INTEGRATING ELECTRIC VEHICLES INTO INTEGRATED RESOURCE PLANNING

by

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ABSTRACT

ABHIJITH RAVI. Integrating Electric Vehicles into Integrated Resource Planning. (Under the direction of DR. LINQUAN BAI)

Electric Vehicles (EVs) stand at the forefront of decarbonization initiatives in the United States. State, federal, and utility incentives play a pivotal role in establishing the necessary charging infrastructure to support EVs. In North Carolina, Executive Order No. 246 has called for a 50% reduction in statewide greenhouse gas emissions from 2005 by 2030 and set a goal of at least 1,250.000 registered zero-emission vehicles (ZEV) in the state by 2030. Since an EV charging infrastructure can range from 3.3 kW- 500 kW, it is essential to analyze the impact of EVs on the prevailing power infrastructure. Integrated Resource Planning (IRP) serves as a "guideline" outlining possible strategies for a utility to address future energy needs and demand, weighing the risks and advantages for its customers. This thesis focuses on integrating EVs into the IRP process. Four power distribution feeders F1, F2, F3, and F4 of residential, commercial, urban-commercial, and industrial loads, respectively, were considered for this study. A bottom-up methodology was adopted in this study to analyze the impact of EV adoption on the distribution network and then the total demand of the feeders in the Carolinas. Realistic assumptions were developed to estimate the location, size, and charging behavior of different types of EVs. The results from the distribution level analysis were scaled up using the "Scale-Up Model" developed during the study. The results indicate that while some distribution feeders may be overloaded, others can host the expected EV load of 6.2%. Based on the assumptions, the impact at the system-level can be met by the planned resources.

DEDICATION

This work is wholeheartedly dedicated to my beloved wife, Aswathi Manden, whose unwavering support and encouragement have been my anchor and my guiding light. To my cherished son, Shiva Manden, who inspires me every day to be the best version of myself and to strive for excellence in all endeavors.

I extend this dedication to my caring mother, Ajitha Kumari, whose love and sacrifices have shaped me in innumerable ways. And in loving memory of my late father, Ravi Iyyatil, whose values and teachings continue to guide me. His legacy remains a cornerstone of my life's work.

Their collective belief in my potential has been the wind beneath my wings, propelling me forward through this journey. This accomplishment stands as a tribute to their immeasurable contributions to my life.

ACKNOWLEDGEMENTS

First and foremost, I express my deepest gratitude to my advisor, Dr. Linquan Bai, whose expertise and thoughtful mentorship have significantly shaped my research journey from its inception to completion.

My sincere thanks go to the Center for Advanced Power Engineering Research (CAPER) members for welcoming me into the project CAPER-PG02. The opportunity to engage from the ground up in such impactful work has been both an honor and a profound learning experience.

I am also indebted to my dedicated colleagues Chance Stowe, Elaina Stuckey, and Grant Wollam, graduates in Electrical Engineering from Clemson University. Although they joined at different stages, their contributions to the analyses of Feeders F1 and F3 were vital to the project's overall success. The knowledge exchange and collaborative spirit we shared have been a cornerstone of my time with the project.

This thesis stands as a testament to the collective effort and shared aspirations of all those who contributed to its underlying work. I am truly appreciative of the support, camaraderie, and shared vision that each of you brought to this endeavor.

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LIST OF ABBREVIATIONS

BESS	Battery Energy Storage System
EV	Electric Vehicle
EVCS	Electric Vehicle Charging Station
EVI	Electric Vehicle Infrastructure
HEV	Heavy-duty Electric Vehicle
IRP	Integrated Resource Planning
LEV	Light-duty Electric Vehicle
MEV	Medium-duty Electric Vehicle

CHAPTER 1: INTRODUCTION

1.1 Electric Vehicle Overview

Transportation was the main source of greenhouse gas (GHG) emissions in the United States in 2021, contributing 28 percent of the country's overall emissions. Total emissions from burning fossil fuels in transportation grew by 19% between 1990 and 2021. Light-duty trucks, which include sport utility vehicles, pickup trucks, and minivans (37%), medium- and heavy-duty trucks (23%), passenger cars (21%), commercial aircraft (7%), other aircraft (2%), pipelines (4%), ships and boats (3%), and rail (2%) were the top sources of transportation-related GHG emissions in 2021 [1]. The rapid adoption of innovative transportation technology, such as zero-emission cars, in as many light-, medium-, and heavy-duty applications is a key element of the United States' long-term transportation strategy. Increased electric vehicle (EV) adoption and industry targets for even higher EV sales are already being sparked by the growing popularity of EVs, which is aided by incentives and ongoing advancements in battery technology [2]. In addition to reducing pollutants to the environment, EVs also cost less to operate and maintain for their owners than cars with internal combustion engines (ICEVs).

1.1.1 Reemergence of Electric Vehicles in the U.S

Robert Anderson from Scotland built the first EV between 1832 and 1839. In the United States, mechanical engineer Henry G. Morris and chemist Pedro G. Salom from Philadelphia designed and built the first successful electric car, called "The Electrobat" in 1894. William Morrison created a six-wheeled EV with a top speed of 23 km/h in 1895. Research and development in the area of EV attracted a lot of researchers in the years 1898–1930. Around 40 % of vehicles in the US were electric in the early 1900s [3].Factors like improvements to roads and the discovery of crude oil led to the fall of EVs in the early 20th century in the US [4]. While limited charging infrastructure and battery technology were challenges for the EVs, ICEV benefited from an established fueling network and mature engine technologies [5]. Furthermore, the petroleum crisis that occurred in the United States during the 1970s resulted in a redirection of policymakers' attention away from EVs and towards providing support for the importation of oil from countries belonging to the Organization of the Petroleum Exporting Countries (OPEC).

The resurgence of interest in EVs on a worldwide and national scale can be attributed to various factors, such as growing apprehensions regarding climate change, the instability of oil prices, and notable breakthroughs in battery storage technology. The global awareness of climate change contributed to the rise of strict greenhouse gas emission control in the automobile industry. EVs are the cleanest technological alternative to ICEVs. During the second quarter of 2022, there was a notable increase of 66 percent in the sales of light-duty EVs (LEVs) in the United States, as compared to the corresponding time in 2021. This surge in sales accounted for 5.3 percent of the total new vehicle sales [6]. The available evidence indicates that the progress of technology in EVs has played a significant role in driving the adoption of battery EVs (BEVs). Therefore, the ongoing enhancement of EV technology has the potential to contribute to a rise in the market share of EVs [7]. Nevertheless, the adoption of EVs could potentially lead to an upsurge in electricity usage, requiring the expansion of a decarbonized power system and a concerted effort to encourage the use of smaller and lighter automobiles. [8]. Therefore, it is imperative for utilities to ascertain the effects of EV adoption on the power grid. The adoption of EVs exhibits a significant degree of regional variation. The adoption rate of EVs exhibits variability at the county or state level. This thesis centers on estimating the impacts of EVs in the Carolinas region, encompassing the states of North Carolina and South Carolina.

1.1.2 State-Led Initiatives: Policies Driving EV Adoption in the Carolinas

To achieve the goal of GHG-emission-free transportation, several EV-friendly policies have been proposed at the federal and state levels. At the federal level, the U.S. Department of Energy has introduced EV tax credits to reduce the upfront cost of EVs[9]. To increase the availability of refueling infrastructure from alternative fuels, the Federal Highway Administration is working towards an Alternative Fuel Corridor initiative [10]. Apart from federal initiatives, policies at the state level are also motivating EV customers. On October 29, 2018, North Carolina's Executive Order No. 80 defined the state's goal for zero emission vehicle (ZEV) adoption for the year 2025 [11]. Governor Roy Cooper, on October 25, 2022, officially endorsed Executive Order 271, which mandates the Department of Environmental Quality (DEQ) to commence the rulemaking procedure for the implementation of an Advanced Clean Trucks (ACT) program [12]. Both North Carolina and South Carolina are part of the Drive Change Drive Electric campaign in the north-east. This is a campaign to advance consumer awareness about EVs [13]. Based on the above policies motivating EVs, the utilities in the Carolinas area are also providing schemes for LEV and heavy-duty electric vehicle (HEV) adoption. Duke Energy has proposed initiatives like the Electric Transportation Program in North Carolina. This program provides customer incentives for residential EV charging, public charging, fleet EV charging, EV school bus charging stations, etc. [14]. Duke Energy has introduced similar initiatives for South Carolina as well.

1.2 Potential Impact of EV adoption on Power Grid Infrastructure

Transportation accounts for 27 % of total U.S. energy consumption in 2022 [15]. Therefore, the transition to EVs drastically loads the existing power grid infrastructure. Meanwhile, there has been a growing need for the transition to clean energy generators on the grid. With several fossil fuel generation plants being retired, the integration of EVs into the power grid poses both challenges and opportunities for grid operators. It is essential to carefully manage the impact of EV adoption while maintaining the stability and reliability of the grid. The International Energy Agency's "Global EV Outlook 2023" provides a comprehensive analysis of this trend, noting that the adoption of EVs will significantly increase electricity consumption [16].

The integration of EVs into the power grid requires significant upgrades to the existing infrastructure. The necessity of updating the antiquated electric transmission and distribution (T&D) grid to accommodate the augmented load and operational hazards presented by the exponential adoption of EVs is acknowledged by utilities and policymakers. The report by McKinsey & Company focuses on the shifting nature of electric networks and sheds light on several difficulties that arise in this context [17]. These challenges encompass the incorporation of distributed energy resources (DERs), such as EVs, as well as the mounting strain on the T&D grid. The effective management of EV charging is of paramount importance to address potential grid limitations and cope with peak demand issues.

The Smart Electric Power Alliance (SEPA) [18] emphasizes the significance of utility-managed charging schemes in converting EVs into profitable grid assets. These programs have the capability to synchronize the power supply, which is becoming more varied and sporadic as a result of the integration of renewable energy sources, with adaptable demand. The establishment of open technical standards plays a fundamental role in the implementation of managed charging, as it facilitates the compatibility and smooth flow of data between utilities and market participants. The adoption of EVs presents both challenges and opportunities for power grid infrastructure.

1.3 Introduction to Integrated Resource Planning

Considering the changing landscape of the generation and consumption of energy, state regulatory commissions require utilities to submit an Integrated Resource Plan

(IRP) to meet the energy demand for the next 10 to 15 years. An IRP serves as a strategic framework that outlines prospective strategies for a utility company to fulfill forthcoming energy and demand needs, considering the corresponding advantages and disadvantages for customers.

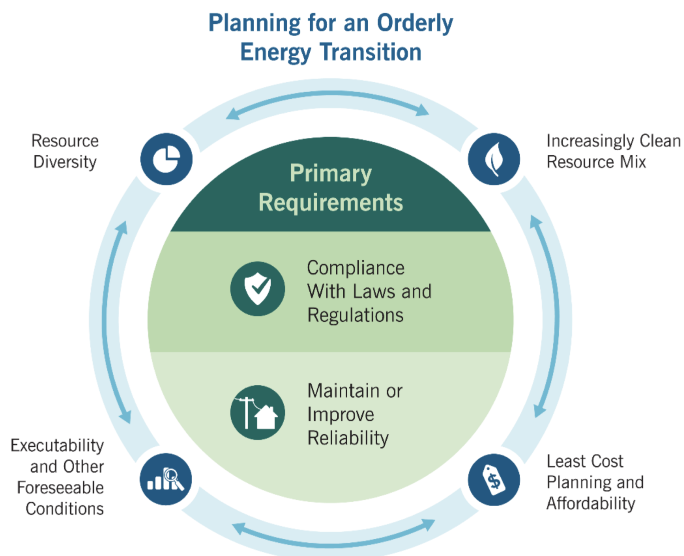


Figure 1.1: Long-term resource planning objectives[19]

As depicted in Figure 1.1, the foremost objective of long-term resource planning is to guarantee an adequate supply of generation resources to satisfy future demand. In the process, it is imperative for the planners to prioritize resource variety and promote a progressive integration of clean energy sources to mitigate emissions stemming from fossil fuel usage. The implementation of the IRP necessitates adherence to relevant planning, environmental, and other legal frameworks, with the overarching goal of preserving or enhancing the reliability of the power system. The IRP is tasked with evaluating and contrasting multiple avenues of resource adoption to determine the optimal equilibrium between the principles of least-cost planning and environmental sustainability.

1.4 Relevance of Integrating EVs into North Carolina's IRP Process

The incorporation of EVs within the IRP process in North Carolina is crucial to effectively managing the state's energy transition and achieving its sustainability objectives. Duke Energy's Carolinas Resource Plan outlines a plan for switching to cleaner energy sources. This plan aims to strike a balance between conventional energy sources and an increasing proportion of renewable energy, with the ultimate goal of achieving carbon neutrality by the year 2050 [20]. The significance of this transition lies in the fact that the transportation sector in the United States is the largest contributor to carbon emissions. Consequently, the shift from petroleum-based fuels to electricity as a source of power for vehicles represents a substantial stride toward the process of decarbonization.

Nevertheless, the incorporation of EVs into the IRP process also poses certain difficulties. The existing market penetration of EVs, which stands at 2%, now exerts a minimal influence on the electric utility grid. However, if the adoption of EVs escalates, the grid will encounter additional demands. According to the NREL, there is a projected 38% rise in energy consumption in a scenario where EV adoption is high. This underscores the necessity for significant grid planning and investment [21]. According to the 2035 Report of the University of California, Berkeley, it is projected that there will be a gradual and controllable annual increase of 2% in demand for EVs. Consequently, investments in renewable energy generation will be required to adequately fulfill this need [22].

The incorporation of EVs into North Carolina's IRP represents a strategic endeavor aimed at fostering a sustainable energy trajectory. The proposed solution is in line with the state's objectives of achieving carbon neutrality and effectively tackles the obstacles posed by the rising demand for electricity and the need for system upgrades. By implementing proactive legislation and fostering utility cooperation, North Carolina has the potential to emerge as a front-runner in the shift toward electric transportation.

As of 2020, Duke's IRP did not consider EVs in resource planning. This thesis presents part of the analysis done for CAPER's PG02 project, which focuses on integrating EVs in the IRP process.

1.5 Research Objectives and Questions

While integrating EVs into the IRP process is essential, several research questions need to be addressed to fully understand the implications and potential of this integration. This thesis will focus on following a bottom-up modeling approach to analyze the impact of EVs on the grid. It starts with analyzing the impact of EVs on the distribution feeder level and then moves on to the system-wide implications of EV integration in resource planning. To incorporate the behavior of different types of EVs and their charging patterns, feeders with different demographic characteristics were considered. Another factor that separates this thesis from other analyses on the impact of EVs is the use of real distribution feeders in a simulation tool that matches the industry standard. The research questions that guided this study are as follows:

Question 1: What are the unique impacts of increasing EV adoption rates on individual distribution feeders?

Question 2: How can the driving and charging behavior of different EV loads be modeled?

Question 3: What are the potential vulnerabilities in customer transformers, voltage regulators, and substation transformers due to increased EV adoption?

Question 4: What mitigation strategy might work best for EVs at the distribution level?

Question 5: What is the effect of EV adoption at the system level?

1.6 Summary

Chapter 1 gives a background on the trend of electric vehicle adoption in the United States and the Carolinas. It provides an insight into the integrated resource planning process of the utility. The research questions guiding this thesis are also presented in the chapter.

Chapter 2 discusses the assumptions that led to the methodology adopted for this study. It starts with how the distribution feeders were selected for this analysis. This chapter also presents trends in EV adoption and how each distribution feeder has gone through an extensive load classification and possible EV load identification. It presents the assumptions developed to integrate the realistic driving habits of consumers into this study. Then, the methodology for analyzing the impacts of EV adoption at the distribution and system levels is presented.

Chapter 3 presents the results of the analysis based on the assumptions and methodology presented in Chapter 2. It discusses the results of different distribution feeders and the comparison of mitigation measures adopted at the distribution level of the power grid. It presents the data that was extracted from the distribution level and the results obtained from the scale-up model presented in Chapter 2.

Chapter 4 concludes this thesis. It answers the research questions presented in Chapter 1. It also presents the overall impact of electric vehicles at the distribution and system levels.

CHAPTER 2: ASSUMPTIONS AND METHODOLOGICAL FRAMEWORK

A detailed bottom-up methodology has been employed in this study to understand the impact of integrating EVs into the IRP process. Different EVs have different driving and charging behaviors. The first step in the methodology was to identify suitable feeders for the study based on their demographic characteristics and potential for EV adoption. The selected feeders also need to capture the different EV customers in the real world. In the subsequent phase of the process, a series of educated assumptions were developed. Customer loads on each feeder were identified based on available GIS data. Assumptions about the possible EV loads associated with these customer loads were made. This step lays the foundation for understanding the unique impacts of increasing EV adoption rates on individual distribution feeders.

After identifying possible locations for EV loads, assumptions related to infrastructure requirements necessary to support the expected EV loads were made. GIS data, along with real charging infrastructure data, was utilized to create assumptions about EV charging infrastructure. In the next step, the assumptions for EV charging profiles for different types of EVs were generated. These assumptions capture the driving and charging behavior of EVs to accurately model their impact on distribution feeders. Furthermore, assumptions related to the separate modeling of light vehicles and heavy-duty vehicles in the context of EV integration were developed. Hence, different EV adoptions were assumed for light vehicles and heavy-duty vehicles to capture their distinct characteristics and impacts on the distribution network. This is also related to the increased fleet electrification policies adopted by governments and businesses.

The potential impacts of integrating EVs at the distribution level were assessed using LEV adoption, HEV adoption, and time of year. The vulnerabilities in the feeder were analyzed using load flow analysis in Cyme. The monitored vulnerabilities include overload, undervoltage, and voltage regulator operations. Then, assumptions for scaling up the impact of the distribution feeders were formed. These assumptions laid the groundwork for the “Scale-Up Model," which aimed to estimate the system-wide impacts of increasing EV adoption on the distribution grid.

2.1 Feeder Selection Process

Four distinct distribution feeders were analyzed. Each feeder represents a unique customer load type and is located in North Carolina. For detailed analysis, these feeders were modeled using Cyme software. A one-line diagram for these feeders is provided in Figure 2.1 for better visualization.

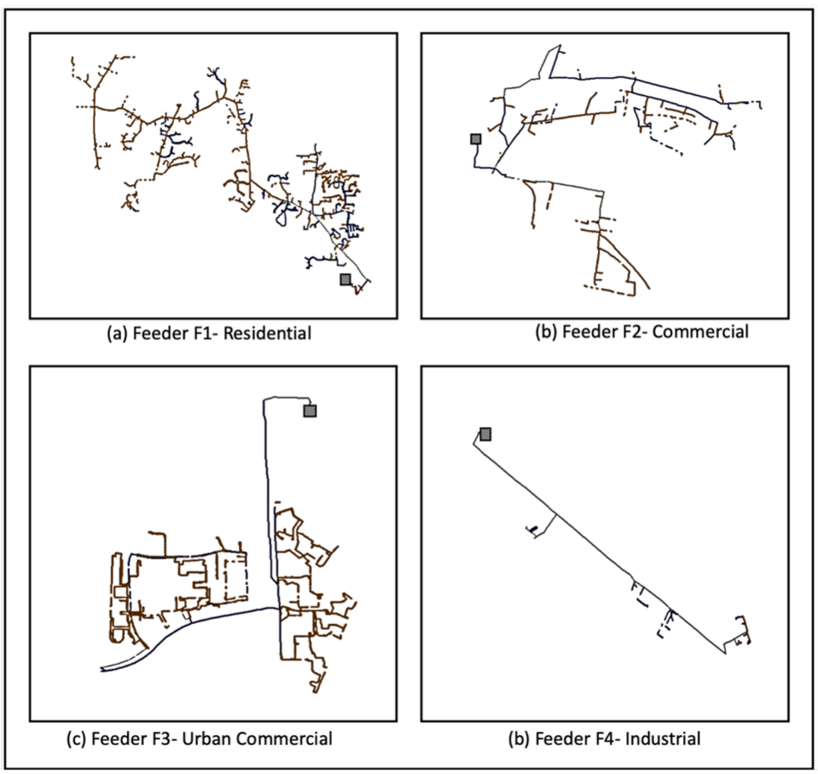


Figure 2.1: One line diagram of selected feeders

Feeder F1 was selected to represent residential loads, with the aim of understanding the impact of EV adoption on this sector. With a peak demand of 15.2 MVA, this heavily loaded feeder serves as a valuable case study for residential impacts.

Feeder F2 serves as a commercial feeder, powering an electric bus fleet and a diverse range of buildings. The feeder's coverage includes potential sites for future EV charging stations, making it a key focus for understanding commercial load impacts.

Feeder F3, a balanced mix of residential and commercial loads, was chosen to explore the impacts of EV adoption on urban-commercial loads. Unlike F2, this feeder primarily powers shopping centers and quick-service restaurants.

In Phase 2 of the project, a fourth feeder, F4, was introduced to represent industrial loads. This feeder powers manufacturing facilities and office spaces and provides key data on how the industrial sector might be affected by increased EV usage.

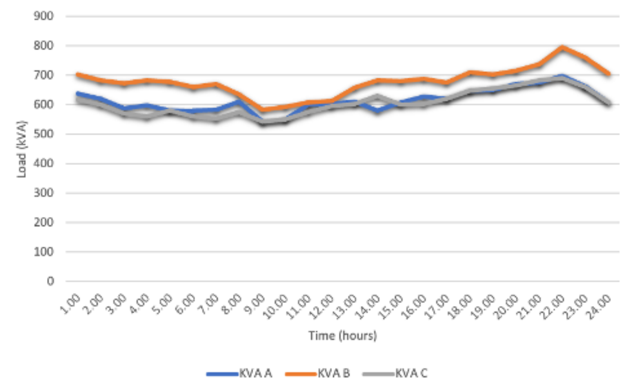
Table 2.1: List of Distribution Feeders Considered for the Study

Feeder	Voltage (kV)	Connected kVA (MVA)	Peak Demand (MVA)
Feeder 1	12.5	20	15.2
Feeder 2	12.5	20	2.1
Feeder 3	24	20	9.5
Feeder 4	24	46.8	5.2

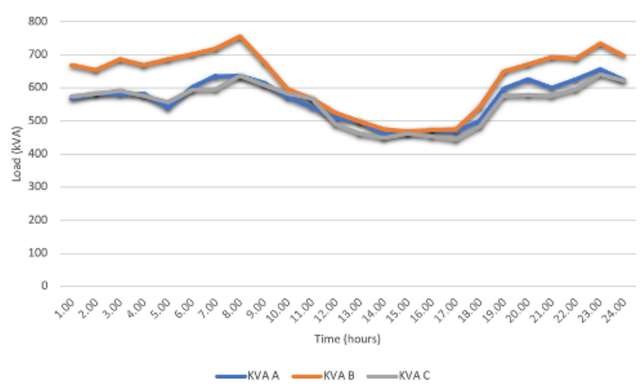
Through the analysis of these feeders, a comprehensive understanding of the various impacts of EV adoption at the distribution level was gained. This information is pivotal for scaling up the findings to understand the broader impacts on all feeders in the selected Carolinas region.

2.2 Constructing Base load Profiles

To determine the expected base load, historical load data for the selected feeders in 2020 was used. This large data set was divided into hourly intervals to provide a comprehensive view of demand fluctuations throughout the day. The primary objective was to identify instances of peak demand; consequently, historical peak load data for both the summer and winter was meticulously extracted for further analysis. This data was then plotted to create a visual representation of a 24-hour load profile for the most demanding day of these seasons.



(a) Summer peak



(b) Winter peak

Figure 2.2: Historical peak loads of feeder F2

Figure 2.2 offers a comprehensive visual presentation of the historical load of a lightly loaded feeder F2. It depicts the behavior of the feeder during days of highest demand. Similar peak load instances for summer and winter were identified for all feeders included in the study, allowing for a comprehensive comparison of the behavior of various feeders under peak load conditions during different seasons. Subsequently, base load profiles were devised for each of the feeders, with the exception of the industrial feeder designated as feeder F4. Initially, the loads were determined using GIS data. Then, the loads were classified into various types of loads, such as midrise apartments, residential houses, elementary schools, office buildings, hotels, quick-service restaurants, full-service restaurants, strip malls, warehouses, etc. This helped in defining a realistic load distribution on the feeder, which is essential to the formulation of effective and efficient load management strategies. The Open Energy

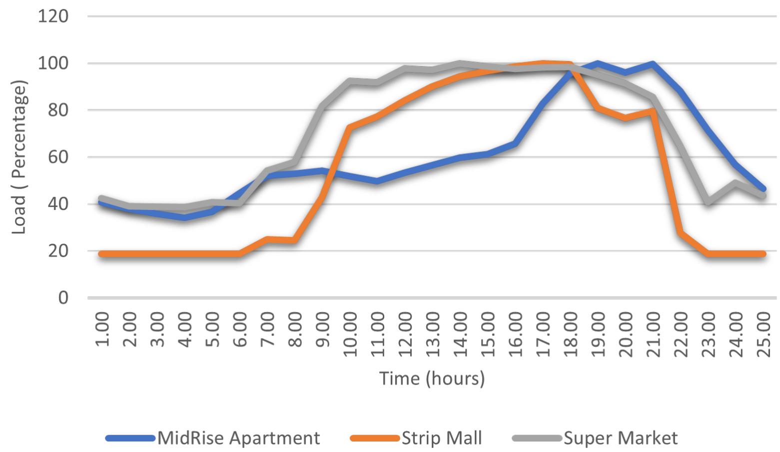


Figure 2.3: Customer load profiles

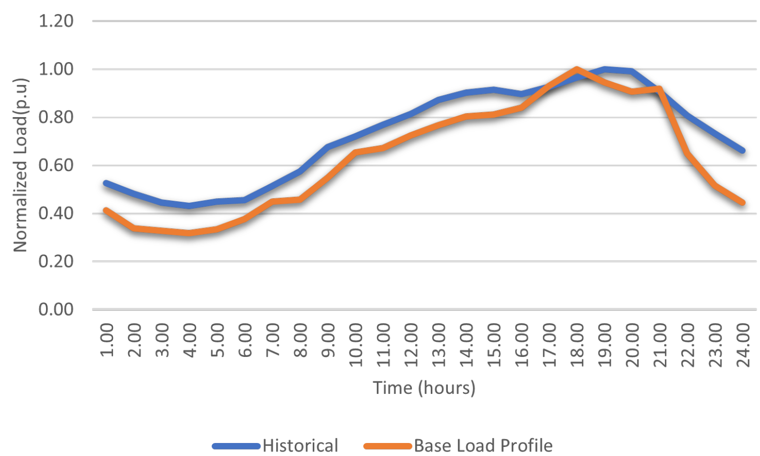


Figure 2.4: Comparing the historical and base load profile of feeder F3

Data Initiative published end-use load profiles for U.S. building stock, referred to as [23]. The published data included load profile shapes for typical building types in several U.S. cities, including the city where the feeders under the analysis are located. A mid-rise apartment, a strip mall, and a supermarket located in Mecklenburg County, North Carolina, were selected from this database to illustrate typical load profiles. Figure 2.3 provides a graphical representation of these examples. Using load profiles and spot load ratings of customers, the base load profile for each feeder was generated. This data was then compared with the historical load profile. Figure 2.4 illustrates the comparison of the summer peaks of the created base load profile with the historical load profile for feeder F3. This comparison provides a precise visualization of the similarities between the created and historical load profiles.

2.3 Electric Vehicle Assumptions

To include electric vehicles in the integrated resource planning process, several assumptions were made regarding their adoption and charging behavior. Key assumptions for EV adoption rate, EV load identification and classification, EV infrastructure estimation, and EV load profile generation. Assumptions related to EV adoption were formed for LEVs and fleets separately. LEV adoption was assumed to follow a gradual growth rate. EV fleets, on the other hand, were assumed to grow faster based on the increasing demand for electric vehicle adoption in the commercial and public transportation sectors. EV loads were identified and classified based on the customers connected to each distribution feeder. Then, assumptions related to EV infrastructure for each identified EV load were formed. Assumptions related to the charging behavior of each type of EV load are used to generate customer-specific EV load profiles. Clear and consistent assumptions regarding EV adoption, load identification, infrastructure estimation, and load profile generation are crucial for accurate integrated resource planning when incorporating electric vehicles.

2.3.1 EV Adoption Trends

In line with ensuring preventive measures, a plan was laid out to methodically evaluate possible system vulnerabilities at different intervals over the upcoming fifteen years. This forward-looking review aims to pinpoint when and where certain issues might arise, facilitating timely responses. Key insights were gathered for the years 2025, 2030, and 2035, with 2020 as the baseline. In this regard, projecting the anticipated level of EV adoption for each milestone year was crucial. The Edison Electric Institute (EEI) data [24] was instrumental in aiding this projection, spotlighting the recent uptick in EV sales in the US, current EV stock, and forecasts for 2030.

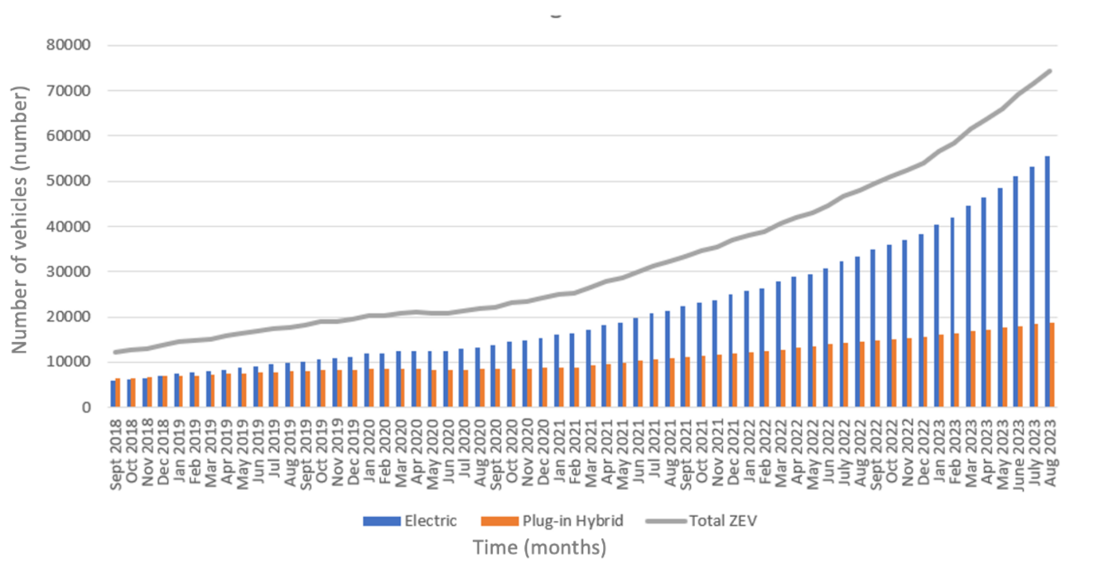


Figure 2.5: EV adoption in North Carolina

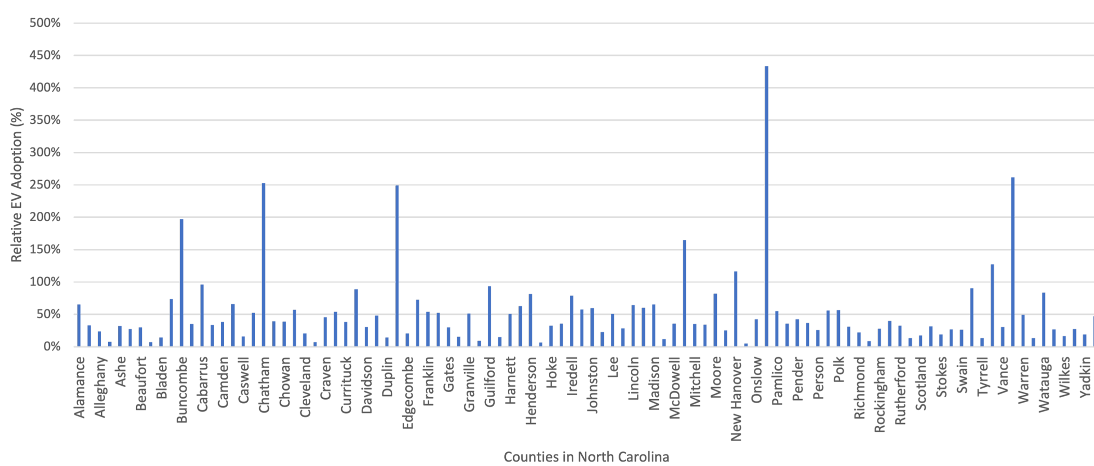


Figure 2.6: Relative EV adoption in NC counties when compared to national average

For this initiative, it was vital to extend the EEI projection to 2035 using Microsoft Excel's advanced forecasting tool, aligning well with the project's timeline. ZEV Registration Data on the North Carolina Department of Transportation (NCDOT) website [25] provides an insight into the trend of adoption of EVs in the state of

North Carolina. Accounting for regional variations in EV adoption was key, allowing for a more accurate assessment of EV adoption rates across counties. The regional variability of EV adoption in North Carolina for different counties is shown in Figure 2.6.

The Duke Energy Carbon Plan [26], forecasting a 6.2% rise in EV adoption in the Carolinas by 2035, contributed essential data. After this data sharing, the 6.2% EV adoption rate was embraced as the core assumption for Feeder F3's EV adoption. It's worth mentioning that different, yet similar, levels of EV adoption were contemplated for various feeders.

2.3.2 Identification and Classification of EV Loads

GIS data using Google Maps was utilized to identify and classify EV loads connected to each distribution feeder. The load-specific longitude and latitude coordinates from Cyme were used to create a GIS-based map of the distribution network and locate the customers connected to each feeder. The customers The loads were then classified into various customer types, such as residential houses, midrise apartments, elementary schools, office buildings, hotels, quick-service restaurants, etc. Identification and classification of customers were carried out for each customer in Feeders F1, F2, F3, and F4. This step plays a key role in defining regional patterns of EV adoption and understanding the distribution of EV loads across different types of customers.

Based on the customer demographics of the different feeders, Feeder F1 was predominantly residential, with residential house loads. Loads on Feeder 2 were a mix of warehouses, commercial buildings, hotels, and parking areas. Feeder F3 was mainly composed of urban commercial loads like quick-service restaurants, strip malls, parking areas, and midrise apartments. Feeder F4 had industrial loads like manufacturing factories and warehouses.

2.3.3 EV Charging Infrastructure and Load Profiles

Once the customers were identified and classified, the assumptions related to EV infrastructure for each identified EV load were formed. It was assumed that every residential house would have two vehicles. The customers were assumed to adopt level-1 and level-2 chargers in a ratio of 1: 5. Level-1 chargers were assumed to be 3 kW, and level-2 chargers were assumed to be 10 kW. A normal distribution with a mean of 6 p.m. and a standard deviation of 1 hour was adopted to represent customers arriving at their homes. All EVs were assumed to plug in as soon as the customers arrived at their homes. For workplace charging or office charging. All chargers were assumed to be level-2 in nature. It was assumed that only 20% of residential customers would choose to charge from their workplace. Moreover, the EV charging infrastructure at office buildings was assumed to be lower than the number of EVs being charged at the workplace. This would lead to EVs charging in a staggered manner at offices to avoid overloading the charging infrastructure. The size of EV infrastructure at the workplace was determined using the number of parking areas available for a building. The number of parking places for the office building was assumed to be equivalent to the number of vehicles. This in turn was used to estimate the size of EV infrastructure of office buildings. Similar assumptions were adopted for EVs in hotels, and warehouses.

Warehouses with fleets were identified using Google Maps. The size of the fleet was estimated based on the number of vehicles and the parking spaces of the customers. The charging infrastructure size for customers involved in delivering goods was assumed to be 20kW level-2 chargers. This assumption is based on the duty cycle data of such vehicles available in NREL's Fleet DNA project. The customer data and Fleet DNA data were used to develop assumptions for fleet vehicles delivering goods. The proposed EV infrastructure size of the electric bus fleet on Feeder F2 was provided by the utility. Figure.2.7 shows the identified EV loads on Feeder F2. 25

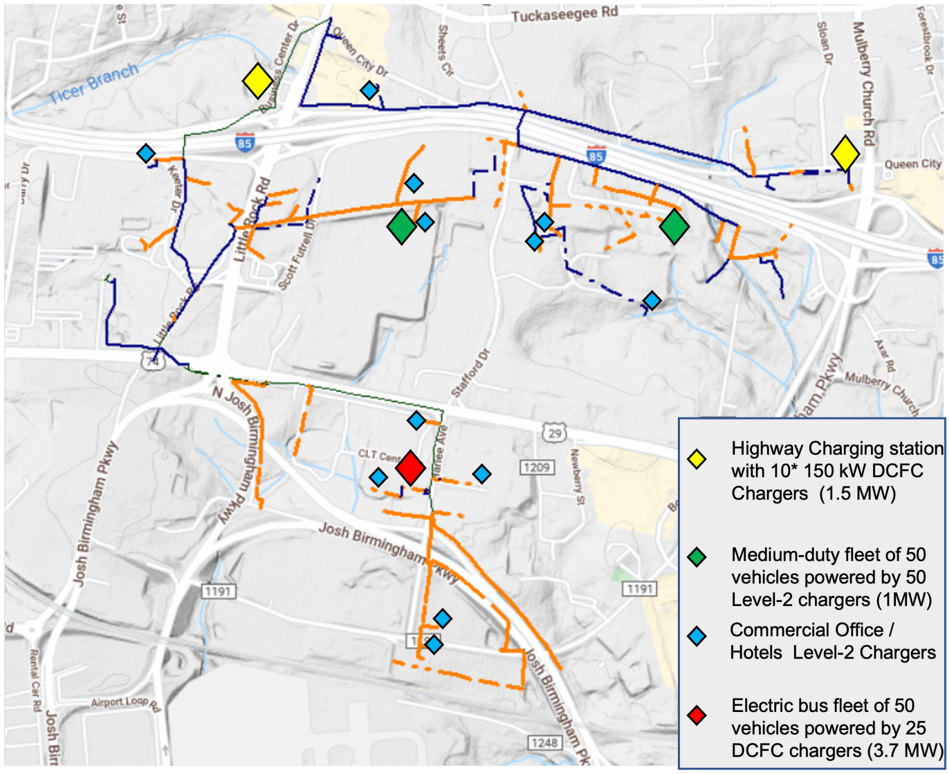


Figure 2.7: Possible EV loads on feeder F2

Direct Current Fast Chargers (DCFC) of 125 kW were proposed for the fleet electrification of the ground transportation bus fleet at the airport. Driving behavior data for ground transportation was collected from the airport's fleet manager. Based on the mentioned data, the existing electric buses (EBs) have an initial state of charge (SOC) of 35% on arrival after an 8-hour shift during which the vehicle miles traveled is 125 miles. The existing EB has a storage capacity of 440 kWh with a nominal range of 251 miles. The charging power of the electric bus was assumed to be related to the SOC at the time of arrival. The relationship shown in Figure.2.8 was assumed to define the relationship between charging power and the SOC of the vehicle. The Regional EV Charging Infrastructure Location Identification Toolkit (ILIT) is a comprehensive planning tool developed by Georgetown Climate Center and M.J. Bradley & Associates [27]. It aims to assist state and local governments in the Northeast, Mid-Atlantic, and Southeast states with equitable and informed investments in EV

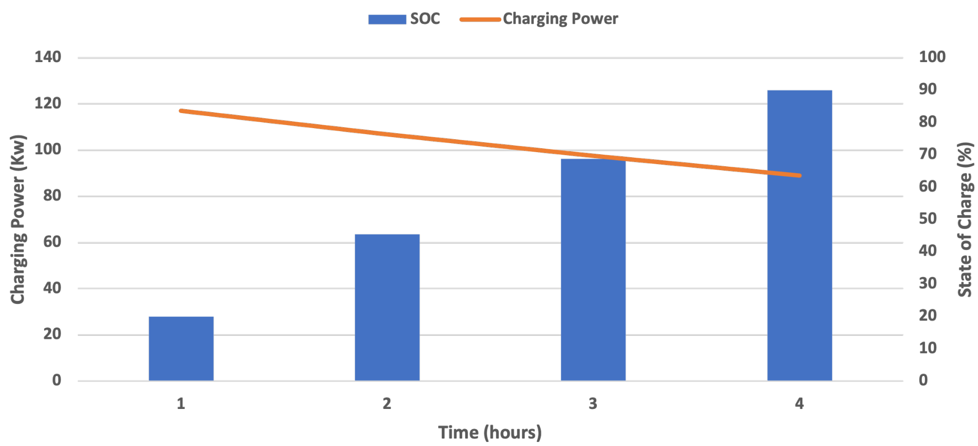
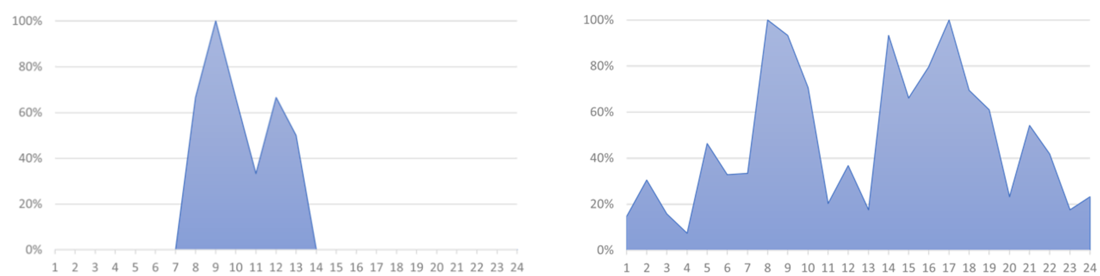


Figure 2.8: Assumed charging power and SOC relationship for electric bus

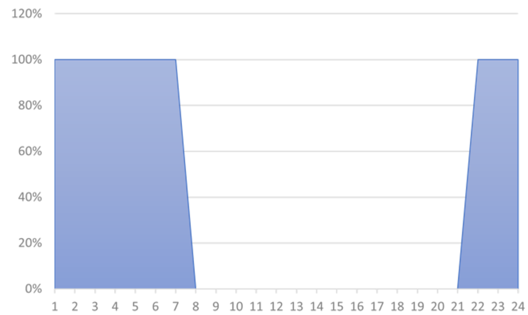


(a) Office load

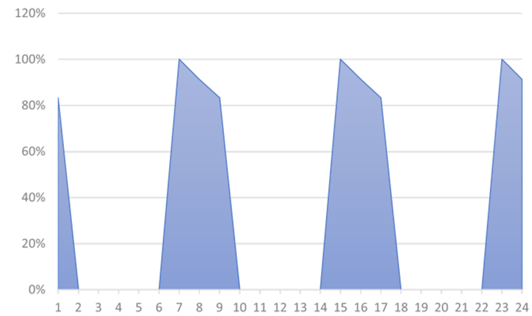
(b) Highway charging

Figure 2.9: LEV profiles

charging infrastructure. Inspired by this, the tool was used to locate possible highway charging locations on the feeders. For Feeder F2, two highway charging stations were assumed at two interstate exits in the feeder area. A standard infrastructure size of 10 chargers of 150 kW capacity was assumed for a highway charging station. The assumed customer behavior was used to develop EV load profiles for all the above-mentioned EV loads. HOMER Grid is a software tool designed to model and optimize microgrid and grid-connected systems. One of its key features is the ability to model EV charging station loads [28]. The HOMER Grid tool was utilized to develop a charging profile for highway charging stations. Office load and highway charging EV load profiles have been shown in Figure 2.9. Similarly, the medium-duty EV fleet profile and the EB fleet profile are illustrated in the Figure. 2.10



(a) Medium-duty fleet



(b) Electric Bus fleet

Figure 2.10: HEV profiles

2.4 Methodology for Distribution System Analysis

Feeders F1, F2, and F3 were studied for the impacts and vulnerabilities of EV adoption at the distribution level. For each feeder, the generated base load profile for the summer and winter was used as the base case for the analysis. The base case's hosting capacity was analyzed using Cyme. Figure.2.14 shows the hosting capacity of Feeder F2 in the year 2023. Then, substation transformers were integrated to capture the behavior of substation transformers due to increased EV adoption. Other feeders on the same substation transformers were converted to spot loads with their historical load profiles. The voltage profile of the feeder before and after adding the substation transformer was analyzed. The voltage profile of selected nodes of feeder F2 is shown in Figure 2.12. The utility's Cyme models represented each customer transformer as spot loads. EVs on residential loads were assumed to be powered by the same spot transformer, hence, no change in the model was required. For every other EV infrastructure, the existing load was assumed to be able to energize the bigger EV infrastructure loads. It was assumed that all the other loads would need new transformers. All the EV loads except residential loads were modeled in Cyme as spot loads of the charging infrastructure's capacity. EV adoption scenarios for LEV and HEV adoption were assumed based on the location of the feeder. Each feeder was studied for different levels of LEV adoption, considering the regional variation

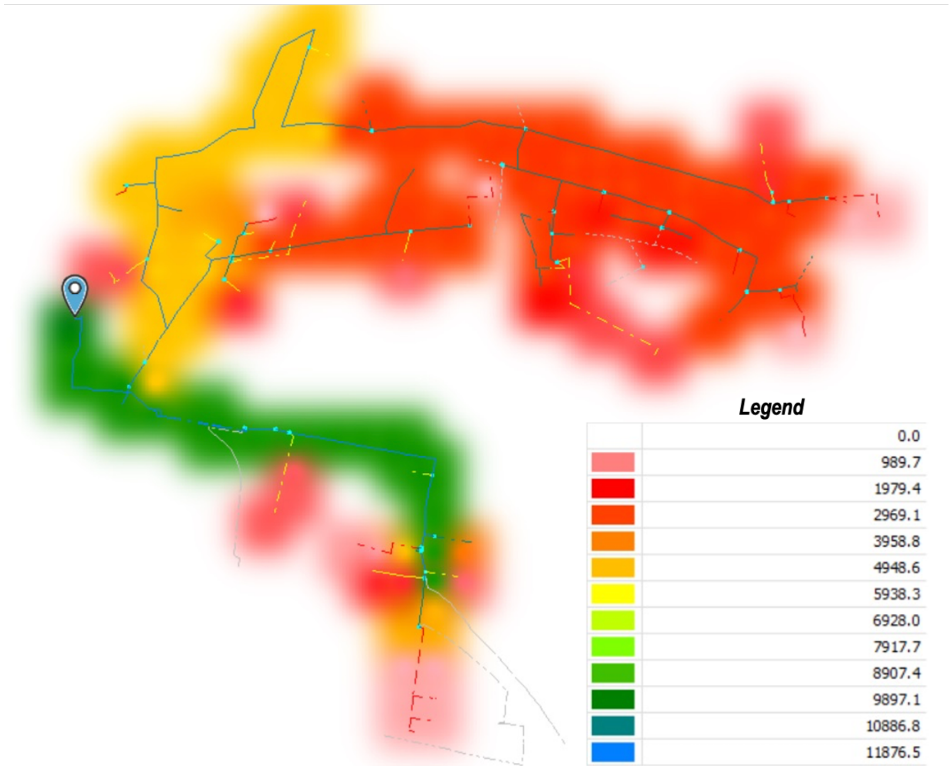


Figure 2.11: Cyme generated hosting capacity of feeder F2's base case in 2023

of EV adoption. The load growth on other loads on the feeder was assumed to be constant every year. This standard growth rate was provided by the utility. Since this analysis focused on a 15-year window, years 2025, 2030, and 2035 were selected for distribution level analysis. After a time period is selected, the number of years to the selected year from the current year is used to apply the load growth of other loads on the feeder. Then, LEV adoption and HEV adoption scenarios, along with the EV infrastructure assumptions, were utilized to generate EV load values for the selected year. After applying these values to the Cyme model, power flow analysis and quasi-static power flow were employed to analyze the feeder. Vulnerabilities like overloads, undervoltage, and tap changes were observed and recorded. The results were analyzed for 2025, 2030, and 2035.

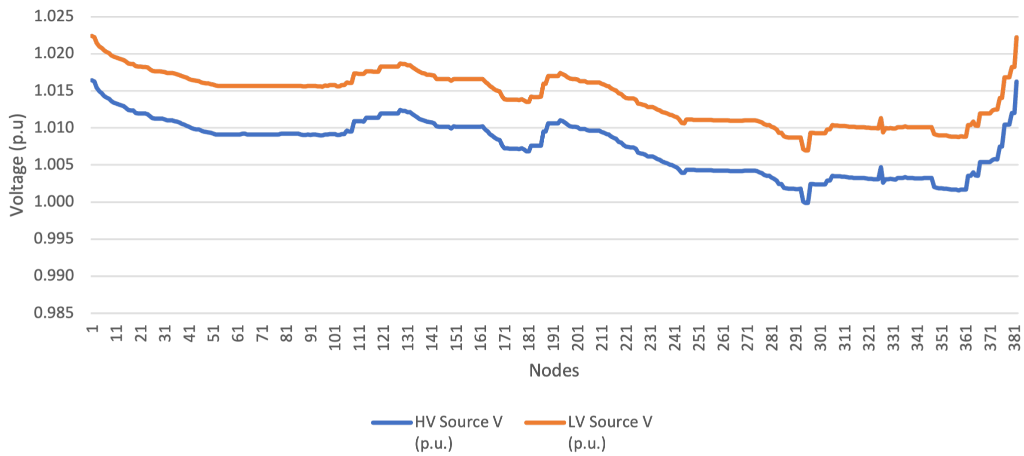


Figure 2.12: Voltage profiles before and after adding the substation transformer on feeder F2's base case in 2023

2.5 Methodology for Mitigation Strategies at the Distribution-level

Once the vulnerabilities and issues were analyzed through the power flow and quasi-static power flow of the Cyme models of the distribution feeders, several strategies to mitigate the impacts of EV adoption were explored and evaluated in this thesis. Some strategies involved influencing customer behavior through demand response through incentives, time-of-use pricing, and promoting smart charging or managed charging infrastructure at the load end. Other strategies focused on utility infrastructure-focused methods like conventional infrastructure upgrades, introducing a battery energy storage system (BESS) at the substation level, and distributed BESS systems at strategic points on the feeder. V2G was not explored for most feeders, since extensive adoption of V2G for all feeders involves complex communication and infrastructure requirements. For estimating the conventional system upgrades, the feeder was analyzed for potential infrastructure upgrades like upgrading transformers, reconductoring of lines, etc. Paper was used for the sizing and location of the BESS. The cost of infrastructure upgrades and BESS was provided by the utility. For time-of-use (ToU), the incentives to the customers were not considered for cost analysis. The cost of managed charging was not considered, since it was assumed that the cost would be borne by the EV owners who opt for this service. Different mitigation options were based on their effectiveness and cost to the utility.

For estimating the cost of the system upgrades required for mitigating the vulnerabilities on the feeder, the San Diego Gas and Electric Unit Cost Guide's pricing was referred to [29]. The values relevant to the analysis available in this thesis are shown in Table.2.2. The costs associated with BESS from [30] used for this analysis is shown in Table.2.3.

Table 2.2: Estimated Unit Cost of Equipment Upgrades

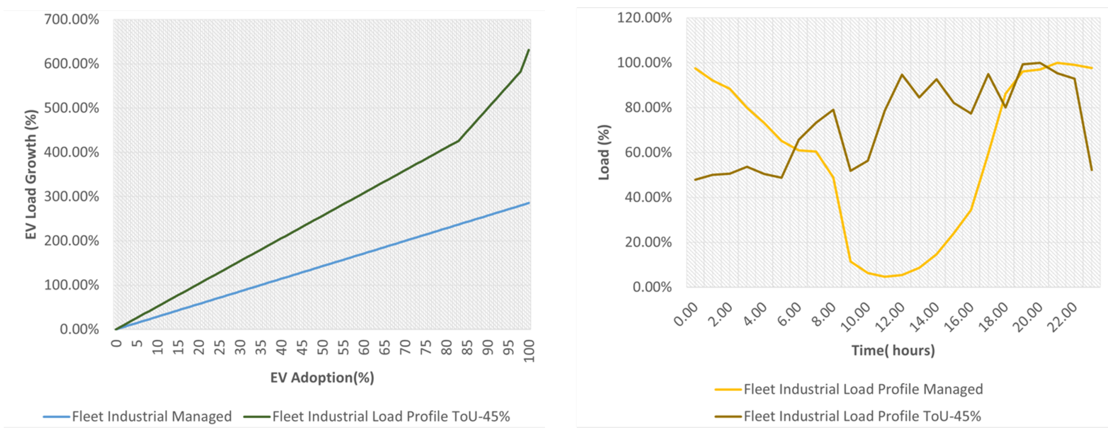
Equipment	**Unit Cost**
28 MVA Substation Transformer	$1,250,000
Overhead Reconductoring (Rural)	$253/ft
Voltage Regulator	$614,300

Table 2.3: Estimated costs of BESS systems

Parameter	**Cost**
Capital Cost- Capacity	$271/kWh
Power Conversion System	$288/kWh
Balance of Plant	$100/kW
Construction & Commissioning	$101/kW

2.6 Methodology for System-Level Analysis

One of the key challenges of this research is to assess the impact of EVs on the system level with limited access to data from the utility. The methodology for the bottom-up analysis of the system-level impacts started with the analysis of three different types of distribution feeders, residential, commercial and urban-commercial feeders. To scale up the features of the distribution level impacts of EVs to the system level, characteristic data of EV load was extracted from the results. EV load growth rate and EV load profiles are the two characteristics that capture the nature of the EV load at the distribution level. To capture all customer demographics, an industrial feeder's analysis was required. Feeder F4 was added to the list of feeders to extract characteristic data of the industrial sector.



(a) EV Growth Rate (b) EV Load Profile

Figure 2.13: EV load characteristics of feeder F4

The primary objective of this thesis was to integrate EVs into the IRP process. An innovative scale-up methodology was developed for this project to utilize distribution feeder characteristics and other scale-up-related inputs to estimate the system-level load on the utility's network in the Carolinas. The EV load characteristics of Feeder F4, which captures the load growth of EV loads on industrial feeders, are shown in Figure. 2.13. The scale-up model developed for estimating the total load at the system level is presented in the next subsection.

2.6.1 The Scale-Up Model

The scale-up methodology was developed to utilize the impacts of EV adoption at the distribution level of the power grid to the total load at the system level. Some relevant inputs for the scale-up model include LEV adoption rate, fleet electrification rate, season, and year of the estimated system-level load. The utility system considered has 3932 distribution feeders. While these feeders serve a diverse range of customers, the customers can be broadly classified as residential, commercial and industrial loads. This customer demographic nature was utilized to extend the analysis of a few feeders from the distribution level to the total impact at the system level.

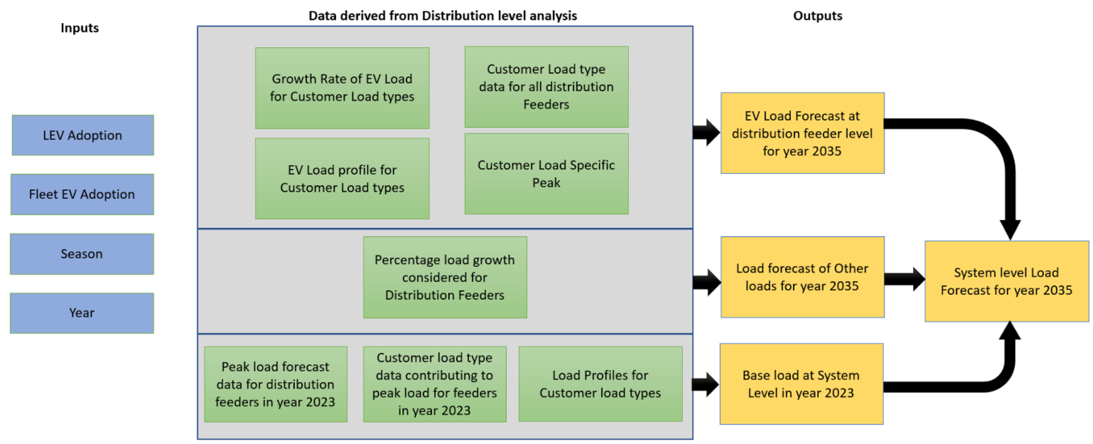


Figure 2.14: The scale-up model

The layout of the scale-up model is shown in the Figure. The customer demographics data for all the feeders were provided by the utility. Peak load data and generic load profiles for residential, commercial and industrial customers were utilized to generate the base load of 2023 for the scale-up model. Standard load growth data for all feeders were provided by the utility. The load growth data provided by the utility was used to account for the anticipated load growth due to other loads. The scale-up methodology presented in this thesis utilizes the EV load growth characteristics from the four real distribution feeders to estimate the total load at the system level. The inputs, such as LEV adoption rate, fleet electrification rate, season, and year, are employed to generate 24-hour snapshots of system-level load data for summer and winter peaks.

2.7 Simulation Tools

The software utilized for simulation includes Cyme, Python, and Excel. Cyme facilitates the conduct of sophisticated power analysis for individual systems, encompassing load allocation, load flow, and various other investigations. Python scripts are developed for each feeder, enabling the creation of a customizable graphical user interface (GUI) that facilitates the modification of any underlying assumptions. The Python script additionally integrates Microsoft database (MDB) files that have been uploaded from Cyme. The primary data source for analysis is derived from the MDB files, which provide spot load data. The Python script uses the input MDB files and the inputs from the graphical user interface (GUI) to compute the outcomes for each feeder. Each individual feeder is associated with a specific Python script, and the execution of these scripts requires the corresponding MDB files. This requirement arises due to the various characteristics of each feeder. The scale-up methodology involves the utilization of a Python script that possesses comparable characteristics to the distribution feeders. Excel is utilized for the generation of load profiles that are not derived explicitly from empirical investigations, such as home load profiles or electric vehicle time-of-use (ToU) profiles.

CHAPTER 3: RESULTS

In this chapter, the results from the distribution-level analysis of three feeders, F1, F2 and F3 are presented. Based on the presented assumptions and methodology to carry out distribution level analysis, these distribution feeders were analyzed using Python and Cyme. Load flow of the Cyme models of these feeders was carried out for peak load periods to identify vulnerabilities like Overload and Undervoltage. After identifying the vulnerabilities of a feeder, different mitigation techniques to minimize the impact of EV adoption at the distribution level were analyzed and compared. Data required for the scale-up model was extracted from distribution-level analysis data. Then, the scale-up model was used to estimate the impact of EV adoption at the system-level. The results from the distribution-level analysis are presented in the next section.

3.1 Distribution Level Impacts and Mitigation Strategies

The distribution-level analysis presented in the thesis has focused on the commercial feeder F2. Summarized results from the feeders F1 and F3 are presented in this section.

3.1.1 Residential feeder- F1

3.1.1.1 Impact of EV adoption

The impact of EV adoption on the residential feeder F1 was analyzed based on the assumptions and methodology described in the chapter 2. Since feeder F1 is a summer peaking feeder, the analysis carried out was focused on summer peak days. A residential feeder's challenge due to EV adoption would be to host level-1 and level-2 chargers for customer transformers while maintaining reliable voltage for the customers. To consider this, the focus of the analysis on feeder F1 was to identify vulnerabilities in the form of overload, undervoltage, customer transformer overloads, and tap-changing operations for voltage regulators. Since the focus if this analysis is

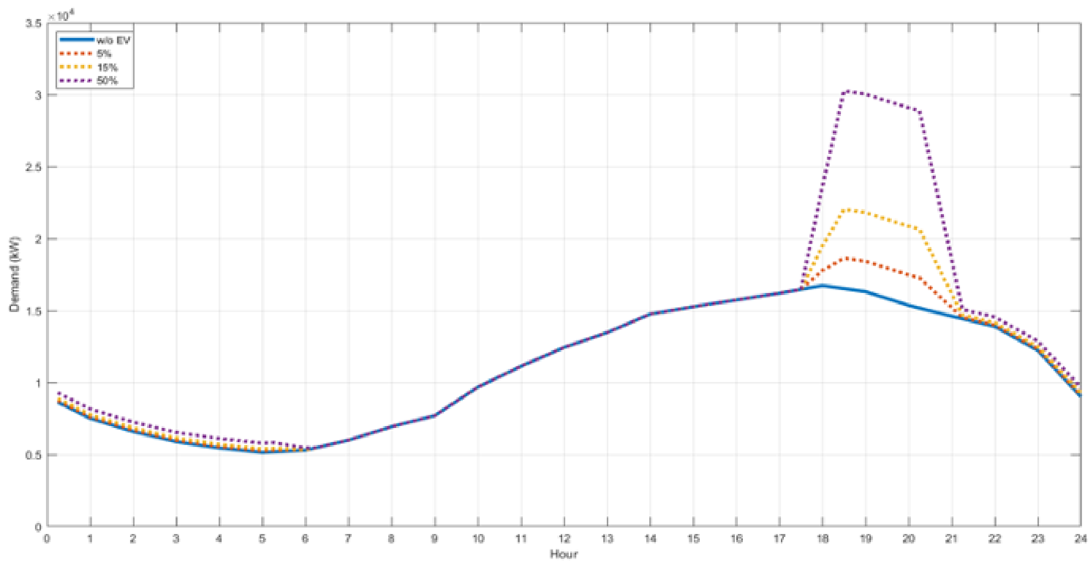


Figure 3.1: Feeder F1 demand curve at various EV penetration levels

to integrate EVs into IRP, the worst-case was explored to evaluate the preparedness of existing utility infrastructure for the feeder. The time of arrival of the vehicles was spread out from 05:30 - 06:30 pm. All the customers were assumed to plug in to the charger as soon as they returned home. The quasi-static load flow of the feeder for a summer peak day for different levels of EV adoption is shown in the Figure.3.1. With increased LEV adoption, we expect a heavy increase in load, which is highly dependent on the driving behavior of the residential customers. This also stresses the need for effective management of customer behavior in residential areas to mitigate the potential impact of EV adoption on the distribution feeder. For an LEV adoption of 6.2%, the maximum demand increased by 16.2%. Based on the assumptions used in this thesis, the peak demand time for a residential feeder is from 06:30 pm to 07:30 pm.

Assuming that the customer transformers in the residential areas will be upgraded if needed, an analysis of customer transformer loading with increased EV adoption was carried out for the residential feeder. The customer transformers available in feeder F1 range from 5 kVA to 167 kVA.

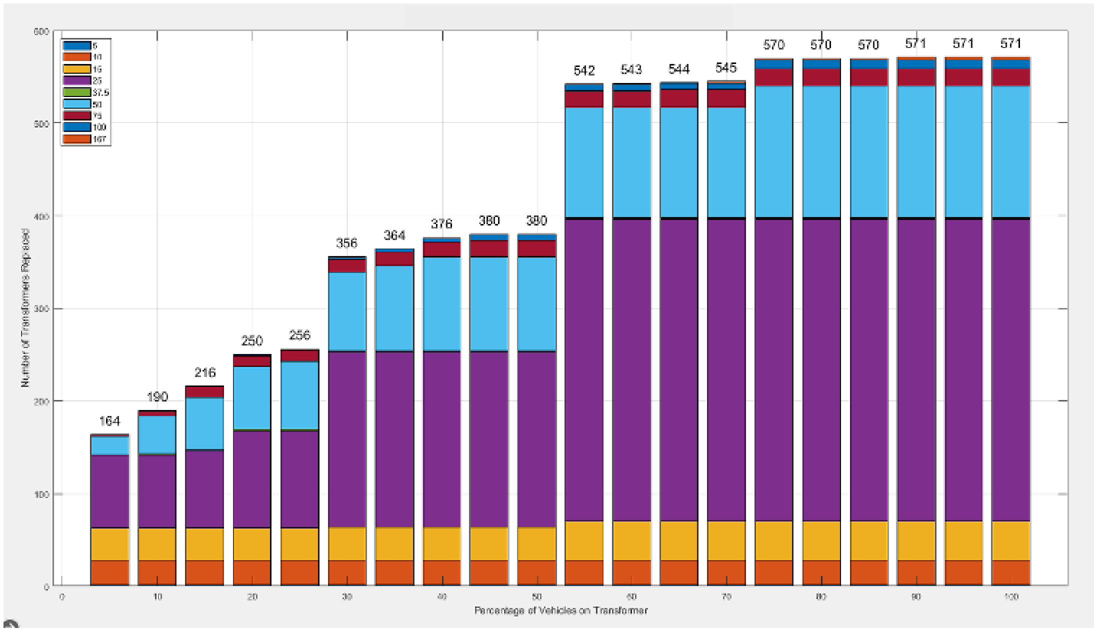


Figure 3.2: Customer transformer analysis for feeder F1

Table 3.1: Observed Vulnerabilities on Feeder F1

Year	**2020**	**2025**		**2030**		**2035**
LEV Adoption	**0%**	**1%**	**7%**	**2%**	**23%**	**15%**
Line Overload (ft)	0	0	6,285	5,655	18,377	12,713
Regulator Overload	0	2	3	2	4	4
Fuse Overload	1	1	2	1	3	3
Zones Undervoltage	0	0	0	0	5	5
Cumulative Tap Changes	113	143	181	144	306	285
Substation Xfmr Overload (hours)	0	0	3	0	3.5	3.5

The analysis found that with increased EV adoption, there is a possibility of customer transformers becoming overloaded, especially in areas with higher adoption rates. Figure. 3.2 shows the number of overloaded transformers with the increase in LEV adoption rates for feeder F1.

For this analysis, any distribution transformer with a load greater than 100 % of the rated capacity was considered to be overloaded. More than 50% of the transformers have to be upgraded at 30 % of LEV adoption. Almost all customer transformers would need an upgrade at 60% of LEV adoption. For the expected LEV adoption rate of 6.2% in 2035, about 25% of customer transformers would have to be upgraded. Table.3.1 presents the vulnerabilities on feeder F1 when different levels of LEV adoption is applied for the years 2025, 2030 and 2035. Different levels of LEV adoption from 1 to 50% were applied on feeder F1 during the study. Overloads on lines, regulators, and fuses increase with increased LEV adoption. Moreover, for a scenario with 23% LEV adoption in 2030, the feeder exhibits undervoltage condition for few nodes in the system. The total number of tap changes for 3 regulators on feeder F1 increased as the EV adoption increases. The substation transformer is observed to be under overload 3.5 hours for a 23% LEV adoption in 2030. For a 50% LEV adoption in 2035, the Cyme model does not converge. The results from feeder F1 provide us with the characteristics of residential EV load and how it varies with increase in EV adoption.

3.1.1.2 Mitigation

Several mitigation techniques like conventional system upgrades, ToU and BESS were utilized to minimize the vulnerabilities on the feeder. BESS was explored as a mitigation option to reduce the overload on the feeder with the smallest ratings possible. Since the vulnerabilities were in distributed sections, distributed BESS were utilized for mitigation in the residential feeder F1. Table.3.2 presents the cumulative storage capacity and power ratings of the distributed BESS chosen for mitigation on feeder F1.

Table 3.2: Sizing BESS for Mitigating Vulnerabilities on Feeder F1

Year	EV adoption (%)	Energy (MWh)	Rating (MW)
2025	0	7.5	1.2
	2	9	1.6
2030	0	16.56	2.04
	7	21.55	3.2
2035	0	23.25	2.4
	15	37.01	6.3

Table 3.3: Impact of ToU Participation on System Vulnerabilities for Feeder F1

Year (EV Adoption (%))		2025 (2)			2035 (15)		
ToU Participation (%)		0	10	40	0	10	40
Line Overloads (ft)		0	0	0	12,713	12,713	12,713
Regulators Overloaded		2	2	2	4	4	4
Fuses Overloaded		1	1	1	3	3	3
Zones Undervoltage		0	0	0	5	4	2
Cumulative Tap Changes		142	142	142	285	269	249
Substation Xfmr	OA(hours)	9.5	9.25	9	7.75	7.25	6.25
	FA(hours)	8	8.25	8.5	5.75	6	5.5
	FOA(hours)	6.5	6.5	6.5	7	7.25	9.25
	Overload(hours)	0	0	0	3.5	3.5	3

ToU scheme, which motivated the user to charge more late at night, was adopted for analysis for this feeder. Table.3.3 presents the impact of different levels of ToU participation with different EV adoption rates on the vulnerabilities of the feeder. For increased ToU participation levels, there is not much significant difference in overloads at the feeder level. However, overloaded hours of the substation transformer have been reduced in the case of 15% EV adoption combined with 40% ToU participation. ToU alone has not been very effective in mitigation for the residential feeder. Hence, a combination of BESS and ToU strategies was explored to mitigate the vulnerabilities on feeder F1. The comparison of estimated mitigation costs for an EV adoption of 15% and for different mitigation strategies is presented in the Table. 3.4. More analysis on feeder F1's analysis is provided in [31, 32].

Table 3.4: Impact of ToU Participation on System Vulnerabilities for Feeder F1

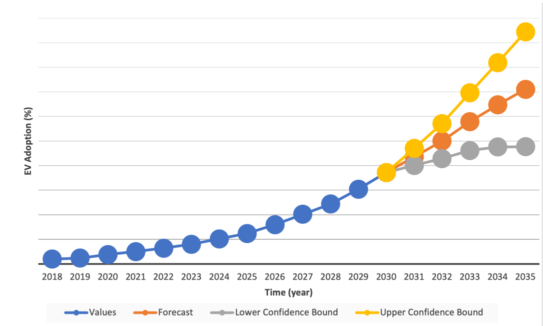
Case	Estimated Mitigation Costs (Million $)
System Upgrades	6.92
BESS	13.11
BESS+TOU 10%	12.23
BESS+TOU 40%	11.47

3.1.2 Commercial feeder- F2

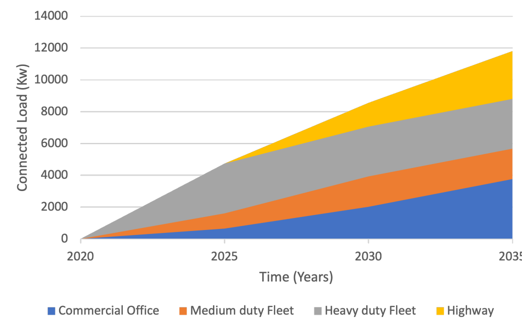
The most common EV loads on the commercial feeder considered for the study include LEV loads like office buildings and highway charging stations, medium-duty electric vehicle (MEV) loads like courier delivery fleets, and HEV loads like electric bus fleets used for ground transportation in the airport. While LEV adoption has been considered employing a rate of adoption, MEV and HEV loads were loaded based on loading scenarios presented in Figure.

3.1.2.1 Impact of EV adoption

The analysis of the feeder F2 has utilized an adoption rate of 0-35% for LEV. However, for the worst-case analysis, the infrastructure for MEV/LEV has been assumed to be fully electrified at a rate of 100%. To project the adoption of EVs realistically, three feeder-specific adoption scenarios, namely A, B, and C, were considered for the feeder's load analysis. The scenario exhibiting the least widespread adoption of EV



(a) LEV adoption



(b) EV infrastructure adoption scenario C

Figure 3.3: EV adoption considered for feeder F2

infrastructure is Scenario A, characterized by complete adoption of MEV infrastructure, 50% adoption of HEV infrastructure, and 50% adoption of highway charging infrastructure by the year 2035. Scenario B examines the complete adoption of HEV infrastructure, reaching a saturation level of 100% by the year 2035. In the worst-case scenario, it is projected that there will be complete adoption of all EV infrastructure by the year 2035. Figure.3.3b depicts the assumed HEV adoption scenario C on feeder F2. Given that feeder F2 is a commercial feeder with a relatively low load, the introduction of any EV load into the feeder may necessitate the installation of a new transformer. The analysis of the customer transformer was not conducted for this specific feeder. The year of analysis was employed to assess the increase in demand for other electrical loads on the feeder. A growth rate of 1% specific to the feeder was considered. The analysis for feeder F2 is conducted with a temporal granularity of 1 hour due to the absence of voltage regulators in the network. To conduct the distribution analysis of feeder F2, the adoption rates of EVs were utilized to estimate the peak load of EV spot loads. The estimation of the growth of additional loads on the feeder was conducted by utilizing the load growth rate and time. The long-term dynamics module in Cyme was employed to estimate the 24-hour snapshot of the load of a specific year. The analysis of system vulnerabilities was conducted during the period of the highest load. To conduct a detailed analysis at the distribution level, this research incorporated three hypothetical HEV adoption scenarios—termed A, B, and C—along with the maximum predicted LEV adoption rate for feeder F2. Recognizing F2 as a feeder with peak demand in summer, all scenarios were rigorously evaluated against its summer baseline load profile, ensuring a thorough and realistic assessment. System vulnerabilities specific to feeder F2 under these scenarios are detailed in Table.3.5, highlighting critical areas.

Table 3.5: Vulnerabilities on Feeder F2

HEV adoption Scenario		A	B	C	A	B	C
LEV adoption (%)		6	12	18	12	24	35
Year	2020	2030			2035		
Line Overload (ft)	0	0	0	0	0	0	1178
Fuse Overload	0	0	1	3	0	1	4
Overvoltage	0	0	0	0	0	0	0
Zones Undervoltage	0	0	0	0	0	0	0
Tap Changes	1	0	0	0	0	0	0

The analysis of scenarios A and B for the year 2035, combined with a 35% LEV adoption rate, revealed no significant vulnerabilities on feeder F2. This indicates F2's capability to support high EV adoption levels without the need for major infrastructure enhancements. This result has considerable implications, potentially lowering costs associated with widespread EV adoption and easing their integration. However, the analysis of Scenario C for 2035, which assumes a worst-case condition for feeder F2, presents a contrasting situation.

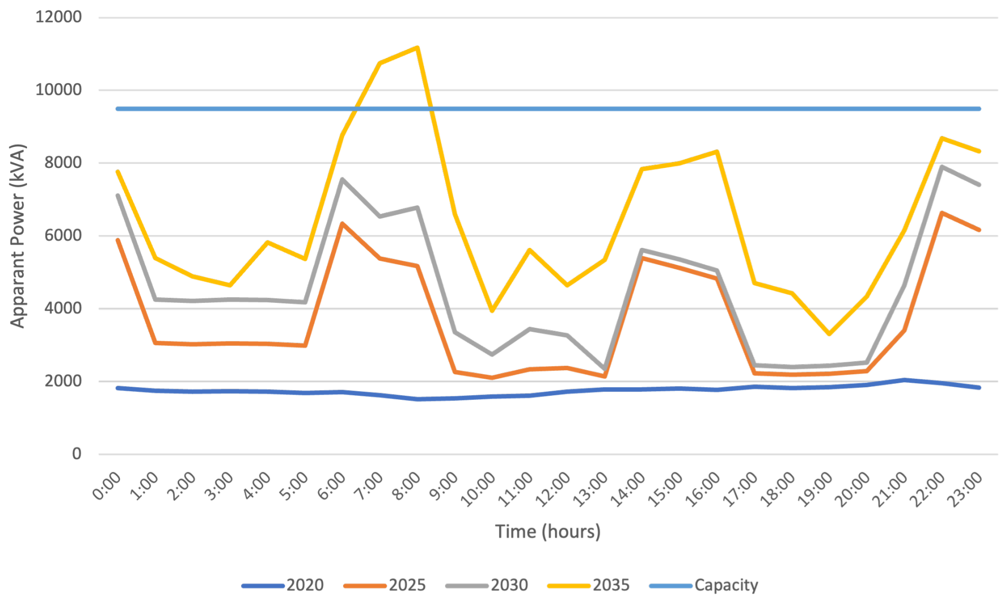


Figure 3.4: Load on feeder head for feeder F2 in the years 2020-35

Figure 3.5: Cyme model of the overloaded feeder F2

In this scenario, the EV infrastructure on feeder F2 is maximized to its full capacity of 100%. Under these conditions, Scenario C caused a 17% overload, highlighting the importance of strategic planning and readiness for peak EV adoption rates. This overload scenario is depicted in Figure 3.4, showing an overload near the feeder head for a two-hour period during the peak summer. Additionally, Figure 3.5 indicates a section of the feeder in yellow, representing "abnormal conditions" in the Cyme model.

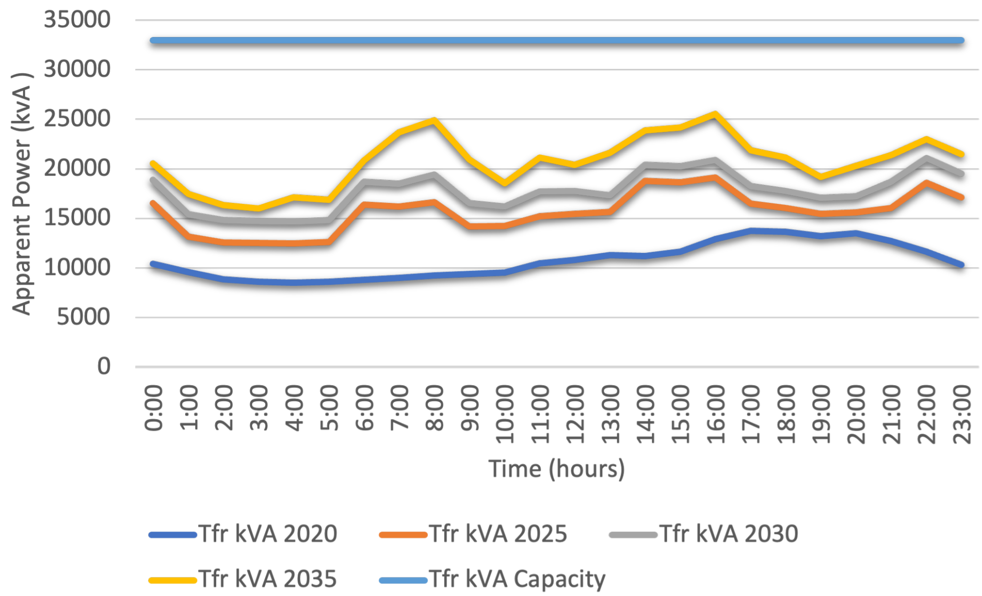


Figure 3.6: Substation transformer load for feeder F2 in the years 2020-35

For assessing the impact of EV loads on the performance of the substation transformer, data from the utility was utilized to integrate the substation transformer into the Cyme model. The study also modeled two other feeders connected to the same transformer as spot loads, using their respective historical load profiles and growth rates. The results, shown in Figure 3.6, reveal that under Scenario C with a 35% EV infrastructure adoption rate, the transformer loading reached 80%. Interestingly, despite this increased load, the number of tap changes on the substation transformer was minimal, suggesting that extreme EV adoption scenarios may not significantly impact the operations of the substation transformer.

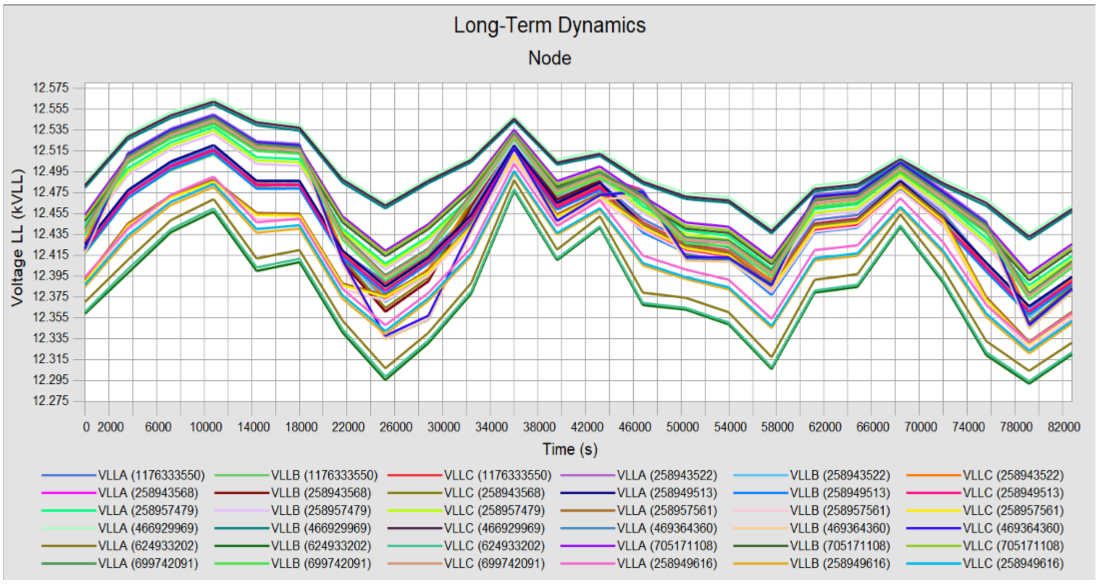


Figure 3.7: Voltage profile of selected nodes of feeder F2

Finally, Figure .3.7 presents the 24-hour voltage profile for selected points on feeder F2. Despite different load scenarios and the potential for overloading, the voltage at all nodes remained within the predefined limits. This underlines the strength of the existing infrastructure and its ability to accommodate increased EV loads in various situations.

3.1.2.2 Mitigation

In response to vulnerabilities that emerged under a worst-case scenario, which anticipates a 35% adoption rate of LEVs and a complete uptake of EVI at 100%, a comprehensive assessment of various mitigation strategies was undertaken. This assessment focused on conventional system reinforcements, the deployment of BESS, the implementation of managed charging, and the application of ToU tariffs. The aim was to identify the most effective and economically feasible methods to address the potential overloads, thereby enhancing the network's robustness and facilitating a smoother transition towards extensive EV adoption. The traditional upgrade, to address the overload, would require the replacement of around 1,178 feet of overhead conductor.

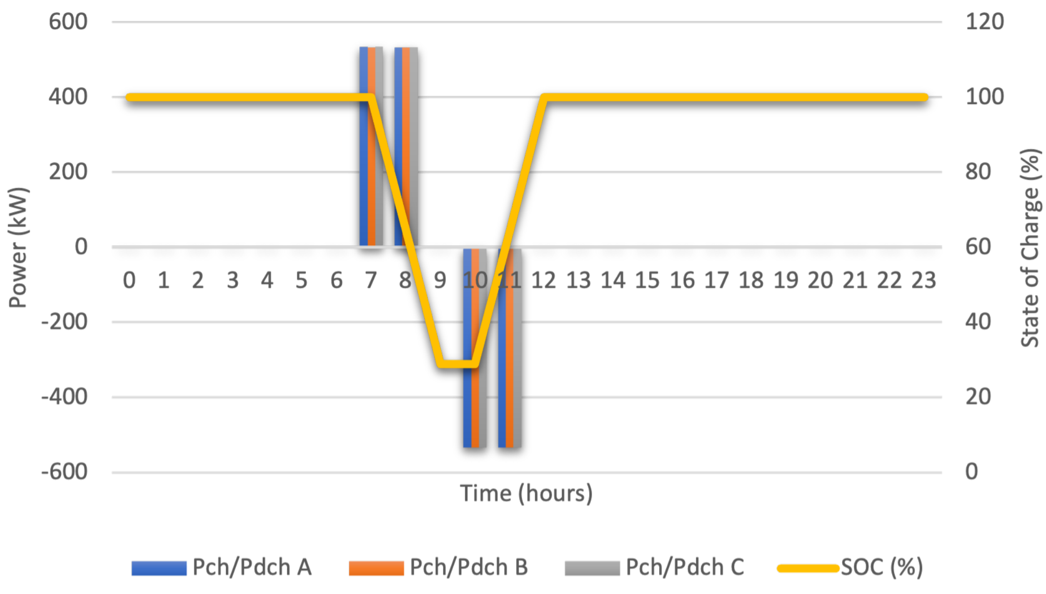


Figure 3.8: Charging and SOC of the BESS on feeder F2

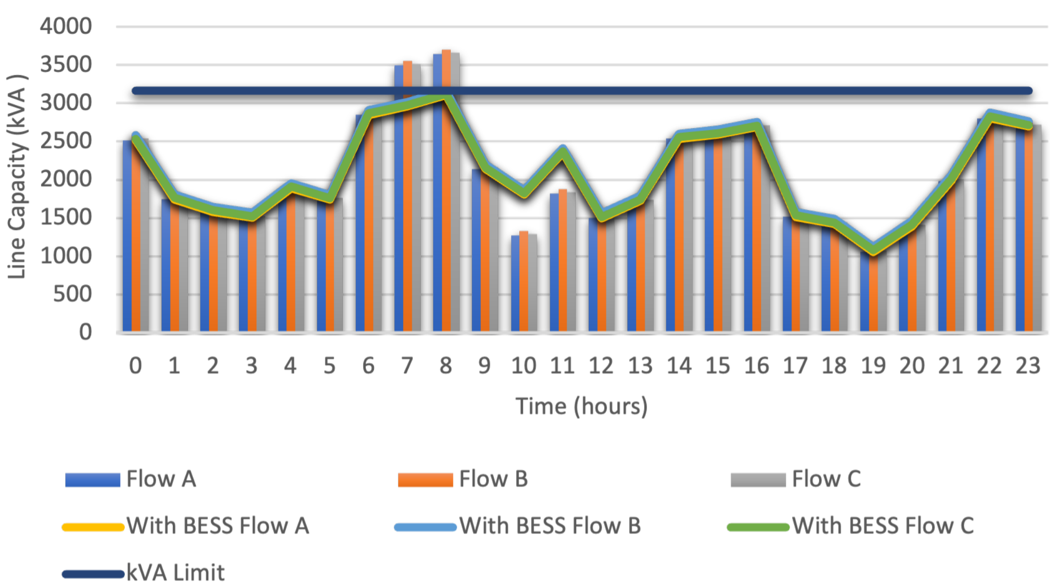


Figure 3.9: Impact of BESS on feeder F2

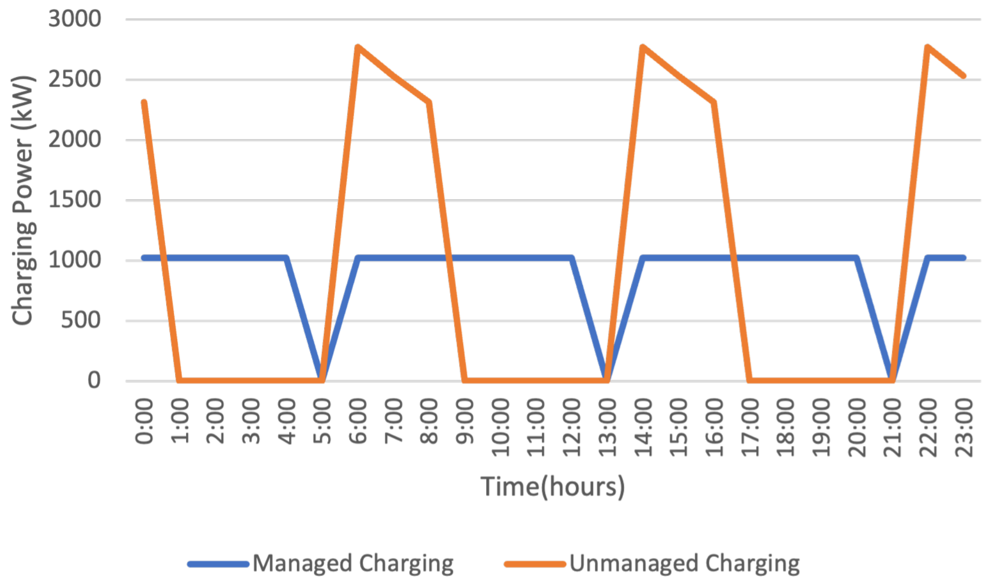


Figure 3.10: Generated profile for managed charging

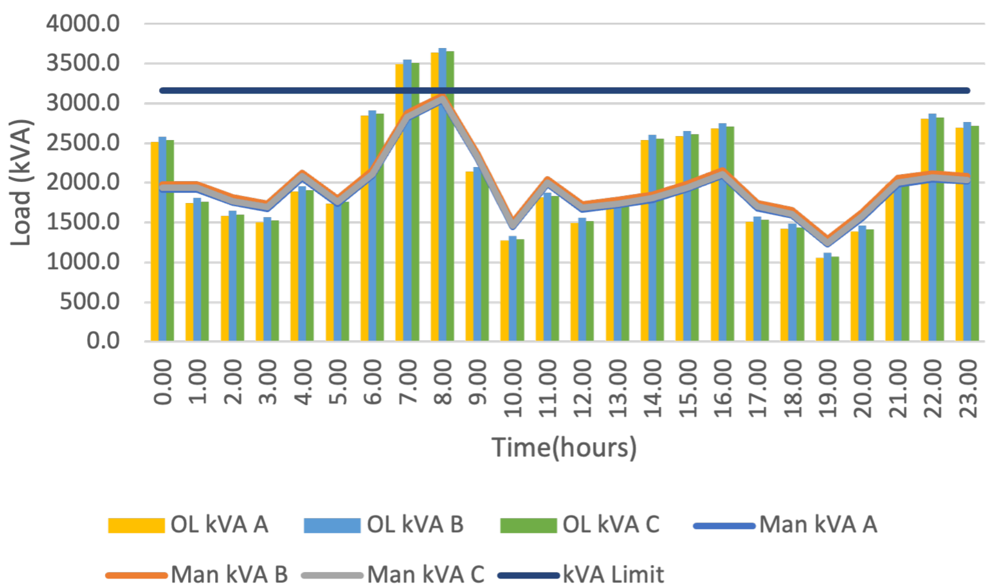


Figure 3.11: Impact of managed charging on feeder F2

Exploring alternatives, the research considered the application of BESS, determining the appropriate size necessary to alleviate the overload using the approach outlined in reference [33]. The analysis indicated that a BESS of at least 1.6 MW and 4.5 MWh would be required to manage the scenario effectively. Another strategy, managed charging, entails users adjusting their EV charging patterns to lessen peak demand. Illustrations of how the BESS's state of charge fluctuates during the mitigation of overload are presented in Figure 3.8, with the clear advantages of integrating a BESS shown in Figure 3.9.

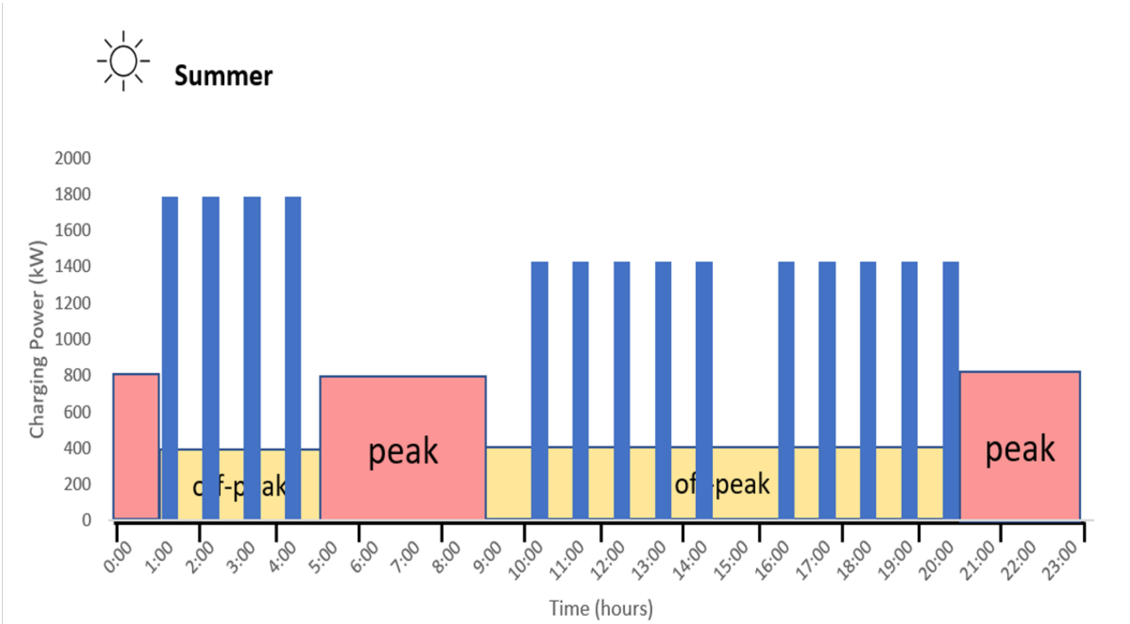


Figure 3.12: Generated profile for ToU

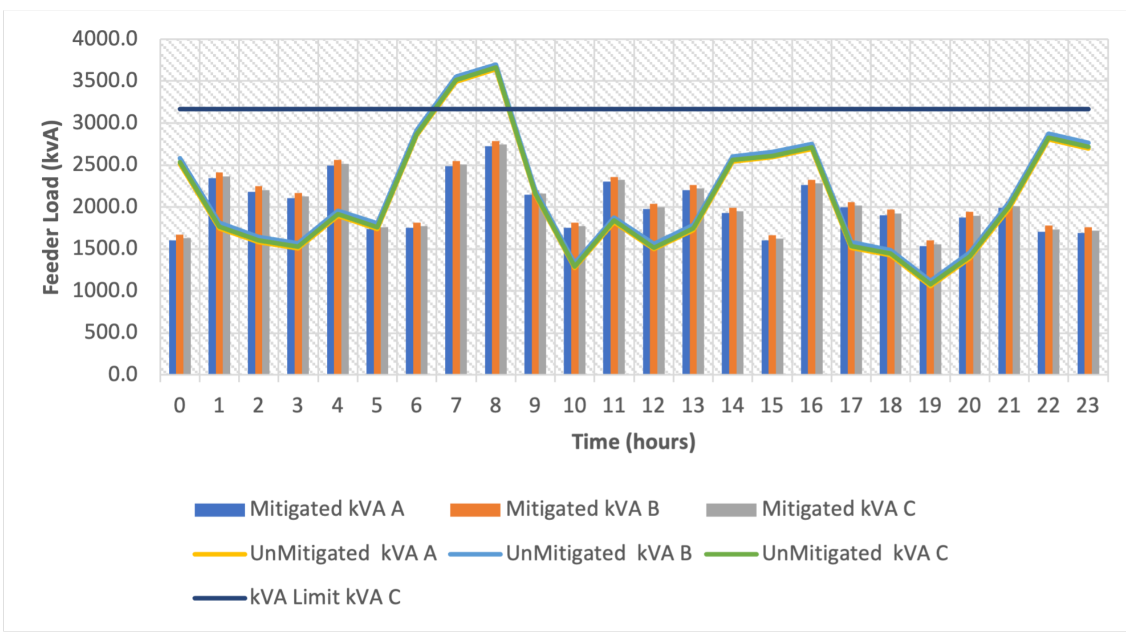


Figure 3.13: Impact of ToU of electric bus fleet on feeder F2

It's noteworthy that commercial consumers have an incentive to reduce peak demand due to its significant impact on energy expenses. An optimization model was utilized to demonstrate a managed charging system for the HEV fleet, aiming to reduce peak load, with the outcomes of this model depicted in Figure 3.10. This strategy's efficacy in mitigating the feeder's overload condition is evidenced in Figure 3.11. Additionally, the ToU pricing mechanism is evaluated for its effectiveness, particularly in commercial settings with EV fleets managed by charging systems. In this instance, peak times are proposed to be designated from 5 a.m. to 9 a.m. and from 9 p.m. to 1 a.m., as the effects on the electric bus fleet's charging patterns are observed in Figure 25. The response of the feeder's overload to the adjusted charging patterns of a single HEV fleet is shown in Figure 26. This comprehensive examination of managed charging and ToU pricing reveals that commercial EV fleets, if incentivized correctly, can play a substantial role in peak demand shifting and overload mitigation.

Table 3.6: Estimated Mitigation Cost Comparison for Feeder F2 in 2035

Case	Estimated Mitigation Cost (Million $)
System Upgrades	0.02
BESS	2.6
Managed Charging	0
ToU	0

For decision-making support, a comparative cost analysis of the different mitigation strategies was performed, as exhibited in Table 3.6. It should be noted that the potential loss of revenue from the ToU scheme was not included in this analysis, suggesting an area for further investigation.

3.2 Additional Feeders Considered

While residential feeder F1 considered the impact of LEVs on residential loads, commercial feeder F2 considered the impact of LEVs, MEVs and HEVs on commercial loads. Apart from feeder F1 and F2, distribution level analysis was also carried out on urban commercial feeder F3. Feeder F3 captures the EV adoption impacts for an area with residential and commercial loads. Public EV charging infrastructure and residential EV loads were the dominant EV loads on feeder F3. The results from the analysis are not presented in this thesis, as they are similar in nature to the findings in feeders F1 and F2. More data related to the feeder level analysis is available in [34]. As mentioned in the methodology, an industrial feeder F4 was integrated into the case study to capture the EV load characteristics of industrial loads. This step was key to scaling up results from the distribution-level analysis to the transmission level, or the system level.

3.3 System-Level Impacts

The system-level impacts presented in this section are the key outputs of this thesis. The primary outputs of the distribution-level analysis are the load growth of the feeders due to the adoption of EVs, and the profile of the load. For scaling up the results to estimate the total load of the system, these features of the results from distribution-level analysis were extracted by increasing the EV adoption rates from 0 to 100% and recording the peak load growth and the load profile of all the distribution feeders. This comprehensive analysis of the distribution-level impacts of EV adoption provides valuable insights for estimating the system-level load due to EVs. This was carried out for results with different mitigation measures by utilizing several scenarios of customer response behaviors. Different scenarios considered for analyzing the impact of EV adoption are presented in the Table.3.7. While U represents unmanaged charging in the table, M represents managed charging. Scenario S1 represents the worst-case scenario, where all the EV loads are unmanaged. Scenario S2 represents the least likely scenario, where all fleets and residential EVs are managed.

Table 3.7: Scenarios for Scale-up Analysis

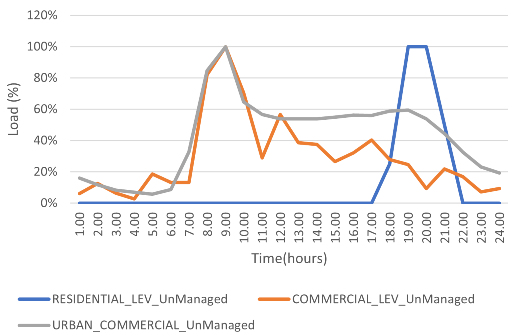
Feeder Type	EV Load	Scenarios			
		S1	S2	S3	S4
Feeder F1	Residential- LEV	U	M	ToU	U
Feeder F2	Office- LEV	U	U	U	U
	Electric Bus Fleet-HEV	U	M	ToU	U
	Medium-duty Fleet- MEV	U	M	ToU	M
	Highway Charging- LEV	U	U	U	U
Industrial	Heavy duty Fleet -HEV	U	M	ToU	M
	Highway Charging- LEV	U	U	U	U
	Office- LEV	U	U	U	U
Urban Commercial	Public Infrastructure	U	U	ToU	U
	Residential- LEV	U	M	ToU	U

The ToU participation from some loads is considered in scenario S3. Scenario S4 is assumed to be the most likely scenario, with only some fleets being managed. The inputs to the scale-up model are LEV adoption, fleet EV adoption, season, and year. The data extracted from the distribution-level analysis is utilized for estimating the EV load at the feeder level and then at the system level. The forecasted load growth rate of the distribution load was provided by the utility. A feeder with growth rates exceeding 10% was considered an outlier, and its growth rate was limited to 10%. The summer and winter base profiles for residential, commercial, and industrial feeders were also provided by the utility. Season-specific peak load and demographic load composition of the peak load were also provided by the utility. The season-specific peak load, demographic load composition, and load profiles for residential, commercial, and industrial feeders were utilized to estimate the base load profiles for all the feeders. The base load at the system level, the load growth for the other loads, and the EV load growth for the desired year are the results of the scale-up model.

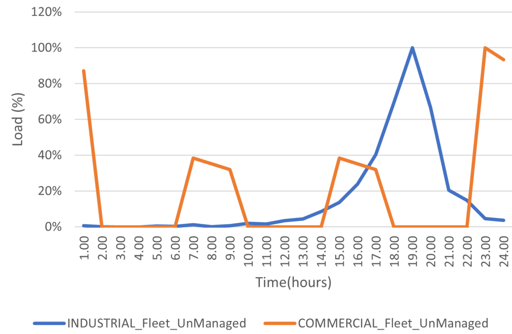
3.3.1 EV Load Growth Characteristics

The data that links the distribution-level analysis with the system-level analysis are EV load profiles and EV load growth rate data. EV characteristics are extracted using feeder-specific Python codes that record the impact of the growth of EV adoption on the peak load of the feeder. Figure 3.14 shows the load profiles of different LEVs and fleets generated from different customer load types on the analyzed distribution feeders. The characteristics of LEVs and fleet EVs were generated separately by increasing their adoption rates individually while keeping the others at 0. This enabled us to capture the characteristics of LEVs and fleets separately.

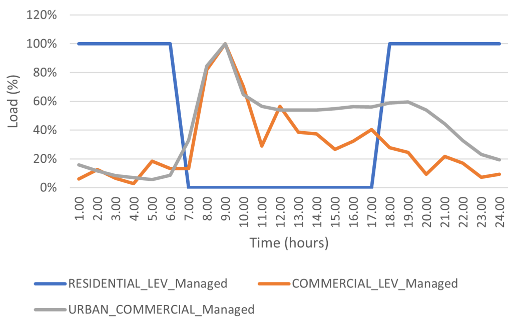
Several scenarios were created for generating different variations of these EV load characteristics to analyze the impact of different scenarios at the distribution level, scaled up to the system level. Scenarios to compare managed and unmanaged charging and several participation rates for EV-ToU were generated. Some loads, like highway charging, office charging, and public infrastructure, are considered to be independent of managed charging's influence. Similarly, highway charging and office charging loads are considered to be immune to ToU. Table 3.7 clearly shows the loads that respond to managed charging and ToU. Figure 3.15 shows the growth of the peak load of the feeders with the increase in EV adoption.



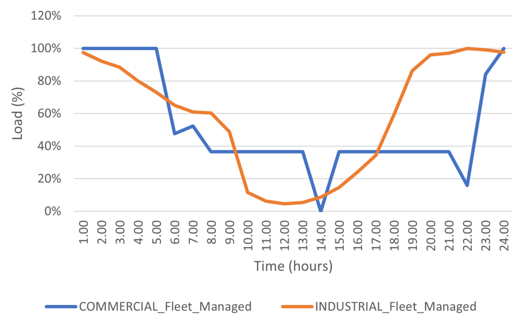
(a) Unmanaged LEV



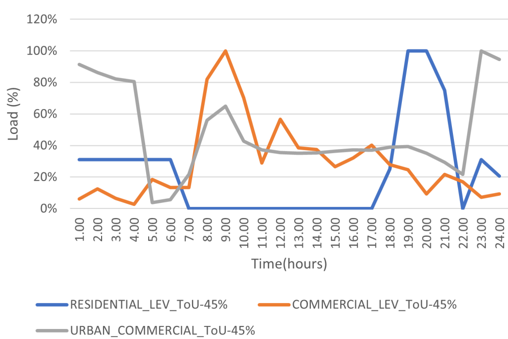
(b) Unmanaged fleet



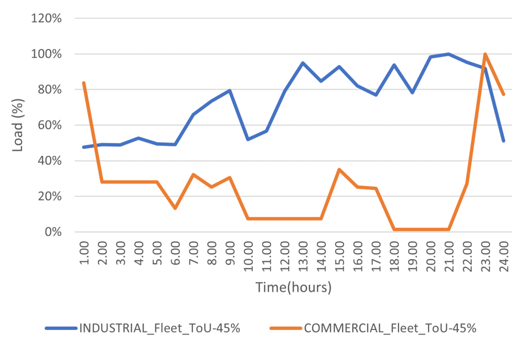
(c) Managed LEV



(d) Managed fleet

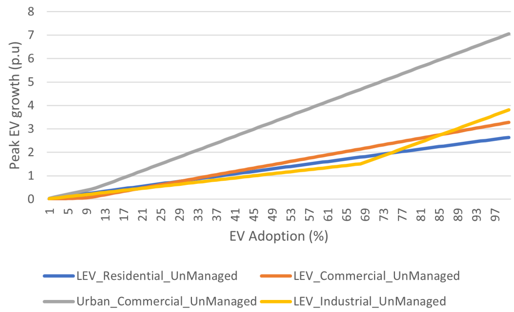


(e) ToU LEV

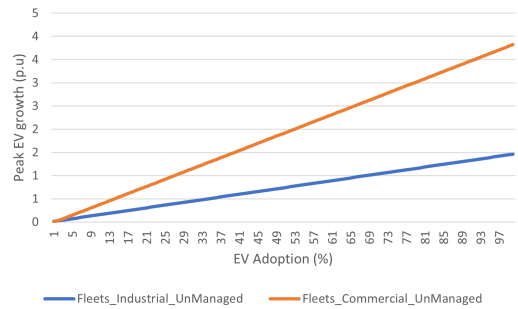


(f) ToU fleet

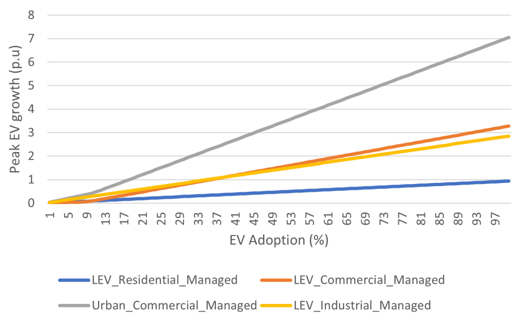
Figure 3.14: EV load profiles generated from distribution analysis



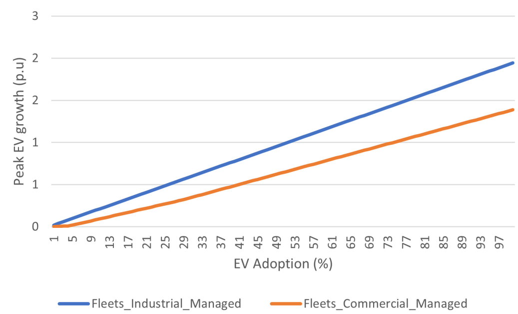
(a) Unmanaged LEV



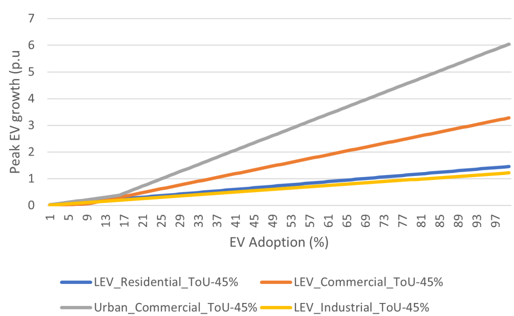
(b) Unmanaged fleet



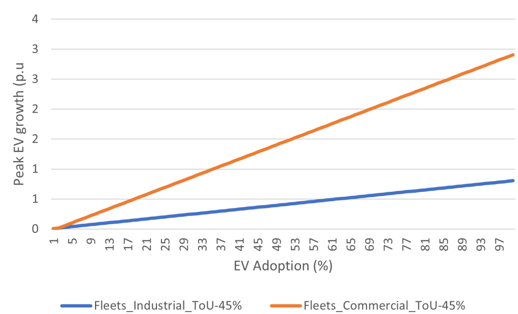
(c) Managed LEV



(d) Managed fleet



(e) ToU LEV



(f) ToU fleet

Figure 3.15: EV growth rate generated from distribution level analysis

3.3.2 Analyzing the Impact of Fleet Electrification on the System-level Load

The scale-up tool with the data generated from distribution-level analysis was used to estimate the system-level load of all the feeders in the utility's network. Figure 3.16 presents the summer peak of the total system load for 10% fleet electrification. For 6% LEV adoption in 2035, the peak load in 2035 is 30,829 MW, which is an 8.1% increase from the predicted peak load in 2023. Although there is an increase in the system-level load due to EV adoption, the impact is relatively minimal and manageable within the existing infrastructure.

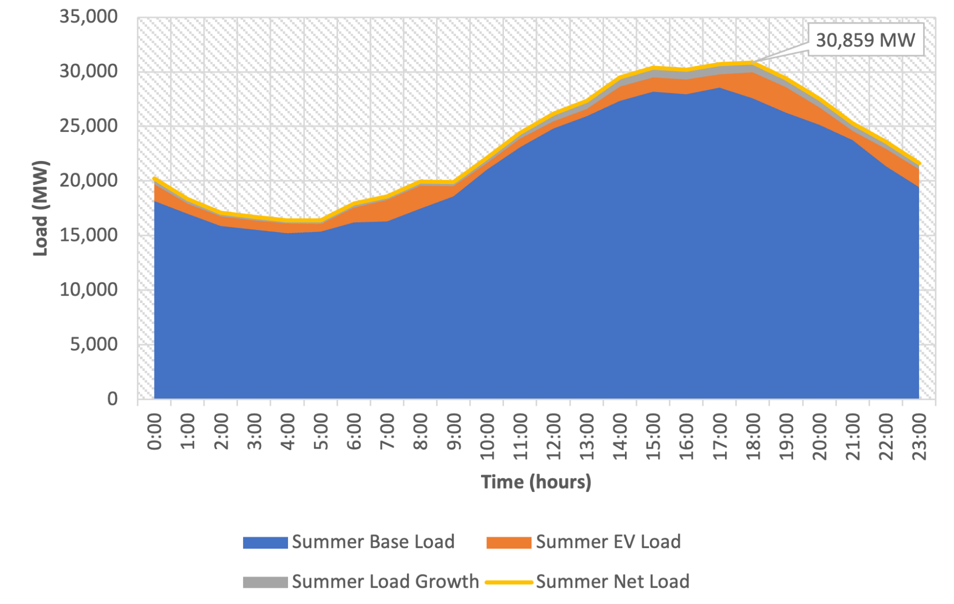


Figure 3.16: Total load of the system for 10% fleet electrification

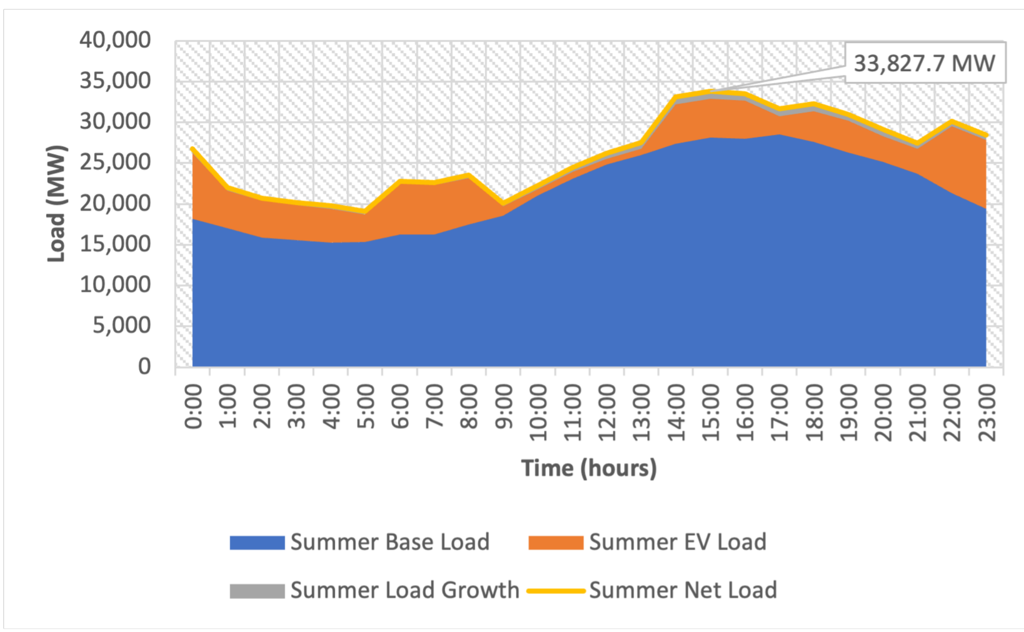


Figure 3.17: Total load of the system for 50% fleet electrification

While there was an 8.1% increase in the peak load of the system, 3.1% increase in the peak load was due to other loads, and 5% of the increase in the peak load was attributed to the adoption of EVs. The shape of the load profile at the system level has remained relatively unchanged, showing a slight increase in peak load and a similar distribution throughout the day. However, only 10% of the fleet vehicles were considered to be electrified for the presented scenario.

When the fleet electrification of the presented scenario in 2035 was increased to 50%, the peak load of the system increased to 33,827 MW. The figure represents the total load of the system in summer for 6% LEV adoption and 50% fleet electrification. The system-level peak load increased by 18.5% of the 2023 base load. EVs have contributed 82.7% to the increase in peak load. For each 1% increase in fleet adoption, the peak load increases by 72.2 MW. There is a slight change in the load shape during the late night and early morning hours of the day. This is the contribution MEV and HEV fleets being charged at night. The early morning EV load demand is also caused by the daily commuting patterns of EV owners going to the office or using highway charging stations.

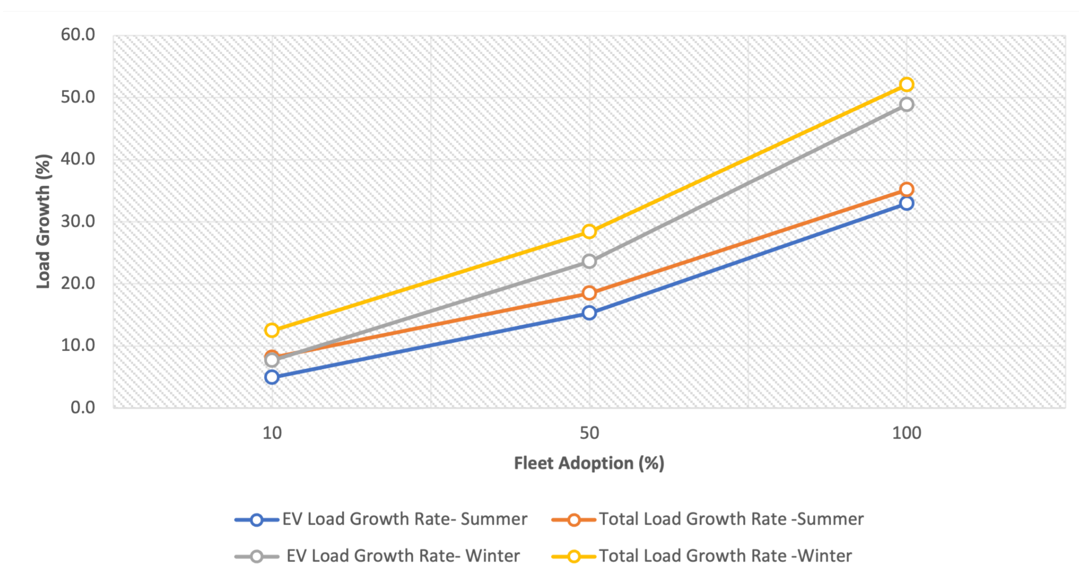


Figure 3.18: EV load growth rate's variation with fleet adoption

In summer, for an increase in fleet electrification from 10% to 100% in 2035, the peak load of the system increases from 8.1% to 35.2%. In winter, for an increase in fleet electrification from 10% to 100% in 2035, the peak load increases from 12.5% to 52.1%. As shown in the Figure 3.18 the peak load growth in winter is much higher than in summer due to the base load shape in the winter. With increased fleet electrification, we could see more LEV, MEV and HEV fleets being charged during the late-night hours. This charging behavior could be mostly due to the duty cycle of these vehicles. In such a scenario, a lot of bigger EV loads may naturally charge during the conventional off-peak hours, filling the existing valley in the summer load shapes. However, since winter peaks may occur during the day, the increased electrification of fleets will affect the winter peak more than the summer peak of the system-level load.

3.3.3 Analyzing the Impact of Managed Charging on the System-level Load

Managed charging plays a crucial role in minimizing the peak load at the customer's transformer, thereby leading to a reduction in the utility bill. By adopting managed charging strategies, customers can effectively control and optimize their EV charging patterns, resulting in a more efficient utilization of electricity resources. Figures 3.19 and 3.20 provide a visual representation of the impact of managed charging on the total load of the system. In summer, when considering a 6% LEV adoption rate and a 50% fleet electrification rate, unmanaged charging leads to a system-level load of 33,929.9 MW. However, if all fleets and residential customers adopt managed charging practices, the peak load during summer experiences a significant reduction of 715.5 MW or 2.1%. This reduction in peak load not only helps in optimizing the overall electricity demand but also contributes to cost savings and improved grid stability during high-demand periods.

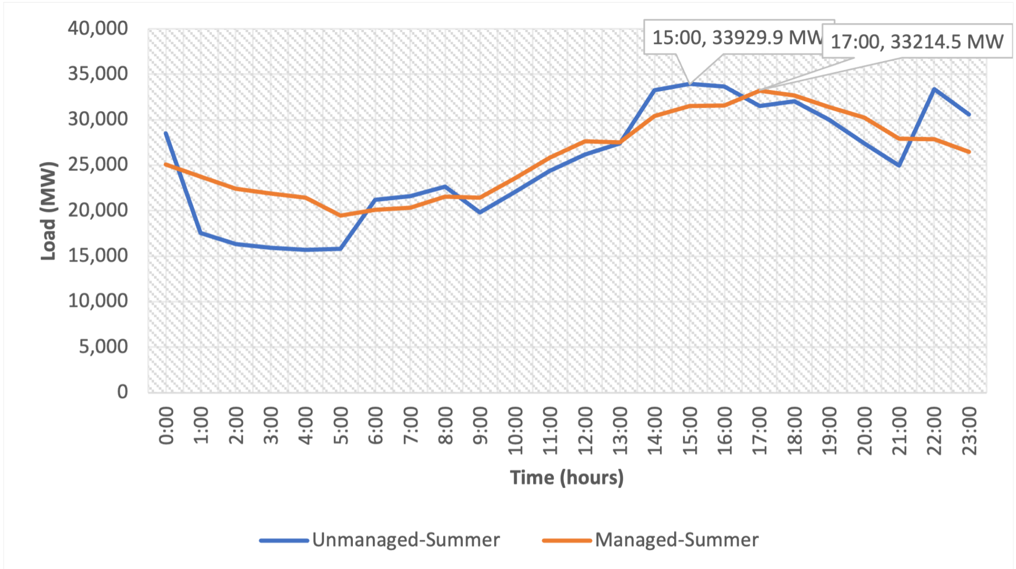


Figure 3.19: Managed charging (S2) vs unmanaged charging (S1) in summer

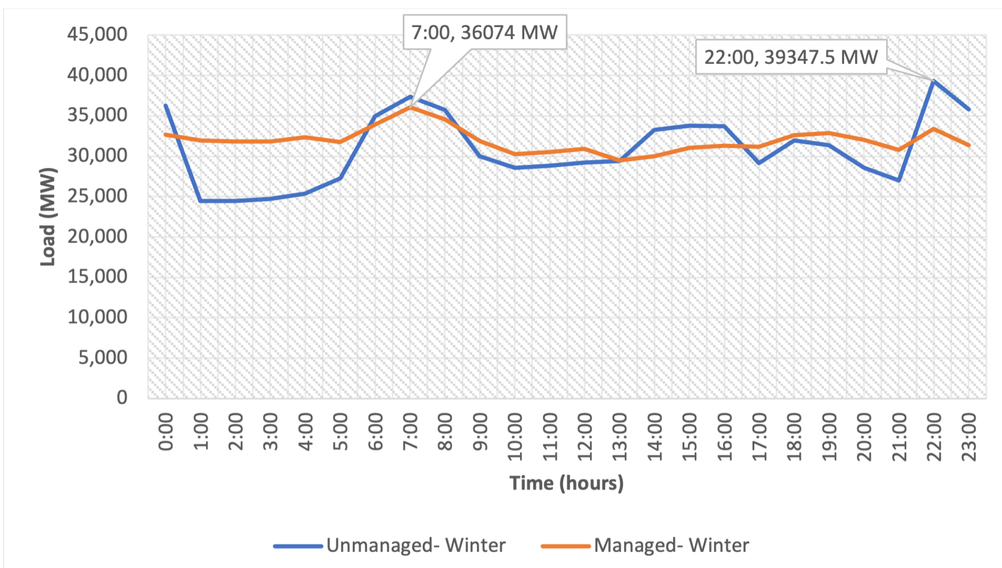


Figure 3.20: Managed charging (S2) vs unmanaged charging (S1) in winter

Similarly, during winter, unmanaged charging with a 6% LEV adoption rate and 50% fleet electrification rate results in a system-level load of 38,369.4 MW. However, with the implementation of managed charging, the winter peak load experiences a substantial decrease of 3273 MW or 8.5%. This reduction in peak load during winter is particularly crucial, as energy demand typically spikes due to increased heating requirements and other seasonal factors. By effectively managing EV charging patterns, customers can mitigate these demand surges, leading to a more balanced and optimized energy system. The implementation of managed charging strategies not only benefits individual customers but also contributes to the overall stability and efficiency of the power grid. By shifting and distributing the charging load over different time periods, managed charging helps to flatten the load curve, ensuring a more consistent and manageable distribution of electricity. This not only reduces the strain on the grid infrastructure but also minimizes the need for expensive infrastructure upgrades to accommodate the additional EV load.

The analysis clearly demonstrates the significant impact of managed charging on the total load of the system. By adopting managed charging practices, both during summer and winter, customers can achieve substantial reductions in peak load, resulting in improved grid stability, cost savings, and optimized energy utilization.

3.3.4 Analyzing the Impact of EV-ToU Participation on the System-level Load

EV load growth characteristics were analyzed for various levels of Time-of-Use (ToU) participation, including 15%, 30%, and 45%. The analysis focused on a designated ToU peak window from 10 pm to 5 am. Considering a 6% LEV adoption rate and 50% fleet electrification, the impact of EV-ToU participation was examined for both summer and winter seasons. The results depicted in Figure 3.21 reveal that with increased EV-ToU participation, up to 45%, the summer peak load reduces from 33,940 MW to 32,211 MW. This reduction in peak load demonstrates the effectiveness of Time-of-Use pricing and incentives in shifting EV charging to off-peak hours.

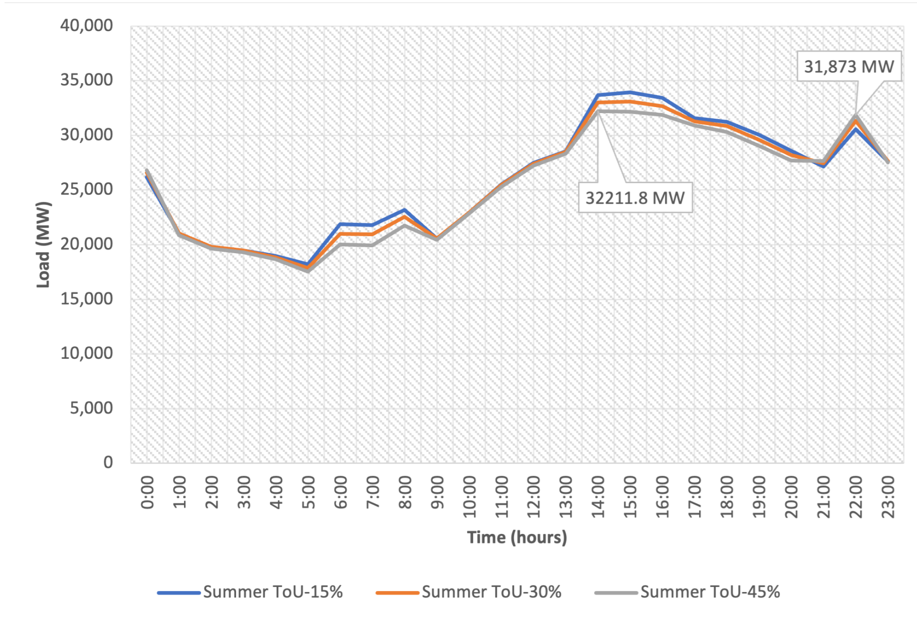


Figure 3.21: Impact of EV-ToU participation in summer

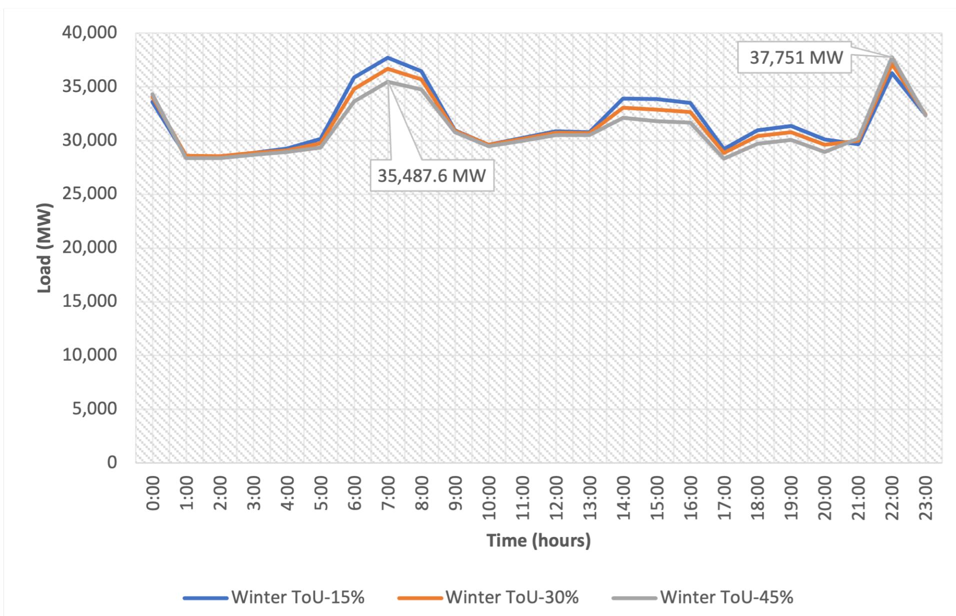


Figure 3.22: Impact of EV-ToU participation in winter

As illustrated in Figure 3.22, when considering 45% EV-ToU participation, the summer peak load reaches 32,211.8 MW, which is marginally higher than the ToU peak load of 31,873 MW. This suggests that with high levels of EV-ToU participation, the summer peak load closely aligns with the ToU peak load, indicating a successful synchronization between EV charging and off-peak periods.

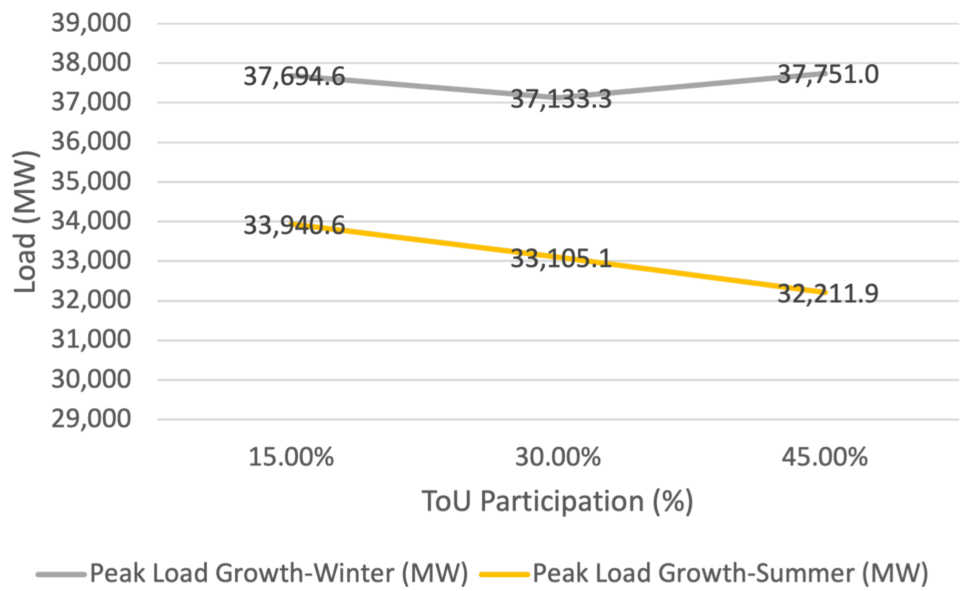


Figure 3.23: Impact of different levels of ToU participation of EV loads in summer & winter

Figure 3.23 provides a comparison between summer and winter peaks under 45% EV-ToU participation. In this scenario, the winter peak load is 37,751 MW, which exceeds the summer peak load of 35,487.6 MW. This disparity can be attributed to the specific load characteristics and patterns during winter, such as increased heating requirements and other seasonal factors. Furthermore, the analysis reveals that as the level of EV-ToU participation increases from 30% to 45% in winter, the peak load of the feeder experiences an increase. This indicates that achieving an optimal balance between EV charging and off-peak periods is crucial to managing the overall load and ensuring grid stability during the winter months. Based on the findings presented in the figures, it is evident that the most favorable EV-ToU participation for summer is 45%, whereas for winter, the optimal level is 30%. These results highlight the importance of implementing effective ToU pricing strategies and encouraging EV owners to actively participate in off-peak charging. By aligning EV charging patterns with periods of lower electricity demand, utilities can achieve load optimization, cost efficiency, and improved grid performance

The analysis of EV-ToU participation reveals that higher levels of participation lead to a reduction in summer peak load, indicating successful load shifting to off-peak hours. However, the impact of EV-ToU participation in winter is more nuanced, with the need to carefully balance load growth and grid stability. By selecting appropriate EV-ToU participation levels, utilities can achieve harmonized integration of EVs into the electricity grid, optimizing load distribution and promoting sustainable energy consumption.

CHAPTER 4: CONCLUSIONS

4.1 Answering the Research Questions

This paper has addressed all four of the research questions asked in the introduction.

Question 1 asked about the unique impacts of increasing EV adoption on different types of distribution feeders. The analysis in the thesis indicates that the impacts on the feeders are dependent on the customer demographic composition of the loads connected to the feeder. For an expected LEV adoption of 6%, the peak load increases for feeders in decreasing order: 25.3 % for the urban commercial feeder, 17.1% for the industrial feeder, 15.8% for the residential feeder, and 3.5% for the commercial feeder. Similarly, for the expected fleet electrification of 50%, the peak load increase is 105.6% for the commercial feeder and 97.2% for the industrial feeder. These results are heavily dependent on the assumptions adopted in the study and the individual characteristics of the considered feeders.

Question 2 asked about the assumptions and methodology for modeling the driving and charging behavior of different EV loads. This question was answered in the chapter 2. Different EV loads on the feeders were identified and classified into residential, workplace, highway charging, package delivery fleets, beverage delivery fleets, electric bus fleets, wholesale bakery fleets, etc. Then, assumptions on driving behavior and charging behavior were formed for each EV load to generate load profiles specific to each EV load. These well-thought-out assumptions captured the realistic driving and charging behavior of the EV loads.

Question 3 asked about the potential vulnerabilities in customer transformers, voltage regulators, and substation transformers due to increased EV adoption. Several vulnerabilities were identified for different distribution feeders. While the heavily loaded residential feeder F1 exhibited overload and undervoltage, commercial feeder F2 showed no vulnerabilities due to EV adoption. Urban commercial feeder F3 showed vulnerabilities for high EV adoption with extremely high public infrastructure charging. Almost 25% of residential customer transformers have to be upgraded for the expected LEV adoption of 6%. For other larger EV charging infrastructures, new customer transformers will have to be installed. As expected, the number of tap changes of the voltage regulators at the distribution level increased with increased EV adoption. Moreover, most substation transformers showed little to no overloads due to EV adoption.

Question 4 asked to compare mitigation strategies to identify the best mitigation strategy at the distribution level. Several mitigation strategies were explored for different feeders. Managed charging proved to be highly effective for all kinds of EV loads. Customers with large EV loads may be naturally interested in adopting managed charging, as a reduction in peak demand is related to a reduction in utility bills. Other EV customers may require additional incentives from the utility for the widespread adoption of managed charging. ToU and combined ToU and BESS approaches have been the best options to mitigate the impact of EV adoption for some feeders. However, the best ToU scheme is highly dependent on the type of distribution feeder. While adoption of ToU can mitigate the impact of EV adoption to a certain degree, increased EV ToU participation can result in undesired peak shifting.

Question 5 asked about the impact of EV adoption on the total load of the system. For the expected LEV adoption of 6% and fleet electrification of 50%, the peak load on the system-level increases by 18.5% in summer and 28% in winter. The EV load is expected to stay the same for summer and winter, considering the weather in the Carolinas. However, the difference in the load shapes of summer and winter loads at the system-level results in different increases in peak load growth for the summer and winter. With increased EV adoption, the load shapes at the system level may be heavily influenced by EV load shapes.

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