ANL/ESIA-24/6

Charging Demand in the Chicago Metropolitan Area Through 2030

Energy Systems and Infrastructure Analysis Division

ANL/ESIA-24/6

Electric Vehicle Charging Demand in the Chicago Metropolitan Area through 2030

by
Limon Barua, Nazib Siddique, Yan Zhou and Marianne Mintz
Energy Systems and Infrastructure Analysis Division, Argonne National Laboratory

July 2024

CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACKNOWLEDGMENTS

This activity was primarily supported by Commonwealth Edison Company (ComEd), an Exelon utility, under the Argonne-Exelon CRADA (A16155). The authors would like to thank Ryan Burg, Vincent Westfallen, and Kevin Happ from ComEd for their support and constructive feedback. The authors would also like to thank Md Rakibul Alam for his contributions to the development of ATEAM.

LIST OF ACRONYMS

ATEAM	Agent-Based Transportation Energy Analysis Model
BEV	Battery electric vehicle
CEJA	Climate and Equitable Jobs Act
CMAP	Chicago Metropolitan Agency for Planning
CRADA	Cooperative Research & Development Agreement
DCFC	Direct-current fast charger
EJCs	Environmental Justice Communities
EV	Electric vehicle
GIS	Geographic Information System
GUI	Graphical User Interface
MUD	Multi-unit dwelling
NACS	North American Charging Standard
PHEV	Plug-in hybrid electric vehicle
SOC	State of charge
SUD	Single unit dwelling
VMT	Vehicle miles traveled
ZEV	Zero-emission vehicle

CHARGING DEMAND IN THE CHICAGO METROPOLITAN AREA THROUGH 2030

ABSTRACT

This report outlines the collaborative efforts between Argonne National Laboratory and Exelon in advancing the Agent-Based Transportation Energy Analysis Model (ATEAM). Aligning with ComEd's beneficial electrification plan, this study developed eight scenarios to access the temporal and spatial distribution of charging load and demand stemming from the widespread adoption of battery electric vehicles (BEV) adoption, augmented public charging infrastructure deployment, and increased multi-unit dwelling (MUD) charging availability. Enhancements to the ATEAM model encompassed the simulation of multiple days of travel behavior, estimation of total public charging infrastructure needs, user interface refinements, and output tracking at both vehicle and charging station levels.

The total electricity consumption for residential and public charging to support over 800,000 BEVs in Chicago in 2029 is projected at approximately 10.2 GWh. Enhanced MUD home charging accessibility (70%) amplifies the home charging load in the study area by 1.5% compared to the baseline scenario (10%). The widespread adoption of BEVs reduces peak charging loads, owing to their inclusion across households with diverse income levels, thus fostering a more dispersed charging activity pattern. However, widespread BEV adoption increases the peak home charging load in areas with lower median household incomes, reflecting a higher BEV concentration in these locales and, subsequently, heightened peak charging demands. In the Widespread BEV adoption scenario, fewer census tracts exhibit elevated peak loads for combined home and public charging, indicating a more even distribution of charging demand across the study area. Predominantly, peak loads for combined charging—both home and public—occur between 2 p.m. and 10 p.m. across all scenarios, encompassing the majority of census tracts.

1 INTRODUCTION

The U.S. National Blueprint for Transportation Decarbonization identifies the need to invest in infrastructure supporting low- and zero-emission vehicles, especially in low-income and overburdened communities, to eliminate nearly all greenhouse gas emissions from the transportation sector by 2050 (DOE, 2023). Many states also have embraced aggressive carbon neutrality and zero-emission vehicle (ZEV) initiatives. In Illinois, the recent signing of the Climate and Equitable Jobs Act (CEJA) signals a significant change on the horizon (Illinois Environmental Protection Agency, 2022). CEJA is an ambitious legislation that aims to accelerate the use of clean energy sources like solar and wind power, put one million electric cars on Illinois roads, and phase out coal and natural gas by 2050. This comprehensive goal, one of the most ambitious in the country, will have widespread consequences, including the transformation of Illinois' current electric vehicle (EV) adoption from fewer than 40,000 to one million (CEJA, 2021). ComEd's beneficial electrification plan is an investment strategy to support the adoption of decarbonization technologies. It is designed to benefit all customers, and especially those in environmental justice communities (EJCs) most affected by climate change and pollution. Moreover, achieving this transition from modest to widespread EV adoption will necessitate a combination of public and private investment to not only promote vehicle adoption but also to develop the essential charging infrastructure required to facilitate and sustain the shift toward electrified transportation. ComEd supports the growing adoption of EVs by readying and incentivizing charging infrastructure, especially for equity-eligible customers and communities which may face the biggest barriers in transitioning to EVs. The rapid EV growth and resulting charging demand will put extra demand on the grid, which requires proactive moves to reduce grid and capacity impact. Understanding the magnitude of charging demand at both residential and public locations, as well as its impact on the grid, is crucial, particularly in areas where grid capacity nears its limit.

The analysis of EV charging demand has been a focal point for several studies. Among them, Qian et al. (2010), Kristoffersen et al. (2011), Kiviluoma and Meibom (2011), Paevere et al. (2014), and Muratori (2018) investigated charging load from EVs across broad study areas. For instance, Qian et al. (2010) developed an analytical model to assess EV charging load demand for the entire U.K. Kristoffersen et al. (2011) used driving patterns from western Denmark to estimate EV energy demand. Similarly, Kiviluoma and Meibom (2011) used travel survey data from Finland to develop driving profiles and forecast EV charging demands. Studies such as Muratori (2018) and Lopez et al. (2021) simulated individual EV user characteristics to project EV charging demand for the U.S. Midwest and Manila, Philippines, respectively. These studies provide insights into charging demand for broader study areas rather than focusing on small-scale regions like census tracts or block groups.

Other studies have focused on determining EV charging demand at a smaller level of analysis. For instance, Paevere et al. (2014) developed a methodology to project spatial and temporal EV charging demand by integrating models for EV adoption and household travel analysis specifically for Victoria, Australia. Adenaw and Lienkamp (2021) as well as Yi et al. (2023) utilized MATSim to analyze EV charging load across different traffic analysis zones within the cities of Munich and Salt Lake City, respectively. Furthermore, Liu et al. (2023) developed a trip-chaining-based modeling framework, including EV adoption modeling, to project EV charging demands and load profiles for the state of Virginia in the United States.

Argonne National Laboratory (Argonne), in collaboration with Exelon and local utilities under a Cooperative Research & Development Agreement (CRADA), has developed an agent-based model known as ATEAM. Initially focused on simulating the growth of battery electric vehicle (BEV) adoption and charging infrastructure in the Chicago metropolitan area, ATEAM has been expanded to incorporate additional geographies and capabilities, enabling its application to the Baltimore–Washington region (Zhou et al., 2022, Mintz et al., 2019), its extension to a longer planning horizon, and the refinement of several initial conditions. This study is part of that expansion process: updating the ATEAM model with the latest travel pattern and charging behavior data, refining state-of-charge (SOC) assumptions, and quantifying charging demand by census tract with increased BEV adoption, especially by medium-income households and multi-unit dwelling (MUD) households in the Chicago metropolitan area. The study area for the ATEAM application described herein includes Cook, DuPage, Kane, Kendall, Lake, McHenry, and Will counties.

2 DATA AND METHODOLOGY

We first updated the ATEAM model with the most recent travel data, BEV registration, and public charging station information. Table 1 shows the data used in this study and their sources. Subsequently, we focused on refining several key functionalities of the ATEAM model to enhance both its accuracy and user-friendliness. Specific enhancements included:

- Simulation of multiple days of travel behavior. This allowed us to obtain a more accurate estimate of initial SOC and, thus, an unbiased daily home-charging load profile by capturing potential overnight home-charging sessions that were initiated on the previous day.
- Updated driver behavior and charger utilization functions to reflect differences in driving (i.e., commuter vs. non-commuter) and home charging availability. This allowed us to generate a more realistic estimate of the total number of public chargers needed in the study area.
- Output tracking at the vehicle and charging station agent levels. This enhancement validated the accuracy of each vehicle and charging station within the model, thereby ensuring the credibility of the model's output.
- User interface enhancement to facilitate easy selection of parameters and scenario design (see Appendix A).

This study focused on BEV charging needs and excluded plug-in hybrid electric vehicles (PHEVs) from scenario analysis. PHEVs have an internal combustion engine and can switch to gasoline when necessary, reducing their reliance on public charging infrastructure. Furthermore, our study does not account for the effects of traffic congestion. We assumed that drivers always choose the shortest path for their journeys, and travel times remain unaffected by road congestion.

2.1 ATEAM Model Framework

Argonne and Exelon co-developed the ATEAM model that projects future charging deployment needs and resulting charging demand by census tract. The model framework is built on Repast Simphony 2.7, a cross-platform, Java-based agent-based modeling system (Repast, n.d.). This framework allows for the modeling of interactions among drivers, charging stations, and utilities. ATEAM built on Repast offers increased flexibility in configuring and controlling the simulation process, considering the dynamic interplay between BEV adoption, travel patterns, charging behavior, and charging infrastructure deployment (Alam et al., 2023).

ATEAM models the interaction between drivers, households, and charging infrastructure investors. Drivers make decisions regarding travel routes, charging preferences (including times and locations), and the intensity and duration of charging sessions. Household-level decisions revolve around vehicle adoption preferences which are based on various socio-demographic characteristics. Charging infrastructure investors play a crucial role in determining the location and scale of new charging infrastructure based on their specific objectives (outlined in Section 3.2). Figure 1 illustrates the input details used in the ATEAM model. Details about ATEAM methodology can be found in previous reports (Zhou et al., 2022; Mintz et al., 2019).

In this study, we updated ATEAM with the latest data on travel patterns, EV registrations and public charging locations by census tract. Travel patterns were obtained from The Chicago Metropolitan Agency for Planning (CMAP) 2018–2019 travel survey which estimated travel demand within the six-county study area based on a representative sample of households (CMAP, 2020). Table 1 lists the data and sources used in this study.

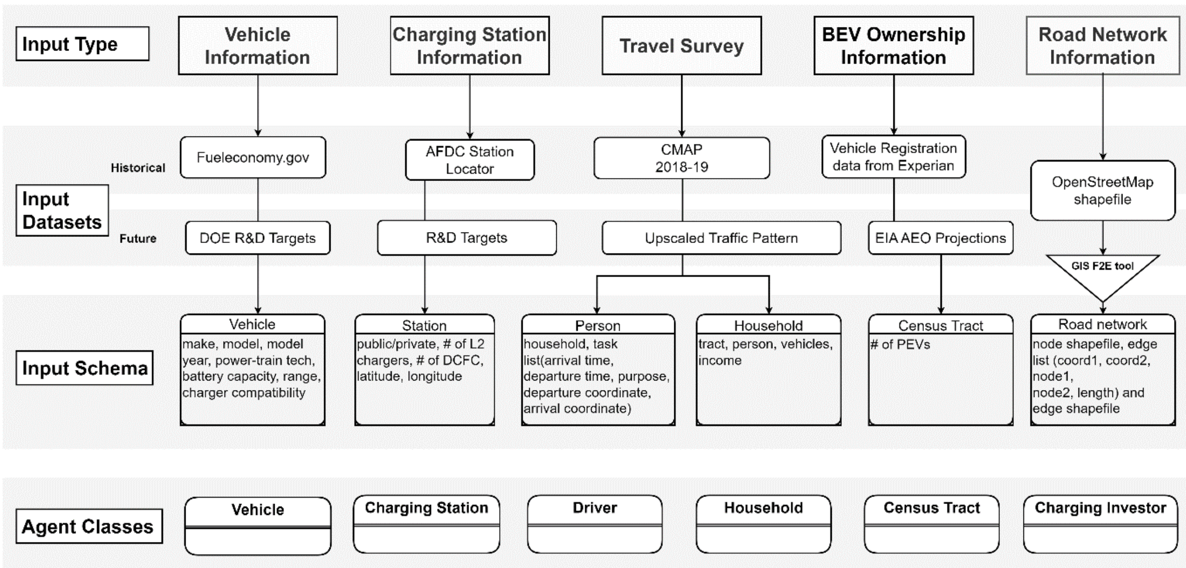

Figure 1 Input details used in the ATEAM model.

Table 1 Data sources

Data	**Source**
Household and driver daily travel	CMAP, 2020
Existing BEV registrations by ZIP code	Experian, 2022
Future BEV registrations	ComEd IRA BEV projection
Public charging locations and levels	AFDC, 2022
Existing BEV information	DOE fueleconomy.gov, 2022
Home charging percentages	Blonsky et al., 2021
BEV share by electric range (BEV100/200/200)	Energy Information Administration’s Annual Energy Outlook, 2022
Future BEV efficiency (in kWh/100 mi)	Energy Information Administration’s Annual Energy Outlook, 2022
Single-unit dwellings by census tract	U.S. Census Bureau, 2022
Multi-unit dwellings by census tract	U.S. Census Bureau, 2022
Household income distribution by census tract	U.S. Census Bureau, 2022
Road network	TIGER/Line Shapefiles, 2023

2.2 Baseline Scenario

This study's analysis horizon extends from 2022 to 2029. CMAP travel survey data provide the foundation for simulating vehicle travel patterns, supplying comprehensive details about travelers' activities and trip chains. This trip chain data encompasses all trips made by drivers in a single day, including details about the location, purpose, and start- and end-time of each trip.

To ensure the accuracy and representativeness of our analysis, we integrated sampling weights for each driver. These weights account for variations in the likelihood of individuals being included in the CMAP sample, facilitating meaningful inferences about the broader population. Note that higher weights indicate a higher probability of reproducing population values from the sample.

The number of BEVs within a census tract is derived from registration records provided by Experian Automotive (Experian, Q2 2022). The categorization of BEVs into range categories (BEV 100/BEV 200/BEV 300) is determined by projections outlined in the U.S. Energy Information Administration's 2022 Annual Energy Outlook. Subsequently, following the determination of the number and types of BEVs in each census tract, a random allocation process is employed to distribute these vehicles, along with their respective types, among the households within the tract.

Home charging availability is defined using the following equation:

$$Number\ of\ home\ chargers\ per\ census\ tract = (T_{SUD} * P_{SUD} + T_{MUD} * P_{MUD}) * N_{BEV}$$

Where:

- T_{SUD} is the percent of single unit dwellings (SUD) in the tract,
- P_{SUD} is the percentage of SUDs with home chargers,
- T_{MUD} is the percent of the MUDs in the tract,
- P_{MUD} is the percentage of MUDs with home chargers, and
- N_{BEV} is the total number of BEVs in the tract.

The values for T_{SUD} and T_{MUD} are obtained from the 2017–2021 American Community Survey (U.S. Census Bureau, 2022). P_{SUD} and P_{MUD} are assigned values between 0 and 1, with different values used for scenarios described in Section 3.3.

Public charging station information for the base year (2022) was obtained from the Alternative Fuels Data Center (AFDC, 2022). This dataset provides information on the current number of public charging ports and charging types (L2/DCFC) at each location. Three charging levels were considered: L2, DCFC 50kW, and DCFC 150kW, and public charging was defined as being available to all BEVs. Although several automakers have announced they will implement Tesla's North American Charging Standard (NACS) connector on vehicles starting in the 2025 model year (Barry, 2024), it is unclear when or at what price premium future BEVs will be able to use Tesla's network. Moreover, since most pre-2025 model year BEVs (and many post-2025 BEVs) will be unable to use that network, we exclude Tesla's superchargers from our analysis. The geospatial distribution of the charging stations is shown in Figure 2.

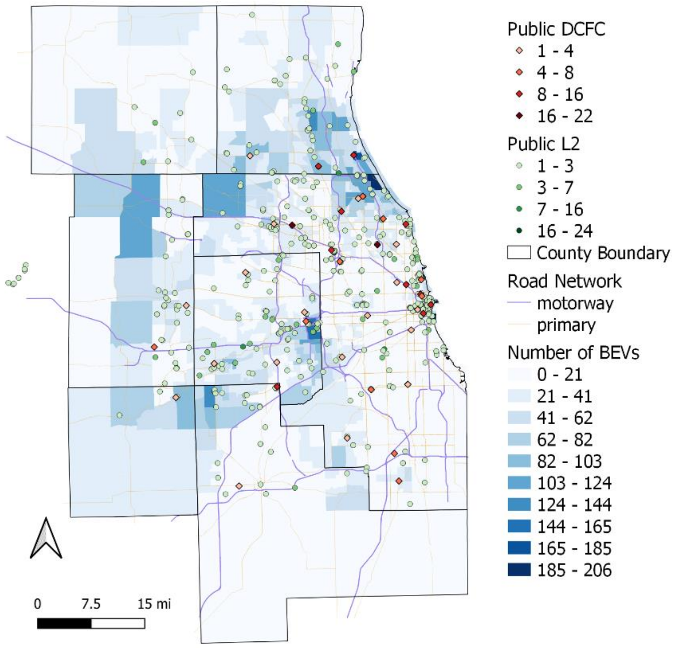

Figure 2 Distribution of charging stations and BEV adoption in the study area (2022).

In the baseline scenario, ATEAM simulates drivers operating vehicles on a representation of the seven-county road network. This network — comprised of primary, secondary, and trunk roads within the study area— was constructed from region-specific TIGER/Line shapefiles and verified using diverse Geographic Information System (GIS) tools to ensure the accuracy and dependability of all links used in our study.

2.2.1 Daily Simulation

In the daily simulation (from 3:00 a.m. to 3:00 a.m. the following day) BEV drivers engage in their travel activities based on trip chains derived from the CMAP travel survey. The vehicle is assumed to have a full charge when drivers start their first trip of the day. For subsequent days, if the driver has access to home charging, the vehicle is assumed to start the day with a full charge; otherwise, the battery state of charge (SOC) at the commencement of the first trip is determined by the SOC at the completion of the last trip from the preceding day. The simulation is run for two days, with the activities of the second day serving as a representative sample for daily simulation.

It is assumed that the vehicle follows the shortest path between the centroids of the tract of origin and the tract of destination for each trip. Throughout the day's travel, electricity consumption and resulting battery SOC are estimated based on the vehicle efficiency and trip distance.

Unlike internal combustion engine (ICE) vehicles that typically refuel enroute, BEVs are assumed to rely on "destination charging" due to their relatively longer charging time. At the start of each trip, drivers are assumed to anticipate the subsequent three trips in their travel schedule and evaluate whether their remaining SOC might dip below a predetermined comfort level. The comfort level is imputed to each driver based on the distribution of the observed SOC, shown in Figure 3. When the SOC falls below a certain threshold, drivers are presumed to search for available chargers within walking distance (assumed as 0.25 miles) of the next three destinations. Charging location selection prioritizes charging speed and the expected dwell time (based on the driver's trip chain) for the charging event. Once charging is complete, the driver proceeds to the next trip in his/her schedule.

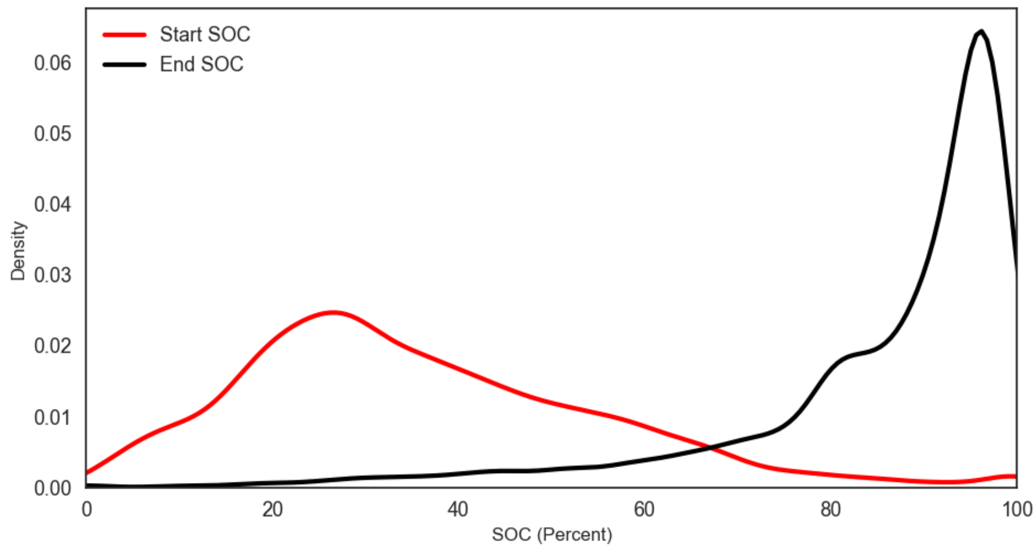

Figure 3 SOC at plug-in and plug-off, summarized from ChargePoint data[1].

The daily simulation also monitors each BEV's charging demand at both home and public charging locations. Additionally, the simulation tracks the use of chargers at any given time and estimates the corresponding charging load and energy delivered by each station. The total energy delivered within each tract is estimated by aggregating charging demand from all stations. Similarly, the total home charging load and electricity consumed within each census tract are estimated with assumed home charging availability.

2.2.2 Yearly Simulation

After completing the two consecutive days of travel simulation, the model progresses to the next simulation year. At the onset of each year, newly adopted battery electric vehicles (BEVs), along with corresponding home charging availability and public charging infrastructure, are introduced into the study area in accordance with predefined vehicle adoption and charging infrastructure deployment trajectories. Household agents within each census tract acquire new BEVs based on a utility function, as detailed in Section 2.3.1. Simultaneously, charging infrastructure investor agents deploy new charging stations (categorized by charging level) based on projected charging demand, utilizing various strategies, as described in Section 2.3.2.

[1] ChargePoint data were obtained for approximately 493,000 sessions in the Baltimore-Washington, D.C. area for April 2019-March 2020. Of these sessions, 18,690 involved fast charging.

2.3 Future EV Adoption and Charging Infrastructure Deployment

2.3.1 BEV Adoption

Future BEV adoption in the study area is based on ComEd projections which consider the impact of Inflation Reduction Act (IRA) and state incentives on BEV adoption, and which are more aggressive than Illinois' target of having 1 million EVs on the road by 2030. Figure 4 shows the number of BEVs anticipated to be on the road in the study area through 2029.

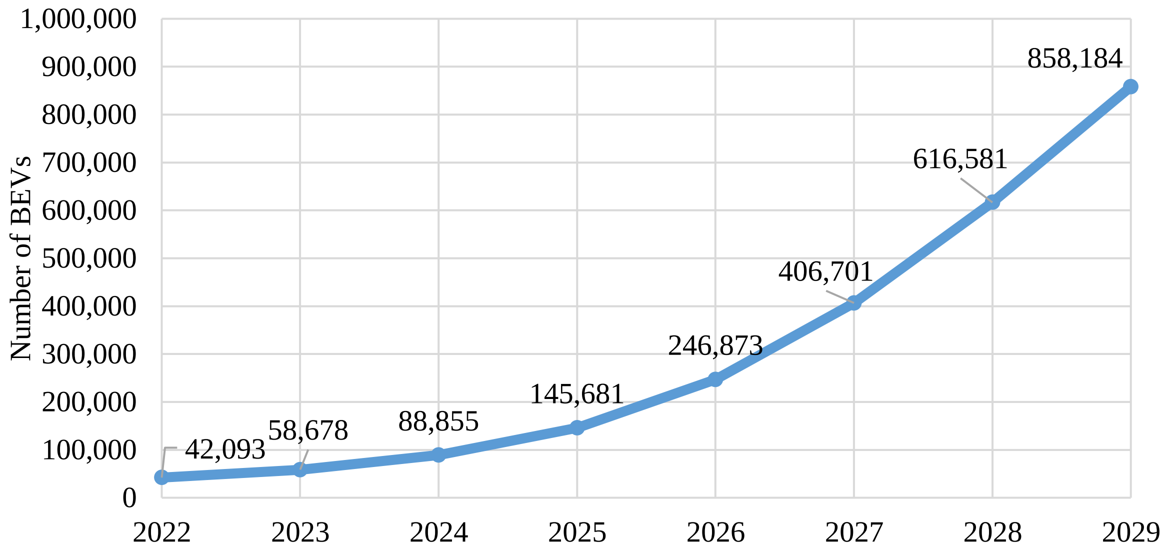

Figure 4 Projected BEV adoption in the study area.

BEV adoption within census tracts is assumed to be influenced by socioeconomic factors such as household income, existing BEV adoption rates, and the percentage of SUDs in that tract. To represent the propensity for BEV adoption at the census tract level, we devised a tract score by assigning varying weights to each factor in scenario analysis (see Appendix B for the methodology). A higher score indicates a greater likelihood of adopting a new BEV within the tract. Subsequently, BEVs are randomly distributed among households within each tract (and randomly distributed to each driver within the household). It is important to note that the objective of our study is to estimate charging demand by census tract, with a predetermined total BEV adoption target for the study area. This methodology does not aim to forecast BEV adoption by income level.

2.3.2 Charging Infrastructure Deployment

Drawing on the methodology outlined in Bauer et al. (2021) and Nicholas and Lutsey (2020), we estimated the requisite number of public chargers needed to accommodate anticipated BEV adoption levels. This approach leveraged available data from the study area, as illustrated in Figure 5.

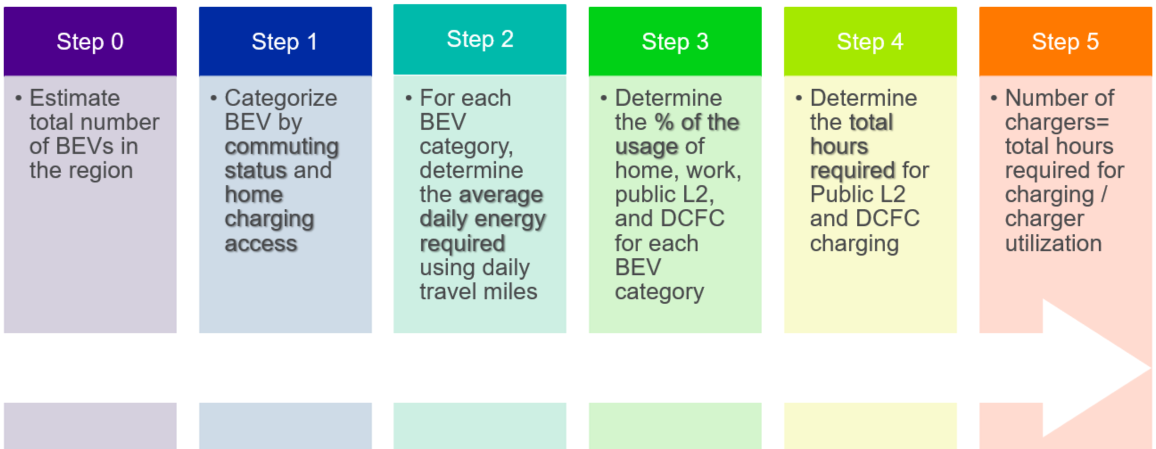

Figure 5 Steps for determining the total number of public chargers in the study area.

Based on the projected number of BEVs each year, drivers were classified into four categories based on commuting status and access to home charging, as determined by the CMAP travel survey. These categories include Commuter – with home charging, Commuter – without home charging, Non-commuter – with home charging, and Non-commuter – without home charging. This classification framework is designed to capture variations in daily travel distances and possibility for workplace charging among potential BEV drivers. The total daily energy required for each BEV category was then determined using the following equation:

$$Average\ daily\ energy = Number\ of\ BEV * Daily\ travel\ distance * BEV\ efficiency$$

The number of BEVs in each category is estimated by multiplying each category's percentage from the CMAP travel data with the total number of BEV drivers. The average daily travel distance of drivers in each category also comes from CMAP data. The BEV efficiency in 2022 is assumed to be 0.3 kWh/mile, with an annual increase rate of 0.89 (as documented in Bauer et al., 2021). Consequently, estimates of the total daily energy required to charge all BEVs in the study area account not just for growth in BEV adoption but also anticipated improvements in BEV efficiency.

Next, we estimated the total energy to be served by each charger type—home Level 1 (L1), home Level 2 (L2), public Level 2 (L2), and public DCFC chargers—in the study area. We assumed that home chargers could serve 66% of the energy, while 17% each could be served by public L2 and public DCFC chargers, based on findings from Bauer et al. (2021). We computed the hours required for charging by charger type, assuming that the power supplied by public L2 chargers increases from 6.6 kW in 2020 to 8.3 kW in 2030, as per Bauer et al. (2021). Similarly, we assumed the average power supplied by a DC fast charger increases from an average of 55 kW in 2020 to 110 kW in 2029. Ultimately, the total number of chargers in the study area was determined using the equation:

$$Number\ of\ chargers\ = \frac{Total\ hours\ required\ for\ charging}{Charger\ utilization}$$

Charger utilization is pivotal to estimating the number of chargers needed to support a given number of BEVs. In this study, we assumed average public charger utilization of 2.1 hours per day, based on findings from Tal et al. (2018) which captured self-reported charging behavior over seven days. Additionally, data from EV WATT indicates, at a national level, that public chargers are utilized for approximately 0.75 -5 hours per day, varying by charging type and location. Though beyond the scope of this study, it is hoped that future studies will explore the sensitivity of charger utilization to the spatial and temporal distribution of charging demand.

After estimating the total number of public chargers in the study area, the ATEAM simulation deployed them to all census tracts using variables historically associated with a tract's higher or lower probability of having public chargers. These variables include the historical number of public chargers, the ratio of work trips to total trips, total travel demand, tract-level unmet charging demand, and the percentage of SUDs within the tract. Different scenarios of charging infrastructure deployment were then defined by adjusting the weights assigned to each of these variables. Appendix C provides further detail on how this methodology was applied to distributing public chargers among the tracts in the study area.

3 SCENARIO ANALYSIS

We developed eight scenarios to explore the variations in the adoption of BEVs, public charging infrastructure deployment, and MUD charging availability. These scenarios were devised to inform ComEd of possible charging demand in the future, particularly with widespread BEV adoption among medium-income households and increased home charging accessibility at MUDs. A visual representation of the eight scenarios is presented in Figure 6, where a rubric outlines the distinctions among them. For example, "Widespread BEV adoption" scenarios project increased charging demand resulting from BEV adoption spreading to medium-income households, whereas "Widespread Public Charger Deployment" scenarios envision chargers being more evenly dispersed among tracts in the study area.

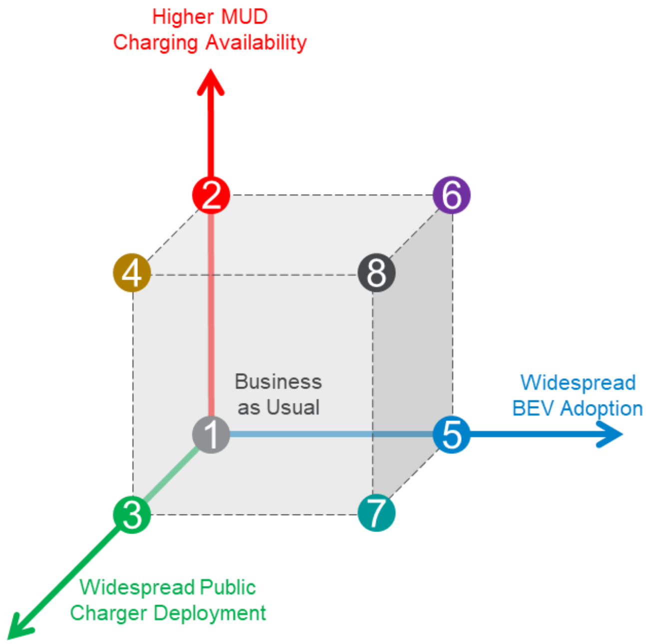

Figure 6 Visual representation of how the eight scenarios examined in this study differed.

Scenarios 1, 2, 3, and 4 assume BEV adoption patterns mirroring historical trends, while the remaining scenarios explore more widespread BEV adoption. For public charger deployment, Scenarios 1, 2, 5, and 6 adhere to historical trends, whereas the others involve a more widespread deployment of public chargers. Regarding the availability of MUD charging, Scenarios 1, 3, 5, and 7 assume low MUD charging availability, while the remaining scenarios consider high MUD charging availability. Subsequent sections provide in-depth discussions about these criteria, elucidating the nuances and implications of the various scenarios.

3.1 Widespread BEV Adoption

In this study, we investigated two distinct scenarios regarding the adoption of BEVs: one aligning with current adoption trends and another envisioning a broader adoption pattern. Following the current trend implies that new BEVs will be embraced predominantly in census tracts characterized by affluent household incomes and above average BEV adoption rates. Conversely, a more widespread adoption scenario posits that BEVs will become increasingly accessible to middle-income households, leading to adoption in tracts with such socio-economic profiles.

To accomplish this, we adjusted the weights assigned to variables used in distributing the total number of BEVs to tracts across the study area. In baseline BEV adoption scenarios (scenarios 1, 2, 3, 4), we assigned greater weights to the percentage of high-income households (those with incomes above $150,000) in the census tract and relatively high existing BEV registrations. Conversely, in scenarios envisioning broader adoption, we allocated greater weight to the percentage of middle-income households in the tract while disabling the weight attributed to existing BEV registrations. Appendix B elaborates on the specific weights employed.

3.2 Public Charging Infrastructure Deployment

In the baseline scenario, we hypothesized that the deployment of public chargers mirrors past trends, with chargers concentrated in census tracts that have historically served as destinations for current BEV drivers. Conversely, in the widespread public charger deployment scenario, we simulated a more even distribution of public chargers across all tracts within the study area. Consequently, we assigned a negative weight to the variable representing “historical chargers” to mitigate the emphasis on census tracts already equipped with a high number of chargers, while assigning moderately positive weights to other variables (see Appendix C for details).

3.3 Home Charging Availability

In the future, as more middle-income families living in MUDs adopt BEVs, having charging stations in apartment complexes will be essential. At present, however, MUD residents face constraints in accessing home charging facilities. In Chicago, only 26% of MUDs have garages where home charger installation could be pursued (Borlaug et al., 2020; Zhang et al., 2023). Today, while 80% of EV charging takes place at home (Ge et al., 2021), less than 5% of home charging takes place at MUDs (NOVA Workforce Development, 2015). Hence, we assumed a 10% availability of home charging in MUDs in baseline charging scenarios, and that residents of MUDs who adopt BEVs are likely to depend heavily on public charging infrastructure. Despite substantial public and private investments in MUD charging (Teebay, 2023), we assume home charging remains severely limited in baseline charging scenarios.

To evaluate the impact of heightened availability of home charging at MUDs, we investigated an alternative scenario wherein 70% of MUDs are assumed to have access to home charging, in contrast to the 10% assumed in the scenarios with low MUD charging availability. By integrating the three criteria outlined in sections 3.1, 3.2, and 3.3 (and shown in Figure 6) we defined the following eight scenarios:

- Historic BEV adoption and public charging deployment (*Baseline*)
- Historic + greater MUD charging *(Base + MUD*)
- Historic + widespread public charging deployment (*Base + public charging*)
- Historic + widespread public charging deployment + greater MUD charging (*Base + public charging + MUD*)
- Widespread BEV adoption + historic public charger deployment (*Widespread BEV*)
- Widespread BEV adoption + historic public charger deployment + greater MUD charging (*Widespread BEV + MUD*)
- Widespread BEV adoption + widespread public charging deployment (*Widespread BEV + public charging*)
- Widespread BEV adoption + widespread public charging deployment + greater MUD charging (*Widespread BEV + public charging + MUD*)

4 VALIDATION

To ensure the accuracy of our simulation results, we conducted a careful examination at a micro level, focusing particularly on the location, charging behavior, and travel patterns of driver agents as well as the distribution of charging stations. Using the ATEAM model, we extracted the activity logs of driver agents for each 15-minute time increment in the yearly simulation. Given the substantial volume of data generated, the validation was confined to two years.

Initially, validation entailed verifying the home locations of drivers on the first and second simulation days, ensuring that drivers commenced their trips from home on the second day as expected. For drivers whose travel indicated the likely use of public charging, we cross-validated their location to ensure an exact match with a public charger location from the station location file. Next, we verified total annual charging demand by all driver agents at public locations and confirmed its alignment with total public charging delivered by each station. Finally, we scrutinized the usage of home chargers at any given time, confirming that it did not exceed the number of home chargers allocated to that tract. The same validation was applied to public chargers, ensuring that the number of public chargers used at any given time within a tract did not surpass the total number of public chargers allocated to that tract.

Moreover, we conducted a comparative analysis of the total number of BEVs and total public chargers for each year across all scenarios outlined in Section 3. This comparison was essential to ensure consistency, confirming that the total number of BEVs and public chargers remained consistent across all scenarios.

5 RESULTS AND ANALYSIS

As shown in Figure 7, public chargers (L2 + DCFC) are spread more widely in the four widespread public charger scenarios. While public chargers in the *Baseline* scenario are concentrated in the downtown area, there is significantly greater dispersion to suburban locations in the *Base + public charging* scenario. The number of public chargers needed to accommodate the demand for BEVs rises progressively over time due to the increasing adoption of BEVs. As shown in Figure 8, there is exponential growth in the number of L2 public chargers, while the rate of increase for DCFCs is comparatively lower. By 2029, the simulation indicates approximately 52,000 L2 public chargers and 8,000 DCFC public chargers are in use.

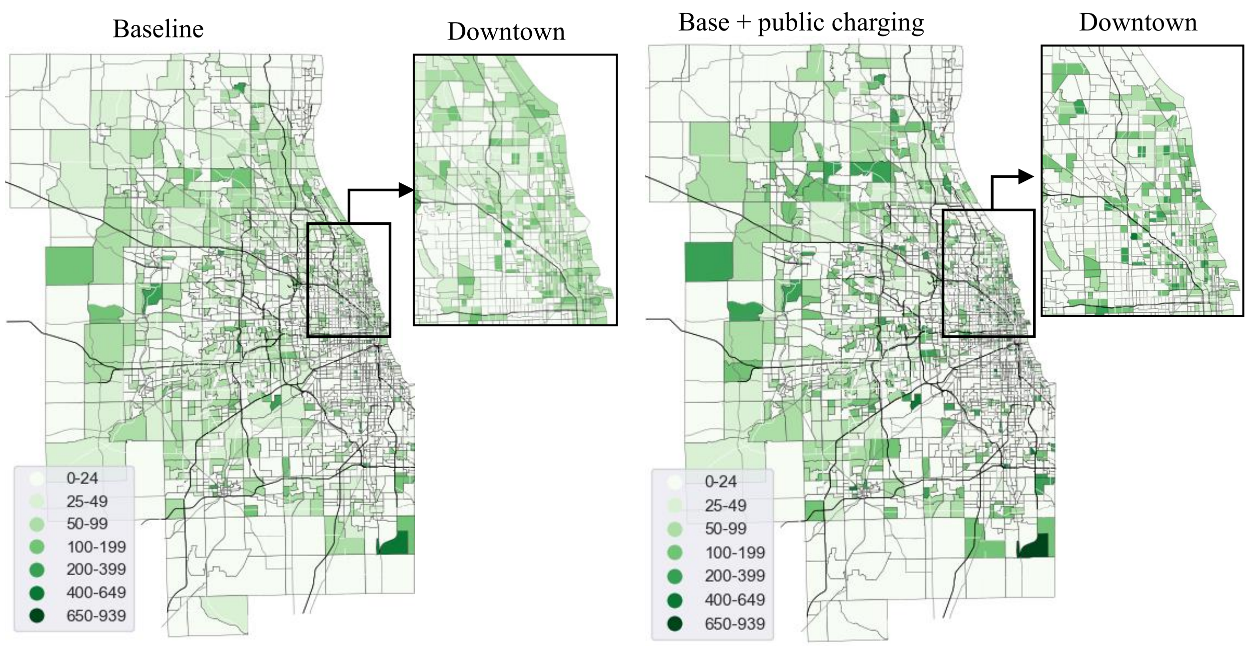

Figure 7 Number of public chargers: *Baseline* vs *Base + public charger* scenarios.

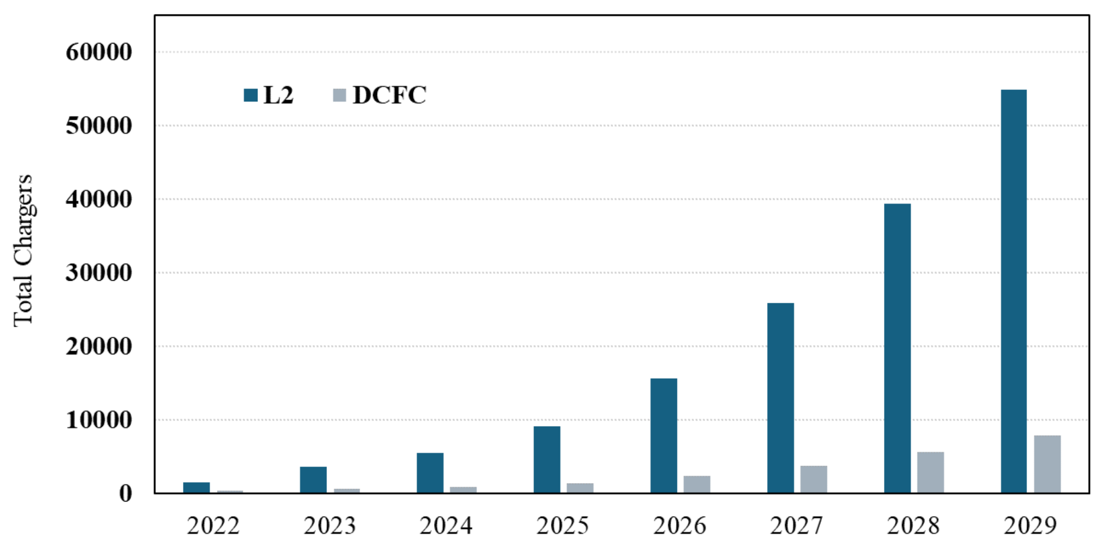

Figure 8 Total number of chargers in the study area.

Total energy (electricity) consumption for charging BEVs at both home and public charging locations in 2029 is approximately 10.2 GWh across all scenarios. However, there is a slight variation in home charging demand due to different assumptions of home charging availability, and the stochastic nature of BEV drivers and their travel patterns simulated in the model. Specifically, the *Base + MUD* scenario increases home charging demand by 1.5% compared to the *Baseline* scenario due to higher MUD home charging availability.

The peak charging load for home charging typically occurs between 7 p.m. and 10 p.m., as illustrated in Figure 9. This pattern is consistent across all scenarios. Notably, there is a discernible increase in load beginning around 3 p.m. – with load rising through the evening hours, then gradually falling – a trend suggesting that home charging occurs after daily travel activities are complete and vehicles can be conveniently plugged in. Note that there is considerable variation among individual census tracts, as indicated by the range in hourly observations as well as the increasing dispersion beginning around 3 p.m.

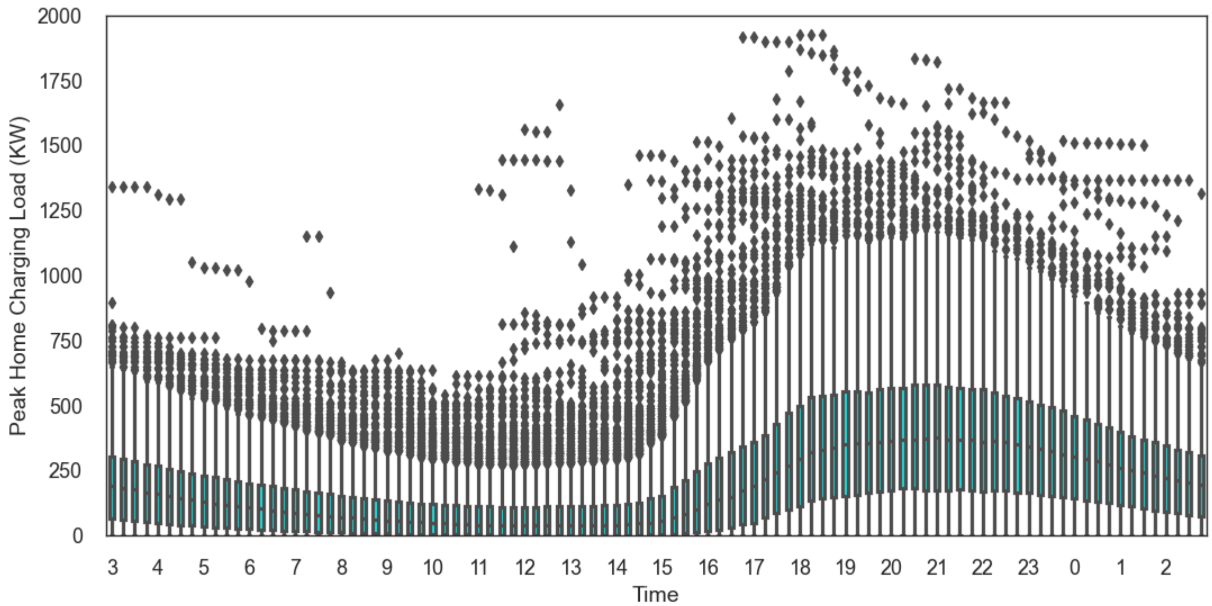

Figure 9 Distribution of peak home charging load in 2029 in *Baseline* scenario (each point represents the peak home charging load for each census tract).

As shown in Figure 10, the magnitude of peak home charging load varies across different scenarios, with the baseline BEV adoption scenarios (*Baseline*, *Base + MUD*, *Base +public charging*, and *Base + MUD + public charging*) showing a higher peak as compared to the widespread BEV adoption scenarios (as observed in *Baseline* vs. *Widespread BEV*; *Base + MUD* vs. *Widespread + MUD*, etc.). Peak loads in the widespread BEV adoption scenarios are less than in the baseline scenarios, a reflection of the more dispersed patterns of travel activity of households with diverse income levels. Additionally, peak home charging loads are higher in scenarios with greater MUD charging access, as expected, owing to the increased availability of home charging.

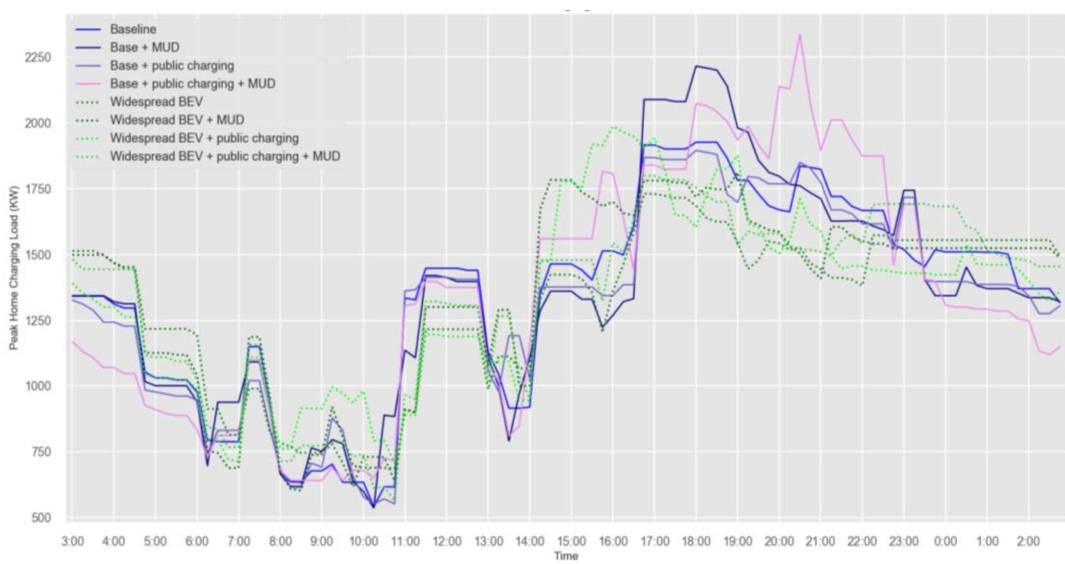

Figure 10 Peak home charging load for different scenarios in 2029.

Figure 11 is a plot, by income category, of BEV adoption vs. peak load, both relative to the regional average, by census tract. In the *Widespread BEV* scenario, peak home charging load is higher in most tracts with lower median household incomes compared to the *Baseline*. In this scenario, tracts with lower median household incomes adopt relatively more BEVs compared to the *Baseline*, leading to a higher peak home charging load. Conversely, most tracts with higher median household incomes have fewer BEVs compared to the *Baseline*, resulting in a lower peak home charging load in the *Widespread BEV* scenario.

Figure 11 Change in peak home charging load versus change in BEV adoption in *Widespread BEV* compared to *Baseline* scenario in 2029 (each point represents a census tract).

Figure 12 provides additional detail on changes in peak home charging load. In the *Widespread BEV* scenarios, approximately 60% of tracts show higher peak home charging loads as compared to the *Baseline* (see the four right-most bars in Figure 12 [c]). Figures 12 (a) and (b) illustrate that tracts experiencing higher peaks in the *Baseline* scenario see a lessening of that peak in the *Widespread BE*V scenario. Conversely, tracts with lower peaks in the *Baseline* scenario see increases in the magnitude of peak home charging load in the *Widespread BEV* scenario.

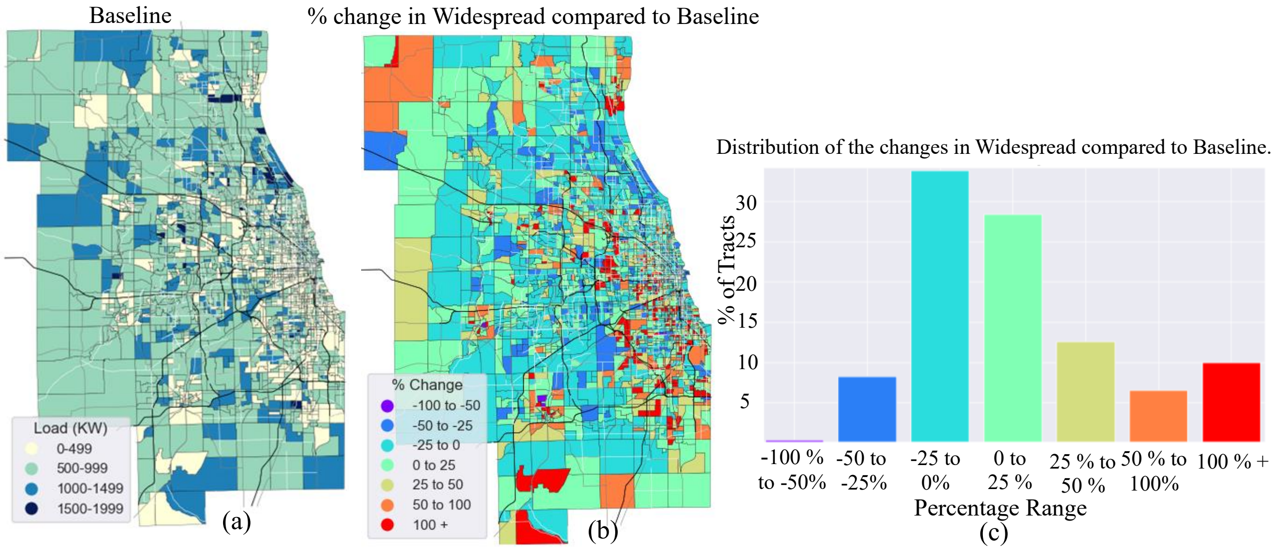

Figure 12 Peak home charging load in *Baseline* in 2029 (a), change of peak home charging load in *Widespread BEV* scenario compared to *Baseline* (b), distribution of the changes in (b) among tracts (c).

The 24-hour period is categorized into four segments based on ComEd's Time-of-Use rate: peak hours from 7 p.m. to 10 p.m., off-peak hours from 10 p.m. to 6 a.m., peak hours from 6 a.m. to 2 p.m., and super-peak hours from 2 p.m. to 7 p.m. (Citizens Utility Board, 2022). In our study, most tracts experience peak loads from combined home and public charging between the hours of 2 p.m. and 10 p.m. According to Figure 13 (left), approximately 40% of tracts experience peak loads between 2 p.m. and 7 p.m., while another 40% experience peak loads between 7 p.m. and 10 p.m. Tracts that exhibit peak loads at specific times tend to maintain consistent peak load times across scenarios, albeit with varying magnitudes. For instance, 80% of tracts have peak loads occurring between 7 p.m. and 10 p.m. in both the *Baseline* and *Widespread BEV* scenarios, as depicted by the dark-brown color in Figure 13 (right).

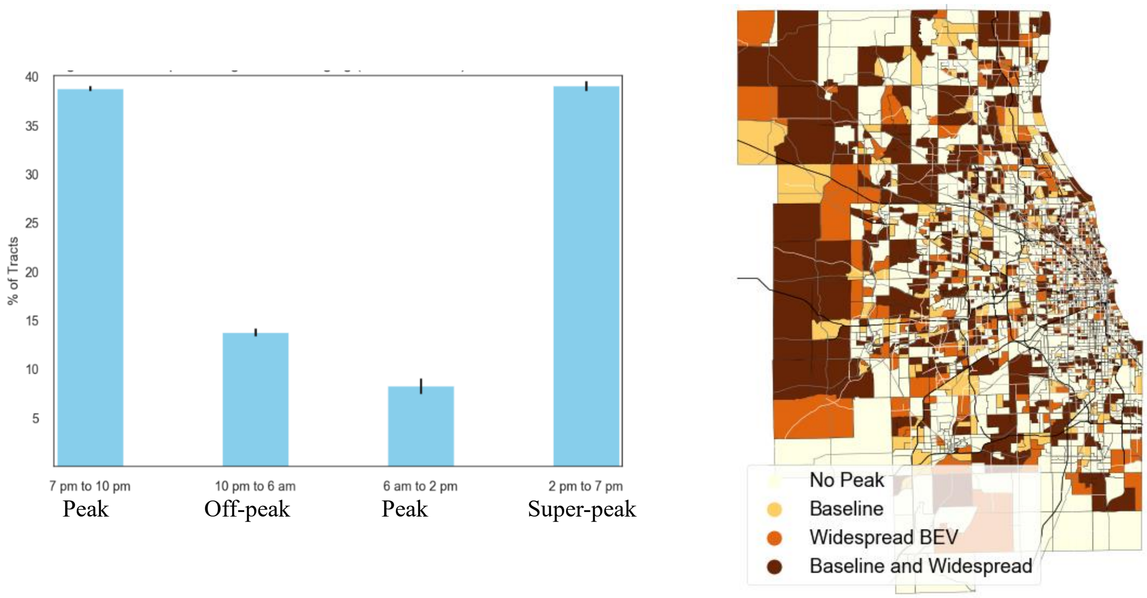

Figure 13 Percent of census tracts experiencing peak charging load by time of day*(left)* and spatial distribution of the 7 to 10 pm peaks in *Baseline* and *Widespread BEV* scenarios *(right)*.

Note that in the *Widespread BEV* scenario, fewer tracts experience high peak loads compared to the *Baseline* scenario. As depicted in Figure 14, in the *Widespread* BEV scenario, 56 tracts (2.8% of all tracts) have peak loads surpassing 1500 kW (as indicated in Figure 9, where most of the higher outlier peaks hover around 1500 kW), whereas in the *Baseline* scenario, this number is 70 (see Figure 14 on the left). This difference may be attributed to BEVs being distributed more evenly across the study area in *Widespread BEV* scenario, thereby reducing the concentration of BEVs in specific tracts and resulting in fewer tracts experiencing peaks above 1500 kW compared to the *Baseline* scenario. Only a few tracts exhibit peak loads in multiple scenarios. For example, six tracts have peak loads exceeding 1500 kW in the *Base*, *Base + MUD + public charging*, and *Widespread BEV* scenarios (see Figure 14 on the right).

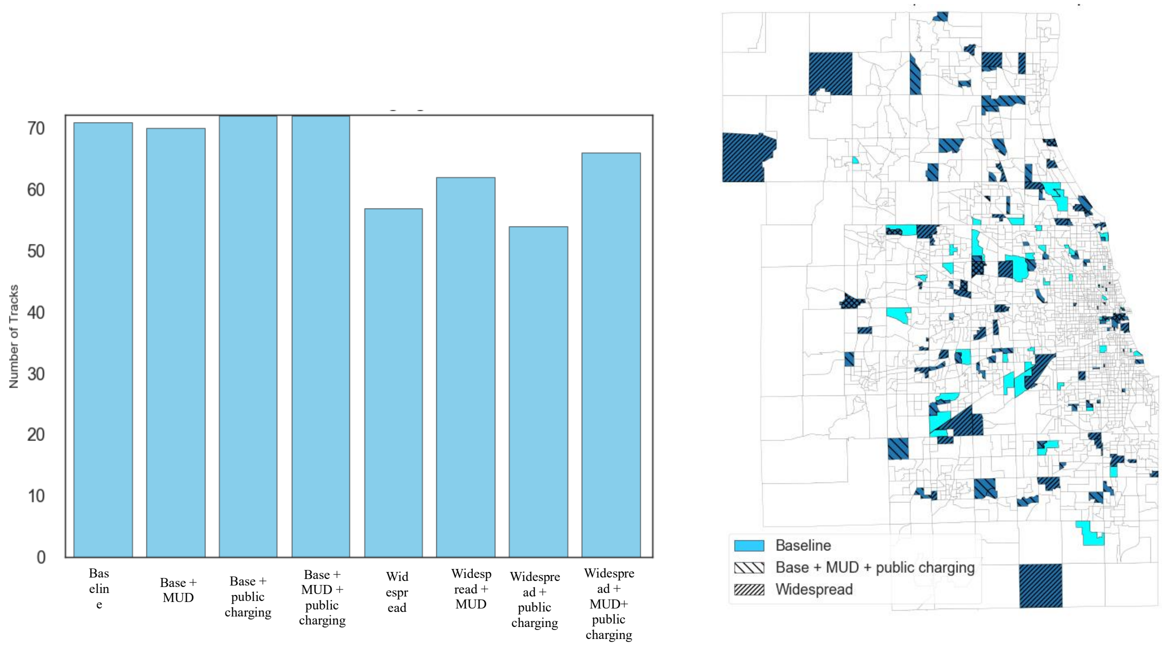

Figure 14 Number of tracts with peak charging load (home +public) above 1500 KW in different scenarios in 2029 *(left),* the spatial distribution of the tracts with peak above 1500 KW in *Baseline*, *Base + MUD +public charging*, and *Widespread BEV* scenarios *(right).*

6 CONCLUSIONS AND FUTURE DIRECTIONS

This report summarizes the collaborative efforts between Argonne and Exelon to develop and employ an agent-based model (ATEAM) for analyzing charging demand and infrastructure expansion in the seven-county Chicago metropolitan area from 2022 to 2029. For this effort, the ATEAM model was updated, expanded and exercised to explore the ramifications of alternative assumptions. Updates reflected the most recent initial conditions for the study area, including household demographics, regional trip-making behavior, BEV registrations, and public charging infrastructure. Functional improvements included simulating multiple days of travel behavior, estimating total public charger needs, updating the graphical user interface, and tracking outputs at both vehicle and charging station levels. Alternative assumptions were explored via eight scenarios which altered the temporal and spatial distribution of charging load and demand due to more widespread BEV adoption, greater public charger deployment, and increased MUD charging availability.

Simulation results indicate that home and public charging of more than 800,000 BEVs in the seven-county Chicago region will require approximately 10.2 GWh of electricity in 2029. Higher MUD home charging availability will amplify home charging load by 1.5%, as compared to the baseline, while more widespread adoption of BEVs will have a mixed effect. In some locations, it will reduce peak loads and lead to a more dispersed pattern, while in areas with lower median household incomes it will increase loads. ComEd will need to monitor such shifts to ensure sufficient capacities to support communities experiencing elevated load. However, it should be noted that if BEV adoption spreads to medium-income communities (as under the

Widespread BEV adoption scenario) charging demand will be more evenly distributed across the overall study area, and fewer census tracts will experience high peak loads from combined home and public charging. Across all scenarios, the majority of census tracts experience peak loads from combined home and public charging between 2 pm. and 10 p.m.

Our study has several limitations. First, the CMAP travel survey captured only a small sample of households on a single travel day in 2019 which means it does not capture variations in travel behavior. Estimating households' future travel behavior involves attributing these patterns to much larger numbers of future households (in effect, duplicating the same households) which may not capture the diversity of behavior, potentially misrepresenting the true peak charging load in a tract. Second, the analysis is based on travel behaviors on a typical day, overlooking variations across different days of the week or seasons. Third, our analysis concentrates primarily on vehicle charging upon returning home, possibly neglecting scenarios where vehicles charge when electricity rates are lower. Additionally, the study's scope is confined to project charging demand at the tract level, whereas a feeder-level load profile is needed to further evaluate the impact on the grid. Future research is needed to address these limitations.

APPENDIX A OPERATIONAL IMPROVEMENTS: GUI

We used Repast Simphony's GUI for easy control over the model parameters. Users can adjust these settings to create different simulation scenarios. Figure 15 shows the GUI of ATEAM, accessible via the "Parameters" tab. Below is a concise overview of each field's functionality.

Simulation End Year: Allows users to specify the concluding year of the simulation. The model will simulate all years leading up to, but not including the chosen end year.

BEV Adoption Target: Users can select one of three options for total number of BEV adoption in the study area's future years: ComEd Projection, Exelon Projection, or ZEV Target.

BEV Adoption Weight: Determines the allocation of BEVs within census tracts. In 2(a), users can customize BEV adoption. Subsequently, parameters for weight assignment discussed in Section 3.1 can be assigned in 2(b) to 2(k).

Home Charging Availability: Users can assign weights for home charging availability for SUD and MUD in 3(a) and 3(b), respectively.

Public Charger Deployment Scenario: Allows users to select from three deployment scenarios: Historic, Widespread, and Custom. If Custom is selected, users can assign weights for the charger deployment scenario in 4(b) to 4(g).

Total Charger Estimation Method Parameters: Parameters required to estimate the total number of chargers, as described in Section 2.3.2, can be assigned in 5(a) to 5(e). These include BEV efficiency, utilization, and Vehicle Miles Traveled (VMT).

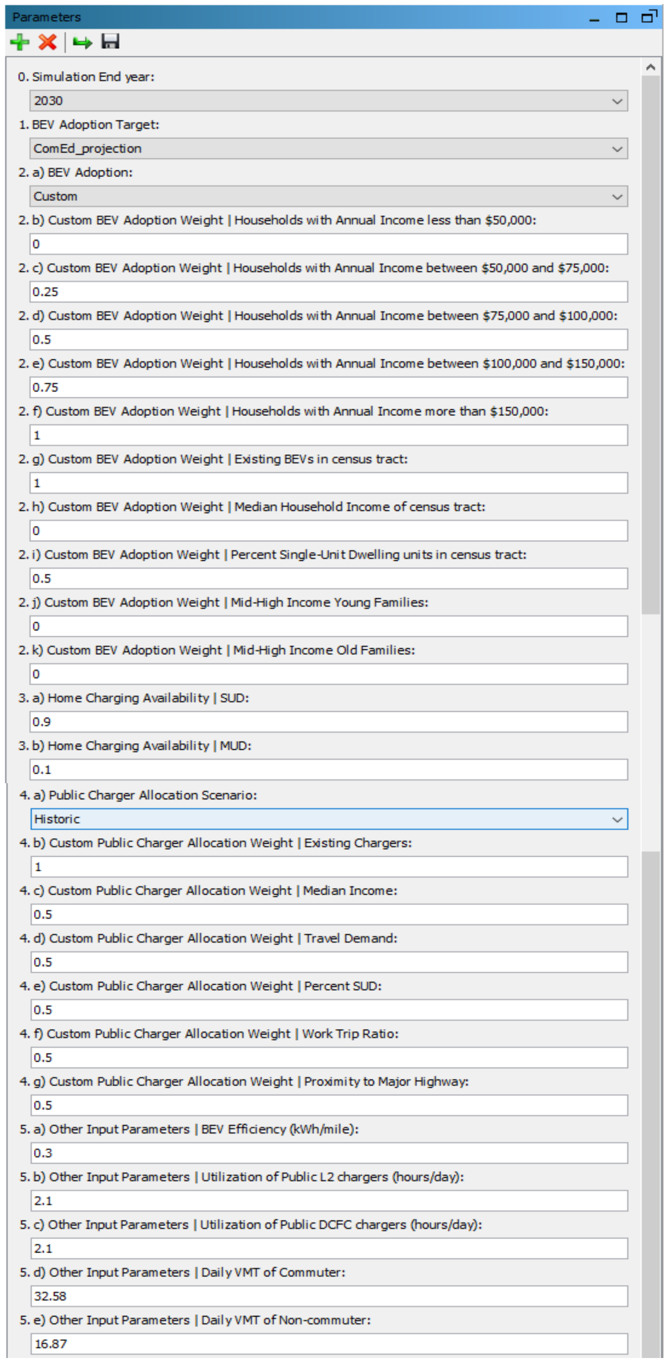

Figure 15 A screenshot of the ATEAM GUI.

APPENDIX B DISTRIBUTION OF BEV AMONG THE TRACT

We developed a tract score to simulate the BEV adoption by census tract. The tract score is determined based on such variables as the income distribution of households, the historical BEV adoption (BEVs in the base year), and the percentage of SUD in that tract. Income groups are displayed by percentage of households with annual income less than \$50,000; from \$50,000 to \$75,000; from \$75,000 to \$100,000; from \$100,000 to \$150,000; and above \$150,000. Tract scores are computed using a linear utility equation, where the normalized values of tract-level variables are multiplied by their respective weights as follows:

$$t_{BEV} = w_1x_1 + w_2x_2 + w_3x_3 + w_4x_4 + w_5x_5 + w_6x_6 + w_7x_7$$

Where:

x_1 = percentage of household annual income less than \$50,000,

w_1 = weight associated with percentage of household annual income less than \$50,000,

x_2 = percentage of household annual income from \$50,000 to \$74,999,

w_2 = weight associated with percentage of household annual income from \$50,000 to \$74,999,

x_3 = percentage of household annual income from \$75,000 to \$99,999,

w_3 = weight associated with percentage of household annual income from \$75,000 to \$99,999,

x_4 = percentage of household annual income from \$100,000 to \$149,999,

w_4 = weight associated with percentage of household annual income from \$100,000 to \$149,999,

x_5 = percentage of household annual income above \$150,000,

w_5 = weight associated with percentage of household annual income above \$150,000,

x_6 = historical count of BEVs,

w_6 = weight associated with historical count of BEVs,

x_7 = percentage of SUD, and

w_7 = weight associated with percentage of SUD.

The weights' values vary for different scenarios, as described in Section 3.1. Table 2 shows the value of the weight for each scenario.

Table 2 Weights of tract-level variables for BEV adoption by scenario

Scenario	Less than \$50,000	\$50,000 to \$74,999	\$75,000 to \$99,999	\$100,000 to \$149,999	\$150,000 or more	Historic BEVs	Percent SUD
Business as Usual	0	0	0.25	0.75	1	1	0.5
More Widespread	0	0.5	1	1	1	0	0.5

After calculating the tract scores for BEV adoption, new BEVs are distributed to each census tract through a weighted random draw, using the tract scores as weights. In a weighted random draw, all tract scores are summed to obtain the total score, S. Subsequently, a random number R in the range $[0, S]$ is generated. The algorithm involves iterating through the tracts. For each tract i, if its score S_i is less than R, the tract is skipped, and R becomes $R - S_i$. The process repeats until a tract with a score greater than R is reached, and this tract is selected to adopt a BEV. The entire procedure, starting with generating R, is reiterated until all new BEVs have been adopted. This algorithm assigns higher probabilities of receiving a BEV to tracts with higher scores. A positive weight for a specific tract variable raises the tract score, increasing the probability of obtaining a new BEV. Conversely, a negative weight reduces the tract score, decreasing the probability of adopting a new BEV.

APPENDIX C DISTRIBUTION OF PUBLIC CHARGERS AMONG TRACTS

Similarly, we developed another set of tract scores for the deployment of public chargers among the tracts. Six variables were selected to calculate tract scores for each charger type: historical charger numbers, median income, the percentage of households in SUDs, total travel demand, the ratio of work trips, and unmet charging demand. Depending on the scenario, the relative weights for these tract-level variables are adjusted. Table 3 provides the relative weights of tract variables by scenario. After calculating the tract scores for each charger type, new chargers are distributed to each census tract using a weighted random draw, as described in Appendix B.

Table 3 Weights of tract-level variables for charger deployment by scenario

Charger Type	Tract Variable	Historical	Widespread
Level 2	Historical Chargers	1	-1
	Median Income	0.01	0
	Percent SUD	0.01	0
	Unmet Demand	0.05	0.05
	Work Trip Ratio	0.15	0.5
	Total Travel Demand	0.3	0.5
DC50 kWh	Historical Chargers	1	-1
	Median Income	0.02	0
	Percent SUD	0.02	0
	Unmet Demand	0.05	0.05
	Work Trip Ratio	0.1	0.5
	Total Travel Demand	0.4	0.5
DC150 kWh	Historical Chargers	1	-1
	Median Income	0.02	0
	Percent SUD	0.02	0
	Unmet Demand	0.05	0.05
	Work Trip Ratio	0.05	0.5
	Total Travel Demand	0.1	0.5

REFERENCES

U.S. Census Bureau, 2017–2021 American Community Survey 5-Year Estimates. Available at https://data.census.gov/.

Adenaw, L. and Lienkamp, M., 2021. Multi-criteria, co-evolutionary charging behavior: An agent-based simulation of urban electromobility. World Electric Vehicle Journal, 12(1), p.18.

Alam, M.R., Hou, C., Aeschliman, S., Zhou, Y., and Guo, Z., 2023. Optimization-based trip chain emulation for electrified ride-sourcing charging demand analyses. Transportation Letters, 15(6), pp. 510–526.

Alternative Fuels Data Center (AFDC), 2022. U.S. Department of Energy, Energy Efficiency & Renewable Energy. Available at https://afdc.energy.gov/.

Nalley, S. and LaRose, A., 2022. Annual energy outlook 2022 (AEO2022). Energy Information Agency, 23.

Argonne National Laboratory (ANL), 2023. EV and Mobility Technologies Tracking. September 08, 2023. [Data Set]

Barry, K., 2024. Automakers move to a common plug standard to allow their EVs to use Tesla superchargers, *Consumer Reports*. Available at https://www.consumerreports.org/cars/hybrids-evs/tesla-superchargers-open-to-other-evs-what-to-know-a9262067544/#:~:text=Mazda%2C%20Stellantis%2C%20and%20Volkswagen%20Group,in%20the%202025%20model%20year.

Bauer, G., Hsu, C. W., Nicholas, M., and Lutsey, N., 2021. Charging up America: Assessing the growing need for US charging infrastructure through 2030. International Council on Clean Transportation, Washington.

Blonsky, M., Munankarmi, P., and Balamurugan, S.P., 2021. Incorporating residential smart electric vehicle charging in home energy management systems. In 2021 IEEE Green Technologies Conference (GreenTech) (pp. 187–194). IEEE.

Borlaug, B., Salisbury, S., Gerdes, M., and Muratori, M., 2020. Levelized cost of charging electric vehicles in the United States. Joule, 4(7), pp. 1470–1485.

Chicago Metropolitan Agency for Planning (CMAP), 2020. My Daily Travel Survey, 2018–2019. Available at https://datahub.cmap.illinois.gov/dataset/.

Citizens Utility Board, 2022. ComEd's Time-of-Day Pricing Program. Available at https://www.citizensutilityboard.org/time-use-pricing-plans/.

Climate and Equitable Jobs Act (CEJA). Available at https://epa.illinois.gov/topics/ceja.html.

ComEd IRA BEV projection, 2022. Collected via personal communication with ComEd.

Experian, 2022. Auto Registration Database. Available at https://www.experian.com/automotive/auto-vehicle-data.

Ge, Y., Simeone, C., Duvall, A., and Wood, E., 2021. There's no place like home: residential parking, electrical access, and implications for the future of electric vehicle charging infrastructure (No. NREL/TP-5400-81065). National Renewable Energy Lab.(NREL), Golden, CO (United States).

Illinois Environmental Protection Agency, 2022. Climate and Equitable Jobs Act. Available at https://epa.illinois.gov/topics/ceja.html#:~:text=CEJA%20includes%20provisions%20to%20phase,fuel%2Dfired%20electrical%20generation%20units.

Kristoffersen, T.K., Capion, K. and Meibom, P., 2011. Optimal charging of electric drive vehicles in a market environment. Applied Energy, 88(5), pp.1940-1948.

Liu, Z., Borlaug, B., Meintz, A., Neuman, C., Wood, E. and Bennett, J., 2023. Data-driven method for electric vehicle charging demand analysis: Case study in Virginia. Transportation Research Part D: Transport and Environment, 125, p.103994.

Lopez, N.S., Allana, A. and Biona, J.B.M., 2021. Modeling electric vehicle charging demand with the effect of increasing EVSEs: A discrete event simulation-based model. Energies, 14(13), p.3734.

Mintz, M., Macal, C., Guo, Z., Kaligotla, C., Wang, Y., and Zhou, Y. J., 2019. Agent-Based Transportation Energy Analysis Model: Methodology and Initial Results Argonne National Lab.(ANL), ANL/ESD-19/7. Available at https://dx.doi.org/10.2172/1618117.

Muratori, M., 2018. Impact of uncoordinated plug-in electric vehicle charging on residential power demand. Nature Energy, 3(3), pp.193-201.

Muratori, M., Kunz, T., Hula, A., and Freedberg, M., 2023. US National Blueprint for Transportation Decarbonization: A Joint Strategy to Transform Transportation (No. DOE/EE-2674). United States. Department of Energy. Office of Energy Efficiency and Renewable Energy.

Nicholas, M., and Lutsey, N., 2020. Quantifying the electric vehicle charging infrastructure gap in the United Kingdom. International Council on Clean Transportation, London, UK.

NOVA Workforce Development, Electric Vehicle Charging in Apartment-Based Housing, April 2015. EVS35 International Battery, Hybrid and Fuel Cell Electric Vehicle Symposium.

Paevere, P., Higgins, A., Ren, Z., Horn, M., Grozev, G. and McNamara, C., 2014. Spatio-temporal modelling of electric vehicle charging demand and impacts on peak household electrical load. Sustainability science, 9, pp.61-76.

Qian, K., Zhou, C., Allan, M. and Yuan, Y., 2010. Modeling of load demand due to EV battery charging in distribution systems. IEEE transactions on power systems, 26(2), pp.802-810.

Repast, Undated. The Repast Suite. Available at https://www.repast.github.io.

Tal, G., Lee, J. H., and Nicholas, M. A., 2018. Observed charging rates in California. Institute of Transportation Studies, University of California, Davis.

Teebay, R., 2023. Multi-Unit Dwelling Plug-in EV Charging Innovation Pilots (No. DOE-CSE-8473–1).

TIGER/Line Shapefiles, 2023. U.S. Census Bureau. Available at https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html.

U.S. Census Bureau, 2022. 2017–2021 American Community Survey 5-Year Estimates. Available at https://data.census.gov/.

Yi, Z., Chen, B., Liu, X.C., Wei, R., Chen, J. and Chen, Z., 2023. An agent-based modeling approach for public charging demand estimation and charging station location optimization at urban scale. Computers, Environment and Urban Systems, 101, p.101949.

Zhang, R., Horesh, N., Kontou, E., and Zhou, Y., 2023. Electric vehicle community charging hubs in multi-unit dwellings: Scheduling and techno-economic assessment, Transportation Research Part D: Transport and Environment, Volume 120, 2023,103776,ISSN 1361-9209, https://doi.org/10.1016/j.trd.2023.103776.

Zhou, Y., Siddique, N., Mintz, M., Aeschliman, S., and Macal, C., 2022. Electric Vehicle and Infrastructure Systems Modeling in Washington DC and Baltimore (No. ANL-22/28). Argonne National Lab.(ANL), Argonne, IL (United States); Exelon, Chicago, IL (United States).

Energy Systems and Infrastructure Analysis Division
Argonne National Laboratory
9700 South Cass Avenue, Bldg. 362
Lemont, IL 60439-4832

www.anl.gov