ABSTRACT

SUN, LISHA. Customer-Oriented Distribution Planning Framework for Analyzing Grid Edge Technologies. (Under the direction of Dr. David Lubkeman).

Distribution planning is becoming increasingly more challenging due to the integration of grid edge technologies such as photovoltaic generation, energy storage and electric vehicles (EV). As the penetration of distributed energy resources (DER) increases, the distribution grid will be further stressed with respect to voltage regulation, capacity loading, energy losses and accelerated component aging. Moreover, the increased DER penetration level impact is closely related to customers' behavior including decision-making on PV or EV adoption, utilization habits of EV and charging, and participation willingness for utility DER programs. Utility planners will need to incorporate a customer-oriented distribution planning methodology and further develop skills and tools to identify and mitigate the issues associated with DER integration. The skills and tools will include methods to forecast the DER diffusion regarding both penetrations and locations, model DER loads, evaluate the potential impact via circuit analysis and propose the most cost-effective mitigation methods considering both traditional feeder upgrades and new grid edge technologies.

This dissertation proposes a new customer-oriented distribution planning framework for analyzing grid edge technologies. Grid edge technologies and their applications in distribution system are analyzed including PV, smart inverter, FREEDM solid-state transformer (SST), DC house and EV. An actual utility feeder model has been utilized to evaluate the impact of high penetration of PV, and compare mitigation methods including smart inverter, in-line power regulator and FREEDM SST. The cost benefit analysis from utilities' perspective has been performed for each mitigation method. The FREEDM solid-state transformer can also support a DC house configuration. A DC house configuration is found to more efficient compared to an AC house given that DER and many residential household appliances are based on DC technology. A

FREEDM SST based DC and hybrid house configurations are proposed with a comprehensive cost benefit analysis performed from customers' perspective. The impact of home EV charging is also incorporated.

A new customer-oriented distribution planning framework is developed and demonstrated using a comprehensive example of EV diffusion and integration based on a Python-based tool. Residential EV adoption is treated as a multi-criteria decision-making problem modeled via analytic hierarchy process (AHP). Customer characteristics such as car age, EV attractiveness, neighbor influences and customer economics (CANE) are considered. Distribution feeder topology is fused with property geographic information system (GIS) parcels and household travel survey data to model customer behaviors as well as geographic and electric locations for EV and charging stations. The proposed diffusion model is demonstrated using actual distribution feeder data. Using the diffusion results, EV impacts on system annual peak, energy, losses, transformer aging and feeder upgrades are evaluated using quasi-static time-series power flow analysis.

A new optimal distribution system horizon planning method is proposed to mitigate the EV charging load impact considering customer responsiveness. Optimal customer response rates for the planning horizon in future years is solved using dynamic programming to minimize the net present value of the total distribution infrastructure cost and EV managed charging program expenses. Three charging management strategies including TOU rate, charge by departure time and smart charging are selected to represent possible load controls by EV managed charging programs. The impact of implementing these managed charging strategies with various customer response rates are evaluated. Optimal customer response rates for these three EV managed charging programs are solved and found to achieve about 35% cost reduction compared with the base scenario without an EV managed charging strategy.

Customer-Oriented Distribution Planning Framework for Analyzing Grid Edge Technologies

by
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DEDICATION

To my mother Longying Xue, my father Hongzhao Sun, my husband Liqi Zhang and my beloved daughter Joy Sun Zhang

BIOGRAPHY

Lisha Sun was born in Henan, China. She received her B.S. degree in electrical engineering from Shandong University, Jinan, China in 2012. She is currently pursuing the Ph.D. degree in electrical engineering at North Carolina State University, Raleigh, NC. Her current research interests include electric vehicle diffusion forecast, managed charging programs design, distribution system analysis, high PV penetration integration, energy storage cost-benefit analysis and electricity markets.

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Chapter 1. Introduction

1.1 Challenges of Utility Distribution Planning and Dissertation Overview

Traditional utility distribution planning has been mainly focused on maintaining the safety and reliability of the distribution grid at a reasonable cost. The core distribution planning supports utilities' investment decisions [1]. The main tasks include load forecasting; evaluating distribution feeders for new loads and load growth; planning for infrastructure upgrades including the substation, distribution transformers, and lines; making sure the voltages are within ANSI limits; and checking that reliability and power quality are adequate. All of these tasks help a utility to make better investment decisions for now and in the future while providing decent service to customers.

However, all of these tasks are becoming more difficult nowadays due to the integration of distributed energy resources (DER) like photovoltaic generation, electric vehicles and energy storage. Moreover, the penetrations of the DERs are increasing at a rapid rate. Distributed generation such as photovoltaics creates reverse power flow and potential issues like over-voltage and increased losses. Electric vehicles are being planned for higher charging power that could overload the distribution transformers and significantly increase power demand during system peak. The existing distribution system needs to be evaluated carefully to be prepared for these new changes on the distribution system. Meanwhile, new technologies and programs are showing up like smart inverters, solid-state transformers and demand response. to accommodate DERs. These technologies and programs need to be considered and reviewed as well so the investment plan can be made wisely.

The load forecast has also been changed and the traditional load growth has been slowing down due to the energy efficiency program and distributed renewable generation. The load forecast

is becoming more closely related to the adoption of DERs like photovoltaics and electric vehicles. As the distribution system is changing dramatically then so does the distribution planning. The electric utility planners need new skills sets and new tools to better handle these tasks.

There are existing tools that can be utilized and incorporated into the distribution planning analysis. In addition, there is also a need for developing new tools to help accommodate DER [2]. Software such as OpenDSS [3] that can perform quasi-static time-series power flow analysis can provide tremendous help in performing DER interconnection studies, quantifying DER impacts and analyzing emerging technologies. Repast Simphony [4] is an agent-based modeling platform that can be integrated to provide feeder-level DER diffusion analysis for load forecasting. New tools that utilize optimization methods should also be investigated to better assist utility planners in making optimal investment decisions towards the system upgrades and new technologies.

In this dissertation, grid edge technologies including FREEDM solid-state transformer, smart inverter, in-line power regulator and DC houses are modeled and evaluated using a real distribution feeder [5]–[7]. Cost benefit analysis from utilities' and customers' point of view has been performed for different technologies. From there, a new customer-oriented distribution-planning framework is proposed with an example on electric vehicle growth. The proposed customer-oriented distribution-planning framework includes four parts: technology diffusion model, load modeling with grid edge technologies, distribution feeder impact analysis and mitigation strategies. Technology diffusion model uses agent-based modeling technique considering the social-economic background and interactions between customers and charging stations. Grid edge technologies and associated impact on load profile are modeled in OpenDSS and Python. Quasi-static time-series power flow analysis is performed in OpenDSS to accurately estimate feeder impacts including annual peak, system loss, transformer loss of life, substation and

line capacity and infrastructure upgrade plan. Finally, several EV managed charging strategies are evaluated and the optimal customer response rate are solved to minimize the potential cost to the utility in accommodating the increasing penetration of EV. A tool based on Python and OpenDSS has been created for the EV example with proposed distribution planning analysis as well.

1.2 Grid Edge Technologies

Grid edge technologies refer to many types of connected technologies at the edge of the electricity grid [8]. For example, technologies including distributed generation like rooftop PV, distributed energy storage, smart inverters and those at end-use customers like smart metering infrastructure, smart appliance, smart thermostat and electric vehicles. [8], [9]. These grid edge technologies help build the smart distribution system while also bringing great challenges. Meanwhile, some of the grid edge technologies are designed to better support the grid operation and mitigate issues associated with the smart inverter and in-line power regulator. As mentioned in the previous section, the grid edge technologies need to be carefully reviewed and assessed by the utility to make better investment and distribution planning strategies. In this dissertation FREEDM Solid-State Transformer, smart inverter, in-line power regulator, DC house and electric vehicle are evaluated and analyzed. Cost benefits analysis for these technologies from the utilities' and customers' point of view are been performed as well.

1.2.1 FREEDM Solid-State Transformer (SST)

To facilitate seamless integration of distributed energy resources (DER) at high penetration levels, the FREEDM system uses power electronics technology to replace the conventional distribution transformers with Solid-State Transformers (SSTs) [10]. FREEDM SST connects directly to the primary distribution voltage feeder (2kV – 35 kV). FREEDM SST not only increases

DER hosting capacity of a distribution system considerably, above 100% penetration, but in it also offers other significant benefits including customer side voltage regulation and reactive power compensation. There is also a DC port which can be used to connect to a renewable resource like PV, electric vehicle, battery as well as serve DC load. Figure *1.1* shows the configuration of SST.

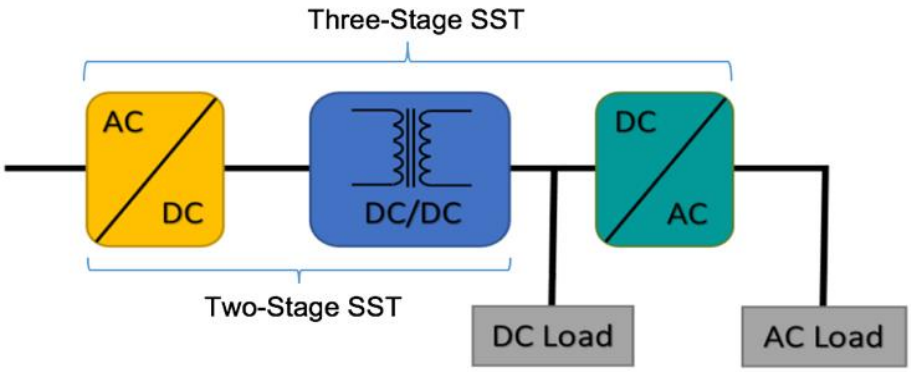


Figure 1.1 Solid-State Transformer Configuration

1.2.2 Smart Inverter and In-line Power Regulator

Smart inverter is an intelligent device with advanced real and reactive power control for both voltage and frequency regulation. Smart inverter can help in integrating more solar and mitigate integration issues like over-voltages issue caused by reverse power flow. Smart inverter technology has been widely used and mandated under California's Rule 21 [11].

In-line power regulator is a low voltage, solid-state device that combines utility-scale power electronics, high accuracy sensors and advanced algorithms. It has been developed to connect to the secondary side of the distribution transformer to help control customer voltage and provide reactive power compensation. In-line power regulators can help customers mitigate the voltage issue caused by the DER as well. So, it can also help increase the hosting capacity of DERs.

1.2.3 DC House

Currently, many residential household appliances are already based on DC technology like phones, computers, TV, gaming consoles and rely on an AC/DC converter to connect to the existing AC system. Large loads such as heat pumps and refrigerators may utilize motor drives with DC links. It is often the case that DC-based home devices could operate more efficiently if directly connected to DC, rather than AC sources. In a recent study, DC technology appliances are estimated to provide a weighted average energy saving of 36.5% for cooling loads and 32.8% for non-cooling loads [12]. This suggests that a residential DC house is potentially a more economical and efficient option in the near future. Moreover, most of the fast-growing distributed energy resources including PV, energy storage and electric vehicles are DC technology based as well. FREEDM SST can help build the future DC house due to the DC link feature. Figure *1.2* shows the proposed hybrid DC house and DC house structures based on the FREEDM SST.

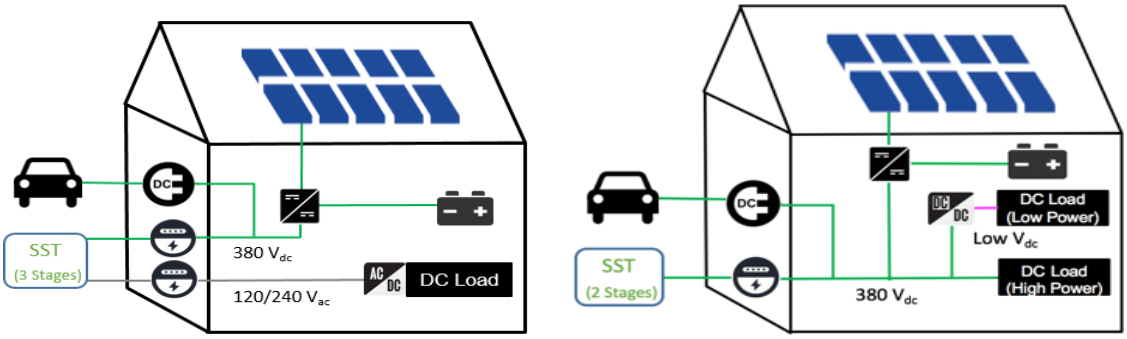


Figure 1.2 Proposed FREEDM hybrid House (left) FREEDM DC House (right)

1.2.4 Electric Vehicles (EV)

The electric vehicle market is growing quickly due to the advancement in technology development and the significant environment benefits. Increasing numbers of customers are starting to purchase or lease electric vehicles because EVs are cheaper to run and maintain. The price of the electric vehicles has been falling while the mileage range is increasing [13]. Utilities

also embrace EV because it provides the opportunity to increase the demand and even reverse the trend towards the gradually decrease in electricity sales [14]. As the penetration of electric vehicle increases, it will bring challenges to the current electricity grid including stress on peak demand supply and accelerating transformer aging. Distribution grid is the first place for these issues to show up since most of the charging activities happen at home or work.

1.3 Customer-Oriented Modeling using Agent-Based Simulation Technique

In order to have an accurate forecast of the electricity load, it is crucial to analyze the technology adoption process and make proper estimation of the penetration and even the location where these technologies connect in. Technology adoption is usually a long-time process. Photovoltaic generation has been adopted very quickly in recent years and the electric vehicle is still at the beginning part of its adoption. In addition, technology adoption is usually closely related to the social-economic backgrounds and interactions with the environment and between the customers. People with higher income, higher education level may be more likely to adopt new ideas and technologies compared to those who are not. As far as the author's knowledge, technology adoption, especially the technology adoption considering customers' demographic, social-economic backgrounds and interactions has been very commonly ignored by the existing literatures when performing load forecast analysis.

Agent-based techniques have been commonly used in stock market, supply chains, consumer markets and predicting the spread of epidemics [15]. It simulates the actions and interactions of autonomous agents. The advantage of the agent-based model lies in using natural description and its capability to analyze and test policies in a complex system with large numbers of individual agents and interactions between agents [15]. Study in [16] used agent based approach to analyze customers' behavior and the impact on electric vehicle charging loads. However, agent-

based methods have not been used in forecasting a process like the electric vehicle adoption. The electric vehicle diffusion forecast will be a good fit since the adoption process need to consider a good number of agents' characteristics and interactions.

Fig.1.3 shows the agent-based modeling results for the electric vehicle adoption on a local utility feeder at year 1, 5, 10 and 30. Red dots represent the electric vehicle owners and blue dots are non-EV customers. From the results, one can observe the most likely locations of electric vehicles and charging stations given the customer demographic and social-economic backgrounds and feeder and GIS parcel information. One can see the EV owners are showing up in clusters because the neighborhood impact is considered as well. All of this information will contribute to a more accurate feeder impact analysis, safer and proper distribution planning strategy and wiser investment decisions.

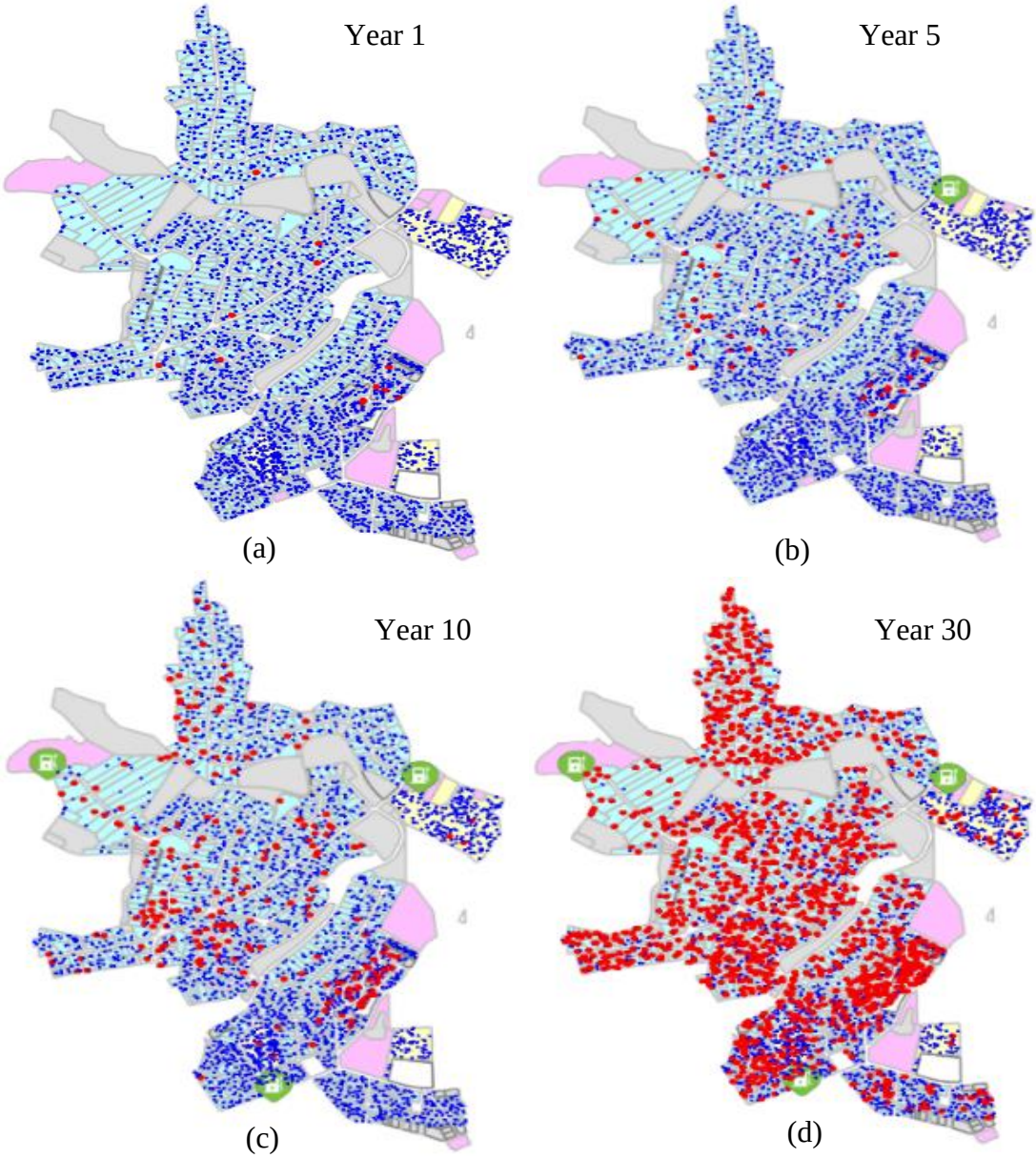


Figure.1.3 EV Adoption and Charging Station Placement Simulation Results for (a) Year 1, (b) Year 5, (c) Year 10 and (d) Year 30

1.4 Utility Feeder Modeling, Mitigation Strategies and Cost Benefit Analysis

Utility distribution feeder analysis evaluates the current distribution system with regards to voltage, peak demand, losses and loading conditions. to help utilities making planning strategies and investment decisions. Power flow is commonly used to perform the feeder analysis study.

Traditional feeder analysis only looks at certain representative cases like peak and off-peak situations. Tools like OpenDSS can perform quasi-static time series power flow, which can simulate the feeder operation yearly at minutes or even seconds level. More accurate assessment of the peak demand, losses, and transformer loss of life can be obtained with tools like OpenDSS. Existing literature that studies the potential impact of grid edge technologies [17]–[19] always started with assumed penetrations and seldom considered the adoption process of different technologies and forecasting the most likely locations of DERs on distribution feeders. With proper forecast of the adoption process and the most likely locations of DER on the distribution grid, a utility planner can better assess the impact of the emerging DERs.

Traditional mitigation methods for distribution planning include substation and component upgrading, line reconfiguration and distribution transformer replacement. New mitigation methods such as special rates and programs such as time-of-use rate, dynamic rate and demand response grogram can be utilized to provide a more efficient grid if properly designed and implemented. For example, EV managed charging programs can benefit both customers by reducing energy bills and utilities by mitigating the potential EV charging impact and even leading to a more cost efficient operation grid [20].

There are two types of managed charging strategies. One is indirect managing the charging by appropriate rate structures such as time of use (TOU) rate, dynamic rate and demand charge rate; another one is a more direct charging management like smart charging, which can be in various forms including demand response, one-way controlled charging or vehicle-to-grid [21]. Existing practices among utilities in US or Europe use direct or indirect managed charging strategies which are reviewed and summarized in [21]. A decentralized optimal demand-side management of EV charging is proposed to flatten the load cure of every distribution transformer

in [22]. A demand response strategy is proposed to minimize the impact of charging EVs on a distribution circuit in [23]. A centralized control algorithm is described to mitigate the thermal and voltage issued caused by EV in [24]. However, existing literature does not consider the long-term comprehensive distribution system planning cost and the optimal amount of customer responsiveness needed. The cost for the customer participation is usually missing from the objective when solve for the managed charging strategy either.

Customer responsiveness is the key to the success of most of the EV charging management strategies. Utilities offer incentives to drive customers to participate in the program to reduce system cost. Meanwhile, higher participation and response rate usually are associated with higher compensation payments to customers. An optimal customer response rate that demonstrates this trade-off needs to be resolved by utilities. Compensation methodologies for three demand responsive programs in US are presented in [25]. An incentive design for a demand response program with targeted reduction in a diverse set of buildings is proposed in [26]. Customer acceptance and response to time-based rate and price are introduced in [27]. However, there is a gap for integrating customer responsiveness and compensation cost integrated with the distribution system horizontal planning to create a more efficient grid considering future EV charging load.

Dynamic programming can be used for problems involving a sequence of interrelated decisions. Dynamic programming is a recursive optimization procedure[28]. One of the advantages of dynamic programming is that it breaks down a complex problem into a series of subproblems and the global optimal is reached while considering the complete planning horizon. In addition, dynamic programming is flexible and allows applications to other types of mathematical programming problems like integer programming. Dynamic programming has been used to control the EV charging or energy storage to reduce peak demand and energy arbitrary

with analyzing the daily load profile [29], [30]. Dynamic programming could also be used in distribution planning analysis to figure out the optimal long-term EV managed charging program customer response rate for a utility. Using dynamic programming for optimal customer response design for EV managed charging programs has not been explored much.

Cost benefit analysis is commonly used in making investment decisions. With the quantified impacts of DERs, cost benefits analysis can be performed. This dissertation adopts the cost-benefit assessment approach developed through an EPRI project [31]. The process has the following major steps:

- Identify the functions of the project that will provide new and/or additional benefits (that has value to the utility, customer, society). In addition, develop a mapping between the functions the project will provide, and the benefits identified.
- Quantify the benefits and costs.
- Perform a cost-benefit analysis.

1.5 Proposed Customer-Oriented Distribution Planning Framework

A new customer-oriented distribution-planning framework is proposed in this work, which is shown in Fig. 1.4. The first step is the customer adoption model, which will provide the penetration and location forecast for the evaluated technology during the planning horizon. The adoption model will be implemented in Repast Simphony using agent-based modelling technique. Then the load model for the new technology with proper control algorithm will be studied. With the adoption results and the load model, feeder impact analysis will be performed, and the potential impacts can be identified and evaluated. Mitigation plans including traditional feeder upgrades and control strategies such as special rates and demand response programs can be designed to optimize

utilities' cost to accommodate the new technology. Utilities could also implement some programs to influence the technology diffusion process such as building charging station infrastructures and various rebate programs. All of the above aspects are integrated into the newly developed customer-oriented distribution planning framework.

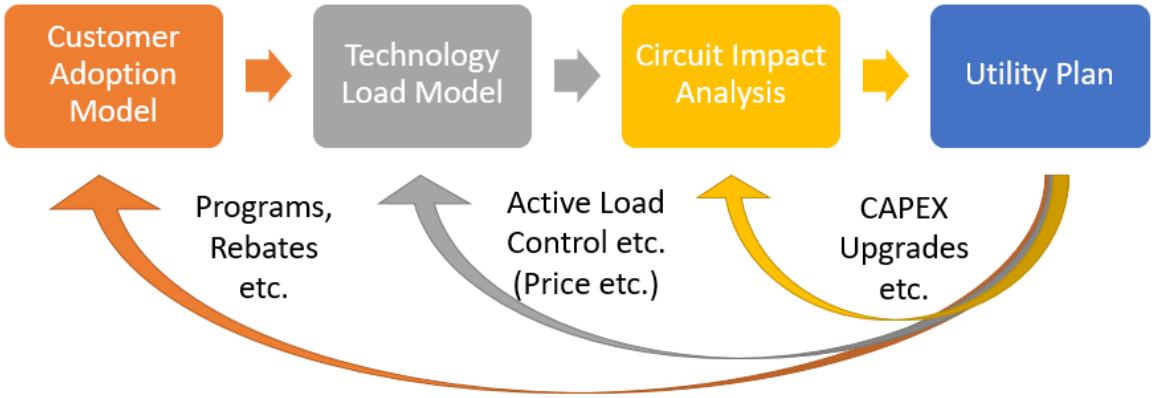


Figure 1.4 Proposed Distribution Panning Framework

1.6 Distribution Planning Tool Developed for Electric Vehicle Study

A tool has been developed using the customer-oriented distribution planning framework proposed above with the example of electric vehicle penetration. The tool is developed in Python with screen shots associated with the tool part 1, part 2 and part 3 as shown in Fig. 1.5, Fig. 1.6 and Fig. 1.7 respectively. Part 1 loads the results from the adoption model and performs Monte Carlo and various scenarios analysis regarding utility programs such as EV purchase rebates and charging station infrastructure development. Part 2 calls OpenDSS to perform feeder impact analysis. Impact on annual peak kW, energy MWh, single-phase and three-phase conductor loading is clearly shown. Number of distribution transformers that need to be replaced during the planning horizon of 30 years are also shown in the example. Part 3 shows the implementation of the EV managed charging programs to incentivize customers in moving the charging time. Feeder

impacts for different EV management programs at various customer response rates are shown and the optimal customer response rate for 30 years is solved using dynamic programming. Sensitivity analysis is also provided to analyze the change in key variables including peak demand charge, expense to change the program and cost to incentivize customers.

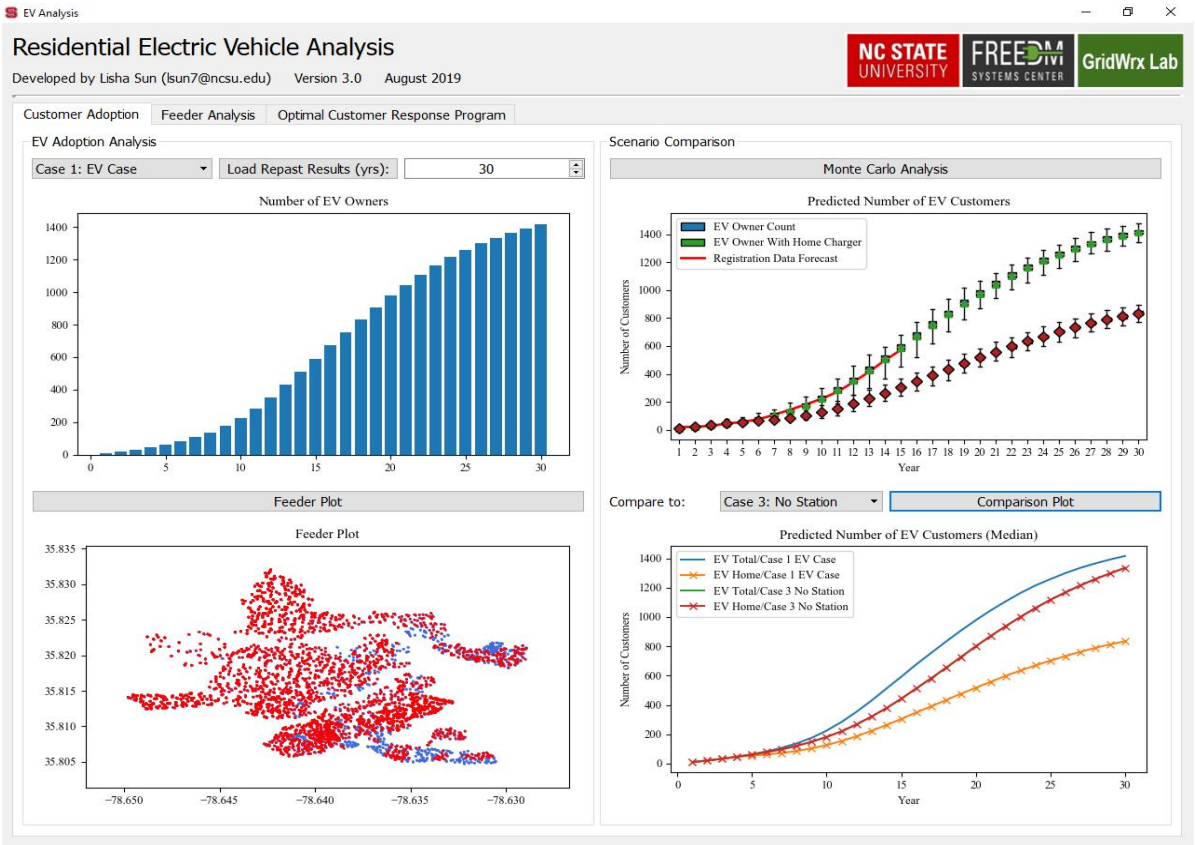


Figure 1.5 Tool (Part 1) EV Diffusion Analysis and Scenario Studies

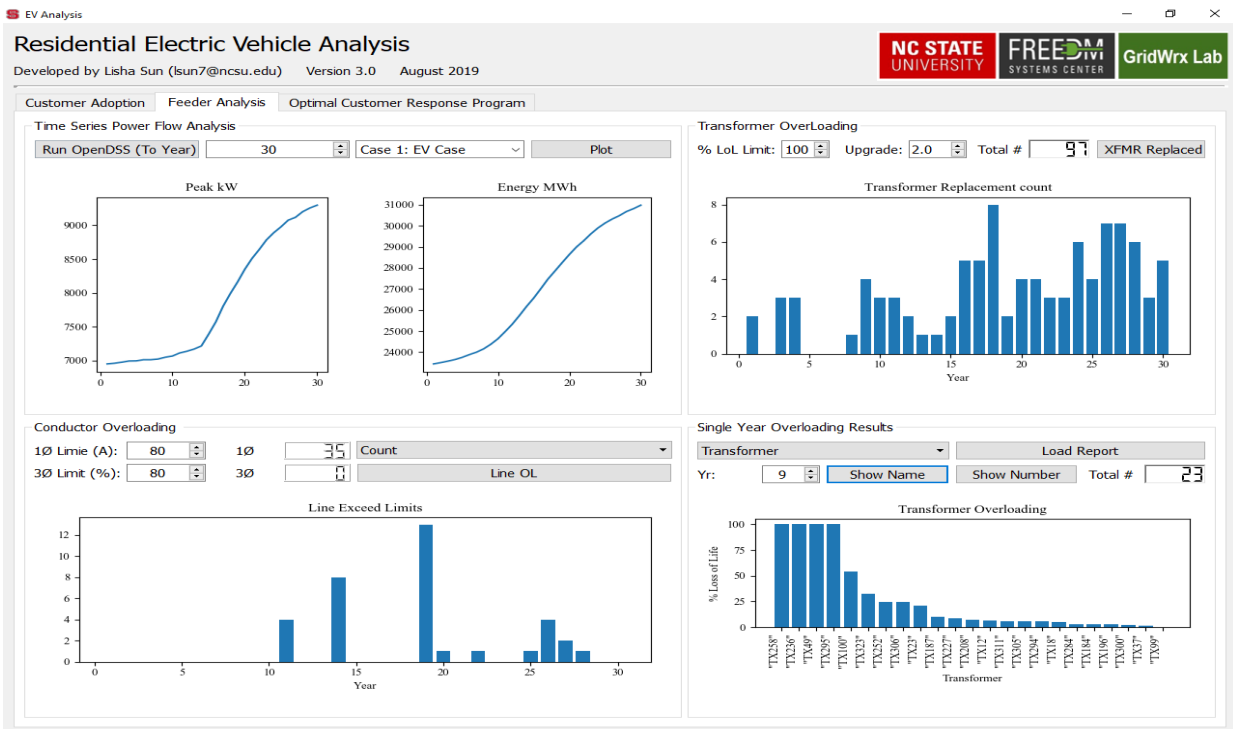


Figure 1.6 Tool (Part 2) Distribution Feeder Impact Analysis

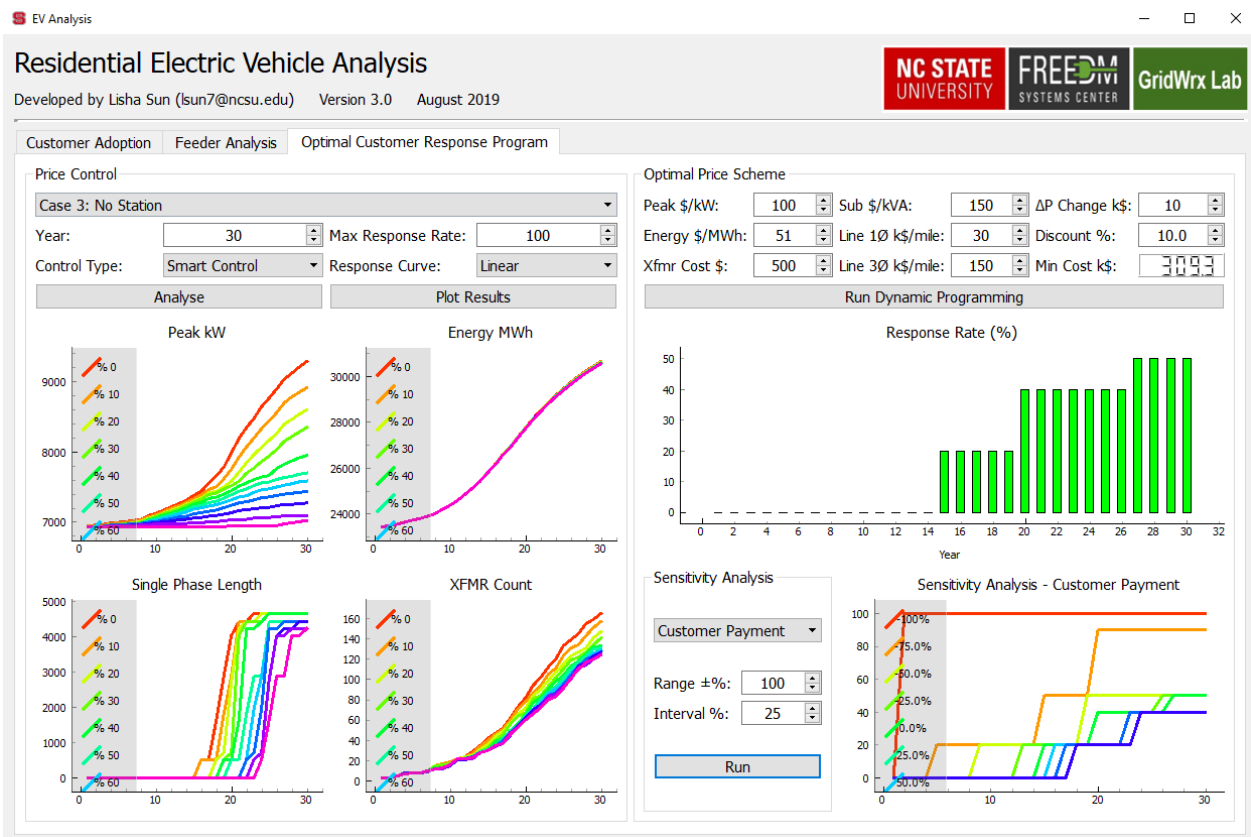


Figure 1.7 Tool (Part 3) Optimal Customer Response Rate

1.7 Organization of the Dissertation

Chapter 2 presents the assessment of FREEDM Solid-State Transformer (SST) and its impact to the distribution grid. SST is modeled in OpenDSS and cost benefit analysis from utility's point of view is performed. Chapter 3 evaluates the smart inverter and in-line power regulator and compares those two technologies with the FREEDM SST in mitigating the over-voltage issue caused by the high penetration of rooftop PV. Utility cost benefit analysis is performed and compared between these three technologies. Chapter 4 proposes DC house structures based on FREEDM solid-state transformer and analyzes the efficiency of four types of house structures: AC house, retrofit DC house, FREEDM hybrid DC house and FREEM house. For this chapter, cost benefit analysis is performed from customers' point of view. Chapter 5 gives an agent-based model of electric vehicle penetration for distribution planning analysis. The impact of EV on a local distribution feeder is identified and quantified and the required infrastructure upgrade plan is analyzed as well. Then the optimal distribution system planning considering customer response problem is formulated and solved in Chapter 6. Dynamic programming is used to solve for the optimal customer response rate for EV managed charging programs to minimize the utility cost for peak demand, energy loss, substation and line upgrades, transformer replacements and EV managed charging programs. Chapter 7 summarizes the dissertation and recommendations for future work.

Chapter 2. FREEDM Systems Solid-State Transformer Assessment for High PV Penetration and Cost Benefit Analysis

The FREEDM system is a technology for a smarter and resilient distribution system that facilitates a higher level of distributed energy resource (DER) integration by offering effective voltage regulation, reactive power compensation and real time monitoring and control. This chapter provides a framework for conducting a cost-benefit analysis for such a smart distribution system. The method first identifies the benefits, and then quantifies and monetizes them. OpenDSS time-series based power flow simulation is used to quantify the benefits accurately. The costs associated with the new components of the system are estimated based on prototype units. A cost-benefit analysis is adopted to identify the scenarios where employing such a system by a utility becomes economically attractive.

2.1 Introduction

Over the last two decades, technologies have been developed towards increased level of automation for the distribution system monitoring and operation/control [32]. One of the challenges has been economic assessment of these technologies. With the recent efforts on smart distribution systems to accommodate higher level of DERs on the system, the economic assessment of the new technologies/systems becomes a critical task [31], [33]–[37]. Although there are standard approaches for economic assessment of a given technology, the system-level assessment becomes more challenging, as estimating the benefits can be difficult and they cannot be easily converted to payments (revenues) [34]. As [38] points out, the usual practice considers only the costs and benefits of individual technology investments in smart grids, and only the economic values that can be captured by the utility deploying the technology are considered. A

recent example which provides a cost-benefit analysis assessment for a smart distribution system with capability to perform electric vehicle charging is presented in [39].

In this chapter, challenges of cost-benefit assessment for a new smart distribution system have been demonstrated through a case study - FREEDM system [40]. To facilitate seamless integration of distributed energy resources (DER) at high penetration levels, the FREEDM system uses power electronics technology to replace the conventional distribution transformers with Solid-State Transformers (SSTs) [40]–[42]. The system uses a feeder level communication backbone to implement an intelligent power and energy management system –DGI. The system also employs solid state fault isolation Devices –FIDs [43], [44], to facilitate fast fault interruption. Hence, this system not only increases DER hosting capacity of a distribution system considerably, above 100% penetration, it also offers other significant benefits.

Table 2.1 show the main features of the system and the benefits the system offers through these features. In a cost-benefit analysis, these benefits need to be identified and quantified. The analysis includes identifying and quantifying the benefits on actual circuits with high renewable penetration using time-series simulation, monetizing the benefits and estimating the realistic cost. Net present value-based approach is used to determine economic feasibility of the smart distribution system considered.

The remainder of the chapter is organized as follows. Section 2.2 introduces the cost-benefit method. The benefits of the FREEDM system is identified and quantified by conducting a time series simulation for a year using OpenDSS. The cost of the FREEDM system cost is estimated in Section 2.2 as well. Section 2.3 presents the cost-benefit analysis and the results for the three actual feeders. Net present value and discounted payback period are calculated. Section 2.4 concludes the chapter.

2.2 Cost Benefit Method

This dissertation adopts the cost-benefit assessment approach developed through an EPRI project, which was developed to provide guide for assessment of smart grid projects [31]. The process has the following major steps:

- Identify the functions of the project that will provide new and/or additional benefits (that has value to the utility, customer, society). In addition, develop a mapping between the functions the project will provide, and the benefits identified.
- Quantify the benefits and costs.
- Perform a cost-benefit analysis.

For the analysis, one first need to identify the "base system" and then identify the additional benefits that the base system FREEDM Features-Benefits Matrix does not offer. The cost-benefit analysis will then be applied based on the additional cost and benefits the FREEDM system will offer with respect to the base case.

The base system considered is the conventional distribution system with high penetration of new DERs. Note that with such high level of DER penetration, the system usually needs upgrades in order to host these DERs.

2.2.1 FREEDM SST System Features and Benefits

This step involves identifying the main features and functions, which the new system provides and the base system cannot support. Table 2.1 lists the new functions for the FREEDM, grouped under the desirable features of a "smart distribution" system. The next step is to identify the benefits these functions will provide. Table 2.1 shows these benefits also and the corresponding function-benefit mapping. The benefits in the table are adapted from the EPRI report, and they fall

under three categories: economic, reliability, societal. The next step in the assessment process involves quantifying the benefits associated with each function.

Table 2.1 FREEDM Features-Benefits Matrix

FREEDM System Features/Functions	Benefits
Accommodate High DER Penetration • Effective Volt/Var Control • Plug and Play • ES + DGI	• Reduced peak demand and energy demand • Mitigate voltage issues • Reduce power loss • Simplify DER integration • Mitigate variability of power
High Reliability and PQ • Looped Primary • Automated Fault Isolation and service restoration • Fast Protection with FID • Regulated Service voltage	• Very high reliability • Minimize fault impact on system • Very high PQ
Real Time Mon and Control • Enhanced DEMS • CVR	• Reduced operation and maintenance • Optimal capacity use • Load management: peak demand and energy reduction
Resiliency • Microgrid at Node, Feeder Section, Whole Feeder	• High resiliency

As Table 2.1 shows, the FREEDM system not only offers a comprehensive set of functions that facilitates high penetration of DERs, it also offers other sets of smart grid features, such as very high reliability, advanced real-time monitoring and control which enables customer participation, and others listed in the table. However, it is expected that the early adoption of this system will be for the main benefit the system offers – to accommodate high penetration DER on a system. I call such a deployment case a partial deployment scenario, as in this case only the components needed to mitigate the issues DER introduces will be deployed. In this chapter, such a scenario is considered. Hence, I will focus only on the benefits related to this function/feature.

Benefits of DERs has been studied and illustrated in many cases [33]. The main benefits of DERs will be: (i) Reduced demand and energy from conventional power plants, and (ii) Demand reduction during peak load conditions. Energy savings provides savings mainly for the customers, and the peak demand reduction allows for deferment of new generation build/purchase.

2.2.2 Quantifying FREEDM System Benefits

Benefits of the new FREEDM system is quantified with respect to the base case. The base case corresponds to the system before any mitigation measure is implemented.

To help illustrate the process, three actual residential feeders have been used. These are 12 KV residential feeders with 270-440 distribution transformers and peak load of 6800 – 7900 KW. To quantify the benefits, operation of these feeders has been simulated over a year, for both the base system and the new system with FREEDM system components. Actual feeder load and PV profiles for a year with a 15 min resolution are used in the study. Time-series based power flow simulations have been conducted, for both the base system and the new system. OpenDSS was used as the main simulation tool [3].

From these simulations, the following benefits have been quantified: high DER hosting capacity, demand and energy reduction due to real time load monitoring and management. These benefits are discussed in more detail below.

1) High DER Hosting Capacity

Conventional distribution systems need upgrades when the DER penetration approaches 30% or higher [33]–[35]. I envision that in the near future, some new feeders will have penetration levels of 70% or higher and such high levels of penetration will need substantial upgrading in order to enable the full benefit from DERs.

To assess the DER hosting capacity of the sample feeders, a high PV penetration scenario is considered where PVs are assumed at all load points. The PV penetration is adjusted to 100% (penetration is defined as the total size of PV systems divided by the peak load for a year). Fig. 2.1 shows the voltage heat map of one of the three feeders under both heavy loading and light loading conditions. Fig. 2.1(a) and (c) show the voltage profile when there is no PV; Fig. 2.1(b) and (d) show the voltage profile with distributed PV at all residential nodes. Fig. 2.1 shows that the voltage levels increase with PV integration. During the heavy loading condition with high penetration of PV, the voltage profile is in the green zone (around 124V) as shown in Fig. 2.1(b) and the voltages are within the 0.95 to 1.05 per unit ANSI limits. However, during the light loading condition, since the voltage is already high when there is no PV as shown in Fig. 2.1(c), power injection from PVs pushes the voltage even higher into the red zone (around 126V) which is above 1.05 per unit. Overvoltages occur towards the end of the feeder. Through these simulations, hosting capacity of the feeder A, B and C was determined to be 70%, 70% and 45% respectively.

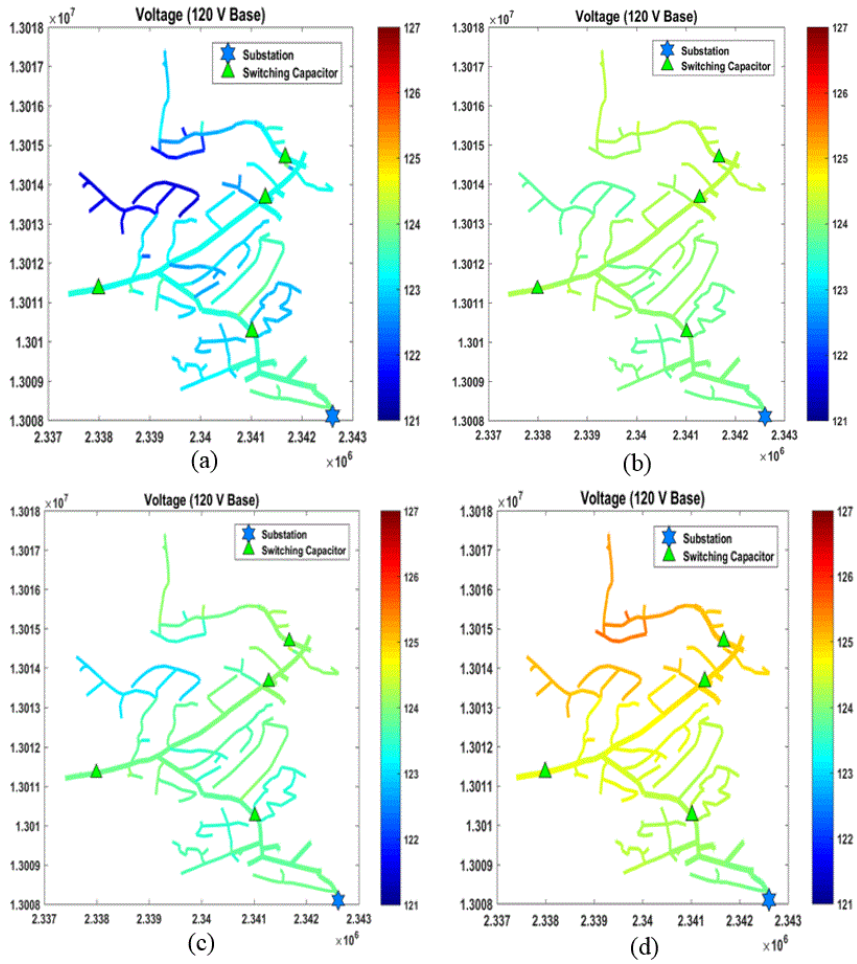


Figure 2.1 Voltage heat map (a) Heavy loading with no PV (b) Heavy loading with high PV penetration (c) Light loading with no PV (d) Light loading with high PV penetration

2) Partial FREEDM Deployment

To assess the conditions for a more likely scenario of PV penetration, a moderate level of PV penetration in the form of clusters located towards the ends of the feeders was simulated. The hosting capacities of the three feeders for this scenario are estimated to be 32%, 46% and 33%. Note: this is lower than the hosting capacity determined above in subsection B. 1) because each node in the cluster has a higher PV penetration. This scenario forms the base case for the following FREEDM deployment case studies where the PV penetration is increased to 43%, 54% and 43% for the 3 feeders. A partial FREEDM deployment scenario was constructed by adding SSTs to fix

the overvoltage issues caused by PV. SSTs are also added at low voltage nodes to allow for effective conservation voltage reduction (CVR). This resulted in deploying 36, 16 and 58 SSTs on feeders A, B and C respectively. These partial FREEDM system deployments helped to mitigate the overvoltage violations on the feeder and allow a 4V conservation voltage reduction.

Fig. 2.2 shows the load and voltage profiles at the secondary of a distribution transformer during light loading conditions. As the figure shows, the voltage goes above 1.05 per unit due to the relatively large power backfeeding. With the FREEDM system, these voltage violations are eliminated. This illustrates that indeed FREEDM system can accommodate high levels of PV systems on a distribution system.

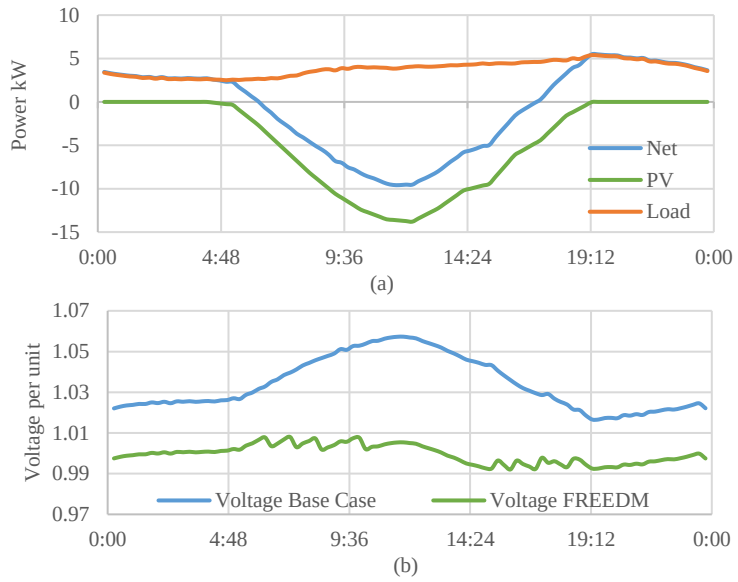


Figure 2.2 (a) Light-loading Day Load and PV Curves (b) Voltage Profiles

3) Demand and Energy Reduction

From these simulations the benefits in terms of energy saving, peak demand reduction and loss reduction was also determined. To get a detailed power loss estimation, the distribution transformers in the base case and the SSTs in the FREEDM case have been represented. A model

for the SST has been developed to incorporate the load dependent power loss characteristics of the SST. The SST loss model is based on the lab experimental data which fits a quadratic function of $y = ax^2 + b$, with a = 0.0141, b = 0.0052. In OpenDSS, it is modeled as a transformer with no load loss corresponding to coefficient b and the series resistance using coefficient a.

The simulation results are shown in Table 2.2. As expected, PV penetration in the circuit reduces the energy consumption. However, PVs do not help in reducing peak demand too much because the peak usually happens in the early morning or late afternoon when there is not too much PV output. In addition, there is a small increase in transformer losses due to the relatively larger SST losses compared to the traditional transformer and the large PV backfeeding.

Table 2.2 Partial FREEDM Deployment Results

#	Diff Δ	Energy MWh-yr.	Peak kW	Losses MWh-yr.		
				Circuit	*XFMR*	*Total*
Feeder A	PV	-1,227	4	-1	18	16
	CVR	-540	-169	1	-31	-31
	Total%	-2.3%	-2.4%	-0.002%	-0.06%	-0.1%
Feeder B	PV	-969	0	-4	0	-5
	CVR	-483	-92	0	-21	-20
	Total %	-1.4%	-1.2%	-0.01%	-0.06%	-0.1%
Feeder C	PV	-1,344	-16	-18	16	-2
	CVR	-559	-149	3	-36	-33
	Total %	-1.7%	-2.0%	-0.05%	-0.06%	-0.1%

Note that these energy benefits are accrued mainly to the customer, and thus they will not be included in the cost-benefit analysis here as the analysis is from the utility perspective. Reduced energy and peak demand however help the utility at the generation and transmission level. I refer to these benefits as the system benefits and the approach used to estimate them is given later in the cost-benefit analysis step.

4) Real Time Load Monitoring and Management

SSTs also offers tight voltage regulation at every customer load point [40]. This capability can be used to achieve effective Conservation Voltage Reduction (CVR), which has recently been adopted by many utilities as part of their energy efficiency efforts. The effectiveness of the CVR scheme is measured by the CVR factor, which indicates percentage reduction in demand ΔPd for a given percentage reduction in voltage ΔV. In a conventional system the secondary voltage can normally only be reduced by a maximum of 3V in order to avoid the low voltages at the end of feeder segments. However, in a FREEDM system, since the voltage is controlled at each SST, the voltage can normally be lowered by up to 6V to get the maximum benefits of CVR.

For the sample feeders simulated in OpenDSS, an exponential load model is used with a CVR factor of 0.7, as this load model is typically used for conservation voltage reduction studies [45]. Low voltage nodes are examined to determine how much the voltage can be lowered before load voltage drops below the lowest limit. The limit is set to be 117 V to leave enough margin for other additional secondary voltage drop on service lines up to the meter. CVR is simulated in the test feeders for both the base case and the FREEDM case, with the results given in Table 2.2. It can be seen from Table 2.2 that CVR provides energy conservation and reduction on peak demand and transformer losses.

2.2.3 FREEDM System – Cost Estimation

The main component in partial FREEDM deployment is the SST which is the new power electronics based device that is under development [40] for smart distribution applications. Hence, the starting point for a cost analysis is the actual production cost of the prototype SST [46].

For a single SST with an ‘Optimized Design’ the prototype cost is estimated to be around $455/kVA, and this is based on 7.2 kV, 25 KVA design. When extended to larger production

quantities, the cost falls to $300/kVA for single-phase units up to 75 kVA; the price for larger three-phase units is in the $200/kVA range. The amount of the reduction is approximated by reviewing several other product development cycles. The price further decreases as the product matures. One example of such maturation can be seen in the projected cost of automotive Lithium-ion battery packs [47]. The conclusion to be drawn from these projected data is that the overall price decrease ratio is around 3.5:1 from introduction to full maturation. Hence, it is assumed that the manufactured price, after the technology matures, will be in the ratio of 3:1 as based on the present large-scale production cost. When applied to SST, the final production cost is estimated to be the following:

Single-phase units up to 75 kVA: $90/kVA; Three phase units: $70/kVA

In partial deployment scenario, it is assumed that the utility will replace the existing transformers with SSTs at selected locations. The replaced transformers will be considered 100% depreciated and have no book value, which will make the cost benefit analysis more conservative. Hence, the cost differential between the SST and the distribution transformer to be replaced is defined as the cost of the SST.

2.3 FREEDM SST Cost Benefit Analysis Results

A cost-benefit analysis (CBA) was performed to estimate the benefits and costs accrued to the utility. The analysis estimates the net present value (NPV) and the discounted payback period (DPBP) associated with upgrading a conventional feeder to the partial FREEDM deployments considered. Each benefit category is monetized by utilizing a variety of methods, including literature review, industry surveys, and by using the benefits quantified through system simulations presented above.

A. High DER Hosting Capacity

This is the main benefit FREEDM system offers. As noted in section 2.2.B.1), PV penetration above 30% may require grid upgrades before additional capacity can be added, due to voltage violations. Hence, the economic benefits of increasing PV above the hosting capacity of the original feeder can be attributed to an investment in FREEDM system.

Existing literature has attempted to quantify the marginal economic value of PV as a function of increasing penetration. Net benefits to utilities include avoided energy costs, deferred investment in capacity expansion, and forecast errors associated with PV uncertainty (+ or -) [48], [49]. Fig. 2.3 presents a summary of these findings from Arizona, California, and Hawaii. Note that the PV penetration definition is the percentage of PV energy generated divided by the total load energy consumption of the feeder [48], [50], [51]. This curve was used to estimate the associated system benefits: the area under the curve between the two penetration levels – the level corresponding to the hosting capacity and the new level achieved by the FREEDM deployment – represents the additional economic benefit that can be attributed to FREEDM. The increase in PV penetration level the FREEDM system enables is determined from system simulations as indicated in previous section.

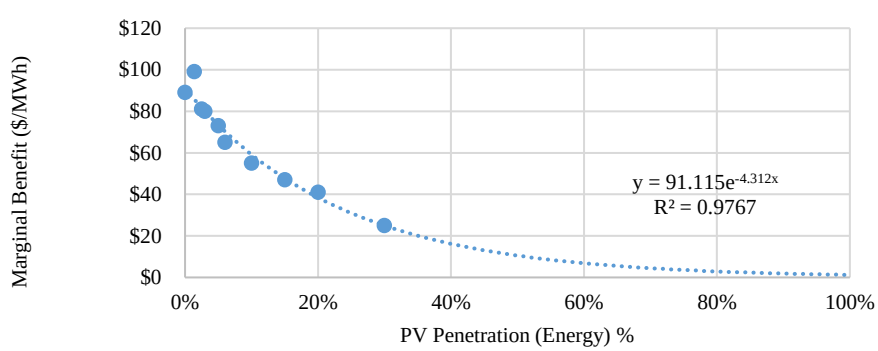


Figure 2.3 Marginal Benefit of PV

B. Real Time Monitoring and Control

SSTs have embedded real-time monitoring and control capability, which can be used to improve system operation and efficiency. The main benefit that is quantified and monetized is the Conservation Voltage Reduction (CVR). CVR helps reducing the energy consumption and peak demand, which incurs avoided electric energy and capacity costs to electric utility. The avoided cost of energy includes both fixed and variable cost that can be avoided as electricity usage decreases; the avoided capacity cost consists mainly of the costs associated with purchasing/building peak generation facilities [52].

C. CBA Results

A spreadsheet tool was developed to evaluate the annualized benefits and costs in order to calculate the NPV and discounted payback period (DPBP) for different FREEDM deployment scenarios. Table 2.3 presents the results for the three feeders considered. The benefits shown in the table are calculated as follows: the system benefits of DER is calculated by using the marginal benefit of PV curve. The DER avoided capital cost is due to the peak reduction caused by PV. The reduction in energy and peak caused by CVR is considered as feeder benefits. A 10% discount rate was used, which represents the weighted average cost of capital (WACC) used by utilities [53]. Annual cash flows were assumed constant over the lifetime of the SSTs, currently estimated at 25 years. The avoided energy cost used in the calculation is 0.051$/kWh and the avoided capital cost is 55$/kW. These costs are obtained from [52] for seven electric distribution companies.

Table 2.3 NPV and Discounted Payback Period Results

#	Cost	DER Benefits (yr.)		Feeder Benefits (yr.)		NPV	DPBP (yrs.)
	SST	*System*	*Avoided Capital*	*Avoided Energy*	*Avoided Capital*		
A	$145k	$53k	$0	$27k	$9k	$669k	2.9
B	$41k	$42k	$0	$25k	$5k	$606k	1.6
C	$244k	$62k	$872	$29k	$8k	$657k	4

Sensitivity analysis has also been conducted. In Fig. 2.4, eight parameters are varied, first by +25%, then by -25%. The impact on NPV is recorded and the corresponding importance of each parameter is ranked. This confirms that the price of the SST and the discount rate are the most influential factors on the NPV.

These results indicate the following:

- The FREEDM system is likely to be deployed first in niche markets where a combination of economics and policy require it.
- The economic feasibility of the partial deployment scenarios considered indicates that early adoption of FREEDM systems is likely in near feature.

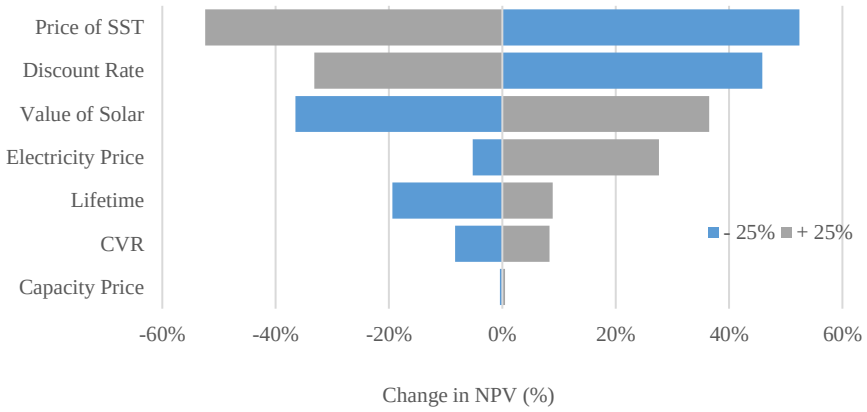


Figure 2.4 Sensitivity Analysis for FREEM SST

2.4 Conclusion

In this chapter, a cost-benefit analysis case study for the FREEDM system deployment has been presented using three sample feeders from a utility. The simulations on these feeders also clearly demonstrate that FREEDM system increases DER hosting capacity considerably. These benefits are quantified and monetized from the utility perspective that includes avoided energy costs and deferred investment in capacity expansion. Other benefits are due to more effective real time monitoring and control which is monetized as CVR benefits.

The cost-benefit analysis results presented a positive net present value for a partial deployment case with less than 5-year payback period for the sample feeders. The above results indicate that the partial FREEDM deployment is likely to be utilized on feeders with moderate DER penetration in near future.

Chapter 3. Smart Inverter, In-Line Power Regulator Assessment and Cost Benefit Analysis with Comparison to FREEDM SST

This chapter provides an economic comparison of three technologies that enable high PV penetration on the distribution system: Medium voltage solid-state transformer (SST), grid edge regulator and smart inverter. In order to compare these three technologies, simulations are performed on a representative utility feeder using OpenDSS. Quasi-static time series analysis over a year is used to predict the effectiveness of high PV penetration and more aggressive conservation voltage reduction enabled by each technology. Comprehensive cost benefit analyses are conducted based on these simulation results. The cost benefit analysis results indicate that the medium voltage solid-state transformer (MV SST) is the most cost-effective option with a 3-year payback period for utilities that are trying to accommodate high PV penetration in the distribution grid.

3.1 Introduction

Recently, residential distributed PV capacity has increased significantly due to the economic viability, incentives and public commission requirements. [54]. As distributed PV penetration increases, the resulting power backfeed can disrupt the operation of a conventional radial distribution grid. The potential impacts of high PV penetration have been studied by many researchers, with overvoltage being one of the most critical issues that need to be addressed [34]. Possible mitigation methods include feeder upgrades and reconfiguration, PV power factor regulation and integrated Volt/VAR control [55]. Currently there are many new technologies that have already been adopted in constructing PV systems or will be used in the future to mitigate high PV integration issues. While many of these new technologies provide a technical solution, a detailed comparison and comprehensive cost benefit analysis is needed to obtain a better understanding of the relative economic value of these technologies.

After a review of the current technologies, three distribution component-based solutions have been selected for further comparison in this chapter. These are the medium voltage solid state transformer [10], grid edge voltage regulation device and the smart inverter. The smart inverter has already been commercialized and manufactured by multiple vendors. At this time, there are several companies producing and selling grid edge regulators. The MV SST is currently under development in NSF FREEDM systems center at North Carolina State University. The characteristics of each device considered in this chapter are as follows:

- Medium voltage SST (MV SST) is a solid-state based power electronics device that connects directly to the primary distribution voltage feeder (2kV – 35 kV). There is also a DC port, which can be used to connect to a renewable resource like PV, battery as well as serve DC load.
- Grid edge regulator is a low voltage, solid-state device that combines utility-scale power electronics, high accuracy sensors and advanced algorithms to control customer secondary voltage.
- Smart inverter is an intelligent device with advanced real and reactive power control for both voltage and frequency regulation.

The purpose of this chapter is to provide an economic comparison of the MV SST, grid edge regulator and smart inverter for enabling high levels of PV penetration. Section 3.2 discusses the three technologies further and their capabilities in addressing the high PV integration overvoltage issue. Section 3.3 describes the case study setup and shows the simulation results of the quasi-static time series analysis. Section 3.4 discusses the economic results of the cost benefit analysis. Conclusions are provided in Section 3.5.

3.2 High PV Penetration Overvoltage Mitigation Technologies

Overvoltage issues that limit the PV penetration level on the distribution feeder have been discussed in previous research papers [5], [34]. Fig. 2.1 shows the voltage map of an actual utility feeder with and without 100% distributed PV during the light loading conditions. It can be seen from Fig. 2.1(c) and (d) that during the light loading condition, the high penetration of PV pushes the voltage into the overvoltage (red) zone, which is above 1.05 per unit.

Many technologies have been developed to address overvoltage issues in order to enable higher PV penetration. The MV SST addresses the overvoltage issue by regulating the voltage on the customer side and isolating the customer from seeing overvoltage on the distribution primary [5]. The MV SST can also provide reactive power compensation directly to the primary feeder to help regulate primary voltage and reduce system losses. Fig. 3.2 shows the power and voltage profile of one load with PV system during the light loading day with and without the MV SST. It can be seen from Fig. 3.2 that the customer overvoltage issue has been addressed by the MV SST.

The grid edge regulator is another technology that can be used as a mitigation method by regulating the voltage on the customer side of the distribution transformer. It is similar to the MV SST, except that the grid edge regulator is connected to the low-voltage secondary of the customer distribution transformer. This means the grid edge regulator still needs the traditional AC voltage step-down transformer when used in the distribution system. It is an “add-on” retrofit device between the traditional AC transformer and load. One benefit of the grid edge regulator is that it has a relatively higher efficiency compared to the MV SST. From the currently available specifications, the efficiency can be over 99%.

The smart inverter is a new technology that is being promoted for use in new PV interconnections. The smart inverter does not regulate voltage directly. Instead, it controls the

reactive power injection to impact the local customer voltage. For a PV system, the power factor at the point of interconnection is usually unity, which means there is no reactive power injection. With a smart inverter, the power factor can be controlled to be either leading or lagging to impact the voltage at the point of interconnection. Fig. 3.1 shows an example of the Volt/VAR behavior of the smart inverter [56]. The goal is to keep the voltage between 0.95-1.05 per unit. When the voltage is relatively low, the inverter is working in capacitive mode and injecting reactive power to the grid to boost the voltage; when the voltage is high, the inverter is running in inductive mode and absorbing reactive power from the grid to help lower or "buck" the voltage.

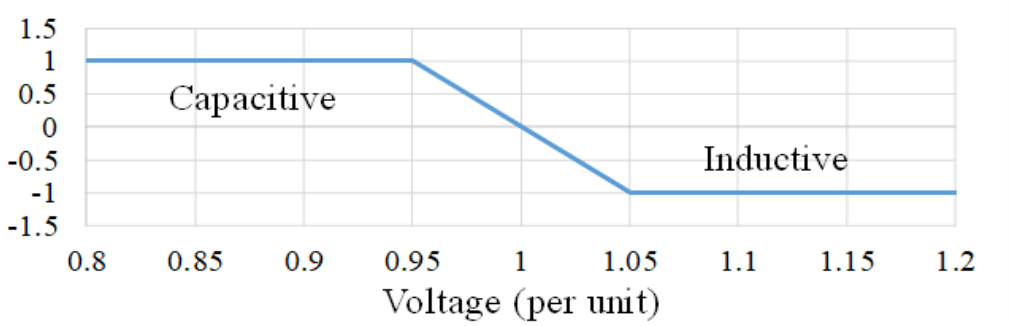


Figure 3.1 Smart Inverter Volt/VAR behavior [6]

The daily power and voltage profiles of one PV inverter with and without the smart inverter control are shown in Fig. 3.2 These curves are obtained from the utility circuit simulation run in OpenDSS. It can be seen from Fig. 3.2(a) that during the peak loading condition, there is no overvoltage issue, regardless of the smart inverter control. However, an overvoltage issue occurs in the light loading condition in Fig. 3.2(b) when there is no smart inverter control. With smart inverter control, shown as the grey line in Fig. 3.2(b), the overvoltage issue has been mitigated. Fig. 3.2(c) and (d) shows the real power and reactive power drawn by the inverter. When there is no inverter control, the power factor is unity, so the reactive power is zero. The reactive power is positive for the smart inverter control cases, which means the inverter is drawing reactive power

from the grid to help lower the voltage. The small dip in the middle of the reactive power curve in the Fig. 3.2(d) smart inverter control case is due to the inverter size limitation. The dip will go away if the inverter is oversized by a small margin. Since the overvoltage issue has been mitigated, there is no need to oversize the inverter. In cases where the overvoltage is not corrected, the inverter can be oversized to achieve a better control of the voltage.

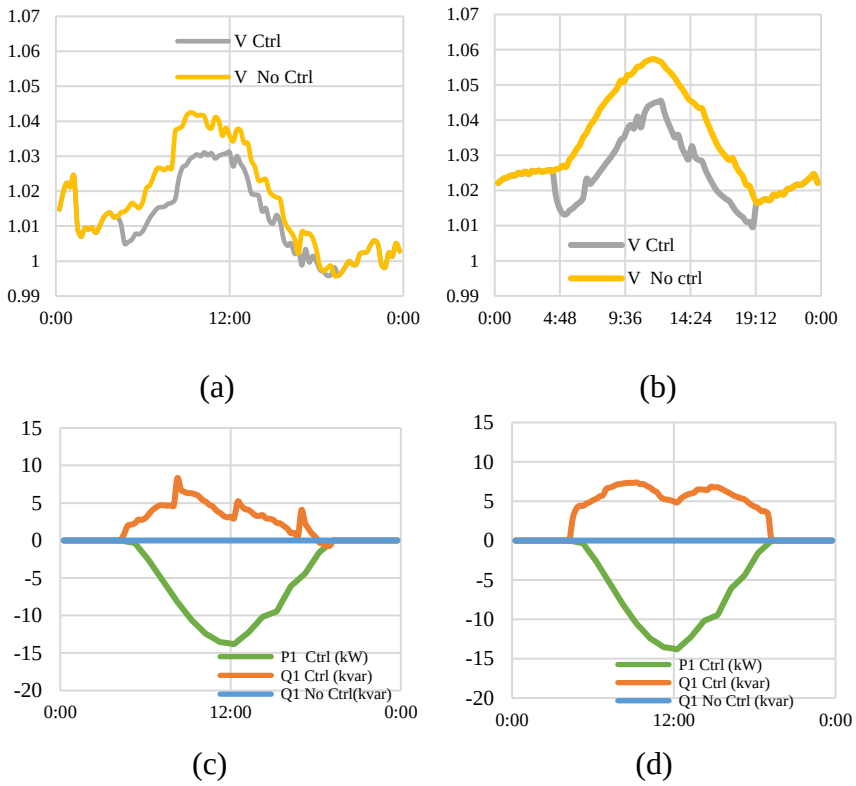


Figure 3.2 Daily Voltage and Power Plot of the Inverter (a) Peak Loading Day Voltage Profile (b) Light Loading Day Voltage Profile (c) Peak Loading Day Power Profile (d) Light Loading Day Power Profile

A utility could also benefit from using these same technologies to achieve a more aggressive conservation voltage reduction (CVR) effect, since the MV SST, grid edge regulator and the smart inverter all have the capability of controlling the voltage. CVR is an approach used by many utilities to reduce peak demand and energy consumption by compressing and lowering

the voltage profile to the lower part (114-120V) of the ANSI standard voltage band (114-126V). These three technologies can control the voltage on the lower voltage nodes, which removes the limits often encountered when trying to adjust CVR control for further voltage drop and energy reduction. The CVR factor used later in this chapter is 0.7, which is defined as the percent decrease of active power (watts) per 1% reduction in voltage.

Table 3.1 summarizes the specifications of the MV SST, grid edge regulator and the smart inverter considered in this chapter. MV SST specifications are based on a prototype model developed in the FREEDM laboratory. The specifications for the grid edge regulator and smart inverter are based on the published product datasheets that are available online. In order to perform the comparisons, the grid edge regulator is assumed to have the same power rating ranges as the SST.

Table 3.1 Technical Comparison of MV SST, Grid Edge Regulator and Smart Inverter

Product	MV SST	Grid Edge	Smart Inverter
Power Rating	0-100 kVA	50 kVA	12 kW - 30 kW
Input Voltage	3.6 kV Vac	240 Vac	1000 Vdc
Output Voltage	120Vac/200Vdc	240 Vac	480/277 Vac
Volt. Regulation	Any	± 10%	-
VAR Compensation	Any	10% of rating (lead. Or lag.)	0-1power factor (lead. Or lag.)
Efficiency	97%	≥ 99%	98.30%
DC Port	Yes	No	No

3.3 OpenDSS Simulation and Results

In order to quantify the benefits of the MV SST, grid edge regulator and smart inverter, OpenDSS quasi-static time series simulation are performed based on a representative utility feeder. This section introduces the case study scenarios and presents the simulation results.

3.3.1 Case Studies and OpenDSS Modeling for Smart Inverter and In-line Power Regulator

Three cases are studied for each technology scenario in order to test the effectiveness in facilitating a higher PV penetration and quantify all of the benefits. Table 3.2 shows the case study category setup. In (a) Base Case, the distributed PV penetration is set to be the hosting capacity of the feeder. In addition, the hosting capacity is defined as the amount of PV a feeder can accommodate without having overvoltage issues. No extra devices are needed. For (b) Higher PV case, devices are added to mitigate the overvoltage issue caused by the increased PV penetration. In (c) Higher PV plus CVR case, additional devices are applied to enable a tighter voltage range required for CVR. For the SST scenario, 32 SSTs are needed to accommodate both the high PV penetration and 4-volt CVR. Additional details for this scenario are given in [5]. By selecting the same PV cluster as the SST scenario, 32 grid edge regulators are needed to achieve the same PV penetration and the 4-volt CVR. For the smart inverter scenario, it is assumed all the PV systems in this PV cluster are using a smart inverter when connecting to the grid. So, 133 smart inverters are used to integrate the same PV penetration. Due to the limited capability of voltage control, the smart inverters allow 1-volt CVR as determined by the simulation.

Table 3.2 Case Set Up for SST, Grid Edge and Smart Inverter

Cases	Devices (SST/Grid edge/Smart Inverter)
(a) Base Case	Feeder + 32% PV
(b) Higher PV	Feeder + 43% PV + Devices
(c) Higher PV plus CVR	Feeder + 43% PV + Devices +CVR

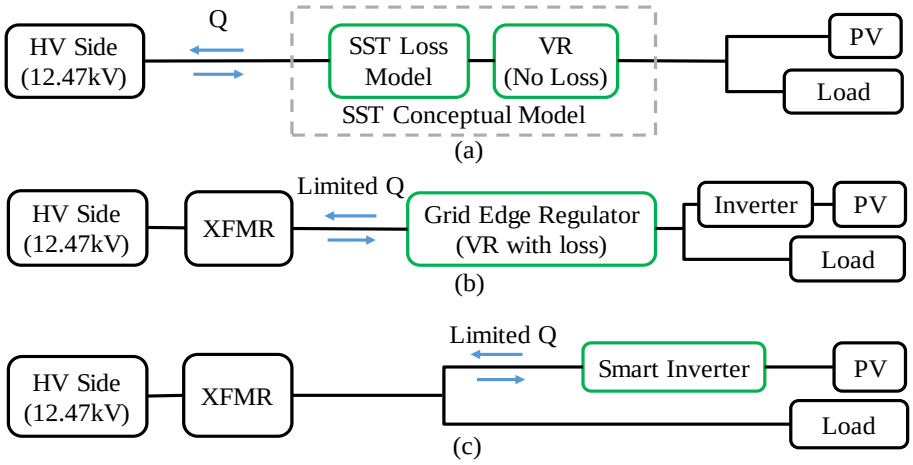


Figure 3.3 (a) FREEDM SST (b) Grid Edge Regulator (c) Smart Inverter

MV SSTs, grid edge regulators and smart inverters are modeled in OpenDSS using the structures shown in Fig. 3.5 Models are setup based on available datasheets published online by vendors. Grid edge regulators are modeled using the voltage regulator block in OpenDSS, with losses set according to the datasheets. Smart inverters are simulated using the Volt/VAR mode for PV inverters in OpenDSS [56] with the setting shown in Fig. 3.3 The smart inverter loss curves are set based on information from the CEC inverter test database [57]. As for the interconnection, the grid edge regulator and smart inverter need the traditional OpenDSS transformer (XFMR) model to connect to the distribution medium voltage side of the circuit.

3.3.2 Feeder Simulation Results

The summary of the simulation results for the MV SST, grid edge regulator and smart inverter compared to the Base Case (Feeder with 32% PV) are shown in Table 3.3. The DER savings is the difference between (b) higher PV case and (a) base case. The CVR savings are the difference between (c) higher PV plus CVR case and (b) higher PV case. It can be seen from the table that the MV SST has the most benefits with respect to energy and peak reductions. The resulting improvements shown for the grid edge regulator and the MV SST are close. The smart

inverter has the least reductions in energy and peak demand kW. This is mainly because the smart inverter is not effective at the precise voltage control needed for optimizing CVR benefits. The smart inverter only allows for 1V conservation voltage reduction. Both the MV SST and grid edge regulator can achieve about 4V conservation voltage reduction.

Table 3.3 SST, Grid Edge and Smart Inverter Simulation Results

Diff Δ to Base	MV SST (32 used)		Grid Edge (32 Used)		Smart Inverter (133 used)	
	Energy MWh-yr.	*Peak kW*	*Energy MWh-yr.*	*Peak kW*	*Energy MWh-yr.*	*Peak kW*
DER	-1,187	-2	-1,110	-3	-1,082	-11
CVR	-534	-146	-534	-146	-153	-36
Total	-1,721	-147	-1,644	-149	-1,236	-46

3.4 Cost Benefit Analysis for Smart Inverter and In-line Power Regulator with Comparison to FREEM SST

This session describes the cost and benefits estimation and discusses the cost benefit analysis results. A comprehensive cost estimation is performed, and the benefits quantified by the quasi-static circuit simulation discussed in the previous section are monetized.

3.4.1 Cost Estimation

A full cost estimation of the MV SST, grid edge regulator and smart inverter placement must consider not only the device cost itself but also the additional system costs from the perspective of the utility. For this analysis, cost estimates from industry experts were used to calculate costs of stranded assets, scheduled transformer replacements, installation and maintenance costs.

MV SST cost is estimated based on the prototype cost in the lab and the details are discussed in [5]. The price varies from $90/kVA to $125/kVA based on sizes. The size of the 32

SSTs used in the feeder varies from 10 kVA to 100 kVA. The average cost for these 32 SSTs is $4,305 per piece. The exact price for the grid edge regulator could not be obtained since it is a relatively new product offering. An estimated price of $4,450 was derived based upon similar commercially available devices. Pricing for the smart inverter was obtained through authorized distributors and the price is $4,051 per piece (15kW). In addition to being installed alongside traditional distribution transformers as "grid edge add-on devices", each of these product types may require an auxiliary component. The grid edge regulator requires a small inverter ($150), and the smart inverter requires a DC disconnect ($408). The cost of these components is included in the analysis. In addition, the smart inverter is a device that would be installed by customers with solar DER. Due to the benefits gained by utilities when customers install these devices, a utility subsidy is assumed. Based on a review of utility subsidies for energy efficient appliances [58], this analysis assumes the utility covers 25% of the cost of smart inverters.

The stranded asset value represents the value utilities must write off when distribution transformers are removed from service and replaced with SSTs. Discussions with industry experts indicated that distribution transformers are depreciated on a 30-year schedule. However, they are routinely refurbished and reused in other feeders if they meet certain criteria. Transformers can be refurbished for approximately 30-40% of the price of a new unit. Thus, installation of the MV SST or grid edge or smart inverter will not incur stranded asset costs to utilities, as in most cases these transformers can be reused in other feeders, reducing the need for new transformers. Industry experts also indicate that when a transformer is beyond repair, no salvage value is captured. Any transformers removed during the installation of MV SST that cannot be repaired have a salvage value of zero, and any that can be used elsewhere must simply be refurbished. Because it is not

possible to guarantee that the utility will choose to refurbish all transformers replaced with SSTs, the refurbishing cost is excluded from the analysis.

The MV SST and the grid edge regulator have similar installation costs since they have similar size. Replacement costs for a standard transformer are approximately $1,150, which includes labor, bucket truck usage, and replacement parts. This replacement cost is used as an estimate for the installation cost of a MV SST and grid edge regulator. The installation cost of the smart inverter is paid by the consumer and is not included in the analysis.

Finally, consider the fact that standard distribution transformers have a 40-year life, and in a feeder with 300-450 transformers, it will be necessary to make some replacements over the 25-year life of the SST. In the grid edge regulator and smart inverter case, because they do not replace transformers, there are 31 additional transformers in the feeder than in the MV SST case. Each year, it is estimated that 1/40=2.5% of these transformers will be replaced with a new transformer. For grid edge regulator and smart inverter devices, a $5,000 annual cost is added to account for the replacement of 2.5% of the distribution transformers that were not supplanted by an SST, as described above. Accurate estimates of annual maintenance costs of the MV SST and grid edge regulator are not yet available. The maintenance cost is estimated based on the service labor and parts cost of a regular transformer and assumed that each device would have approximately equal annual maintenance costs. The smart inverter's maintenance cost is not considered since it is a device that would be maintained by customers. Table 3.4 summaries all the costs considered for the MV SST, grid edge regulator and smart inverter.

3.4.2 Benefit Monetization

Based on the simulation results from the quasi-static circuit analysis described above, the benefits of deploying MV SSTs, grid edge regulators and smart inverters are summarized in Table

3.5. The avoided demand cost, avoided energy cost and value of solar used for monetization are derived from utility averages in the northeastern U.S. [52] and a review of value of solar studies [48], [50], [51]. System Benefits PV is the net benefits of the incremental addition of DER beyond the circuit's base hosting capacity enabled by the technology to utilities, include avoided energy costs and deferred investment in capacity expansion. [5]. Here the System benefits PV is monetized at $43/MWh. Peak reduction PV is the reduction in peak demand from the incremental DER and is negligible. The avoided demand cost is assumed to be $53/kW. Energy savings CVR is the reduction in peak energy consumption due to the increased CVR effect allowed by each technology. Peak reduction CVR is the resultant drop in peak demand due to the more aggressive CVR allowed by each device and is monetized using the avoided demand cost.

Table 3.4 Annual Benefits of MV SST, Grid Edge Regulator and Smart Inverter

Devices	System Benefits PV	Peak Reduction PV	Energy Savings CVR	Peak Reduction CVR	Total Annual Benefits
MV SST	$51k	$0k	$32k	$8k	$91k
Grid Edge	$48k	$0k	$32k	$8k	$88k
Smart Inverter	$47k	$1k	$9k	$2k	$58k

3.4.3 Comparison Cost Benefit Results and Discussion for Three Technologies

The final results of the cost benefit analysis for each technology, based on the stated assumptions concerning costs and benefits, are shown in Table 3.4. The net present value is calculated assuming a 25-year life span for each of the three technologies using a discount rate of 10%. For the representative feeder analyzed, the MV SST emerges as the most financially attractive option for first adopters. Under these assumptions, utilities looking to accommodate high levels of DER penetration would find the largest net benefit in choosing the MV SST, followed closely by the grid edge regulator. The smart inverter does not provide enough benefits to justify

the cost, and it should be noted that in practice, the deployment of the smart inverter is dependent upon the DER prosumer's willingness to purchase with the given utility subsidy. The MV SST and grid edge regulators are the devices fully within the utility's control to install. Were the utility to cover 100% of the smart inverter cost to ensure full deployment, the net present value of the smart inverter becomes negative over the 25-year time horizon.

Table 3.5 Comparison of Financial Metris for SST, Grid Edge and Smart Inverter

Technology	Estimated Utility Investment Cost	Estimated Annual Benefits	Estimated Net Present Value	Discounted Payback Period
MV SST	$160k	$91k	$665k	3.0 years
Grid Edge	$163k	$82k	$590k	3.5 years
Smart Inverter	$148k	$53k	$330k	4.8 years

However, it is useful to test the cost estimates to find the breakeven price. The breakeven price of the grid edge regulator and smart inverter is the per unit device cost that provides an NPV equal to the MV SST. The breakeven price of the grid edge regulator is $1,500, which is a 65% reduction in the cost estimate used. There is no breakeven price for the smart inverter, indicating that even with full deployment and 0% utility subsidy, this device does not provide equal net benefits as the MV SST. Alternatively, the breakeven price of the MV SST which would provide the same benefits as the grid edge regulator option is $6,600, a 50% increase in estimated cost. These breakeven prices indicate that the relative results are robust to large variations in device cost. Under the described assumptions, partial deployment of the MV SST is the most attractive option for utilities.

3.5 Conclusion

In this chapter, three technologies including the MV SST, grid edge regulator and the smart inverter are identified as feasible solutions to mitigate the overvoltage issues caused by high PV penetration on the distribution grid. By using these technologies, utilities could accommodate a higher penetration level of PV on the distribution grid and also achieve a more aggressive conservation voltage reduction with respect to avoided demand and energy cost. In order to form the basis for an economic comparison, these three technologies are applied on a sample utility feeder circuit and the benefits analyzed and quantified via a quasi-static time series simulation. Then, a comprehensive cost benefit analysis has been performed to form a relative economic comparison of these three technologies. It can be seen from the results that the MV SST shows the greatest net present value with 3-year payback period for a utility trying to integrate more PV. Other features of the MV SST, such as providing DC service, have not been considered in this study. The grid edge regulator has a 3.5-year payback period which is very close to the SST. The drawback of the grid edge device is that it has to be used together with the traditional AC transformer. The smart inverter deployment can have a feasible business case; however, the utility may not have full control of the inverters' operation since it is normally installed and maintained by the customers.

Chapter 4. DC House and Cost Benefit Analysis

DC houses have a number of advantages over conventional AC houses in scenarios where DC distributed resources are integrated and much of the load is also DC. This chapter proposes two types of DC house configurations based on FREEDM system solid-state transformer (SST) technology. In order to make a financial case for the DC house, a simulation test bed has been developed. Four types of houses with rooftop PV are modeled: AC house, retrofit DC house, FREEDM hybrid and FREEDM DC house. Annual simulation has been performed for five different locations and the hourly energy usage is estimated. From this, a comprehensive cost benefit analysis has been performed. Net present value and internal rate of return are used as the basis of comparison. The results show that FREEDM DC house is the most cost-effective configuration among these four types of houses in the future where rooftop PV and EV are more commonly adopted.

4.1 Introduction

Currently, many residential household appliances are already based on DC technology like phones, computers, TV, gaming consoles and rely on an AC/DC converter to connect to the existing AC system. Large loads such as heat pumps and refrigerators may utilize motor drives with DC links. It is often the case that DC-based home devices could operate more efficiently if directly connected to DC, rather than AC sources. In a recent study, DC technology appliances are estimated to provide a weighted average energy saving of 36.5% for cooling loads and 32.8% for non-cooling loads [12]. This suggests that a residential DC house is potentially a more economical and efficient option in the near future. Moreover, most of the fast-growing distributed energy resources including PV, energy storage and electric vehicles are DC technology-based as

well. These future DC houses use many power electronic converters which add to the cost and have losses as well. Hence, new “residential circuit” concepts for DC houses with associated cost benefit analysis are needed in order to develop a cost-effective DC configuration. This chapter investigates such new designs and performs cost benefit analysis.

An investigation in [12] estimates that a residential house with net-metered PV could save 5% of energy if the house is using a DC configuration. There are other studies that propose a DC house as an alternative solution for rural electrification [59], [60]. The loss and cost are analyzed, and the results show that solar powered DC rural electrification is economically feasible compared to solar powered AC houses. The Emerge Alliance has DC standards available for commercial building and data centers and supported a number of pilot projects [61]. Adoption of the new circuits in DC houses will depend on its cost effectiveness. This chapter presents a cost-benefit study performed to assess the economic feasibility of new residential circuits considered for DC houses.

One of the new options considered in this chapter is to use a utility DC service to the house rather than conventional AC service, as there are new technologies available that could be applied. One promising device considered in this study is the FREEDM Systems Center solid-state transformer (SST) which is a power electronics device that provides not only the voltage step down function of a conventional transformer, but also reactive power compensation, voltage regulation and a DC link [10] [62]. SST can also be used to build DC fast chargers [63]. Therefore, an SST can be used to provide DC service to houses. As shown in Fig. 4.1, a three-stage SST can provide both AC and DC services while a two-stage SST is totally DC. Note that the two-stage SST has a higher efficiency and lower cost due to the simpler configuration.

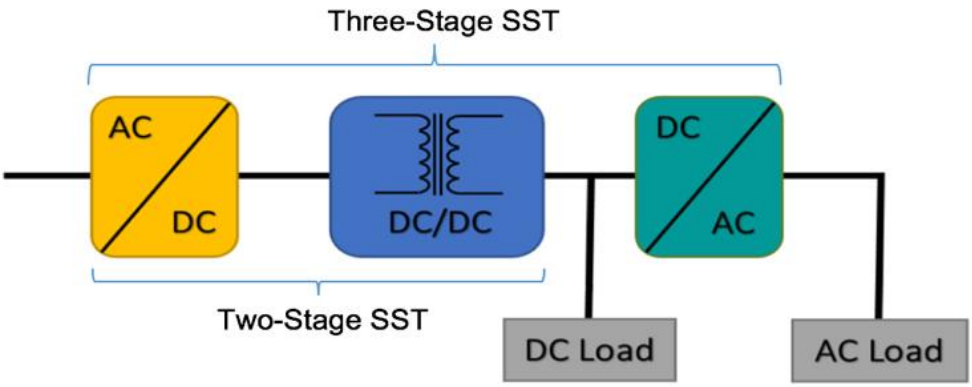


Figure 4.1 Solid-State Transformer Configuration

This chapter proposes two types of DC house configurations: (1) FREEDM hybrid house using a three-stage SST and (2) FREEDM DC house using a two-stage SST. These two proposed FREEDM-based houses are compared to both an AC house and a retrofit DC house which is a house retrofitted with a bi-directional converter and DC circuits on customer side. The comparison is made using an estimate of annual power and energy usage based on a test bed developed in MATLAB and Simulink. A comprehensive cost benefit analysis is performed and the impact of an electric vehicle (EV) has been incorporated. A sensitivity analysis has been provided as well.

The reminder of the chapter is organized as follows: Section 4.2 introduces the DC house configurations considered. Section 4.3 introduces the simulation test bed that has been developed. Section 4.4 presents the case studies, simulation and cost benefits analysis results as well as the sensitivity analysis. Section 4.5 provides the conclusions.

4.2 House Configurations

This section reviews different DC house configurations and proposes two new configurations based on FREEDM concepts: FREEDM hybrid and FREEDM DC house. It is assumed that since many of the home appliances are already using DC technologies and DC

technology appliances are proved to be more efficient [12], that same DC load is used for all four types of houses.

4.2.1 AC House

This represents the power distribution configuration utilized today. Fig. 4.2a shows the circuit for this case. Note that the house is serviced through the conventional distribution transformer and all the loads are considered DC, and thus connected through an AC/DC converter. In addition, as the figure shows, in this system the rooftop PV system requires an inverter and an AC/DC car charger is needed for an electric vehicle.

4.2.2 Retrofit DC House

Fig. 4.2b shows this circuit where the house is retrofitted with a bi-directional converter [12] on the customer side that is connected to the distribution transformer on the low-voltage side to convert AC to DC in the house. Rooftop PV connects through a maximum power point tracking (MPPT) DC/DC device and a DC/DC car charger can be used to charge the electric vehicle. Note that there are two DC voltage levels used in the house: high-voltage DC 380V and low-voltage DC (48V/24V). According to the Emerge Alliance, 380V DC is a standard voltage used for data centers and 24V is being used for commercial buildings [61]. There is no standard available for residential systems yet. However, India has a pilot residential demonstration project using 48V as the DC voltage level [59]. In this study, 380V is used for PV, EV and high-power appliances like HVAC and water heater. Low voltage DC (48V/24V) is used for low-power appliances including lights and small electronics devices. A DC/DC converter is used to transform 380V DC to low-voltage DC.

4.2.3 FREEDM Hybrid House

A FREEDM hybrid house uses a three-stage SST and provides both 380V DC and 120/240V AC to the house. Fig. 4.3a shows the proposed house configuration. The PV system and EV are connected to the high voltage DC and all other appliances stay AC connected. For an existing house, this configuration can be easily adopted and will improve the efficiency of both the rooftop PV and EV charging. Note that I am using DC load plus an AC/DC converter which is same as the AC house.

4.2.4 FREEDM DC House

This is a pure DC house configuration as shown in Fig. 4.3b. The FREEDM DC house uses a two-stage SST that has a relatively higher efficiency and a lower cost. The two-stage SST provides only 380V DC to the house. There are two DC voltage levels as well. A DC/DC converter is needed to convert the high-voltage DC (380V) to low-voltage DC (48V/24V) for low-power appliances. The PV system and electric vehicles are connected to the high voltage as are the high-power appliances. This configuration would be most easily realized for new construction houses.

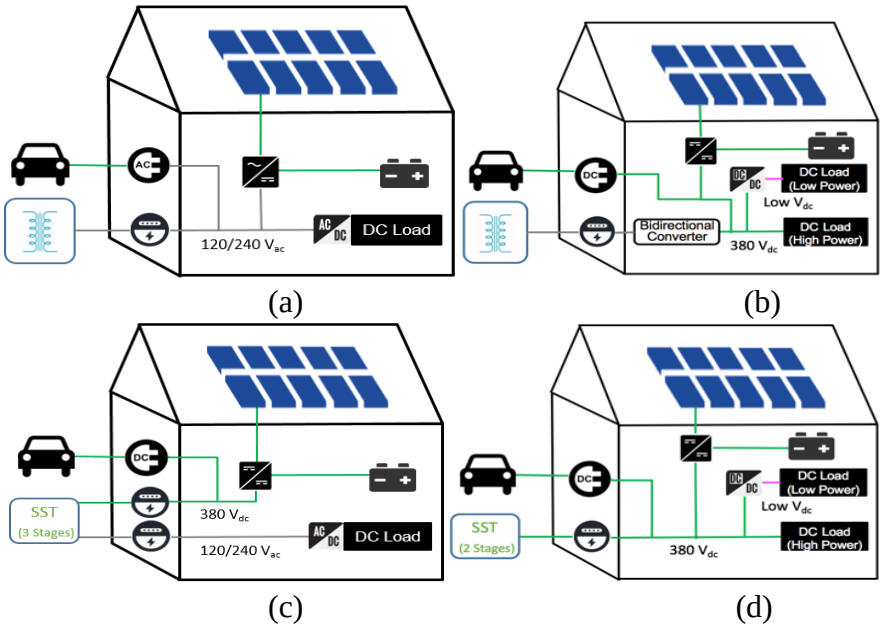


Figure 4.2 (a) AC House (b) Retrofit DC House (c)FREEDM Hybrid (d)FREEDM DC

4.3 Simulation Test Bed for Different House Configuration Analysis

In order to estimate the power and energy usage for each type of houses and perform the cost benefits analysis, a simulation test bed is developed using MATLAB and Simulink. There are three parts: (1) a load profile generator (2) a house energy loss model and (3) a cost benefit analysis tool. Fig. 4.4 shows the simulation test bed structure.

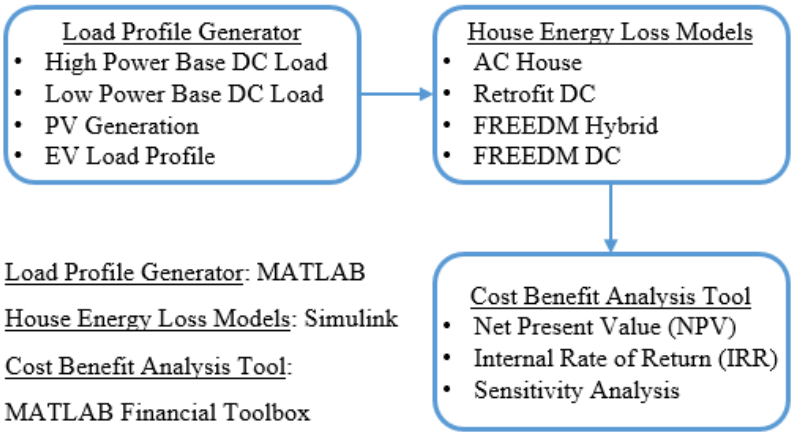


Figure 4.3 House Simulation Test Bed Structure

4.3.1 Load Profile Generator

The load profile generator provides inputs to the house loss models. There are three load profiles: base DC load, PV generation and the electric vehicle load profile.

1) Base DC Load

Simulated residential hourly load profiles for all typical meteorological year 3 (TMY3) locations in the United States are published by the US Department of Energy on OpenEI and are used to calculate the base DC load [64]. One advantage of this dataset is that it provides detailed data for different load type categories in a residential house like HVAC, water heater, interior equipment, interior and exterior lights. This makes it possible to group the load into high-power loads and low-power loads that will be served through the DC/DC converters in the retrofit DC

house and FREEDM DC house. Since the load profiles from the dataset is for AC loads, the cooling loads and non-cooling loads are reduced 36.5% and 32.8% respectively to represent the base DC load [12]. This DC load profile is used in all four house configurations.

2) PV Generation.

PV generation is estimated based on PV system size and the irradiance data available in the national solar radiation data base published by NREL [65]. The database includes the hourly solar irradiance data for all TMY3 locations. If the PV system is connected to an AC system, the inverter losses will be subtracted. If the PV system is connected directly to a DC system, MPPT DC/DC converter loss will be considered. Inverter efficiency is estimated based on Sandia National Lab's inverter testing results [57]. The efficiency for a grid-connected inverter exceeds 95% under most of the operating conditions. The efficiency is fitted into a third-order polynomial curve with a 95% efficiency for the light loading condition and 97% for heavy loading. MPPT is also modeled as a third-order polynomial curve, but it has a higher efficiency of 98% [66].

3) EV Load Profile.

Electric vehicle load is simulated hourly based on the EV charger charge rate and different charging strategies. According to Tesla charging guidelines, a 75 kWh configured vehicles has a maximum charge rate of 11.5 kW [67]. In the case study in Section 4.4, two charging strategies have been evaluated. The AC charger AC/DC converter efficiency is modeled to be 85% to 90% [68] and the DC/DC charger has a higher efficiency which is in the range of 90% to 96% [69]. The loading-efficiency curve is fitted into a third-order polynomial model.

4.3.2 House Energy Loss Estimation

House energy losses for all the cases are estimated by using converter loss models. Power conversion devices used in different house types are simulated to capture the losses during the

year. According to [12], the weighted average AC/DC appliance converter efficiency is 90% for cooling load and 87% for non-cooling load. The efficiencies used for all other devices are listed in Table 4.1. A fitted third-order polynomial loading-efficiency curve is defined for these devices. Note that SST and traditional transformer losses are not considered in the analysis because these are not behind-the-meter devices. It is assumed that the electric utility charges customers a fixed cost for using the SST to provide DC services. Also, previous work has shown that even if SST has a higher loss compared to a traditional AC transformer, this part of the losses can be canceled by the feeder benefits that SSTs can provide to the utility through reactive compensation and conservation voltage reduction [5].

Table 4.1 House Device Efficiency Curve Parameters

Device	Efficiency	Cost	Life	Ref.
Inverter	95%-97%	$3025 for 8 kVA	12 yrs.	[57]
MPPT	98%	$605 for 4 kVA	12 yrs.	[66]
DC-DC	95%-98%	$214 for 1.5 kVA	5 yrs.	[70]–[72]
Bi-directional (DC to AC)	95%-97%	Same as SST $124/kVA	25 yrs.	[73]
Bi-directional (AC to DC)	84%-93%			[74]

4.3.3 Cost Benefit Analysis Model

The benefit is calculated by determining the reduction in the annual electricity bill between houses with rooftop PV case and AC house with no PV case. So, both net-metered PV benefits and energy efficiency benefits are included. The electricity rate used is $0.1/kWh. The cost is estimated for each type of house which includes all of the converter components within the house and the PV cost. The cost of the conductors and the line losses of DC house and AC house are assumed to be the same according to [60]. The cost for those converter devices is estimated based on the available market products. The price and lifetime for DC-DC converter, PV inverter and MPPT are listed in Table 4.1. The cost scales with the size of the devices.

The SST is estimated to have a lifetime of 25 years at a cost of $124/kVA SST [5]. Since it is hard to obtain the price for the bi-directional converter, it is assumed to have the same cost and lifetime as the SST. Electric utility charges customers a monthly fee to recover the SST cost at a MARR (minimum acceptable rate of return) of 10% and the customer MARR is assumed to be 6%. The PV cost is based on NREL's report which is estimated as $2.93 per watt for a 5.6 kW residential rooftop PV [75]. A 30% Tax credit is included for the PV installation. Since the solar cost is a quite large investment which is in the level of $10,000, a 15-yr solar loan with a fixed 4% interest is considered with $0 down payment. Net metering is assumed for solar energy sold back to the grid.

4.4 Case Studies and Results for Four House Configuration

This section presents the simulation and cost benefit analysis results for five locations in the southern part of the United States. The reason to choose these locations is because the residential load profiles [64] in these areas use a mix of electricity for air-conditioning, water heating and space heating. Electric vehicle's impact is analyzed using the Wilmington, NC location with an associated sensitivity analysis.

4.4.1 Simulation and Cost Benefit Analysis Results

The simulation is performed for five cases for each location. The energy usage for each case is simulated and the electricity bill is calculated. The benefits in energy bill savings is obtained as the difference between the corresponding case and Case 1.

- Case 1: AC house with no PV
- Case 2: AC house with PV
- Case 3: Retrofit DC house with PV
- Case 4: FREEDM hybrid house with PV

- Case 5: FREEDM DC house with PV

In the simulation, a 5 kW PV system is used for Cases 2-5. The size of the inverter, MPPT, DC-DC converter, bi-directional converter and SST is shown in Table 4.2. The load characteristics of the five locations are listed in Table 4.3. Fig. 4.4 shows the daily load curve for Wilmington, NC. Note that the load obtained from [64] is AC load, so the DC load needs to be calculated to serve as the base load for all four types of houses.

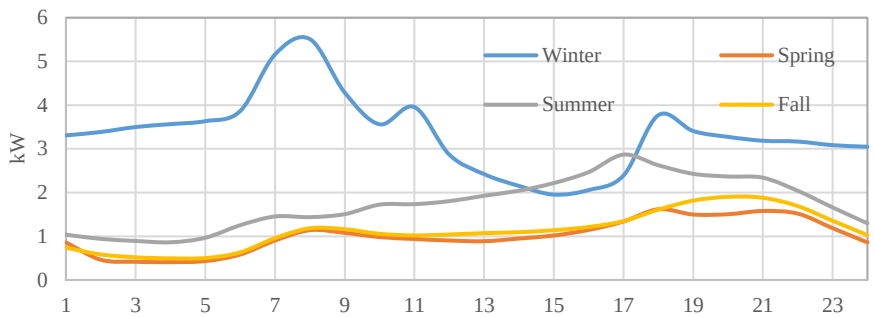


Figure 4.4 Daily Load Curve

Table 4.2 House Model Component Sizes

	Inverter	MPPT	DC-DC	Bi-directional Converter	SST
Size	5 kVA	5 kVA	1.5 kVA	6 kVA	6 kVA
House	AC	All DC	Retrofit DC FRD hybrid.	Retrofit DC	FRD hybrid. FRD DC

Table 4.3 Residential House Load Characteristics

Location	Peak kW	Load MWh-yr.	Load Factor
NC-Wilmington	7.6	15.2	0.23
FL-Orlando	4.8	13.8	0.32
GA-Columbus	4.7	13.6	0.32
LA-New Orleans	6.9	14.8	0.24
TX-Austin	6.4	14.8	0.26

The individual end user load has been grouped into HVAC load, high-power load and low-power load to form the inputs to the house models. According to 2016 EIA residential energy consumption survey by end user [76], 27% of the load is for HVAC, 41% for high-power load and 32% for low-power load. Using the load data from [64] for these five locations and grouping them into these three categories, the percentage division is very similar to EIA's results. Table 4.4 shows the net energy usage for four house types at five locations over a year. Green coloring is used to highlight a smaller number.

It can be seen from the results that the FREEDM DC house uses the least cost benefit results are shown in Tables 4.5 and 4.6. Table 4.5 shows the results for a net present value (NPV) calculation and Table 4.6 includes the internal rate of return (IRR) results. The MARR used in the NPV calculation is 6%. The three-stage SST cost is $6 per month ($70 per year) and the two-stage SST cost is $4 per month ($46 per year). The SST cost is charged by the electric utility to provide the DC service to the customer. Note the two-stage SST is assumed to be 2/3 of the cost of a three-stage SST. The SST cost is estimated at a 10% MARR for 25 years.

The FREEDM DC house has the highest NPV for all five locations and also an 11.5% IRR. The FREEDM hybrid case results are similar but slightly better than the retrofit DC house case. The AC house has the lowest NPV value and also the worst IRR. So, for an existing house, it would be better to upgrade to the FREEDM hybrid house; have the PV connected directly to the DC system and all other appliances can stay on the AC system. For a new construction house, one will get the most benefits in using the FREEDM DC house configuration.

Table 4.4 Yearly Net Energy for Four Types of House Configurations

Net Energy (MWh)	AC	Retrofit DC	FREEDM hybrid	FREEDM DC
NC-Wilmington	3.30	3.09	3.19	2.07
FL-Orlando	2.13	2.00	2.02	1.03
GA-Columbus	1.87	1.77	1.76	0.81
LA-New Orleans	2.96	2.77	2.85	1.77
TX-Austin	2.79	2.60	2.68	1.59

Table 4.5 Net Present Value (NPV) Results for Four Types of House Configurations

NPV ($)	AC	Retrofit DC	FREEDM hybrid	FREEDM DC
NC-Wilmington	-$254	-$90	-$50	$1,258
FL-Orlando	-$103	-$43	$99	$1,232
GA-Columbus	$87	$122	$292	$1,377
LA-New Orleans	-$206	-$63	-$3	$1,255
TX-Austin	$16	$150	$220	$1,478

Table 4.6 Internal Rate of Return (IRR) Results for Four Types of House Configurations

IRR	AC	Retrofit DC	FREEDM hybrid	FREEDM DC
NC-Wilmington	5.3%	5.8%	5.8%	10.6%
FL-Orlando	5.7%	5.9%	6.3%	10.5%
GA-Columbus	6.2%	6.3%	7.0%	11.1%
LA-New Orleans	5.4%	5.8%	6.0%	10.6%
TX-Austin	6.0%	6.4%	6.7%	11.5%

4.4.2 House Configurations with Electric Vehicles

A 75-kWh electric vehicle is added to the house at Wilmington, NC. The maximum charge rate is assumed at 11.5 kW. A fully charged vehicle has a 300 mile driving range [68]. It is assumed that the house owner drives 300 miles per week. Two charging strategies are considered: 1) Weekly high-power charging to the full range 2) Daily low power charging for three hours. Charging strategy one is more similar to a current consumer's habit of filling up the gas tank when near empty. Charging strategy two makes more sense for EV users that want to start with a fully charged

battery each day. These two charging strategies represent boundary cases and likely consumer charging habits will combine these two strategies.

1) Charging Strategy One

This involves charging the EV 9 hours on Sunday night from 00:00 to 9:00am to the full range. Then there is no need to charge the EV for the rest of the week. The charging power rating used is 9 kW. A 13 kVA SST is needed for FREEDM houses and the same size bi-directional converter is used for the retrofit DC house. The monthly charge for three-stage SST is $15 and $10 for two-stage SST. Table 4.7 shows the results for NPV and IRR.

Table 4.7 Charging Strategy One – 9 kW Charging Power Rate

House Types	Net Energy (MWh)	EV (MWh)	NPV	IRR
AC house	7.5	4.2	-$254	5.3%
Retrofit DC	7.8	4.1	-$1,731	2.4%
FREEDM hybrid	7.3	4.1	-$1,296	2.2%
FREEDM DC	6.2	4.1	$478	7.6%

2) Charging Strategy Two

This involves charging the EV 1/7 of the full capacity 75 kWh every day for 3 hours from 23:00 to 2:00 am at 4 kW power rating. Smaller size (7 kVA) SSTs and bi-directional converter is required for FREEDM houses and retrofit DC house respectively. The monthly charge for three-stage SST is $8 and $6 for two-stage SST. Table 4.7 shows the results.

Table 4.8 Charging Strategy Two – 4 kW Charging Power Rate

House Types	Net Energy (MWh)	EV (MWh)	NPV	IRR
AC house	7.8	4.5	-$254	5.3%
Retrofit DC	7.6	4.1	-$346	5.1%
FREEDM hybrid	7.3	4.1	$77	6.2%
FREEDM DC	6.2	4.1	$1,502	11.6%

It can be seen from the results that for both charging strategies, the FREEDM DC house has a positive NPV and highest IRR. The FREEDM hybrid house is better than retrofit DC for

both charging strategies and has a positive NPV case in low power charging strategy two. However, both FREEDM hybrid and retrofit DC houses are not economically feasible for the high-power charging case in strategy one due to the high cost of a larger size SST and bi-directional converter.

4.4.3 Sensitivity Analysis

Two sensitivity analysis are discussed in this section. The first is for the best case FREEDM DC house with rooftop PV and no EV at Wilmington, NC. The electricity rate, PV size, SST cost and interest rate have been varied from -50% to 50% to check the impact on NPV and determine the most influencing factors. It can be seen from the results in Fig. 4.6 that the NPV stays above $0 for most of the situations except when the electricity price is -10% of the original assumption, or less than $0.09/kWh. According to EIA's electricity rate census, it is very rare for the price to go under $0.09/kWh. The slope of the curve represents the impact of the parameter on NPV. The higher the slope, the greater the impact. One can see that electricity price has the greatest impact on the NPV while the PV size and SST cost has relatively lower impact.

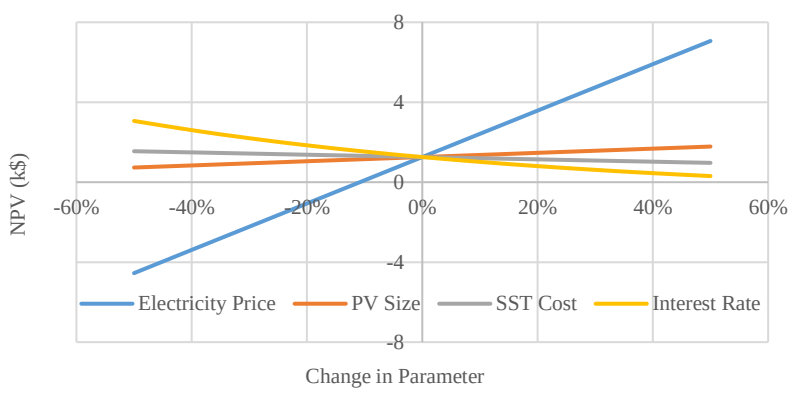


Figure 4.5 Sensitivity Analysis for FREEDM DC House

A second sensitivity analysis is performed for EV charging strategy one. The SST and bi-directional converter cost have been varied from -100% to 50%. The resulting NPVs for the four

types of houses are shown in Fig. 4.7. Note that the AC house case won't be affected since only SST and bi-directional converter cost are changed. It can be seen from Fig. 4.7 that FREEDM DC house is still the best case with a positive NPV. The FREEDM hybrid house will be more economical than the AC case when the SST price drops around 50%.

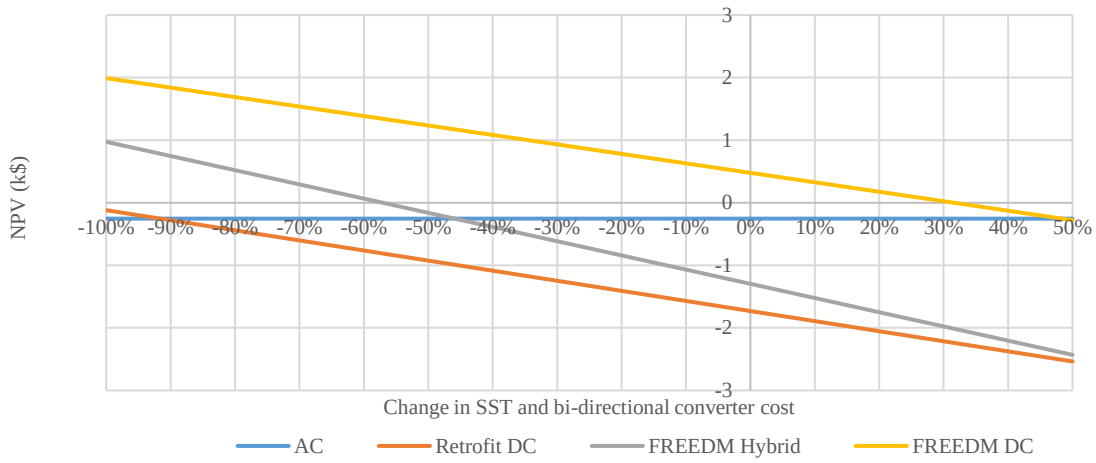


Figure 4.6 Sensitivity analysis for EV charging strategy one

4.5 Conclusion

In this chapter, two residential DC house configurations using the FREEDM Solid-State Transformer are proposed: FREEDM hybrid house and FREEDM DC house. The financial benefits of the two FREEDM configurations were compared to both the present-day AC and retrofit DC house. This comparison was based on a simulation test bed that modeled house consumption under a variety of loading conditions with an associated cost benefit analysis.

The results show that indeed the new FREEDM-based configurations considered are economically feasible. The FREEDM DC house is estimated to be the most energy efficient configuration with the highest NPV among the four types of houses with an IRR higher than 10%. The FREEDM DC house shows a positive NPV in both of the sensitivity analyses for most of the situations. The results indicate that the FREEDM DC house is an economical house configuration

that can be utilized in the future to better integrate rooftop PV and electric vehicles, especially for new house construction.

A FREEDM hybrid house is more economical than a retrofit DC house in both the PV and the EV charging cases, especially the low power EV charging case. For the high power EV charging case, the FREEDM hybrid case will be economically feasible if the SST price drops 50%. The results show that the FREEDM hybrid concept is good for existing house upgrades since all legacy load devices can maintain the AC connection while PV and EV can be connected to DC.

Chapter 5. Agent-Based Modeling of Feeder-Level Electric Vehicle Diffusion for Distribution Planning Analysis

5.1 Introduction

Transportation electrification provides electric utilities opportunities to increase electricity sales and offer new services [77]. However, as EV penetration increases, utilities will face a variety of challenges to accommodate added EV load. The impact will be especially significant on distribution circuits where EVs and charging stations will be interconnected to the grid. Issues arising from EV diffusion include increases in system demand, circuit losses, and element overloading [17]–[19]. Utility planners need to forecast and evaluate potential EV load in order to better plan for future generation, capacity expansion, component upgrades, and other mitigation strategies. However, specifically when and where the additional EV-related load will appear on distribution circuits cannot be easily forecasted by utilities. The rate and locations of EV diffusion will rather be a complex function of customer characteristics, economics and external influences. External influences include neighbor EV adoption, EV market offerings, charging infrastructure availability and government/utility incentives.

Distribution planners require a customer-oriented and location-specific modeling strategy to account for EV diffusion. The challenge will be to forecast the number and locations of potential EV customers and charging stations per feeder by year. Based on this forecast, feeder power flow analysis can be used to examine the impacts related to peak loading, losses and component overloading. After the impact is quantified, mitigation methods like circuit upgrades and utility strategies such as building charging stations can be evaluated as means for accommodating the additional EV charging load.

5.1.1 Literature Review

Various papers have been published on the impact of residential EV load on distribution systems. EV impact on system peak load demand and voltages on an actual feeder is studied with several mitigation schemes evaluated in [17]. Accelerated loss-of-life of distribution transformers due to EV is analyzed in [18]. The impact of EV load on power losses and voltage is analyzed with a coordinated charging scheme proposed to minimize the power losses and maximize the grid load factor [19]. A spatial-temporal model was developed to evaluate the impact of assumed penetrations of EV in a distribution network based on integration of power system and transportation analyses [78]. However, the limitation of these previous studies is that they are based on assumed penetrations of EV on the feeder without considering time and location-specific EV load growth caused by EV diffusion.

Methodologies proposed for EV diffusion analysis include data analytics using regression, spatial forecasting and agent-based modeling. Data analytics studies have used regression analysis to provide a good understanding of potential EV adopter characteristics and drivers [79]–[81]. Spatial regression and load forecasting with GIS described in [82], [83] shows the EV adoption rate per subareas and the clustering patterns. However, in existing literature, data analytics is commonly applied to geographic regions such as states or counties, while spatial regression is more suited for subareas, like squares on a map. It is difficult to use these previous methods to predict specific EV diffusion locations such as feeder-level adoption, which is required for distribution planning. In addition, influence between neighbors as well as availability of charging station networks are seldom considered.

Agent-based techniques simulate actions and interactions of autonomous agents [84]. An agent-based model for buying, charging and driving EV is proposed to assist stakeholders in

defining public policy and business strategies in [85]. Reference [86] presents an integrated dynamic method based agent-based model to detect possible EV scale evolution patterns and charging demand characteristics. An EV diffusion agent-based model that integrates complex behavioral rules is developed in [87] and uses survey data to parameterize the agent architecture. EV adoption with an agent-based model that simulates a detailed car market is presented in [88]. A zip-code level EV diffusion analysis is described in [89] where an agent-based model is utilized to capture neighbor impact between zip-code agents with regression analysis of customer characteristics. The combined regression and agent-based modeling enables analysis of both customers' characteristics and interactions. However, distribution feeder topology is not considered in the above agent-based model references. Accurate feeder modeling plays an important role in estimating EV impact and charging station locations for distribution planners. The interaction between EV adoption and charging infrastructure development on a feeder model basis has not been considered either.

5.1.2 Contribution

This chapter proposes a new customer-oriented distribution planning framework based on a feeder-specific agent-based model to forecast EV and charging station diffusion, as shown in Fig. 5.1. An AHP-based customer adoption model CANE (accounts for car age, EV attractiveness, neighbor influence and customer economics) is developed to calculate the probability of vehicle purchase decisions. EV attractiveness is determined using logistic regression on customer characteristics such as education, age, income, resident state and status that whether the customer live in an urban area or not. Influence between EVs and charging stations siting are considered. Due to the stochastic adoption process, Monte Carlo analysis is performed, and the model is then calibrated with forecast based on vehicle registration data. The distribution feeder topology,

property GIS parcel and survey data are combined to parametrize agents. Using the diffusion results and the modeled charging load, EV impact on the distribution system is then analyzed through time-series quasi-static power flow analysis. Feeder upgrades are recommended annually based on the EV adoption level. Utility strategies such as EV rebates and charging facility investment are also factored into the framework.

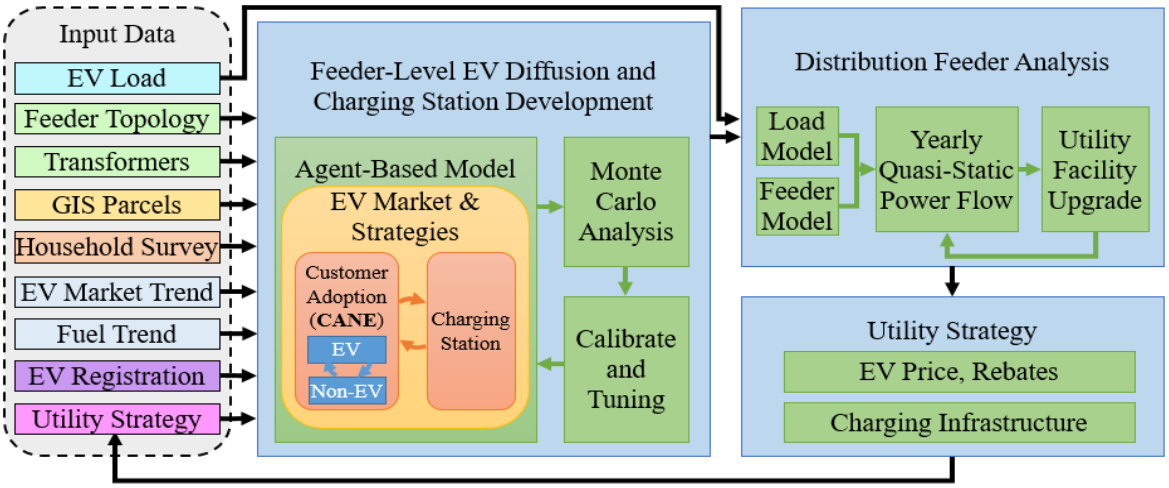


Figure.5.1 Customer-Oriented Distribution Planning Framework for EV

The rest of the chapter is organized as follows. Section II introduces the agent-based EV diffusion model. Section III presents the agent-based simulation algorithms, Monte Carlo analysis and model calibration. Section IV describes the EV charging load model and distribution feeder analysis. Section V provides a case study on a sample feeder that illustrates the application of the agent-based model. Distribution feeder analysis, upgrade recommendations and two scenarios that examine the effect of EV price and charging station placement are provided and discussed. Section VI summarizes the chapter.

5.2 Agent-Based EV Diffusion Model

A temporal-spatial diffusion forecast technique for EVs and charging stations is developed using agent-based modeling as described below. Three types of agents are included in the proposed model: EV customers, internal combustion engine (ICE) customers and charging stations. The agent environment is modeled and updated annually which include the EV market, charging station network, and utility EV strategies. The EV market considers EV price at various ranges/sizes, fuel price and charger costs. Customers are assumed to be influenced by their neighbors, the EV market, utility EV strategies and charging station network availability.

5.2.1 AHP-Based Customer EV Adoption Model

Customer EV adoption is modeled as a multi-criteria decision-making problem using AHP. The AHP is an effective tool for representing complex decision-making behavior with the advantage of decomposing the decision problem into a hierarchy of more easily solved sub-problems [90], [91]. The AHP-based customer EV adoption model CANE is organized as shown in Fig. 5.2. The AHP generates weights for each criterion and assigns a score to each alternative-criterion pair. Then the probabilities for alternatives are calculated based on the weighted sum of the scores. The four criteria ($c1\ to\ c4$) car age, attractive, neighbor and economics are discussed below along with the scoring calculation for alternative-criterion pairs.

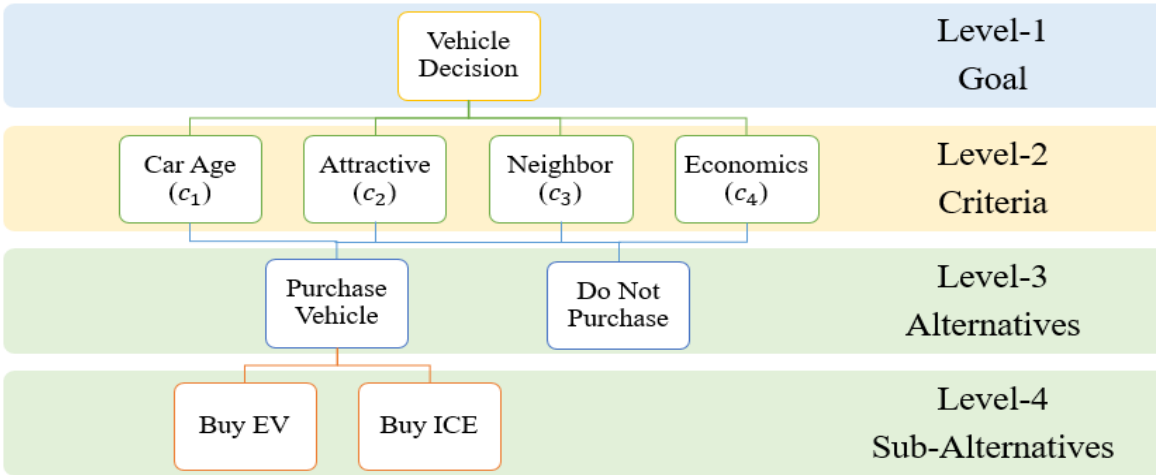


Figure.5.2 AHP-based CANE Model

1) Car Age

Car age is an important factor when considering either purchasing a vehicle or deferring the purchase. Scores for a purchase ($S_{buy,\ c1}$) or deferring a purchase ($S_{defer,\ c1}$) based on car age ($c1$) are calculated using Table 5.1. Customers are assumed to sell their existing car before expensive maintenance is required or wait until they have to replace it. Car age decides the probability of customer liking to purchase or a need to replace a car [92]. Let Idx_{LTP} and Idx_{NTR} denote Boolean variables for customer who likes to purchase or needs to replace their vehicle. Different combinations of the two Boolean variables describe different customer situations. Variable ψ represents the total score for these criteria. Factors α_1 and α_2 are within range of [0-1]. Note that car age only affects the decision on purchase or deferring the purchase, and does not influence purchasing EV or ICE.

Table 5.1 Score Calculation for Car Age Criterion

$[Idx_{LTP},\ Idx_{NTR}]$	$S_{buy,\ c1}$	$S_{no,\ c1}$
$[0, 0]$	- ψ	ψ
$[1, 0]$	$\alpha_1 \times$ ψ	0
$[0, 1]$	$\alpha_2 \times$ ψ	- $\alpha_2 \times$ ψ
$[1, 1]$	ψ	- ψ

2) Attractiveness

Attractiveness represents customers' possible attitudes towards adopting EV based on customers' characteristics and backgrounds. Logistic regression is used to quantify this value. Household income, age, education, family size, living in an urban area or not and resident state are selected since these factors are predictors of early EV adopters [79], [80]. The logistic regression model is as follows:

$$\begin{aligned} y = \beta_0 + \beta_1 Age + \beta_2 FamilySize + \beta_3 Income_{Dummy} \\ + \beta_4 Education_{Dummy} + \beta_5 Urban_{Dummy} \\ + \beta_6 State_{Dummy} \end{aligned} \tag{1}$$

where Boolean variable y represents the status of an EV adoption while β represents the regression model coefficients. Dummy variables are created for education, income, urban area classification and resident state because each of these attributes has several categories, and the numerical values do not have intrinsic meaning. In this chapter's case study, household income and family size are estimated based on house values and heated area square footage from GIS parcel data. Education and age are estimated based on household travel survey data [93].

Given that the current state of EV adoption is currently at a relatively low level, the existing dataset is usually extremely imbalanced regarding the number of EV verses ICE vehicles. For example, a recent national household travel survey (NHTS) [93] has about 240,000 data entries for vehicles and only about 1,000 of them are EVs. Since the data set is highly imbalanced with very low number of EV adopters, direct applications of classification models tend to predict all "0"s, which means no EV adopters and still yields a high accuracy prediction model. However, this model has no value for classifying EVs. Therefore, an oversampling technique is needed to adjust the class distribution of the data set. For the case study presented in this chapter, the adaptive

synthetic sampling approach (ADASYN) [94] is used. With the logistic regression model, the attractiveness score for purchasing EV ($S_{EV,\ c2}$) and ICE ($S_{ICE,\ c2}$) for attractiveness ($c2$) can be calculated by:

$$S_{EV,\ c2} = \frac{\exp\left(\beta_0 + \sum_{i=1}^{6} \beta_i x_i\right)}{1 + \exp\left(\beta_0 + \sum_{i=1}^{6} \beta_i x_i\right)} \times \psi \tag{2}$$

$$S_{ICE,\ c2} = \psi - \frac{\exp\left(\beta_0 + \sum_{i=1}^{6} \beta_i x_i\right)}{1 + \exp\left(\beta_0 + \sum_{i=1}^{6} \beta_i x_i\right)} \times \psi \tag{3}$$

where ψ is the total score for the criterion attractiveness. Scores for car purchase ($S_{buy,\ c2}$) and deferring purchase ($S_{defer,\ c2}$) are assumed to be equal to $S_{EV,\ c2}$ and $S_{ICE,\ c2}$ respectively.

3) Neighbor Influence

Neighbor influence considers the impact from both the neighbors owning EV and local availability of charging stations. Both of these can improve EV visibility to a future EV adopter. Having a charging station nearby may also avoid the cost of a Level 2 home charger installation. The scores for neighbor influence ($c3$) of purchasing EV ($S_{EV,\ c3}$) versus ICE ($S_{ICE,\ c3}$) are calculated by:

$$S_{EV,\ c3} = (\gamma_1 \times N_{station} + \gamma_2 \times P_{EV}) * \psi \tag{4}$$

$$S_{ICE,\ c3} = \psi - (\gamma_1 \times N_{station} + \gamma_2 \times P_{EV}) * \psi \tag{5}$$

where ψ represent the total score. Factors γ_1 and γ_2 are within the range of [0-1]. $N_{station}$ is the number of stations nearby and P_{EV} is the penetration of EV in the neighborhood. The score for purchasing a vehicle, maybe thinking of changing to EV ($S_{buy,\ c3}$) and for staying with ICE ($S_{defer,\ c3}$) are assumed to be equal to $S_{EV,\ c3}$ and $S_{ICE,\ c3}$ respectively.

4) Customer Economics

Vehicle price and cost of ownership are other important factors for potential EV adopters. Given that EV price is still high compared to ICE, economic affordability is examined before making a purchase decision. The cost for owning EV versus ICE includes vehicle price, annual fuel, maintenance and cost of a home Level 2 charger if needed. The price of EV is foreseen to decrease as the technology gets more mature, battery pack prices drops and EV sales increase [95]. The ICE vehicle price may increase slightly considering the increased fuel economy improvements required for conventional gasoline vehicles [95]. The forecast of vehicle price for different sizes at various ranges for a 30-year study based on [95] is shown in Fig. 5.3. Customers' preferences for vehicle range and size are estimated based on trip miles and family sizes from [93].

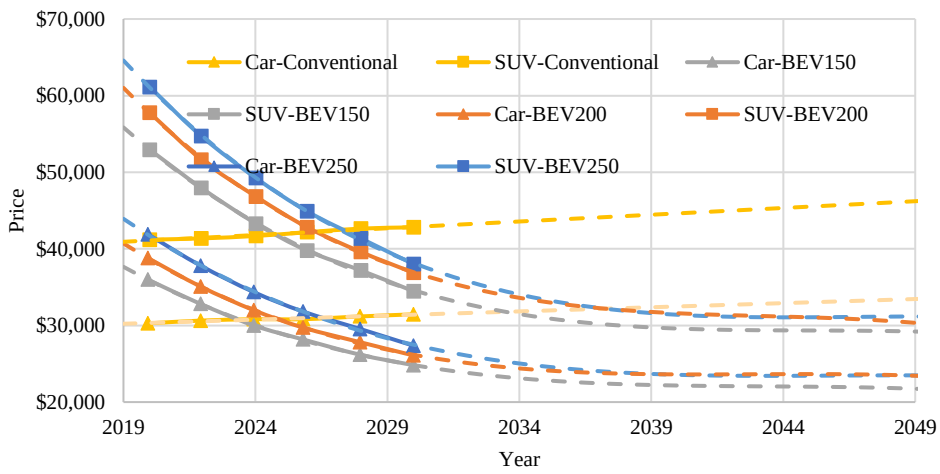


Figure 5.3 Vehicle Price Forecast

Assuming that customers are willing to spend $p\%$ of their annual income on a vehicle. Then the annualized amount that the customer is willing to spend on vehicle δ can be calculated considering an n-year auto loan with interest rate i using (6). Scores for customer economics ($c3$) with each alternative are calculated using (7) – (10):

$$\delta = p\% \times Income \times \frac{i \times (1+i)^n}{(1+i)^{n-1}} \tag{6}$$

$$S_{buy,\ c4} = \begin{cases} -\dfrac{\min(C_{EV}, C_{ICE})}{\delta} \times \psi, & if\ \ \delta < C_{min} \\ \left(1 - \dfrac{\min(C_{EV}, C_{ICE})}{\delta}\right) \times \psi, & if\ \ \delta \geq C_{min} \end{cases} \tag{7}$$

$$S_{defer,\ c4} = \psi \tag{8}$$

$$S_{EV,\ c4} = \begin{cases} -\dfrac{C_{EV}}{\delta} \times \psi, & if\ \ \delta < C_{EV} \\ (1 - \dfrac{C_{EV}}{\delta}) \times \psi, & if\ \ \delta \geq C_{EV} \end{cases} \tag{9}$$

$$S_{ICE,\ c4} = \begin{cases} -\dfrac{C_{ICE}}{\delta} \times \psi, & if\ \ \delta < C_{ICE} \\ (1 - \dfrac{C_{ICE}}{\delta}) \times \psi, & if\ \ \delta \geq C_{ICE} \end{cases} \tag{10}$$

where ψ represents the total score for the customer economics criterion. C_{min} is the minimum of C_{EV} and C_{ICE}. From customer economic perspective, the score for deferring the purchasing ($S_{defer,\ c4}$) is the highest. If δ is smaller than C_{min}, it means the customer is unlikely to afford any kind of the vehicle. Therefore, the score for purchase will be negative. The higher the minimum cost for vehicles, the more negative the score. If the customer can afford the purchase, the amount of money left after buying the vehicle is used to calculate the score. A similar concept is used in the score calculation for purchasing EV versus ICE shown in (9)-(10).

5) Weight and Decision-Making Probability Calculation

After the score for each alternative and criterion is calculated, weights for the AHP Level 3 and Level 4 can be calculated using pairwise matrixes. The probabilities for purchasing or deferring the purchase are calculated based on a weighted score using (11)-(12). According to Bayes' theorem, the probability of purchasing EV or ICE can be calculated using (13)-(14):

$$P_{buy} = \sum_{i=1}^{4} w_{level3i} * s_{buy,\ ci} \tag{11}$$

$$P_{defer} = \sum_{i=1}^{4} w_{level3i} * s_{defer,\ ci} \tag{12}$$

$$P_{EV} = P_{buy} * k * \sum_{i=2}^{4} w_{level4i} * s_{EV,\ ci} \tag{13}$$

$$P_{ICE} = P_{buy} * k * \sum_{i=2}^{4} w_{level4i} * s_{ICE,\ ci} \tag{14}$$

where P_{buy} and P_{defer} are the probabilities for buying a vehicle or deferring the purchase. The weight for Level 3 and Level 4 for criterion i are denoted by $w_{level3i}$ and $w_{level4i}$. Scores calculated in (2)-(5) and (7)-(10) are used in (11)-(14). The factor for tuning the agent-based model is denoted as k.

5.2.2 Charging Station Development Model

Charging stations provide the potential for EV owners to charge vehicles at high speeds but can contribute added stress to the distribution grid. The rating of charging stations could range from 20 kW to the megawatt level. The development of charging stations and EV adoption also influence each other.

Three factors are considered to decide when and where the charging stations will be located. The first factor is the type of land use. Shopping malls, hotels and office buildings are usually preferred sites for charging stations. The second factor is the number of EVs in the nearby area. Charging stations located in an area that has a relatively high density of EV may be utilized more and can further accelerate the EV adoption. The third factor is the distance to three-phase utility service. Charging stations can draw considerable amounts of power from the grid and therefore are usually connected to three-phase feeders. Shorter distances to three-phase poles reduces the extra cost for feeder connection and avoids excessive costs to upgrade single or two-

phase laterals. Moreover, three-phase poles are usually along main roads, which is desired for cars passing by and charging. The algorithm for the charging station location forecast is discussed in the next section.

5.3 EV Diffusion Algorithms and Model Calibration

This section introduces the algorithms developed for the agent-based EV diffusion and model calibration with forecast based on EV registration data using Monte Carlo analysis. The overall structure of the agent-based EV diffusion modeling is shown in Fig. 5.4. For an N-year simulation, the market is updated every year followed by two algorithms: one for the charging station development and one for the customer EV adoption. The N-year simulation is then run repeatedly with random seeds in Monte Carlo analysis to obtain the most likely results for model calibration.

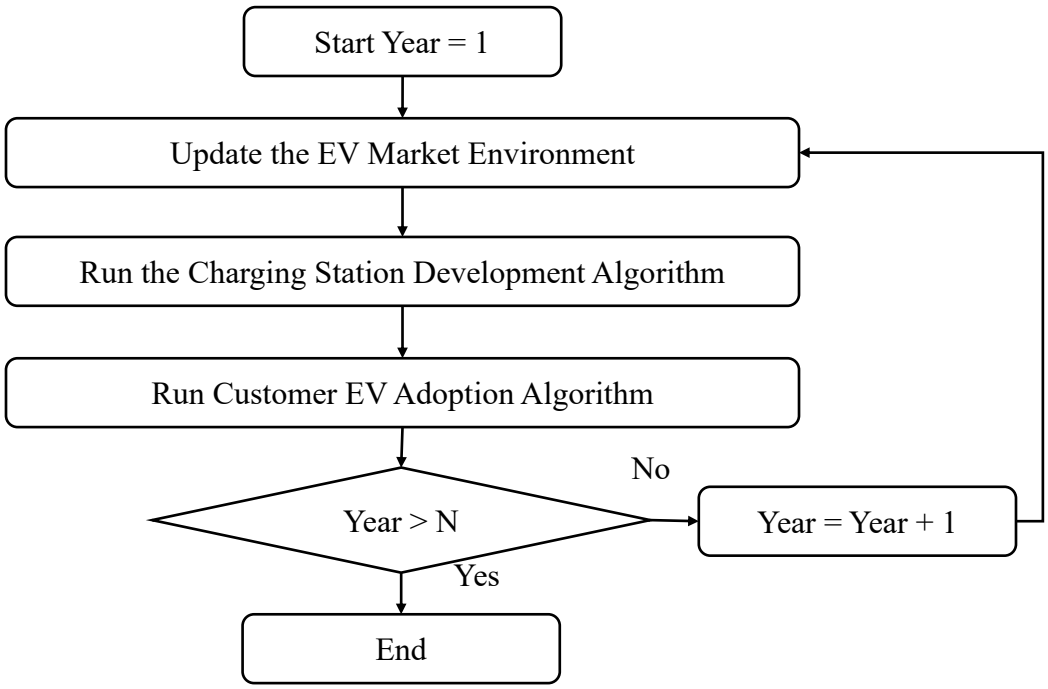


Figure.5.4 The Overall Structure of the Agent-Based EV Diffusion Model

An example scenario that better illustrates the EV diffusion agent-based simulation approach is shown in Fig. 5.5. The GIS property parcels overlay with the feeder topology to provide the basis for a feeder specific EV diffusion forecast for distribution planning. Triangles represent distribution transformers: blue for three-phase and black for single or two-phase transformers. Therefore, when and which transformer the new EV load will be added to the feeder can be linked. Parcel information such as types of land uses, house values and heated area values are utilized to parameterize agents. Cyan polygons represent residential houses, yellow areas are apartment complex and pink ones are hotels-shopping malls. Small blue dots represent ICE agents while red dots are EV agents. Red dots will gradually replace blue dots as EV volume increases according to the customer EV adoption algorithm, while the green charging stations will appear on parcels based on the charging station development algorithm.

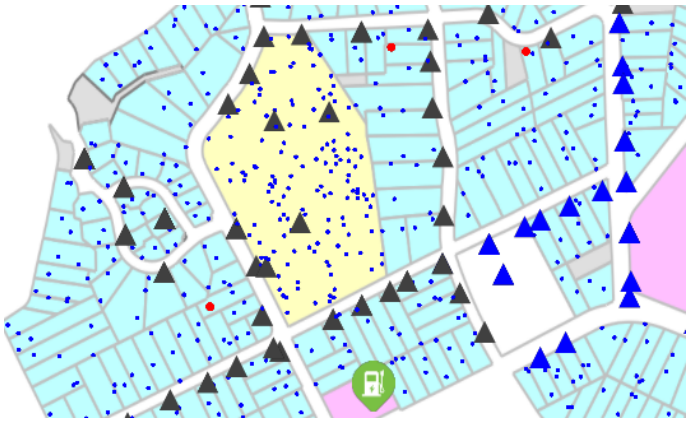


Figure.5.5 Feeder-Level EV Diffusion Algorithm

5.3.1 Customer EV Adoption Algorithm

The customer EV adoption algorithm is based on the CANE model, as shown in Fig. 5.6. First, the information for the EV market, utility strategy and customer neighborhood are gathered for the CANE model calculation. Then the probability to purchase EV, ICE or stay with the current vehicle are calculated using CANE. The algorithm loops though all the customers annually.

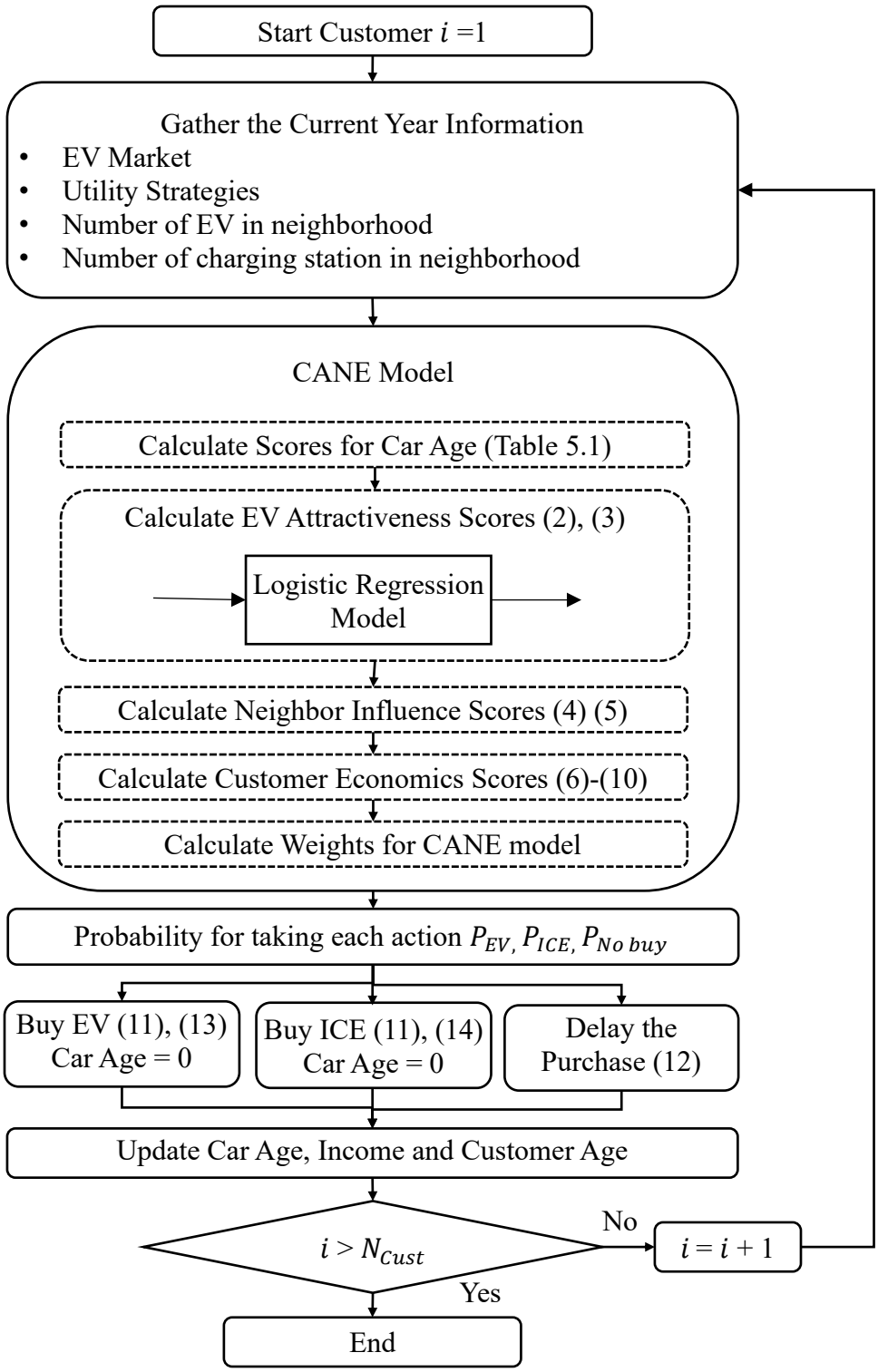


Figure.5.6 Customer EV Adoption Algorithm

5.3.2 Charging Station Development Algorithm

Charging stations are developed as the customer adoption evolves and all the potential parcels for charging station sites are examined every year, as shown in Fig. 5.7. A score system is utilized for the charging station development. The score is calculated based on local EV penetrations, types of land use and distance to three-phase poles. Shopping malls, schools, office buildings and medical areas have the highest score; church, clubs, parks, nursing homes are the next highest while vacant parcels have the least score. Higher scored parcels that exceed the threshold will be converted into charging station locations.

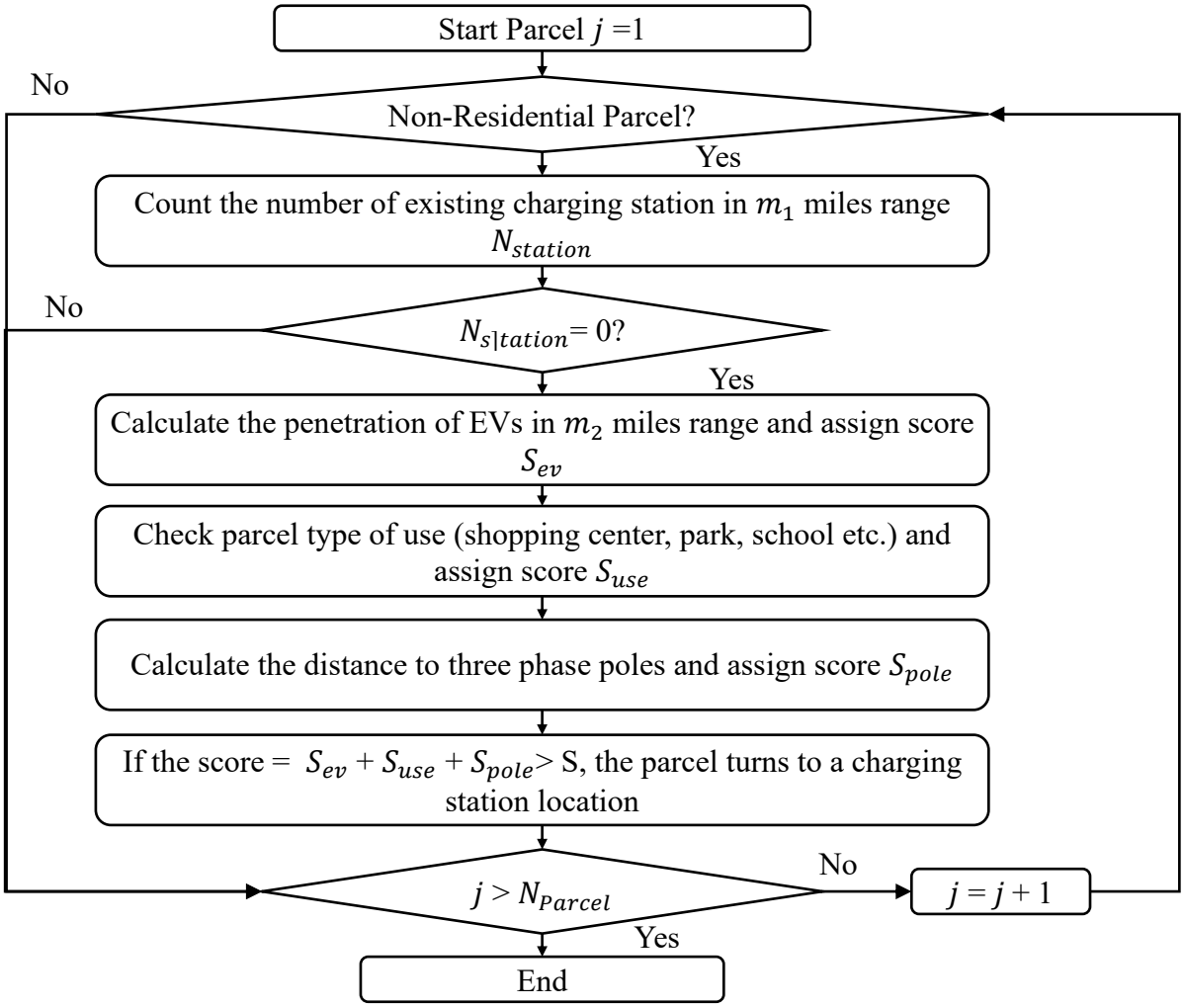


Figure.5.7 Charging Station Development Algorithm

5.3.3 Model Calibration using Monte Carlo Analysis

Monte Carlo analysis is deployed to obtain the most likely results from the stochastic agent-based simulation as well as calibrate the agent-based model. The agent-based EV diffusion model has many random and stochastic parameters. For example, the customer EV adoption is based on probabilities calculated for actions using the CANE model. In order to obtain the most likely results from the stochastic adoption process, Monte Carlo method is introduced to repeat the agent-based simulation with random seeds. In addition, the Monte Carlo analysis is applied to calibrate the agent-based model to a guideline: such as a regional forecast curve for EV registration. The median of the Monte Carlo simulation results can be then compared to the guideline for model calibration. In the example study below, the EV diffusion for an actual feeder over a 30-year planning timeframe is run 500 times. Then the model is calibrated with the area forecast based on cumulative EV registration data [96] that has been scaled down to number of customers on one feeder. Ideally, the proposed agent-based EV diffusion method can be applied on feeders in one area and calibrated towards the area forecast directly without any scales.

5.4 Distribution Feeder EV Impact Analysis

The agent-based EV diffusion model provides a forecast of when and where EV home chargers and charging stations could connect to a specific distribution circuit. In order to convert this forecast into a circuit loading impact, the load profiles for both home and station charging need to be incorporated. This can then be followed by an analysis of the distribution circuit impact and subsequent mitigation recommendations.

5.4.1 EV Home Charging and Station Charging Load Profiles

Home charging is convenient but limited to 20 kW for Level 2 chargers. Daily profiles of EV home charging obtained from [97] are analyzed and used in the example study shown in Fig. 5.8. Residential customers often charge their cars when they arrive home after work or extended trips. Common hours for weekday home charging occur around 19:00, which gets pushed back to later times for weekends, as illustrated in Fig. 5.8.

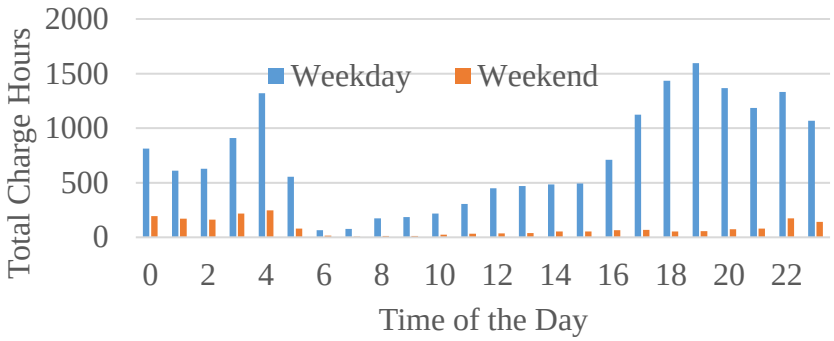


Figure.5.8 Home EV Charging Hour Histogram

EV charging station profiles are required for the impact analysis as well. Actual charging event measurements, which can be obtained from public resources like [98], are used for the following example analysis. A histogram for the charging event start hour is shown in Fig. 5.9. It can be seen that most EV charging station activities occur during the noon period and charging continues into the late evening hours.

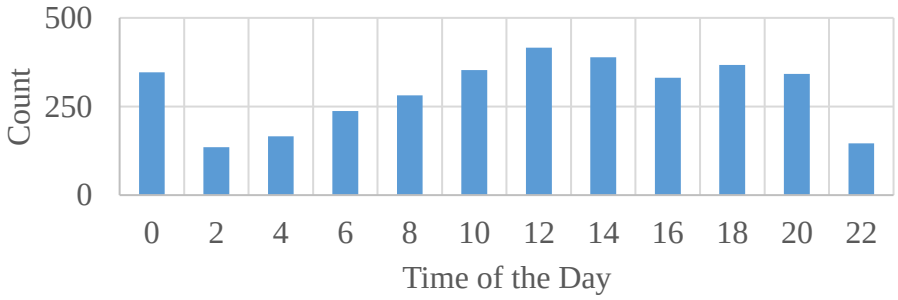


Figure.5.9 Station Charging Events Start Hour Histogram

5.4.2 Distribution Impact Analysis and Plan for Improvements

With the feeder-specific EV diffusion forecast, more targeted upgrades and mitigation strategies can be planned to accommodate the increasing EV load. Quasi-static time-series power flow analysis can be utilized to quantify the EV load impact. Specific impacts analysed are as follows:

1) Annual Energy, Losses and System Peak Impact

Distribution system losses can be estimated more accurately with the locations and growth rate of EV loads forecasted from the agent-based model. Increased energy sales and added peak demand can also be quantified.

2) Annual Load Factor Impact

The annual load factor measures the utilization efficiency of the distribution system and can be calculated as the average load divided by the peak load during a year. A higher load factor is more desirable since it reduces the cost to serve electricity in terms of both capital and operational expenditures. How the increase of EV penetration will affect the annual load factor as time goes can be evaluated with the agent-based model results.

3) Substation Capacity Impact

Substation upgrades are expensive investments which a utility would like to defer if possible. With the proposed EV diffusion analysis, it is possible to estimate when the substation will need upgrades and then come up with mitigation methods enabled by better location information to defer the upgrade.

4) Customer Distribution Transformer Impact

Distribution transformers, which were initially installed decades ago, will experience overloading and accelerated aging due to the increased EV charging load. In order to estimate the

life of customer distribution transformers, one needs to know the locations of EV charging loads by connected transformers and the rate of load growth. The loss-of-life of transformers is an accumulative process related to temperature and overloading percentage. The analytic model for calculating transformer loss-of-life can be developed based on the IEEE standard C57.91 [99][28].

5) Distribution Line Loading Impact

Location specific EV diffusion forecast also enables the impact analysis on single and two-phase lateral loading. Utilities typically have additional criteria for single and two-phase lateral loading in addition to the conductor's thermal limit. This can be for protective device sizing and coordination, better reliability, loss reduction and load balancing [100]. For primary distribution lines, conductor loading should be limited to 80% of the capacity. In the example study, single and two-phase conductor loading is limited to 80 amps and the three-phase loading limit is set to 80% of the thermal rating.

6) Voltage Regulation Impact

Excessive EV charging load may also cause low-voltage issues for the distribution system. According to the ANSI standard limit, the voltage should be maintained within ± 5% of the nominal value for residential customers. In addition, large charging station loads may adversely affect voltage regulation controls.

5.5 EV Distribution Planning Case Study

Case studies based on an actual distribution feeder are used to illustrate the application of the proposed agent-based EV diffusion forecasting methodology. The agent-based model is programmed using Java in Repast Simphony [4] and the distribution impact analysis is performed using quasi-static power flow in OpenDSS [101] for 30-years with 15-minute intervals. The feeder

topology (triangle dots) overlaps on the associated GIS parcels (polygons) map is shown in Fig. 5.10. Blue triangles are three-phase backbone transformers and black triangles are single or two-phase transformers. Cyan parcels are residential homes and yellow ones are apartment complexes. Pink parcels are the most likely areas for EV charging stations including shopping centers, hotels, schools, office buildings and medical areas. White parcels are secondary options including churches, clubs, parks and nursing homes. The study feeder is a 12.47 kV circuit with a 3-mile primary backbone, 300 customer distribution transformers and 1240 customers. It is assumed that every residential customer has two vehicles.

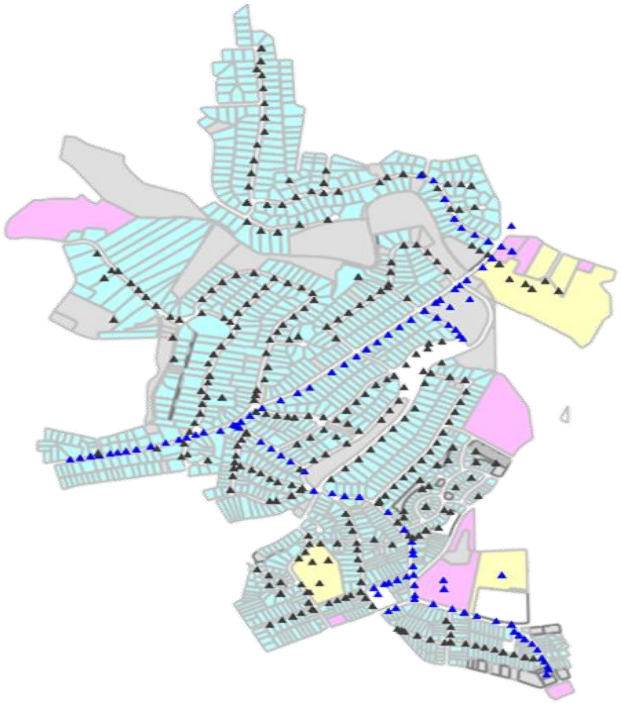


Figure.5.10 GIS Property Parcel Overlay with Feeder Topology

5.5.1 Agent-Based EV Diffusion Model Results and Validation

The agent-based EV diffusion model is configured for a 30-year analysis with CANE model parameters shown in Table 5.2 and logistic regression model parameters shown in Table

5.3. Monte Carlo simulation involves 500 runs and the agent-based EV diffusion model is calibrated with a scaled-down forecast based on EV registration data [96].

Table 5.2 CANE Model Parameters

α_1 :	0.4	γ_1 :	0.1	ψ :	100	i :	5%	m_1 :	1 mile
α_2 :	0.8	γ_2 :	0.9	k :	0.4	n :	*5 year*	m_2 :	1 mile
Home Charger Cost:			$1000		Fuel Price Trend:			[102]	
Maintenance ($/mile):			0.061(ICE)		0.026(EV, 3miles/kWh)			15,000 mile/yr.	

Table 5.3 Attractiveness Logistic Regression Coefficients

Age (β_1)	0.010374				
Family Size (β_2)	0.001897				
Income Dummy (β_3)	-1.27002	-0.68168	-0.38681	0.170506	0.59211
Education Dummy (β_4)	-0.88103	-1.10332	-0.46057	0.261457	0.607559
Urban Dummy(β_5)	-0.56766	-1.00823			
State Dummy (β_6)	0.075482	(for NC)			
Intercept (β_0)	-1.57589				

Results of the EV diffusion forecast for this circuit model are shown in Fig. 1.3 for Years 1, 5, 10 and 30. It can be seen that EV adopters are showing up in clusters in Year 5 and Year 10 due to the neighbor influence. The forecast shows a charging station is built within 5 years and located on the parcel of a medical office building with apartments nearby. The second and third charging stations are placed at a hotel-shopping center and a school respectively within 10 years.

The results of the Monte Carlo analysis is compared to the scaled-down existing forecast [96] in Fig. 5.12. The forecast is scaled down for the population size of this feeder shown as the red line. Green boxes represent the total number of EV adopters and red boxes show the number

of EVs with Level 2 home chargers. It can be seen that the results of the agent-based simulation match very well with the existing data forecast.

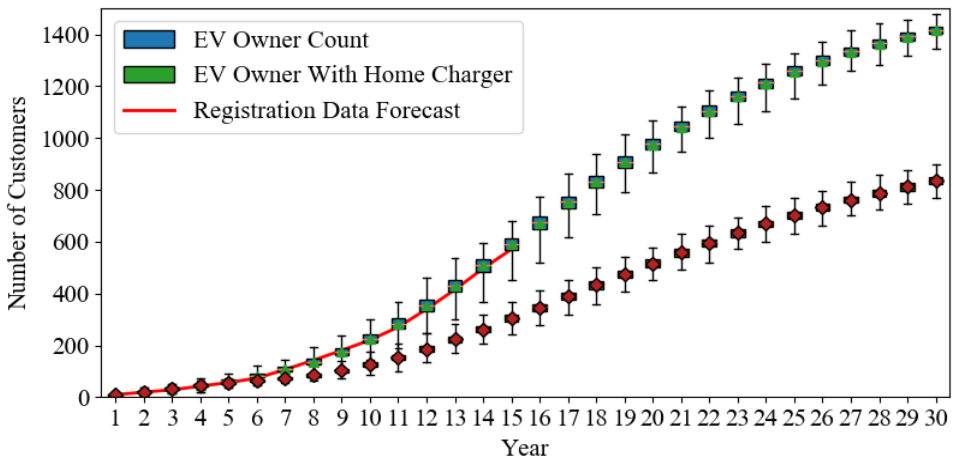


Figure.5.11 EV Adoption Monte Carlo Analysis Results

5.5.2 Distribution Feeder Impact Analysis Results

Case 1 evaluates the impact of the EV charging load on the grid with respect to a no-EV Base Case. The feeder simulation results are shown in Table 5.4. The EV load contributes to 34% increase in peak, 33% increase in energy and 49% increase in losses in 30 years. The peak demand increase may overload the substation depending on the adjacent feeders, which will require an expensive upgrade. No primary circuit over or under-voltage violations occur for this system.

Table 5.4 Feeder Impact Analysis Results

Case	Base	Case 1				Final Change
Case description	No EV (Yr. 30)	Yr. 5	Yr. 10	Yr.20	Yr. 30	
Peak (kW)	6,936	6,993	7,065	8,348	9,297	2,361
Energy (MWh)	23,371	23,756	24,638	28,639	30,977	7,606
Losses (MWh)	669	707	755	875	998	329
XFMR Replacement	9	8	16	49	97	88
# of 1Ø or 2Ø > 80A	0	0	4	26	35	35
Feeder Load Factor	0.385	0.388	0.398	0.392	0.380	-0.005

Note: No load growth apart from EV is considered given the energy efficiency improvement programs. It also makes it a clearer case for EV analysis

The annual load factor increases slightly for Years 5 and 10, but starts to drop at Year 20, and eventually drops below the no-EV Base Case at Year 30. The charging load fills in the non-system peak without adding too much to the peak and improves the load factor at a lower EV penetration level. As the penetration gets higher, the aggregate EV load contributes more to the annual system peak, which makes the load factor worse.

EV penetration will also accelerate transformer aging, leading to the need for additional transformer replacements. Without the EV load, the original circuit load over 30 years only results in 9 replacements. With the EV load, the number of transformers replacements in this circuit increases to 97. This equates to about one third of the distribution transformers needing to be replaced in the circuit.

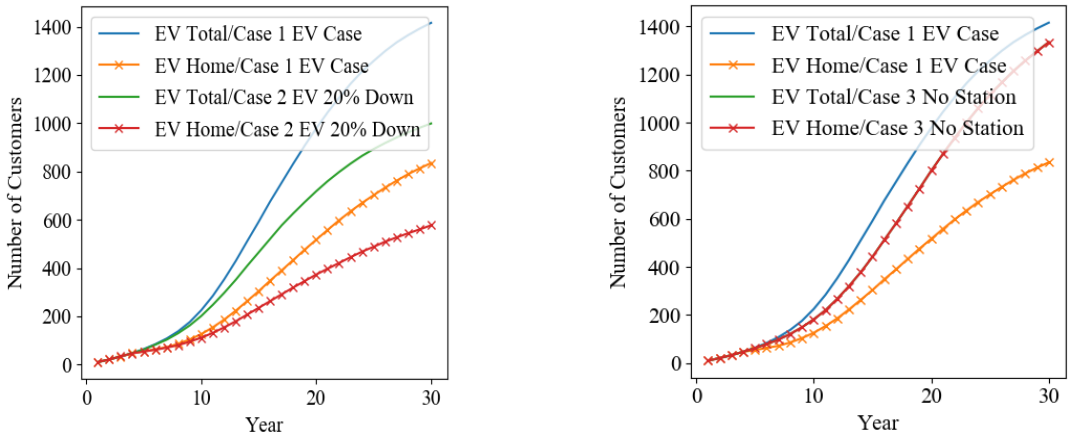
The analysis also shows that a number of single and two-phase laterals need to be upgraded. The number of single-phase and two-phase lines that have loadings over 80A increased from 0 to 35 for a total upgrade of 12, 272 ft. Line upgrade projects can be expensive ranging from $600k to $1, 000k per mile [103].

5.5.3 EV Price and Charging Station Sensitivity Scenarios

Case 2 considers the sensitivity of the forecast to the EV price factor and results are in TABLE 5.5. The EV price is estimated to decrease about 40% by the end of the 30-year analysis in Case 1. Case 2 considers a more conservative scenario of a 20% decrease in EV price. One can see from Fig. 5.13 (a) that the total EV adoption and home charger count is reduced by about 30% for Case 2. There are slight decreases for system peak (-11%) and energy (-7%) as well. The count of transformers that need to be replaced decreases from 97 to 61 (-37%). However, the stress from EV is still significant compared to the Base Case.

Table 5.5 Feeder Impact Results Comparison

Case	Base	Case 1	Case 2	Case 3
Case Description	No EV	With EV	20% Down	No Station
Peak (kW)	6,936	9,297	8,288	9,283
Energy (MWh)	23,371	30,977	28,793	30,631
Losses (MWh)	669	998	899	1,070
Xfmr Replaced	9	97	61	165
# of 1Ø or 2Ø > 50A	0	35	27	39
Load Factor	0.385	0.380	0.397	0.377



(a) (b)

Figure.5.12 Scenario Analysis Diffusion Results (a) Case 2 (b) Case 3

Case 3 evaluates the impact of not having any charging stations installed and results are in Table 5.5. Without having any charging station installed, Case 3 forecasts only slightly less (about 4%) EV adopters compared to Case 1, as illustrated in Fig. 5.14 (b). However, EV adopters now have Level 2 home chargers installed instead of having the option to charge at local charging stations. With all EVs charging from home through distribution transformers, the transformer replacement count increased 70% (from 97 to 165). In addition, there is also about 7% more losses and 11% more overloaded branches compared to Case 1. The peak and energy are slightly increased as well. One can see that the utility is better off having a few optimally located charging stations in place as opposed to customers installing their own chargers. By installing charging

stations, the system losses, overloading on distribution transformer and branch conductors can be reduced and alleviated.

5.6 Conclusion

This chapter proposes an agent-based diffusion model to analyze when and where EV and charging stations will appear on an electric power distribution feeder. A new customer-oriented distribution-planning framework is also introduced to help distribution planners forecast EV diffusion, estimate the feeder impact and make decisions on mitigation methods. A customer adoption model CANE is developed with logistic regression embedded considering car age, EV attractiveness, neighbor influence and customer economics. Feeder modeling is combined with GIS parcel data to enable a feeder-specific locational forecast for distribution planners. Monte Carlo analysis is performed to calibrate the stochastic model.

The developed diffusion methodology and framework are demonstrated via a case study on an actual distribution feeder. With the diffusion results, the EV impact for a 30-year horizon is analyzed through time-series power flow analysis. There is about a 34% increase in the peak and energy and a 49% increase in losses for the feeder studied. One third of transformers on the feeder need to be replaced which is about 10 times greater than the no-EV Base Case. Two additional scenario studies are presented which consider impacts of a slower EV price drop and a no-charging stations situation. The results show that the stress to the feeder decreases with a slower EV price drop but is still significant. In addition, a utility can alleviate EVs' adverse impact on distribution transformers, branch conductors and system losses by installing charging stations at an early stage as opposed to letting EV owners install their own chargers at home. The use of this framework for evaluating a wider range of mitigation strategies will be the focus of future work.

Chapter 6. Optimal Distribution System Horizon Planning for Residential EV Considering Customer Responsiveness Using Dynamic Programming

6.1 Introduction

Transportation electrification generates significant loads as well as challenges to the electricity grid. The distribution system will be the first to experience the challenges since most electric vehicle drivers do more than 80% of charging at home due to the convenience and inexpensiveness [104]. The impact of residential EV charging on the distribution grid include potential substations overload, increase in system peak and losses, and accelerating distribution transformers aging [17]–[19]. Many EV managed charging programs such as special EV rate and demand response have been proposed, studied and implemented in pilot projects trying to alleviate issues of residential charging [21]–[24], [105], [106]. All of these EV managed charging programs require customers' involvement and customers' responsiveness as the keys to success. However, higher customer response usually requires higher incentives, which means a higher cost to the utility. Distribution planners face the problem of how to utilize the managed charging programs to minimize the cost, including not only distribution system cost but also customers compensation while maximize the mitigation performance. Therefore, a customer-oriented distribution planning method is needed to evaluate various EV managed charging programs and optimize the distribution system planning cost to better accommodate future EV loads.

6.1.1 Literature Review

EV managed charging programs can benefit customers by reducing energy bills and utilities by mitigating the potential EV charging impact, even leading to more cost efficient grid operation [20]. There are two types of managed charging strategies. One is indirectly managing the charging by appropriate rate structures such as time of use (TOU) rate, dynamic rate and demand charge rate. Another strategy is a more direct charging management like smart charging,

which can be in various forms including demand response, one-way controlled charging or vehicle-to-grid [21]. Existing practices among utilities in US or Europe using direct or indirect managed charging strategies are reviewed and summarized in [21]. A decentralized optimal demand-side management of EV charging is proposed to flatten the load cure of every distribution transformer in [22]. A demand response strategy is proposed to minimize the impact of charging EVs on a distribution circuit in [23]. A centralized control algorithm is described to mitigate the thermal and voltage issued caused by EV in [24]. However, existing literature does not consider the long-term comprehensive distribution system planning cost and the optimal amount of customer responsiveness needed. Neither is the cost for the customer participation integrated into the objective when solve for the managed charging strategy.

Optimal distribution system horizon planning oversees a horizon for 20+ year period to minimize the net present cost of total investment and operation [107], [108]. A comprehensive distribution system planning considers substation and distribution transformer capacities, distribution feeders and voltage. The review study in [107] pointed out that although much research has been done in the area of distribution planning, these studies fail to approach planning in a way that takes advantage of distributed energy resources (DERs), new loads including EV, and intelligent distribution management system. A feeder investment model for distribution system planning including energy storage is presented in [109]. This chapter fills in the gap by proposing a method to provide the optimal distribution system horizon planning considering the growing EV load, EV customers' responsiveness and the associated cost.

Customer responsiveness is the key to the success of most of the EV charging management strategies. Utilities offer incentives to drive customers to participate in the program to reduce system cost. Meanwhile, higher participation and response rates are usually associated with higher

compensation payments to customers. An optimal customer responsive rate that demonstrates this trade-off needs to be resolved by utilities. Compensation methodologies for three demand responsive programs in US are presented in [25]. An incentive design for a demand response with targeted reduction in a diverse set of buildings is proposed in [26]. Customer acceptance and response to time-based rate and price are introduced in [27]. However, there is a gap for integrating customer responsiveness and compensation cost integrated with the distribution system horizontal planning to create a more efficient grid considering future EV charging load.

6.1.2 New Strategy for EV Planning

This chapter proposes an optimal distribution system horizon planning method to accommodate the future residential EV charging load considering customer responsiveness. Optimal customer response rates for the planning horizon is solved using dynamic programming to minimize the net present value of the total traditional distribution cost and EV managed charging program expenses. The distribution system impact of three charging management strategies – TOU rate, charge by departure time and smart charging, are investigated with a real distribution feeder. Previous work on EV diffusion analysis using agent-based simulation has been adopted to provide EV load growth forecast for the case study presented in this chapter. Comprehensive traditional distribution costs have been considered including high voltage substation and low voltage distribution transformer upgrades, feeder upgrades and reconfiguration and annual system peak and losses.

The rest of the chapter is organized as follows. Section II introduces the optimization problem formulation. Section III presents the solution methodology of dynamic programming. Section IV provides a case study on a sample feeder that illustrates the application of the proposed optimization method. Section VI summarizes the chapter as well as future work.

6.1.3 Nomenclature

C_{peak_i}	Cost of the increased annual peak kW by EV load at year i.
C_{loss_i}	Cost of the increased annual loss MWh by EV load at year i.
C_{sub_i}	Annualized cost of substation upgrade at year i.
C_{xfmr_i}	Cost of transformer replacement at year i.
$C_{1\emptyset line_i}$	Cost of single or two-phase line upgrade at year i.
$C_{3\emptyset line_i}$	Cost of three-phase line upgrade at year i.
C_{Incent_i}	Cost of incentivizing customers to response in the EV managed charging program at year i.
C_{pc_i}	Cost of changing the program that happens on year i, applied on year $i+1$.
$R_{EV,\,i}$	Customer response rate for the EV managed charging program at year i, %.
$Peak_i$	Increased annual peak kW by EV load at year i. It is a function of $R_{EV,\,i}$.
$Loss_i$	Increased annual loss MWh by EV load at year i. It is a function of $R_{EV,\,i}$.
$Nxfmr_i$	Number of distribution transformer need to be replaced due to the EV load at year i. It is an integer and a function of $R_{EV,\,i}$.
$LLen_{1\emptyset i}$	Length of the single or two-phase line upgrade at year i.
$LLen_{3\emptyset i}$	Length of the three-phase line upgrade at year i.
Upg_{idx_i}	Binary index factor indicates whether an upgrade is needed for year i.
Cap_{upg}	Substation capacity expansion kVA rating
Cap_{limit}	Substation capacity limit in kVA.
$Base_{kW}$	Annual peak kW when there is no EV.
$LossBase_{kW}$	Annual loss MWh when there is no EV.
FCR	Fixed capacity recovery factor.

p_{peak}	Price for annual peak \$/kW.
p_{energy}	Price for losses \$/MWh.
p_{sub}	Price for substation upgrade \$/kVA.
p_{pc}	Price for changing EV managed charging program \$.
α	Discount factor.
Δ_i	Customer response rate change from year $\mathrm{i} - 1$ to year i.
N	Planning Study Horizon in Years.
T_{HS}	Winding hottest-spot temperature, °C.
T_A	Average ambient temperature, °C.
ΔT_{TO}	Top-oil rise over ambient temperature, °C.
ΔT_w	Winding hottest-spot rise over top-oil temperature, °C.
K	Ratio of load to rated load, per unit.
R	Ratio of load loss at rated load to no-load loss.
$\Delta T_{TO,U}$	Ultimate top-oil rise, °C.
$\Delta T_{w,\ U}$	Ultimate winding hottest-spot rise, °C.
$\Delta T_{TO,i}$	Initial top-oil rise, °C.
$\Delta T_{w,i}$	Initial winding hottest-spot rise, °C.
τ_{TO}	Oil time constant of transformer for any load.
τ_w	Winding time constant at hot spot location.
FAA	Aging acceleration factor.
LoL	Transformer loss of life.
Δt	Time interval, h.

6.2 Problem Formulation

The objective of the problem is to minimize the cost to serve the increasing EV load from utility's standpoint by proposing the optimal customer responsiveness requirement for a planning horizon of 20+ years. This section first introduces the cost considered in the distribution system horizon planning for EV and then presents the problem formulation.

6.2.1 Distribution System Horizon Planning Considering EV Load and Customer Responsiveness

1) Substation Transformer Capacity Upgrade

A substation may need upgrade if the increased EV loads lead to capacity overloading. In order to account for future growth, the upgrade project usually involve upgrading the circuit to 1.25 to two times of its original capacity. This could be an expensive investment a utility would like to defer if possible. The average marginal cost for transformers and substations is $140/kW [16]. The annual charging to own the substation upgrade or deferral benefit per kW can be calculated as the marginal cost times the fixed capital recovery factor (FCR). FCR be calculated based on interest i and number of years n. Note that if a upgrade project is deferred, then the avoided payment is treated as if it is avoided forever[110].

2) Distribution Transformer Upgrade

Residential EV charging connects to the grid through distribution transformers located in neighborhoods. A distribution feeder can include hundreds of these transformers. A utility needs to replace these distribution transformers when they reach the end of life and may upgrade it to a larger size to account for future load growth if needed. The increased EV charging load may also accelerate transformer aging especially with high power charging. The life of the transformer relates closely to temperature, transformer overloading percentage and duration. The analytic

model for transformer loss of life is built according to the IEEE standard C57.91 [99] and report [111]. The normal insulation life is 180,000 hours. Equations (15)-(21) are used to model the transformer loss-of-life (LoL):

$$T_{HS} = T_A + \Delta T_{TO} + \Delta T_w \tag{15}$$

$$\Delta T_{TO,U} = \Delta T_{TOR} * (\frac{K^2 R + 1}{R + 1})^n \tag{16}$$

$$\Delta T_{w,U} = (\Delta T_{wR} - \Delta T_{TOR} + 15) * (K^2)^m \tag{17}$$

$$\Delta T_{TO} = \left(\Delta T_{TO,U} - \Delta T_{TO,i}\right)\left(1 - e^{\frac{\Delta t}{\tau_{TO}}}\right) + \Delta T_{TO,i} \tag{18}$$

$$\Delta T_w = \left(\Delta T_{w,U} - \Delta T_{w,i}\right)\left(1 - e^{\frac{\Delta t}{\tau_w}}\right) + \Delta T_{w,i} \tag{19}$$

$$FAA = \exp\left(\frac{15000}{383} - \frac{15000}{T_{HS} + 273}\right) \tag{20}$$

$$LoL = \frac{FAA * \Delta t}{Normal\ Insulation\ Life} \tag{21}$$

3) Feeder Upgrade

Feeder upgrades based on accepted utility practices are utilized in this chapter's analysis [100]. Single and two-phase loading is subject to a lower ampere limit, such as 50 A, in addition to the thermal constraint in order to provide greater reliability and improving load balance. This lower ampere limit also improves protective device sizing, protection coordination, and loss reduction. Upgrades to three-phase will be recommended for violated single or two-phase lines. For planning purposes, primary distribution line conductor loading should be limited to 80% of the capacity. For distribution circuits supporting open tie switches for load transfer capacity, the loading should not be over 50% of the capacity. According to [112], the cost of a distribution three phase feeder can range from $55,000 to $500,000 per mile with an average cost of $150,000 per mile. Lateral lines cost between $5 to $15 per kW-mile overhead and direct buried underground is priced between $30 to $100 per kW-mile ducted.

4) System Peak and Losses

The increased EV charging load may contribute to annual system peak and losses as well. When EV loads are coincident with the system yearly peak, utility may need to turn on or purchase power from very expensive peak power plants only to serve this extra load. The additional system losses should also be part of the cost for the utility to serve the added EV loads. The concept of avoided cost for system demand and energy are utilized to monetize this part of the cost. According to an energy efficiency study for multiple electric distribution companies [113], the avoided peak capacity cost is around $55/kW and the avoided energy cost is $51/MWh.

5) Customer Responsiveness Cost Model

In addition to the traditional distribution planning cost, cost associated with customer response in EV managed charging programs should also be considered. EV charging management strategies can be utilized to deliver a potentially more efficient grid and mitigate adverse impacts caused by the EV charging loads. However, higher customer participation usually means more cost as well. The relationship between customer acceptance and incentive cost can be obtained by a customer behavior study like [27]. An exponential relationship is used in the example presented in this chapter as shown in (22):

$$p_{Incent} = b + k \times {R_{EV}}^{h} \tag{22}$$

where p_{Incent} denotes the annual incentive payment to customers by the utility to drive R_{EV}% EV customers to participate and response in the EV charging management program. Apart from the customer compensation cost, there will also be expenses related to the study, design, getting the new rate or program permitted.

6.2.2 Optimal Distribution System Horizon Planning Problem Considering EV Customer Responsiveness Formulation Model

Based on the discussion of the previous section, the optimal distribution system horizon planning model can be formulated considering EV customer responsiveness. The objective is to minimize the net present value of both the traditional distribution planning and EV program implementation cost over a long-term of N years.

$$\text{Min} \sum_{i=1}^{N} \theta^{i}\big(C_{peak_i} + C_{loss_i} + C_{sub_i} + C_{xfmr_i} + C_{1\emptyset line_i} + C_{3\emptyset line_i} + C_{Incent_i} + C_{pc_i}\big) \tag{23}$$

subject to

$$C_{peak_i} = (Peak_i(R_{EV,\ i}) - Base_{kW}) \times p_{peak} \tag{24}$$

$$C_{loss_i} = (Loss_i(R_{EV,\ i}) - LossBase_{MWh}) \times p_{energy} \tag{25}$$

$$C_{sub_i} = Upg_{idx_i} \times p_{sub} \times Cap_{upg} \times FCR \tag{26}$$

$$Upg_{idx} = 1 \text{ if } Peak_i\big(R_{EV,\ i}\big) > Cap_{limit} \tag{27}$$

$$Upg_{idx} = 0 \text{ if } Cap_{limit} \leq Peak_i\big(R_{EV,\ i}\big) \tag{28}$$

$$FCR = \frac{i \times (1+i)^n}{(1+i)^{n-1}} \tag{29}$$

$$C_{xfmr_i} = Nxfmr_i(R_{EV,\ i}) \times p_{xfmr} \tag{30}$$

$$C_{1\emptyset line_i} = LLen_{1\emptyset i}\big(R_{EV,\ i}\big) \times p_{1\emptyset line} \tag{31}$$

$$C_{3\emptyset line_i} = LLen_{3\emptyset i}\big(R_{EV,\ i}\big) \times p_{3\emptyset line} \tag{32}$$

$$C_{Incent_i} = p_{Incent}\big(R_{EV,\ i}\big) \times N_{Cust} \times R_{EV,\ i} \tag{33}$$

$$\Delta_i = |R_{EV,\ i} - R_{EV,\ i-1}|, \tag{34}$$

$$C_{pc_i} = \frac{\Delta_i}{\Delta_i} \times p_{pc} \tag{35}$$

$$\theta = 1 \div (1+\alpha) \tag{36}$$

$$0 \leq R_{EV,\ i} \leq 100\% \tag{37}$$

$$Nxfmr_i \in \mathbb{Z} \tag{38}$$

where $R_{EV,\ i}$ is the EV customer responsive rate for year i. C_{Incent_i} represents the cost for incentive payments to customers and C_{pc_i} denotes the cost for changing the program to achieve a

different customer responsive rate. Equation (24)-(32) captures the traditional distribution system planning cost at a customer response rate $R_{EV,\ i}$ for year i. Equations (33)-(35) account for the EV managed charging strategy cost.

6.3 Solution Methodology Using Dynamic Programming

In order to solve for the optimization problem formulated in the previous section, first the distribution system impact of residential EV charging at different customer responsive levels needs to be studied. Then the optimal customer responsiveness required to achieve the minimum total utility cost to serve the additional EV load can be solved using dynamic programming.

6.3.1 Residential EV Charging Distribution System Impact with Different Customer Responsiveness Levels

Utility residential EV charging management strategies can be categorized into two: indirect such as special EV rate and direct like demand response and smart charging [21]. Three types of EV managed charging strategies are selected and studied given the popularity and implementation potential. In addition, the selected strategies are trying to cover the possible residential load control at different degrees.

1) TOU Rate Program

Strategy 1 is the TOU rate, which is the simplest way for utilities to encourage customers to shift their loads. Typically, there is a peak demand time, which has a higher price, and an off-peak time when price is lower. The TOU rate is usually designed to be revenue neutral. Customers may delay the load until the start of the off-peak times. According to the customer behavior analysis in [27], the customer responsiveness is also closely related to the TOU rate design of the peak to valley price ratio. For example, the 4:1 ratio TOU generally has a better effect in demand

reduction than 2:1. This strategy works well with a low penetration of EV. However, as the EV volume increases, then a secondary peak may occur since customers are trying to start all together at the off-peak time.

2) Charge by Departure Program

Strategy 2 can help ease the second peak problem caused by the TOU rate when the EV penetration is high. The goal is to schedule the end of charging by departure time so the start time can be staggered [21]. This is a relatively simple control method. No communication is needed. A program can be designed, and customers are incentivized to opt in or out. A time controller is needed which can schedule the charging by getting the customer departure time.

3) A Smart Charging Control Program

Strategy 3 represents a more complex control for residential charging. Residential charging will be planned to fill the valley of a given load profile so the charging can be finished before the departure time the customer indicated. Two-way communications will be needed since the customer side needs the load profile or valley time to plan for the charging. Also, the aggregator or the upper level controller needs to gather the scheduled charging in order to get the load profile updated. A well-designed real time pricing strategy can also achieve this.

6.3.2 Dynamic Programming Problem Formulation

Dynamic programming has the advantage of solving complicated problems that can be broken down into stages in a recursive manner [114]. For the problem formulated in the previous section, dynamic programming can be applied to solve for the optimal customer responsive rate of each year for the planning horizon. The formulation of the dynamic programming regarding stage, state and action definitions as well as the recursive equation (39) and others is as follows:

- Stage: Year i, $i = 1 \ldots N$
- State: $R_{EV,\ i}$, EV electricity price at year i
- Action: Δ_i, EV electricity price change at year i that will be applied on year $i + 1$
- $f_i(R_{EV,\ i})$:The minimum cost from year i to year N with customer response rate $R_{EV,i}$ at year i
- Recursive equation:

$$f_i(R_{EV,\ i}) := \min_{\Delta_i} \{ C_{peak_i} + C_{loss_i} + C_{sub_i} + C_{xfmr_i} + C_{1\emptyset line_i} + C_{3\emptyset line_i} + C_{Incent_i} + C_{pc_i} + \theta \times f_{i+1}(R_{EV,\ i} + \Delta_i) \} \tag{39}$$

$$\theta = \frac{1}{1 + \alpha} \tag{40}$$

- Boundary:

$$f_N(R_{EV,N}) = C_{peak_N} + C_{loss_N} + C_{sub_N} + C_{xfmr_N} + C_{1\emptyset line_N} + C_{3\emptyset line_N} + C_{Incent_N} \tag{41}$$

- Solve for: $f_1(0)$

The goal is to solve for $f_1(0)$ which represents the minimum cost from Year 1 to Year N starting with customer response rate as zero. The decision variable is the customer responsive rate at each year. The zero customer response rate means no EV managed charging program is applied and the optimal solution will indicate whether and how much customer response rate are required to minimize the utility distribution planning cost over the planning horizon. Note that the cost of changing the program for a different responsive rate happens incurs on year i will lead to a changed response rate implemented on year i +1. For example, for the last year N, if the response rate is

different from year N-1, the cost of change the program happens in year N-1. This is more realistic since it usually takes time to change the program design.

6.4 Optimal EV Managed Charging Program Customer Response Case Study

The proposed optimal distribution system horizon planning method for residential EV charging is illustrated using an actual distribution feeder. Case studies are designed for the three EV managed charging strategies described in the previous section. Actual residential charging profiles are obtained from [97] as the baseline for managed charging controls. The study feeder is a 12.47 kV circuit with a 7 MVA annual peak load, 3-mile primary backbone and 300 customer distribution transformers shown in Fig. 6.1 (a). The distribution impact analysis is performed using quasi-static power flow in OpenDSS [101] for 30-year at 15-minute interval. The dynamic programming is scripted and solved in Python.

The EV diffusion forecast from the study feeder in the previous chapter is adopted for this analysis, as shown in Fig. 6.1(b). It is assumed that three equal size feeders are connected to a 25 MVA substation. If any substation expansion upgrade is required, the plan is to double the substation size by adding another 25 MVA transformer to account for the future load growth. Customer distribution transformers will be replaced with new ones that have double the original kVA rating if the loss-of-life reaches 100%. Single- and two-phase feeders that have over 80A of their thermal loading will be recommended for upgrading to three-phase feeders. The three feeders have a limit of 80% of their thermal loadings for planning purposes.

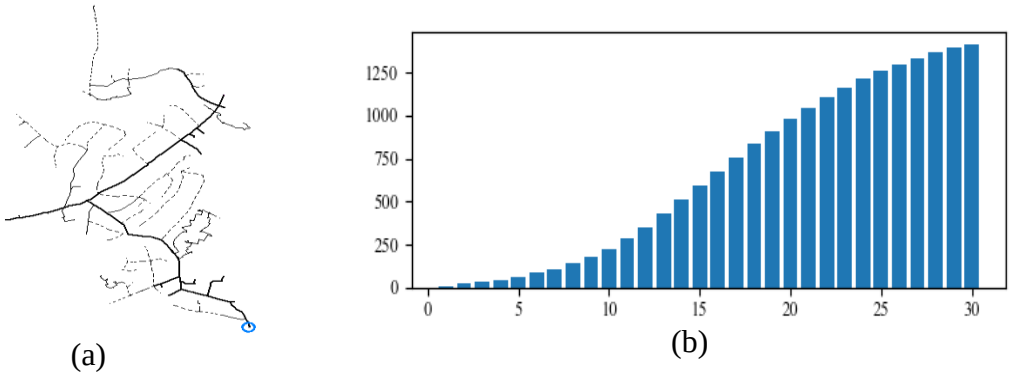


Figure.6.1 Feeder Model (a) and EV Customers Forecast for 30 Years (b)

6.4.1 Distribution System Impact Results

Distribution system impact of the three EV managed charging strategies with various levels of customer response rates are obtained from quasi-static time-series power flow analysis using OpenDSS. The annual system peak, energy, losses and transformer replacement count are shown in Fig. 6.2. Substation upgrade will be required at year 21 if no EV management strategy is applied. One can see from Fig. 6.2(a) about how the annual peak changes as the EV penetration increases. For Strategy 1 with the TOU rate, higher customers' response rates can effectively cap the system peak until the penetration of EV approaches year 15. Strategy 2 can keep the peak demand lower longer than Strategy 1 until the peak starts to pick up around year 20 for the high customer responsiveness case. Strategy 3 achieves the best performance in peak reduction. The higher the customer response rate, the more the peak reduction and there is no secondary peak as the penetration increases.

Fig. 6.2(b) shows the energy MWh consumed annually. The electricity sales are increasing, and the increase is the same at different customer response rates, which proves that charging activities are just being managed and not reduced. Fig. 6.2(c) (d) and (e) presents the annual losses, transformer replacement count and single-phase feeder length that need to be upgraded at different customer response rates. Strategy 1 and 2 have very similar results for different customer

responsiveness levels. Strategy 3 shows decreases and deferral in system losses, transformer replacement counts and single-phase line upgrades length as customer response rate increases. Based on the distribution impact analysis, there is no three-phase feeder loading and voltage violations for the studied feeder.

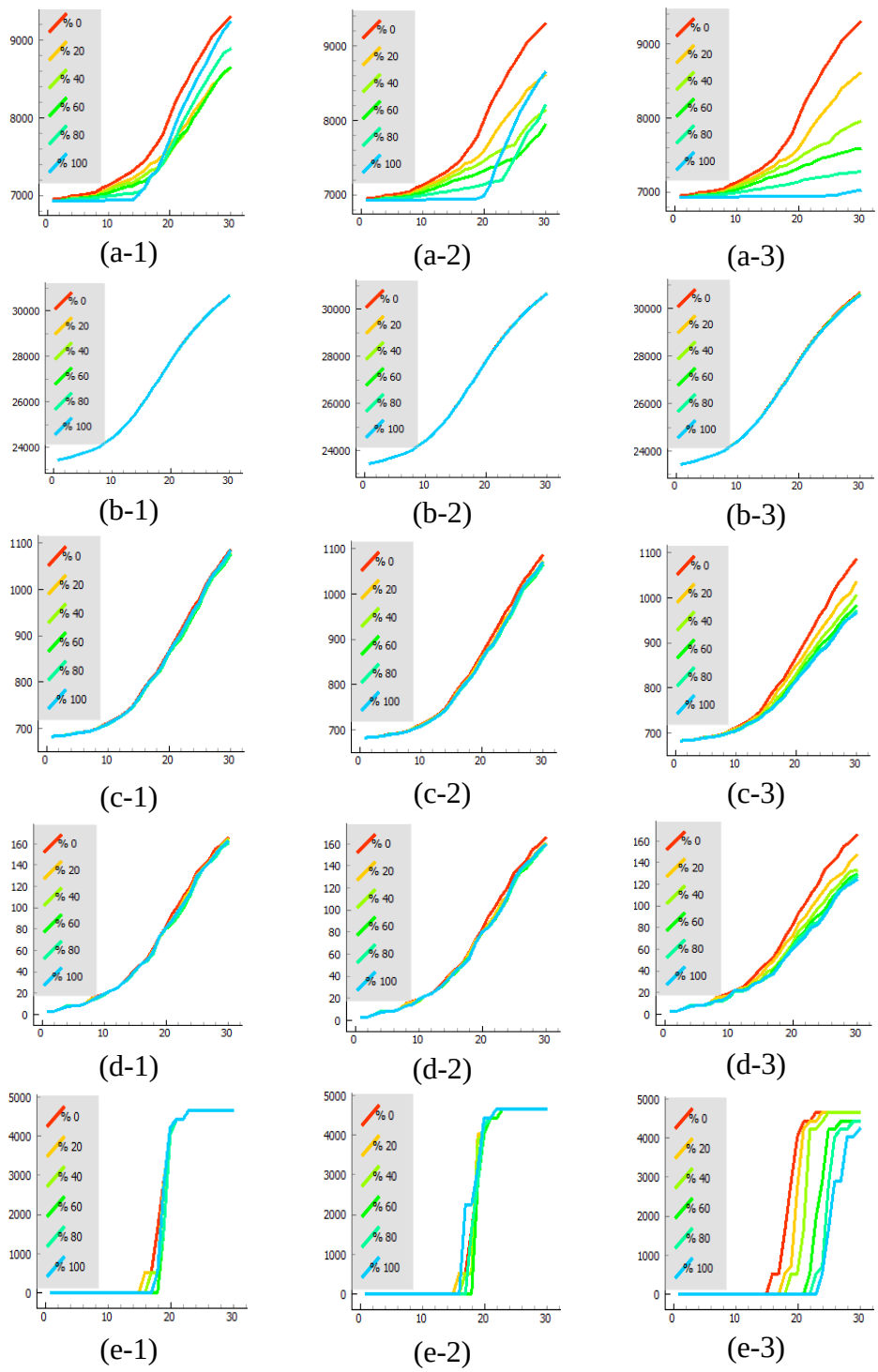


Figure.6.2 Distribution Feeder Impact Analysis Results for 30 Years (a) System Peak kW (b) Energy MWh (c) Losses MWh (d) Transformer Replacement Count(e) Single Phase Upgrade Length ft. (1) Strategy 1 TOU rate (2) Strategy 2 Charge by Departure (3) Strategy 3 Smart Charging

6.4.2 Dynamic Programming Results

With the distribution system impact analysis results, the formulated dynamic programming is solved. Parameters including the cost for peak demand, substation upgrade, energy, transformer, line upgrade and EV programs are shown in Table 6.1. The $Base_{kW}$ and the $LossBase_{kWh}$ used in (24) and (25) are obtained from the Base Case that has no EV. The discount rate used in the study is 10%. The solved optimized customer response rate for 30 years is shown in Fig. 6.3. The minimum cost for the three strategies is $333.1k, $322.3.5k and $315.1k respectively. If there is not any EV managed strategy applied, the total distribution cost will be $519.5k.

Table 6.1 Dynamic Programming Parameters

N	30 years
TOU Peak Hour Window	18:00 – 22:00
p_{peak}	$100/kW
p_{energy}	$51/MWh
p_{xfmr}	$500/piece
p_{sub}	$150/kVA
$p_{1\emptyset line}$	$30k/mile
$p_{3\emptyset line}$	$150k/mile
p_{price_change}	$10,000
$Base_{kW}$	6,933 kW
$LossBase_{kWh}$	682 kWh
α	10%
b	10
h	2
k	0.01

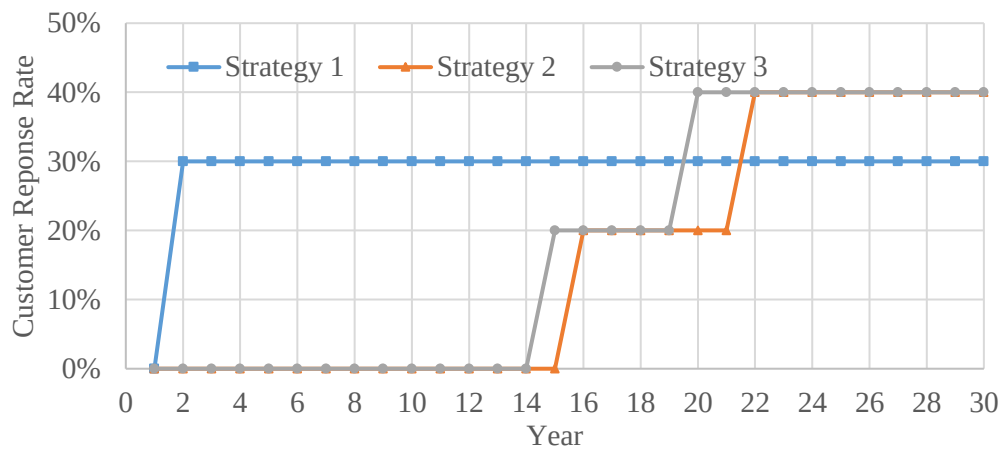


Figure.6.3 Optimal Customer Response Rate

Strategy 3 has the minimum cost and is associated with a 40% customer response rate. Although the simulation results show that higher peak demand reduction and more benefits can be obtained by a higher customer responsiveness, 40% customer responsive rate at year 30 leads to minimum cost over the study period considering overall economic cost aspects. This is due to the cost of the incentives needed to drive customers to response. Note that since the Strategy 1 TOU rate is usually designed to be revenue neutral, no incentive cost is considered for Strategy 1. However, according to [27], the TOU program can achieve about 15% average demand reduction at a design of peak to off-peak ratio of 4:1. So, an extra constraint is added for Strategy 1 TOU rate which capping the maximum customer response rate at 30%.

6.4.3 Sensitivity Analysis and Discussion

Given that there are many assumptions of the cost parameters for the optimization problem, sensitivity analyses are conducted to evaluate the impact of changing the key parameters on the resulting optimal solutions. The most cost effective managed EV charging Strategy 3 is utilized as the example study here. The parameters studied are cost of annual peak kW (p_{peak}), customer incentive payment (C_{Incent_i}) and cost to change the program (p_{pc}).

1) Cost of Annual Peak kW

The cost of the annual peak kW is varied to examine the impact on the optimal customer response rate results as shown in Fig. 6.4. In the previous example, p_{peak} is equal to $100/kW. One can see that the solution is no longer optimal if the peak price is reduced to $85/kW (-15%) or increased to $120/kW (20%). As the cost of the peak demand decreases, it becomes less expensive to have a higher annual kW than spend money to incentivize customers to reduce the annual kW. Therefore, the increase to a higher response rate is delayed. As the cost for peak increases, utilities can save the total cost by implementing a higher customer response rate earlier. A 20% increase in the peak demand cost will result in a 50% customer response rate at the end of the 30-year study compared to the 40% customer response rate. Even if the cost of peak is doubled, the maximum optimal customer response rate is still 50%, which means that it is too expensive to drive a higher customer responsiveness compared to the cost of the peak.

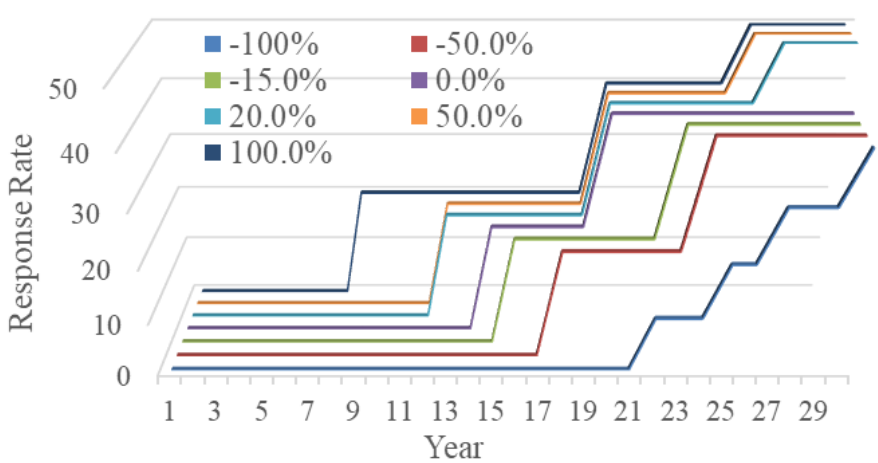


Figure.6.4 Cost of Peak Sensitivity Analysis Results

2) Incentive Payment to Customers Cost

The second sensitivity analysis is on the customer incentive payment cost. Fig. 6.5 shows the results for varying the cost from -100% to 100%. One can see that the previous solution will still be optimal if the change is within ± 15%. As the price to incentivize customers gets higher, it would be better to delay the jump to a higher customer response rate level. If the cost decreases 75%, the final optimal customer responsive rate would be 80% compared to the 40% achieved in the original case. This demonstrates that the cost to drive customer response is a very important factor in order to get the optimal solution in the proposed model.

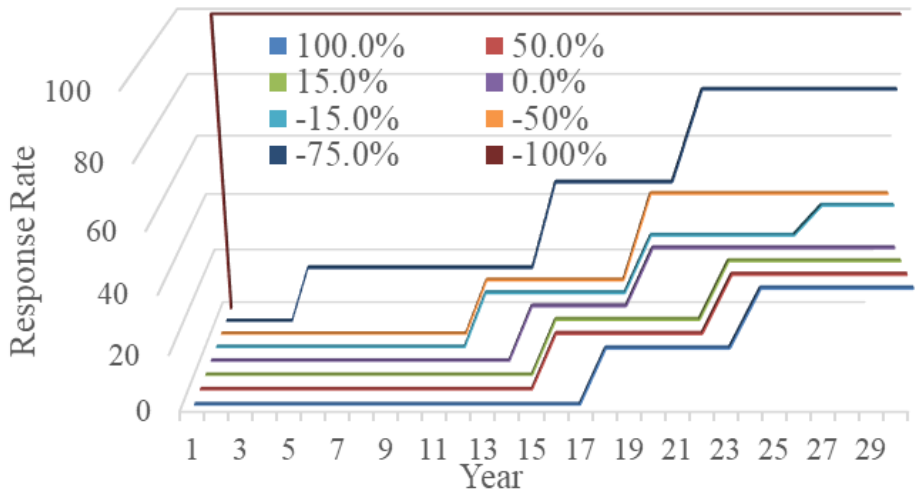


Figure.6.5 Customer Incentive Payments Sensitivity Analysis Results

3) Cost to Change the Program

The cost to change the program has been varied from -100% to 100% ($0 to $20,000) and the optimal customer response rate results are plotted in Fig. 6.6. It can be seen from the results that the previous policy stays optimal until the cost of program change decreased to $9000 (-10%). For the extreme case when the cost to change the program is $0, there will be more program changes happening, but one still ends up with 40% customer response rate at the end of the 30-

year study. If the cost of the price change is $20,000 (doubled), the previous policy is no longer optimal. The increases to a higher customer response rate have been delayed. This is because the cost of program changes is so high that it would be cheaper to have a higher cost of distribution system and upgrade cost (because of the lower customer response rate) compared to having additional program change costs.

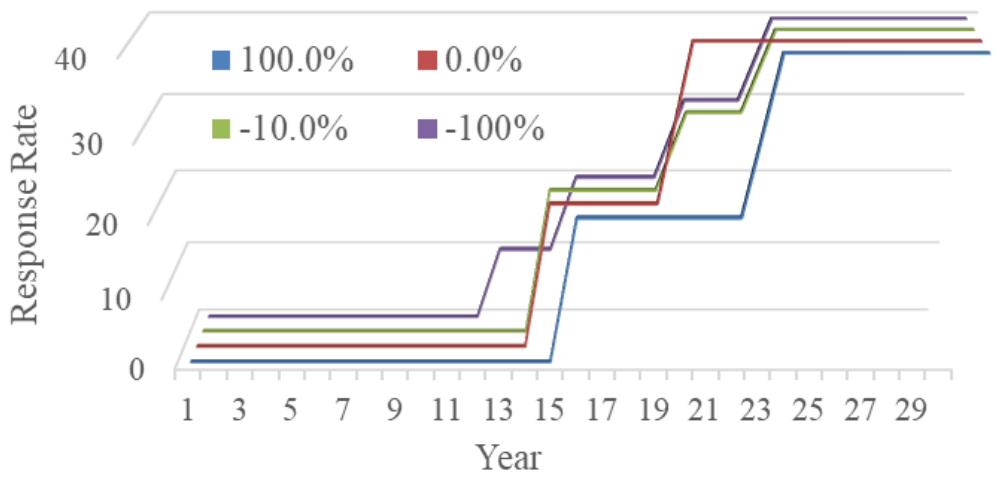


Figure.6.6 Cost to Change Program Sensitivity Analysis Results

6.5 Conclusion

This chapter proposes an optimal distribution system horizon planning methodology to accommodate the future residential EV charging load considering customer responsiveness. In order to determine the optimal customer response rates that a utility can target to minimize the cost to serve the future EV load, an optimization problem is formulated and solved using dynamic programming. The optimization objective is to minimize the net present value of utility expenses in N years including the cost for additional peak, energy loss, transformer replacement, single-phase and three-phase line upgrade, substation capacity expansion and EV management charging strategy cost such as incentive payments to customers and program design expense.

The developed optimal distribution horizon planning model is then demonstrated via a case study on an actual distribution feeder. Time-series power flow analysis for a horizon of 30 years is performed with three different EV managed charging programs include the TOU rate, charge by departure and smart charging in place. The optimal customer response rate is solved in dynamic programming for these three EV managed charging programs with a final customer response rate required at 30%, 40% and 40%. The minimized cost is $333.1k, $322.3.5k and $315.1k respectively, which is a 35% decrease comparing to the total cost of $519.5k if there is no EV managed charging strategy applied. A sensitivity analysis is conducted to evaluate the impact of cost of annual peak kW, cost to incentivize customers to response and cost to change program. The results show that the optimal solution will hold if the change is within in -15% to 20% for the cost of peak, -15% to 15% for the cost to incentivize customers to response and -10% to 100% for the cost to change the program.

Chapter 7. Summary and Future Work

7.1 Summary

This section summarizes the previous work in assessing grid edge technologies and the new distribution planning method proposed for analyzing electric vehicle penetration.

7.1.1 FREEDM SST Assessment and Cost Benefit Analysis

A cost-benefit analysis case study for the FREEDM system deployment has been presented using three sample utility feeders. The simulations on these feeders also clearly demonstrate that the FREEDM system increases DER hosting capacity considerably. These benefits are quantified and monetized from the utility perspective that includes avoided energy costs and deferred investment in capacity expansion. Other benefits are due to more effective real time monitoring and control which is monetized as CVR benefits. The cost-benefit analysis results presented a positive net present value for a partial deployment case with less than 5 years' payback period for the sample feeders. The above results indicate that the partial FREEDM deployment is likely to be utilized on feeders with moderate DER penetration in the near future.

7.1.2 Smart Inverter and In-line Power Regulator Assessment and Cost Benefit Analysis with comparison to SST

Three technologies including the MV SST, grid edge regulator and the smart inverter are identified as feasible solutions to mitigate the overvoltage issues caused by high PV penetration on the distribution grid. By using these technologies, utilities could accommodate a higher penetration level of PV on the distribution grid and also achieve a more aggressive conservation voltage reduction with respect to avoided demand and energy cost. In order to form the basis for an economic comparison, these three technologies are applied on a sample utility feeder circuit and the benefits analyzed and quantified via a quasi-static time series simulation. Then, a

comprehensive cost benefit analysis has been performed to form a relative economic comparison of these three technologies.

It can be seen from the results that the MV SST shows the greatest net present value with 3-year payback period for a utility trying to integrate more PV. Other features of the MV SST, such as providing DC service, have not been considered in this study. The grid edge regulator has a 3.5-year payback period which is very close to the SST. The drawback of the grid edge device is that it has to be used together with the traditional AC transformer. The smart inverter deployment can have a feasible business case; however, the utility may not have full control of the inverters' operation since it is normally installed and maintained by the customers.

7.1.3 FREEDM DC House and Cost Benefit Analysis

Two residential DC house configurations using the FREEDM Solid-State Transformer are proposed: FREEDM hybrid house and FREEDM DC house. The financial benefits of the two FREEDM configurations were compared to both the present-day AC and retrofit DC house. This comparison was based on a simulation test bed that modeled household consumption under a variety of loading conditions with an associated cost benefit analysis.

The results show that indeed the new FREEDM-based configurations considered are economically feasible. The FREEDM DC house is estimated to be the most energy efficient configuration with the highest NPV among the four types of houses with an IRR higher than 10%. The FREEDM DC house shows a positive NPV in both sensitivity analyses for most of the situations. The results indicate that the FREEDM DC house is an economical house configuration that can be utilized in the future to better integrate rooftop PV and electric vehicles, especially for new house construction.

A FREEDM hybrid house is more economical than a retrofit DC house in both the PV and the EV charging cases, especially the low power EV charging case. For the high power EV charging case, the FREEDM hybrid case will be economically feasible if the SST price drops 50%. The results show that the FREEDM hybrid concept is good for existing house upgrades since all legacy load devices can maintain the AC connection while PV and EV can be connected to DC.

7.1.4 Customer-Oriented Distribution Planning Method: Example of Electric Vehicle

A new customer-oriented distribution planning method is proposed to help distribution planners forecast EV diffusion, estimate the feeder impact and make decisions regarding mitigation methods. An agent-based diffusion model is developed to predict when and where EV and charging stations will appear on an electric power distribution feeder. A customer adoption model CANE is developed with logistic regression embedded considering car age, EV attractiveness, neighbor influence and customer economics. Feeder modeling is combined with GIS parcel data to enable a feeder-specific locational forecast for distribution planners. Monte Carlo analysis is performed to calibrate the stochastic model.

The developed diffusion methodology and framework are demonstrated via a case study on an actual distribution feeder. With the diffusion results, the EV impact for a 30-year horizon is analyzed through time-series power flow analysis. The results show a 34% increase in the peak and energy and a 49% increase in losses for the feeder studied. One third of transformers on the feeder need to be replaced which is about 10 times greater than the no-EV Base Case. Two additional scenario studies are presented which consider impacts of a slower EV price drop and a no-charging stations scenario. The results show that the stress to the feeder decreases with a slower EV price drop but is still significant. In addition, a utility can alleviate EVs' adverse impact on

distribution transformers, branch conductors and system losses by installing charging stations at an early stage as opposed to having all EV owners install their own Level 2 chargers at home.

In addition, an optimal distribution system horizon planning method is proposed to accommodate the future residential EV charging load considering customer responsiveness. In order to figure out the optimal customer response rates that a utility can target to minimize the cost to serve the future EV load, an optimization problem is formulated and solved using dynamic programming. The objective is to minimize the net present value of utility expenses in N years including cost for additional peak, energy loss, transformer replacement, single-phase and three-phase line upgrade and substation capacity expansion. Additional cost items also included EV management charging strategy cost such as incentive payments to customers and program design expense. Sensitivity analysis is also performed to study the influence of changing key variables in the optimal results

The developed optimal distribution horizon planning model is demonstrated via a case study on the same distribution test feeder. Time-series power flow analysis for a horizon of 30 years is performed with three different EV managed charging programs including the TOU rate, charge by departure and smart charging in place. The optimal customer response rate is solved in dynamic programming for these three EV managed charging programs with a final customer response rate required at 30%, 40% and 40%. The minimized cost is $333.1k, $322.3.5k and $315.1k respectively, which is a 35% decrease comparing to the total cost of $519.5k if there is no EV managed charging strategy applied. A sensitivity analysis is conducted to evaluate the impact of the cost of annual peak kW, cost to incentivize customers to respond and cost to change program. The results show that the optimal solution will hold if the change is within in -15% to

20% for the cost of peak, -15% to 15% for the cost to incentivize customers to respond and -10% to 100% for the cost to change the program.

7.2 Recommendations for Future Work

The proposed distribution planning method has been applied to electric vehicle analysis including the diffusion model, load control, feeder impact analysis, distribution system upgrades analysis and mitigation strategies. More applications can be analyzed, such as PV system or energy storage penetration. Also, the tool developed could be improved to incorporate other technologies to make it more powerful.

To apply the proposed distribution planning framework to PV, the adoption of residential PV, load modeling of PV, system impact and potential mitigation strategies for PV systems need to be analyzed. For PV adoption model, one needs to consider similar customer characteristics and interactions. Besides, the rooftop area, surrounding situation and the cost benefit assessment for PV system needs to be considered. For example, a house in a heavily wooded area will be harder to have PV installed due to the shade. If the PV system is costing too much and the business case will not work from the customer's point of view, the adoption will be slowed down as well. The benefits form the PV system is highly related to the electric price, rebate programs from the utility, tax credit and incentive programs. For PV system modeling, the output is heavily related to the solar radiation. The distribution feeder impact needs to be analyzed as well. PV could help the distribution system during the heavy loading days as well as creating problems during light loading days. The most common issue is the over-voltage during the light loading days. Then proper price scheme or other programs could be provided to better utilize the PV generation like using PV to charge EV.

REFERENCES

[1] M. Coddington, K. Schneider, and J. Homer, "Utility Distribution Planning 101, Distribution Systems and Planning Training for New England Conference of Public Commissioners, Sept. 2017. Available [Online]: https://emp.lbl.gov/sites/default/files/3._utility_distribution_system_planning_101_v10-ls.pdf," p. 29.

[2] J. Homer, E. Stewart, and M. Coddington, "Distribution Planning Modeling Tools, Distribution Systems and Planning Training for New England Conference of Public Utility Commissioners, Sept. 2017, Available, [Online] https://emp.lbl.gov/sites/default/files/15._distribution_planning_modeling_tools_v5-ls.pdf," p. 45.

[3] "OpenDSS Program," *SourceForge*. https://sourceforge.net/projects/electricdss/.

[4] "Repast Suite Documentation, Repast Simphony, Argonne National Laboratory." https://repast.github.io/.

[5] L. Sun *et al.*, "Cost-benefit assessment challenges for a smart distribution system: A case study," in *2017 IEEE Power Energy Society General Meeting*, Jul. 2017, pp. 1–5, doi: 10.1109/PESGM.2017.8274167.

[6] L. Sun, D. Lubkeman, M. Baran, J. Thomas, and J. DeCarolis, "Cost Benefit Analysis of Technology Options for Enabling High PV Penetration," in *2018 IEEE Power Energy Society General Meeting*, Aug. 2018, p. 5.

[7] L. Sun, D. Lubkeman, and M. Baran, "Residential DC House Cost Benefit Analysis," in *2018 IEEE PES T&D*, Apr. 2018, p. 5.

[8] "What is the grid edge? (And does it really mean cheaper energy bills), Mar. 2017," *World Economic Forum*. https://www.weforum.org/agenda/2017/03/what-is-grid-edge-electricity/.

[9] "So What Exactly Is This 'Grid Edge' Thing, Anyway? June. 2016," *Alliance to Save Energy*, Jun. 20, 2016. https://www.ase.org/blog/so-what-exactly-grid-edge-thing-anyway.

[10] A. Q. Huang, "Medium-Voltage Solid-State Transformer: Technology for a Smarter and Resilient Grid," *IEEE Ind. Electron. Mag.*, vol. 10, no. 3, pp. 29–42, Sep. 2016, doi: 10.1109/MIE.2016.2589061.

[11] "Rule 21 Interconnection, CA.GOV." http://www.cpuc.ca.gov/Rule21/.

[12] K. Garbesi, "Optimizing Energy Savings from Direct-DC in U.S. Residential Buildings. Lawrence Berkeley National Laboratory. 2012. [Online] Available: http://escholarship.org/uc/item/66c8n9s8.," Jul. 2012, Accessed: Aug. 15, 2018. [Online]. Available: https://escholarship.org/uc/item/66c8n9s8.

[13] "Costs and benefits of electric cars vs. conventional vehicles, EnergySage, 2018." https://www.energysage.com/electric-vehicles/costs-and-benefits-evs/evs-vs-fossil-fuel-vehicles/.

[14] "Mike Salisbury, Will Toor, How Leading Utilities are Embracing Electric Vehicles, Southwest Energy Efficiency Project, 2016." Accessed: Aug. 15, 2018. [Online]. Available: https://www.swenergy.org/data/sites/1/media/documents/publications/documents/How_Leading_Utilities_Are_Embracing_EVs_Feb-2016.pdf.

[15] C. M. Macal and M. J. North, "Agent-Based Modeling and Simulation," *Proc. 2009 Winter Simul. Conf.*, pp. 86–98.

[16] K. S. Chaudhari, N. K. Kandasamy, A. Krishnan, A. Ukil, and H. B. Gooi, "Agent Based Aggregated Behavior Modelling For Electric Vehicle Charging Load," *IEEE Trans. Ind. Inform.*, pp. 1–1, 2018, doi: 10.1109/TII.2018.2823321.

[17] A. Dubey and S. Santoso, "Electric Vehicle Charging on Residential Distribution Systems: Impacts and Mitigations," *IEEE Access*, vol. 3, pp. 1871–1893, 2015, doi: 10.1109/ACCESS.2015.2476996.

[18] M. R. Sarker, D. J. Olsen, and M. A. Ortega-Vazquez, "Co-Optimization of Distribution Transformer Aging and Energy Arbitrage Using Electric Vehicles," *IEEE Trans. Smart Grid*, vol. 8, no. 6, pp. 2712–2722, Nov. 2017, doi: 10.1109/TSG.2016.2535354.

[19] K. Clement-Nyns, E. Haesen, and J. Driesen, "The Impact of Charging Plug-In Hybrid Electric Vehicles on a Residential Distribution Grid," *IEEE Trans. Power Syst.*, vol. 25, no. 1, pp. 371–380, Feb. 2010, doi: 10.1109/TPWRS.2009.2036481.

[20] "A Comprehensive Guide to EV Managed Charging," SEPA, May 2019.

[21] D. Hall and N. Lutsey, "Literature Review on Power Utility Best Practices Regarding Electric Vehicles," *ICCT White Pap.*, Feb. 2017.

[22] Y. Mou, H. Xing, Z. Lin, and M. Fu, "Decentralized Optimal Demand-Side Management for PHEV Charging in a Smart Grid," *IEEE Trans. Smart Grid*, vol. 6, no. 2, pp. 726–736, Mar. 2015, doi: 10.1109/TSG.2014.2363096.

[23] S. Shao, M. Pipattanasomporn, and S. Rahman, "Grid Integration of Electric Vehicles and Demand Response With Customer Choice," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 543–550, Mar. 2012, doi: 10.1109/TSG.2011.2164949.

[24] J. Quirós-Tortós, L. F. Ochoa, S. W. Alnaser, and T. Butler, "Control of EV Charging Points for Thermal and Voltage Management of LV Networks," *IEEE Trans. Power Syst.*, vol. 31, no. 4, pp. 3028–3039, Jul. 2016, doi: 10.1109/TPWRS.2015.2468062.

[25] D. A. Gagne, D. E. Settle, A. Y. Aznar, and R. Bracho, "Demand Response Compensation Methodologies: Case Studies for Mexico," NREL/TP--7A40-71431, 1452706, Jun. 2018. doi: 10.2172/1452706.

[26] K. Kandhway, A. Vasan, S. Nagarathinam, V. Sarangan, and A. Sivasubramaniam, "Incentive Design for Demand-Response Based on Building Constraints: A Utility Perspective," in *Proceedings of the 4th ACM International Conference on Systems for Energy-Efficient Built Environments - BuildSys '17*, Delft, Netherlands, 2017, pp. 1–10, doi: 10.1145/3137133.3137142.

[27] "Customer Acceptance, Retention, and Response to Time-Based Rates from the Consumer Behavior Studies," U.S. Deparment of Energy, Nov. 2016. Accessed: Nov. 15, 2019. [Online]. Available: https://www.energy.gov/sites/prod/files/2016/12/f34/CBS_Final_Program_Impact_Report_Draft_20161101_0.pdf.

[28] "Dynamic Programming, https://www.slideshare.net/paramalways/dynamic-programming," [Online]. Available: https://www.slideshare.net/paramalways/dynamic-programming.

[29] S. Sarabi and L. Kefsi, "Electric vehicle charging strategy based on a dynamic programming algorithm," in *2014 IEEE International Conference on Intelligent Energy and Power Systems (IEPS)*, Jun. 2014, pp. 1–5, doi: 10.1109/IEPS.2014.6874180.

[30] F. Hafiz, P. Fajri, and I. Husain, "Load regulation of a smart household with PV-storage and electric vehicle by dynamic programming successive algorithm technique," in *2016 IEEE Power and Energy Society General Meeting (PESGM)*, Jul. 2016, pp. 1–5, doi: 10.1109/PESGM.2016.7741717.

[31] M. Wakefield, "Methodological Approach for Estimating the Benefits and Costs of Smart Grid Demonstration Projects," *Electr. Power Res. Inst. EPRI*, p. 178, 2010.

[32] X. Mamo, S. Mallet, T. Coste, and S. Grenard, "Distribution automation: The cornerstone for smart grid development strategy," in *2009 IEEE Power Energy Society General Meeting*, Jul. 2009, pp. 1–6, doi: 10.1109/PES.2009.5275540.

[33] "Impacts of Power Penetration from Photovoltaic Power Systems in distribution networks, International Energy Agency, Feb. 2002." Accessed: Aug. 16, 2018. [Online]. Available: http://www.hme.ca/gridconnect/IEA_PVPS_Task_5-10_Impacts_of_PV_Power_Penetration.pdf.

[34] R. Seguin, J. Woyak, D. Costyk, J. Hambrick, and B. Mather, "High-Penetration PV Integration Handbook for Distribution Engineers," NREL/TP--5D00-63114, 1235905, Jan. 2016. doi: 10.2172/1235905.

[35] P. Denholm *et al.*, "Methods for Analyzing the Benefits and Costs of Distributed Photovoltaic Generation to the U.S. Electric Utility System," NREL/TP-6A20-62447, 1159357, Sep. 2014. doi: 10.2172/1159357.

[36] X. Zhu *et al.*, "Voltage-load sensitivity matrix based demand response for voltage control in high solar penetration distribution feeders," in *2017 IEEE Power Energy Society General Meeting*, Jul. 2017, pp. 1–5, doi: 10.1109/PESGM.2017.8273887.

[37] Q. Nguyen, H. V. Padullaparti, K.-W. Lao, S. Santoso, X. Ke, and N. Samaan, "Exact Optimal Power Dispatch in Unbalanced Distribution Systems With High PV Penetration," *IEEE Trans. Power Syst.*, vol. 34, no. 1, pp. 718–728, Jan. 2019, doi: 10.1109/TPWRS.2018.2869195.

[38] S. Hall and T. J. Foxon, "Values in the Smart Grid: The co-evolving political economy of smart distribution," *Energy Policy*, vol. 74, pp. 600–609, Nov. 2014, doi: 10.1016/j.enpol.2014.08.018.

[39] L. Zhou, F. Li, C. Gu, Z. Hu, and S. L. Blond, "Cost/Benefit Assessment of a Smart Distribution System With Intelligent Electric Vehicle Charging," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 839–847, Mar. 2014, doi: 10.1109/TSG.2013.2282707.

[40] A. Q. Huang, M. L. Crow, G. T. Heydt, J. P. Zheng, and S. J. Dale, "The Future Renewable Electric Energy Delivery and Management (FREEDM) System: The Energy Internet," *Proc. IEEE*, vol. 99, no. 1, pp. 133–148, Jan. 2011, doi: 10.1109/JPROC.2010.2081330.

[41] A. Q. Huang, Q. Zhu, L. Wang, and L. Zhang, "15 kV SiC MOSFET: An enabling technology for medium voltage solid state transformers," *CPSS Trans. Power Electron. Appl.*, vol. 2, no. 2, pp. 118–130, 2017, doi: 10.24295/CPSSTPEA.2017.00012.

[42] Q. Zhu, L. Wang, D. Chen, L. Zhang, and A. Q. Huang, "Design and implementation of a 7.2kV single stage AC-AC solid state transformer based on current source series resonant converter and 15 kV SiC MOSFET," in *2017 IEEE Energy Conversion Congress and Exposition (ECCE)*, Oct. 2017, pp. 1288–1295, doi: 10.1109/ECCE.2017.8095938.

[43] X. Song, C. Peng, and A. Q. Huang, "A Medium-Voltage Hybrid DC Circuit Breaker, Part I: Solid-State Main Breaker Based on 15 kV SiC Emitter Turn-OFF Thyristor," *IEEE J. Emerg. Sel. Top. Power Electron.*, vol. 5, no. 1, pp. 278–288, Mar. 2017, doi: 10.1109/JESTPE.2016.2609845.

[44] C. Peng, X. Song, A. Q. Huang, and I. Husain, "A Medium-Voltage Hybrid DC Circuit Breaker—Part II: Ultrafast Mechanical Switch," *IEEE J. Emerg. Sel. Top. Power Electron.*, vol. 5, no. 1, pp. 289–296, Mar. 2017, doi: 10.1109/JESTPE.2016.2609391.

[45] R. C. Dugan, D. Montenegro, and A. Ballanti, "Reference Guide, the Open Distribution System Simulator (OpenDSS), Electrical Power Research Institute, 2016.," p. 199, 2018.

[46] J. E. Huber and J. W. Kolar, "Volume/weight/cost comparison of a 1MVA 10 kV/400 V solid-state against a conventional low-frequency distribution transformer," in *2014 IEEE Energy Conversion Congress and Exposition (ECCE)*, Sep. 2014, pp. 4545–4552, doi: 10.1109/ECCE.2014.6954023.

[47] I. Mareels, J. de Hoog, and V. Muenzel, "Valentin Muenzel, Iven Mareels, Julian de Hoog, 'Affordable batteries for green energy are closer than we think', (2014)," *The Conversation*. http://theconversation.com/affordable-batteries-for-green-energy-are-closer-than-we-think-28772.

[48] A. Mills and R. Wiser, "Changes in the Economic Value of Variable Generation at High Penetration Levels: A Pilot Case Study of California," LBNL--5445E, 1183176, May 2012. doi: 10.2172/1183176.

[49] H. R. Varian, *H.R. Varian, "Microeconomic Analysis", 3rd Edition, W. W. Norton & Company, 1992*, 3rd ed. New York: Norton, 1992.

[50] "Arizona Public Service (2013). 2013 Updated Solar PV Value Report. Tysons Corner." http://appsrv.pace.edu/voscoe/?do=viewFullResource&resID=GSPA5080416023725.

[51] "Energy and Environmental Economics, Inc (2014) Evaluation of Hawaii's Renewable Energy Policy and Procurement. San Francisco, CA, [Online], Available: https://puc.hawaii.gov/wp-content/uploads/2013/04/HIPUC-Final-Report-January-2014-Revision.pdf." Accessed: Aug. 16, 2018. [Online]. Available: https://puc.hawaii.gov/wp-content/uploads/2013/04/HIPUC-Final-Report-January-2014-Revision.pdf.

[52] "Electric Energy Efficiency Potential for Pennsylvania, Final Report, Prepared for Pennsylvania Public Utility Commission, 2012." Accessed: Aug. 16, 2018. [Online]. Available: http://www.puc.state.pa.us/Electric/pdf/Act129/SWE_EE_Potential_Study-No_Appendices.pdf.

[53] D. J. M. Antonio Apap, "A Survey of Capital Budgeting in Publicly Traded Utility Companies," p. 8.

[54] "EIA adds small-scale solar photovoltaic forecasts to its monthly Short-Term Energy Outlook - Today in Energy - U.S. Energy Information Administration (EIA)." https://www.eia.gov/todayinenergy/detail.php?id=31992.

[55] F. Ding, B. Mather, and P. Gotseff, "Technologies to increase PV hosting capacity in distribution feeders," in *2016 IEEE Power and Energy Society General Meeting (PESGM)*, Jul. 2016, pp. 1–5, doi: 10.1109/PESGM.2016.7741575.

[56] "Modeling High-Penetration PV for Distribution Interconnection Studies: Smart Inverter Function Modeling in OpenDSS, Rev. 2," p. 76.

[57] "PV Performance Modeling Collaborative | CEC Inverter Test Protocol." https://pvpmc.sandia.gov/modeling-steps/dc-to-ac-conversion/cec-inverter-test-protocol/.

[58] "Database of State Incentives for Renewables & Efficiency, North Carolina Clean Energy Technology Center (NCCETC). 2017," *DSIRE*. http://www.dsireusa.org/.

[59] T. Taufik and M. Muscarella, "Development of DC house prototypes as demonstration sites for an alternate solution to rural electrification," in *2016 6th International Annual Engineering Seminar (InAES)*, Aug. 2016, pp. 262–265, doi: 10.1109/INAES.2016.7821945.

[60] N. C. Sahoo, S. Mohapatro, A. K. Sahu, and B. S. Mohapatro, "Loss and cost evaluation of typical DC distribution for residential house," in *2016 IEEE International Conference on Power and Energy (PECon)*, Nov. 2016, pp. 668–673, doi: 10.1109/PECON.2016.7951644.

[61] "Emerge Alliance." https://www.emergealliance.org/Standards/OccupiedSpace/StandardFAQs.aspx.

[62] Jiahong Yan, Xiangqi Zhu, and Ning Lu, "Smart hybrid house test systems in a solid-state transformer supplied microgrid," in *2015 IEEE Power Energy Society General Meeting*, Jul. 2015, pp. 1–5, doi: 10.1109/PESGM.2015.7286550.

[63] L. Sun, D. Lubkeman, and M. Baran, "Levelized Cost Analysis of Medium Voltage DC Fast Charging Station," in *2019 IEEE Power Energy Society General Meeting (PESGM)*, Aug. 2019, pp. 1–5, doi: 10.1109/PESGM40551.2019.8973498.

[64] "Commercial and Residential Hourly Load Profiles for all TMY3 Locations in the United States - OpenEI DOE Open Data." https://openei.org/doe-opendata/dataset/commercial-and-residential-hourly-load-profiles-for-all-tmy3-locations-in-the-united-states.

[65] "National Solar Radiation Data Base, NSRDB: 1991- 2005, Typical Meteorological Year 3, National Renewable Energy Laboratory (NREL)." https://rredc.nrel.gov/solar/old_data/nsrdb/1991-2005/tmy3/.

[66] S. Joshi, V. Pandya, and B. Bhalja, "Maximum Power Point Tracking and MPPT efficiency for wind and solar energy conversion standalone system," in *2014 Annual IEEE India Conference (INDICON)*, Dec. 2014, pp. 1–6, doi: 10.1109/INDICON.2014.7030544.

[67] "Tesla Charging." https://www.tesla.com/charging.

[68] N. Bodo, E. Levi, I. Subotic, J. Espina, L. Empringham, and C. M. Johnson, "Efficiency Evaluation of Fully Integrated On-Board EV Battery Chargers With Nine-Phase Machines," *IEEE Trans. Energy Convers.*, vol. 32, no. 1, pp. 257–266, Mar. 2017, doi: 10.1109/TEC.2016.2606657.

[69] P. Dost, A. Bouabana, and C. Sourkounis, "On analysis of electric vehicles DC-quick-chargers based on the CHAdeMO protocol regarding the connected systems and security behaviour," in *IECON 2014 - 40th Annual Conference of the IEEE Industrial Electronics Society*, Oct. 2014, pp. 4492–4497, doi: 10.1109/IECON.2014.7049179.

[70] Y. Hayashi, D. Takai, and A. Matsumoto, "Multi-cell rectifier using GaN-FET for highly efficient next generation 380-V dc distribution system," in *2015 IEEE International Telecommunications Energy Conference (INTELEC)*, Oct. 2015, pp. 1–6, doi: 10.1109/INTLEC.2015.7572470.

[71] F. Xue, R. Yu, and A. Q. Huang, "A 98.3% Efficient GaN Isolated Bidirectional DC–DC Converter for DC Microgrid Energy Storage System Applications," *IEEE Trans. Ind. Electron.*, vol. 64, no. 11, pp. 9094–9103, Nov. 2017, doi: 10.1109/TIE.2017.2686307.

[72] S. Guo, P. Liu, L. Zhang, and A. Q. Huang, "Design and optimization of the high frequency transformer for a 800V/1.2MHz SiC LLC resonant converter," in *2017 IEEE Energy Conversion Congress and Exposition (ECCE)*, Oct. 2017, pp. 5317–5323, doi: 10.1109/ECCE.2017.8096892.

[73] L. Zhu, H. Wu, T. Mu, F. Yang, and X. Ma, "An asymmetrical three-level dual-input bidirectional DC/AC converter with improved conversion efficiency for vehicle-to-grid application," in *2017 IEEE Applied Power Electronics Conference and Exposition (APEC)*, Mar. 2017, pp. 2062–2067, doi: 10.1109/APEC.2017.7930983.

[74] F. Chen, R. Burgos, and D. Boroyevich, "Efficiency comparison of a single-phase grid-interface bidirectional AC/DC converter for DC distribution systems," in *2015 IEEE Energy Conversion Congress and Exposition (ECCE)*, Sep. 2015, pp. 6261–6268, doi: 10.1109/ECCE.2015.7310538.

[75] R. Fu, D. Chung, T. Lowder, D. Feldman, K. Ardani, and R. Margolis, "U.S. Solar Photovoltaic System Cost Benchmark: Q1 2016," *Renew. Energy*, p. 48, 2016.

[76] "How is electricity used in U.S. homes? - FAQ - U.S. Energy Information Administration (EIA) 2016." https://www.eia.gov/tools/faqs/faq.php?id=96&t.

[77] M. Salisbury and W. Toor, "How Leading Utilities Are Embracing Electric Vehicles," Southwest Energy Efficiency Project, Feb. 2016. [Online]. Available: https://www.swenergy.org/data/sites/1/media/documents/publications/documents/How_Leading_Utilities_Are_Embracing_EVs_Feb-2016.pdf.

[78] Y. Mu, J. Wu, N. Jenkins, H. Jia, and C. Wang, "A Spatial–Temporal Model for Grid Impact Analysis of Plug-in Electric Vehicles," *Appl. Energy*, vol. 114, pp. 456–465, Feb. 2014, doi: 10.1016/j.apenergy.2013.10.006.

[79] A. Priessner, R. Sposato, and N. Hampl, "Predictors of Electric Vehicle Adoption: An Analysis of Potential Electric Vehicle Drivers in Austria," *Energy Policy*, vol. 122, pp. 701–714, Nov. 2018, doi: 10.1016/j.enpol.2018.07.058.

[80] R. J. Javid and A. Nejat, "A Comprehensive Model of Regional Electric Vehicle Adoption and Penetration," *Transp. Policy*, vol. 54, pp. 30–42, Feb. 2017, doi: 10.1016/j.tranpol.2016.11.003.

[81] A. Soltani-Sobh, K. Heaslip, A. Stevanovic, R. Bosworth, and D. Radivojevic, "Analysis of the Electric Vehicles Adoption over the United States," *Transp. Res. Procedia*, vol. 22, pp. 203–212, 2017, doi: 10.1016/j.trpro.2017.03.027.

[82] J. L. Rodrigues, H. M. Bolognesi, J. D. Melo, F. Heymann, and F. J. Soares, "Spatiotemporal Model for Estimating Electric Vehicles Adopters," *Energy*, vol. 183, pp. 788–802, Sep. 2019, doi: 10.1016/j.energy.2019.06.117.

[83] F. Heymann, C. Pereira, V. Miranda, and F. J. Soares, "Spatial Load Forecasting of Electric Vehicle Charging using GIS and Diffusion Theory," in *2017 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe)*, Sep. 2017, pp. 1–6, doi: 10.1109/ISGTEurope.2017.8260172.

[84] C. M. Macal and M. J. North, "Tutorial on Agent-Based Modelling and Simulation," *J. Simul.*, vol. 4, no. 3, pp. 151–162, Sep. 2010, doi: 10.1057/jos.2010.3.

[85] A. Hoekstra and P. Hogeveen, "Agent-based Model for the Adoption and Impact of Electric Vehicles in Real Neighbourhoods," *EVS30 Symp. Stuttg. Ger.*, Oct. 2017.

[86] W. Yang, Y. Xiang, J. Liu, and C. Gu, "Agent-Based Modeling for Scale Evolution of Plug-in Electric Vehicles and Charging Demand," *IEEE Trans. Power Syst.*, vol. 33, no. 2, pp. 1915–1925, Mar. 2018, doi: 10.1109/TPWRS.2017.2739113.

[87] A. Kangur, W. Jager, R. Verbrugge, and M. Bockarjova, "An Agent-based Model for Diffusion of Electric Vehicles," *J. Environ. Psychol.*, vol. 52, pp. 166–182, Oct. 2017, doi: 10.1016/j.jenvp.2017.01.002.

[88] D. Chaoxing, "Exploring EV Adoption Using An Agent-based Modeling Approach," Master Thesis, TU Eindhoven, 2017.

[89] A. Ahkamiraad and Y. Wang, "An Agent-Based Model for Zip-Code Level Diffusion of Electric Vehicles and Electricity Consumption in New York City," *Energies*, vol. 11, no. 3, p. 640, Mar. 2018, doi: 10.3390/en11030640.

[90] T. L. Saaty, "Decision Making With The Analytic Hierarchy Process," *Int. J. Serv. Sci.*, vol. 1, no. 1, p. 83, 2008, doi: 10.1504/IJSSCI.2008.017590.

[91] C. Macharis, J. Springael, K. De Brucker, and A. Verbeke, "PROMETHEE and AHP: The Design of Operational Synergies in Multicriteria Analysis.: Strengthening PROMETHEE with Ideas of AHP," *Eur. J. Oper. Res.*, vol. 153, no. 2, pp. 307–317, Mar. 2004, doi: 10.1016/S0377-2217(03)00153-X.

[92] A. Bento, K. Roth, and Y. Zuo, "Vehicle Lifetime Trends and Scrappage Behavior in the U.S. Used Car Market," *Energy J. Int. Assoc. Energy Econ.*, Jan. 2016.

[93] "2017 National Household Travel Survey," U.S. Department of Transportation, Federal Highway Administration. [Online]. Available: https://nhts.ornl.gov/.

[94] H. He, Y. Bai, E. A. Garcia, and S. Li, "ADASYN: Adaptive Synthetic Sampling Approach for Imbalanced Learning," in *2008 IEEE International Joint Conference on Neural Networks (IEEE World Congress on Computational Intelligence)*, Jun. 2008, pp. 1322–1328, doi: 10.1109/IJCNN.2008.4633969.

[95] Nic Lutsey and Michael Nicholas, "Update on Electric Vehicle Costs in the United States Through 2030," *ICCT Work. Pap.*, Jun. 2019, [Online]. Available: http://www.mdpi.com/1996-1073/10/9/1314.

[96] L. Reynolds, "Duke Energy Electric Transportation Presentation," Nov. 2017, [Online]. Available: https://www.ncleg.gov/documentsites/committees/BCCI-6576/2017-2018/Nov%208%202017/Duke%20Energy%20Presentation.pdf.

[97] "Source: Pecan Street Inc. Dataport 2019." https://dataport.pecanstreet.org/.

[98] "Electric Vehicle Charging Stations and Viewlet | raleighnc.gov." https://www.raleighnc.gov/environment/content/AdminServSustain/Articles/PublicEVChargingStations.html.

[99] "IEEE Guide for Loading Mineral-Oil-Immersed Transformers and Step-Voltage Regulators," *IEEE Std C5791-2011*, pp. 1–123, Mar. 2012, doi: 10.1109/IEEESTD.2012.6166928.

[100] "Electric System Transmission and Distribution Planning Study," R. W. BECK, Utilities Commission City of New Smyrna Beach, May 2006.

[101] R. C. Dugan, D. Montenegro, and A. Ballanti, "The Open Distribution System Simulator (OpenDSS)," p. 214, 2019.

[102] "United States | Energy Policy Solutions." https://us.energypolicy.solutions/scenarios/home.

[103] K. Horowitz, F. Ding, B. Mather, and B. Palmintier, "The Cost of Distribution System Upgrades to Accommodate Increasing Penetrations of Distributed Photovoltaic Systems on Real Feeders in the United States," National Renewable Energy Laboratory, 2018. [Online]. Available: https://www.nrel.gov/docs/fy18osti/70710.pdf.

[104] "Charging at Home," *Energy.gov*. https://www.energy.gov/eere/electricvehicles/charging-home.

[105] X. Ke, D. Wu, and N. Lu, "A Real-Time Greedy-Index Dispatching Policy for Using PEVs to Provide Frequency Regulation Service," IEEE Trans. Smart Grid, vol. 10, no. 1, pp. 864–877, Jan. 2019, doi: 10.1109/TSG.2017.2754241.

[106] D. Wu, X. Ke, N. Radhakrishnan, and A. Reiman, "Optimization Methods for Evaluating PEV Charging Considering Customer Behavior," in 2018 IEEE Power Energy Society General Meeting (PESGM), Aug. 2018, pp. 1–5, doi: 10.1109/PESGM.2018.8586401.

[107] P. S. Georgilakis and N. D. Hatziargyriou, "A review of power distribution planning in the modern power systems era: Models, methods and future research," Electr. Power Syst. Res., vol. 121, pp. 89–100, Apr. 2015, doi: 10.1016/j.epsr.2014.12.010.

[108] R. H. Fletcher and K. Strunz, "Optimal Distribution System Horizon Planning - Part I: Formulation," IEEE Trans. Power Syst., vol. 22, no. 2, pp. 791–799, May 2007, doi: 10.1109/TPWRS.2007.895173.

[109] K. Masteri, B. Venkatesh, and W. Freitas, "A Feeder Investment Model for Distribution System Planning Including Battery Energy Storage," Can. J. Electr. Comput. Eng., vol. 41, no. 4, pp. 162–171, Fall 2018, doi: 10.1109/CJECE.2018.2865176.

[110] J. M. Eyer, "Electric Utility Transmission and Distribution Upgrade Deferral Benefits from Modular Electricity Storage : A Study for the DOE Energy Storage Systems Program.," SAND2009-4070, 966946, Jun. 2009. doi: 10.2172/966946.

[111] P. K. Sen, “Transformer Overloading and Assessment of Loss-of-Life for Liquid-Filled Transformers,” Power Syst. Eng. Res. Cent., p. 5, Feb. 2011.

[112] H. L. Willis, Power Distribution Planning Reference Book. CRC Press, 1997.

[113] “Energy Efficiency Potential Study For Pennsylvania,” 2015. Accessed: Nov. 17, 2019. [Online]. Available: http://www.puc.pa.gov/pcdocs/1345079.pdf.

[114] W. L. Winston and J. B. Goldberg, Operations Research: Applications and Algorithms, 4th ed. Belmont, CA: Thomson/Brooks/Cole, 2004.