario, especially on the west side of the city.

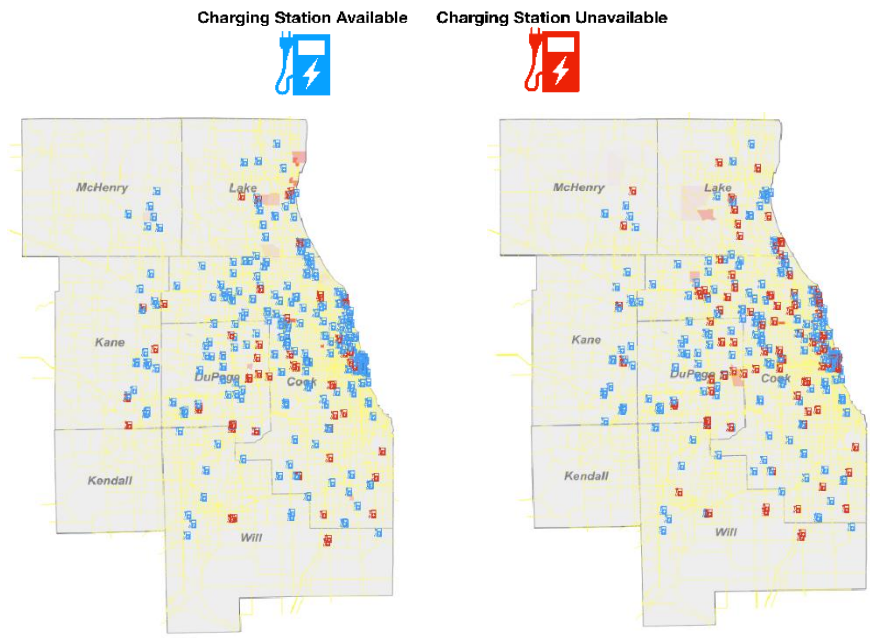

Figure 5: Station availability in the base (left) and TOU (right, *P* = -2.0) scenarios. 391 total stations.

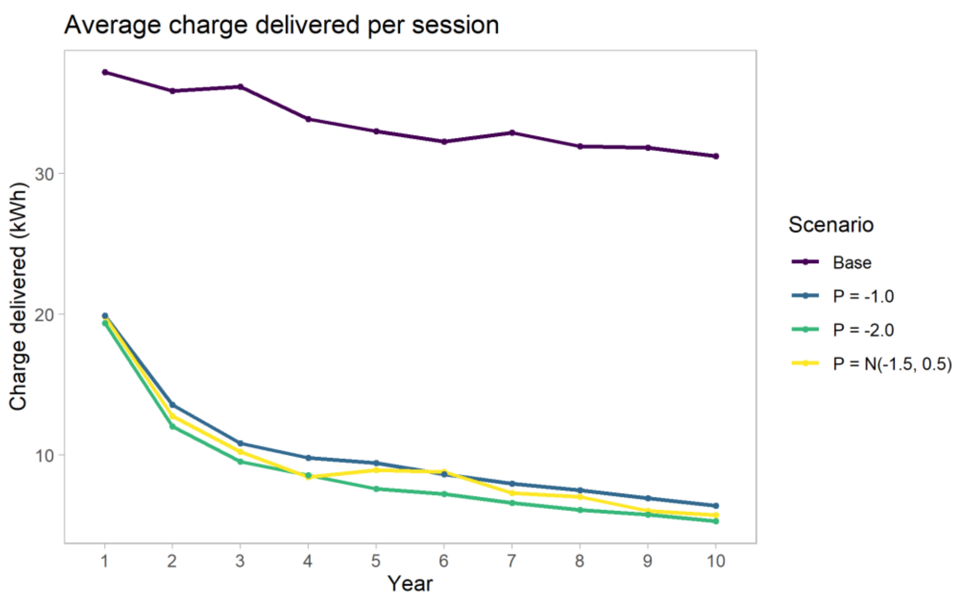

Figure 6: Charge delivered per charging session

We also find that the amount of charging done in each session is far lower in TOU scenarios, reaching below 7 kWh/session by year 10. Fig. 6 shows this trend clearly. Because drivers are charging proactively, they have higher SOCs on average, and thus need less time to charge their batteries. In the 10th year of the base case, the average public charging session length is 243 minutes. When P = -2.0, the average session length is 41 minutes in year 10. We see that charging session length is quite insensitive to P as long as drivers use the behavioral heuristic for charging.

Fig. 7 shows census tract-level unmet charging demand at the end of the first year of simulation. Both the base and TOU scenarios have sparsely located unmet demand spread across the study region. However, there are more pockets of unmet demand in the TOU scenario on the northwest side of the city, as well as other regions in the upper part of the study region. In both scenarios, higher demand on the north side of the study area corresponds to higher levels of BEV adoption there.

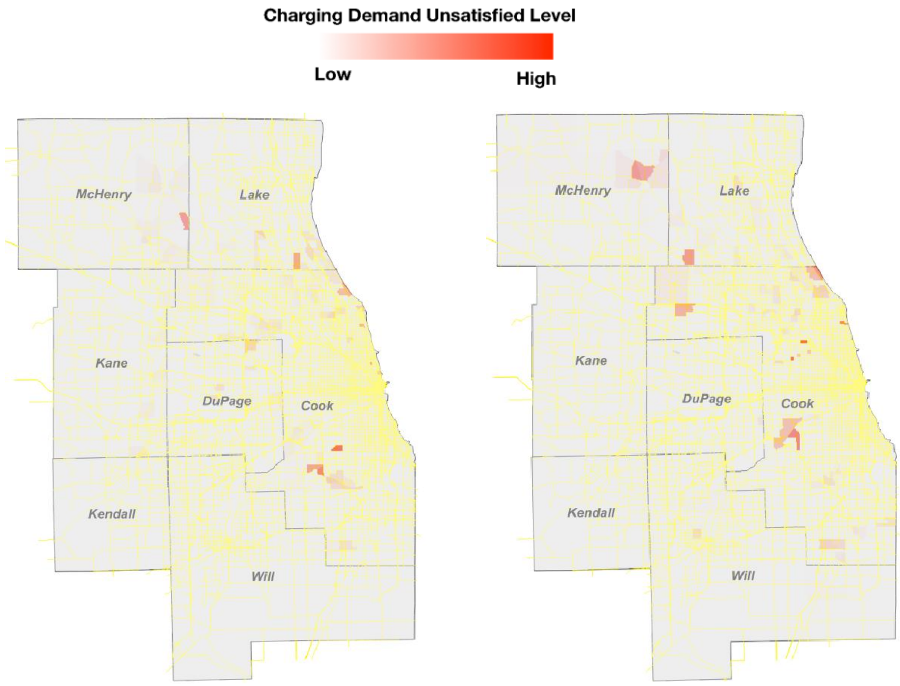

Figure 7: Spatially distributed unmet charging demand in the base (left) and TOU (right, P = -2.0) scenarios

5 Conclusions

In this study we developed a behavioral heuristic for public charging to simulate how BEV drivers respond to charging prices in the Chicago area on a daily and annual basis. A combination of range anxiety and lower-than-normal prices can lead to a desire to charge proactively. Although driver-side unmet charging demand would be lower than if there were no TOU rates, utilization of public chargers may skyrocket, providing an incentive for increasing charger supply. With this in mind, we see that TOU rates could drive demand for public charging much higher than it is today. Not only could the amount of public charging increase, but the patterns of public charging themselves may see changes. Charging sessions could become much shorter, reaching an average of 41 minutes in our simulations. With a higher prevalence of fast and ultra-fast charging, this effect could become even more pronounced. This presents an opportunity for investors to deploy infrastructure to meet this new type of demand created by a proactive charging strategy. For the drivers, if charging infrastructure investors provide more DC-fast charging at common destinations (malls, restaurants, etc.), charging strategies similar to the employed behavioral heuristic will be effective at reducing range anxiety. There is an incentive for utility companies to implement TOU prices as well since they achieve the goal of reducing energy impact at peak times while encouraging more public charging in general.

Although the behavioral heuristic was designed with realistic behavior in mind, it does not escape the drawbacks that come with the absence of good data. To improve upon this case study, we must incorporate better data on public charging station prices and how that affects drivers' decisions to charge. This ABM is not to be taken as a predictive tool, but as a way to gain insights into potential outcomes given reasonable assumptions and various possible real-world situations. Rather than prediction, the goal of an ABM is to guide decision-making in a plausible future scenario.

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