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ANL-25/31

ATEAM4Py: An Efficient and Scalable Python-Based Model for Charging Demand

Transportation and Power Systems Division

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ANL-25/31

ATEM4Py: An Efficient and Scalable Python-Based Model of EV Charing Demand

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LIST OF ACRONYMS

ATEAM - Agent-based Transportation Energy Analysis Model

ATEAM4Py - Python-based version of ATEAM

ABM - Agent-Based Modeling

BEV - Battery Electric Vehicle

BGE - Baltimore Gas and Electric Company

DCFC - Direct Current Fast Charger

EV - Electric Vehicle

EVWATTS - Electric Vehicle Widescale Analysis for Tomorrow's Transportation Solutions

HPC - High-Performance Computing

L1 - Level 1 Charger

L2 - Level 2 Charger

MUD - Multi-Unit Dwelling

PEPCO - Potomac Electric Power Company

PHI - Pepco Holdings, Inc.

RSR - RMSE-Standard Deviation Ratio

SCM - Smart Charge Management

SUD - Single-Unit Dwelling

EXECUTIVE SUMMARY

This report details the development and implementation of ATEAM4Py, a Python-based simulation model that projects demand for battery electric vehicle (BEV) charging based on adoption trends and consumer behavior. With Exelon's support, Argonne National Laboratory converted the original Java-based Agent-based Transportation Energy Analysis Model (ATEAM) into Python, resulting in a faster and more efficient tool for forecasting the timing, location, and scale of charging demand growth. ATEAM4Py tackles key challenges in simulation efficiency and runtime, supporting the strategic development of cost-effective grid capacity expansion strategies and ensuring reliable service for stakeholders.

ES.1 Key Benefits of ATEAM4Py:

- **Enhanced Processing Speed**: Delivers a 20-fold improvement in processing speed, facilitating rapid large-scale simulations. This capability supports detailed scenario analyses and sensitivity studies critical for energy infrastructure planning.
- **Scalability and Interoperability**: Seamlessly integrates data from Exelon service territories, including Chicago, Baltimore, and Washington, DC, while remaining adaptable to diverse regional datasets.
- **Advanced Scenario Analyses**: Accounts for uncertainties such as BEV adoption patterns and charging infrastructure accessibility, equipping stakeholders with tools to optimize grid impacts and develop effective energy infrastructure strategies.
- **Data-Driven Insights**: Provides actionable insights by analyzing EV charging behaviors, station utilization, and demographic trends, enabling accurate forecasting of charging demand
- **Grid Impact and Load Management**: Supports detailed grid capacity assessments, enabling utilities to plan upgrades effectively and reduce peak demand through smart charging strategies.

ES.2 Insights from Scenario Analyses

Using ATEAM4Py, we conducted scenario analyses across three Exelon utility territories: ComEd, BGE, and PHI. Specifically, the analysis focused on the impact of three critical parameters on the EV charging load: BEV penetration rates, access to home charging, and the characteristics of home chargers. Here are the key insights from the analysis results.

- EV charging demand varies based on BEV penetration, home charging access, and the ratio of Level 2 (L2) chargers. For instance, in ComEd's EV growth scenario with 80% home charging access and 100% L2 home charger adoption, peak load is projected to increase from 0.26 GW in 2025 to 1.66 GW by 2030, reaching 4 GW by 2035.

- In Chicago, a 1% increase in EV penetration adds 660 MWh to electricity usage. Similarly, a 1% rise in home charging access and L2 charger adoption contributes 190 MWh and 57 MWh, respectively.
- Greater adoption of L2 home chargers intensifies evening peak loads and demand ramps, presenting significant challenges for grid planning and infrastructure development.

ES.3 Feeder-Level Analysis and Managed Charging:

The project also assessed feeder-level BEV home charging loads in BGE and Pepco territories to determine capacity constraints. Overloaded feeders—those exceeding 80% of available capacity—are projected to rise due to the increasing charging demand. In Pepco territory, overloaded feeders increase from 1% in 2025 to 20% by 2035, while BGE territory sees a rise from 5% to 34% over the same period.

Smart Charge Management (SCM) strategies were evaluated to mitigate feeder overload. Simulations showed that load balancing[1] reduces overloaded feeders in Pepco territory from 20% to 13% with 50% SCM enrollment. However, in BGE territory, SCM had limited impact, reducing overloaded feeders by just 1%.

These findings highlight the importance of proactive planning and targeted strategies to ensure grid resilience amidst rising charging demand.

[1] Manage charging load at the individual asset level (i.e. transformer, circuit, feeder) to enhance electric grid resiliency. The general approach is to limit home charging load for smooth ramping in the overnight period.

1. INTRODUCTION

As battery electric vehicle (BEV) adoption accelerates, forecasting the infrastructure required to support large-scale BEV deployment and associate charging demand has become a critical challenge. To address this, Argonne National Laboratory, in collaboration with Exelon, developed the Agent-based Transportation Energy Analysis Model (ATEAM), which simulates the co-evolution of EV adoption and charging infrastructure deployment in key metropolitan areas such as Chicago, IL, and the Washington, DC – Maryland region (Mintz et al., 2029). ATEAM leverages agent-based modeling (ABM) to evaluate evolving EV adoption trends and infrastructure needs, with regular updates that incorporate new data and enhanced agent behaviors (Barua et al., 2024).

ATEAM was initially developed using Repast Simphony, a Java-based ABM framework created at Argonne. While the framework offers robust features and flexibility, it has limitations in processing speed, particularly for large-scale simulations involving millions of EVs and charging stations. For example, running a single 10-year scenario can take over a week. Argonne converted ATEAM from Java to Python using Repast4Py, an advanced Python-based ABM framework with multi-core processing capabilities to overcome this limitation. This conversion significantly reduced model runtime and streamlined future development.

In addition to improving computational efficiency, the project enhanced ATEAM's ability to forecast charging demand and electrical grid loads. By incorporating real-world data on EV charging behaviors, station utilization, and driver demographics, the model quantifies the impact of factors such as charging station location, charger type, and home charging access. These upgrades provide stakeholders with actionable insights for planning future EV charging infrastructure within Exelon's service territory.

With ATEAM4Py's enhanced processing speed, comprehensive scenario analyses and sensitivity studies were conducted to explore variables such as EV growth rates, home charging access, and charger characteristics. These analyses capture a range of potential future outcomes, offering valuable insights into infrastructure planning. Additionally, this study examined charging station utilization—an essential factor for planning and deploying EV charging infrastructure. Key influences on public charger utilization, such as demographics, EV density, and public charger density, were analyzed to better understand utilization patterns and improve planning strategies.

This report has been structured to provide a comprehensive overview of the project. Chapter 2 details the conversion of ATEAM to Python and the resulting value added to Exelon. Chapter 3 explores insights gained from a charger utilization study based on real-world data. Chapter 4 presents the results of the scenario analysis conducted using ATEAM4Py in a high-performance computing environment. Finally, Chapter 5 concludes with a discussion of potential future research and development opportunities.

2. PYTHON CONVERSION AND HIGH-PERFORMANCE COMPUTING

ATEAM4Py was developed using the Repast4Py distributed ABM toolkit, part of the open-source Repast ABM Suite of toolkits, all of which utilize the Python programming language. Python has become the primary language for artificial intelligence (AI) and is widely used across many scientific disciplines for machine learning (ML) and other applications. It also boasts a vibrant ecosystem of libraries that exploit the latest advances in algorithmic development and emerging hardware architectures.

The architectural design of Repast4Py is based on central principles important to agent modeling and software design, resulting in a set of modular, layered, and pluggable components that provide flexibility, extensibility, and ease of use. In addition to flexibility and ease of use, Repast4Py also aims to run simulations much more quickly than previously possible. Agent-based models with large populations of agents can be prohibitively slow to execute. Moreover, ABMs often need to be executed many times to account for stochastic variation in model outputs and characterize their parameter spaces, e.g., for calibration, optimization, or uncertainty quantification. By reducing the time needed to evaluate individual model runs, Repast4Py allows an ABM to be used as the foundation of an electronic laboratory, where sophisticated sampling techniques can be used for these analyses.

While ATEAM4Py has the same overall model design as ATEAM with respect to the types of agent classes (Travelers, Vehicles, etc.), charging station allocations, daily task schedules, and geospatial vehicle routing along road networks, performant design and optimization of model logic are dramatically improved, thereby significantly reducing the runtime of baseline scenarios. Additionally, by redesigning the geospatial engine, there are substantially fewer lines of model code, the overall code structure is easier to understand, and the model's codebase is easier to maintain and extend by the ATEAM4Py project team. Note that the model's data structure, function, and agent behavior are fully documented in the code. In addition to its simplified and maintainable codebase, ATEAM4Py provides several technical and operational benefits, as detailed in the following subsections.

2.1. LARGE-SCALE PARAMETER EXPLORATION AND SENSITIVITY ANALYSIS

ATEAM4Py is now suitable for exploring large-scale model parameter spaces, sensitivity analyses, and uncertainty quantification. As with other Repast4Py models developed for various domains (healthcare, economics, energy) by Argonne's Computing Resource Center, ATEAM4Py clusters can be run using the workflow shown in Figure 1. This process follows a similar approach regardless of the modeled system. The overall goal is to identify model process or policy variables that project stakeholders can control and which also make the most difference in the model outputs of interest, e.g., cost or energy use. Stakeholder-defined research questions guide the proper identification of the relevant model inputs and outputs the analysis intends to answer. Next, model parameter sensitivity analysis is performed to create a matrix of sensitivity indices (0-1) that relate the contribution of each model input to each model output variance. This step further serves as a parameter screening step to reduce the set of model inputs to only those parameters with the most significant impact on model output variance. Reducing the model input parameter space is critical to performing additional stochastic model runs because the set of model inputs needed to sample the full parameter space is generally too large for computational feasibility, even using HPC resources. Finally, important model input parameters identified in the sensitivity analysis are randomly sampled to generate confidence intervals on model outputs.

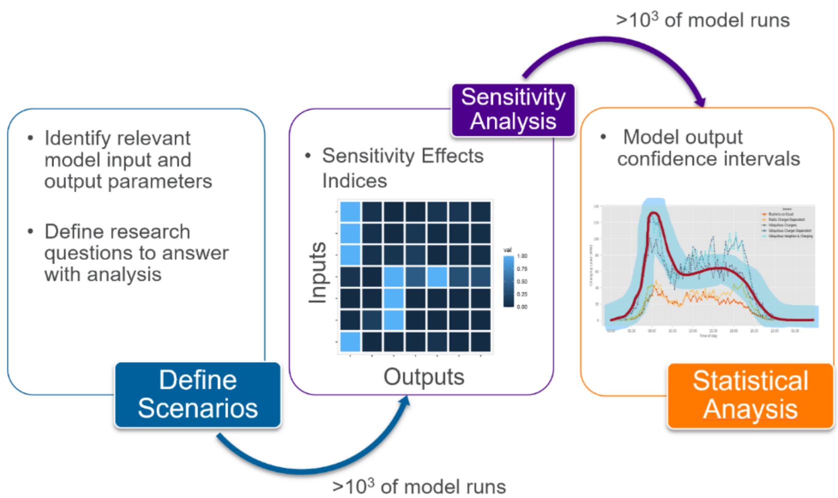

Figure 1 Sensitivity analysis workflow. Stakeholder-defined research questions help shape the model design and inputs and outputs (left). Model parameter sensitivity analysis is next performed to create a matrix of sensitivity indices (0-1) that relate the contribution of each model input to each model output variance (center). Important model input parameters identified in the sensitivity analysis are randomly sampled to generate confidence intervals on model outputs (right).

2.2. IMPROVED COMPUTATIONAL EFFICIENCY

On average, ATEAM4Py is approximately 20 times faster in computational time than the original Java version. For example, running the model for the Chicago region from 2024 to 2035, with the number of BEVs growing from 0.1 million to 2.2 million, takes just 8.35 hours with the Python version, while the Java version requires 165.9 hours. Figure 2 shows how computational time increases exponentially with the number of BEVs for both versions of ATEAM (note the log scale). However, by virtue of its significantly lower runtime, ATEAM4Py can examine many more scenarios within limited timeframes than its Java-based predecessor.

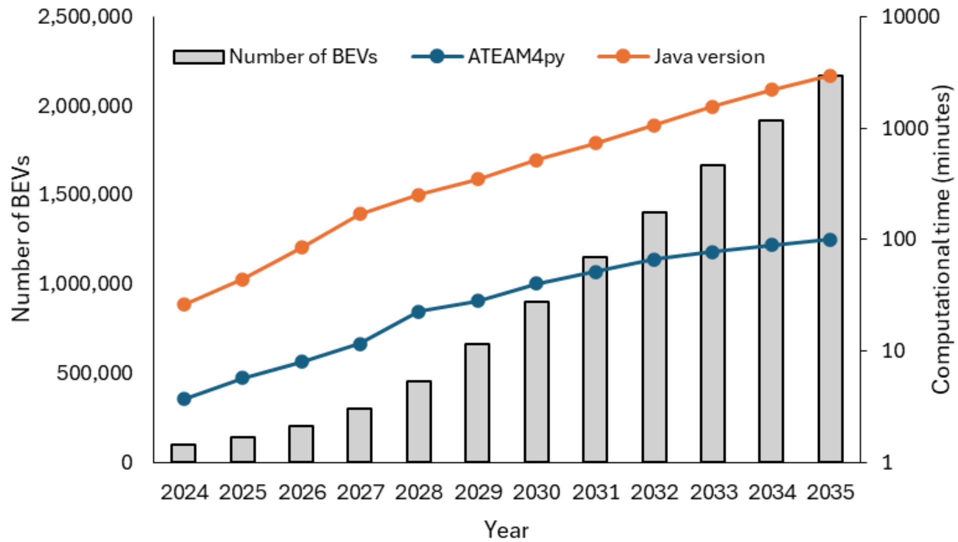

Figure 1 Computational time by model version for different simulation years and BEV populations (Chicago region). Note computational time is displayed on a logarithmic scale.

2.3. IMPROVED BASELINE DATA

In addition to the Python conversion, ATEAM4Py has been updated with more recent baseline data, aligned to a 2024 base year, and features a streamlined process for specifying scenario inputs. The model integrates multiple baseline data sources, including existing vehicle registrations, specifications of current BEV make/models, travel and charging behaviors of BEV drivers, home and public charging infrastructures, and forecasts of BEV adoption and infrastructure growth. Additionally, ATEAM4Py's enhancements also include a simplified method for customizing different inputs to define a scenario. These improvements enhance the scalability of ATEAM4Py, enabling it to accommodate a broader range of inputs as the system grows in complexity. Figure 3 illustrates the key inputs and outputs of ATEAM4Py, with parameters updated in the latest release highlighted in bold.

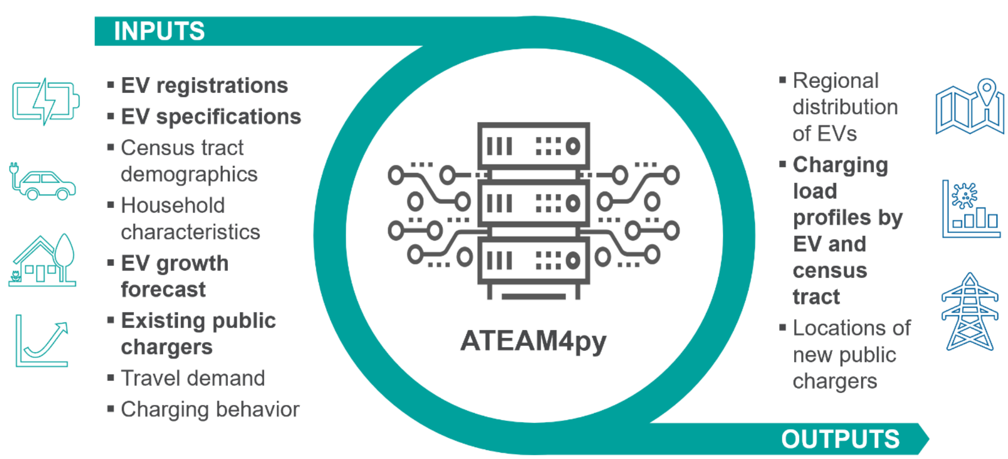

Figure 2 Inputs and outputs of ATEAM4Py

2.4. FLEXIBILITY FOR REGIONAL ANALYSIS

A key advantage of ATEAM4Py is its seamless interoperability with various Exelon service territories. The model currently is preloaded with input data for two different study areas – Chicag (seven counties in IL) and the Washington D.C.- Maryland metropolitan region. This allows an easy switch between ComEd, BGE, and PEPCO service territories. Moreover, ATEAM4Py can be adapted to other service territories by incorporating regional inputs such as road networks, travel patterns, demographics, existing BEV registrations, and projected BEV adoption growth. By using CSV files for input data, ATEAM offers significantly greater flexibility and ease of modification compared to its predecessor, which relied on XML files.

2.5. IMPROVED OUTPUT RESULTS REPORTING

ATEAM4Py provides detailed outputs at the census tract level, including the number of vehicles charged at home and public charging stations. These outputs enable analyses of charging loads at 15-minute simulation intervals, helping to identify BEV charging hotspots, public charging demand across regions, peak charging loads, and the timing of peak BEV charging. For example, Figure 4 shows peak BEV home charging loads in ComEd (Chicago), BGE, and PEPCO territories in 2035 (based on Exelon's projected BEV adoption). This scenario analysis assumes BEV growth follows historical trends, with 80% of single-unit dwelling (SUD) BEV owners and 20% of multi-unit dwelling (MUD) BEV owners having access to home charging (Powell et al., 2022).

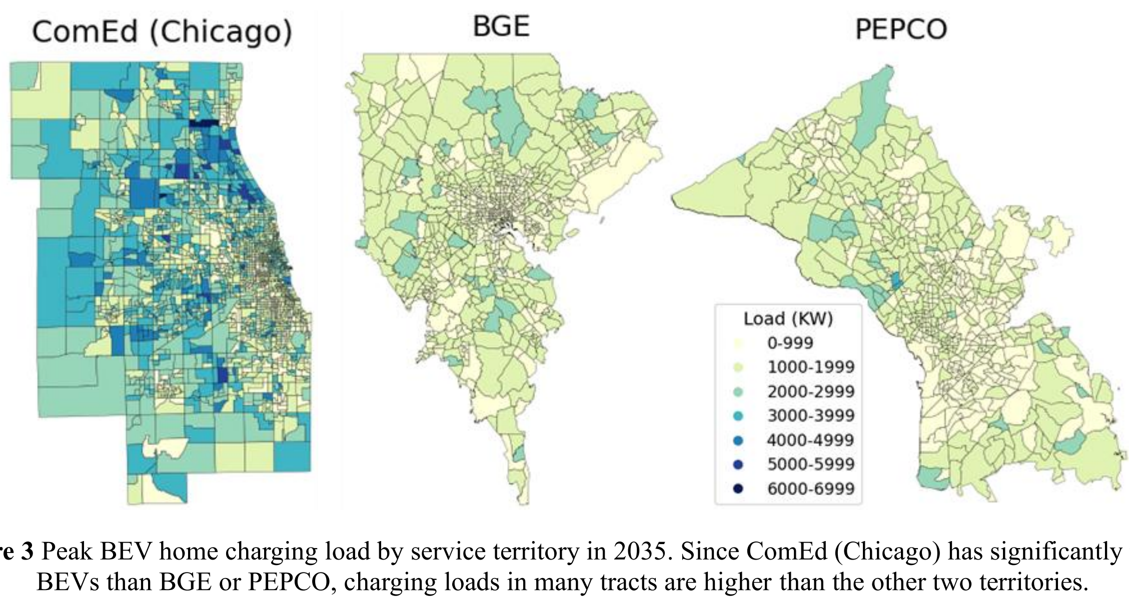

Figure 3 Peak BEV home charging load by service territory in 2035. Since ComEd (Chicago) has significantly more BEVs than BGE or PEPCO, charging loads in many tracts are higher than the other two territories.

2.6. FLEXIBILITY FOR SCENARIO ANALYSIS

ATEAM4Py offers the flexibility to model a wide range of future scenarios, capturing the effect of various parameters on projected BEV charging load. Given the inherent uncertainties in forecasting these parameters, conducting sensitivity analyses is crucial for interpreting the results accurately. Table 1 lists key variables that can be adjusted in ATEAM4Py to support comprehensive sensitivity analysis.

Table 1 Key inputs for designing scenarios

Input	Description
BEV growth rate	Growth in year-over-year BEV registrations in the study area, enabling analysis of BEV charging demand under various scenarios.
BEV adoption	BEV adoption across census tracts to reflect different scenarios of BEV preference by income or another socio-demographic characteristic. For instance, BEV adoption may follow historical trends or target middle- or lower-income populations.
Home charger access	The likelihood that a household can charge a BEV at home can be varied, for instance, by varying the percentage of households residing in multi-unit dwellings that have on-site charging.
Public charger deployment	The option to allocate public chargers based on historical deployment patterns or in a more widespread manner, given the uncertainty of future public charger deployment.
Charging speed	Enable the selection of charging power levels for L1, L2, and DC fast chargers (DCFC) and define the proportion of each charger type in the system.
Public charger utilization	The number of hours a public charging station operates per day. Daily utilization plays a crucial role in estimating the number of public chargers needed to fulfill EV charging demand

3. CHARGING STATION UTILIZATION ANALYSIS

Charging station utilization is a critical factor for effective BEV charging infrastructure planning and deployment. It also serves as an essential input to ATEAM, where public charging utilization informs estimates of the required number of charging stations in a study area. Argonne analyzed key factors influencing the daily utilization of public EV charging stations using data from the EVWATTS project (Energetics, 2023) to explore how location type affects charging station utilization. This analysis evaluated the effects of variables such as demographics, EV density, and public charger density on utilization by connecting charging session data with additional datasets, including the American Community Survey (ACS, 2023) and Experian (Experian, 2023). The variables examined are summarized in Table 2.

Table 2 Variables used in predicting public charger utilization

Variable group	Variables
Charging station utilization	Energy delivered per charging port on a daily basis (KWh/port/day)
Charger type	L2, and DCFC
Location category	Hotel, Leisure, Medical/Educational, Fleet, Municipal, Office, Parking lot/garage, Retail, Transit[2]
Access type	Private, Limited, and Public
EV pricing category	Free or paid
Curbside station	Yes or no
AFDC corridor designation	Yes or no
Charger density	DCFC charger per 1000 EV in the zip code L2 charger per 1000 EV in the zip code
Demographic factors	Population density of the county that the zip code is in Single-unit house per 1000 EV in the zip code Percentage of higher income (>$100000) households in the zip code
Number of ports	Discrete (1 or 2)

Multiple machine learning (ML) models, known for their predictive capabilities, were employed to forecast public charger utilization. These models included decision trees, random forests, gradient boosting, and artificial neural networks (ANN). Among them, the gradient boosting model demonstrated the best performance, achieving the highest testing R^2 of 0.65, indicating relatively strong generalization. The other models—decision tree, random forest, and ANN—produced testing R^2 values ranging from 0.53 to 0.63, reflecting satisfactory generalization capabilities. Regarding error metrics, the gradient boosting model also achieved the lowest RMSE-standard deviation ratio (RSR) of 0.59 (where lower is better), closely followed by the random forest model at 0.6. Meanwhile, the linear regression, decision tree, and ANN models exhibited slightly higher RSR values, ranging from 0.63 to 0.82.

To deepen the analysis, Shapley Additive Explanations (SHAP) values were used to interpret the models' predictions by attributing contributions to individual input features. As shown in Figure 5, SHAP analysis highlights factors such as the number of ports at a station, charger type, charger location, and DCFC charger density significantly influence utilization predictions.

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[2] **Hotel:** hotel parking lots provided for patron use; **Leisure:** parks and recreation facilities, museums, sports arenas, or national parks/monuments; **Medical/Educational:** hospital campuses, medical office parks, or educational facilities such as training centers, universities, or schools; **Municipal:** city, county, state, or federal government facilities; **Office:** business offices, office parks/campuses, or industrial facilities; **Parking lot/garage:** parking lots or garages operated by private parking management companies, property management companies, or municipalities offering direct access to a variety of venues; **Retail:** retail locations both large and small, including shopping malls, strip malls, and individual stores; **Transit:** parking locations with direct pedestrian access to other forms of transportation such as airports, metro-rail stations, or ferry ports.

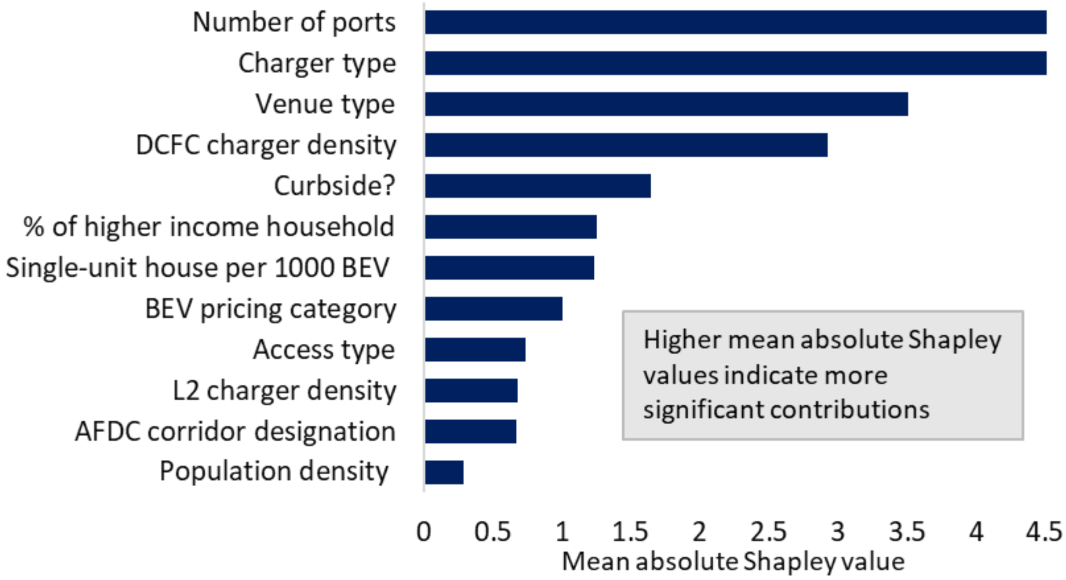

Figure 5 Importance of Input Variables. The mean absolute Shapley values indicate the relative significance of each input variable in predicting charging station utilization.

Additionally, Accumulated Local Effects (ALE) plots (Apley and Zhu, 2020) offer a clearer understanding of how charging station utilization changes in response to variations in input variables. ALE analyzes the impact of one input feature at a time while keeping all other features constant at their mean values in the gradient-boosting model. For example, the ALE analysis of station location's effect on charger utilization reveals that higher utilization occurs at locations where EVs are likely to park for extended periods (Figure 6).

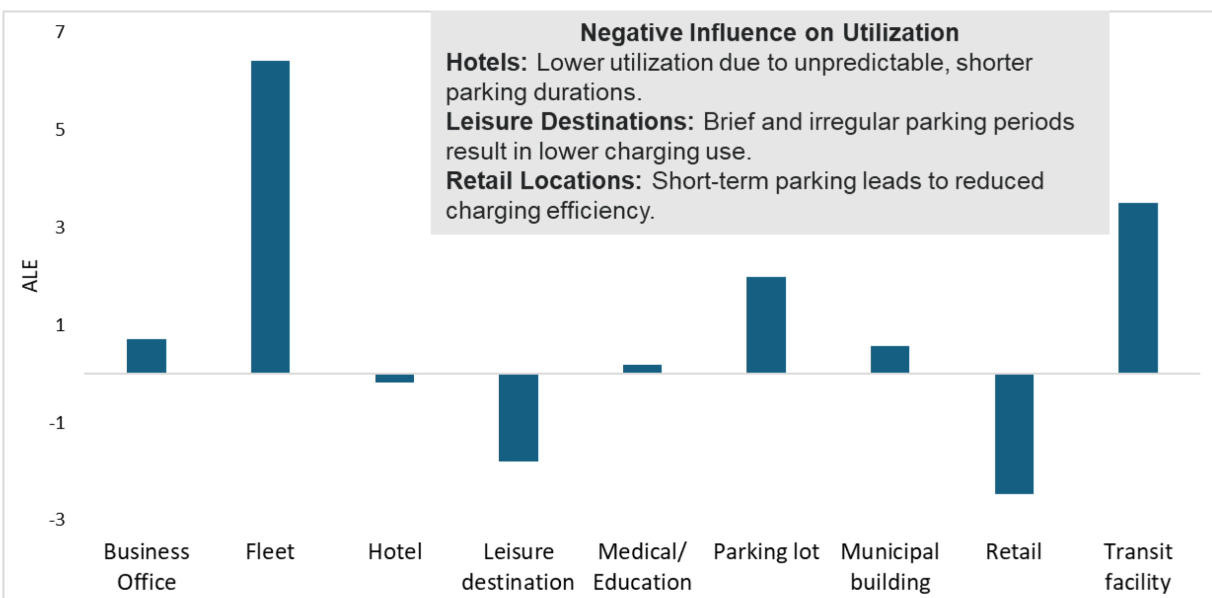

Figure 6 ALE plot of the station location type. The ALE values represent the average effect of station location on charging station utilization, indicating how utilization changes as the location variables are varied while holding other variables constant.

4. MODELING FUTURE CHARGING LOAD WITH LARGE-SCALE BEV ADOPTION

We simulated a range of scenarios to explore how variations in key input assumptions influence future charging loads under projected EV penetration. Specifically, the analysis focused on three critical parameters: BEV penetration rates, access to home charging, and the characteristics of home chargers.

The primary objective of this scenario analysis was to address the following research questions:

- How will BEV growth and variation by community impact charging load?
- How will home charging availability and charging speed affect charging load?
- How do different managed charging strategies affect charging load?

To answer the first two questions, we leveraged the HPC capabilities of ATEAM4PY to run scenarios with varying input parameters. Section 4.1 describes the variations in the input parameters. The insights from this scenario analysis are presented in Section 4.2.

For the third research question on managed charging, we developed a separate set of managed charging scenarios. These scenarios analyzed charging loads at the feeder level, leveraging feeder-level data provided by BGE and Pepco. This analysis compared the EV charging load generated by ATEAM4PY simulations against available feeder capacity and investigated how managed charging strategies could mitigate feeder overloading. Details of this analysis are presented in Section 4.3.

4.1. SCENARIO DESIGN FOR SENSITIVITY STUDY

We analyzed the sensitivity of three input parameters by exploring a range of values:

- **BEV growth projection:** three types of BEV growth rates are considered.

Exelon projection: Based on communication with Exelon, this scenario reflects an aggressive growth rate. By 2035, BEV penetration is projected to reach approximately 33% in Chicago, with around 2.17 million BEVs on the road (see Figure 7).

Moderate growth rate: This scenario follows the trajectory of the Exelon projection initially but begins to slow around 2029, resulting in a more conservative growth rate. By 2035, BEV penetration is projected at 21%, with 1.38 million BEVs.

Gradual growth rate: Assuming linear growth, this scenario projects the lowest BEV penetration, with 0.8 million BEVs in Chicago by 2035, equating to 13% penetration.

- **Home charging access:** According to Powell et al. (2022), in a high home charging access scenario, 80% of Single-Unit Dwelling (SUD) residents and 20% of Multi-Unit Dwelling (MUD) residents with BEVs have access to home charging. We modeled five levels of home charging access, ranging from high access (80% of SUD residents) to low access (20% of SUD residents), as outlined in Table 3. Each scenario is named according to the percentage of SUD residents with access, such as "80% home charging access."

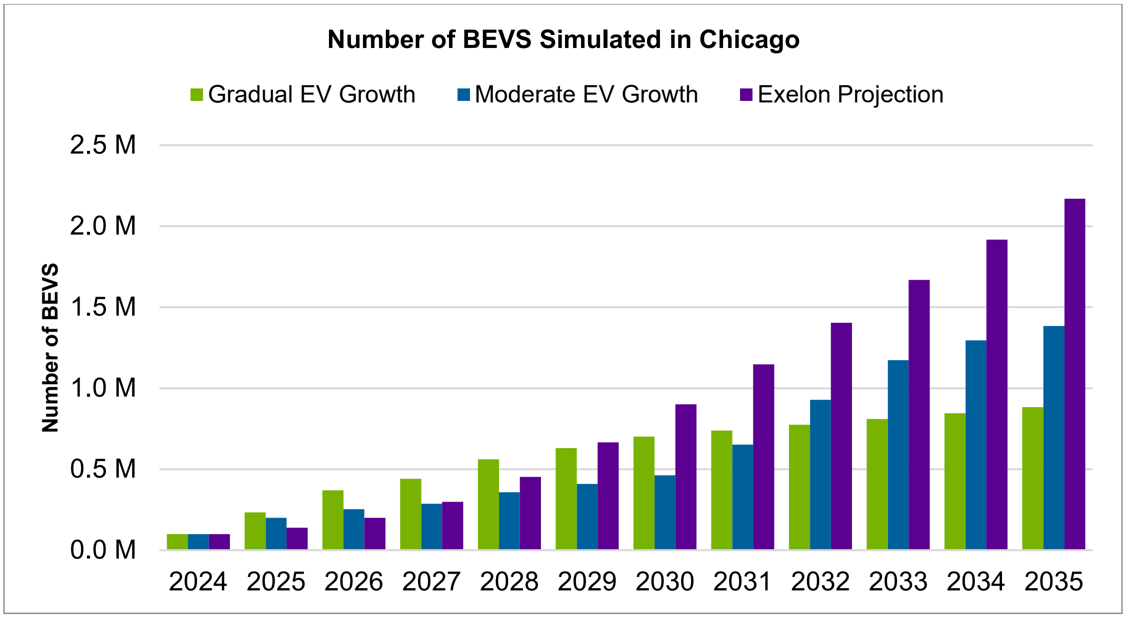

Figure 7 Number of BEVs in Chicago with different BEV growth projections

Table 3 SUD and MUD home charging access in different scenarios

Home charging access	SUD home charging access	MUD home charging access
80%	80%	24%
65%	65%	19%
50%	50%	14%
35%	35%	9%
20%	20%	3%

- **Ratio of L2 chargers:** Home chargers can be either L1 or L2. The percentage of L2 chargers in homes, referred to as the L2 ratio, was modeled across six scenarios: 0%, 20%, 40%, 60%, 80%, and 100%.

Based on the three input parameters, 90 scenarios were developed. These scenarios were applied to two study areas: Chicago and the DC-Maryland regions.

4.2. INSIGHTS FROM THE SENSITIVITY STUDY

The daily total home charging load profiles for various 2035 scenarios (Figure 8) highlight how electricity usage and peak home charging loads are shaped by BEV growth projections, home charging access, and L2 charger ratio. Scenarios based on Exelon's projections show the highest peak loads in 2035, aligning with the largest projected number of BEVs. As home charging access increases from 20% to 80%, the peak load grows significantly, driven by greater demand from more BEVs charging at home. Similarly, increasing the proportion of L2 chargers from 20% to 100% further intensifies the peak load, as L2 chargers, with their higher power capacity, deliver larger charging loads compared to L1 chargers.

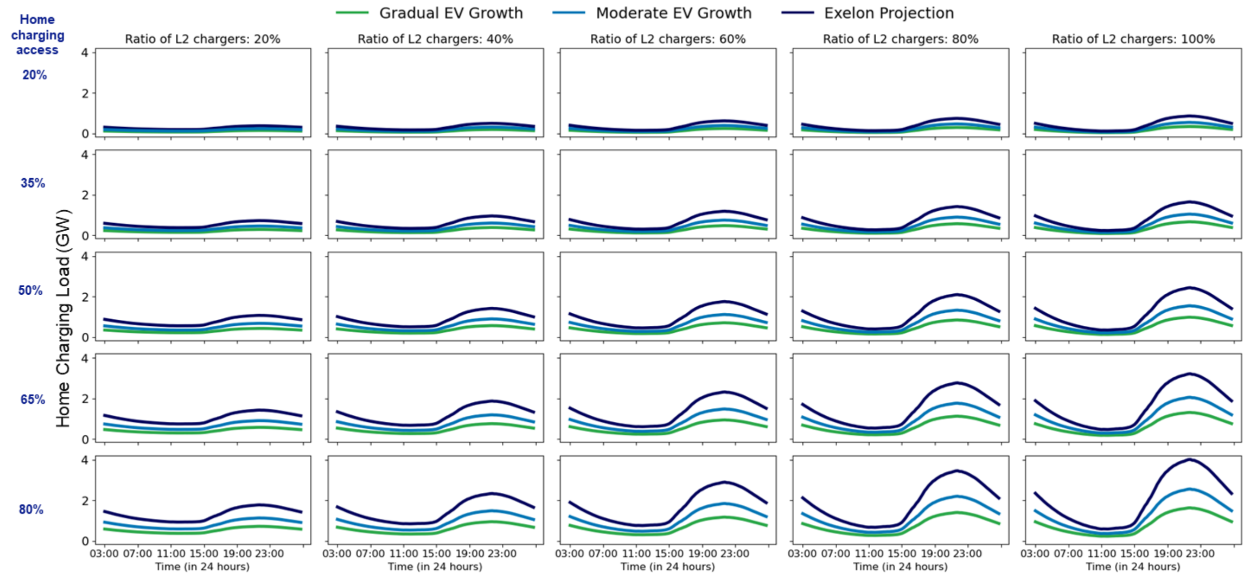

Figure 8 Home charging load profile in Chicago for 2035

In Chicago, with Exelon's BEV growth projection with 80% home charging access and 100% L2 charger adoption, the peak charging load is approximately 0.26 GW in 2025, 1.66 GW in 2030, and 4 GW in 2035. These correspond to BEV penetration levels of 2.2%, 13.8%, and 33%, respectively. Across all scenarios, the peak home charging loads occur in the evening hours, gradually declining overnight—a pattern consistent with post-travel charging behavior, as vehicles are typically plugged in after daily use.

Similar patterns were observed in the DC-Maryland region, where the peak home charging load in 2035 reaches approximately 2 GW, corresponding to 1.38 million BEVs, assuming the same parameters of 80% home charging access and 100% L2 charger adoption.

The public charging load profiles (Figure 9) exhibit consistent load shapes across all scenarios, with variations in magnitude. The highest peak public charging load occurs under Exelon's BEV projection, corresponding to the highest BEV adoption in 2035. The profiles also show that the peak public charging load decreases as home charging access increases (progressing from the top to the bottom charts). This trend highlights the impact of increased home charging access, which reduces reliance on public charging by enabling more BEVs to charge at home.

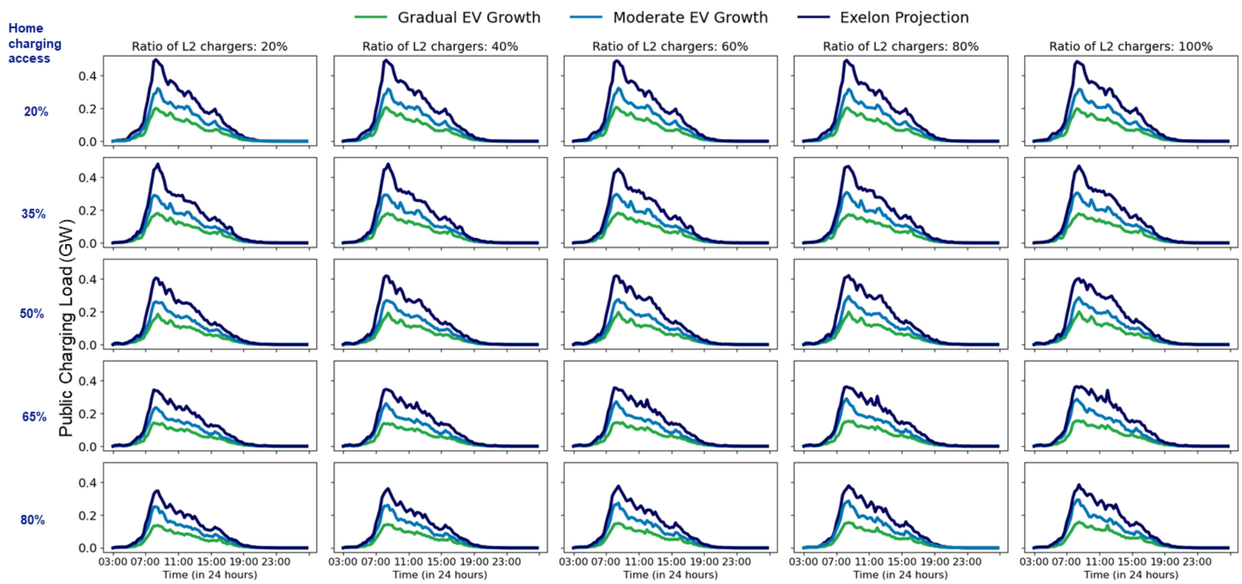

Figure 9 Public charging load profile in Chicago for 2035

Total daily electricity usage is significantly impacted by BEV growth projections, home charging access, and the L2 charger ratio. Figure 10 shows that total home charging electricity usage grows linearly with increasing BEV penetration. Furthermore, scenarios with higher home charging access exhibit a steeper rise in electricity usage, reflecting the increased demand from more BEVs being charged at home.

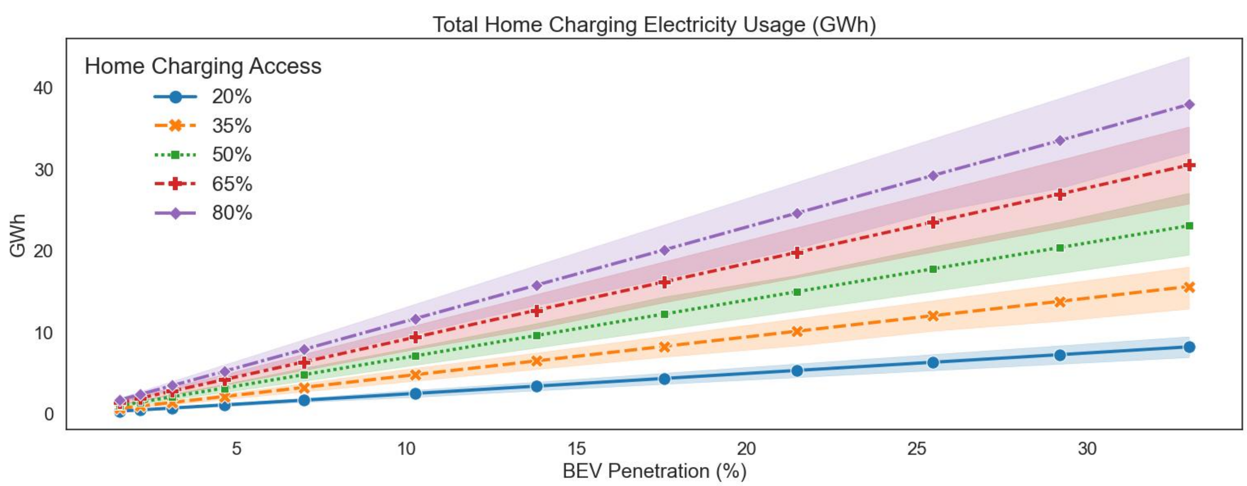

Figure 10 Total home charging electricity usage at varying BEV penetration levels in the Exelon BEV projection scenario for Chicago.

To quantify the impact of BEV penetration, home charging access, and the ratio of L2 chargers on total home charging demand, a linear regression model was developed, achieving a strong fit with an R-squared value of 0.85. The results show that all three variables—BEV penetration, home charging access, and the ratio of L2 chargers—are statistically significant at the 95% confidence level, emphasizing their critical influence on charging demand. Here are some key findings from the analysis.

- **BEV Penetration:** A 1% increase or decrease in BEV penetration results in a 660 MWh change in total home charging demand in Chicago. This finding highlights the dominant role of BEV adoption rates in driving overall demand. As BEV penetration grows, the demand for home charging rises substantially, underscoring the importance of long-term infrastructure planning and load management to accommodate this growth.
- **Home Charging Access:** A 1% change in home charging access contributes to a 190 MWh variation in charging demand. This underscores the critical role of access to home charging infrastructure in shaping electricity demand. High home charging access enables a larger proportion of BEV owners to charge at home, increasing residential grid demand. Conversely, limited home charging access may shift demand to public or workplace chargers, altering the grid distribution of electricity demand.
- **Ratio of L2 Chargers:** A 1% change in the proportion of L2 chargers leads to a 57 MWh change in total home charging demand. While the effect is smaller compared to BEV penetration or home charging access, the adoption of L2 chargers is still significant due to their higher charging power. Increased L2 charger adoption amplifies peak loads and overall charging demand, as these chargers deliver energy faster and at higher capacities than L1 chargers.

The regression analysis reveals the dominant role of BEV penetration in shaping home charging demand, emphasizing the need for accurate vehicle adoption forecasts to guide grid capacity planning. Additionally, policies and incentives that improve home charging access or encourage L2 charger adoption can significantly affect the spatial and temporal distribution of electricity demand, necessitating tailored grid management strategies.

As home charging access increases, the overall load profile retains its shape but grows substantially in magnitude, with higher peaks (Figure 11). Greater home charging access results in a larger total load, particularly amplifying the evening peak, while maintaining the consistent profile shape. This suggests that while increased home charging access drives greater demand, it does not fundamentally alter the temporal distribution of the load.

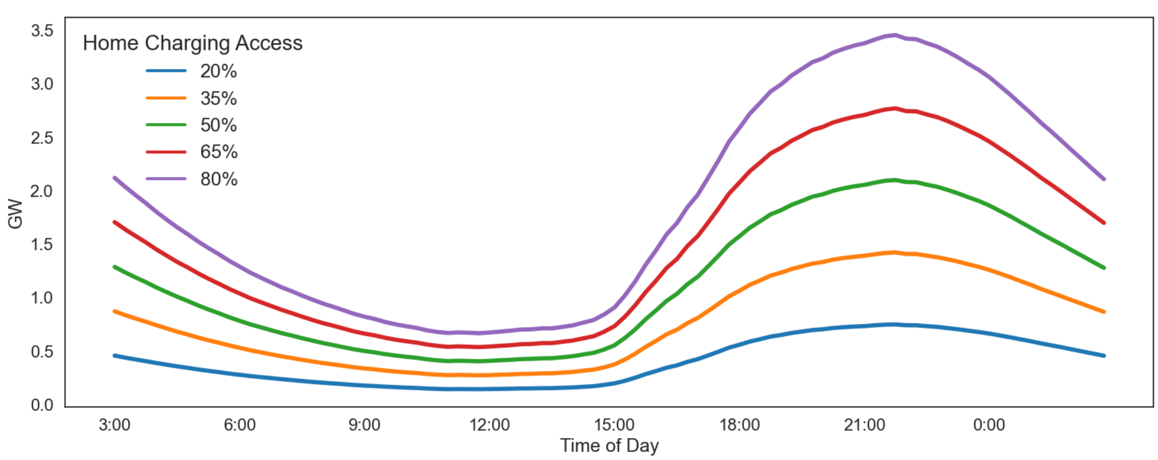

Figure 11 Daily home charging load profile for different home charging access scenarios in Chicago for 2035 (L2 charger ratio is 80%).

As the ratio of L2 chargers increases from 0% to 100% (Figure 12), the load profile undergoes significant changes. At lower ratios (e.g., 0%–20%), the load remains relatively flat, with a smaller and less pronounced evening peak. However, as the ratio of L2 chargers increases, the evening peak becomes significantly larger, and the ramp-up in demand during the late afternoon steepens. This reflects the influence of faster-charging technologies on load profiles. Unlike L1 chargers, which deliver approximately 1.4 kW and provide a slow, steady charge over several hours (requiring about 8 hours to fully recharge a depleted battery with a 40-mile electric range for a mid-size EV), L2 chargers operate at around 7.6 kW, allowing for significantly faster charging. They typically need only 1.6 hours to fully recharge a similarly depleted battery (AFDC). Consequently, when BEVs are plugged in after drivers return home—typically in the late afternoon and evening—the concentrated and shorter charging periods associated with L2 chargers lead to higher and more pronounced peaks in the load profile.

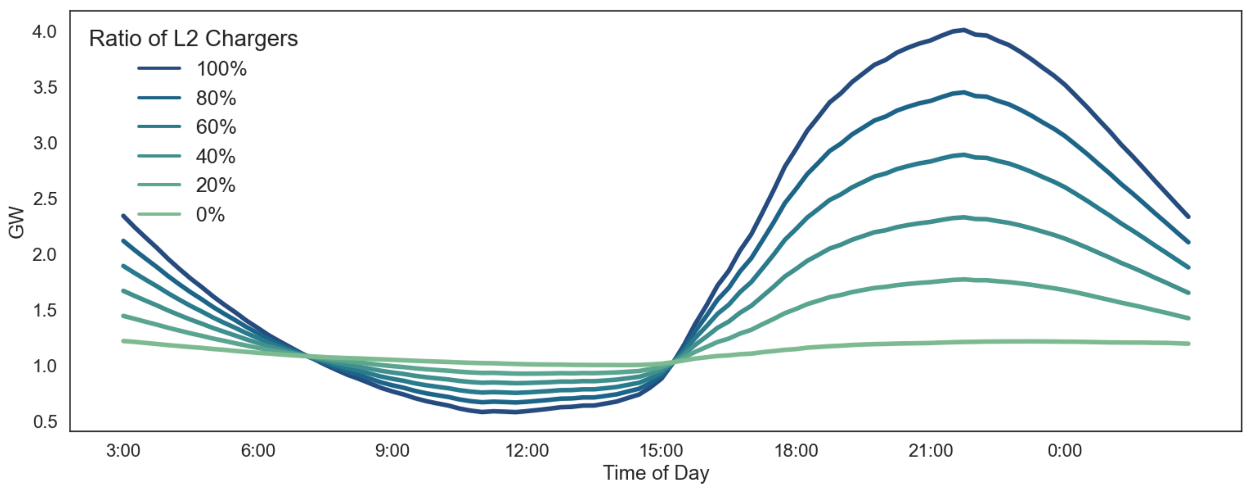

Figure 12 Daily home charging load profile for different proportions of L2 chargers in Chicago for 2035 (home charging access is 80%).

4.3. INSIGHTS FROM THE MANAGED CHARGING SCENARIO ANALYSIS

ATEAM4py provides detailed BEV-level activities, enabling the simulation of managed charging scenarios and creating BEV charging load profiles at the feeder level. For the U.S. Department of Energy-funded Smart Charging Management (SCM) Pilot project, we analyze how different SCM strategies reduce peak load and affect the grid under various enrollment scenarios. One key strategy, load balancing, optimizes BEV charging schedules to protect specific asset groups (e.g., feeders). Using BEV-level data from ATEAM simulations, we model individual BEVs' charging times to distribute demand more evenly.

The study assumed Exelon's projection for BEV growth rates for the SCM scenarios, with home charging access set at 80%. Four future SCM enrollment scenarios were analyzed for BGE and PHI service territories: no enrollment (unmanaged charging), maximum enrollment (with 50% of BEV owners enrolled by 2035), minimum enrollment (adding 1,000 BEVs annually), and steady growth (a linear increase from 2% to 8% between 2023 and 2029, followed by exponential growth reaching 38% by 2035). Figure 13 shows the yearly increase of BEVs and customer enrollment assumptions for different scenarios in Exelon territories in Maryland.

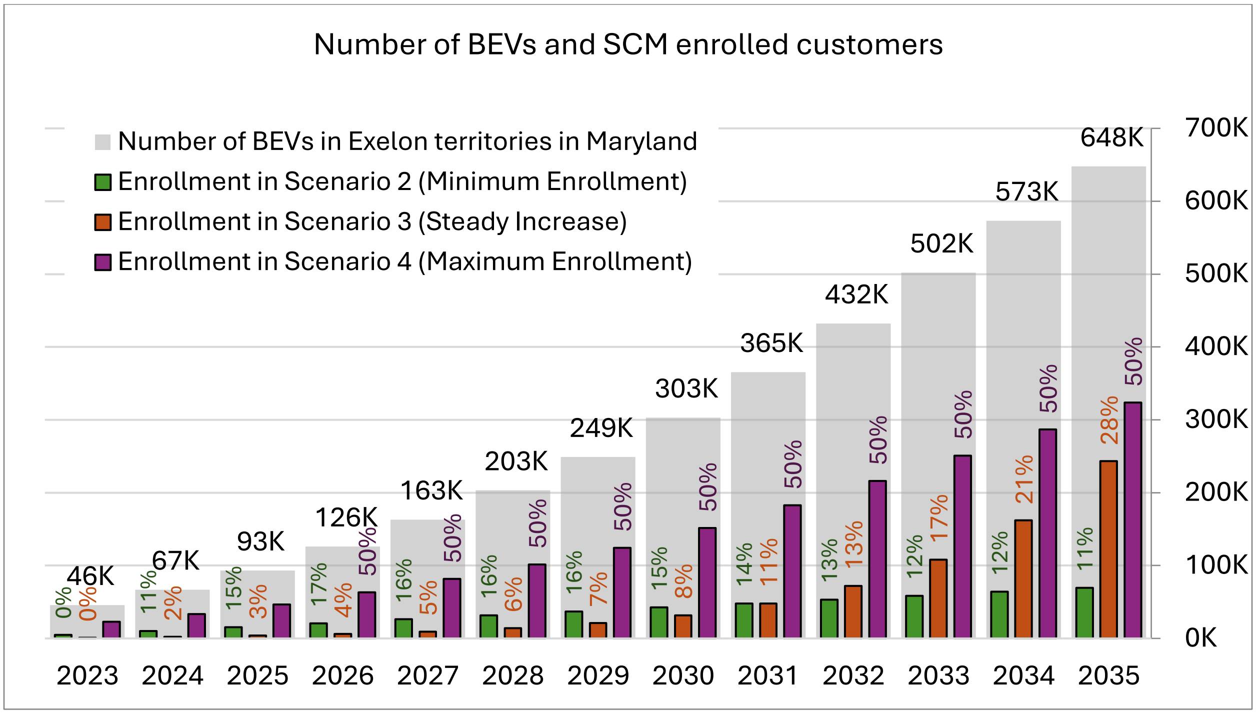

Figure 13 Number of BEVs and SCM-enrolled customers across different enrollment scenarios.

The outputs of the SCM scenarios include the daily home charging load profiles at a feeder level. Figure 14 compares the daily BEV charging load profile for an example feeder under unmanaged scenarios with managed charging scenarios at three different enrollment levels in 2035. At a 50% enrollment level, managed charging reduces BEV peak load by 38%.

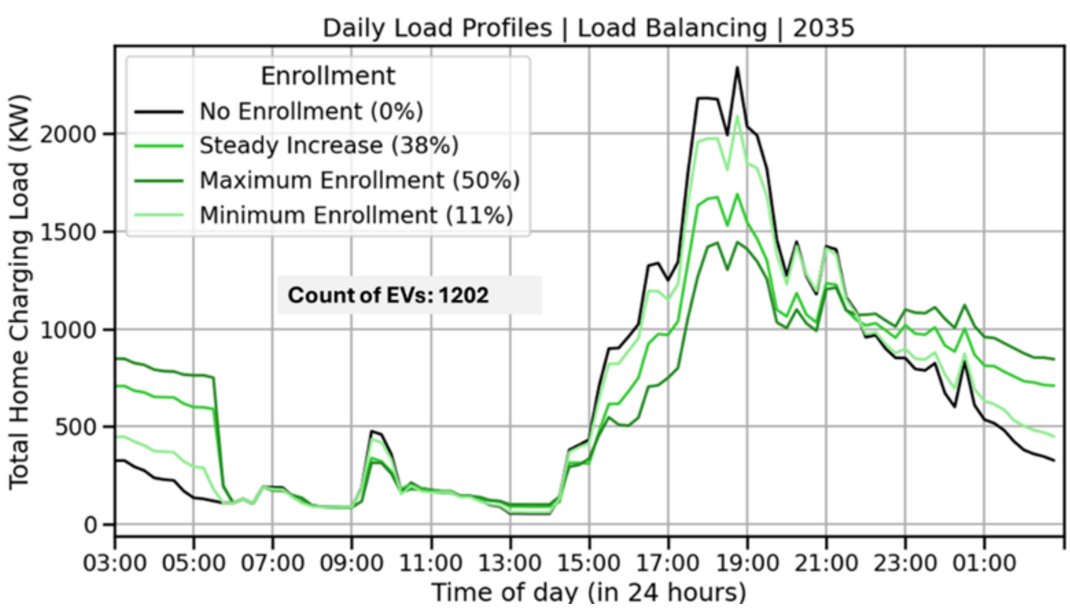

Figure 14 BEV charging load profile for an example feeder, comparing unmanaged and managed charging scenarios across different enrollment levels.

The feeder capacity and peak electricity load from other sectors (referred to as the base peak load) in the BGE and Pepco areas are analyzed to determine the capacity for future BEV home charging. To evaluate the impact of BEV charging load and assess how SCM can mitigate feeder overloading, the ratio of EV charging peak load to available capacity ratio is analyzed. Based on this ratio, feeders are categorized into three groups: 1) Moderate (ratio < 65%), 2) Moderately High (ratio between 65% and 80%), and 3) Overloaded (ratio > 80%). Feeders exceeding the 80% threshold are classified as overloaded, as network operators typically set this limit to ensure the secure and reliable operation of the distribution network. For feeders surpassing this threshold, reinforcement is recommended (ITF, 2024).

Results show that the percentage of overloaded feeders increases annually due to the growing BEV charging load. In the Pepco territory, approximately 1% of feeders will be overloaded in 2025, rising to 20% by 2035 if charging loads remain unmanaged (Figure 15). In the BGE territory, the situation is more critical, with around 5% of feeders overloaded in 2025, increasing to 34% by 2035, even with managed charging loads. SCM strategies can help reduce feeder overloads. For example, load balancing reduces the proportion of overloaded feeders in the Pepco territory from 20% to 13% under maximum enrollment scenarios. In contrast, in the BGE territory, load balancing achieves only a 1% reduction. This is due to the large number of feeders in the BGE territory with lower available capacity to handle EV charging, leading to higher overloading and less significant impacts from load management strategies.

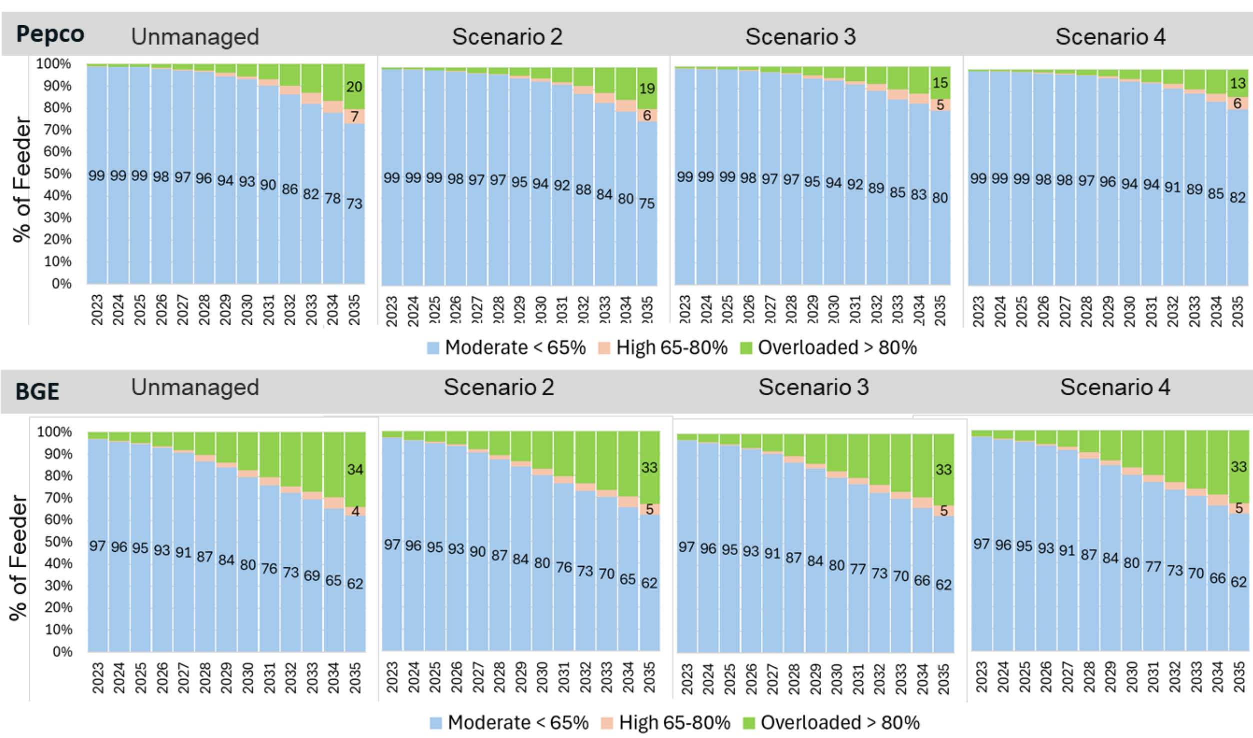

Figure 15 The share of feeders in different BEV peak load to available capacity ratio categories for different SCM scenarios.

5. FUTURE RESEARCH

Compared to the previous versions, the updated ATEAM4PY offers a much-improved modeling framework for future EV charging scenarios. However, there are a few limitations of the model which can be addressed in future work. Briefly, follow-on work could include:

- More granular examination of daily and seasonal variations in demand. Since travel and charging behavior vary not only across different days of the week but also by season, moving beyond the typical day modeled in the ATEAM applications conducted as of this writing to a more granular analysis could provide key insights into the potential for different load management strategies to deal with variable loads.
- Additional scenario analyses focusing public charging. New scenarios could be developed to account for different public charger locations and charging speeds, offering a more comprehensive assessment of their possible impact on regional load distribution.
- Further exploration of the potential future shift from home charging to public and workplace charging.
- Expanding EV charging analysis to include heavy-duty vehicles. A companion model could be developed to project charging demand of medium- and heavy-duty electric trucks at existing and planned distribution hubs. Since many of those hubs will have loads of 1 MW or more, an ABM incorporating the home bases or hubs where vehicles are housed overnight or for long durations, the destinations or distribution centers they serve, and driver behavior could provide insight into not only necessary infrastructure upgrades, but also opportunities for load management and vehicle to grid opportunities.

6. REFERENCES

American Community Survey (ACS), 2023. 2023. 2017–2021 American Community Survey 5-Year Estimates. U.S. Census Bureau. Available at: https://data.census.gov/.

Apley, D.W. and Zhu, J., 2020. Visualizing the effects of predictor variables in black box supervised learning models. Journal of the Royal Statistical Society Series B: Statistical Methodology, 82(4), pp.1059-1086.

Alternative Fuels Data Center (AFDC), (n.d.). Electric Vehicle Charging Stations. Available at: https://afdc.energy.gov/fuels/electricity-stations

Barua, L., Siddique, N., Zhou, Y. and Mintz, M., 2024. Electric Vehicle Charging Demand in the Chicago Metropolitan Area through 2030 (No. ANL/ESIA-24/6; A16155). Available at: https://www.osti.gov/biblio/2427945.

Collier, N.T., Ozik, J., and Tatara, E. Experiences in Developing a Distributed Agent-based Modeling Toolkit with Python, in 2020 IEEE/ACM 9th Workshop on Python for High-Performance and Scientific Computing (PyHPC), Nov. 2020, pp. 1–12. Available at: https://doi.org/10.1109/PyHPC51966.2020.00006.

Energetics, 2023. Electric Vehicle Widescale Analysis for Tomorrow's Transportation Solutions (EVWATTS). Available at: http://www.energetics.com/evwatts.

Experian, 2023. Auto Registration Database. Available at: https://www.experian.com/automotive/auto-vehicle-data.

ITF, 2024. "Advancing Sustainable Mobility in Greece: Promoting the Uptake of Electric Vehicles", International Transport Forum Policy Paper, OECD Publishing, Paris. Available at: https://www.itf-oecd.org/sites/default/files/advancing_sustainable_mobility-greece-ev_full_en.pdf.

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.

Powell, S., Cezar, G.V., Min, L., Azevedo, I.M. and Rajagopal, R., 2022. Charging infrastructure access and operation to reduce the grid impacts of deep electric vehicle adoption. Nature Energy, 7(10), pp.932-945.

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