ANL-25/14

Advancing Grid Resilience through Smart Charge Management: Findings from Maryland's Pilot

Transportation and Power Systems Division

Energy Systems and Infrastructure Analysis Division

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Advancing Grid Resilience through Smart Charge Management: Findings from Maryland's Pilot

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LIST OF ACRONYMS

AMI - Advanced Metering Infrastructure

ANL - Argonne National Laboratory

ATEAM - Agent-based Transportation Energy Analysis Model

BGE - Baltimore Gas and Electric

DPL - Delmarva Power & Light

DOE - U.S. Department of Energy

EJMU - Exelon's Joint Maryland Utilities

EV - Electric Vehicle

LB - Load Balancing

NPV - Net Present Value

Pepco – Potomac Electric Power Company

PJM - Pennsylvania-New Jersey-Maryland

PUC - Public Utility Commission

SCM - Smart Charge Management

SEPA - Smart Electric Power Alliance

TOU - Time-of-Use

Executive Summary

This report presents research findings from a four-year Smart Charge Management (SCM) pilot program conducted by Maryland's largest electric utilities—Baltimore Gas and Electric (BGE), Potomac Electric Power Company (Pepco), and Delmarva Power & Light (DPL)—to evaluate strategies for optimizing electric vehicle (EV) charging loads and enhancing grid stability. Supported by the U.S. Department of Energy (DOE), Argonne National Laboratory collaborated with all project partners and examined the effectiveness of Time-of-Use (TOU) and Load Balancing (LB) strategies in managing peak demand, deferring costly infrastructure upgrades, and reducing grid constraints at the feeder level.

Using charging data from over 4,600 EV drivers, the study analyzed SCM's impact on the distribution systems of BGE and Pepco, which consists of over 2000 feeders. Unlike prior research that focused on system-wide trends or synthetic feeders, this analysis offers granular, feeder-level insights based on real-world operational data. It highlights how transformer density, load profiles, and infrastructure constraints influence smart charging performance. Results show feeder-level conditions play a crucial role in SCM effectiveness, with most feeders benefiting more from LB, while TOU-based SCM may be sufficient for others. By 2035, LB reduced peak charging loads by 27% on average, compared to 23% under TOU-based SCM, though some feeders saw reductions exceeding 35%, while others experienced minimal impact. Feeders with higher transformer utilization and limited capacity benefited more from LB, which more effectively distributed charging demand during off-peak hours.

Beyond reducing grid constraints, SCM offers long-term operational and financial benefits. By shifting EV charging demand strategically, utilities can optimize asset utilization, delay infrastructure investments, and enhance grid performance. In terms of infrastructure upgrade deferrals, at the feeder level, LB consistently reduced peak charging loads and resulting infrastructure upgrade costs, particularly in high EV enrollment areas, decreasing the number of overloaded transformers by up to 35%, while TOU-based SCM achieved 20-30% reductions depending on feeder characteristics. At the system level, LB has the potential to defer total upgrade costs by $186 million for BGE, compared to $159 million under TOU-based SCM. For Pepco, TOU-based SCM performed slightly better, deferring upgrade costs by $30 million, compared to $29 million under LB. Section 4.5 reviews some of the system differences between BGE and Pepco. However, as EV adoption scales, TOU-based SCM will introduce secondary peak charging loads, reinforcing the need for more advanced, adaptive SCM approaches to prevent new grid challenges.

As EV adoption continues to grow, feeder-level managed charging strategies will be essential for mitigating grid stress, improving infrastructure efficiency, and maintaining energy affordability for consumers. This report provides critical insights for utilities, Public Utility Commissions (PUCs), and state agencies on the role of feeder-specific smart charging in infrastructure planning, policy development, and grid modernization. The findings underscore the importance of tailored, data-driven SCM solutions that align with local grid conditions, ensuring a resilient, cost-effective response to increasing demand while safeguarding distribution system performance. The primary finding of this study is that implementing grid integration strategies yields major benefits, chiefly through avoided infrastructure upgrade costs in the studied region.

1 Introduction

Since 2021, Maryland's largest electric utilities—Baltimore Gas and Electric Company (BGE), Potomac Electric Power Company (Pepco), and Delmarva Power & Light (DPL), collectively known as Exelon's Joint Maryland Utilities (EJMU, referred as the Joint Utilities in the rest of the report)—have been conducting a Smart Charge Management (SCM) pilot supported by the U.S. Department of Energy (DOE). This four-year pilot, which concluded on December 31, 2024, aimed to develop and demonstrate a large-scale utility SCM system to optimize EV charging for grid resilience and cost-effectiveness. Argonne National Laboratory (Argonne) collaborated with the Joint Utilities, WeaveGrid, and the Smart Electric Power Alliance (SEPA) on various research tasks, including charging protocol and standard testing, cybersecurity assessments, charging behavior modeling, and grid economic impact analysis. This report covers the research findings from the last two research tasks.

Unlike other electricity loads, EV charging is highly adaptable, providing a key opportunity to strategically shift demand away from peak periods, reduce grid stress, and improve system resilience. By testing increasingly sophisticated SCM strategies, the pilot sought to optimize home charging to align with grid reliability needs while ensuring customer convenience. Starting in May 2023, the Joint Utilities partnered with WeaveGrid to implement advanced SCM strategies that created charging schedules tailored to both driver preferences and grid needs. Customers voluntarily opted SCM controls, allowing automated charge scheduling while retaining the ability to override the WeaveGrid-optimized schedule if necessary. Participants could set their preferred "ready-by" time and target state of charge, informing the system's dynamic charging windows. As part of the pilot, WeaveGrid collected real-world charging session data and compiled weekly charging reports. Argonne leveraged data from these reports to analyze charging behavior and developed future EV adoption scenarios with expanded SCM enrollment.

Argonne's research focused on assessing the impact of EV charging on local distribution operations and quantifying how smart charging can defer costly grid upgrades by reducing peak demand and improving asset utilization. A key component of the research involved comparing the effectiveness of different utility-scale SCM strategies in shifting and optimizing EV charging loads, and the resulting reduced upgrade costs of distribution systems. Operational conditions of real-world distribution feeders under different SCM methods and various enrollment scenarios were considered. The analysis spans from 2022 to 2035, assessing EV charging demand patterns of SCM, distribution systems upgrade requirements, and the deferred infrastructure investment for the Joint Utilities. EV in this analysis refers to battery electric vehicles that operate solely on electricity.

Following this introduction, Section 2 presents the data sources and methodology used in the study, including feeder modeling techniques. Section 3 describes the scenarios analyzed, while Section 4 discusses the results, focusing on home charging loads under different SCM strategies, particularly for BGE and Pepco. Finally, Section 5 summarizes key insights and their implications for future infrastructure planning.

2 Data and Methodology

This chapter outlines the framework and methods used to assess the impact of EV charging on power distribution systems and to determine necessary infrastructure upgrades. The Argonne analysis integrates diverse datasets, including Advanced Metering Infrastructure (AMI) base load profiles, EV charging behavior, and distribution feeder characteristics. These inputs form the basis for a load flow analysis using simulation tools to model distribution system behavior under various scenarios. Figure 1 illustrates the framework of the analysis. Argonne utilizes the Agent-based Transportation Energy Analysis Model (ATEAM) to simulate EV charging loads and project future charging infrastructure needs, as detailed in Section 2.1. The study evaluates two smart charging strategies—Time-of-Use (TOU) and Load Balancing (LB)—across multiple enrollment scenarios from 2022 to 2035, reflecting different levels of EV adoption and smart charging participation for a representative day, which are further explored in Chapter 3.

Real-world feeder data collected from BGE and Pepco is converted and analyzed to understand the electrical characteristics of the power grid system, as described in Section 2.2. Upgrade strategy along with cost estimations for necessary infrastructure upgrades were conducted using data from the National Renewable Energy Laboratory (NREL), as outlined in Section 2.3.

Detailed load profiles are created by integrating the base load and EV load for representative feeders, allowing for a comprehensive assessment of the distribution system's capacity and performance, as explained in Sections 2.4 and 2.5. A time-series load flow analysis identifies system vulnerabilities, guiding targeted upgrade strategies, which are discussed in Section 2.6. Finally, an economic analysis estimates the costs of scaling up infrastructure upgrades across the entire service territory for BGE and Pepco, using clustering and regression techniques, as described in Section 2.7.

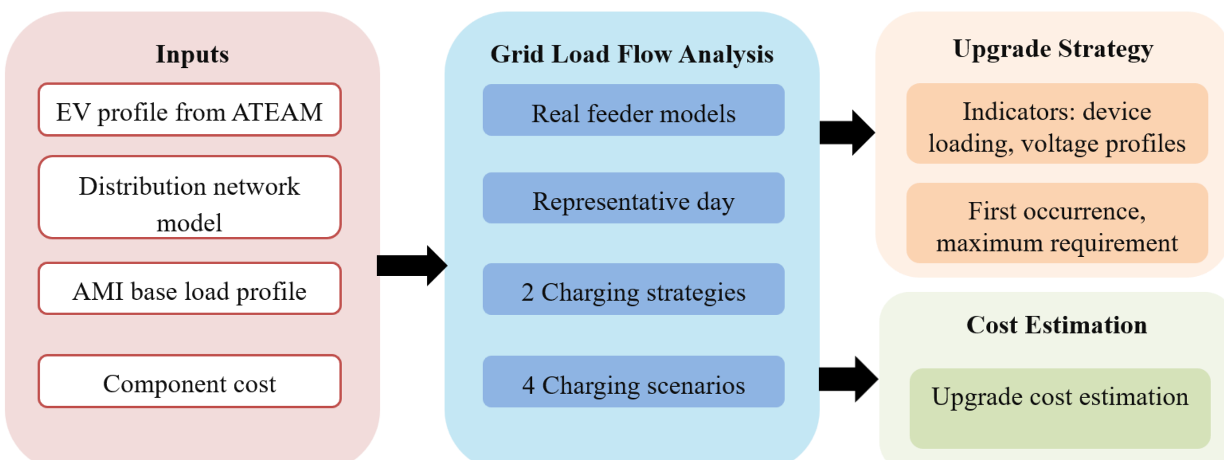

Figure 1 Workflow diagram of feeder level grid impact analysis

This structured approach provides a thorough evaluation of the impacts of EV charging on distribution power systems, offering insights into effective strategies for grid management and infrastructure planning.

2.1 EV Charging Simulation using ATEAM

This study used ATEAM, an agent-based simulation model co-developed by Argonne and Exelon, to estimate the daily and annual EV charging load at a census tract-level based on various inputs and scenario-based assumptions. The model incorporates diverse baseline data, including existing vehicle registrations, charging infrastructure, household characteristics, travel demand patterns, charging behaviors, and forecasts of future EV growth. The simulation outputs include the regional distribution of EVs, recommended charging infrastructure deployment locations, and daily charging load profiles. An overview of ATEAM's inputs and outputs is presented in Figure 2. Mintz et al. (2019) and Zhou et al. (2022) provide detailed explanations of the ATEAM model methodology.

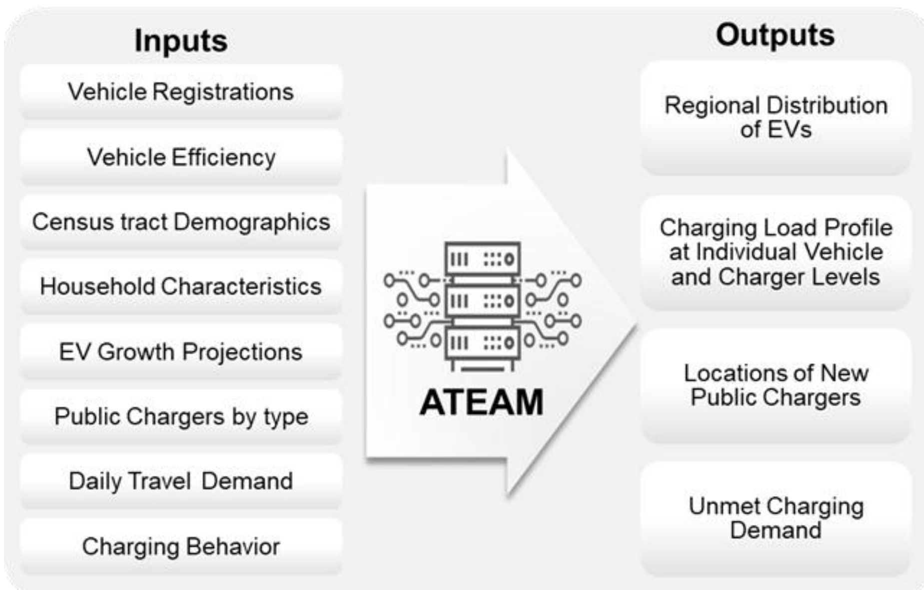

Figure 2 Inputs and outputs of ATEAM

The EV charging simulation in ATEAM is initiated by first estimating the number of EV drivers in each census tract. The base-year EV adoption is derived from the Maryland Vehicle Administration (MVA, July 2022) (Maryland Gov., 2020) and Experian (Q3 2022) (Experian, 2022), while future EV growth is informed by BGE forecasts (Exelon, 2022). Once EV fleet composition for each census tract is established, vehicles are randomly assigned to households within those tracts. Vehicle travel patterns are simulated using data from two complementary travel surveys: the 2018–2019 Maryland Travel Survey (MTS, 2020) and the 2017-2018 Regional Travel Survey (RTS, 2021). These surveys, conducted concurrently, provide detailed information on households' daily travel patterns, trip characteristics, and socio-demographic profiles, ensuring comprehensive spatial and temporal coverage of the study area.

The input data used in ATEAM for this study is summarized in Table 1. This study assumed that EV adoption follows historical patterns, where census tracts with higher household income and existing EV adoption exhibit higher future adoption rates.

Table 1 Input parameters of ATEAM

Topic	Key Input Parameters	Source/Value
EV	Existing EV Distribution	MVA (July 2022) + Experian (Q3 2022)
	EV Drivers' trip-chain	MTS, 2020 + RTS, 2021
	EV Adoption Target	BGE Projection
	Future EV efficiency (in kWh/100 mi)	Energy Information Administration's Annual Energy Outlook, 2022
EVSE	Home Charger Availability	80%
	Existing Public Chargers	AFDC (AFDC, 2022)
	Share of Public DC50/DC150kW chargers	50-50
Simulation	Simulation Start Year	2022
	Simulation End Year	2035
	Daily Simulation Interval	15 minutes
Road	Road network	TIGER/Line Shapefiles (U.S. Census Bureau, 2023)

ATEAM simulates driver activity over a two-day period based on trip chain data. On the first day, all EVs start with a fully charged battery. For subsequent days, vehicles with home charging also start the day fully charged. Each driver completes daily trips in sequence, following the shortest route within their trip chain. At the start of each trip, drivers anticipate their next three trips and assess whether their remaining state of charge (SOC) might drop below a predefined comfort threshold. If necessary, they use public charging to ensure sufficient range for completing the trip. At the end of the day, drivers with home charging access plug in their vehicles upon returning home, and charging continues until 1) the vehicle SOC reaches a pre-defined threshold or 2) the next day's first trip, whichever comes first. At the conclusion of the simulation, ATEAM generates a vehicle output file that records all EV activities, including home charging start and end times. This data represents the *Unmanaged* home charging profiles used in this study. Figure 3 illustrates a sample load profile for a census tract in 2035 with approximately 850 EVs.

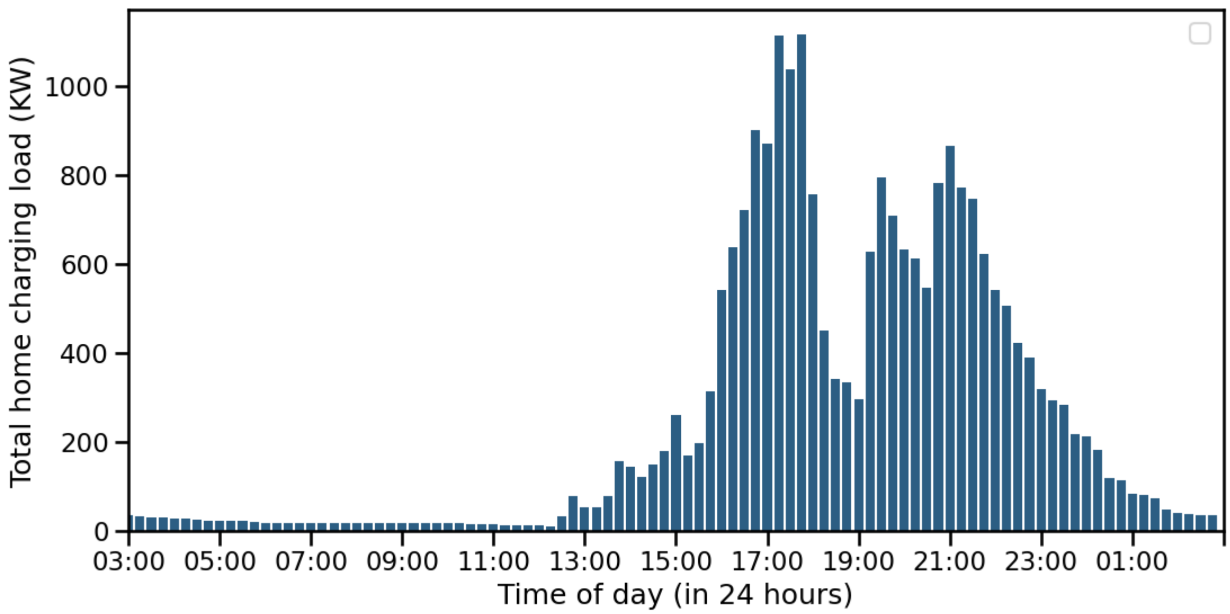

Figure 3 Unmanaged home charging load profile of a census tract in 2035

2.2 Feeder Data from BGE and Pepco

BGE's network comprised a total of 1,320 feeders, while Pepco's network consisted of 722 feeders. Figure 4 and Figure 5 depict the distribution of feeders within BGE and Pepco by voltage class. Both BGE and Pepco have a larger share of feeders with 13.8 kV voltage class.

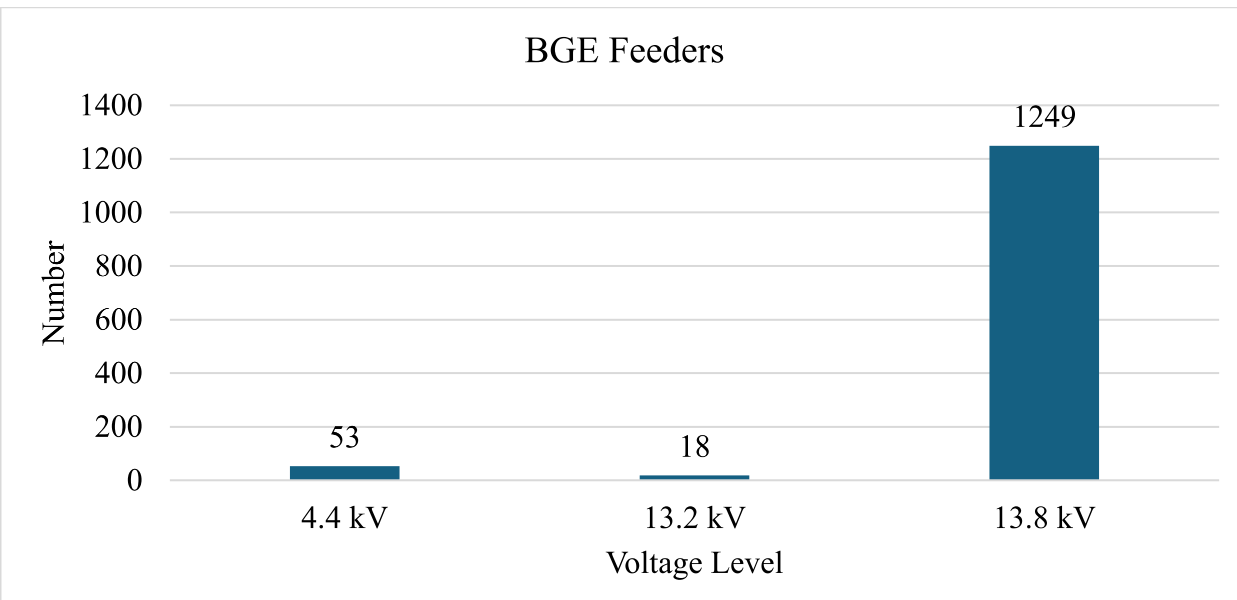

Figure 4 BGE feeders by voltage class

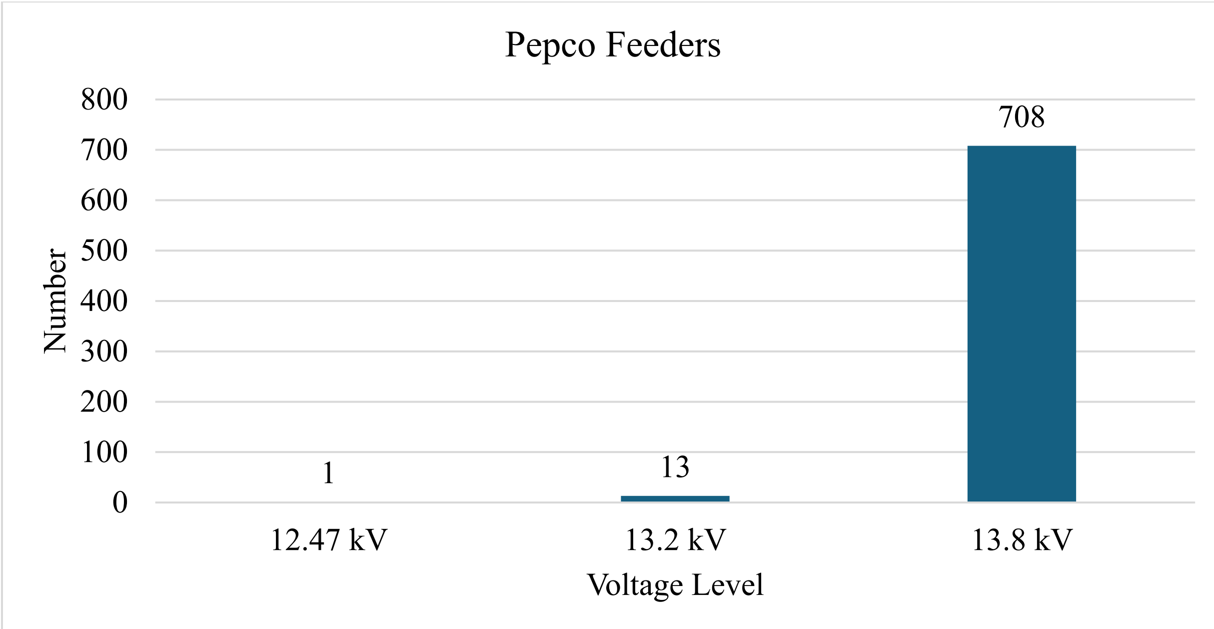

Figure 5 Pepco feeders by voltage class

The feeder characteristics, originally provided in CYME[1] format, were converted to OpenDSS format for power system analysis, as OpenDSS is an open-source software. Since existing conversion tools were primarily designed for single-feeder files and required adaptation for updated versions of CYME, a customized approach was developed. Additionally, variations in file structures from BGE and Pepco were addressed by refining the conversion process to ensure consistency and completeness.

However, there are incomplete load information, and anomalous values such as negative loads in the CYME files. To address these issues, a comprehensive validation and adjustment process was conducted. The load data in the CYME files was cross-referenced with their corresponding OpenDSS files for further analysis to ensure consistency and enhance the data reliability for the power system analysis. These steps were critical for ensuring the accuracy and validity of the analytical results.

Iterative comparisons between the original CYME files and the converted OpenDSS files helped verify data integrity, while targeted modifications addressed differences in conductor specifications, load information, and structural formats across utilities. By refining the conversion code and applying tailored corrections, the process was streamlined, ensuring reliable inputs for analysis.

Figure 6 and Figure 7 illustrate a geographical overlay of the feeder data in the OpenDSS environment, combining geospatial information with the electrical characteristics of the power system. This overlay integrates the physical locations of substations, feeders, transformers, and distribution lines with system topology data, such as distances, connectivity, and geographical

[1] CYME is a suite of power engineering software solutions developed by Eaton. https://www.eaton.com/us/en-us/digital/brightlayer/brightlayer-utilities-suite/cyme-power-engineering-software-solutions.html

alignment. The OpenDSS format enables precise representation of the feeder layout, providing a comprehensive visualization of the system's physical and electrical structure for enhanced analysis.

Due to the large number of feeders for both BGE and Pepco, analyzing each individual feeder for the entire service territory was beyond the scope and time of this study. Therefore, Argonne, BGE and Pepco selected a set of representative feeders for each utility service area- 10 for BGE and 9 for Pepco, for detailed analysis. The selected feeders serve different customer types (residential and commercial) and operate across diverse geographical settings, including urban, suburban, and rural areas. The characteristics of these representative feeders are detailed in Table 2 and Table 3.

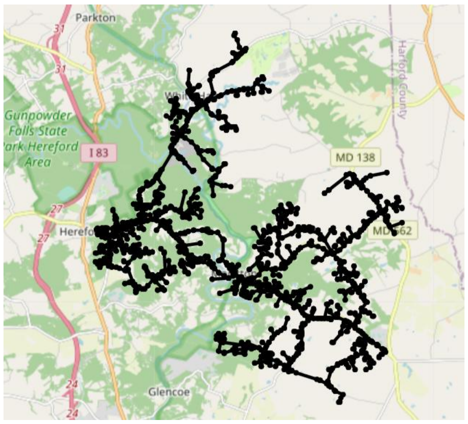

Figure 6 Geographical overlay of BGE feeder B1

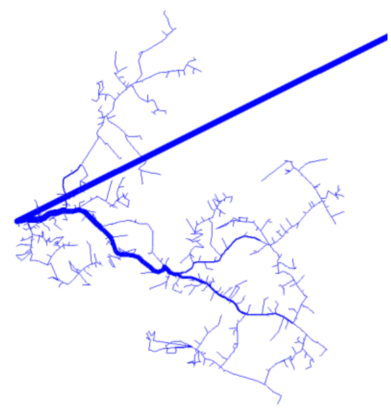

Figure 7 Circuit plot of BGE feeder B1 in OpenDSS

Table 2 Characteristics of 10 BGE feeders

Feeder	Voltage	Feeder Type	Number of transformers	Number of lines
B1	13.8 kV	rural, mainly residential load, heavily populated	685	3099
B2	13.8 kV	suburban, mainly residential load, heavily populated	232	1142
B3	13.8 kV	rural, residential load, not heavily populated	92	448
B4	13.8 kV	suburban, mainly residential load, heavily populated	396	1729
B5	13.8 kV	suburban, mainly residential load, heavily populated	194	812
B6	13.8 kV	suburban, mixed commercial/residential load	52	361
B7	13.8 kV	suburban, mainly commercial load, not heavily populated	69	342
B8	13.8 kV	suburban, mixed commercial/residential load not heavily populated	169	927
B9	13.8 kV	urban, mainly commercial loads, not heavily populated	98	668
B10	13.8 kV	urban, mixed commercial/residential load, heavily populated	126	858

Table 3 Characteristics of 9 Pepco feeders

Feeder	Voltage	Feeder Type	Number of Transformers	Number of Lines
P1	4.33 kV	NA	28	92
P2	13.2 kV	urban, mainly residential, not heavily populated	201	663
P3	13.8 kV	NA	45	383
P4	13.2 kV	urban, mostly mixed use, heavily populated	51	372
P5	13.8 kV	urban, mixed commercial/residential load, not heavily populated	89	386
P6	13.2 kV	urban, mixed commercial/residential load, heavily populated	33	343
P7	13.8 kV	NA	94	546
P8	13.8 kV	downtown urban, mostly commercial, heavily populated	59	345
P9	13.8 kV	NA	61	374

2.3 Base Load

The CYME files provided by BGE and Pepco contain a snapshot of the base load for each feeder in 2022 but do not include 24-hour load values. To develop a full 24-hour load profile, Argonne incorporated hourly load factors derived from AMI data.

To project future load growth, Argonne used the 2022 Pennsylvania-New Jersey-Maryland (PJM) Load Forecast Report, which indicates that the non-EV base load (including residential, commercial, and industrial demand) in the study area increases at an annual rate of 0.8%. Based on this growth rate, the load multiplier is defined as:

$L_t = L_0 \times 1.008^t$

Where:

- L_t = Load at year t
- L_0= Base year load
- t= Number of years from the base year

To generate hourly feeder-level load profiles, Argonne first derived hourly load factors from 2022 AMI data. These factors represent the ratio of load at each time step to the annual peak load and are specific to residential, commercial, and industrial demand patterns. The team then applied these factors to the snapshot load from CYME, scaling them appropriately using a feeder-specific adjustment factor to account for localized demand variations. Finally, Argonne integrated these adjustments with the projected base load to construct 24-hour load profiles for all non-EV base loads.

This methodology aims to represent accurately both temporal and spatial variations in feeder-level demand. Figure 8 illustrates the base load profile of a sample feeder for 2022, alongside the projected base load for 2035. Note that this study does not account for potential significant increases in non-EV loads resulting from cross-sector electrification, such as building heating and industrial electrification.

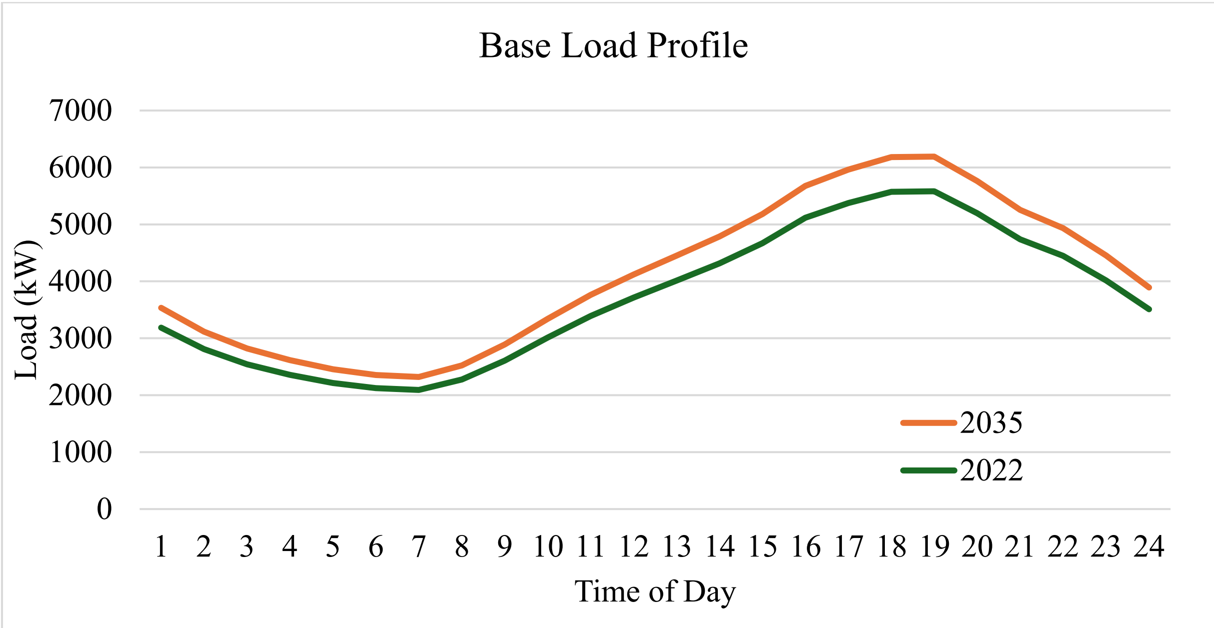

Figure 8 Base load profile for feeder B1

2.4 EV Charging Load

The charging load from ATEAM is available at the census tract level. Each census tract can have multiple feeders passing through it, and each feeder consists of multiple buses. To estimate the charging load at each feeder, Argonne developed a method to spatially map feeder assets (buses) to census tracts by associating their latitude and longitude with the corresponding census tract boundaries.

Ideally, this mapping is exact, meaning every feeder asset is assigned to a census tract. However, this requires access to the full distribution network for the study area. When all feeder assets are mapped, the next step is to distribute the EV load—aggregated at the census tract level—across individual buses within the tract. To do this, Argonne allocated the EV load proportionally based on the existing base load at each bus, ensuring that buses with higher base loads receive a larger share of the EV load.

If some feeder information is missing, certain assets may remain unmapped, which poses a challenge. Distributing the full EV load among only the mapped buses would overestimate their EV demand, as the load that should be shared among all buses would be concentrated on a smaller subset. Additionally, since the base loads of unmapped buses are unknown, their contribution cannot be directly estimated.

To address this, ANL implemented a probabilistic approach to redistribute the EV load when feeder information is incomplete. This method introduces a parameter p, which determines how extensively the load is reassigned:

- **p = 0** results in a zero-radius search (no reassignment of unmapped nodes).
- **p = 1** extends the search radius to encompass the entire census tract.

This method effectively assigns unmapped EV loads to mapped feeder assets, maintaining a realistic spatial distribution of EV charging demand.

2.5 Feeder-level Load Flow Analysis

This study conducted a feeder-level analysis to evaluate the impact of total load—comprising base load and EV charging load—on the power grid for selected BGE and Pepco feeders from 2022 to 2035. To capture seasonal variations in loading conditions, Argonne analyzed three representative dates corresponding to summer, winter, and spring/fall. Among these, summer exhibited the highest peak load, leading to the most severe overloading scenarios. As a result, a representative day in July reflecting summer conditions became the primary focus for detailed analysis and upgrade evaluations.

To assess system vulnerabilities, including overloaded lines, transformer capacity constraints, and voltage violations, a time-series load flow analysis was conducted using the open-source software OpenDSS. OpenDSS is a power distribution system simulator widely used for planning and analyzing distributed generation integration with utility networks. It supports various frequency-domain simulations and employs a current injection model as the default method for load flow analysis. Using a fixed-point iterative approach, OpenDSS efficiently handles most distribution systems with a stiff bulk power source. Its computational speed makes it particularly suitable for yearly-mode and long sequential-time simulations.

The load flow solution is based on solving the nonlinear system admittance equation:

$$I_{inj}(V)=Y_{system}V$$

Where $I_{inj}(V)$ is compensation, or injection, currents from Power Conversion (PC) elements in the circuit, which may be nonlinear elements, V is the voltage and Y_{system} is the main system admittance matrix.

Findings from this assessment inform a targeted upgrade strategy, minimizing premature capital expenditures by scheduling equipment upgrades in the first year an overload is detected. Capacity upgrades are designed to accommodate the highest projected demand during the study period, ensuring long-term system reliability while optimizing investment efficiency.

2.6 Upgrade Strategy and Cost Analysis

The upgrade strategy is determined based on indicators such as voltage profile, transformer loading, and line loading. System upgrades are triggered at the first occurrence of an overload, with capacity added to accommodate the maximum projected load through 2035. For instance, if an overload is first observed in 2025, upgrades are implemented that year to handle anticipated load growth until 2035.

Component upgrade costs were from the NREL cost database (Horowitz 2019), which provides unit costs of various components in distribution networks. The database includes costs for reconductoring distribution lines, transformers, conductors, capacitors and regulators.

A cost estimation is carried out to determine the investment required to upgrade the overloaded infrastructure. The Net Present Value (NPV) of the upgrade cost is calculated using a discount rate of 3% (NYSERDA, 2022), with 2022 as the base year. This framework provides a structured approach to evaluating the impact of EV charging on power distribution, ensuring that infrastructure is upgraded efficiently.

2.7 System-wide Analysis

This study conducted a system-wide analysis to estimate the cost of distribution system upgrades needed across all feeders to mitigate capacity constraints. The flowchart in Figure 9 outlines a structured methodology adopted for system -wide analysis. The process begins with the collection of feeder data, including voltage levels, transformer capacities, line configurations, and existing load conditions, which serve as the foundation for subsequent analysis. To manage the complexity of analyzing numerous feeders, clustering techniques, such as k-means, are applied to group feeders with similar characteristics. From these clusters, a few representative feeders are selected to capture variations in the network while reducing computational effort. Load flow analysis is then performed on these representative feeders to assess key performance indicators, such as voltage profiles, transformer loading, and line loading, under different load conditions, including scenarios involving EV integration. The results from this analysis are used to develop a linear regression model, which estimates the cost of scaling up infrastructure upgrades for the entire distribution network. This predictive model helps utilities estimate investment requirements for various EV penetration scenarios while optimizing grid reinforcement strategies.

Five clusters were identified, with 10 representative feeders selected from each cluster based on their proximity to the cluster centroids. Clustering was based on combined Principal Component Analysis (PCA) and K-Means clustering to categorize feeders based on key characteristics, including:

- Feeder voltage level
- Peak base load
- Peak EV load
- Total transformer capacity
- Transformer type and number
- Line type and line count (underground or overhead sections within the feeder)
- Load type and load value of each type (Residential, Commercial, Industrial or any other load types being served by the feeder)

The linear regression model incorporates key parameters such as base load peak, EV load peak, and transformer capacity to formulate an equation for estimating upgrade costs. This derived model was then applied to the remaining feeders within each cluster, enabling a systematic and data-driven approach to extrapolate upgrade costs across the entire BGE and Pepco service territories.

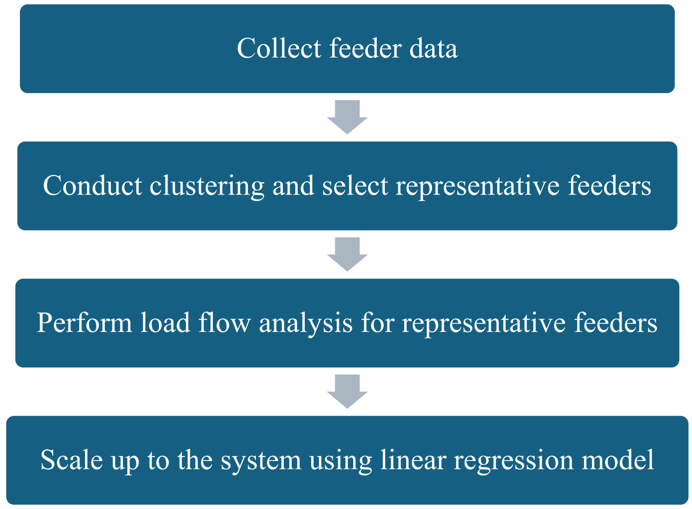

Figure 9 Methodology for system-wide cost estimation

3 Study Scenarios Design

As part of the SCM pilot, WeaveGrid delivered weekly charging reports containing session data from EV drivers participating in the program. From April 2023 to October 2024, the dataset comprised records from 4,661 EV users and 1,203,912 charging sessions. In collaboration with the Joint Utilities and WeaveGrid, several SCM strategies were developed and implemented, including *TOU-based SCM*, *PJM pricing-based SCM*, and *Load Balancing (LB)*. Argonne's analysis specifically examined the TOU-based SCM and LB strategies.

The *TOU-based SCM* strategy aims to reduce charging demand during the TOU peak hours, defined by Argonne as 5 p.m. to 9 p.m. Under this strategy, charging is paused for enrolled EVs which are plugged in during this window and resume charging after 9 p.m. Details on how this strategy is implemented are in Appendix A.

The *LB* strategy groups consumers by grid assets, such as feeders, transformers, or substations, to smooth charging loads within each group. This strategy reschedules charging sessions to prevent overloads, more evenly distributing charging overnight. During periods of high demand, *LB* optimizes the peak load by pausing certain charging sessions and shifting them to lower-demand times. The implementation details of this strategy are provided in Appendix B.

Through discussions with BGE and Pepco, four scenarios were selected for analysis to evaluate future SCM enrollment in their service territories:

- No enrollment (*Unmanaged* charging)
- Minimum enrollment (11% by 2035)
- Steady growth (a linear increase from 2% to 8% between 2023 and 2029, followed by exponential growth reaching 38% by 2035).
- Maximum enrollment (50% of EV owners enrolled each year)

Figure 10 shows the yearly increase in EVs and the customer enrollment assumptions for these scenarios in BGE and Pepco territories in Maryland.

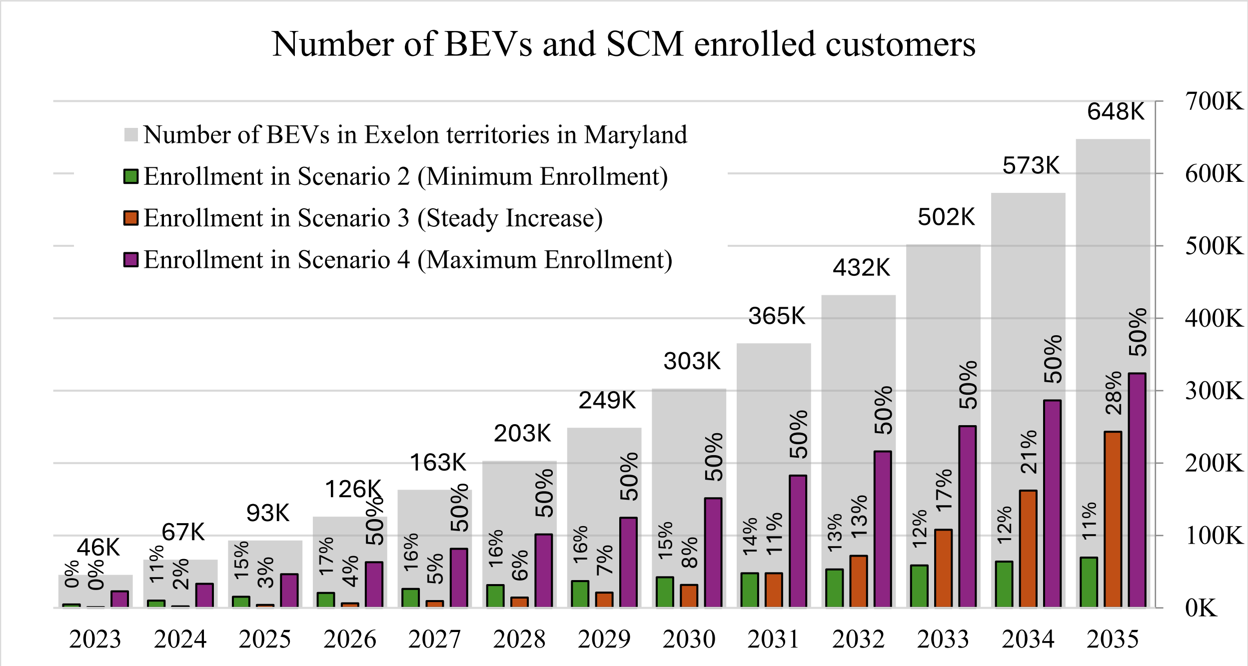

Figure 10 Number of EVs, and SCM enrolled customers in BGE and Pepco service territories for different enrollment scenarios

4 Analysis Results and Discussions

4.1 EV Home Charging Load

Argonne generated home charging load profiles for *Unmanaged, TOU-based SCM, and LB SCM* strategies for each enrollment scenario discussed in Chapter 3. This subsection evaluates the performance of SCM strategies by analyzing EV charging loads across 19 selected feeders (10 from BGE and 9 from Pepco). The analysis in this section focuses solely on home charging loads from EVs.

4.1.1 Home charging load across different SCM strategies

A comparison of the charging load between *Unmanaged* and the two SCM strategies (*TOU-based* and *LB)* under the *Maximum Enrollment* scenario, shown in Figure 11, revealed that the *Unmanaged* scenario generates a sharp peak around 7:00 p.m., coinciding with when EV owners typically return home and plug in their EVs. In this scenario, the charging load gradually builds throughout the day, reaching a peak in the evening before decreasing overnight. The peak charging load rises each year from 2022 to 2035 due to the increasing number of EVs. With a 19.5-times increase in EV adoption in the study area over this period, the peak charging load rises by almost 18 times in this scenario.

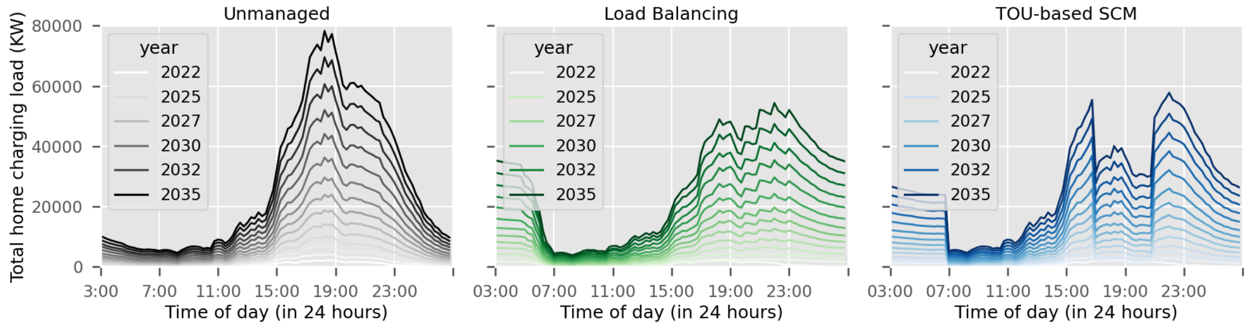

Figure 11 Daily charging load across different years for *Maximum Enrollment* scenarios across 19 feeders, assuming 80% L2 chargers and 20% L1 chargers. The SCM charging load profile includes both managed and *Unmanaged* charging loads for the entire study area.

In contrast, the *LB* scenario significantly flattens the evening peak compared to the *Unmanaged* scenario, leading to a more evenly distributed charging load throughout the day and reducing grid stress during peak hours. By 2035, it lowers the peak charging load by approximately 27% on average. The *TOU-based* SCM shifts a portion of the charging load to the TOU off-peak window, creating a pronounced peak around 9:00 p.m. In 2035, it reduces the peak charging load by an average of 23% compared to the *Unmanaged* scenario.

4.1.2 Impact of customer enrollment in SCM on home charging load

The level of customer participation in the SCM program significantly influences the reduction of peak charging loads. Higher enrollment rates lead to greater reductions in peak charging demand. Figure 12 illustrates the average percentage reduction in peak charging load across 10 BGE and 9 Pepco feeders over different years, highlighting the effectiveness of managed charging strategies. The y-axis in the figure represents the percentage reduction in peak charging load, rather than absolute values, to allow for a consistent comparison across years as EV adoption and home charging demand increase. Among the three levels of enrollment, the *Maximum Enrollment* scenario achieves the most substantial reduction in peak charging load for both *LB* and *TOU-based* SCM strategies.

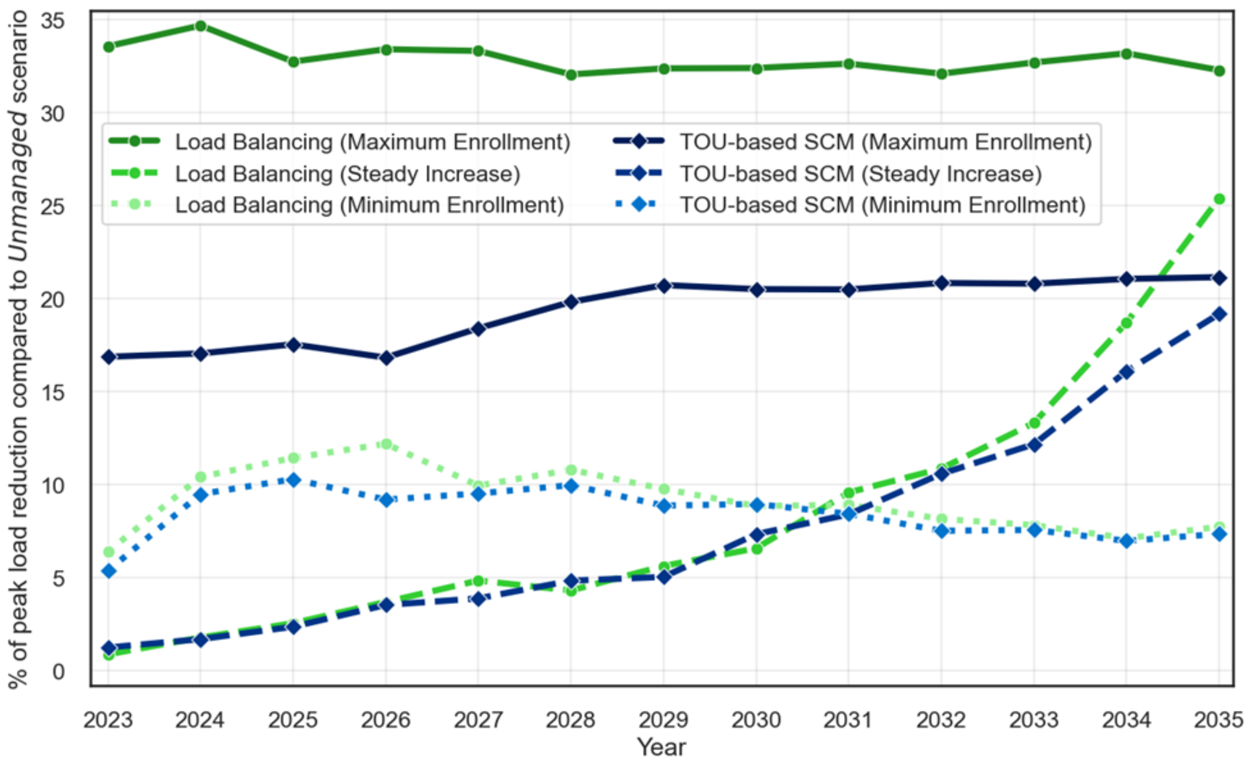

Figure 12 Average reduction in peak charging load, calculated by averaging the reductions from *Unmanaged* scenarios across all 19 feeders

Charging load varies throughout the day based on enrollment levels and the chosen SCM strategy, as depicted in Figure 13. In the *LB* scenario, increased customer enrollment results in reduced charging loads from 7 a.m. to 10 p.m., with a corresponding increase from 10 p.m. to 7 a.m. This shift occurs because LB redistributes charging to overnight hours. Conversely, in the TOU-based SCM, charging loads remain unchanged from 7 a.m. to 5 p.m. across different enrollment levels, as customers can charge without restrictions during this period. However, from 5 p.m. to 9 p.m., charging loads decrease with higher enrollment, as enrolled customers are restricted from charging during this window. After 9 p.m., these customers resume charging, leading to increased loads with higher enrollment.

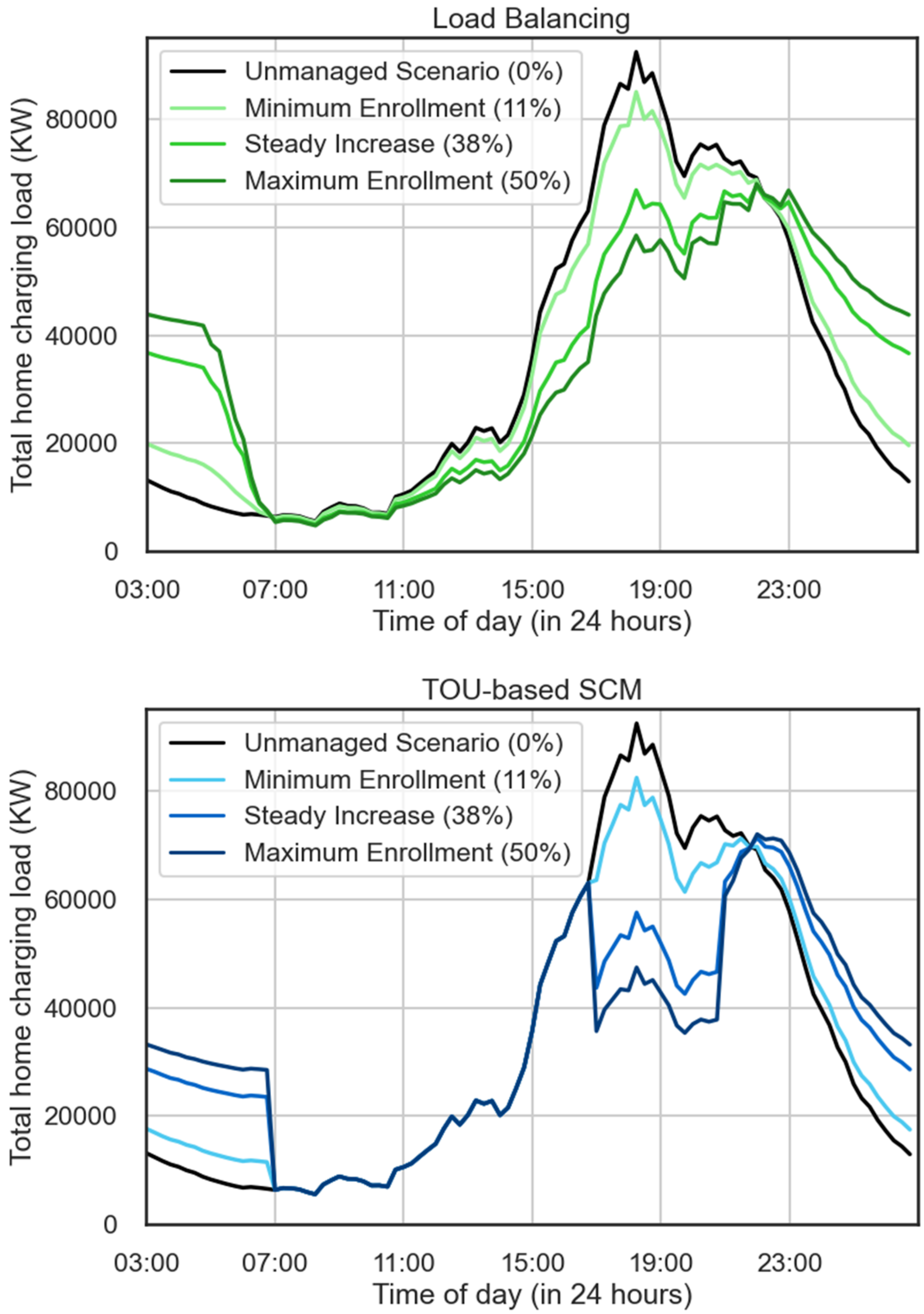

Figure 13 Daily charging load profile in different enrollment scenarios.

4.1.3 Load shifting from peak to off-peak hours

The TOU-based SCM strategy is particularly effective at shifting peak charging loads from peak to non-peak hours. The analysis indicates that higher enrollment ratios in the TOU-based SCM correlate with a greater percentage of feeders successfully moving peak charging loads to non-peak periods. Figure 14 illustrates the relationship between enrollment ratios and the percentage of feeders experiencing peak charging loads during non-peak hours for *LB, TOU-based SCM,* and *Unmanaged* charging scenarios.

In the *Unmanaged* scenario, around 30% of feeders exhibit peak charging load during the TOU non-peak hours. The *TOU-based* SCM shows a clear upward trend, with a significant increase in the percentage of feeders shifting peak loads to non-peak hours as enrollment ratios rise. This suggests that higher enrollment effectively redistributes home charging demand away from peak periods. In contrast, the LB method maintains a relatively stable percentage across different enrollment ratios, indicating that its ability to shift charging loads is less sensitive to changes in enrollment.

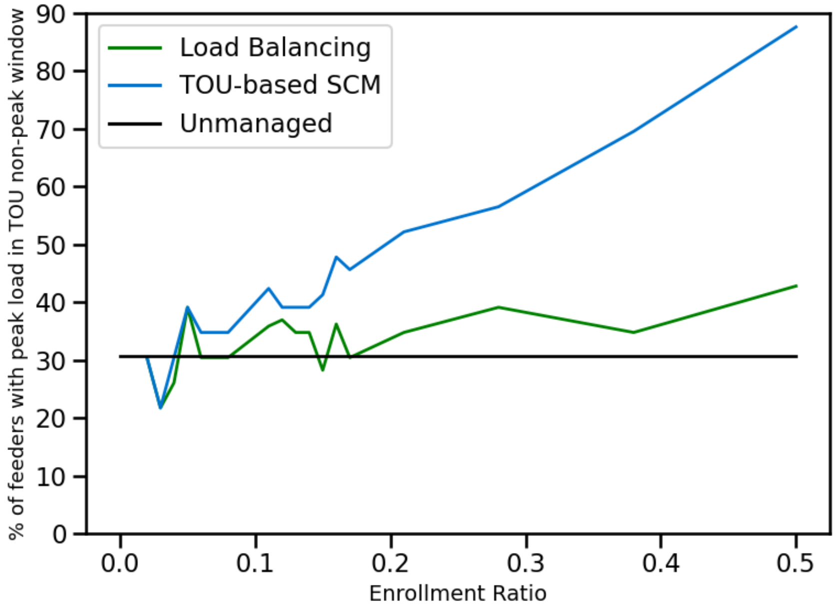

Figure 14 Percentage of feeders with peak charging load during the TOU non-peak window as a function of the enrollment ratio.

4.1.4 Factors affecting the peak charging load reduction

To identify the factors influencing peak charging load reduction, an Ordinary Least Squares (OLS) regression model (Montgomery et al., 2021) is applied using the input variables described in

Table 4. In this context, the percentage reduction in peak charging load is defined by comparing the peak charging loads of each managed strategy to its corresponding *Unmanaged* scenario for each year. The OLS regression equation fitted in the analysis is:

$$\begin{aligned}
&\mathit{Percent\ Peak\ Load\ Reduction} \\
&\qquad = -6.47 + 5.05 \times \mathit{load\ balancing} + 0.49 \times \mathit{enrollment\ ratio} \\
&\qquad - 0.05 \times \mathit{TOU\ ratio} + 0.0006 \times \mathit{number\ of\ EVs\ served\ by\ a\ feeder} \\
&\qquad + 10.36 \times \mathit{peak\ located\ in\ TOU\ peak\ window\ in\ unmnaged\ scenario}
\end{aligned}$$

Table 4 Inputs and outputs used in the OLS model

Variables	Description
Percent Peak Load Reduction	The output variable, representing the reduction in peak charging load compared to the *Unmanaged* scenario, expressed as a percentage.
load balancing	A binary variable where 1 indicates *Load Balancing* is used, and 0 indicates *TOU-based SCM* is used.
enrollment ratio	The percentage of participants enrolled in the SCM program, expressed as a fraction (0 to 1).
TOU ratio	The percentage of participants using TOU rates, expressed as a fraction (0 to 1).
number of EVs served by a feeder	The total number of EVs served by a given feeder.
peak located in the TOU peak window in Unmanaged scenario	A binary variable indicating if the peak charging load occurs in the TOU peak window (5 pm to 9 pm) in the *Unmanaged* scenario.

The positive coefficient suggests that using *an LB* strategy leads to a higher percentage reduction in peak load compared to *TOU-based* SCM. Specifically, LB leads to a 5.05% greater reduction in peak charging load than when compared to *TOU-based* SCM.

The enrollment ratio is positively related to peak charging load reduction, with a coefficient of 0.49. This suggests that a higher enrollment ratio enhances the effectiveness of reducing peak charging load. This is further supported by Figure 15, which shows that as enrollment ratio increases, the average peak charging load reduction also rises.

Conversely, the TOU ratio has a negative coefficient of -0.05. This suggests that a higher TOU ratio slightly diminishes the effectiveness of peak charging load reduction. This occurs because a higher TOU ratio means that more customers are already charging during the overnight TOU off-peak window, leaving less flexibility to distribute or manage their charging times further. As a result, it becomes difficult for the managed strategies to optimize the charging load effectively. Consequently, this leads to an increased peak in home charging demand within the overnight hours.

The number of EVs served by a feeder has a small but positive coefficient of 0.0006, indicating a marginal contribution to peak charging load reduction. This could be due to the fact that, as the number of EVs grows, the impact of SCM strategies becomes more pronounced. With more EVs enrolled in SCM, the charging demand can be spread more evenly across non-peak hour time window, leading to marginal reductions in peak charging load. However, the contribution remains small because the effectiveness of SCM is more dependent on enrollment ratios and the specific strategy used, rather than just the number of EVs alone.

The variable peak located in TOU peak window in unmanaged scenario has a significant positive coefficient of 10.36. This suggests that when peak charging load occurs during TOU peak window in the *Unmanaged* scenario, the SCM strategies are particularly effective at achieving substantial peak charging load reduction. However, when the peak charging load occurs during TOU non-peak window (more specifically, from 9 pm to 7 am) in the *Unmanaged* scenario, the *TOU-based* SCM actually increases the peak charging load, as illustrated in Figure 15. The box plot shows that when the *Unmanaged* peak charging load occurs after 9 pm, the *TOU-based* SCM method leads to an increase in peak charging load, while *LB* still achieves a reduction. This happens because, in the *TOU-based* SCM, customers are shifted to charge their EVs during TOU non-peak hours. As a result, if the peak charging load in the *Unmanaged* scenario already occurs after 9 pm, shifting even more charging to this period under the *TOU-based* SCM can increase the peak charging load. This leads to a higher overall demand during these hours compared to the *Unmanaged* scenario.

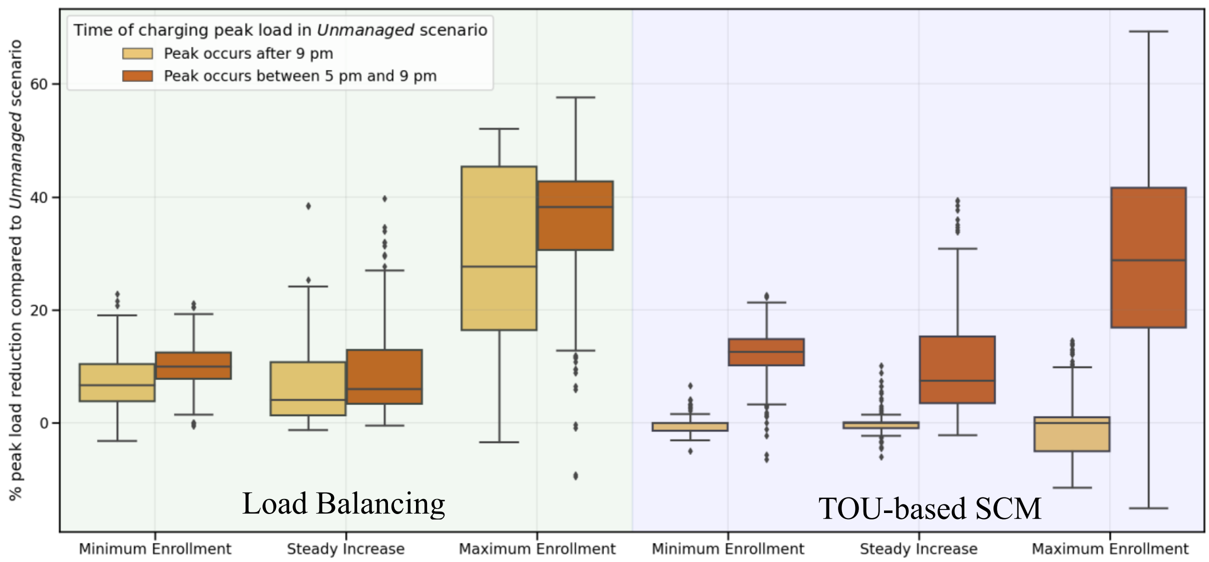

Figure 15 Reduction in peak charging load for different charging times in the *Unmanaged* scenario.

To further illustrate the situation when home charging peak occurs after 9 pm in the *Unmanaged* scenario, Figure 16 compares profiles of two distinct feeders analyzed with two SCM strategies. Notably, under the *TOU-based* SCM, peak charging load increased compared to the *Unmanaged* scenario, whereas the *LB* method led to a peak charging load reduction. These results suggest that when a feeder's *Unmanaged* charging load profile peaks after 9 pm, the *TOU-based* SCM may have little or even a negative impact. This indicates that, when implementing an SCM program, it is crucial to examine the base load profile to understand how the program will effectively influence it and what the impact will be.

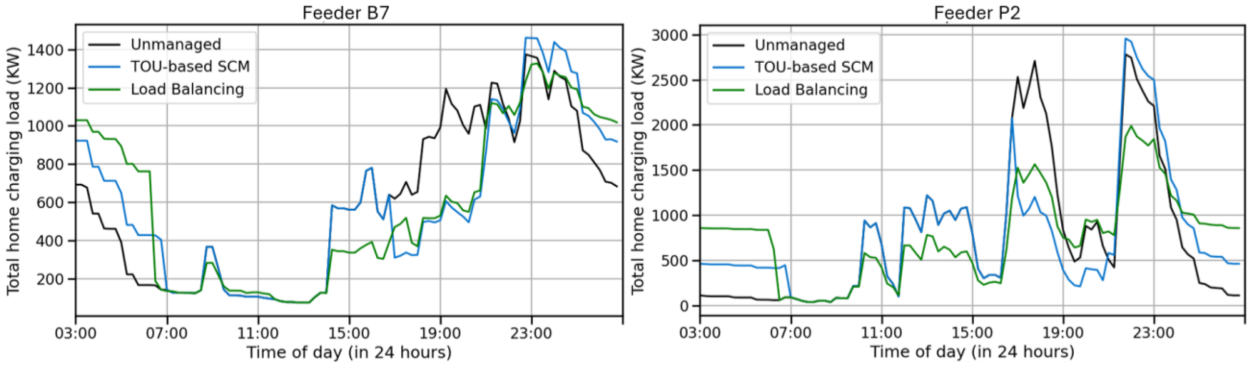

Figure 16 Daily charging load profile for two example feeders for *Maximum Enrollment* scenario where the peak occurs after 9 pm in the *Unmanaged* scenario.

4.2 Feeder-level Load Profiles for SCM Scenarios

Figure 17Figure 18Figure 19Figure 20Each representative feeder includes a base load, an EV load, and the total load, which is the sum of both as described in section 2.5. The base load consists of the regular electricity demand from residential and commercial users, while the EV load comes from both enrolled and non-enrolled drivers in the SCM program. Figures 17 and 18 show total load variations for a BGE feeder (B1), highlighting how the base load and EV load contribute to the overall demand. In contrast, Figures 19 and 20 present similar data for a Pepco feeder (P1) across four enrollment scenarios in 2035, focusing on LB and Time-of-Use (TOU) charging strategies.

Both strategies effectively reduce peak loads across all scenarios (shown in Figures 17-20). The TOU-based strategy shifts peak EV charging to off-peak hours, typically around 9 PM, while the LB strategy distributes charging demand more evenly throughout the day. However, the TOU-based approach may introduce a secondary peak at the beginning of the off-peak period. In such cases, additional enrollment primarily reduces demand between 5 PM and 9 PM but does not significantly lower peak loads outside this timeframe. In contrast, the LB strategy achieves a smoother, more uniform load reduction without introducing a secondary peak. The impact of smart charging strategies varies by feeder. Generally, the LB strategy is more effective in reshaping the load curve to reduce peak loads. **Error! Reference source not found.**The f ollowing figures are for illustrative purposes only and do not reflect the average behavior of the utility. Analysis results show that EV load at each feeder is different, influenced by factors such as EV adoption, charging access, driving habit and managed strategy.

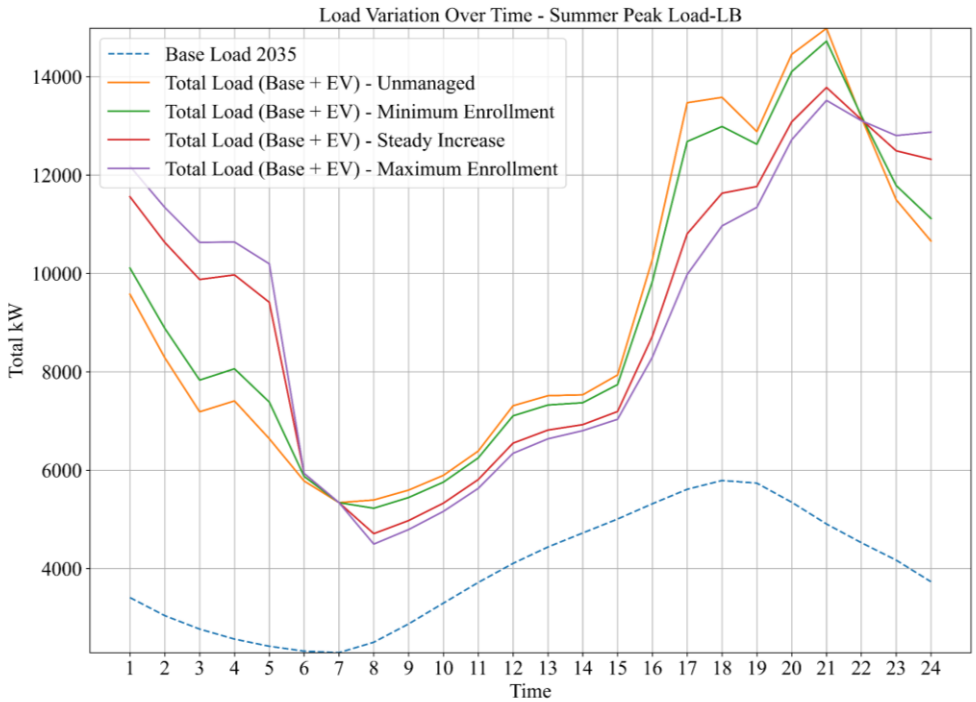

Figure 17 Load variation of BGE feeder B1 for LB scenarios in 2035

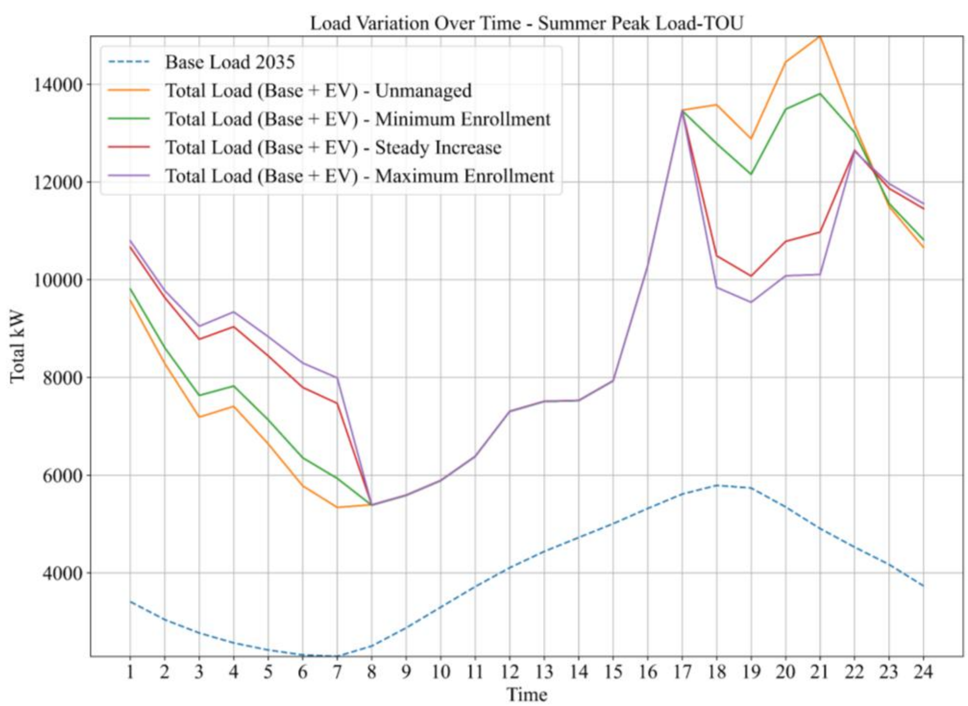

Figure 18 Load variation of BGE feeder B1 for TOU scenarios in 2035

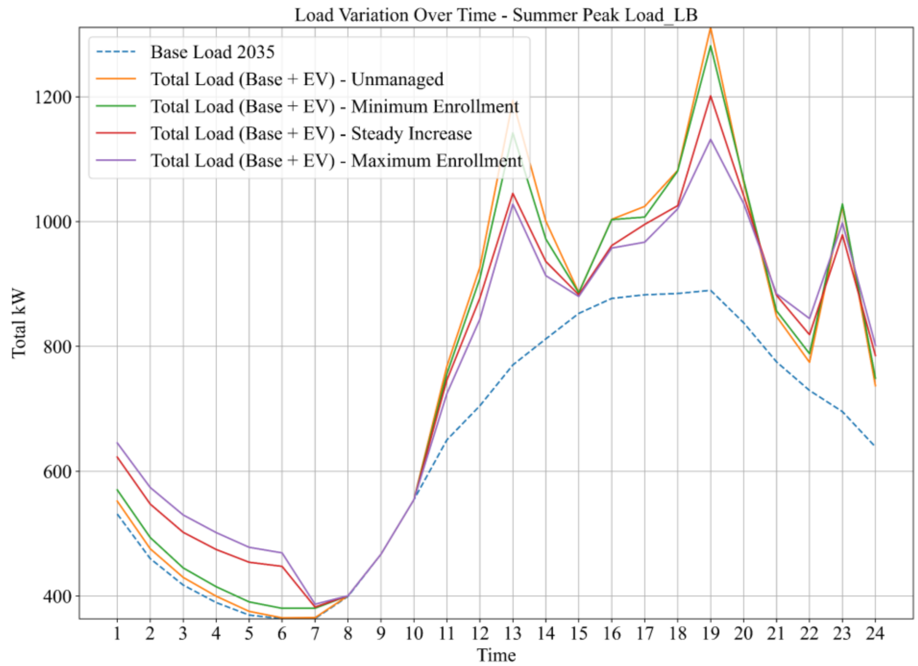

Figure 19 Load variation of Pepco feeder P1 for LB scenarios in 2035

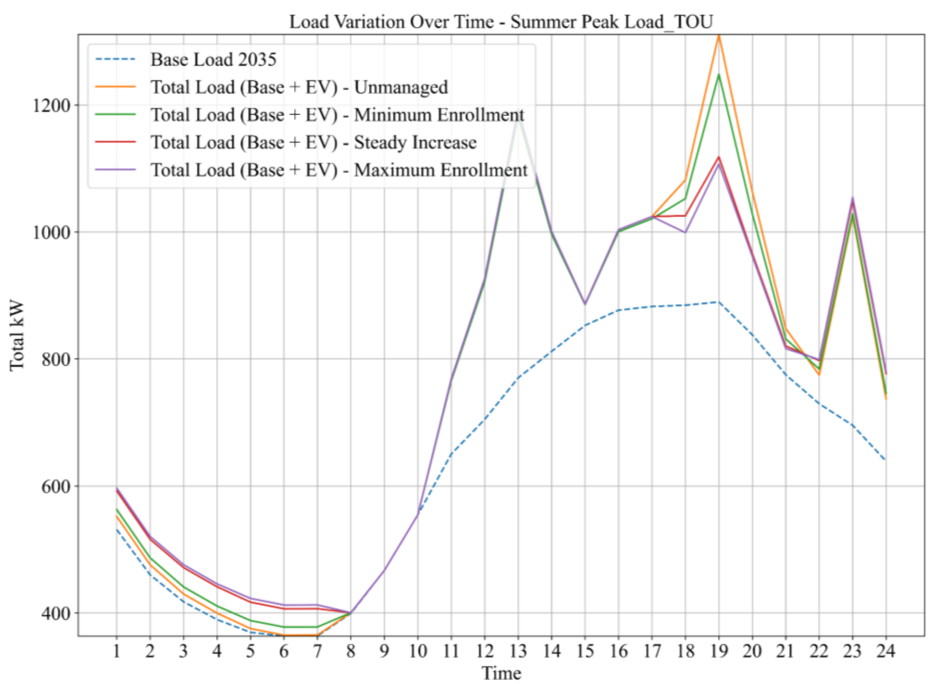

Figure 20 Load variation of Pepco feeder P1 for TOU scenarios in 2035

Evolution of Base Load vs. EV Load Contribution: During the early years of the study period, the total load was predominantly driven by the base load, which includes traditional non-EV consumption from residential, commercial, and industrial users. However, as EV adoption increases, the charging demand grows significantly, altering the overall load composition. Over time, EV load represents a much larger share of the total load profile, even though base load continues its gradual upward trend. Figure 21 shows the variation between base load and EV load for representative feeder B1:

- Up to the year 2027, the base load dominates across all 24-time steps in the day.
- By 2032, the EV load increases to the point where it surpasses the base load during several time steps, highlighting the growing influence of EV charging on grid demand.

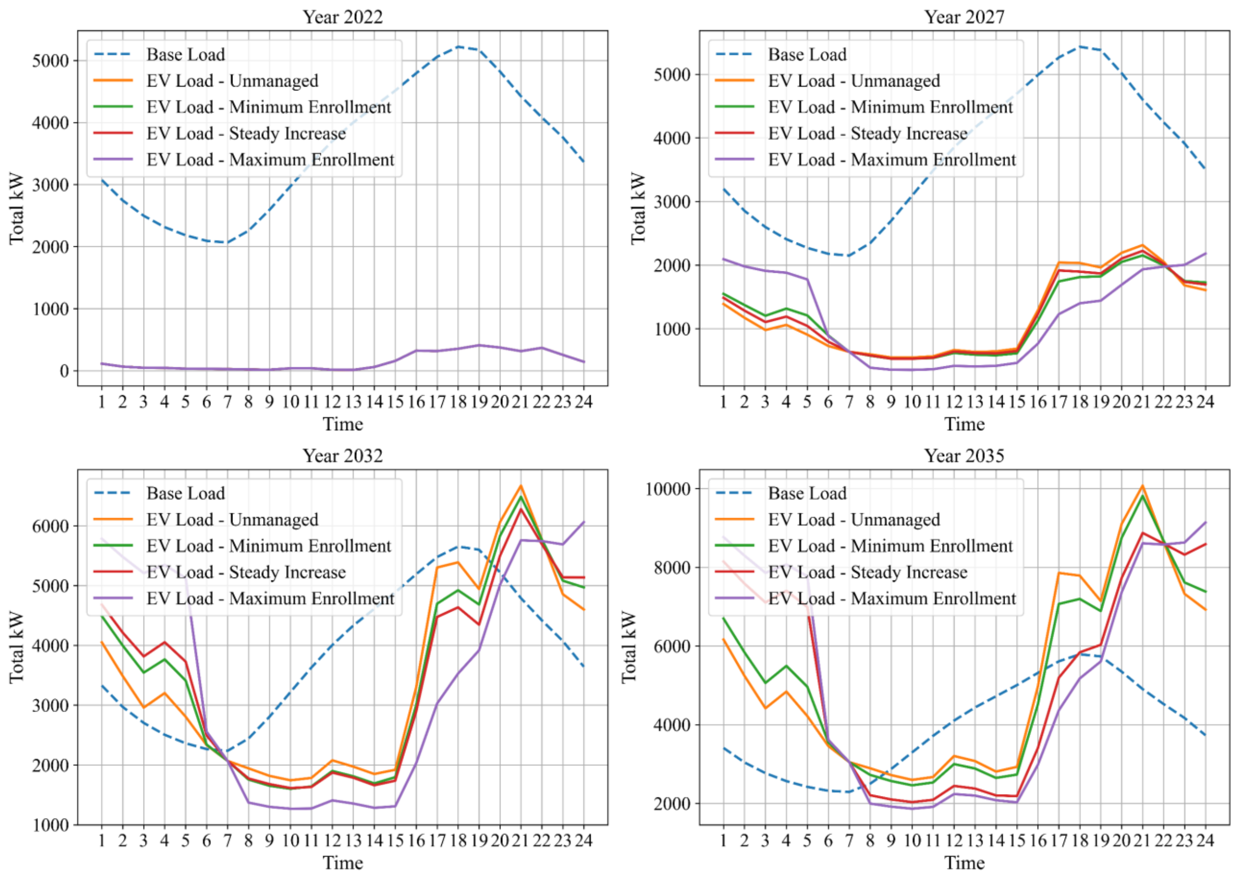

Figure 21 Variation of the Base and EV load over time

4.3 BGE Analysis Results

4.3.1 Feeder level analysis

A. Performance and upgrade costs of LB and TOU-based SCM in 2035

Table 5 and Table 6 compare the performance and resulting upgrade costs for *LB* and *TOU-based* SCM in year 2035. Each column—transformer overloads, upgrade capacity (MVA), upgrade cost (MUSD), line overloads, and line upgrade cost—directly corresponds to the enrollment scenarios, providing a comprehensive assessment of network stress. The results highlight the effectiveness of smart charging in mitigating grid impacts across various feeders.

Both *LB* and *TOU-based* SCM show a consistent decline in transformer overloads, upgrade capacity, and associated costs as enrollment shifts from *Unmanaged* to *Maximum Enrollment*. Feeders such as B1, B2 and B4 experience the highest stress in the *Unmanaged* scenario, with numerous overloaded transformers and significant upgrade requirements. For example, under *TOU-based* SCM, the number of overloaded transformers in feeder B1 decreased from 163 in the *Unmanaged* scenario to 125 in the *Maximum Enrollment* scenario, accompanied by reductions in upgrade capacity needed and associated costs. In contrast, feeders like B5 and B7 remain largely unaffected by enrollment variation, indicating these two feeders are less sensitive to variations in charging demand, due to their inherent load profiles.

As EV enrollment increases, shifting from *Unmanaged* charging to *Maximum Enrollment* lowers the distribution system's burden. Higher SCM enrollment redistributes demand away from peak periods, reducing line and transformer overloads, while minimizing upgrade requirements and costs. However, these benefits are not uniform across all feeders. Some experience significant improvements while others show minimal change due to load profiles and network configurations of the feeders. Table 5 and Table 6 emphasize the benefit of feeder-specific planning to maximize smart charging benefits. Even with higher EV enrollment, well-designed SCM strategies can alleviate distribution system stress and defer infrastructure investment costs, but optimization must account for feeder-specific characteristics.

Table 5 Summary for LB scenarios for BGE

Feeder	Scenario	Number of Overloaded Transformers	Total Transformer Upgrade Capacity (MVA)	Total Transformer Upgrade Cost ($MM)	Number of Overloaded Lines	Total Line Upgrade Cost ($MM)
B1	Unmanaged	158	10.8	1.0	105	1.364
	Minimum Enrollment	146	10.1	0.9	78	1.031
	Steady Increase	102	7.1	0.6	69	0.926
	Maximum Enrollment	122	8.7	0.8	71	0.976
B2	Unmanaged	131	8.9	0.7	2	0.155
	Minimum Enrollment	127	8.5	0.6	2	0.155
	Steady Increase	125	8.3	0.6	2	0.155
	Maximum Enrollment	117	7.7	0.6	2	0.155
B3	Unmanaged	55	10.6	1.2	12	0.071
	Minimum Enrollment	51	9.1	1.1	1	0.002
	Steady Increase	45	6.2	0.8	1	0.002
	Maximum Enrollment	42	5.8	0.8	1	0.002
B4	Unmanaged	220	17.5	1.4	131	5.465
	Minimum Enrollment	212	16.5	1.4	129	4.768
	Steady Increase	200	15.1	1.2	126	4.724

Feeder	Scenario	Number of Overloaded Transformers	Total Transformer Upgrade Capacity (MVA)	Total Transformer Upgrade Cost ($MM)	Number of Overloaded Lines	Total Line Upgrade Cost ($MM)
	Maximum Enrollment	185	13.3	1.1	122	4.459
B5	Unmanaged	4	1.4	0.13	4	0.333
	Minimum Enrollment	2	0.6	0.062	4	0.333
	Steady Increase	2	0.6	0.062	3	0.217
	Maximum Enrollment	1	0.1	0.004	3	0.217
B6	Unmanaged	39	24.5	2.0	23	0.66
	Minimum Enrollment	39	24.3	2.0	23	0.66
	Steady Increase	38	21.7	1.9	23	0.66
	Maximum Enrollment	38	21.7	1.9	23	0.66
B7	Unmanaged	42	18.0	1.9	25	0.62
	Minimum Enrollment	42	18.0	1.9	25	0.62
	Steady Increase	42	18.0	1.9	25	0.62
	Maximum Enrollment	42	18.0	1.9	25	0.62
B8	Unmanaged	24	5.9	0.4	16	4.59
	Minimum Enrollment	24	5.8	0.4	12	3.99
	Steady Increase	23	5.7	0.4	12	3.99
	Maximum Enrollment	22	5.6	0.4	10	3.99
B9	Unmanaged	42	7.0	0.9	21	1.09
	Minimum Enrollment	42	6.9	0.9	20	1.09
	Steady Increase	42	6.1	0.8	9	0.52
	Maximum Enrollment	42	5.9	0.8	8	0.51
B10	Unmanaged	52	10.4	1.1	122	6.22
	Minimum Enrollment	52	10.4	1.1	119	6.2
	Steady Increase	52	9.3	1.0	106	5.75
	Maximum Enrollment	52	9.0	1.0	105	5.26

Table 6 Summary of *TOU-based* scenarios for BGE

Feeder	Scenario	Number of Overloaded Transformers	Total Transformer Upgrade Capacity (MVA)	Total Transformer Upgrade Cost ($MM)	Number of Overloaded Lines	Total Line Upgrade Cost ($MM)
B1	Unmanaged	158	10.80	1.0	105	1.364
	Minimum Enrollment	154	9.90	0.92	112	1.51
	Steady Increase	127	7.80	0.69	110	1.48
	Maximum Enrollment	125	7.73	0.68	111	1.5
B2	Unmanaged	131	8.90	0.7	2	0.155
	Minimum Enrollment	127	8.53	0.65	2	0.16
	Steady Increase	124	8.25	0.63	2	0.16
	Maximum Enrollment	121	8.03	0.62	2	0.16
B3	Unmanaged	55	10.60	1.2	12	0.071
	Minimum Enrollment	54	10.05	1.14	12	0.07
	Steady Increase	52	9.58	1.05	12	0.07
	Maximum Enrollment	51	9.33	1.00	12	0.07
B4	Unmanaged	220	17.50	1.4	131	5.465
	Minimum Enrollment	205	15.65	1.28	129	4.77
	Steady Increase	192	14.20	1.17	125	4.72
	Maximum Enrollment	183	13.58	1.12	125	4.72
B5	Unmanaged	4	1.40	0.13	4	0.333
	Minimum Enrollment	2	0.55	0.06	4	0.33
	Steady Increase	2	0.55	0.06	3	0.22
	Maximum Enrollment	2	0.55	0.06	3	0.22
B6	Unmanaged	39	24.50	2.0	23	0.66
	Minimum Enrollment	39	23.50	1.97	23	0.66
	Steady Increase	38	21.50	1.88	23	0.66
	Maximum Enrollment	38	21.20	1.87	23	0.66
B7	Unmanaged	42	18.00	1.9	25	0.62
	Minimum Enrollment	42	17.98	1.90	25	0.62
	Steady Increase	42	17.98	1.90	25	0.62
	Maximum Enrollment	42	17.98	1.90	25	0.62

Feeder	Scenario	Number of Overloaded Transformers	Total Transformer Upgrade Capacity (MVA)	Total Transformer Upgrade Cost ($MM)	Number of Overloaded Lines	Total Line Upgrade Cost ($MM)
B8	Unmanaged	24	5.90	0.4	16	4.59
	Minimum Enrollment	24	5.88	0.42	12	3.99
	Steady Increase	23	5.73	0.40	12	3.99
	Maximum Enrollment	21	5.58	0.39	12	3.99
B9	Unmanaged	42	7.00	0.9	21	1.09
	Minimum Enrollment	41	6.90	0.88	20	1.09
	Steady Increase	41	5.93	0.82	9	0.52
	Maximum Enrollment	41	5.93	0.82	8	0.51
B10	Unmanaged	52	10.40	1.1	122	6.22
	Minimum Enrollment	50	11.13	1.17	87	5.01
	Steady Increase	50	10.63	1.14	89	5.26
	Maximum Enrollment	50	10.68	1.15	87	5.01

B. Comparison between LB and TOU SCM

Figure 22 compares peak load reduction under *Unmanaged* and *Maximum Enrollment* scenarios for both *TOU-based* and *LB* SCM across 10 feeders in 2035. The peak load, which includes both the base and EV demand, responds differently depending on the feeder. For instance, feeders B3 and B10 show significantly greater reductions under *LB*, while *TOU-based* SCM achieves no reduction. Notably, feeder B10 exhibits a slight increase (0.2%) in *Maximum Enrollment* under *TOU-based* SCM, indicating that load shifting in this case inadvertently raised demand during peak periods. Conversely, feeder B7 sees no peak load reduction under *TOU-based* SCM—since its base load peak falls outside the TOU window—but does experience some reduction under *LB*. Feeders like B1 and B6 demonstrate similar reductions under both strategies. Overall, *LB* consistently outperforms *TOU-based* SCM in reducing peak loads, making it a more effective strategy for managing demand peaks.

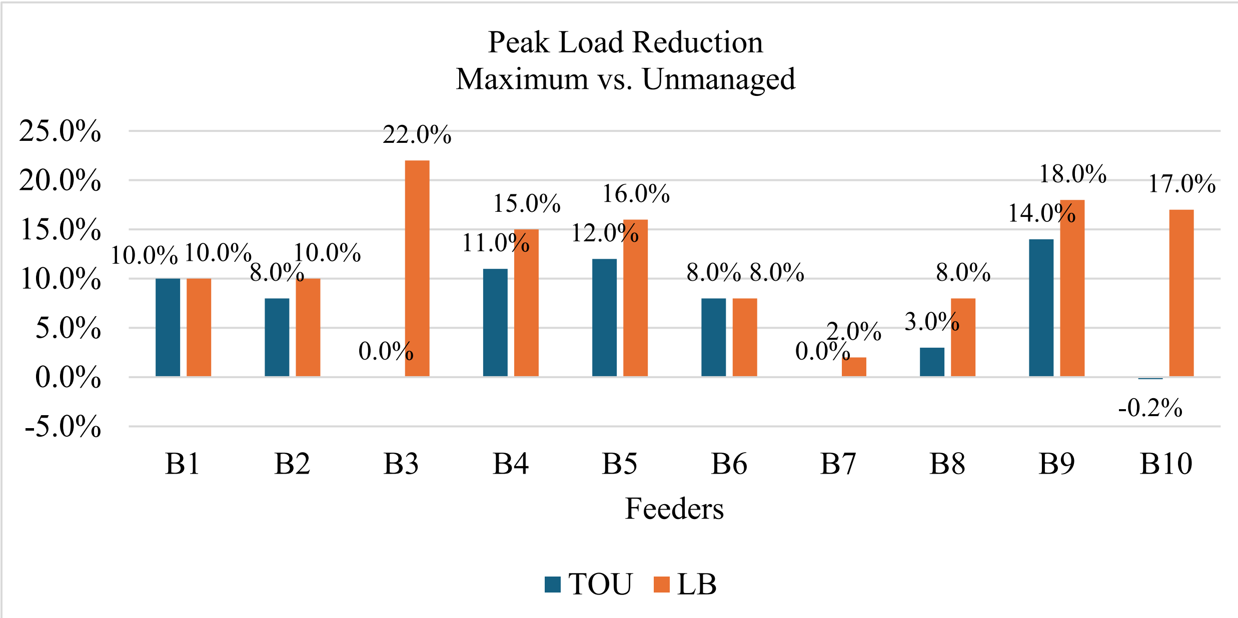

Figure 22 Comparison of LB and TOU-based in terms of peak load reduction for 10 BGE feeders

Figure 23 illustrates transformer upgrade cost reductions comparing *Unmanaged* and *Maximum Enrollment* scenarios for *TOU-based* and *LB* in 2035. Upgrade costs depend on the required transformer capacity (kVA) for each scenario, which varies by feeder. Certain feeders, such as B5, benefit significantly from *LB*, achieving a 97% cost reduction compared to 52% under *TOU-based*. This is due to the lower transformer capacity upgrade requirements under the *LB* strategy. However, feeder like B7 exhibit negligible differences between the two strategies, with cost reductions close to zero. Additionally, the negative reduction for feeder B10 under TOU highlights how some distribution network configurations can produce unexpected results when load shifts do not align with peak demand periods. Overall, *LB* demonstrates greater cost-deferral potential, while *TOU-based* provides moderate reductions in most cases. These findings underscore the variability in smart charging performance across different feeders.

Figure 24 and Figure 25 present the Net Present Value (NPV) of upgrade costs for accommodating EV integration from 2022 to 2035 across BGE feeders. *Maximum Enrollment* under *LB* yields the most favorable outcome, achieving the lowest NPV across feeders.

The analysis identifies small-sized single-phase transformers in BGE feeders as particularly vulnerable to overloading, making them a priority for upgrades. Figure 26 and Figure 27 show the reduction in overloaded transformers over time, highlighting the effectiveness of both *LB* and *TOU-based* SCM in mitigating asset stress from 2022 to 2035. Transitioning from *Unmanaged* to *Maximum Enrollment* leads to a notable decline in transformer overloads, deferring costly distribution system upgrades while supporting higher EV adoption.

Most distribution lines within the 10 BGE feeders had sufficient capacity for EV integration, with only a few laterals experiencing overloading due to their limited current-carrying capacity. Some feeders also exhibited undervoltage issues alongside overloading, which were largely resolved through transformer upgrades. In cases where undervoltage persisted, additional capacitor banks were installed to stabilize voltage levels. These results reinforce the importance of implementing smart charging strategies, particularly in urban and suburban feeders with high demand.

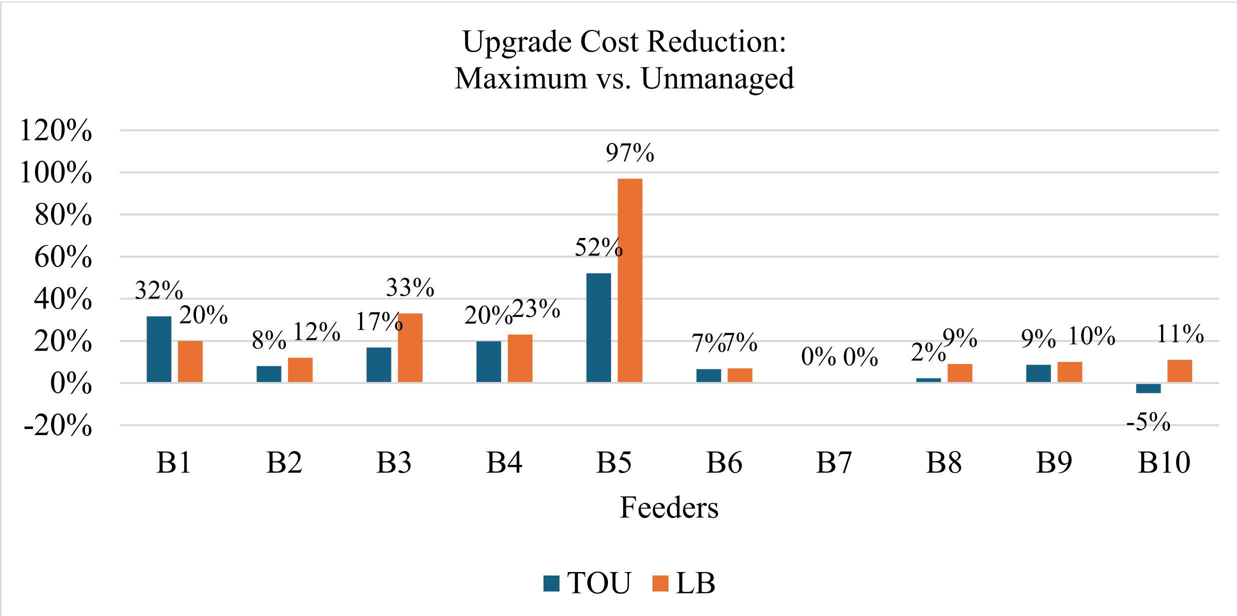

Figure 23 Comparison of *LB* and *TOU-based* transformer upgrade cost reduction for 10 BGE feeders

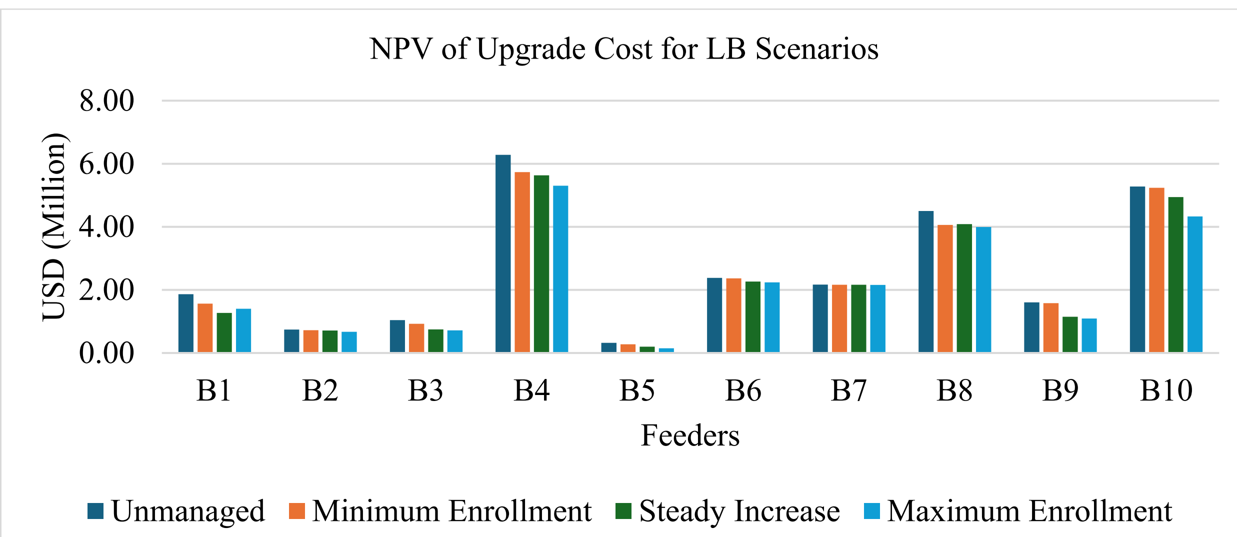

Figure 24 NPV comparison of upgrade costs for LB scenarios across 10 BGE feeders

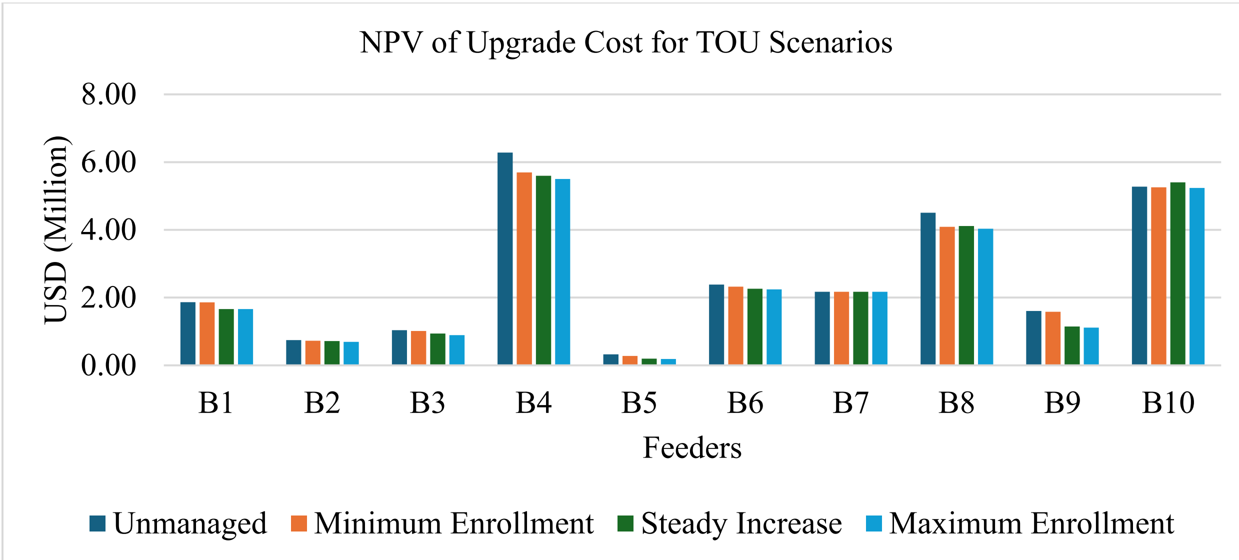

Figure 25 NPV comparison of upgrade costs for TOU-based scenarios across 10 BGE feeders

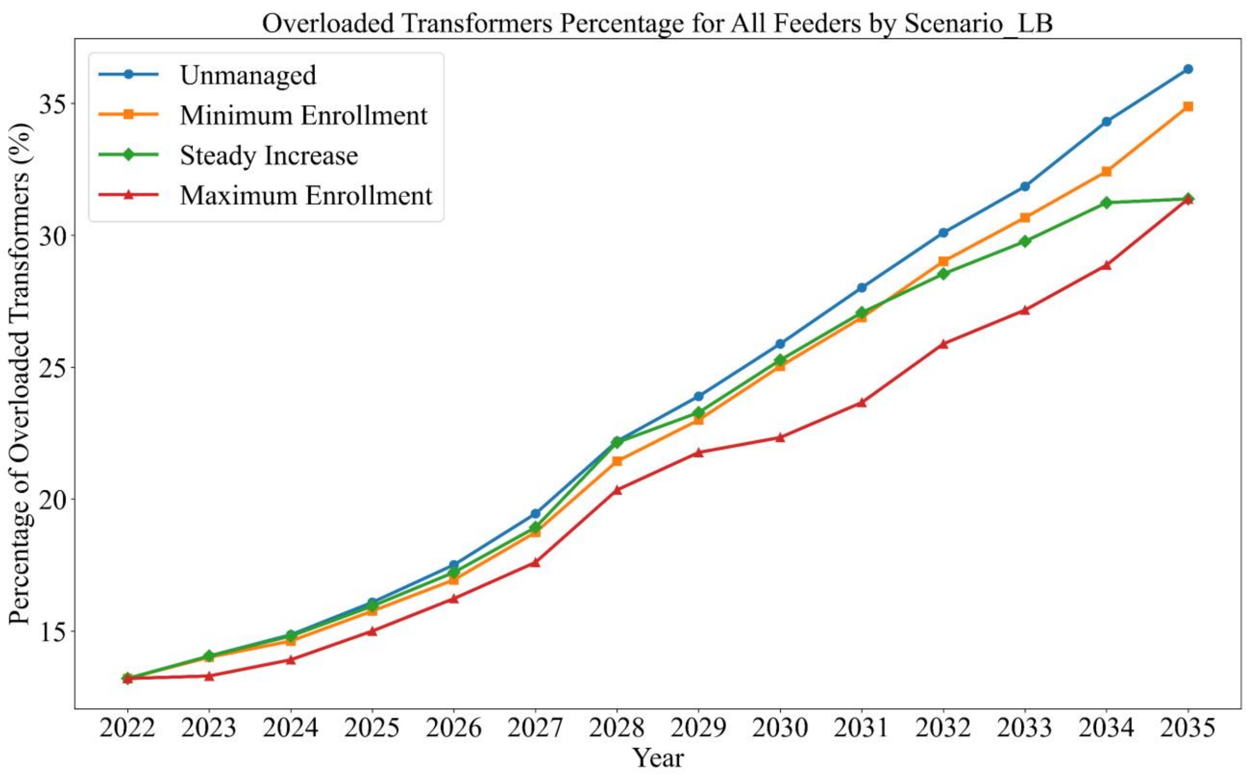

Figure 26 Summary of overloaded transformers under LB for 10 BGE feeders

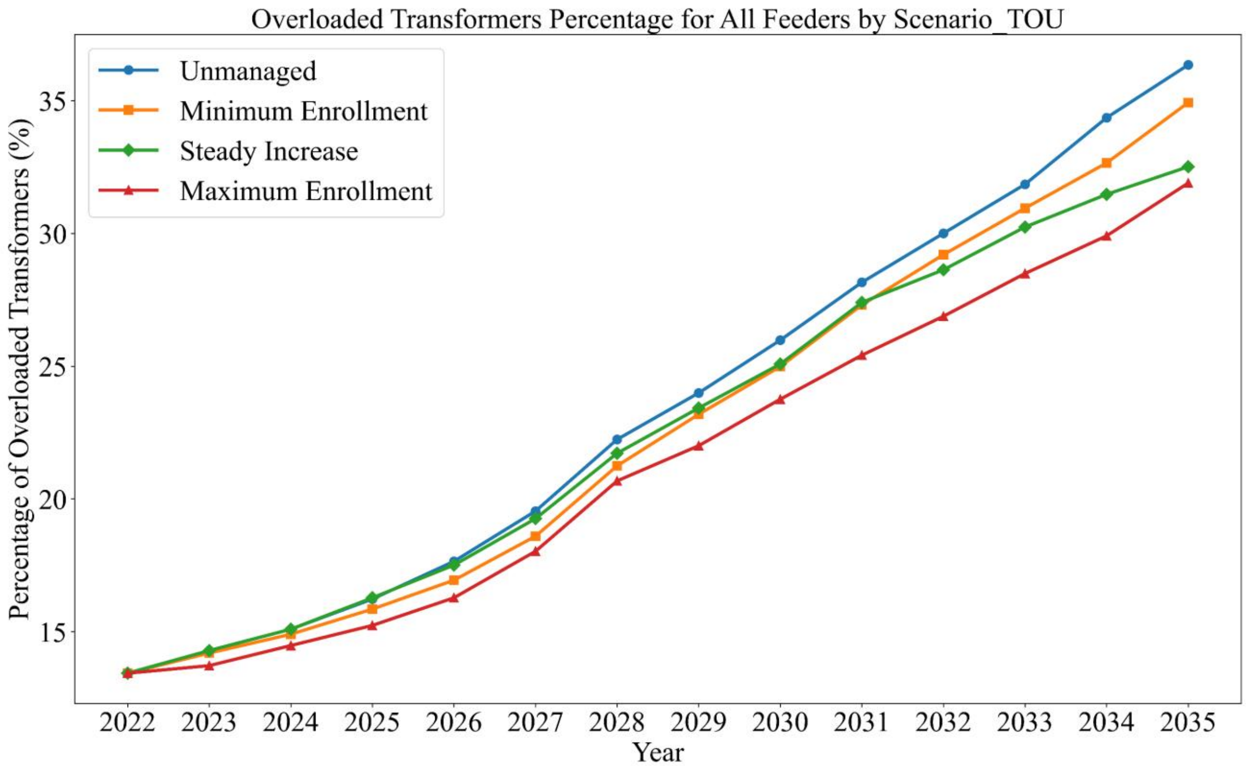

Figure 27 Summary of overloaded transformers under TOU for 10 BGE feeders

4.3.2 System-wide analysis for BGE

Argonne estimated the total system-wide upgrade costs across three scenarios under *LB* and *TOU-based* SCM strategies. For BGE, several feeders had load data missing, load flow convergence errors and other load flow related issues. After accounting for these issues, there were 1031 feeders for the clustering analysis described in Section 2.6. Figure 29 extends these estimates to all BGE feeders using a linear approximation derived from the 1,031-feeder results.

- In the *Minimum Enrollment* scenario, upgrade costs are more greatly deferred out to later years beyond the study for both strategies, with *TOU-based* SCM achieving a slightly greater cost reduction by the year 2035 ($2,079 million) compared to *LB* ($2,137 million).
- However, in the *Steady Increase* scenario, costs continue to decline, with *LB* ($2,031 million) outperforming *TOU-based* SCM ($2,058 million).
- Based on the discussion with the Joint Utilities, *Maximum Enrollment* across all years is not considered a supportable forecast scenario, so the system-wide analysis was not conducted.
- Cost savings by 2035 in millions USD compared to the *Unmanaged* scenario (Figure 28):

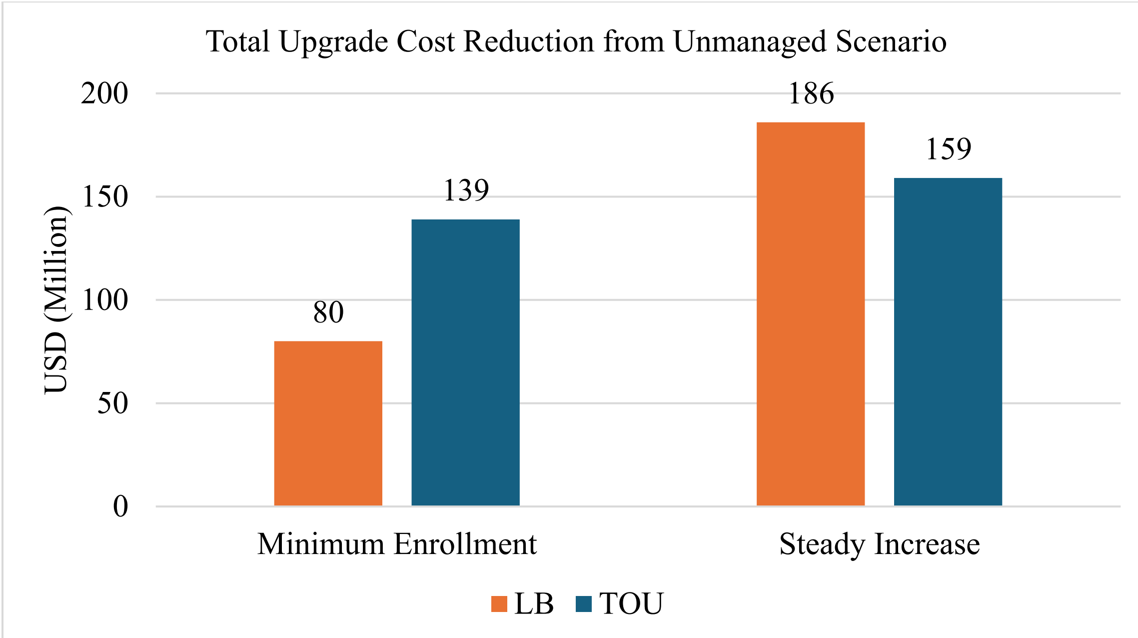

Figure 28 Comparison of upgrade cost with *Unmanaged Scenario* (BGE)

The limited EV enrollment in *Minimum Enrollment* restricts the potential grid benefits of either strategy, as there is less load available to shift or balance. *Steady Increase* achieves the lowest total costs, suggesting that higher EV adoption, when paired with effective load management, yields greater infrastructure savings.

These findings highlight that the cost-effectiveness of *LB* versus *TOU-based* SCM depends on specific enrollment patterns and operational conditions at the feeder level. Aligning SCM strategies with grid characteristics is essential for maximizing grid benefits and minimizing upgrade costs.

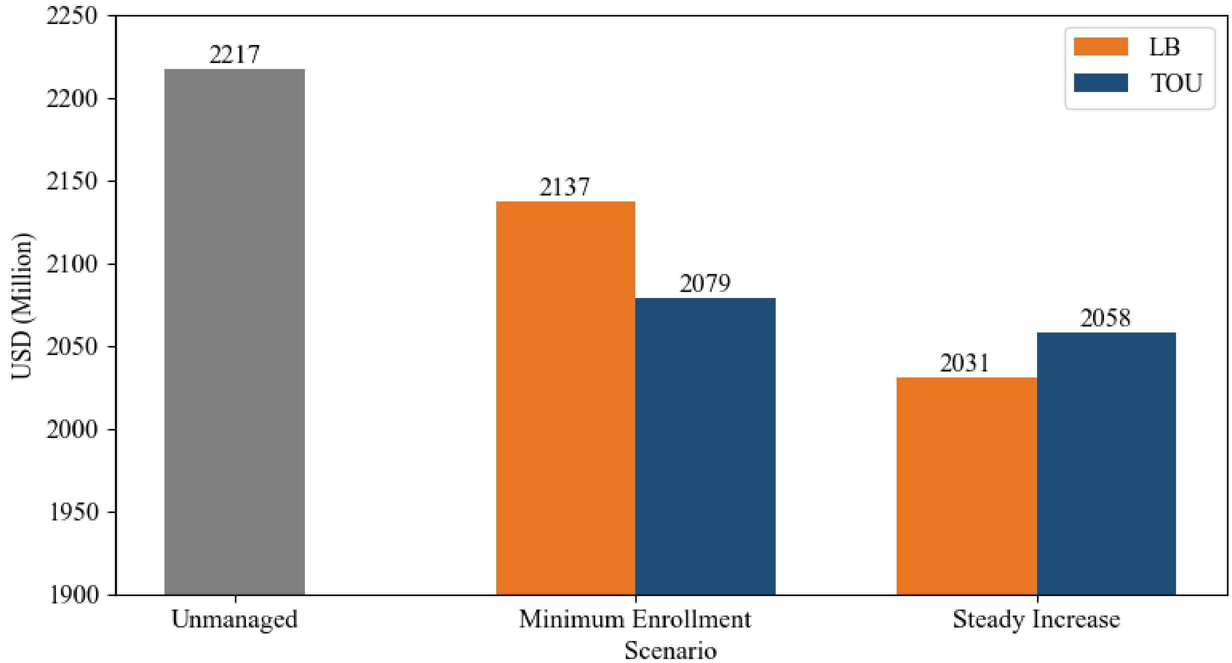

Figure 29 System wide upgrade cost for BGE

4.4 Pepco Analysis Results

4.4.1 Feeder level analysis

A. Performance of LB and TOU-based strategies

Table 7 and

Table 8 compare the performance of *LB* and *TOU-based* SCM strategies across the four scenarios, focusing on overloaded transformers, total upgrade capacity (MVA), and associated costs in 2035. A comparison of these tables reveals key trends-as scenarios progress from *Unmanaged* to *Maximum Enrollment*, most feeders experience reductions in transformer overloads, total upgrade MVA, and upgrade costs. This confirms that SCM is effective in mitigating negative grid impacts under high EV enrollment.

Under *LB*, several feeders—including P4, P6, P7, P8, and P9—require fewer upgrades and incur lower costs in the *Maximum Enrollment* scenario compared to TOU, highlighting *LB*'s potential for greater deferral of infrastructure investments. However, exceptions exist; for instance, feeder P2 performs better under TOU in later scenarios, demonstrating that the optimal strategy depends on each feeder's unique load profile and peak timing. While *LB* generally delivers greater cost reductions, the extent of its advantage varies across feeders, emphasizing the importance of feeder-specific planning.

Table 7 Summary of LB scenarios for Pepco

Feeder	Scenario	Number of Overloaded Transformers	Total Transformer Upgrade Capacity (MVA)	Total Transformer Upgrade Cost (MUSD)
P1	Unmanaged	7.0	0.68	0.06
	Minimum Enrollment	7.0	0.68	0.06
	Steady Increase	7.0	0.63	0.05
	Maximum Enrollment	7.0	0.63	0.05
P2	Unmanaged	34.0	4.30	0.34
	Minimum Enrollment	33.0	3.98	0.30
	Steady Increase	30.0	3.45	0.28
	Maximum Enrollment	28.0	3.20	0.26
P3	Unmanaged	16.0	10.90	0.68
	Minimum Enrollment	15.0	10.05	0.62
	Steady Increase	14.0	8.35	0.57
	Maximum Enrollment	14.0	7.35	0.56
P4	Unmanaged	12.0	2.43	0.24
	Minimum Enrollment	11.0	2.13	0.22
	Steady Increase	10.0	1.90	0.19
	Maximum Enrollment	9.0	1.75	0.17
P5	Unmanaged	4.0	6.00	0.39
	Minimum Enrollment	4.0	5.50	0.37
	Steady Increase	4.0	5.00	0.31
	Maximum Enrollment	4.0	4.75	0.30
P6	Unmanaged	8.0	4.20	0.35
	Minimum Enrollment	8.0	3.95	0.31
	Steady Increase	6.0	2.10	0.19
	Maximum Enrollment	5.0	2.00	0.18
P7	Unmanaged	19.0	8.50	0.59
	Minimum Enrollment	17.0	7.83	0.52
	Steady Increase	15.0	6.28	0.43
	Maximum Enrollment	15.0	5.83	0.43
P8	Unmanaged	20.0	12.15	1.04
	Minimum Enrollment	19.0	10.45	0.91
	Steady Increase	17.0	7.30	0.72
	Maximum Enrollment	15.0	6.50	0.62
P9	Unmanaged	26.0	17.20	0.98
	Minimum Enrollment	25.0	15.05	0.94
	Steady Increase	24.0	12.15	0.83
	Maximum Enrollment	24.0	11.35	0.82

Table 8 Summary of TOU scenarios for Pepco

Feeder	Scenario	Number of Overloaded Transformers	Total Transformer Upgrade Capacity (MVA)	Total Transformer Upgrade Cost (MUSD)
P1	Unmanaged	7.0	0.68	0.06
	Minimum Enrollment	7.0	0.68	0.06
	Steady Increase	7.0	0.63	0.05
	Maximum Enrollment	7.0	0.63	0.05
P2	Unmanaged	34.0	4.30	0.34
	Minimum Enrollment	32.0	3.88	0.30
	Steady Increase	30.0	3.35	0.27
	Maximum Enrollment	25.0	2.60	0.23
P3	Unmanaged	16.0	10.90	0.68
	Minimum Enrollment	15.0	10.05	0.62
	Steady Increase	14.0	8.25	0.56
	Maximum Enrollment	14.0	7.35	0.56
P4	Unmanaged	12.0	2.43	0.24
	Minimum Enrollment	10.0	1.90	0.19
	Steady Increase	10.0	1.90	0.19
	Maximum Enrollment	10.0	1.90	0.19
P5	Unmanaged	4.0	6.00	0.39
	Minimum Enrollment	4.0	5.50	0.37
	Steady Increase	4.0	5.25	0.34
	Maximum Enrollment	4.0	5.00	0.31
P6	Unmanaged	8.0	4.20	0.35
	Minimum Enrollment	7.0	3.45	0.25
	Steady Increase	5.0	2.25	0.18
	Maximum Enrollment	5.0	2.25	0.18
P7	Unmanaged	19.0	8.50	0.59
	Minimum Enrollment	17.0	7.83	0.52
	Steady Increase	17.0	6.83	0.50
	Maximum Enrollment	15.0	6.03	0.42
P8	Unmanaged	20.0	12.15	1.04
	Minimum Enrollment	19.0	10.45	0.91
	Steady Increase	18.0	7.88	0.77
	Maximum Enrollment	17.0	7.78	0.75
P9 15708	Unmanaged	26.0	17.20	0.98
	Minimum Enrollment	26.0	15.20	0.95
	Steady Increase	25.0	13.70	0.89

Feeder	Scenario	Number of Overloaded Transformers	Total Transformer Upgrade Capacity (MVA)	Total Transformer Upgrade Cost (MUSD)
	Maximum Enrollment	25.0	13.20	0.89

B. Comparison between LB and TOU-based SCM

Figure 30 shows the variation in peak load reduction achieved under *Maximum Enrollment* compared to the *Unmanaged* scenario for 9 Pepco feeders in 2035. The results show significant variability in program effectiveness:

- *TOU-based* outperforms *LB* in feeders such as P3 and P6, achieving greater peak load reductions.
- *LB* outperforms *TOU-based* in feeders like P1 and P8.
- Minimal differences are observed in feeders like P4, where both strategies perform nearly identically.

This variability underscores the feeder-specific nature of load management strategies, reinforcing that the effectiveness of *TOU-based* or *LB* depends on the unique operational characteristics of each feeder. Additionally, peak load reduction alone does not always translate directly to cost savings. If reductions occur within the same capacity bucket, upgrade costs remain unchanged. Moreover, the distribution of load reductions across transformers can affect overloading patterns and associated upgrade costs, highlighting the need for a granular approach to cost impact assessment.

Figure 31 further compares upgrade cost reductions achieved under *Maximum Enrollment* for *TOU-based* and *LB* SCM across various feeders, revealing additional variability:

- Feeders such as P1and P6 show identical cost savings under both strategies.
- *TOU-based* yields higher cost reductions for feeders like P2 and P7.
- *LB* achieves greater reductions for feeders like P8 and P9.
- Feeders like P3 Drive exhibit the highest cost reductions, with both strategies performing equally well.

These findings reinforce that the effectiveness of each strategy is highly dependent on feeder-specific characteristics. Optimizing cost efficiency requires tailored implementation rather than a one-size-fits-all approach.

Figure 32 and Figure 33 depict the NPV of upgrade costs for EV integration in Pepco from 2022 to 2035. Like trends observed in BGE, *Maximum Enrollment* under *LB* consistently results in the lowest NPV across most feeders, highlighting its long-term cost-effectiveness.

Figure 34 and Figure 35 show the cumulative trend of overloaded transformers across Pepco feeders. As EV loads increase, transformer overloads steadily rise. However, *Maximum Enrollment* results in the lowest number of overloaded transformers, further demonstrating the effectiveness of high EV enrollment paired with load management strategies in mitigating infrastructure stress.

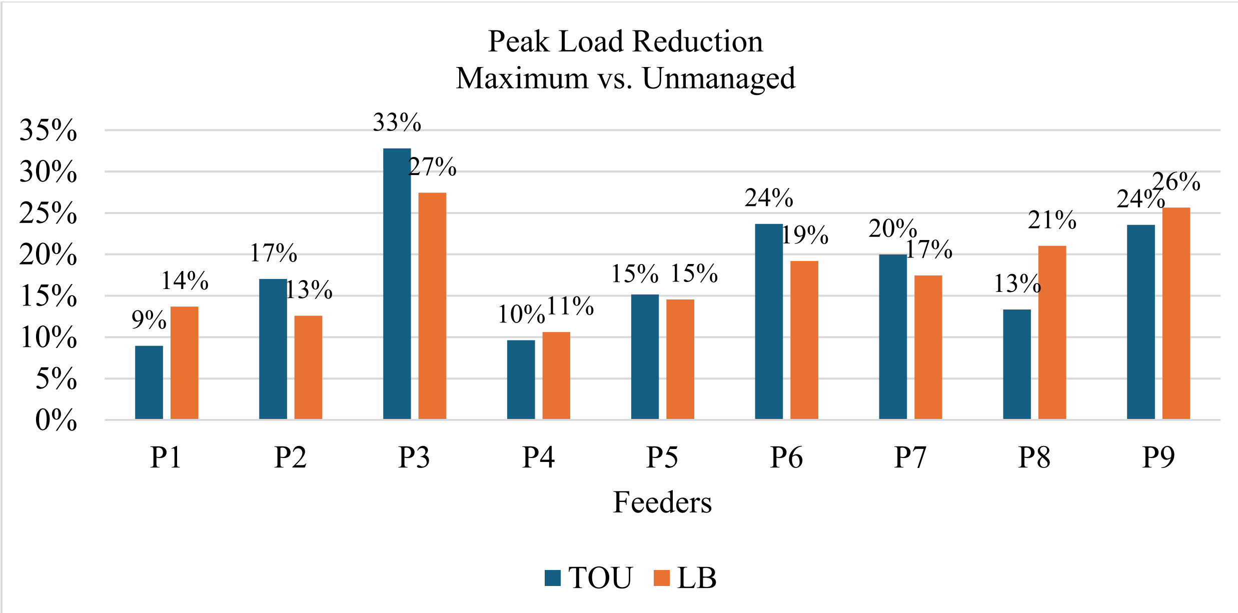

Figure 30 Comparison of LB and TOU in peak load reduction for 9 Pepco Feeders

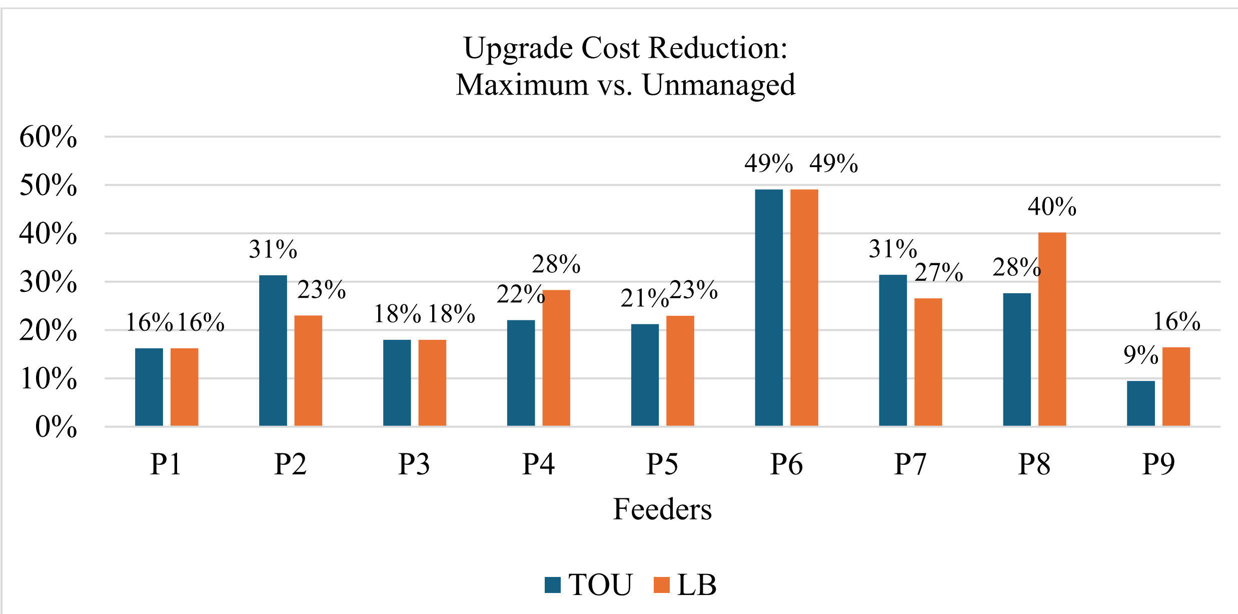

Figure 31 Comparison of LB and TOU-based upgrade cost reduction for 9 Pepco Feeders

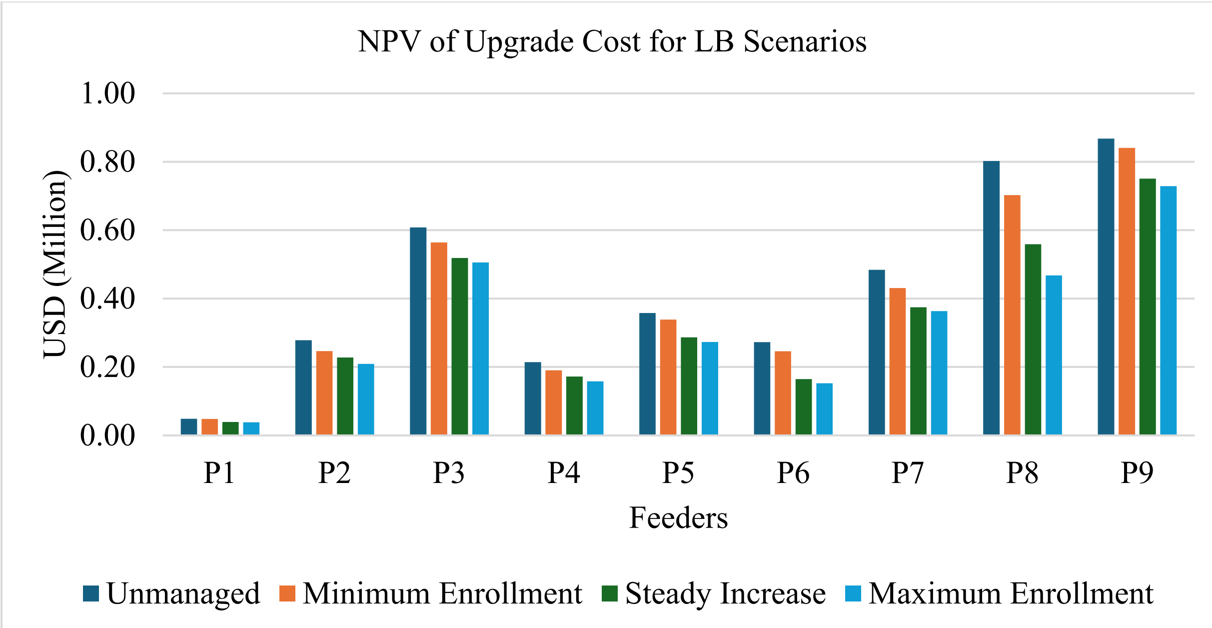

Figure 32 NPV comparison of upgrade costs for LB scenarios across 9 Pepco feeders

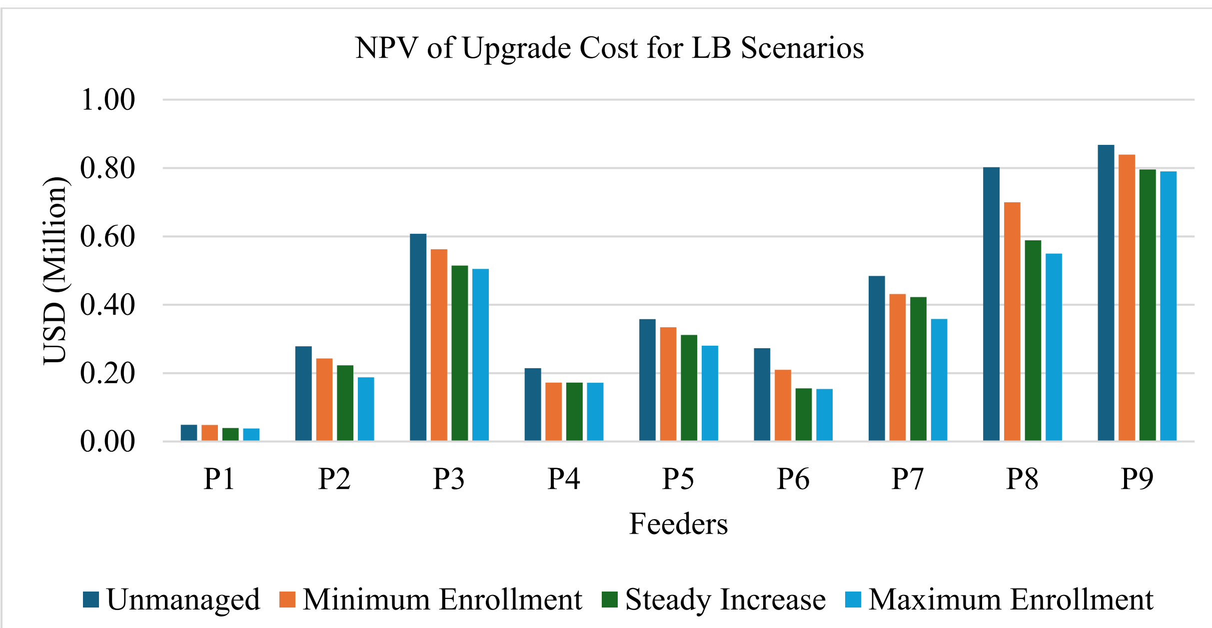

Figure 33 NPV comparison of upgrade costs for TOU scenarios across 9 Pepco feeders

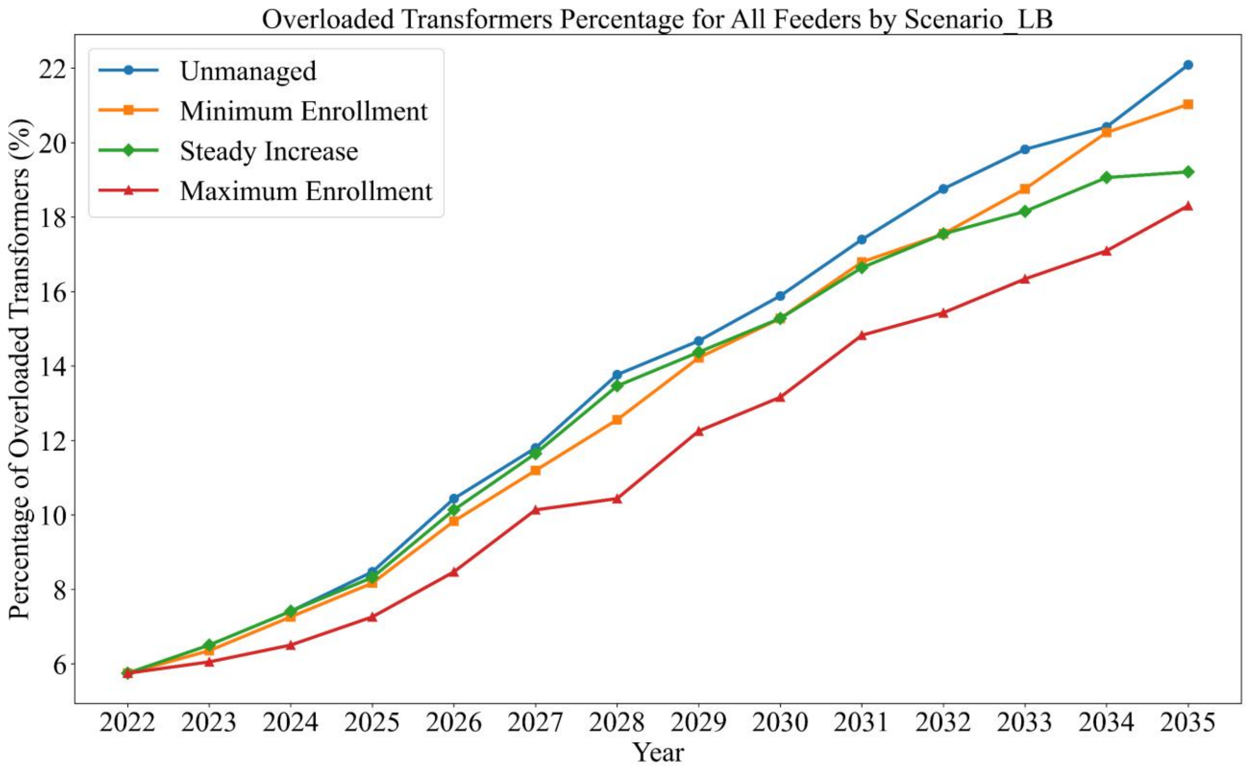

Figure 34 Summary of overloaded transformers under LB for 9 Pepco feeders

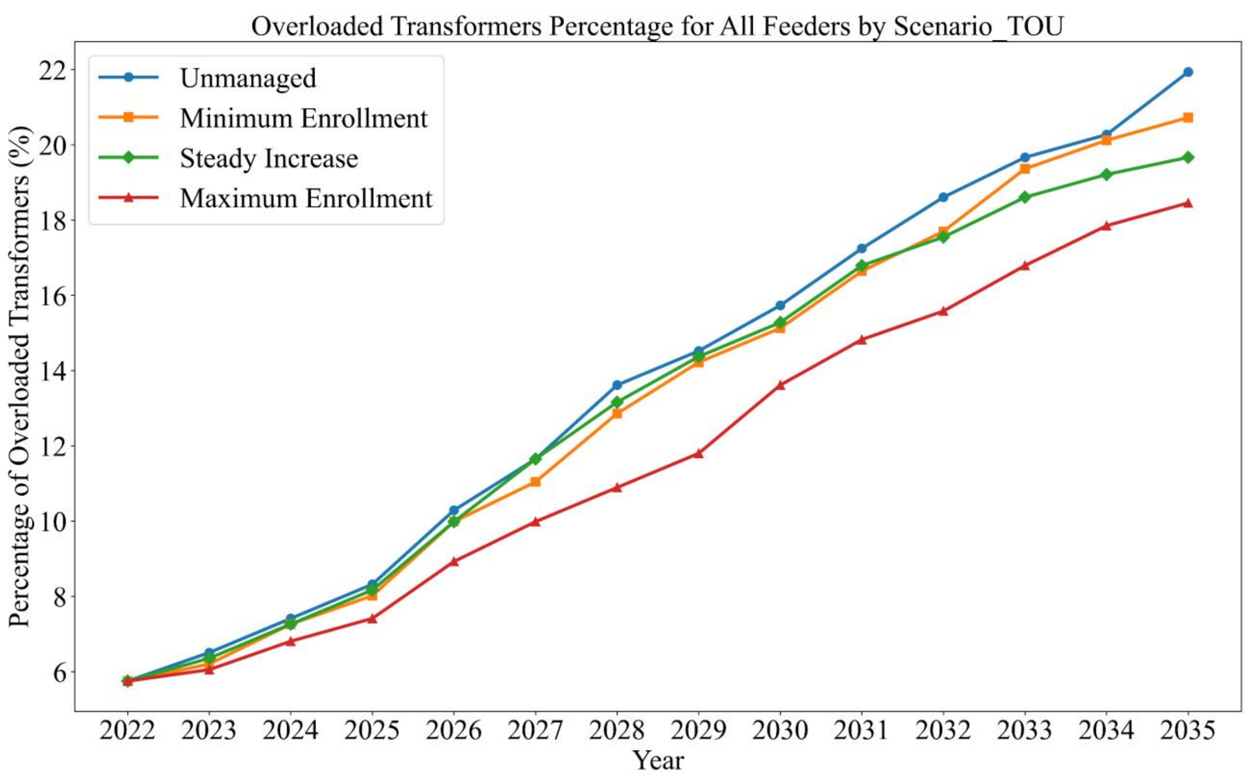

Figure 35 Summary of overloaded transformers under TOU for 9 Pepco feeders

4.4.2 System wide analysis for Pepco

For Pepco,722 feeders remained available for the clustering analysis described in Section 2.6. Figure 37 presents the total upgrade costs (MUSD) across three scenarios under *LB* and *TOU-based* SCM strategies. The results indicate:

- In the *Minimum Enrollment* scenario, upgrade costs shift out to later years, with *TOU-based* achieving slightly lower costs by 2035 ($236 million) compared to *LB* ($240 million).
- In the *Steady Increase* scenario, *LB* achieves total upgrade costs by 2035 of $219 million, slightly higher than *TOU-based SCM*'s $218 million.
- Cost differences in millions USD compared to *Unmanaged* scenario (Figure 36):

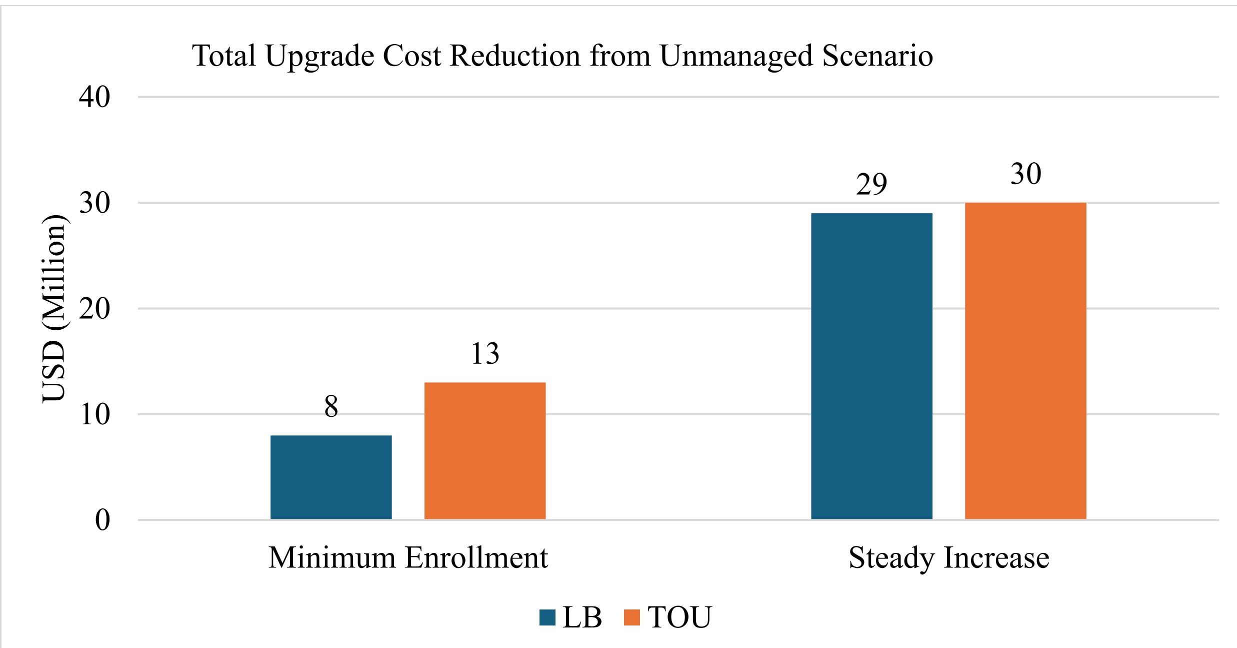

Figure 36 Comparison of upgrade cost with *Unmanaged Scenario* (Pepco)

The differences between *LB* and *TOU-based* are minimal, suggesting that both strategies perform similarly in terms of system-wide cost reductions for Pepco. In the *Minimum Enrollment* scenario, more than half of the feeders exhibit comparable avoided upgrade costs under both *LB* and *TOU-based*, leading to lower data variability. **Error! Reference source not found.**The r esults reinforce that while both *LB* and *TOU-based* can effectively defer distribution system upgrade costs, their relative performance varies by feeder, highlighting the need for strategic alignment of smart charging strategies with local grid conditions.

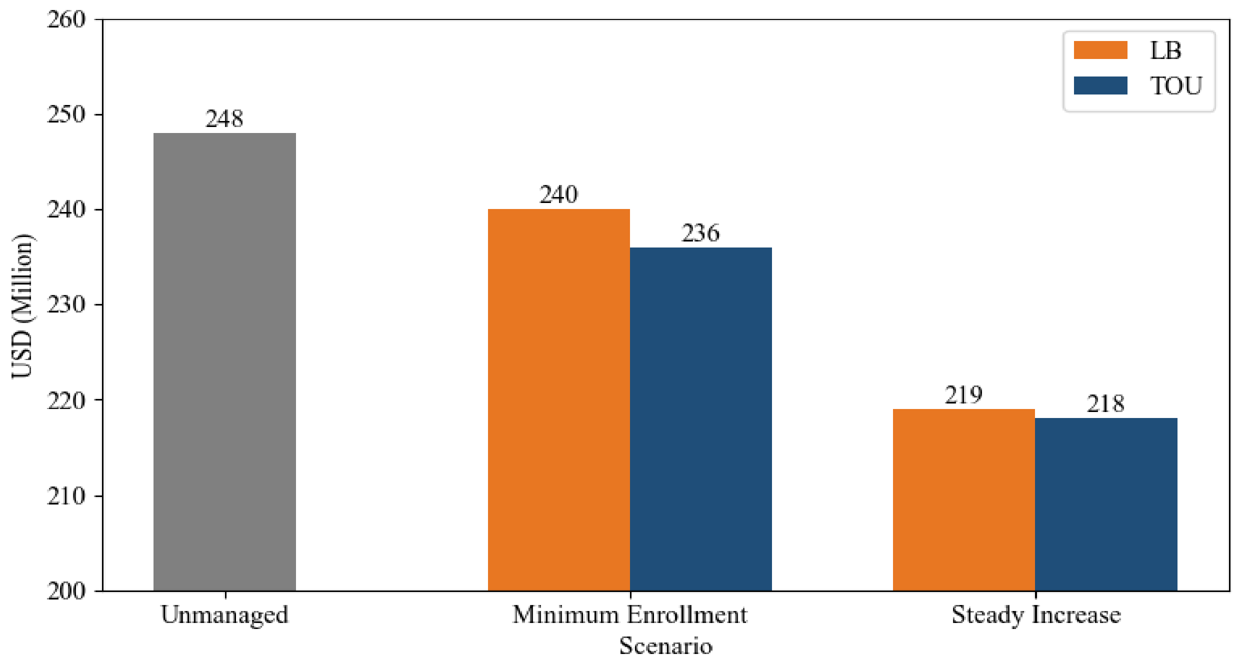

Figure 37 System wide upgrade cost for Pepco

4.5 Comparison of BGE and Pepco feeders

BGE and Pepco exhibit notable differences in their distribution infrastructure, influencing the impact of EV demand integration and the effectiveness of smart charging strategies.

- Transformer Density: BGE has nearly 50% more transformers per feeder than Pepco, averaging 180 transformers per feeder compared to 123 in Pepco.
- Line Density: Despite a slight difference, both utilities maintain a similar number of lines per feeder, with an average of 1,026 lines in BGE and 987 in Pepco.
- Equipment Ratings: Pepco feeders generally have higher equipment ratings relative to their load sizes, which helps mitigate stress on the grid.

Capacity Utilization and Overloading

- Transformer Utilization: 58% of transformers in BGE operate above 50% capacity, compared to 47% in Pepco among the selected feeders.
- Overloading: BGE experiences a higher prevalence of overloaded transformers, with 80% more overloaded units than Pepco.
- Line Overloads: Among the selected feeders, 36 feeders in BGE have overloaded lines, compared to 20 in Pepco, a trend that scales proportionally across the full network.

Infrastructure Upgrade Needs

- Transformer kVA Upgrade Requirements: The transformer upgrade demand in BGE is 45% higher than in Pepco, reflecting greater grid stress.

- Line Lengths: BGE feeders have longer average line lengths—65% greater than those in Pepco, adding complexity to grid management and upgrade planning.

These findings underscore the need for utility-specific strategies to address the distinct challenges of each network. While BGE faces more severe infrastructure constraints, requiring greater investment in upgrades, Pepco's higher equipment ratings and relatively lower transformer utilization suggest different grid management priorities. This also suggests that moving to maximum SCM enrollment scenarios, Pepco might begin to see more constraints consistent with BGE. Tailored smart charging strategies are essential to effectively support EV integration within each utility's unique operational framework.

5 Conclusions

This study demonstrates that ***LB* consistently achieves greater peak load reduction** for EV home charging compared to *TOU-based* SCM. Higher enrollment in SCM enhances peak load reductions for both strategies by improving coordination, shifting demand away from peak hours, and optimizing load distribution. However, **EV plug-in behavior significantly influences the effectiveness of each approach**. When most EVs plug in after 9 p.m. (when off-peak starts), ***TOU-based* SCM offers limited benefits**, making *LB* the more effective strategy for managing home charging loads. Additionally, ***LB* benefits from the flexibility of flat-rate users**, particularly in feeders with a higher proportion of such users, allowing for **more efficient load optimization and greater peak load reduction**.

Both ***LB* and *TOU-based* strategies effectively defer the system upgrade costs** to later years for BGE and Pepco, but their relative advantages vary by scenario and utility:

- *LB* outperforms *TOU*-based in the *Steady Increase* scenario, particularly across BGE's representative feeders and system-wide analysis.
- *TOU-based* SCM shows a slight system-wide advantage for Pepco, though the difference is marginal.
- In the *Minimum Enrollment* scenario, the benefits of managed charging are limited due to low EV participation, leading to only minor differences between *LB* and *TOU-based* and SCM. More than half of Pepco's feeders in this scenario exhibit similar avoided upgrade costs for both strategies, reducing data variability and impacting the accuracy of system-wide cost estimations.

While both strategies contribute to **extending the lifespan of existing infrastructure and deferring—but not eliminating—future distribution upgrades**, ***LB* provides greater flexibility** by **dynamically distributing demand across broader time periods**. This adaptability helps minimize overload conditions more effectively than *TOU-based*, which relies on **fixed peak and off-peak periods that may not align with actual load patterns**.

As **EV adoption continues to rise, *TOU-based* SCM is likely to create a secondary peak** when large numbers of EVs begin charging simultaneously at the start of the off-peak period. This **new peak could shift grid stress from traditional peak hours to later in the evening**, particularly in high-adoption regions. The results suggest that **static TOU pricing alone will not be sufficient in the long term**. More **sophisticated SCM approaches—such as Load Balancing, dynamic pricing, or real-time grid-aware smart charging—will be necessary** to distribute charging demand more efficiently and prevent new grid constraints.

From a **regulatory and utility planning perspective**, managed charging strategies provide **critical benefits**:

- Optimizing asset utilization, reducing transformers and line overloads.
- Delaying capital-intensive infrastructure upgrades, benefiting all rate payers.
- Enhancing grid reliability by preventing localized congestion and overloading.

- Providing a more gradual and cost-effective path toward widespread EV adoption.

Although managed charging can **postpone costly infrastructure investments**, eventually grid upgrades might still be necessary as **EV penetration increases**. However, prioritizing **smart charging—particularly through more advanced strategies like LB—enables utilities to better plan infrastructure investments, improve operational efficiency, and support long-term grid resiliency**. By integrating **flexible, data-driven load management strategies**, utilities, PUCs, and state agencies can **ensure a smoother, more cost-effective response to electrified transportation** while maintaining **grid stability and affordability for all consumers**.

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7 Appendix

Appendix A: TOU-based SCM

Algorithm 1: Load profile calculation in TOU-based SCM		
1	**Input:** Plug-in and plug-out times for each EV, maximum charging speed of each EV, total energy required for a charging session	
2	**Initialization:**	*active ev list* ← [] (list of EVs that can charge) *pending ev queue* ← [] (queue for EVs waiting to charge) *charging load profile* ← [] (store charging load at each time step) *ev charging rate* ← [] (store charging rate for each EV)

3	**Iteration:**	For each time step t from 7:00 a.m. to 7:00 a.m. the next day, in 15-minute intervals:
		  Identify EVs plugged in at t:
		  charge request list ← EVs plugged in at t + *pending ev queue*
		  If time t is between 7:00 a.m. and 5:00 p.m.:
		    Allow all EVs in *charge request list* to charge at maximum rate:
		    active ev list ← *charge request list*
		    Update *charging load profile* with total charging load of *active ev list*
		  Else if time t is between 5:00 p.m. and 9:00 p.m.:
		    Pause charging for all EVs in *charge request list*:
		    Add *charge request list* to *pending ev queue*
		  Else if time t is between 9:00 p.m. and 7:00 a.m.:
		    For EVs in *charge request list*:
		      If EV is plugged in after 9:00 p.m. (late-plugged EV):
		        Allow charging at maximum rate: *active ev list* ← EV
		      Else:
		        Calculate adjusted charging rate for each EV: rate ← remaining required energy / remaining time
		        Update *charging load profile* with adjusted charging rates
		        Update *charging load profile* with total load of *active ev list*
		  Remove fully charged EVs from *pending ev queue*
		End For

4	**Return**	*charging load profile*

Appendix B: Load Balancing Algorithm

The Load Balancing strategy primarily shifts most Load to overnight hours, resulting in the highest peak load during this overnight charging period. We can denote the peak load for this strategy as N, which occurs during the *overnight charging* window. According to WeaveGrid data, the magnitude of peak home charging during the daytime low-demand period is observed to be 10% of the overall peak load throughout the 24-hour cycle. Therefore, the allowable peak load during this period is a fraction of N, represented as $r \times N$. In the peak-hour window, EVs on flat-rate plans are allowed to charge, while the allowable load gradually increases from $r \times N$ to N by midnight. To minimize the peak load during these hours, charging for TOU users is postponed until after 9 pm. By establishing unique peak load limits for each time window and estimating the total home charging demand required from 7 am to 7 am, we calculate the total allowable load N for each feeder using the following equation.

$$N = \frac{2 * (A_1 + A_2 + A_3 + A_4)}{20\,r + 7(r + 1) + 14} \tag{B1}$$

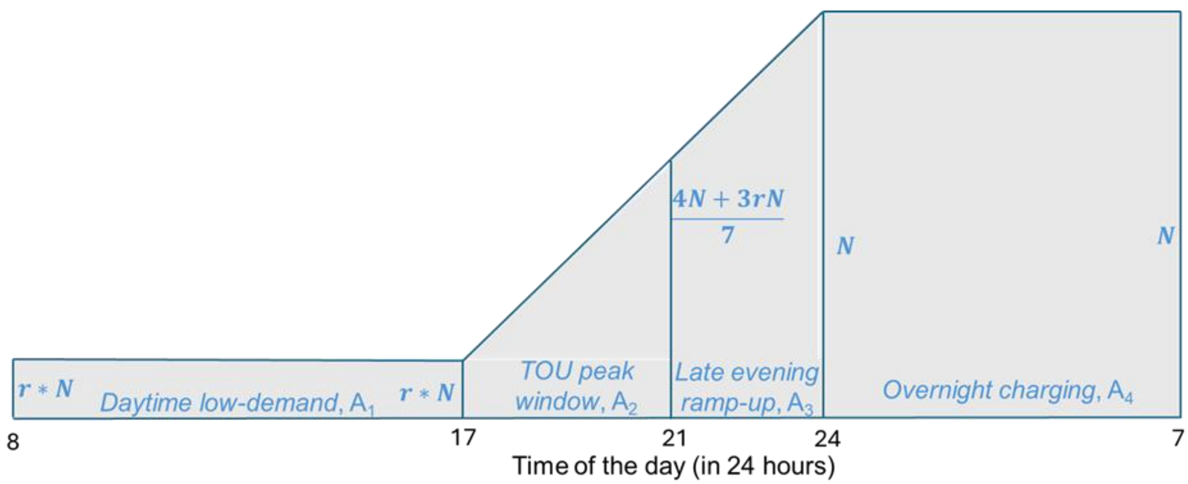

Figure B1: Peak Load limits across daily time windows in the proposed Load Balancing approach.

In this equation, r is initially set to 0.1 but can be adjusted as a variable, providing control over the allowable peak Load. Based on WeaveGrid results, we observed r to be approximately 0.1. Our method leverages knowledge of each EV's plug-in time and total daily energy $(A_1 + A_2 + A_3 + A_4)$ requirement, allowing us to estimate the total energy needed for the day in advance. The overall process for Load Balancing is outlined in Algorithm 2.

Algorithm 2: Load profile algorithm in Load Balancing		
1	**Input:**	Plug-in and plug-out times for each EV
2	**Initialization:**	*active ev list* ← [] (list of EVs that can charge) *pending ev queue* ← [] (queue for EVs waiting to charge) *charging load profile* ← [] (store charging load at each time step)
3	**Calculate**	Maximum capacity N by using Equation B1
4	**Sort**	EVs based on plug-in time, current state of charge (SOC), and target SOC
5	**Iteration**	For each time step t from 7:00 a.m. to 7:00 a.m. the next day, in 15-minute intervals: *charge request list* ← EVs plugged in at t + *pending ev queue* *load request* ← total load from *charge request list* If t is in 7:00 a.m. to 5:00 p.m. Determine the first set of EVs from *charge request list* where load < $r \cdot N$ *active ev list* ← selected EVs meeting the load threshold *non active ev list* ← *charge request list* – *active ev list*

Add *non active ev list* to *pending ev queue*
Update *charging load profile* with total charging load of *active ev list*
If t is in 5:00 p.m. to 9:00 p.m.
For EVs that are flat rate user
Select EVs from *charge request list* (flat-rate) where load is below the threshold for t
active ev list ← selected flat-rate EVs.
non active ev list ← *charge request list* – *active ev list*
Add *non active ev list* to *pending ev queue*
Update *charging load profile* with total charging load of *active ev list*
For EVs that are TOU rate users:
Pause charging for all EVs in *charge request list*:
Add *charge request list* to *pending ev queue*
If t is in 9:00 p.m. to 7:00 a.m.
Determine the first set of EVs from *charge request list* where load is below the threshold for t
active ev list ← selected EVs meeting the load threshold
non active ev list ← *charge request list* – *active ev list*
Add *non active ev list* to *pending ev queue*
Update *charging load profile* with total charging load of *active ev list*
End For
6 **Return** *charging load profile*

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