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Publication Date
2020-09-17

Peer reviewed

Electricity Markets & Policy
Energy Analysis & Environmental Impacts Division
Lawrence Berkeley National Laboratory

Indiana 21st Century Energy Policy: Emerging Technologies on the Electricity Distribution System

Impact on Rates, Reliability, and Resilience

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June 2020

This work was commissioned by the Indiana Utility Regulatory Commission to Lawrence Berkeley National Laboratory under Strategic Partnership Projects Agreement No. FP00009789.

Acknowledgements

The work described in this study was funded by the Indiana Utility Regulatory Commission (IURC) under Strategic Partnership Projects Agreement No. FP00009789. We would like to acknowledge helpful feedback provided by the staff at the IURC: Brad Borum, Bob Pauley, Dale Thomas, Ryan Heater, and Ryan Hadley. We would also like to acknowledge staff at five utilities that provided critical data, useful information, and constructive feedback: Alison Becker, Mark Pallok, and Chad Richwalski (NIPSCO); Matt Fields, Jake Allen, and Justin Sufan (IP&L); Justin Hage, Matthew Rice, Heather Watts, Jason Stephenson, and Ryan Abshier (Vectren); Regiana Sistevaris, Marc Lewis, and Rod Walter (I&M); and Beth Herriman and Nancy Gay (Duke Energy). We would also like to thank Doug Gotham and the staff at Purdue University's State Utility Forecasting Group for their excellent and timely research support. We are grateful for valuable feedback provided by Joachim Seel and Nichole Hanus (LBNL), and Larry Conrad (Conrad Technical Services). All errors and omissions are the responsibility of the authors.

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Acronyms and Abbreviations

ANSI	American National Standards Institute
BAU	Business As Usual
BPS	Bulk Power System
CAIDI	Customer Average Interruption Duration Index
CCCT	Combined Cycle Combustion Turbine
CMI	Customer Minutes Interrupted
DER	Distributed Energy Resources
DG	Distributed Generation
DSM	Distribution Side Management
EE	Energy Efficiency
EV	Electric Vehicle
IEEE	Institute of Electrical and Electronics Engineers
IOU	Investor Owned Utility
IRP	Integrated Resource Plan/Planning
ISO	Independent System Operator
IURC	Indiana Utility Regulatory Commission
LBNL	Lawrence Berkeley National Laboratory
LTC	Load Tap Changer
MED	Major Event Day
MISO	Midcontinent Independent System Operator
NREL	National Renewable Energy Laboratory
PAM	Partitioning Around Medoids
PCA	Principal Component Analysis
PV	Photovoltaic (solar panel)
SEIA	Solar Energy Industry Association
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
SCCT	Simple Cycle Combustion Turbine
SUFG	State Utility Forecasting Group

Glossary

Capacity expansion model: an optimization model of the power system that determines least-cost investment decisions in generation assets to meet resource adequacy requirements over time for a given region.

Feeder: the electrical network operating in primary distribution voltage (typically between 4 kV and 33 kV) that electrically connects the secondary busbar in the transmission substation to distribution step-down transformers.

Line loading: the ratio between the average current flow over a period of time and the ampacity (maximum current, in amperes, that a conductor can carry continuously under the conditions of use without exceeding its temperature rating) of a conductor. A line overloading occurs when the current flow is above the rated ampacity.

Power flow simulation: numerical analysis or simulation of the flow of electricity in an interconnected grid.

Reliability: "The probability that the system will perform its intended function for a given period of time under stated environmental conditions" (Singh and Billinton, 1977)

Resilience: "[T]he ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions. Resilience includes the ability to withstand and recover from deliberate attacks, accidents, or naturally occurring threats or incidents." (PPD, 2013)

Voltage violation: a condition of the distribution system where voltage in any node is below or above an established limit, usually the America National Standard Institute's optimal and normal levels.

Executive Summary

In 2019, the Indiana General Assembly enacted House Enrolled Act No. 1278 to explore the impact that fuel transitions and emerging technologies may have on the state's power system. The Act created the 21st Century Energy Policy Development Task Force, whose work will be informed by a comprehensive study to be conducted by the Indiana Utility Regulatory Commission. As indicated in the Act:

> *"[…] the commission shall conduct a comprehensive study of the statewide impacts, both in the near term and on a long term basis, of:*
>
> *(1) transitions in the fuel sources and other resources used to generate electricity by electric utilities; and*
>
> *(2) new and emerging technologies for the generation of electricity, including the potential impact of such technologies on local grids or distribution infrastructure;*
>
> *on electric generation capacity, system reliability, system resilience, and the cost of electric utility service for consumers. In conducting the study required by this subsection, the commission shall consider the likely timelines for the transitions in fuel sources and other resources described in subdivision (1) and for the implementation of new and emerging technologies described in subdivision (2)."*

The study presented here explores the impacts of emergent technologies that could be deployed across Indiana investor owned utility distribution systems by 2025 and 2040. The statutory task mandated in the Act is broken down in three components: the physical impact on distribution, transmission, and generation capacity; the economic and rate impact on customers; and the reliability and resilience impacts on the distribution system.

This study identifies six adoption scenarios that combine deployment levels of rooftop solar (PV), electric vehicle charging (EV), and battery storage—collectively referred to as DER—in residential and commercial customers connected to Indiana IOU feeders. Five of the adoption scenarios implement a range of expected to optimistic deployment of these resources, while a sixth scenario is presented as a stress-test with very high adoption levels. Figure ES-1 shows 2040 DER penetration by share of customers for each scenario. By 2040, for example, rooftop PV penetration ranges from 0.5% of customers (Base) to nearly 20% (Boundary). In addition, the Boundary scenario assumes over 70% of residential customers will charge EVs in their homes by 2040, compared to 10% in the Base scenario.

This study develops and employs an empirical framework that measures the impact of emerging distributed technologies on the power system for the six scenarios. The framework measures the technical, economic value, and reliability impact of DER:

- The economic value of DER is assessed by developing technical assessments employing capacity expansion and power flow analysis of the generation and distribution segments, respectively, under future hourly demand assumptions based on the six adoption scenarios. The assessment of generation energy and capacity impacts uses State Utility Forecasting Group (SUFG) modeling platform to simulate optimal production and expansion costs. The assessment of distribution impacts employs the industry-standard Cymdist distribution power flow model with an array of strategies to upgrade feeders to address voltage, line loading, and energy losses issues. A simplified model for transmission expansion complements the two technical tools to estimate the economic impact of DER on the three power system segments.

- The reliability impact of DER adoption is measured using a pioneering method first developed for this study. We use a data set of over half a million of historical outages across the five Indiana IOUs to inform this measurement. The method simulates the impact of different levels of behind-the-meter battery storage adoption, with several operational strategies, to reduce the frequency and duration of outages less than 24-hours long from the customer's perspective. This analysis is complemented with an assessment of the impacts of DER on reducing long-duration (more than 24 hours) interruptions as an initial measure of resilience impacts on the distribution system.

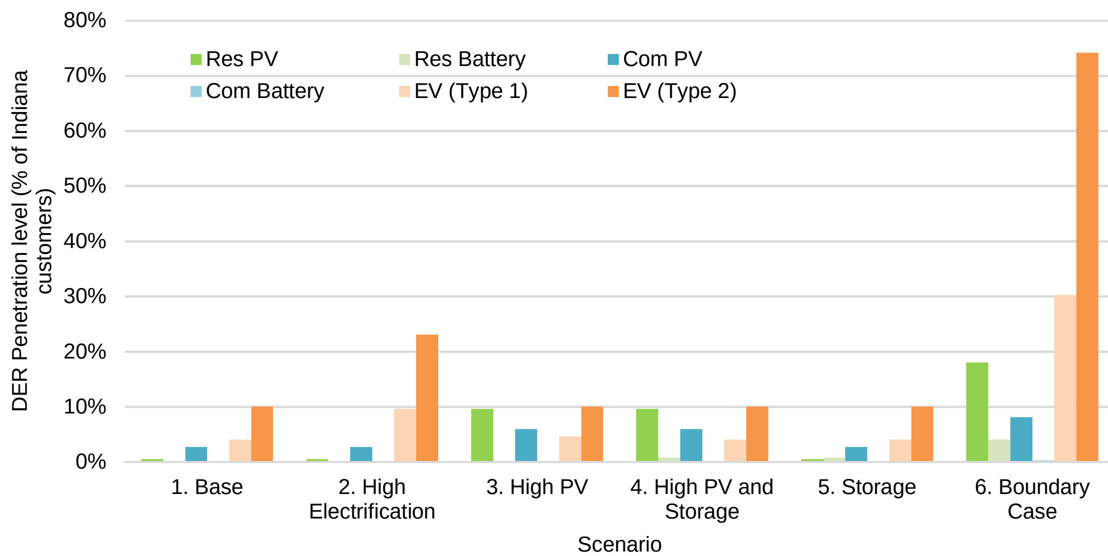

Figure ES-1 DER penetration levels in 2040 for the six adoption scenarios

This study uses statistical techniques to classify over 2,800 feeders across Indiana into one of six groups that represent different types of feeders based on their customer mix, length, reliability, and other variables. Representative feeders from each group are selected to run power flow analyses for DER impacts on distribution systems, which can then be extrapolated to produce state-wide results.

Do these emerging technologies lead to increased voltage violations, line loading, and line losses and, if so, how can these impacts be mitigated?

Results for the distribution system power flow simulations show that voltage violations are relatively rare. Only 159 out of 3,456 simulated hours exhibit voltage violations of the ANSI optimal range levels, generally spanning a relatively small fraction of load nodes in a feeder. The majority of voltage issues arise only in the Boundary Case and the violations are relatively small in magnitude. Voltage violations can be mitigated at a very low cost using a combination of smart inverters in future rooftop PV systems and voltage adjustments in the feeder heads. Line loading issues are minimal, with only eight simulation hours showing loading levels above 100% of capacity in about 3% of segments for feeders in clusters 3, 4, and 5. Line loading issues are addressed by upgrading conductors with relatively low costs given the few affected segments. Line losses are ~4%-10% higher than the Base case in the High Electrification and Boundary scenarios and 11% lower than the Base case in the High PV and High PV and Storage scenarios. Energy losses are not mitigated in this analysis, but monetized using the wholesale generation power costs that are output by the SUFG model.

What is the economic and rate impact of more widespread deployment of DER within the IOU service territories?

We estimate that the incremental economic impact on power system investment and operation costs of increased DER adoption within the IOU service territories will be between -$265 million to +$105 million and -$550 million to +$1.6 billion in 2025 and 2040 relative to the Base Case, respectively (see Tables ES-1 and ES-2). In general, scenarios with high adoption of rooftop solar result in system-wide savings, while scenarios with high adoption and charging of electric vehicles result in large peaks that require substantial new generation capacity and higher system costs. The economic impacts of DER in the power system are concentrated in the generation segment, with about 80% of the cost impacts. It is important to note that the results only account for the infrastructure requirements to maintain resource adequacy and operational standards—they do not account for avoided costs of power interruptions to customers.

Table ES-1 Economic impact of DER adoption by scenario and power system segment relative to the base case (millions of $2017)

	2025 Annual Cost Change Relative to Base				2040 Annual Cost Change Relative to Base			
Scenario	**Gen.**	**Trans.**	**Dist.**	**Total**	**Gen.**	**Trans.**	**Dist.**	**Total**
High Electrification	$79.1	$15.8	$10.7	$105.6	$204.0	$91.3	$25.9	$321.2
High PV	-$242.4	-$32.4	$9.7	-$265.2	-$485.5	-$71.9	$8.2	-$549.2
High PV and Storage	-$242.7	-$32.4	$9.7	-$265.5	-$481.6	-$70.6	$8.2	-$544.1
Storage	$1.7	$0.0	$10.6	$12.3	$2.6	$0.0	$10.6	$13.1
Boundary	-$18.6	$27.5	$10.0	$19.0	$759.7	$734.1	$94.1	$1,587.9

Table ES-2 Economic impact of DER adoption by scenario and power system segment relative to the base case (2017 cents/kWh)

	2025 Annual Cost Change Relative to Base				2040 Annual Cost Change Relative to Base			
Scenario	**Gen.**	**Trans.**	**Dist.**	**Total**	**Gen.**	**Trans.**	**Dist.**	**Total**
High Electrification	0.11¢	0.02¢	0.01¢	0.14¢	0.25¢	0.11¢	0.03¢	0.39¢
High PV	-0.34¢	-0.04¢	0.01¢	-0.37¢	-0.64¢	-0.09¢	0.01¢	-0.72¢
High PV and Storage	-0.34¢	-0.04¢	0.01¢	-0.37¢	-0.63¢	-0.09¢	0.01¢	-0.72¢
Storage	0.00¢	0.00¢	0.01¢	0.02¢	0.00¢	0.00¢	0.01¢	0.02¢
Boundary	-0.03¢	0.04¢	0.01¢	0.03¢	0.96¢	0.93¢	0.12¢	2.01¢

We estimate the impact of DER adoption in average retail rates using the SUFG ratemaking model (see Table ES-3). Rates tend to go down in the short term for the High PV scenarios, but tend to go up for all scenarios in the long term. The increase in rates is due to a combination of lower sales that require higher rates to recover fixed costs, as well as increased peak demand due to uncoordinated EV charging that requires additional generation and transmission infrastructure investments. On average, rates increase from 0.03 ¢/kWh to 1.7 ¢/kWh in the Boundary scenario.

Table ES-3 Impact of DER adoption on electricity rates by scenario and customer type (2017 cents/kWh).

	2025 Rate Change Relative to Base				2040 Rate Change Relative to Base			
Scenario	**Residential**	**Commercial**	**Industrial**	**Average**	**Residential**	**Commercial**	**Industrial**	**Average**
High Electrification	0.25¢	0.24¢	0.19¢	0.22¢	-0.03¢	0.05¢	0.14¢	0.06¢
High PV	-0.06¢	-0.10¢	-0.19¢	-0.13¢	1.01¢	0.73¢	0.23¢	0.59¢
High PV and Storage	-0.06¢	-0.10¢	-0.19¢	-0.13¢	1.00¢	0.71¢	0.22¢	0.58¢
Storage	0.00¢	0.00¢	0.00¢	0.00¢	0.05¢	0.05¢	0.01¢	0.03¢
Boundary	0.52¢	0.47¢	0.18¢	0.35¢	1.88¢	1.96¢	1.46¢	1.70¢

What are the reliability and resilience costs and/or benefits of emergent technologies in the distribution system?

Customer-sited battery storage systems can achieve multiple objectives related to improved reliability/resilience. When sized and operated appropriately, batteries can be used behind-the-meter for peak shaving or mitigating the PV 'duck curve' although their ability to mitigate power interruptions is limited. We find that reliability and resilience improvements are driven more by battery adoption levels than by mode of operation. We study battery storage adoption levels of 0.01% of customers (BAU), 1% of customers (High), 5% of customers (Very high), and 100% of residential and commercial customers (Theoretical Limit). The impact of these adoption levels on system-level average interruption duration (SAIDI) and frequency (SAIFI) and customer-average duration (CAIDI) are reported in Table ES-4. This analysis assumes that the battery discharge could only be consumed behind the meter. It is possible that larger system-wide benefits could be achieved if customer-sited batteries could discharge power back to the grid under direction from utility operations staff.

Table ES-4 Reliability metrics under different behind-the-meter battery storage adoption levels

		Behind-the-meter Battery Storage Adoption Levels			
		BAU	**High**	**Very High**	**Theoretical Limit**
Without MED	**SAIDI**	1.66	1.64	1.58	0.18
	SAIFI	0.81	0.80	0.77	0.08
	CAIDI	2.00	2.00	2.00	2.32
With MED	**SAIDI**	3.09	3.07	2.97	0.96
	SAIFI	0.90	0.89	0.86	0.12
	CAIDI	2.94	2.95	2.97	6.80

There are several definitions of resilience of the power system used in the literature. We define resilience as the capacity of a system to withstand long-duration interruptions – with a duration of over 24 hours. Figure ES-2 shows the number of long-duration customer-outages under the different battery storage adoption levels. These results show that even widespread adoption of relatively large battery storage systems would still leave 60% of long-duration outages unmitigated. Additional technologies and strategies would be needed to further improve resilience of the distribution system.

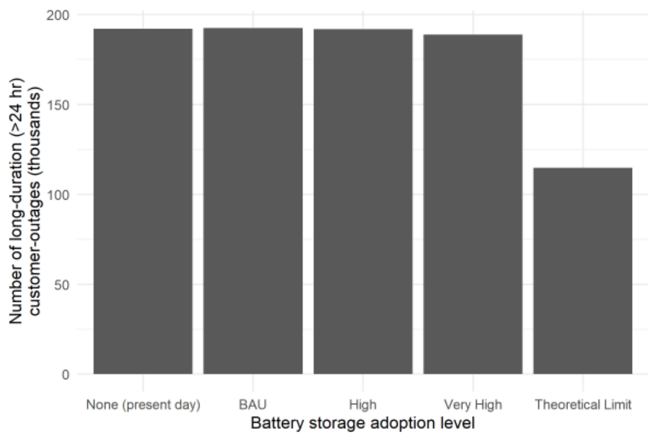

Figure ES-2 Number of long-duration customer-outages by battery adoption level

This report is one of the first manuscripts to estimate the economic impact of increased adoption of distributed technologies across the different segments of the power system—generation, transmission, and distribution—using a forward-looking simulation framework. This study is also novel in that it develops an empirically-based estimation of the impact of behind-the-meter battery storage adoption on reliability indices from the customer and grid operators' perspective. This report identifies a number of future research opportunities including:

- The investigation of impacts to secondary distribution networks.
- More targeted upgrade assessments for representative feeders that consider a wider range of expansion options to integrated DER.
- Estimating the economic value of avoiding power interruptions due to DER adoption.
- A more thorough examination of the impacts of DER adoption on transmission expansion using an optimization model with explicit transmission representation.
- Development and implementation of additional methods to measure and mitigate impacts on distribution system resilience, including integration of battery storage with demand management processes.

The framework developed for this report can serve as a blueprint for utilities, policymakers, and other stakeholders who may be interested in conducting more targeted and expansive technology adoption impact studies.

1. Introduction

In 2019, the Indiana General Assembly enacted House Enrolled Act No. 1278 to explore the impact that fuel transitions and emerging technologies may have on the state's power system. The Act created the 21st Century Energy Policy Development Task Force (see Indiana Code § 8-1-8.5-3.1 (b)), which is tasked with identifying energy policy recommendations for the House focused on affordability and reliability of future electric utility service. A comprehensive study of the impacts of fuel transitions and emerging technologies across Indiana is one of the key inputs for the Task Force.

The Indiana Utility Regulatory Commission (IURC) was tasked with producing a comprehensive study of the statewide impacts of fuel transitions and emerging technologies on generation capacity, reliability, resilience, and rates. As indicated in the Act:

> *"[…] the commission shall conduct a comprehensive study of the statewide impacts, both in the near term and on a long term basis, of:*
>
> *(1) transitions in the fuel sources and other resources used to generate electricity by electric utilities; and*
>
> *(2) new and emerging technologies for the generation of electricity, including the potential impact of such technologies on local grids or distribution infrastructure;*
>
> *on electric generation capacity, system reliability, system resilience, and the cost of electric utility service for consumers. In conducting the study required by this subsection, the commission shall consider the likely timelines for the transitions in fuel sources and other resources described in subdivision (1) and for the implementation of new and emerging technologies described in subdivision (2)."*

The IURC divided the technical aspects of the study into two components: (1) technology and fuel changes in generation-transmission and (2) and emerging technologies in distribution systems. Purdue University's State Utility Forecasting Group (SUFG) is leading the assessment of impacts on generation, while Lawrence Berkeley National Laboratory (LBNL) and Nexant, Inc. are leading the assessment of impacts of distributed technologies across the power system. The study presented here explores the impacts of emergent technologies that could be deployed across Indiana investor owned utility distribution systems by 2025 and 2040. The statutory task mandated in the Act is broken down in three components: the physical impact on distribution, transmission, and generation capacity; the economic and rate impact on customers; and the reliability and resilience impacts on the distribution system.

There are several types of emerging technologies that are being deployed or could be deployed in the distribution system and behind the meter. Technologies can produce electricity (e.g. solar photovoltaic (PV) panels, natural gas micro-turbines), store electricity (e.g. batteries, flywheels), consume electricity in novel ways (e.g. electric vehicles) and improve electricity management and consumption (e.g. smart thermostats, super-efficient appliances). These technologies are grouped and identified throughout this document as Distributed Energy Resources (DER). Given the current landscape in Indiana and the focus of the Task Force, this study is limited to the following DER: solar PV, battery storage, and electric vehicles, with some built in assumptions about availability and penetration of demand response and energy efficiency.

1.1 Distributed resource landscape

Over the last decade, the U.S. has seen increasing uptake of customer-owned DER, particularly rooftop PV. This increase has been driven by policies, prices, consumer attitudes, and attractive financing options for customers. Penetration levels vary by state. Figure 1.1 shows the percentage of small-scale PV generation as a portion of all generation by state. In 2019, four states showed percentages higher than six percent, with Hawaii greater than ten percent. Most states, including Indiana, were below one percent.

Battery storage is still an emerging technology and has not achieved widespread adoption. In 2019, less than 5 percent of solar PV systems were paired with storage. The Solar Energy Industry Association (SEIA) estimates that by 2025, 25 percent of new solar PV installations will be paired with a battery storage system (SEIA, 2020). The number of expected EVs by 2020 reported in the IOUs IRP was approximately 14,000 total in Indiana (Duke Energy, 2019; I&M, 2019; IPL, 2019; NIPSCO, 2018; Vectren, 2016).

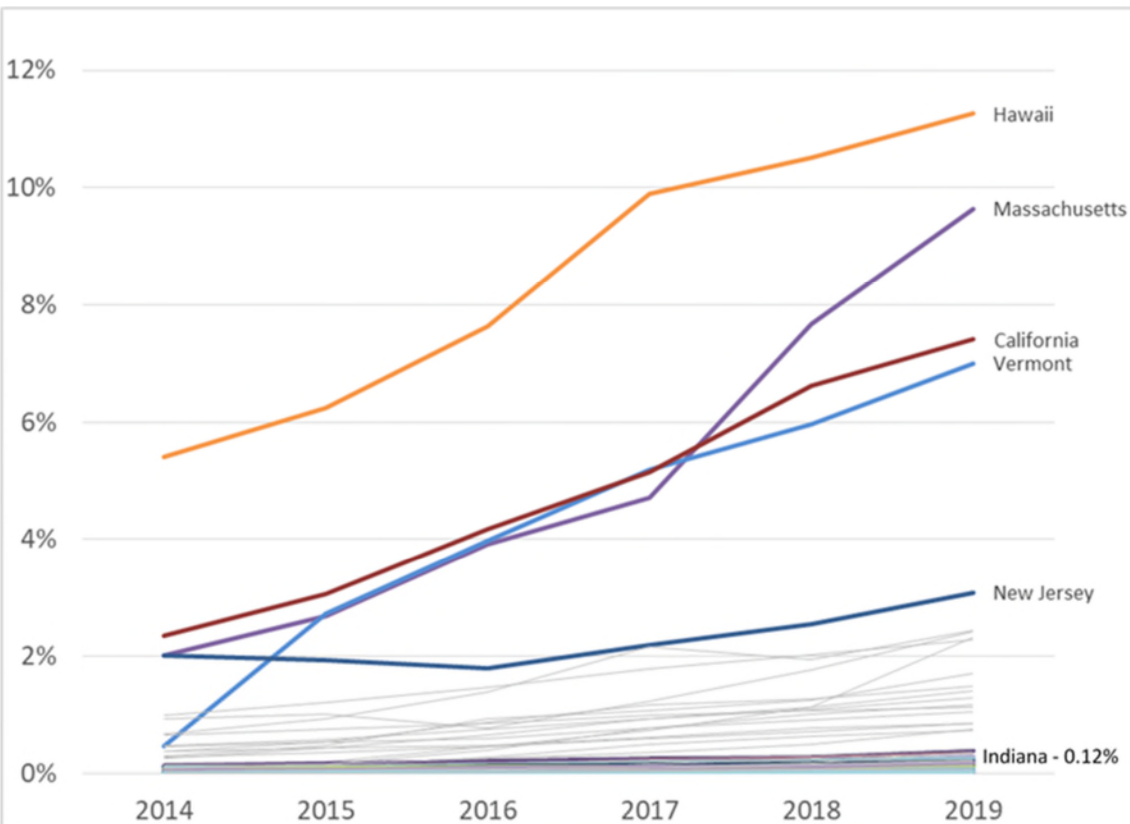

Figure 1.1 Small-Scale PV Generation as a Portion of All Generation
Source: Energy Information Administration (EIA)

Based on the information shared by the five Indiana IOUs that are the subject of this study, the level of DER adoption varies by technology and customer class. Only 0.14 percent of residential customers own a PV system, while that figure is 4.7 percent for commercial customers. Almost no customers in Indiana own a storage system (less than 0.01%).

Integrated Resource Plans (IRPs) are a useful source of data for understanding the expected trajectory of different generation resources in the state. While utility-scale solar and storage were often included in IRPs, this study examined customer-owned generation resources—and the treatment of DER forecasts varied by utility. Table 1.1 summarizes the treatment of DERs in IRPs for each utility. NIPSCO did not explicitly model or vary DER adoption by scenario. Duke Energy modeled customer-owned DER adoption, but did not explicitly vary it by scenario. Vectren modeled customer-owned DER and varied it by scenario. I&M and IPL both included a DER-focused scenario in their IRPs. All of the IOUs except for NIPSCO included a forecast of light duty EV adoption in their IRPs. No utilities forecasted customer-owned batteries or heavy duty EV adoption.

Table 1.1 Treatment of DER and EVs in utility IRPs

Utility (IRP Year)	Energy Efficiency	Demand Response	PV	Battery Storage	Electric Vehicles	Notes on DER Scenarios
Duke Energy (2018)	✓	✓	✓		✓	Customer-owned DER adoption was not explicitly varied by scenario
I&M (2018-2019)	✓	✓	✓		✓	Included a DER-focused scenario
IP&L (2016)	✓	✓	✓		✓	Included a DER-focused scenario
NIPSCO (2018)	✓	✓				DER adoption was not explicitly modeled or varied by scenario
Vectren (2016)	✓	✓	✓		✓	Customer-owned DER adoption varied by scenario

The two main DER forecasts from the utility IRPs that were leveraged for the analysis were customer-owned PV and EV. Section 2 describes how these forecasts were incorporated into the analysis.

1.2 Review of pertinent literature

Several fields of study contribute to the growing body of literature examining the implications of increasing DER penetration. These studies explore current and future DER adoption trajectories and assess the impact across a number of dimensions, including the distribution system, bulk power system, distribution planning processes, ratepayer and societal costs and benefits, and utility business models. These subjects are summarized below.

1.2.1 Impacts of DERs on the distribution system

A number of studies have modeled high PV penetration on feeders and assessed the impacts. Brown and Freeman (2001) found that distributed generation (DG) can have positive impacts (voltage support, deferred capital investments) and negative impacts (protection coordination, voltage regulation, voltage flicker, short circuit levels). They also developed methods to analyze DG impacts using predictive reliability assessment tools. CIRED (2019) presents a flexible DER modelling framework along with recent developments in DER dynamic modelling. It also reviews DER system impact studies in California. PNNL summarizes the major types of analysis conducted on electric distribution systems along with their applications and relative maturity levels (PNNL, 2017a). Special emphasis is placed on distribution system analyses required for increasing levels of DERs. NREL (Seguin et al., 2016) catalogs distribution-level impacts of high PV penetration, including overload-related, voltage-related, reverse power flow, and system protection impacts. It also provides a model-based study guide for assessing PV impacts and lists techniques for mitigating impacts.

EPRI (2015) provides an overview of the hosting capacity method, which was developed to determine the ability of feeders to accommodate PV. The impact of PV penetration on distribution performance and the amount of PV (and other DERs) a feeder can accommodate depend on a number of factors, such as the characteristics of both the feeder and the DER, the location of the DER on the feeder, the feeder operating criteria, and the control mechanisms. EPRI (2010) discusses practical planning limits for adding DG to distribution circuits. The report classifies the limits into four categories: voltage regulation (e.g. voltage rise), rapid voltage change (fluctuations, sudden loss of generation), thermal limits (capacity, losses), and protection limits (overcurrent, islanding). The study used a set of IEEE test feeders to investigate the limits of each category. Over ten years ago, the IEEE developed this set of test feeders for researchers to use when modeling the distribution system (Schneider et al., 2008; K. Schneider et al., 2009; Schneider et al., 2018). Schneider et al. (2018) provides an overview of the existing distribution feeder models and clarifies the specific analytic challenges that they were originally designed to examine. The set of feeders reflect the diversity in design and have been used for a wide range of research (Cale et al., 2014). We explore the literature on representative feeder methodology in section 4.1.

1.2.2 Bulk power system impacts

Several studies have addressed the impacts of DER on the Bulk Power System (BPS). ERCOT identified areas of concern related to reliability impacts of DER to the BPS: increased error in load forecasting, less accurate inputs to ISO functions, and uncoordinated system restoration after a load shed event (ERCOT, 2017). NERC examined the potential reliability risks and mitigation approaches for increased levels of DER on the BPS. The objective was to help regulators, policy makers, and other stakeholders better understand the differences between DER and conventional generation with regards to the effect on the BPS (NERC, 2017). NERC also created a DER Task Force which developed DER modeling recommendations for BPS planning studies (NATF, 2018).

1.2.3 Value of DER

A growing body of literature analyzes the benefits and costs of DER. NREL (2014) reviews methods for analyzing the benefits and costs of distributed PV generation to the U.S. electric utility system. This

NREL review is one of the main sources for the DER valuation framework used in this study. Utilities will occasionally commission “value of solar” studies in their service territories to understand the benefits and costs specific to their geographic location, generation portfolio and customer base. RMI (2013) reviews sixteen distributed PV benefit/cost studies by utilities, national labs, and other organizations. Completed between 2005 and 2013, these studies reflect a significant range of estimated distributed PV value. Some studies examine costs and benefits at a broader level. Cohen et al. (2015) estimated the economic impact of distributed PV in California, and, closer to Indiana, PNNL (Orrell et al., 2018) estimated the value of DG in Illinois.

1.2.4 Utility of the future

Some states have conducted “Utility of the Future” studies. These studies generally examine the role and business model of today’s utilities and explore ways they could change in the face of an evolving business environment measured by customer expectations, DER adoption, and technological advances. In the Midwest, several states have conducted such studies: Ohio, Michigan, Illinois, and Kentucky. Ohio’s PowerForward Roadmap examined potential future regulatory paradigms, distribution grid architecture, and grid modernization (Ohio PUC, 2018). Michigan’s study specifically focused on the near-term challenge of ensuring an adequate electricity supply (Public Sector Consultants, 2014). Illinois’ NextGrid study assessed options for further grid modernization and candidate updates of state regulatory policies (NextGrid Illinois, 2018). Kentucky developed a Smart Grid Roadmap in 2012, where it examined the modernization of the electric power grid (KSGRI, 2012).

1.2.5 DER forecasting and planning integration

A critical input to the body of work on DER impacts is the adoption forecast for DERs. The methods for developing these forecasts can be divided into two categories: top-down and bottom-up (Horowitz et al., 2019). Top-down methods tend to be simpler and require less data and computing power. They include time series models, econometric models, and Bass diffusion models. Time series models are the most straightforward to implement, as they take historical data and extrapolate to future outcomes. Econometric models use statistical methods to explain historical observations by finding relationships between penetration levels and other variables. Researchers can then use these relationships to predict future adoption levels. Bass diffusion models represent adoption patterns of new products or technologies and are the most frequent top-down model used (Horowitz et al., 2019). Bottom-up methods require more data and are more methodologically sophisticated, as they evaluate DER adoption based on characteristics of individual customers. For example, agent-based models simulate the actions of individuals to model the impacts to the larger system. These types of models allow for more complex decision-making processes and can simulate a more heterogeneous customer base (Mills, 2018).

A number of researchers have examined how to incorporate DERs into the distribution planning process. For example, LBNL conducted a comparative analysis and evaluation of roughly 30 recent planning studies, identifying innovative practices, lessons learned, and state-of-the-art tools (Mills et al., 2016). PNNL describes activities in states that have adopted some advanced elements of integrated distribution system planning and analysis and also covers a broader array of state approaches (PNNL, 2017b). State regulators in several states including MN, CA, HI, and NY have developed integrated distribution planning guidelines for their utilities to actively incorporate DER into the distribution planning process (Schwartz, 2020).

This literature review informs the structure and content of the analysis that follows. Figure 1.1 provides an overview of the analytical process developed in this study. The analysis benefited from references on DER adoption forecast methodologies, trends on emerging technologies, methodologies to assess the impacts of DER in power systems, and techniques to identify representative feeders for these analyses, among others. In the rest of the report, section 2 explains the scenario creation and section 3 the assessment framework developed for this study. Section 4 delves into the method and results for selecting representative feeders, and section 5 presents the results for power flow and reliability impact assessments. Section 6 concludes with a summary of methods and results. All monetary values in this report are expressed in real 2017 dollars unless otherwise indicated.

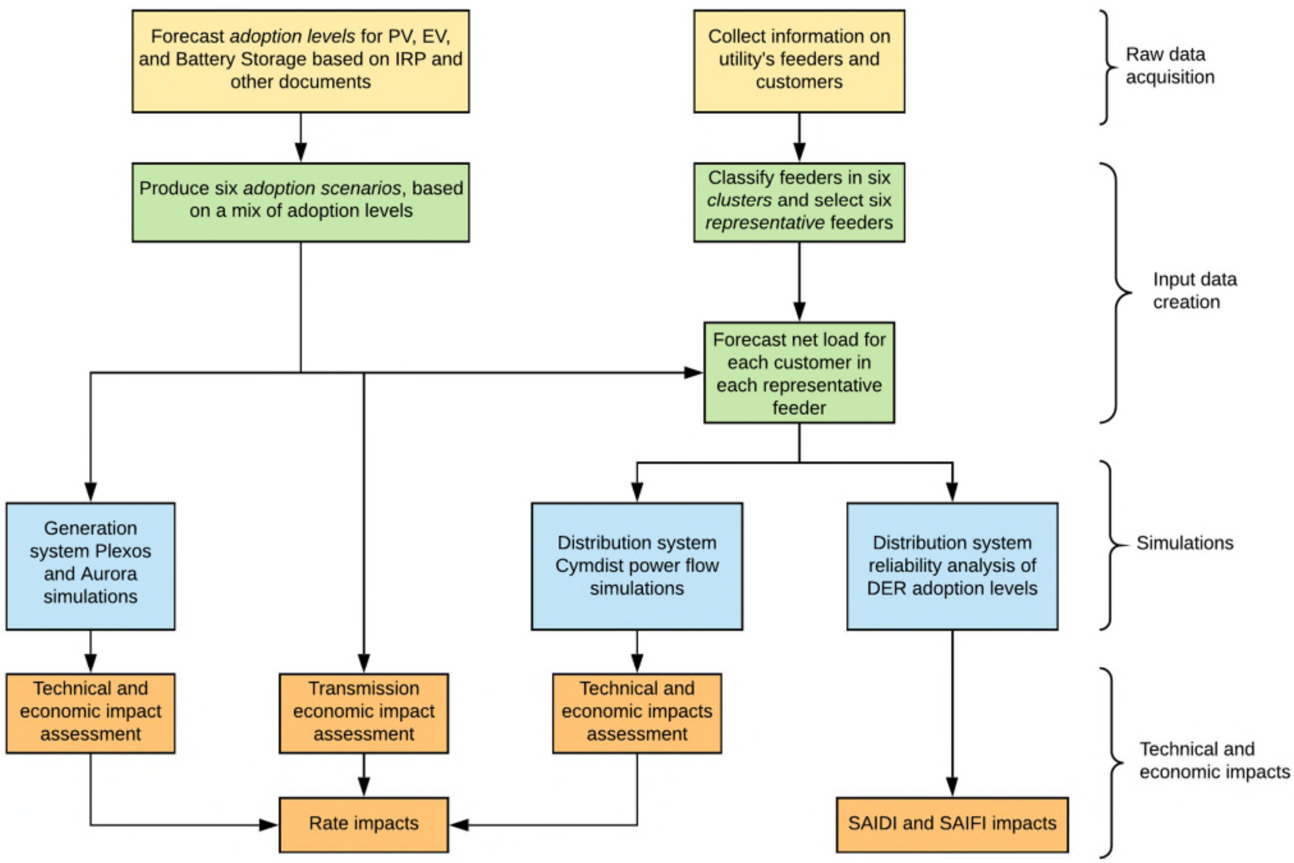

Figure 1.2 Flow diagram describing the analytical process developed in this study

2. Scenarios

This study utilizes six scenarios based on different levels of DER and EV adoption to examine the performance of the distribution system and to examine certain impacts to reliability and resilience. This section describes the scenario development process and the dimensions that define each scenario.

2.1 Scenario logic

The scenarios were developed to explore how the distribution system would perform under different DER adoption and demand levels. DER and demand are characterized across three dimensions: PV adoption, battery storage, and system demand. Each dimension has one of three adoption levels: business as usual (BAU), high, and very high. The scenarios cover two horizons: a short-term horizon (2025) and a long-term horizon (2040).

The scenarios do not represent a prediction of the future trajectory of DER adoption or system demand. Their purpose is to represent a set of possible futures for the purpose of exploring the behavior of the distribution system under different circumstances. This type of scenario exploration can help to identify situations in which the system may perform poorly and thus inform decision-makers. The scenarios are policy-agnostic. We do not assume any type of policy is in place in each scenario. Put differently, there is no assumption whether the DER adoption or system demand levels are attained through a particular policy mechanism. Logically, the adoption levels in these scenarios would be more or less feasible for Indiana depending on the set of policy decisions made over the next twenty years.

The PV and storage dimensions for each scenario reflect the adoption of behind-the-meter DER by customers—and not utility-scale solar or storage. PV systems would thus be customer-installed rooftop PV for residential and commercial customers. Battery storage systems are less common than PV in each scenario and are assumed to be installed at the same site as PV. The batteries were sized to reflect the capacity of a system on the customer side of the meter and did not include any utility-scale batteries. The levels of system demand are driven by the adoption of electric vehicles. While a number of factors could arise to impact system demand, EVs are the most likely option for large-scale changes and provide a means to simplify scenario development.

The six scenarios are as follows:

1. ***Base***: Represents the base case scenario. Each scenario dimension (PV, battery storage, and system demand) are taken from the base case scenarios of the utility IRPs. Note the distinction between “Base” to refer to this scenario and business-as-usual (BAU) to refer to the specific DER projection level as in BAU, high, and very high (see Table 2.2).
2. ***High Electrification***: Represents a scenario where system demand increases beyond base case projections, but DER adoption does not. This allows the analysis to explore the behavior of the distribution system in the case of high EV adoption—but with a configuration that reflects BAU levels of remaining DER penetration.
3. ***High PV***: Tests the scenario where PV adoption increases beyond BAU projections, but without large-scale additional system demand and without a large increase in battery storage adoption.

Battery storage can mitigate some of the integration challenges for the utility of high rooftop PV penetration and this scenario tests the ability of the grid to handle more PV without the customer-side storage.

4. ***High PV and Battery Storage***: Examines a scenario where a high level of rooftop PV penetration is coupled with a relatively high penetration of battery storage systems. The scenario assumes some breakthrough in battery technology, financing, and/or policy that would boost adoption, as current levels are close to zero. Even at a 'high' level, only one percent of customers adopt batteries. In this scenario, all battery storage systems are co-located with rooftop PV—though many rooftop PV systems are installed without batteries due to high PV penetration.
5. ***Battery Storage Arbitrage***: Reflects a scenario where a storage breakthrough occurs, achieving a 'high,' one percent penetration level, with BAU levels of rooftop PV adoption. This scenario allows exploration of the impact of higher-than-expected battery storage adoption, while holding other factors at the baseline level.
6. ***Boundary Case***: Extrapolates adoption of rooftop PV, battery storage, and EVs to 'very high' penetration trajectory levels. The purpose of this scenario is to act as a boundary case and test the behavior of the distribution system with stressors that are beyond even the 'high' project levels. The 'very high' adoption levels are not present in any other scenarios.

Table 2.1 summarizes the six scenarios, and the proposed DER adoption category for each scenario. The colors represent adoption levels as follows:

Table 2.1 Overview of scenarios

Scenario	Description	PV	Storage	EV (system demand)
1: Base	Reference case			
2: High Electrification	BAU DER, high demand			
3: High PV Stress Test	High PV penetration without storage breakthrough			
4: High PV and Battery Storage	High PV penetration with storage breakthrough			
5: Battery Storage Arbitrage	Storage breakthrough with BAU PV			
6: Boundary Case (Distribution system stress test)	Very High PV, storage, electrified demand			

Adoption Levels:

Business as Usual	High	Very High

Table 2.2 reports the details of each level (BAU, High, and Very High) for each scenario dimension and year 2040; values for 2025 are interpolated between current levels and 2040 levels. The base case adoption level was based the forecasted DER adoption for each Indiana IOU. Figure 2.1 depicts forecasted annual EV adoption for Indiana. An aggregate analysis of the IOUs IRP shows that Indiana may have almost 14,000 EVs in 2020 and more than 550,000 EVs by 2040. The 'High' and 'Very High' scenarios for EVs is based on a scenario from MISO (Greenblatt et al., 2019). Figure 2.2 depicts the forecasted installed PV capacity (in MW) for the state of Indiana based on the forecast in the base scenario for the five IOU IRPs. It is estimated that Indiana will have 230 MW of installed PV capacity in 2020 and 830 MW of installed PV capacity in 2040. The 'High' PV scenario is based on a scenario from the IPL IRP. Projecting adoption of battery storage proved challenging, due to very low adoption rates outside of California, a lack of public-available forecasts, and significant uncertainty related to the future of the battery storage market. The adoption levels for the 'High' and 'Very High' scenarios were extrapolated from states with higher penetration levels.

Table 2.2 Quantitative adoption level details

Adoption Level	PV	Storage	Electric Vehicles	System Demand
BAU	Established from base case forecast from utility IRPs.	Established from base case forecast from utility IRPs.	Established from base case forecast from utility IRPs.	Established from base case forecast from utility IRPs.
High	15% of customers by 2040 (Based on scenario from IPL IRP)	1% of customers by 2040	23% of vehicle stock by 2040 (Based on scenario from MISO Study)	Base Demand + EV addition
Very High	25% of customers by 2040 (Extrapolation of High Scenario)	5% of customers by 2040	68% of vehicle stock by 2040 (Based on scenario from MISO Study)	Base Demand + EV addition

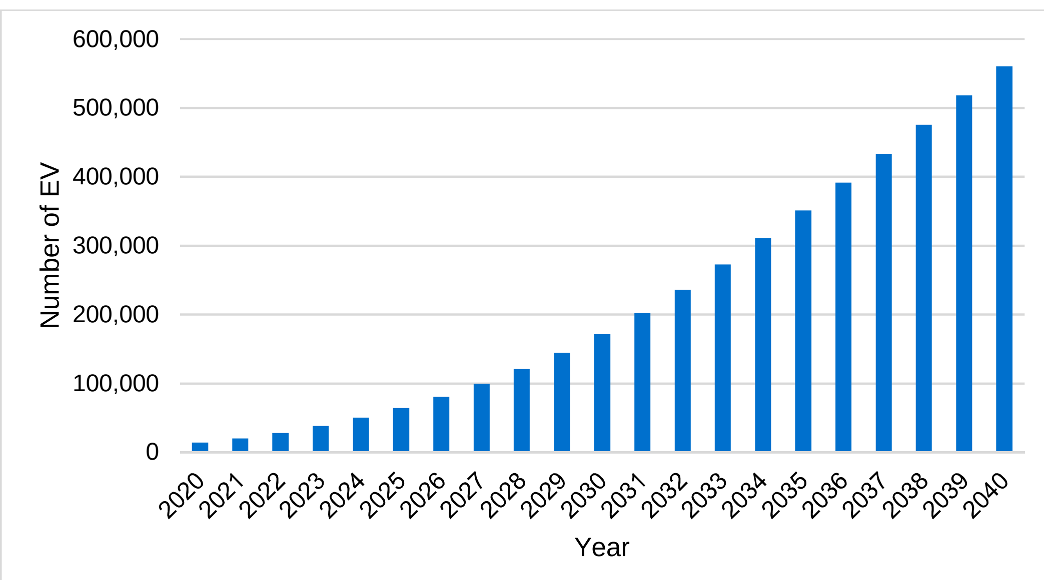

Figure 2.1 EV adoption forecast based on IOU IRPs (BAU)

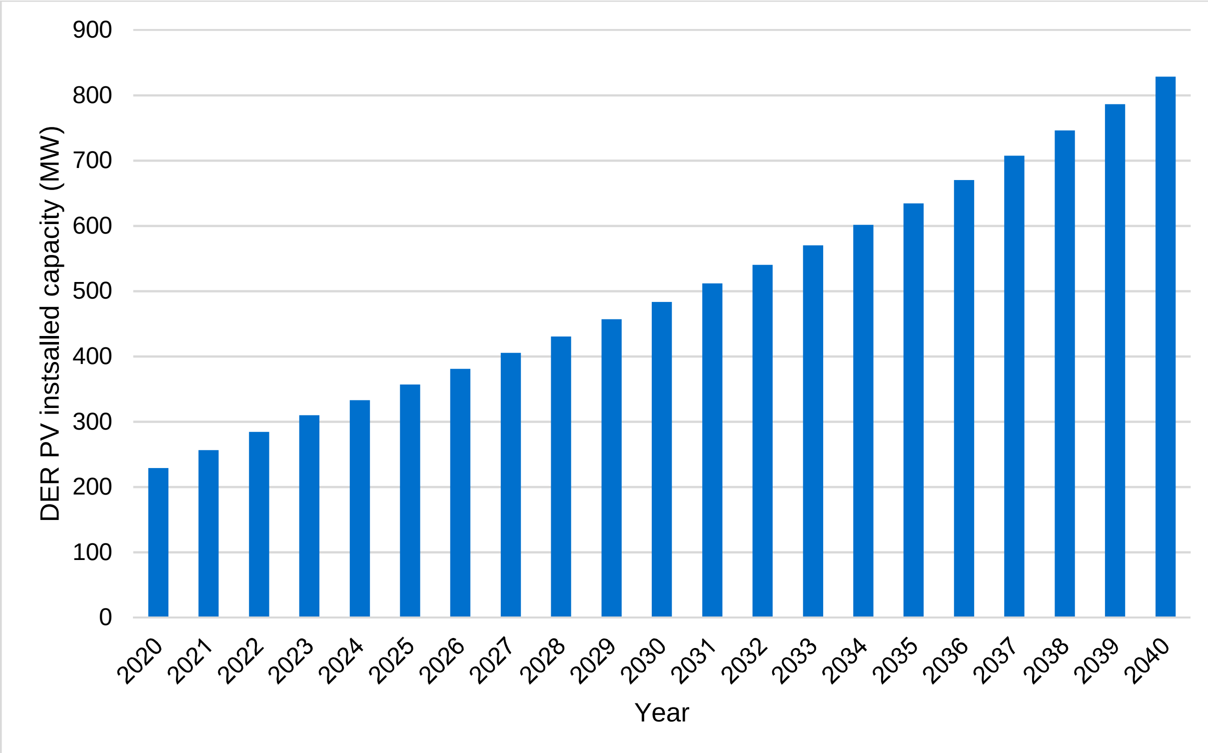

Figure 2.2 DER PV forecast based on IOU IRPs (BAU)

2.2 Scenario outputs

2.2.1 Load forecast by scenario

Figure 2.3 and Figure 2.4 summarize the estimated annual consumption for Indiana in GWh by customer class for each scenario in 2025 and 2040, respectively. Variations in annual consumption for each customer class are due to additional load from EV adoption (residential) and subtracted load due to annual PV generation (residential and commercial). Customer-owned storage is assumed to have small annual net consumption because of the 90% roundtrip efficiency in the charge/discharge patterns. The annual consumption for industrial customers does not vary by scenario, and so is not included in the figures. Industrial customers, however, make up a large portion of Indiana's overall consumption, accounting for 46% of total annual consumption in 2025 and 45% of total annual consumption in 2040.

Overall, there is a relatively small amount of variation in total annual consumption for each scenario in 2025, as DER adoption does not differ greatly between scenarios over the next five years. By 2040, there are comparatively larger changes in annual consumption, with overall consumption levels increasing or decreasing depending on the scenario. The High Electrification and Boundary scenarios have relatively high levels of EV adoption and annual consumption for residential customers increase by 8% and 21%, respectively, compared to the base case. The scenarios with BAU EV adoption and high PV adoption show a 10% decrease in residential annual consumption and an 8% decrease in commercial annual consumption compared to the base case.

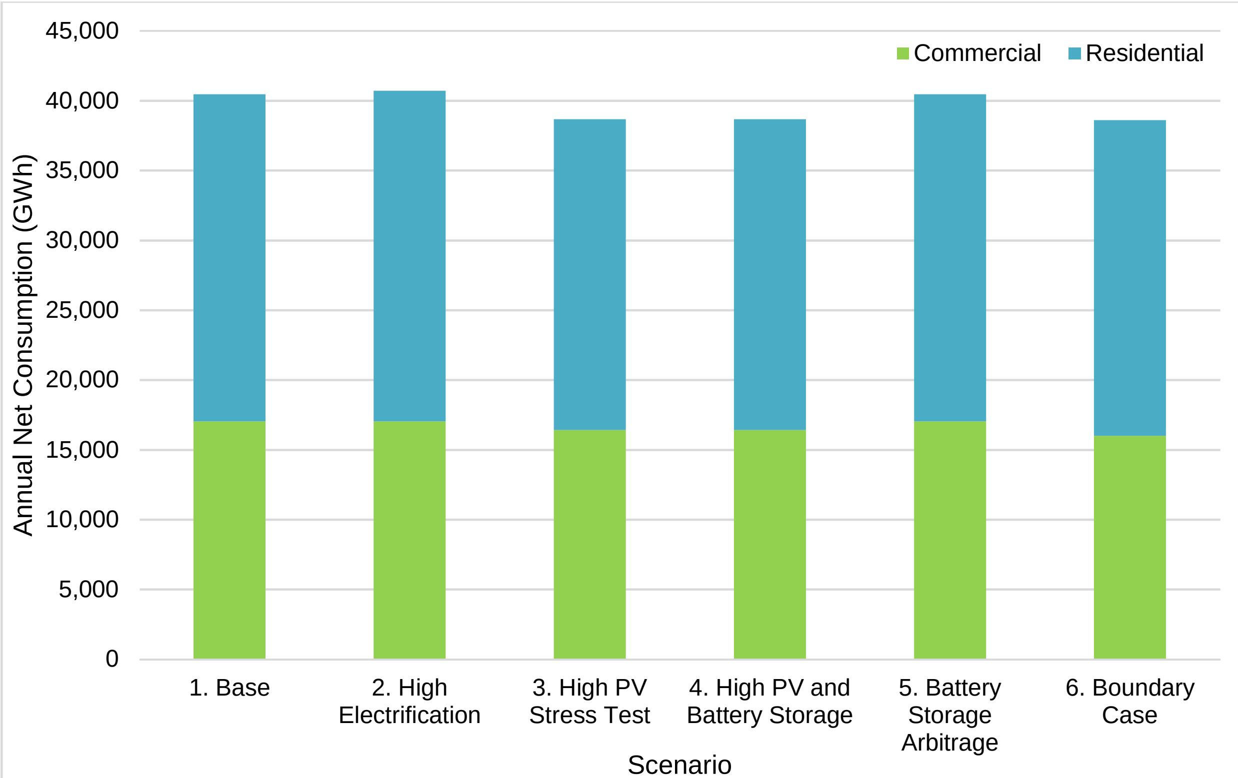

Figure 2.3 2025 annual net consumption by scenario and customer segment

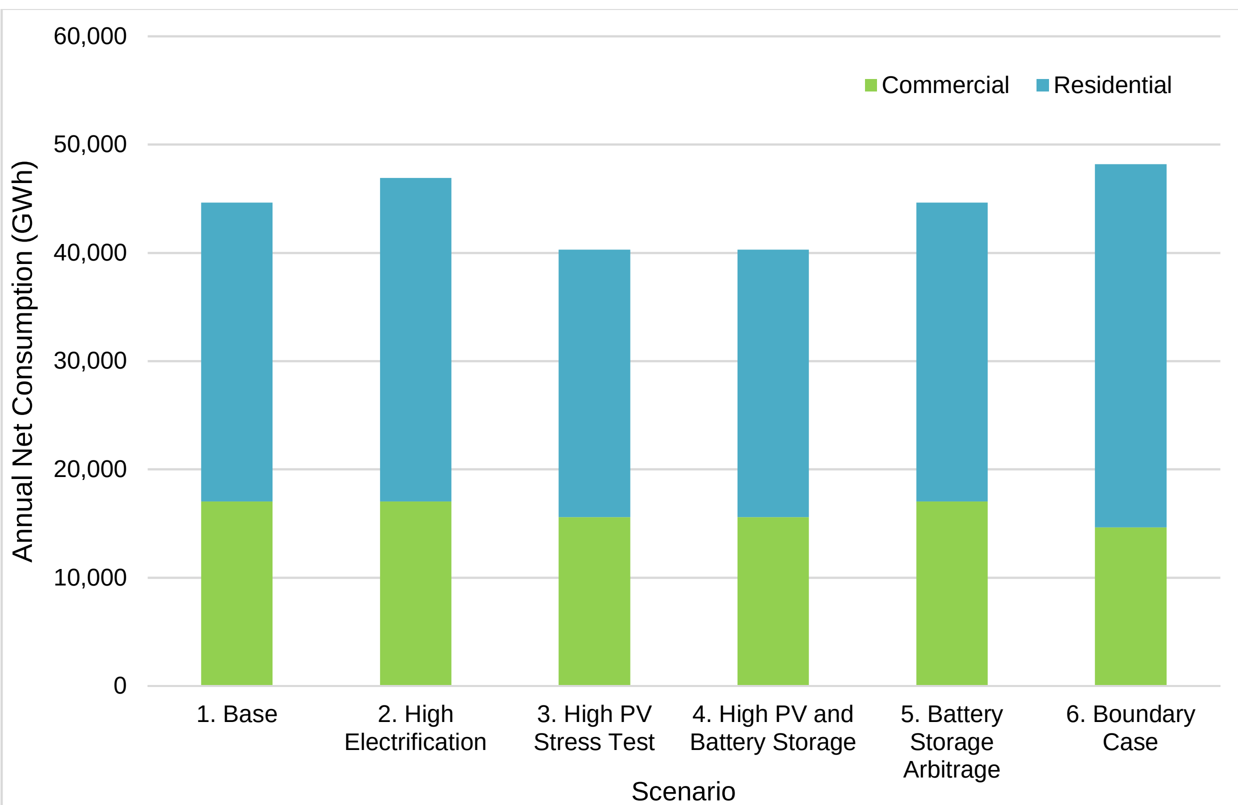

Figure 2.4 2040 annual net consumption by scenario and customer segment

The above figures do not portray the impact of each DER on an hourly basis. Impacts during specific hours of the day exist even though on an annual basis net demand may not change substantially as a result of additional DERs. Solar PV and EV charging, for example, offset each other on an annual basis, but solar discharge and EV charging generally happen at different times during the day. Therefore, there are potentially large changes on an hourly level on each scenario. One of these changes is a shift in the hours that have the highest load concentration on peak days. Figure 2.5 illustrates the timing of state-level aggregate peak day usage for each scenario. The plot shows the average hourly loads over the top ten peak load days in 2040 for each scenario. We can compare scenarios by displaying the percentage of usage in each hour (the area under each curve adds up to 100%). Peak days occur during summer months in all scenarios, but the peak hour changes depending on which DER is dominant. For scenarios with high levels of solar penetration, the peak hour tends to occur later in the evening, between 6-7 pm (hour 19 on the plot). For the Base, High Electrification, and High Storage scenarios the peak occurs earlier in the day, between 3-4 pm (hour 16 on the plot). The Boundary scenario, with large PV and solar penetration, shows a high concentration of load in the evening hours, with load from 6-9 pm, accounting for more than 30% of the daily load on peak days.

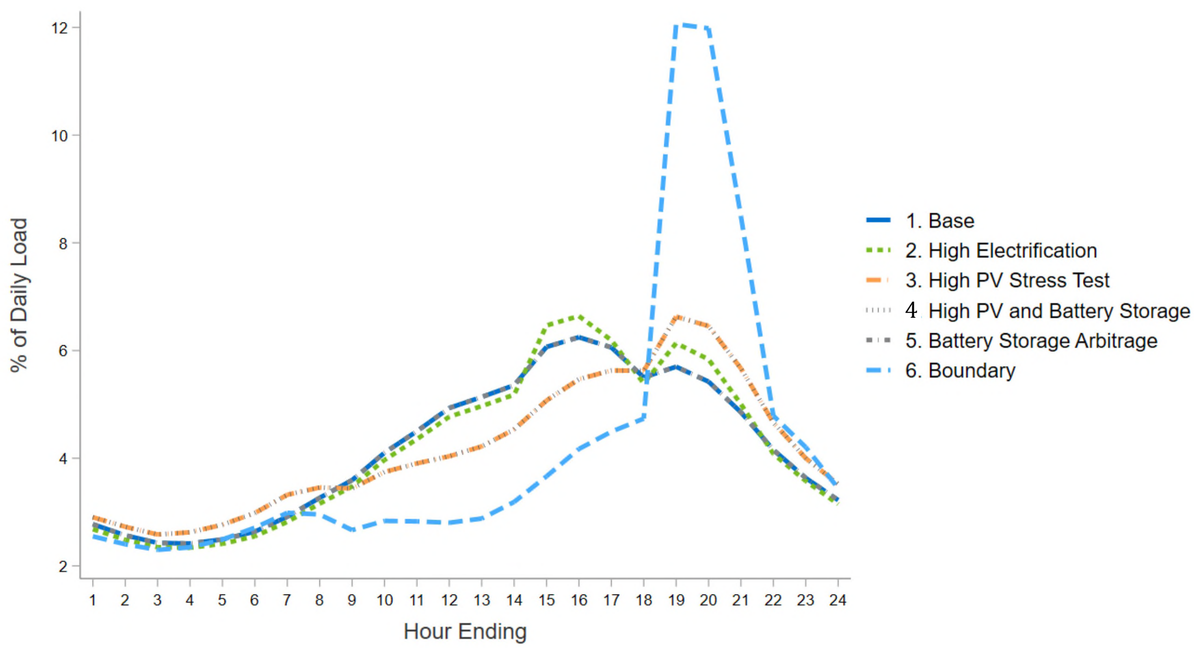

Figure 2.5 Peak day load concentration by scenario

In addition to changes in peak load concentration, the magnitude of the annual peak as compared to the Base Case also changes. The High Electrification and Boundary scenarios have relatively high levels of EV adoption and peak consumption increases by 17% and 83%, respectively. The scenarios with BAU EV adoption and high PV adoption show a 6% decrease in peak consumption.

2.2.2 DER adoption forecasts for Indiana

Figure 2.6 and Figure 2.7 depict the expected Indiana DER installed capacity for each scenario in 2025 and 2040, respectively. These charts present nameplate installed capacity of each DER rather than coincident peak capacity. There is some variation in DER adoption for each scenario in 2025, with much larger variation in 2040. By 2040, in the Base scenario, there is 356 MW of installed PV capacity and 1 MW of installed storage capacity. High PV adoption scenarios deploy 1,667 MW of PV capacity; high storage adoption scenarios install 74 MW of battery storage capacity. Similarly, 2040 BAU installed capacity of EV charging is 1,706 MW, equal to 560,562 vehicles, and a high installed capacity of 3,907 MW of charging equal to 1,282,022 vehicles. EV capacity is broken out by the type of charger used for the vehicle. Type 1 EV charges use less load at any given time, but take longer to charge, while Type 2 EVs charge quickly and use more load during a given hour. As a result, Type 1 EV makes up 21% of EV customers but only 11% of EV capacity. The Boundary scenario has significantly higher DER penetration than the other scenarios with 6,438 MW of PV, 921 MW of storage, and 12,523 MW of EV from 4,115,648 vehicles (see Figures 2.6 and 2.7). The Boundary scenario then acts as a stress-test case to analyze the behavior of the distribution system with adoption levels beyond the most optimistic existing adoption scenarios.

The DER with the highest capacity varies with the scenario. For the Base, High Electrification, and Boundary scenarios, EV charging provides the highest installed capacity. For the other scenarios solar PV has the highest installed capacity. However, it is important to highlight that, in reality, EV charging may occur at different times of day while PV injections across the Indiana territory will be highly correlated. This means that the coincident hourly impact of PV may be higher than that of EV, even in scenarios where the latter has larger installed capacity.

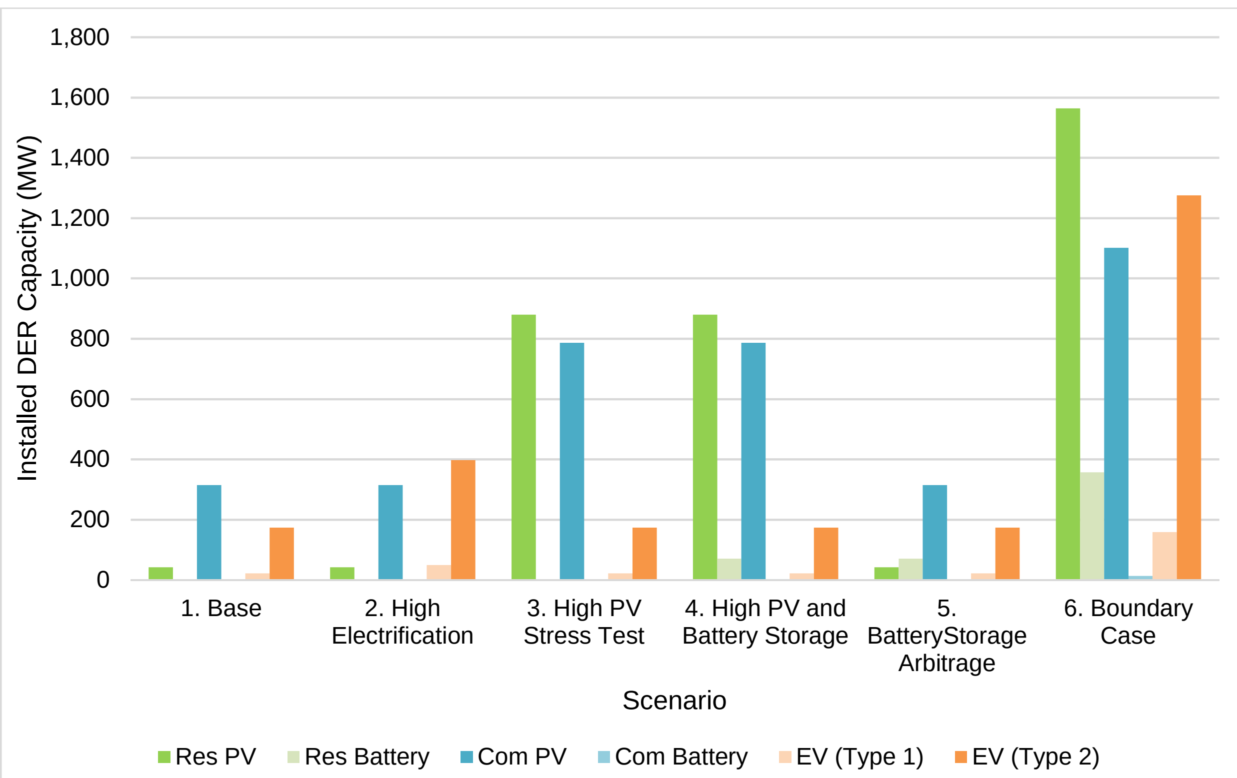

Figure 2.6 2025 Indiana installed DER/EV capacity by scenario

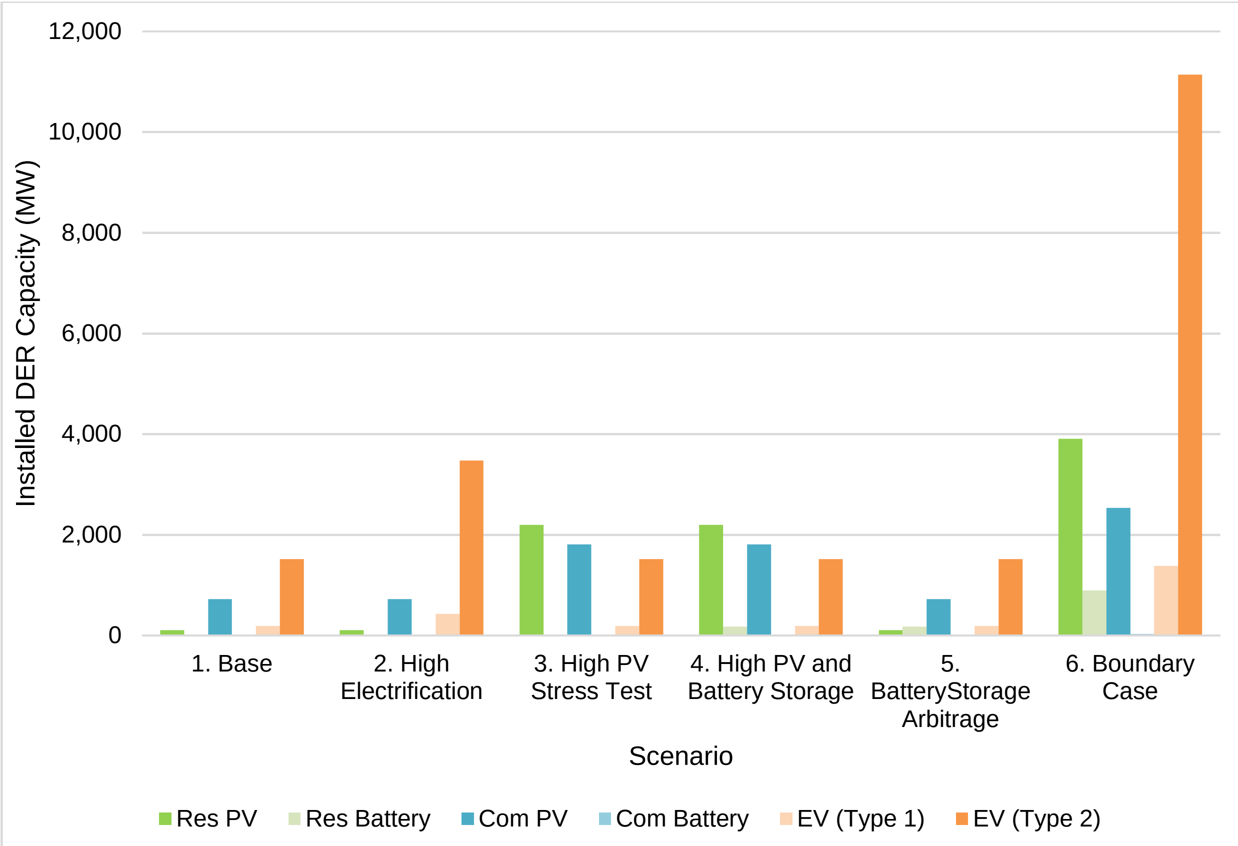

Figure 2.7 2040 Indiana installed DER/EV capacity by scenario

2.2.3 Comments on DR and EE availability/potential

DR and EE availability were based on IRP forecasts provided by the IOUs. Unlike the other DERs, customer participation in EE and DR programs are largely driven by utility efforts. Therefore, EE and DR adoption were not varied in the above scenarios. For both 2025 and 2040, Indiana is expected to have a total DR capacity of almost 750 MW and total annual EE savings of almost 1,900 GWh.

2.3 Equivalence between scenarios in this study and in the SUFG study

The SUFG is developing the assessment of impacts of emergent generation technologies, fuels, and trends in the generation segment of the power system. The scenarios used for that assessment are not influenced by the scenarios employed in this study or vice versa, because each analysis is focused on testing the impacts of technological change on each specific segment.

However, this study does develop a methodology to assess the impacts of DER adoption on the generation segment of the power system. For this, the scenarios developed in this section were ported into the appropriate format to be input as net demand to the production cost and capacity expansion models. More information on this method is available in Sections 3.1.1, 3.1.2 and 4.3.

3. Metrics to assess the impact of emerging DER technologies

This paper seeks to trace emergent technologies in distribution systems and measure their impact across the different segments of the power system. In this section, we present the methodological framework used to measure and monetize the techno-economic impact, and to measure the reliability impacts of different scenarios for DER adoption in Indiana.

In general terms, this paper develops an empirical strategy to make the results directly applicable to the Indiana context. We develop an economic impacts analysis based on the scenarios in Section 2 and representative feeders identified by classifying thousands of Indiana feeders in clusters of circuits with similar characteristics (see Section 4 for more information). We then produce net demand inputs to run power flow simulations in selected feeders using the industry-standard Cymdist model (CYME, 2018). The same inputs are aggregated, scaled, and adapted to be input into the Plexos and Aurora modeling platforms for generation expansion and estimation of production costs. A simplified method is used to assess the impacts of DER on transmission costs. Grouping these three analyzes together allows to estimate rate impacts of DER penetration for different adoption scenarios and years.

Finally, we conduct a reliability impacts analysis using five years of outage data for the five Indiana IOUs. We introduce a methodology to estimate the frequency and duration of interruptions—from the customers' perspective—under alternative DER deployment pathways. We perform these calculations for a consistent set of feeder clusters, and then scale the results to the state-wide level.

3.1 Economic impacts of DER on the power system

DER can impose technical costs to the distribution system due to their impact on voltage levels and line loading, among other impacts. DER can also benefit the distribution system by reducing line and transformer losses and by deferring capacity investments. Due to the integrated nature of power systems, DER costs and benefits can also accrue in the transmission and generation levels. We call these economic outcomes of DER integration "value streams". DER have a wide array of value streams (EPRI, 2014; Frick et al., 2018; Shenot et al., 2019), but this study focuses on a subset of possible value components including energy cost, losses, and capital deferment (capacity value).

Due to technical and resource limitations, a number of additional value streams identified in the literature were not considered. These include DER impacts on ancillary services and fuel price hedging. Ancillary services such as frequency regulation can be a relevant value stream for battery storage (Nassuato et al., 2016). However, there is no simplified method to determine the potential contribution of DER to this value stream that could be applied within our framework.

The framework used in this analysis is largely based on an NREL study titled "Methods for Analyzing the Benefits and Costs of Distributed Photovoltaic Generation to the U.S. Electric Utility System" (Denholm et al., 2014). This study is focused on DER PV, but its methodology can be extended to other types of DER. The DER valuation framework components and measurement methodology specific to our study are described below.

3.1.1 Energy costs

Operation of DER changes the shape and level of the net demand that is supplied by the BPS. The change in shape can produce costs or benefits depending on how the BPS dispatch curve changes and whether more flexible resources for ramping are needed (e.g. to address the "duck curve" phenomenon) that would incur additional fuel charges.

Change in levels can also be bidirectional: net demand can decrease with high levels of PV generation, often resulting in savings from less energy produced at the utility-scale. However, BPS energy consumption can also increase with EV charging. The timing of these changes, captured by the shape component, impacts resource adequacy requirement at the BPS-level. However, these capacity requirements are captured through a different value stream described later.

Changes in energy consumption and their monetization will employ the SUFG's production cost modeling platform with the Plexos and Aurora models. The process follows these steps:

1. Produce hourly net demand differentials between the base case scenario and each one of the five adoption scenarios presented in Section 2.
2. Add the scenario net demand differentials to SUFG's base case to produce five net demand sets that are consistent with their assumptions, but at the same time reflect the adoption levels determined in this study's scenarios.
3. Interpolate the years between 2025 and 2040 to provide the data needed for the capacity expansion model.
4. Input these assumptions in the model and run it for each hour of the year.
5. Calculate the dispatch costs (fuel and non-fuel variable costs, ramping costs, and spinning and non-spinning reserves costs) for each hour, and produce annual totals.
6. Compare state-wide present value of dispatch costs for each adoption scenario against the base case.

3.1.2 Losses

Transmission and distribution losses may be reduced or increased due to the presence of DER. Distribution losses can go in either direction depending on their capacity relative to the hosting capacity and their location within the feeder. Traditionally, distribution feeders follow a "conic" construction method, with higher gauge wire close to the head and lower gauge wire close to the ends. Then, higher power flow levels close to the end of the feeder have a disproportionate impact on losses compared to the same flow levels close to the feeder head. Transmission losses would generally decrease due to reduced loading in the lines. For the purposes of this study, we do not assume that DER deployment results in power flowing back into the transmission system with a corresponding increase in losses.

Distribution line losses for the primary voltage system will be assessed directly from the Cymdist modeling results for each representative feeder. We will prepare and run a specific set of simulations for energy losses using 24 hours on a typical day per season (fall, winter, spring, and summer). The days are selected as the median load day on each season. The objective of this approach is to capture typical losses levels that are representative of the adoption scenario, rather than losses at maximum/minimum load conditions. Feeder-level energy losses levels for each scenario will be compared against the base case. Losses differences can then be monetized using either retail rate or an average wholesale purchase price.

Transmission losses cannot be directly calculated because there is no explicit modeling of the transmission system in the Comprehensive Study. We will estimate transmission losses changes based on the difference between aggregate net demand in the base case scenario and the adoption scenarios. For example, if energy consumption is 10% higher in one adoption scenario compared to base case, then we will assume that transmission system losses will be 10% higher as well. While imperfect, this will allow to monetize transmission losses changes into rates.

3.1.3 Capital deferment (capacity value)

DER operation can defer or increase future investments in generation, transmission, and distribution. As with losses reductions, DER may produce capital deferments in generation and transmission. However, DER deployment can require flow capacity and safety upgrades in the distribution system and can trigger the need for flexible resources at the generation and transmission level to meet additional ramping requirements.

Generation

Capacity value of DER for the generation system can be directly calculated using the results from the Aurora capacity expansion model ran by the SUFG. Typically, most studies estimate the capacity credit of the different DER technologies, accounting for T&D losses (i.e. referring the capacity credit to the transmission network). However, since the SUFG model is able to simulate capacity expansion for different net demand scenarios, we can directly compare the adoption scenarios against the Base scenario to determine the difference in resource type, capacity mix, and cost.

We estimate potential reductions in planning reserve margin that come from peak demand reductions as part of the generation capacity value. We will implement a simple method that values the changes to the reserve margin based on the reserve requirement output from the Aurora and Plexos models.

Transmission

Transmission expansion costs are complex to estimate because of the bulky nature of transmission investments and the spatial distribution of transmission system lines and substations. The NREL study proposes three methods to assess capital deferments in transmission systems. Two of these methods require explicit modeling of the transmission network, which is out of the scope of the Comprehensive Study. The third method proposes obtaining transmission locational marginal prices (LMP) and determining the marginal contribution of DER to reduce those LMPs. This reduction serves as a proxy for transmission capacity values. However, this method assumes that DER penetration levels do not substantially change the underlying LMP data used for the estimates. This assumption can produce large distortions when applied on analysis performed over long time frames such as this study's.

We developed a simplified method that involves linearizing transmission expansion by estimating a cost of transmission per peak MW transported. These costs are estimated by the SUFG using the rate base information separated by functional category.

Distribution

The methods to assess impacts of DER on distribution system vary significantly in complexity and outcomes. Given that this is a focus of the study, we implement a more sophisticated method based on power flow simulation of actual primary voltage feeder and load data as indicated earlier in this Section. This method has three parts. First, we run power flow simulations for each representative feeder for several combinations of adoption scenarios, hours of the year, and horizon (2025 and 2040). Second, we analyze the technical outcome of each power flow simulation by tracking voltage levels per node, line losses, and line loading. These three parameters are drivers of the feeder upgrades. Finally, we scale feeder upgrades for each cluster to the whole cluster level, and then estimate state-wide DER distribution system integration costs and benefits.

Simulations are performed on the Cymdist power engineering software from CYME/Eaton. Cymdist has a Python API that is used to automate simulations[1]. All active and reactive loads from each Cymdist feeder model are overwritten by reading a csv file with pre-determined hourly values based on the Cymdist input data explained in section 4.3. The automated framework allows executing thousands of simulations within a short period of time.

We assume that feeders will be upgraded, if needed, to maintain voltage drop, line and transformer loading and losses, within prescribed and accepted levels. In some cases, the DER scenarios may be such that they will prevent an upgrade that would otherwise be required in the base case, accruing savings to the system. This means that we will estimate upgrades required for the base case and determine a total cost for a representative feeder. We then compare these reference costs against the costs to maintain the representative feeders for other adoption scenarios. The cost differential is the DER integration value, which could be positive (a cost) or negative (a savings).

There are no trustworthy automatic upgrade algorithms for distribution systems that can be applied to our setting (Denholm et al., 2014). Given the volume of simulations performed (close to 1800 individual power flows), we select certain scenarios, years, and hours of the year that reflect maximum and minimum loading levels to manually inspect each representative feeder and decide to implement the following strategies to correct technical issues with feeders:

- Repowering conductors (line loading and losses)
- Add a new voltage regulator or modify the setting of an existing voltage regulator (voltage regulation)
- Modify a substation's tap changers (voltage regulation)
- Adopt and calibrate smart inverters for DER PV (voltage regulation)

Finally, distribution-level capital investments or deferments will be monetized based on current infrastructure costs that were provided by the three Indiana utilities whose feeders were used as the

[1] The Cymdist power flow simulations were performed using models and Functional Mockup Units developed during the DOE-funded project "CyDER: A Cyber Physical Co-Simulation Platform for Distributed Energy Resources in Smart Grids", which delivered a co-simulation platform based on the Functional Mockup Interface standard.

basis of this analysis (see Section 4).

3.1.4 Rate impacts

The methods developed in subsections 3.1.1, 3.1.2, and 3.1.3 produce cost estimates for energy, losses, and capacity in generation, transmission, and distribution systems due to DER adoption. We calculate aggregate energy consumption by utility and year and pass this information along with the DER value changes to the SUFG's ratemaking model. As stated in Phillips et al. (2019, pp. 2–2), "the [ratemaking] models determine annual revenue requirements based on each utility's costs associated with existing and future capital investments, operational expenses, debt, and taxes. Those costs are then allocated to the customer sectors and rates are determined using the annual energy forecasts." We maintain modeling consistency by using the same ratemaking model employed by the SUFG in developing its long-term demand forecasts for Indiana.

3.2 Reliability impacts of DER for the distribution system

DERs have the potential to reduce the frequency and duration of power interruptions[2] for utility customers. This study focuses specifically on battery storage and PV systems—two key dimensions in defining the alternative DER scenarios. PV adoption continues to increase throughout the U.S. and customers are also beginning to have more options for installing battery storage systems behind the meter. These systems could be operated to supply electricity during power interruptions, store electricity generated by a PV system during the day to use at night, and shave system peak load. This analysis examined the ability of behind-the-meter battery storage systems—both with and without coupled PV systems—to mitigate outage impacts to customers under different adoption assumptions and modes of operation. It applied these adoption and operational assumptions to historical outage data to estimate the reliability and resilience improvements. This section describes the framework and approach for assessing these impacts.

3.2.1 Reliability

The IEEE Standard 1366 defines twelve indices that utilities use to measure and benchmark reliability. These include the three most common metrics—SAIFI, SAIDI and CAIDI, explained below. These metrics are reported from the perspective of the utility, meaning that even if a customer had a battery storage system with which to power their site during an outage, the absence of power at the meter would still be considered an outage when calculating the metric. For this analysis, we adjust the metrics to calculate them from the perspective of the customer. Then, an outage from the utility perspective would not be considered as such from the customer perspective if the customer has a battery storage system that can be used for backup.

Indiana IOUs report annual reliability metrics under both normal conditions and inclusive of major event days (MEDs). IEEE Standard 1366 defines how to separate reliability into normal conditions and MEDs. A major event "designates a catastrophic event which exceeds reasonable design or operational limits of the electric power system and during which at least 10% of the customers within an operating

[2] This report uses the words "interruption" and "outage" interchangeably.

area experience a sustained interruption during a 24 hour period."[3,4] Utilities exclude MEDs when reporting reliability metrics to indicate how reliable the grid is during "blue sky" days. For this analysis, we assess reliability under two situations: including MEDs and excluding MEDs.

The definitions for SAIFI, SAIDI, and CAIDI are as follows:

SAIFI (System Average Interruption Frequency Index) is the average number of interruptions per year for a typical customer (see Equation 3.1). Battery storage systems installed onsite can reduce the frequency with which customers experience interruptions when the battery has enough charge and capacity to power the site for entire duration of the interruption to the grid.

Equation 3.1: SAIFI

$$SAIFI = \frac{\sum \lambda_i N_i}{N_T}$$

Where:

- N_i is the number of customers
- N_T is the total number of customers served
- λ_i is the failure rate for location *i*

SAIDI (System Average Interruption Duration Index) is the total annual duration of interruptions for a typical customer (see Equation 3.2). Batteries will reduce the total interruption time per year experienced by customers who install them and thus reduce the average yearly interruption time across all customers.

Equation 3.2: SAIDI

$$SAIDI = \frac{\sum U_i N_i}{N_T}$$

Where:

- U_i is the annual outage time for location *i*
- N_i is the number of customers affected by outages
- N_T is the total number of customers served

CAIDI (Customer Average Interruption Duration Index) is the average length of time that a typical customer outage lasts; or the average restoration time (see Equation 3.3). Note that CAIDI is equivalent to SAIDI divided by SAIFI, or the average duration per interruption. Batteries could increase or decrease CAIDI based on the characteristics of the battery and the distribution of outage durations. It is possible that batteries would help customers avoid shorter duration interruptions, but still experience longer duration outages. In this case, batteries would lead to an increase in system-wide average duration.

Equation 3.3: CAIDI

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[3] IEEE Std. 1333 Section 3.13

[4] It should be noted, however, that not all utilities (or regulatory jurisdictions) follow IEEE standard 1366 when defining what constitutes a major event (LaCommare and Eto, 2008).

$$CAIDI = \frac{\sum U_i N_i}{\sum \lambda_i N_i} = \frac{SAIDI}{SAIFI}$$

Where:

- U_i is the annual outage time for location *i*
- N_i is the number of customers affected by outages
- N_T is the total number of customers served
- λ_i is the failure rate for location *i*

Table 3.1 gives a preliminary overview of the framework for assessing impacts.

Table 3.1 Reliability and resilience assessment metrics

Metric*	Battery Storage Impacts
SAIFI	Some interruptions eliminated when battery has enough charge and capacity to power site for entire duration
SAIDI	Reduction in average yearly interruption time per customer reduced
CAIDI	Average interruption duration may increase when shorter-duration interruptions are eliminated

*Includes assessments both with and without MEDs

This analysis uses two metrics to summarize outages and characterize outages by location and cause. First, the number of customer-outages is the sum of the number of customers interrupted across all outages for the time period. It also corresponds to the numerator for the SAIFI metric. For example, if two outages each interrupted 1,000 customers, then this would be equivalent to 2,000 customer-outages—regardless of whether any customers experienced both outages. A second useful summary metric is customer minutes interrupted (CMI). This is the sum of interruption minutes for all customers, and corresponds to the numerator of the SAIDI metric. To extend the previous example, if each of the two outages lasted 100 minutes, then the total CMI would be 2,000 customer outages x 100 minutes = 200,000 CMI. Customer-outages and CMI are not reliability metrics, but ways to measure outages in electric utility operation.

3.2.2 Resilience

The utility industry does not have a consistently applied definition of resilience (LaCommare et al., 2017; Schwartz, 2019). Presidential Policy Directive 21 (EOP, 2013) on Critical Infrastructure Security and Resilience defines resilience as the “ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions. Resilience includes the ability to withstand and recover from deliberate attacks, accidents, or naturally occurring threats or incidents.” Some researchers have arbitrarily defined a long-duration, severe interruption as any interruption lasting longer than 24 hours in duration (Larsen et al., 2019; Sullivan et al., Under review; Zamuda et al., 2019). The ability to recover quickly from severe power outages is one way of measuring a power system's resilience, but there are other examples of metrics that capture system resilience in theory or in practice (e.g., see Eto, 2018). For the purposes of this study, we narrowly define resilience as the reduction in the frequency of severe power interruptions lasting 24 hours or longer. Future research should be devoted to developing other resilience metrics and the associated benefits to customers.

To assess resilience, this study examines the impacts of battery storage systems on the number of customer outages lasting longer than 24 hours.

3.2.3 Approach

This analysis applied simulated battery storage capacity to historical outage data to determine how the batteries could have mitigated the interruptions. We use outage data from the five IOUs from 2014-2018, where each row of the dataset represented a different outage characterized by utility, circuit, cause, number of customers interrupted, start time, end time, and duration of the interruption. The process of assessing the reliability and resilience impacts followed the five steps outlined in Figure 3.1. The steps are summarized below.

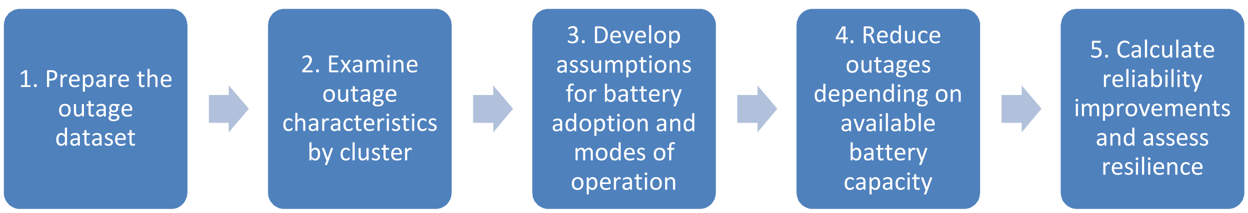

Figure 3.1 Overview of approach for assessing reliability and resilience improvements

1. **Prepare the outage dataset:** We clean the outage data from the five IOUs to remove outliers and inconsistent data, standardize outage cause descriptions, and exclude similar time frames and outage types.
2. **Examine outage characteristics by cluster:** Circuits were grouped into six clusters of similar circuits using the method outlined in Section 4.2. We summarize historical outage characteristics and compared them between clusters to gain an understanding of the 'baseline' level of outages.
3. **Develop assumptions for battery adoption and modes of operation:** We develop assumptions for customer battery adoption (described in Section 4.3) and apply them to each cluster to obtain cluster-level residential and commercial penetration levels. We develop five modes of operation, which characterized the hourly and seasonal charging and discharging patterns for battery storage systems. These modes represented different ways that customers could operate their batteries—including one peak shaving mode that could represent operating the battery from the perspective of the utility.
4. **Reduce outages depending on available battery capacity:** Using the load profile of average residential and commercial customers and the battery capacity profile for each mode of operation, we reduce the impact of each outage in the dataset. The extent of impacts

depended on the season, outage onset hour, battery penetration level, and mode of battery operation.

5. **Calculate reliability improvements and assessed resilience:** We calculate new values for SAIDI, SAIFI, and CAIDI (from the customer perspective) to assess the impacts from battery storage by cluster, adoption level, and mode of operation. We also examine the impact of battery storage on the overall number of customer interruptions longer than 24 hours.

4. Representative feeder selection

4.1 Background

Distribution systems are widespread due to their role in providing electric service to each individual customer across a service area. Despite their expanse, distribution systems are relatively homogenous in terms of the topology of feeders and circuits. This is due, in part, to standardization in their construction, but also because most utilities have similar climates within their service territory. Any differences in distribution system topology are driven by the types and number of connected customers, their density, consumption levels, and specific geographical features. These drivers suggest that there are a common set of distribution system topologies within a utility, or across utilities that share relatively similar climates and design standards.

It follows that commonalities across distribution systems can be leveraged to perform complex analyses on representative systems that would otherwise be very time-consuming to perform over the entire service territory. For example, earlier work by Willis, Tram, and Powell (1985) sought to reduce a set of 1,350 feeders in a utility's distribution system to 12 representative feeders to improve analytical processing times. Feeders are a natural unit of analysis for distribution systems: their topologies are well identified; feeders (i.e. medium voltage) are more "stable" over time than secondary (i.e. low voltage) distribution systems; they encompass all customers connected to both low and medium voltage levels; and utilities track many important metrics at the feeder level including peak demand and reliability indices. The IEEE formed the Test Feeder Working Group in 1991 and detailed a set of five feeders that represented specific distribution system conditions, including load imbalance or non-transposed distribution systems (Kersting, 2001, 1991). These feeders were not intended to represent typical circuits, but their release increased the use of test feeders as a step towards generalization of methods and techniques when performing distribution system analysis (Schneider et al., 2018).

Increasing penetration of DERs has renewed the interest in feeder clustering techniques allowing utilities to simulate a small number of representative feeders to understand the impacts of these resources across their entire service territory. Other researchers produced a set of 24 representative feeders in three voltage levels to represent distribution systems across the U.S. (Schneider et al., 2009). The aforementioned authors obtained 575 distribution feeders from 17 utilities across the nation and classified feeders according to their climate region, producing between four to eight feeders per region. More targeted analyses were developed for the Western U.S. (Broderick and Williams, 2013) and western Australia (Li and Wolfs, 2014) for over thousands of feeders. Broderick and Williams found that four representative feeders in the 12 kV class were enough to capture the range of parameters used to categorize feeders. Li and Wolfs recommended nine clusters to represent the 22 kV feeders that are typical in Australia. Building from these studies, Cale et al. (2014) developed a clustering analysis for 1,295 distribution feeders in the Arizona Public Service territory, resulting in nine representative clusters.

This study employs these techniques, especially the method developed by Cale et al. (2014), to produce a set of six representative feeders for the five IOUs in the state of Indiana. The number of representative feeders balances breadth with the ability to accommodate the number of power flow simulations necessary given the number of customer loads, time horizons, and DER adoption scenarios. On average, each feeder is simulated approximately 570 times. It should be noted that the addition of even a few more feeders would render the simulation process and analysis of results intractable. The number of feeders is also well within the range of typical feeder numbers developed in previous reports, which ranged between four and nine.

4.2 Sampling method

The method to identify the optimal number of representative feeders and ultimately select the final clusters largely follows the most recent work on this topic by Cale et al. (2014). The method employed is based on the following steps:

1. Identify available feeder metrics for clustering
2. Transform the data using Principal Component Analysis (PCA) and identify outliers
3. Determine the optimal number of clusters
4. Select representative feeders for each cluster

The following subsections describe each of these steps in more detail.

4.2.1 Identifying available metrics

A representative feeder analysis depends on the choice of parameters used to classify feeders as well as the quality and availability of data from each utility. The studies cited earlier characterize feeders with varying degrees of complexity, ranging from the six parameters in Broderick and Williams (2013) to the 35 parameters in Schneider et al. (2009). In this study, we initially asked the five Indiana IOUs to provide 23 parameters for all of their distribution feeders between the voltages of four to 33 kV. In a subsequent request, the utilities were asked to provide reliability metrics for each feeder for the years 2014 to 2018. This information was used to calculate five-year average SAIFI, SAIDI, and CAIDI for each feeder, which added three more parameters to the feeder characterization dataset. The completeness of the 26-parameter datasets varied substantially across utilities (see Table 4.1). In addition to the data completeness issue, I&M submitted a set of representative feeders rather than their entire feeder population.

Approximately 92% of the 2,790 feeders submitted by utilities corresponded to the 12 kV family (nominal voltage between 11 and 13.8 kV). Three percent of feeders belonged to the 33 kV family and five percent to the four kV family. This study focused on the 12 kV feeder family only (2,573 feeders) given the predominance of 12 kV family feeders and that most four kV feeders are single-customer feeders.

This report performs a number of data quality detection and cleaning steps for all feeders in the 12 kV feeder family. The report focuses on DER adoption impacts on distribution feeders, hence all non-distribution feeders were excluded from the analysis as they were not considered relevant for the focus of the study. The definition for non-distribution feeders were those shorter than 0.1 mile or with fewer than 10 customers. Subsequently, 2,552 feeders were available for the analysis.

Table 4.1 Share of feeders by utility reporting characterization parameters

		Share of feeders reporting parameter				
Parameter name	**Description**	**Duke**	**I&M**	**IP&L**	**NIPSCO**	**Vectren**
agg_tr_cap	Aggregate MV/LV transformer capacity (MVA)	99%	100%	100%	98%	100%
avg_caidi	Average feeder CAIDI (2014-2018)	98%	100%	100%	97%	98%
avg_saidi	Average feeder SAIDI (2014-2018)	98%	100%	100%	97%	98%
avg_saifi	Average feeder SAIFI (2014-2018)	98%	100%	100%	97%	98%
enclo	Number of underground enclosures	100%	100%	100%	100%	0%
len_oh	Total overhead circuit length (miles)	100%	100%	100%	100%	100%
len_ug	Total underground circuit length (miles)	100%	100%	100%	100%	100%
num_cust_ag	Number of agricultural customers	0%	22%	100%	0%	0%
num_cust_com	Number of commercial customers	98%	97%	100%	98%	0%
num_cust_ind	Number of industrial customers	68%	49%	100%	98%	0%
num_cust_other	Number of other customers	94%	20%	100%	98%	0%
num_cust_res	Number of residential customers	95%	97%	100%	98%	0%
num_cust_tot	Total number of customers in feeder	100%	100%	100%	100%	100%
peak_dm	2018 feeder peak demand (MVA)	0%	100%	90%	100%	100%
poles	Number of poles	100%	100%	100%	100%	100%
sh_cap_ag	Share of connected capacity, agricultural customers	0%	22%	100%	0%	100%
sh_cap_com	Share of connected capacity, commercial customers	98%	97%	100%	98%	100%
sh_cap_ind	Share of connected capacity, industrial customers	98%	48%	100%	98%	100%
sh_cap_other	Share of connected capacity, other customers	98%	20%	100%	98%	100%
sh_cap_res	Share of connected capacity, residential customers	98%	97%	100%	98%	100%
sh_ene_ag	Share of energy sales to agricultural customers	0%	19%	100%	0%	100%
sh_ene_com	Share of energy sales to commercial customers	0%	94%	100%	98%	100%
sh_ene_ind	Share of energy sales to industrial customers	0%	46%	100%	98%	100%
sh_ene_other	Share of energy sales to other customers	0%	18%	100%	98%	100%
sh_ene_res	Share of energy sales to residential customers	0%	94%	100%	98%	100%
tot_len	Total feeder circuit length (miles)	100%	100%	100%	100%	100%

The final step after the 12 kV feeder family filtering and the removal of feeders that were not relevant for the analysis was parameter selection. The varying levels of data completeness, even after requesting utilities to fill in the missing information, created a trade-off between the number of parameters and the size of the definitive dataset. The sample size was dramatically reduced when only feeders that reported all the required data characteristics were included. However, choosing parameters without checking which utility reported it risked leaving an entire utility outside of the sample, which was undesirable.

We selected a subset of parameters that encompassed the largest amount of feeders, included all utilities, and still captured the critical variables identified in previous studies. For example, two utilities did not sufficiently report the number of feeder customers by segment, but all of them reported the total number of customers. Several utilities did not sufficiently report the share of energy sales by customer segment, but they did report the share of installed capacity by customer segment. Table 4.2 shows the selected parameters with summary statistics. The final number of feeders by utility employed in the analysis is shown in Table 4.3. As indicated, the reduced I&M feeder sample resulted in a relatively reduced representation compared to the other IOUs.

Table 4.2 Selected feeder parameters, with summary statistics

Parameter name	Description	Count	Mean	Standard deviation
poles	Number of poles	2,252	549	474
len_oh	Total overhead circuit length (miles)	2,252	13	14
len_ug	Total underground circuit length (miles)	2,252	6	8
agg_tr_cap	Aggregate MV/LV transformer capacity (MVA)	2,252	13,485	8,385
sh_cap_res	Share of connected capacity, residential customers	2,252	57%	30%
sh_cap_com	Share of connected capacity, commercial customers	2,252	29%	23%
sh_cap_ind	Share of connected capacity, industrial customers	2,252	9%	17%
sh_cap_other	Share of connected capacity, other customers	2,252	5%	10%
avg_caidi	Average feeder CAIDI (2014-2018)	2,252	137	55
num_cust_tot	Total number of customers in feeder	2,252	902	659
tot_len	Total feeder circuit length (Derived)	2,252	19	17
sh_len_und	Share of underground length from total length (Derived)	2,252	32%	26%

Table 4.3 Definitive number of feeders by utility with complete data

IOU	Number of feeders
Duke Energy	938
I&M	20
IP&L	364
NIPSCO	756
Vectren	174
Total	2,252

The definitive subset of parameters did not include SAIDI or SAIFI because utilities used a different customer base to calculate these indicators. Two utilities used feeder-level customer counts, while the other three used system-level customer counts. This differences made the SAIFI and SAIDI data not reconcilable. CAIDI was then employed because the metric is indifferent to the number of customers, and also because it summarizes SAIDI and SAIFI and generally reflects feeder-level reliability.

The next steps in finding representative feeders involves transforming the feeder data and then applying a clustering algorithm. These steps are needed to make sure data is comparable across the different feeder variables, and that the feeders are grouped based on a rigorous statistical method.

Details for these steps are reported in Appendix B.1.

The first stage in the clustering process recommended four clusters to represent the IOUs' feeders. In the second stage, we ran the clustering algorithm with five, six, seven, and eight clusters, and manually compared basic metrics between the clusters. This approach follows the lead of Schneider et al. (2009), who sought to define feeder topologies that would describe actual feeders based on their density, location, and customer segments served. We found that six clusters classified feeders in reasonably mutually exclusive categories that were characterized by specific service, topology, and reliability configurations (see Table 4.4)

Table 4.4 Six representative clusters and a sample set of parameter statistics

Cluster	General description of feeders in cluster	Average customer number	Average total length (miles)	Average CAIDI (min)	Share of installed capacity (residential)	Share of installed capacity (commercial)	Share of installed capacity (industrial)	Share of circuit length that is underground
1	Short and high commercial, about 1/3 underground	445	9.5	145.1	25%	58%	6%	30%
2	Short, urban residential	567	11.5	142.4	77%	17%	2%	19%
3	Suburban mostly overhead, residential, relatively dense	1,472	21.7	135.4	70%	21%	7%	20%
4	Very long residential mostly rural	1,133	59.3	148.5	78%	15%	3%	19%
5	Suburban underground residential relatively dense	1,535	26.2	121.4	77%	17%	5%	67%
6	Short, heavy industrial, substantial underground	463	10.0	120.8	15%	31%	51%	39%

As shown in Table 4.4, the basic statistics for each cluster lead to the following cluster interpretation:

1. The first cluster represents circuits with a higher concentration of commercial customer capacity, and with extensive underground sections. This cluster may correlate with urban and suburban commercial areas.
2. The second cluster corresponds to short, urban and suburban feeders.
3. The third cluster corresponds to relatively dense and long, residential feeders served mostly by overhead power lines (i.e., typical of older suburban areas).
4. The fourth cluster groups very long and sparse residential feeders. These types of feeders are common in semi-rural and rural areas.
5. The fifth cluster classifies feeders with substantial underground share of the total circuit length, largely residential with better reliability indices (i.e., may be typical of newer suburban subdivisions).
6. The sixth cluster groups short feeders that serve primarily industrial customers with high levels of reliability. This is the result of undergrounding long portions of the feeder, but also of connecting fewer customers to the feeders to minimize failure points.

4.2.2 Selecting representative feeders

Once the clusters were determined, each feeder was assigned into a cluster based on its principal component decomposition. The resulting assignment by IOU is reported in Table 4.5. The clustering allocation by utility suggests that the largest utility, Duke Energy, has a relatively even distribution of feeders across the six clusters. However, smaller utilities tend to concentrate their feeders in specific clusters. For example, the majority of IP&L feeders were classified in clusters 3, 5 and 6, while most of NIPSCO feeders correspond to clusters 1 and 2. While these concentrations are interesting and possibly logical, it is important to remember that the purpose of the clustering is to analyze feeders based on their characterizing features regardless of the utility it belongs to.

Table 4.5 Count of feeders assigned to representative clusters by IOU

	Cluster					
IOU	**1**	**2**	**3**	**4**	**5**	**6**
Duke	103	237	231	127	201	39
I&M	8	1	5	2	0	2
IP&L	15	5	93	14	110	127
NIPSCO	395	197	49	30	38	47
Vectren	35	55	23	30	28	3

A single representative feeder is selected for each cluster using statistical methods that identify an "average" feeder across multiple dimensions or variables (see Appendix B.1.3 for more details of this process). In processing the existing feeder metrics, Duke Energy feeders had to be excluded because their feeder models are not available in the Cymdist format that will be used for the power flow simulations. No I&M feeders were selected as representative by this method because of the limited number of I&M feeders in the analysis. Definitive representative feeders were then assigned by the D^2 distance analysis to NIPSCO, IP&L, and Vectren (see Table 4.6).

Table 4.6 Definitive representative feeders

Cluster	IOU	Representative feeder
1	NIPSCO	SPRING
2	NIPSCO	WARNER ROAD
3	IP&L	LAWRENCE_08
4	Vectren	HORNVILLE
5	IP&L	TREMONT_04
6	IP&L	EAST_07

These feeder selections were communicated to the respective IOUs to request detailed customer level data that was used to prepare input data for the simulation (see section 4.3). In this process, NIPSCO reported that one of the feeders we had originally selected had suffered a major reconfiguration after a large customer was disconnected from this feeder and connected at the transmission level. That feeder was discarded and the next closest feeder in terms of D^2 distance was selected (shown in Table 4.6). The sampled IOUs also provided individual feeder models that would speed up the simulation process by avoiding the need to simulate larger portions of the distribution system. The next section explains the methodology used to set up and calibrate the simulations of the representative feeders.

4.3 Creating input data for simulations

The next step in the analysis involves selecting a number of representative feeders to run power flow simulations in different DER adoption scenarios, hours of the day, and time horizons. In this section, we explain how the scenarios from Section 2 are used to calibrate net demand for each load in the six representative feeders selected for this analysis.

The basic procedure to create the input data for the Cymdist power flow simulations is detailed as follows:

1. Obtain information for each customer connected to each one of the six feeders
2. Define basic DER configuration parameters by customer segment, such as battery storage size, battery storage operational strategy, and PV system size
3. Develop a method to forecast DER adoption by customer for the two analysis years, 2025 and 2040.
4. Produce hourly demand and production curves for native load and the three DER considered in this study (PV, electric vehicle charging, and storage operation) using synthetic hourly load data derived in part from information provided by the IOUs
5. Create an annual vector of hourly active and reactive net demand for each customer across the six representative feeders

This five-step procedure results in hourly net demand vectors that reflect seasonal, weekly, weekend-weekday, and hourly variation in the demand and production of electricity by each customer. The simulation process will select all the hours in the peak demand day and the lowest demand day to simulate a power flow over the entire feeder. We explain the content of each step in the procedure as follows.

In the first step, we requested information to characterize each customer connected to the representative feeders. This information included the customer's segment, their rate class, facility square footage, annual income, demand response participation (kW reduced), energy efficiency reductions (kWh), consumption (kWh), and whether the customer has DER, among others. Information on income by customer was available only for one utility. Even in this case, it was an estimate based on zip code-level data that did not capture individual customer income levels so it was not considered. Customer-level information was aggregated at the transformer level to locate it within the primary voltage feeders to be simulated.

In the second step, DER systems were designed based on typical existing and forecasted sizes as indicated in Table 4.7. We assumed that industrial customers would not adopt distributed resources. While this is not necessarily true, their adoption patterns do not follow the same generalizable logic as those of residential and commercial customers, and hence would have to be modeled on a case by case basis.

Table 4.7 Assumed size for DER systems by customer segment

DER System	Residential	Commercial	Industrial
Rooftop PV	• 8 kW	• 16 kW	N/A
Battery storage	• 7 kW max discharge capacity • 12 kWh storage capacity • 90% roundtrip efficiency • 25% maximum discharge level	• 14 kW max discharge capacity • 0.1% of annual kWh consumption of storage capacity • 90% roundtrip efficiency • 25% maximum discharge level	N/A
Electric vehicle charging	• T1 charger: 1.75 kW peak capacity • T2 charger: 5.25 kW peak capacity	N/A	N/A

We assume residential customers would adopt 8 kW PV systems on average and commercial customers would adopt a 16 kW system. For battery storage, we used the parameters of a Tesla Powerwall 2 for residential customers (12 kWh useful storage capacity), and a custom-sized system for commercial customers based on their annual consumption. The 0.1% of annual consumption parameter was based on an analysis of existing installed systems for commercial customers. Finally, we assumed that electric vehicles were adopted by residential customers. For simplicity, we assume that charging also takes place at home using Type 1 and Type 2 charging technologies. Type 1 chargers have a peak demand of 1.75 kW, while Type 2 chargers have a peak demand of 5.25 kW. We assumed no vehicle-to-grid interaction or smart charging management since data to calibrate these charging modes is unavailable.

Aggregate scenarios for DER adoption were reported in Section 2. The third step in the input development process involves identifying a method to determine DER adoption at the customer-level to match the state-wide estimates. These customer adoption levels are scaled to the cluster and state level and verified against the aggregate levels by year and scenario defined in Section 2. The DER allocation method has two components: (1) scaling factors for each feeder and; (2) energy consumption thresholds for each DER, customer segment, and adoption level.

First, scaling factors reflect feeder-level DER adoption aggregates at the cluster-level. These factors were calculated for each representative feeder as the ratio between the number of customers at each feeder and the total number of customers for the cluster that the feeder represents. We obtain state-level adoption values by adding the cluster-level scaled adoption values.

Next, energy consumption thresholds were defined for each DER and each customer segment, and for the base, high, and very high adoption levels in the scenarios. Customers that had an annual native load consumption (without considering EV and PV) above those threshold levels would be marked as DER adopters. This method assumes that higher consumption will correlate with higher adoption, which is supported by the fact that, in the absence of policy incentives, the main reason customers adopt solar energy is to save money (Moezzi et al., 2017). The energy consumption thresholds are described in Table 4.8.

Table 4.8 Annual energy consumption thresholds for DER adoption

		Residential		Commercial	
DER	**Adoption level**	**2025 threshold level (kWh)**	**2040 threshold level (kWh)**	**2025 threshold level (kWh)**	**2040 threshold level (kWh)**
PV	Base	50,000	41,000	75,000	34,000
PV	High	24,500	18,500	32,000	7,600
PV	Very High	21,000	14,250	18,000	3,000
EV-T1	Base	44,000	24,500	N/A	N/A
EV-T1	High	36,000	18,500	N/A	N/A
EV-T1	Very High	27,000	11,000	N/A	N/A
EV-T2	Base	34,500	18,100	N/A	N/A
EV-T2	High	28,200	12,800	N/A	N/A
EV-T2	Very High	19,350	4,700	N/A	N/A
Storage	Base	N/A	140,000	N/A	N/A
Storage	High	46,500	37,000	700,000	600,000
Storage	Very High	32,000	24,500	400,000	220,000

In general, threshold levels for residential and commercial customers decrease over time due to higher 2040 adoption rates compared to 2025. Similarly, thresholds decrease for higher adoption levels (e.g. the residential 2025 PV adoption levels is lower in the "high" case compared to the "BAU" case). The resulting DER adoption rates by customer segment, year, and adoption levels are reported in Table 4.9. These adoption rates are calculated as the number of customers that adopt a given DER divided by the total number of customers for the same segment on each feeder. Adoption rates across clusters vary substantially as it follows the customer mix and consumption levels, which are heterogeneous. For example, PV adoption in the base adoption level for 2040 is eight times higher in cluster six compared to cluster three.

Table 4.9 Resulting DER adoption rates by customer segment and year

		Residential		Commercial	
DER	**Adoption level**	**2025 adoption rate (% of customers)**	**2040 adoption rate (% of customers)**	**2025 adoption rate (% of customers)**	**2040 adoption rate (% of customers)**
PV	Base	0.2%	0.6%	12.2%	23.5%
PV	High	4.6%	10.9%	24.6%	51.9%
PV	Very High	7.7%	20.5%	35.5%	70.4%
EV-T1	Base	0.5%	4.6%	N/A	N/A
EV-T1	High	1.0%	10.9%	N/A	N/A
EV-T1	Very High	3.4%	34.4%	N/A	N/A
EV-T2	Base	1.3%	11.4%	N/A	N/A
EV-T2	High	3.0%	26.2%	N/A	N/A
EV-T2	Very High	9.6%	84.3%	N/A	N/A
Storage	Base	0.0%	0.0%	0.0%	0.0%

		Residential		Commercial	
DER	Adoption level	2025 adoption rate (% of customers)	2040 adoption rate (% of customers)	2025 adoption rate (% of customers)	2040 adoption rate (% of customers)
Storage	High	0.4%	0.9%	0.6%	0.6%
Storage	Very High	1.8%	4.6%	1.3%	2.5%

The fourth step in the creation of input data is to use hourly profiles to generate an 8760-hour annual vector for each customer's native load and DER operation. Profiles were generated for native load, EV charging, PV generation, and battery operation. Native load profiles were generated for each customer class (residential, commercial, and industrial), and were based on historic rate class load profiles provided by the utilities. EV profiles were generated for Type 1 and Type 2 chargers. The charging profiles assumed that charging would begin at 6 pm on weekdays and 2 pm on weekends, and would charge each EV enough for the owner to drive the next day. Annual charging assumed each EV would need to be driven 12,000 miles annually, which is the current average distance driven in the U.S. Production profiles for PV were created using NREL's PVWatts model. Storage operational profiles are obtained by assuming that storage owners seek to maximize the netting of their DER PV, subject to a maximum discharge of 25% of their storage capacity. There are no assumptions about time of use rates or other incentives that would inform storage operation within the power flow analysis. Figure 4.3 depicts an example of what a representative residential customer's DER loads with no EV charging might look like on an average summer weekday.

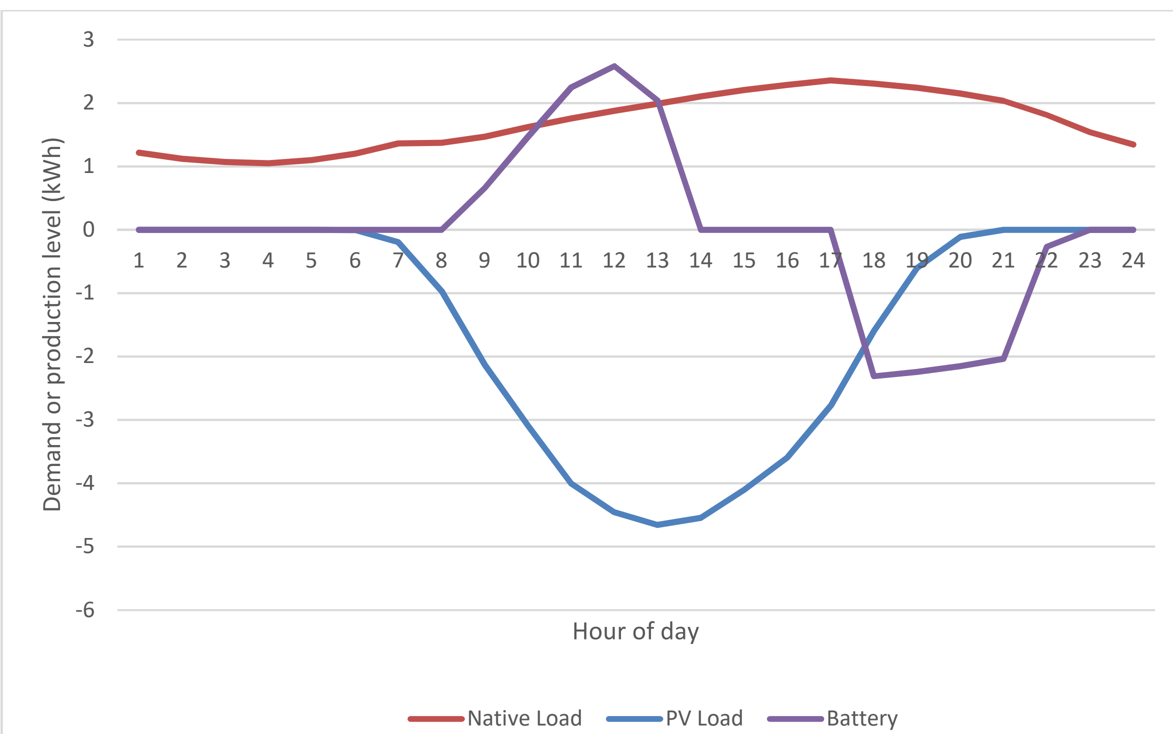

Figure 4.1 Sample residential DER hourly operational profile for average summer weekday (kWh)

The final step involves making assumptions about power factor and phase balancing, as the Cymdist input data is provided for each connected phase and for active and reactive power. The models sent by IP&L and NIPSCO included power factor for each load node; these power factors are used to represent reactive power demand on these feeders. The feeder for cluster four, a Vectren feeder, did not include these values. In their place, we use the median value for the other five feeders. We finally assume that loads are balanced and allocate hourly net demand in equal way to reported connected phases for each load node.

4.4 Output metrics

Three specific variables from the power flow simulation are tracked to inform potential DER integration benefits or costs. These variables include: voltage violation by node, line loading (thermal constraints), and line losses.

Voltage violations by node

Voltage violation will be tracked by each load node in the feeder. Two metrics are tracked: (1) voltages above/below the ANSI C84.1 standard and (2) voltage differences across the adoption scenarios. First, we track whether any load node has a per unit (p.u.) voltage below or above the ANSI C84.1 standard (ANSI, 2016). In the case of 12 kV feeders, the optimal range is 97.5%-105% of nominal voltage (0.975 – 1.05 p.u.) and the acceptable range is 95%-105.8% (0.95 – 1.058 p.u.). Next, we track the differences in voltage by node between the base case and each of the five adoption scenarios. In this case, voltage levels may still be within ANSI standard, but we want to track whether higher levels of DER integration cause relevant voltage deviations compared to the base case.

Line loading (thermal constraints)

Line loading reflects the current flowing over a line segment in proportion to its nominal current carrying capacity given by the wire gauge, type, and configuration. While it is not uncommon to overload lines in normal distribution operation, we use a conservative approach and identify the number of hours in which a line segment is loaded more than 100% of its capacity.

Line losses

Line loss management is largely an economic decision, rather than a technical threat to power quality. A utility may upgrade[5] a conductor that is not permanently overloaded, but whose losses are such that is cost effective to reduce them. Generally, overload and losses issues are correlated. We will measure the variation in losses for the scenarios compared to the base case and monetize them, but we do not suggest intervention strategies to correct losses.

There are several variables that are not captured in the power flow simulations and can also accrue integration costs. These include sub-hourly dynamics such as voltage sag or flicker, reverse power flow issues, and protection coordination issues (Horowitz et al., 2019). The limitations of the available data and limited computational resources do not allow assessment of secondary voltage networks and distribution transformers. For this reason, they are excluded from this analysis.

[5] Upgrading lines with higher gauge conductors than existing is usually called repowering or re-conductoring.

4.5 Method for upgrading feeders

The method for upgrading feeders is largely based on work by NREL in assessing PV integration costs (Horowitz et al., 2018). There are several interventions to respond to substandard conditions in the three tracked variables:

Voltage violations

There are three strategies implemented for voltage violation interventions: installation of advanced inverters in PV systems, adjustment of the substation's load tap changer (LTC), and connecting a voltage regulator.

Modern PV inverters are able to consume or generate reactive power up to 30% of their rated apparent power. They are usually programmed to generate reactive power when voltage drops from a certain level, and consume it when it goes above, with a dead band in between. The installation of advanced inverters in PV systems can be used to regulate voltage drops and increases at the point of injection of the distributed resource.

Adjustment of the LTC at the substation is a traditional mechanism to correct for ongoing voltage excursions. It affects the entire feeder by shifting the head voltage up or down, and it is commonly used to fix voltage drops at the end of the feeder. They are generally not used in real-time, but to permanently adjust voltage in the feeder head. It is worth noting that not all substations are necessarily equipped with LTC.

Connecting a voltage regulator performs a similar function as advanced inverters, with a wider range of operation and significantly higher capacity to manage reactive power. They can be used to correct for voltage drops and increases in real-time.

Line loading

In the case of line loading, installing higher gauge conductors (i.e., re-conductoring), which have higher ampacity, reduces the line loading for similar current levels. As indicated before, we are not able to implement and test feeder reconfigurations as a line loading strategy within the framework for this study although this is a commonly used strategy by distribution utilities.

Line losses

As is the case with line loading, re-conductoring is a common way to reduce line losses. Utilities will occasionally reconfigure a feeder by routing circuits to a different feeder. This has the effect of balancing the load and reducing the overall losses due to their non-linearity. We will not explore feeder reconfiguration in this study, but it is a recommendation under consideration.

5. Results

5.1 Distribution system power flow technical results

Simulations are executed on each of the six representative primary voltage feeders, and characterized by (1) the year of analysis (2025 or 2040), which drives load growth and adoption levels; (2) six adoption scenarios, which establish different combinations for adoption levels of distributed PV, storage, and electric vehicles; and (3) twenty-four hours (a full day) on the minimum and maximum load days, for a total of 48 hours per feeder-scenario-year-cluster combination. These variables result in 576 power flow simulations per representative feeder, for a total of 3,456 simulations.

5.1.1 Voltage regulation

Results for voltage regulation are reported in Figure 5.1 (next page). In this figure, the column panel report the six adoption scenarios while the row panel depict the six representative feeders identified by their cluster CL1 to CL6. The charts show the distribution of voltage in p.u. (per unit or the fraction of nominal voltage) for each simulated node-hour[6], where the red shade represents 2025 and the blue shade 2040. The vertical lines represent the two ANSI voltage violation criteria: orange for the optimal range and red for the acceptable range.

At first glance, voltage violations are rare and minimal. About 0.5% of the node-hours simulated are under the 0.975 p.u. lower voltage range for the optimal scenario and 0.3% node-hours are above the 1.05 p.u. upper range. Only 0.04% of the node-hours are under the 0.95 p.u. lower acceptable range, and none are above the 1.058 upper acceptable range. The absolute minimum and maximum voltages are reasonably close to the ANSI limits for all of the node-hours simulated (Table 5.1).

High voltage violations are very small, exceeding the optimal range by 0.009 p.u. in the worst case. Low voltage violations are also very limited, with a worst case excursion 0.053 p.u. below the optimal limit. Low load day simulation hours fall almost entirely within optimal and acceptable ranges; the majority of the voltage violations occur during high load days.

Table 5.1 Ranges in voltage regulation for low and high load day simulated hours, by year

		Voltage Levels (p.u.)				
Year	Type of Load Day	Minimum	25th Percentile	Median	75th Percentile	Maximum
2025	High	0.957	1.009	1.02	1.033	1.054
2025	Low	0.988	1.016	1.025	1.038	1.046
2040	High	0.908	1.008	1.019	1.031	1.058
2040	Low	0.945	1.016	1.026	1.038	1.057

6 A node-hour is a unique observation for a node on one of the 48 simulated hours. We treat node-hours as a single variable to be able to show results for the same node across different hours in the same chart, and avoid one additional dimension in the visualization.

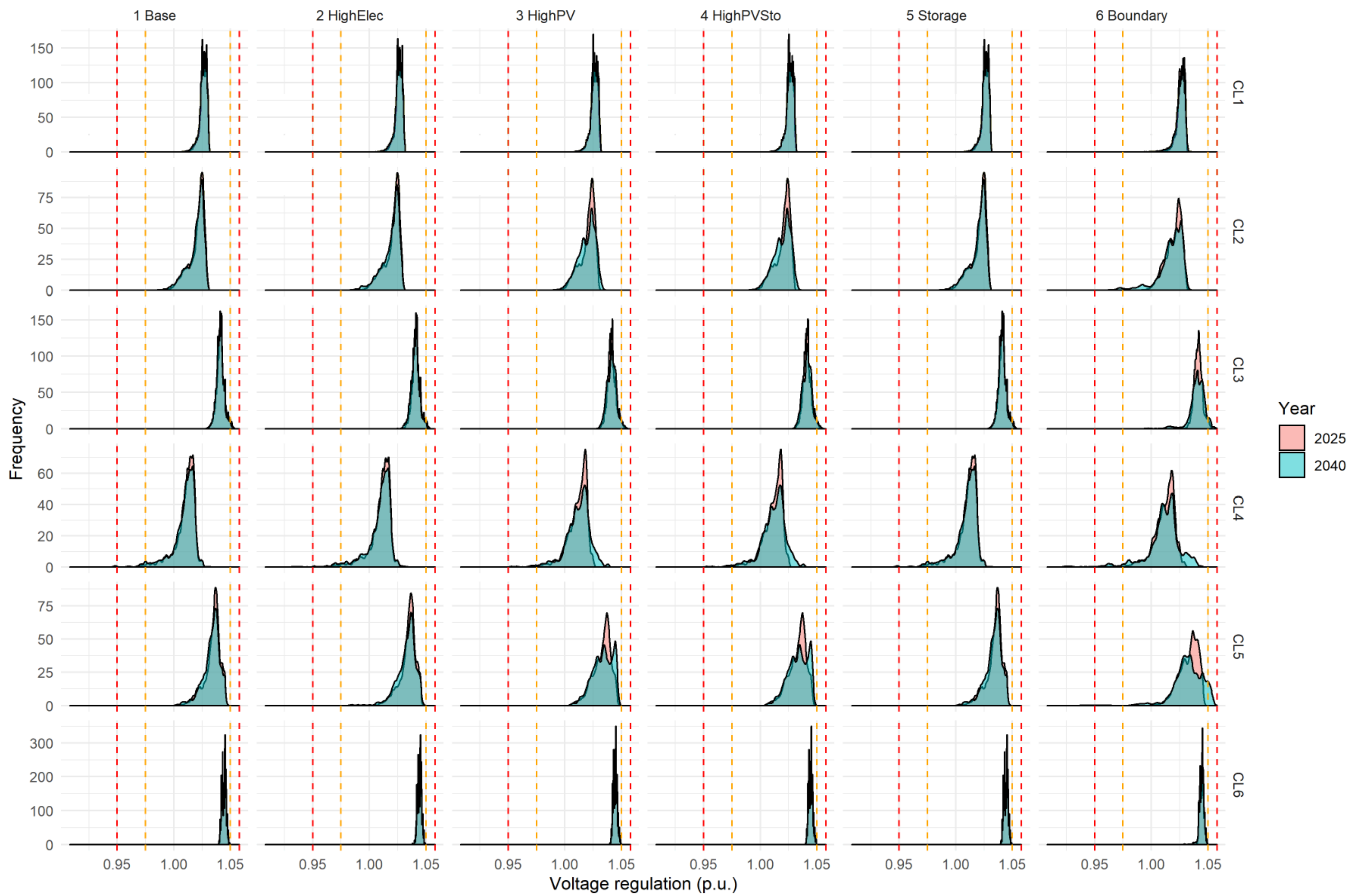

Figure 5.1 Distribution of voltage regulation by node-hour

However, it is important to study power systems in the extreme, because critical issues can be lost in a simple analysis of averages. We find optimal range voltage violations in at least one feeder node on 159 of the 3,456 simulated hours and acceptable range violations in 17 simulated hours (see Table 5.2 for optimal range violations). Representative feeders in clusters 1, 5, and 6 exhibit voltage violations, but only in the Boundary scenario. Cluster 2 feeder has two to three simulation hours with violations in the Base, High PV, High PV and Storage, and Storage scenarios; and five hours in the Boundary and High Electrification scenarios. Feeders for clusters 3 and 4 – among the longest in the sample – have the highest number of hours of voltage violations. In cluster 3, almost 20% of the simulated hours in the Boundary Case show voltage issues.

Table 5.2 Number of simulation hours with ANSI optimal range voltage violations by cluster and scenario for 2025 and 2040

	Scenario					
Cluster	**Base**	**High Electrification**	**High PV**	**High PV and Battery Storage**	**Storage**	**Boundary Case**
CL1	0	0	0	0	0	9
CL2	3	5	2	2	3	5
CL3	9	8	11	11	9	19
CL4	11	11	6	6	11	9
CL5	0	0	0	0	0	8
CL6	0	0	0	0	0	1

This overview of voltage violation results suggests that some representative feeders are much more impacted by DER adoption than others and that the impact produces both low and high voltage issues. A detailed feeder by feeder analysis is included in Appendix B.2.

5.1.2 Line loading

Cymdist calculates the percent loading of each line segment for each simulated hour, based on the line segments' capacity and power flow solution for a specific hour. Results for line loadings are reported in Figure 5.2. In general, lines loading issues are non-existent in the short-term (2025) and minimal in the long-term (2040). Loading issues in 2040 arise in the Boundary scenario for clusters 3, 4, and 5 and in the High Electrification scenario for cluster 4.

Only eight simulation hours out of 3,456 simulated hours have overloaded line segments. In these eight hours, between 0.4% and 8% of line segments are overloaded, depending on the cluster (see Table 5.3). Line overloading takes place in very specific times of day, coinciding with peak residential demand (2-3 pm) or with DER PV production decline coupled with EV charging (6-7 pm). Overloading is also incremental, which means that mitigating the overload for the worst case scenario in each cluster (6 pm at each cluster) will also mitigate issues for the other simulated hours in the same cluster.

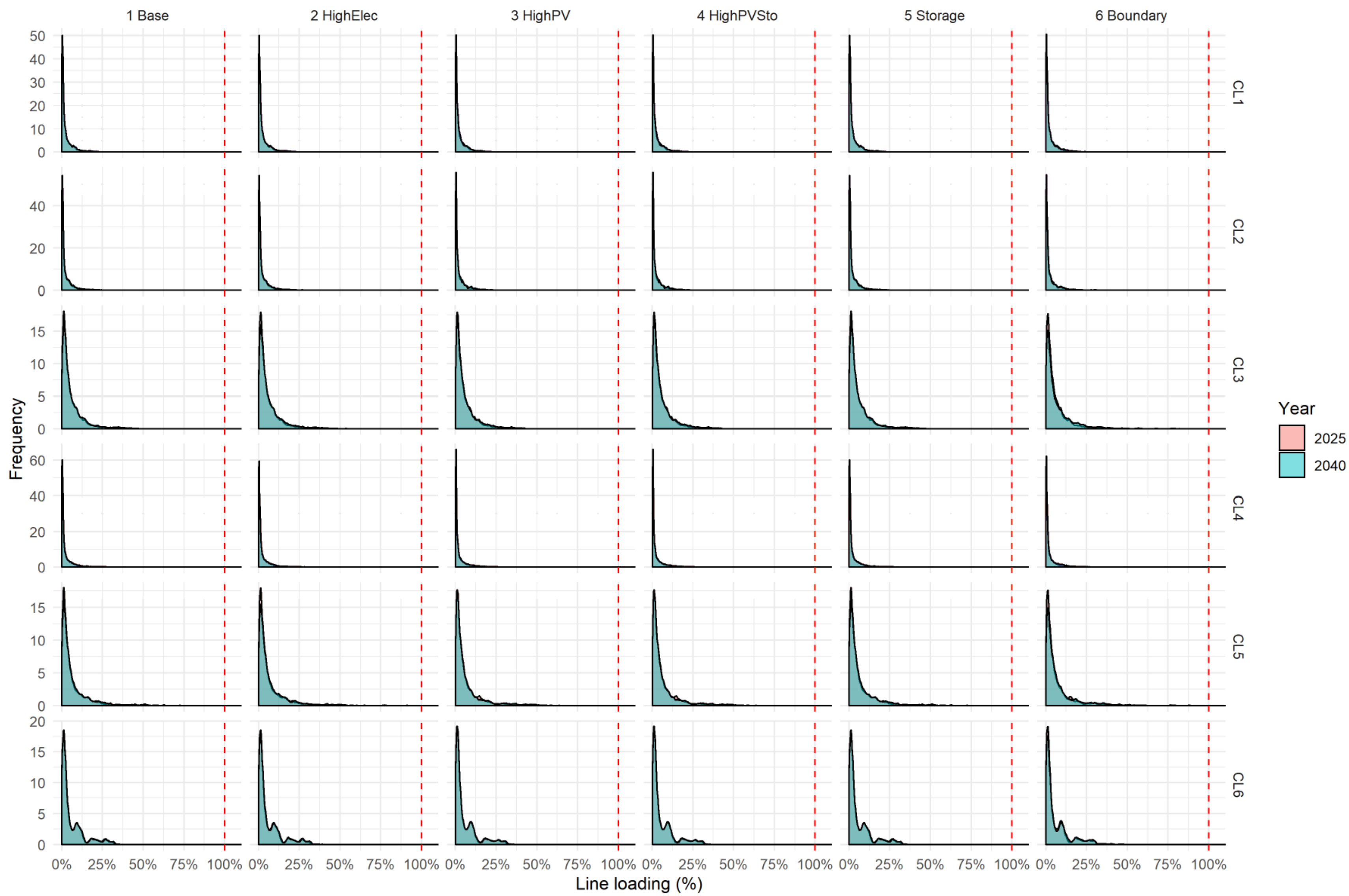

Figure 5.2 Distribution of line loading by node-hour

Table 5.3 Simulation hours with overloading issues

Scenario	Cluster	Hour of Day	Number of Overloaded Segments	Number of Total Segments	Share of Overloaded Segments (% total)
Boundary	CL3	6 pm	31	592	5.2%
Boundary	CL3	7 pm	28	592	4.7%
Boundary	CL4	6 pm	15	1,621	0.9%
Boundary	CL4	7 pm	12	1,621	0.7%
High Electrification	CL4	2 pm	10	1,621	0.6%
High Electrification	CL4	3 pm	10	1,621	0.6%
Boundary	CL5	6 pm	43	535	8.0%
Boundary	CL5	7 pm	42	535	7.9%

Adoption of distributed PV has a beneficial effect in line loading. In the scenarios with higher PV adoption (High PV and High PV with Storage) the worst case line loading is typically 10%-15% less than the High Electrification scenario (with high EV adoption) and 5% less than the BAU scenario (with very little PV adoption). In contrast, it is likely that electric vehicle charging is leading to overloading issues across clusters because the timing of some of the overloading issues coincide with residential type I charging operations.

It is important to highlight limitations of the loading analysis performed in this study. Annual energy consumption by customer was allocated using aggregate load profiles for the three customer types provided by some IOUs due to the lack of actual hourly load shapes or peak power consumption for each customer. The simulation results show that even in the Base case some line segments experience very high loading, while the average line segment loadings are around 5 percent for most clusters and scenarios. These high line loadings may have originated in the method of load allocation, which does not reflect actual customer peak loads. On one hand, the method employed may result in a higher peak load for customers with a relatively flat load demand. On the other hand, the method may produce lower peak load (and lower line loading) for customers with a volatile load profile.

In summary, these results suggest that the existing capacity of line segments in representative feeders would be enough to accommodate the DER deployed under even the most stringent adoption scenario. Required re-conductoring expenditures should be relatively small considering the DER adoption levels. These costs are discussed in Section 5.2. It is important to note that this analysis does not cover distribution transformer loading or secondary network loading. It is possible that these two components do not have the flexibility that the primary distribution system has and would therefore require additional DER integration costs.

5.1.3 Line energy losses

Unlike voltage violations and overloading issues, line energy losses do not translate to power quality issues for customers. However, utilities monitor line losses to maintain a level that is cost-effective for the utility as well as their customers. This means that there is no set standard or benchmark for assessing an acceptable limit for line losses as this cost-effectiveness test will vary across utilities and over time. Consequently, we focus on measuring change in losses between the Base scenario and the other scenarios as a measure of the differential impact of DER adoption.

Feeder losses for the highest hour of the year may be several times higher than average losses calculated using annual aggregates, but it is the latter that informs the overall economic impact of increases or reductions in energy losses. For this reason, we develop a special set of simulations depicting typical conditions in four seasons of the year that are more conducive to aggregate estimates. We select one day per season to capture seasonal patterns in demand and solar PV production. We report hourly losses to show the variation of losses throughout the day and how they correlate with specific DER usage patterns.

Feeder losses for 2025 and 2040 are reported in Figure 5.3 and Figure 5.4, respectively. We report the average percentage change in feeder losses for three selected adoption scenarios: High Electrification, High PV, and Boundary relative to the Base case. We use these three scenarios because results for the High PV and Storage and Storage scenarios are almost identical to the results for the other scenarios and the Base case, respectively.

Results show that line losses follow the new patterns of net demand that arise with PV and EV adoption. Losses are higher than the Base case during the times of day when EV is charging (High Electrification scenario, between 2 pm and 7 pm). Losses are lower than the Base case in the scenarios with higher PV penetration and during the hours of PV production between 10 am and 4 pm. The Boundary scenario in years 2025 and 2040 shows the highest variation in losses compared to the Base case, because it includes very high PV and EV adoption levels. Losses can be 10 to 13 times higher than the Base case during peak demand hours with substantial amounts of residential EV charging.

We estimate annual average losses by calculating the average for each cluster and scenario across all simulated hours for all seasons (see Table 5.4).

Table 5.4 Average hourly change in losses relative to base case (kWh)

	Average Hourly Change in Losses Relative to Base (kWh)					
	High Electrification		High PV		Boundary	
Cluster	2025	2040	2025	2040	2025	2040
CL1	0.01	0.16	-0.15	-0.29	-0.16	2.35
CL2	0.06	0.91	-0.37	-0.78	-0.34	5.80
CL3	0.04	1.57	-0.40	-1.27	-0.44	13.49
CL4	0.42	4.13	-1.84	-2.79	-0.18	8.50
CL5	0.36	5.30	-3.01	-6.45	-2.42	14.24
CL6	0.00	0.10	-0.50	-0.75	-0.73	0.24

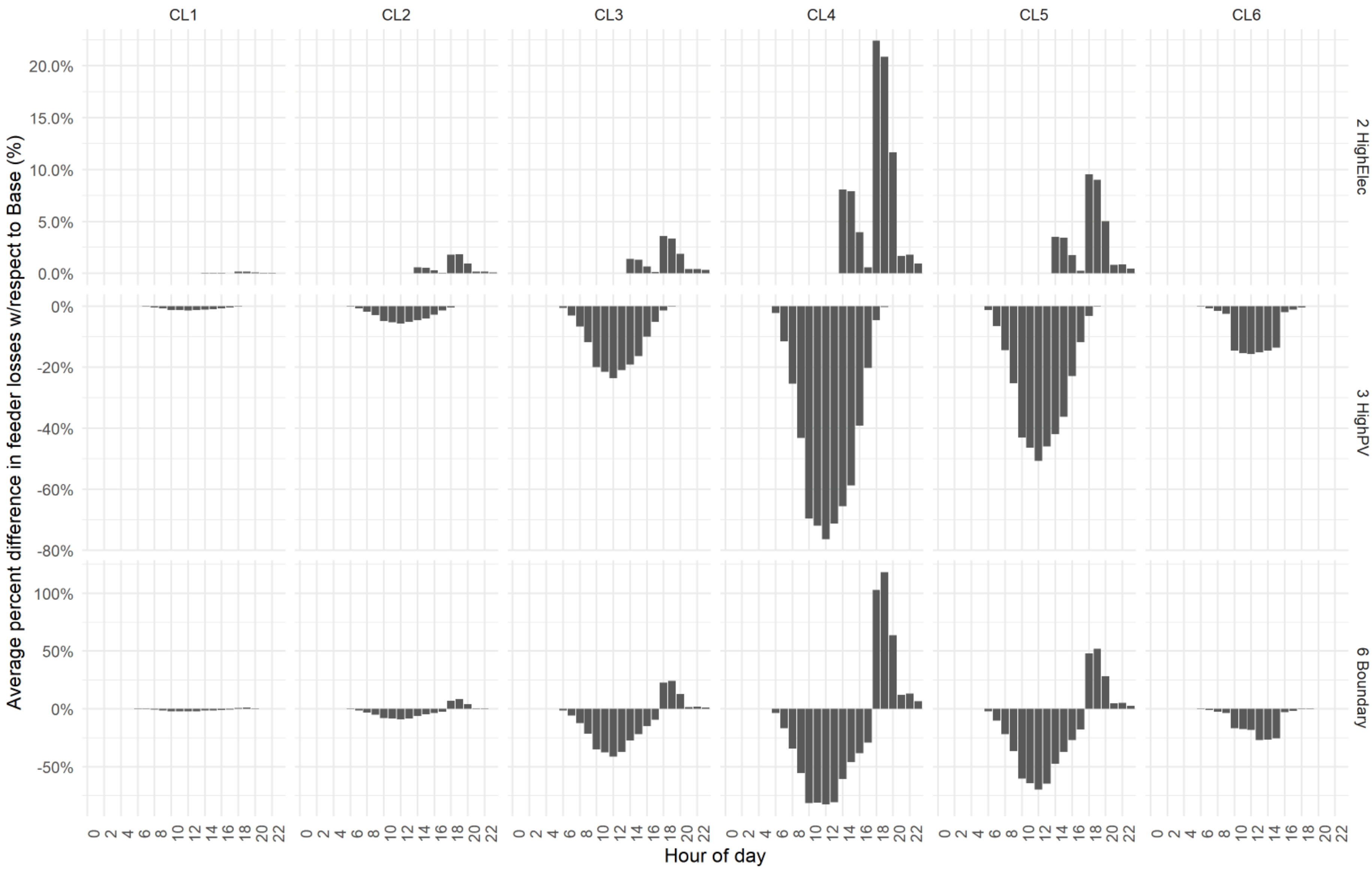

Figure 5.3 Average hourly feeder losses by cluster and scenario (2025)

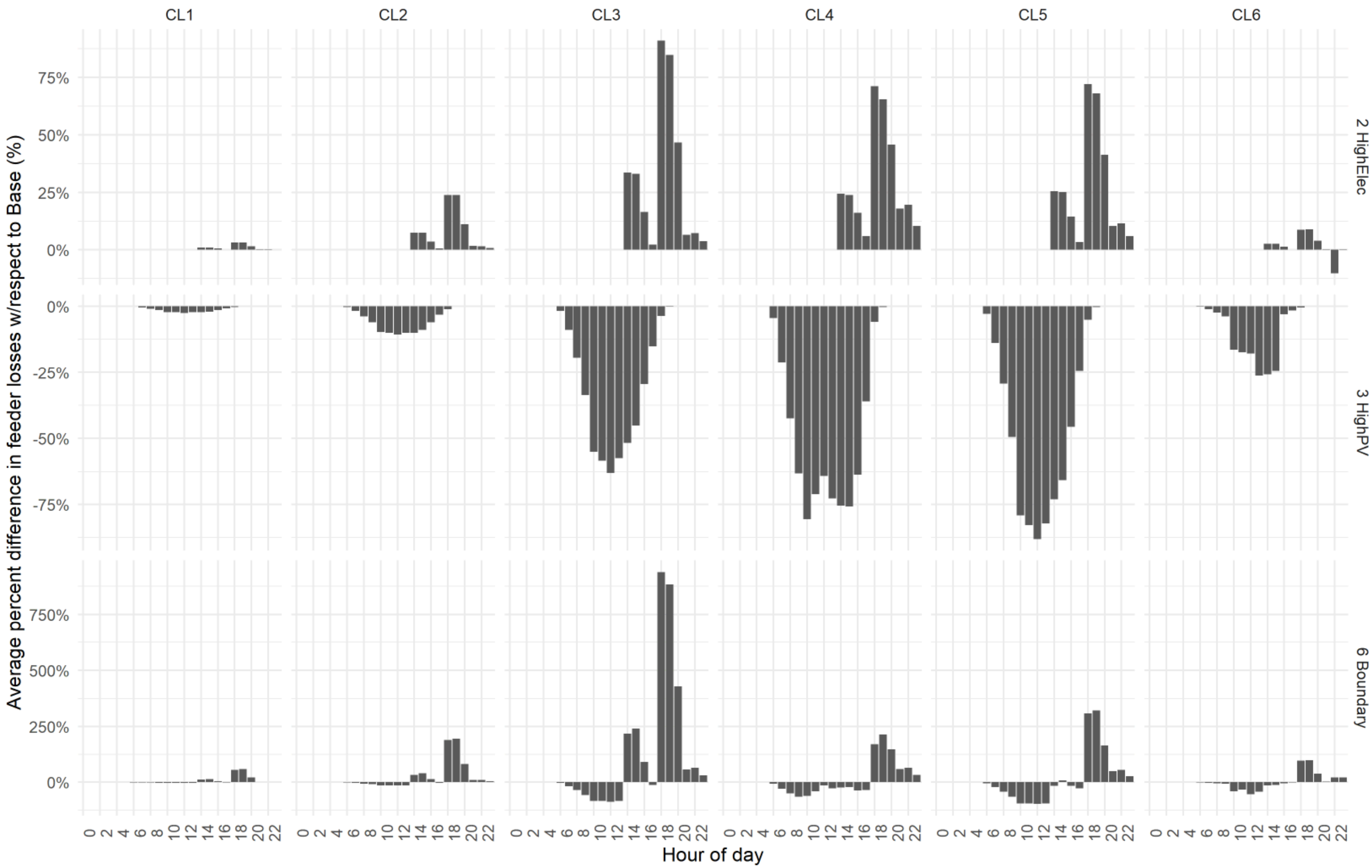

Figure 5.4 Average hourly feeder losses by cluster and scenario (2040)

Average results show moderate increases or decreases in losses across clusters and scenarios for 2025, following the hourly patterns. For 2040, all clusters have higher losses than the base case in the High Electrification scenario, and all clusters have lower losses in the High PV scenario. In the Boundary scenario, losses increase across clusters due to the dominance of EV charging load over PV production.

We extrapolate feeder-level results in Table 5.4 for all IOU service territories by applying the same escalation factors described in Section 4.3 and by multiplying the average hourly losses by 8,760 to extend these estimates to a whole year (Table 5.5). These results will then be used in the following section to provide a first-order estimate of the economic impacts.

Table 5.5 Aggregate change in losses relative to base case for all IOUs (MWh)

	Annual Change in Losses Relative to Base (MWh)					
	High Electrification		High PV		Boundary	
Cluster	2025	2040	2025	2040	2025	2040
CL1	41	709	-656	-1,264	-710	10,348
CL2	306	4,478	-1,817	-3,837	-1,651	28,556
CL3	276	10,289	-2,606	-8,310	-2,861	88,606
CL4	2,005	19,655	-8,739	-13,278	-856	40,458
CL5	985	14,640	-8,310	-17,794	-6,669	39,308
CL6	0	55	-267	-401	-392	129

5.2 Cost and benefits of DER

The costs and benefits of DER are determined separately for the three major components of the power system: (1) generation, (2) transmission, and (3) distribution. Generation and transmission cost impacts are based on simulations performed by the SUFG using input data consistent with the six adoption scenarios developed in this study. Distribution cost impacts are based on the methodology described in section 4.5.

5.2.1 Generation

Hourly net demand for each scenario was shared with the capacity expansion and production cost models. The simulation then reflects the incremental generation investment needs and annual costs to meet those demand levels for years 2025 and 2037[7]. We report four components of generation costs produced by the simulations: (1) annualized capital costs, (2) fixed costs, (3) fuel costs, and (4) non-fuel variable costs (usually O&M).

In the short-term, all scenarios, including the Boundary case, exhibit similar costs relative to the Base case (Figure 5.5). However, over the long-term, the cost differences associated with increased adoption levels become more evident. Scenarios with relatively higher adoption of PV (High PV and High PV and Storage) have 8% lower costs relative to the Base case, largely driven by reduced capital and fixed costs. Costs are roughly 3% higher relative to the Base case in the High Electrification scenario, likely driven by EV charging taking place in the middle of the day. This is supported by the much higher adoption of

[7] This is the latest year available in the SUFG models, hence it is being used as equivalent to 2040 for our purposes.

utility-scale solar PV—whose production peaks midday—in this scenario compared to any other scenario (e.g. twice as much as the Base case).

The Battery Storage scenario is basically identical to the Base case. This is, in part, due to the relatively small levels of adoption of DER storage. However, it also suggests that when customers manage their DER storage without following wholesale market signals, their decisions do not necessarily benefit the system through lower peak demand needs. Finally, the Boundary scenario has ~12% higher costs than the Base case, driven by the strong demand growth of EV charging. It is important to note that the Boundary scenario is serving a 50% higher peak demand than the Base case.

These results suggest that DER adoption, especially PV, could create significant costs savings in both energy and capacity for the Indiana power system. The High PV scenario has 3% higher fuel costs, but 30% lower annual capacity costs compared to the Base case by 2040. In contrast, the higher demand levels of EV charging in the High Electrification scenario result in ~17% additional capital costs relative to the Base case.

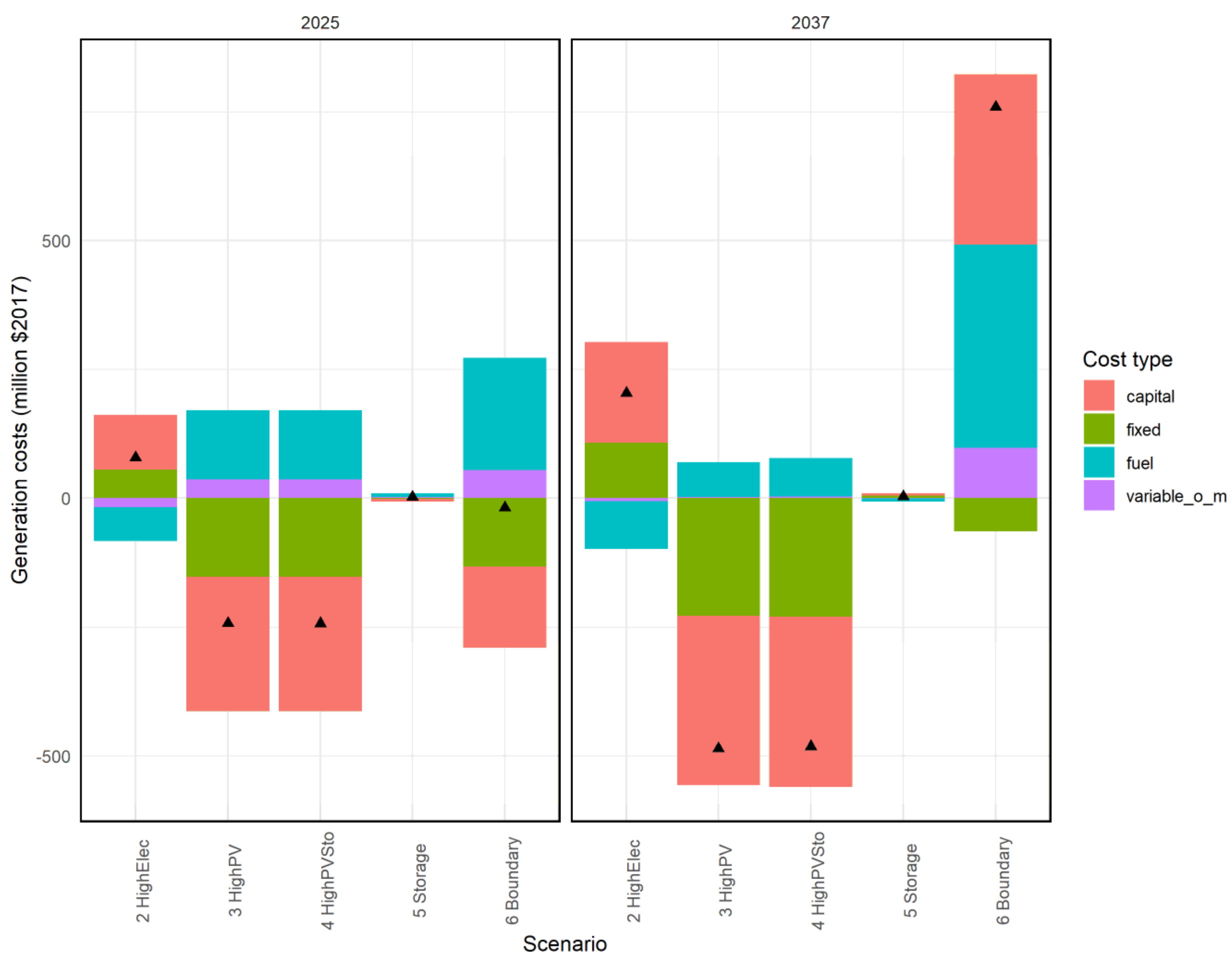

Figure 5.5 Generation costs by type (bars) and net outcome (point) relative to the Base case

We also report differences in capacity additions under each scenario over the long-term (see Table 5.6). Natural gas simple-cycle combustion turbines (SCCT) are deployed in larger amounts in scenarios with higher penetration of electric vehicles, and lower amounts in scenarios with higher PV penetration. The Boundary scenario—dominated by EV adoption—requires more than three times the incremental capacity of SCCTs compared to the Base case despite having only 50% higher peak demand. In contrast, capacity additions of natural gas combined-cycle combustion turbines (CCCT) remain relatively constant across scenarios. The significant adoption of SCCT in the Boundary scenario reflects the flexibility and resource adequacy demands that large swaths of coincident EV charging may impose on the power system.

Table 5.6 Utility-scale resource mix by scenario in year 2037

	Incremental Installed Capacity (MW)			
Scenario	**Natural Gas: Simple Cycle Combustion Turbine**	**Natural Gas: Combined Cycle Combustion Turbine**	**Wind**	**Solar**
Base	4,971	6,034	5,696	579
High Electrification	6,214	5,748	7,000	1,278
High PV	3,879	6,330	2,385	414
High PV and Storage	3,960	6,338	2,384	316
Storage	4,987	6,010	5,766	579
Boundary	16,959	7,360	4,030	55

Wind and solar adoption is substantially higher in the High Electrification scenario compared to any other scenario. This is may be due to coincidence between solar and wind production and EV charging patterns. Higher DER PV adoption in scenarios 3 and 4 correlates with lower wind and solar adoption than the Base case. This is explained by DER PV reducing the capacity value of solar PV given the high production correlation of both resources.

5.2.2 Transmission

Transmission expansion is not modeled directly in the comprehensive study. We estimate the impact of DER on transmission costs by calculating an incremental transmission expansion cost per MW transmitted during peak hours in 2025 and 2037 and multiplying this value by the peak demand in each adoption scenario.

The SUFG estimated the incremental transmission expansion costs by comparing the revenue requirements for the reference scenario in their ratemaking model both with and without incremental transmission expenditures. These expenditures include the return on investment and depreciation of all future capital expenditures, but not from the current rate base, and future transmission system O&M costs. These costs were translated to a dollar per peak MW basis for the revenue requirements in 2025 and 2037 for the reference scenario. This process produces an incremental transmission cost of $55,821 per peak MW in 2025 and $68,896 per peak MW in 2037 that are reasonable approximations for expansion costs in the transmission system.

We apply these values to the statewide peak demand by scenario to estimate transmission costs and calculate the difference from the Base case (see Table 5.7 for cents per kWh costs and Table A.7

Appendix for total costs). DER impact is relatively modest in all but the Boundary scenario, with savings of 3 cents per MWh in the High PV and High PV and Storage scenarios in 2025 to an increase of 57 cents per MWh in the High Electrification scenario in 2037. These figures translate to differences in the -0.3% to 4.7% range.

Table 5.7 Changes to incremental transmission costs relative to the base case

	Cost Change with Respect to Base Case (¢/kWh)		Annual Cost Change with Respect to Base Case (million $)	
	2025	**2037**	**2025**	**2037**
High Electrification	0.01¢	0.06¢	$15.8	$91.3
High PV	0.00¢	0.01¢	-$32.4	-$71.9
High PV and Storage	0.00¢	0.01¢	-$32.4	-$70.6
Storage	0.00¢	0.00¢	$0	$0.01
Boundary	0.07¢	0.64¢	$27.5	$734

The Boundary scenario has the highest cost difference for both planning horizons. Transmission costs are almost 7% higher in 2025 and up to 53% higher in 2037. This is explained due to the peak demand levels of this scenario, which at 31.8 GW in 2037 are roughly 50% higher than the 21.1 GW in the Base scenario.

5.2.3 Distribution

There are three cost components tracked for the integration of DER into the distribution system: (1) voltage regulation, (2) line loading, and (3) line energy losses.

Voltage regulation

Results discussed earlier show that voltage issues are a relatively minor issue across scenarios and that, in some cases, they are driven by the high voltage set point at the substation load tap changer. In this study, we assume that smart inverters are a standard feature in PV systems deployed within every scenario presented. Accordingly, we find that voltage issues for all scenarios can be mitigated by a combination of load tap changer (LTC) adjustments and smart inverter use with PV systems. Consequently, simulations using a combination of volt-var control at PV systems and adjustment of substation LTC result in no voltage issues in the short and long term. This approach and result is consistent with similar studies on management of voltage issues due to rooftop solar adoption (e.g., Horowitz et al. 2018).

The no-cost result for voltage regulation is based on the assumption that LTC is available and adjusted in the IOU-operated electricity substations across Indiana. Unfortunately, we do not have information confirming the reasonableness of this assumptions. For this reason, we include a cost to retrofit half of the existing substations with LTC—assuming the remainder already have LTC installed.

Horowitz et al. (2018) reports that it costs $310,000 per substation to implement LTC based on a Northeastern U.S. utility. We adjust this cost down by 25% to $232,500 based on information from two Indiana utilities. We estimate there are ~1,000 substations serving distribution customers across the Indiana territory. It will cost ~$235 million, or an annual equivalent of $20 million, to retrofit all of these substations. In the end, we assume that half of the substations need the LTC retrofit resulting in an annual cost of ~$10 million.

Line loading

Line loading was addressed by manually replacing conductors in underground and overhead line segments as needed. We re-ran simulations for the affected cluster-scenario combinations to verify that the re-conductoring effectively solved line overloading. Appendix A (Tables A.8 to A.10) include the segment-by-segment details for this re-conductoring process. The lengths of upgraded circuits are reported in Table 5.8

Table 5.8 Length of re-conductored segments by material and cluster

	Underground Cable Length (feet)		Overhead Line Length (feet)	
Cluster	**Copper**	**Aluminum**	**Copper**	**Aluminum**
3	0	0	0	3,634
4	57	0	2,386	0
5	172	0	0	6,461

We monetize re-conductoring using costs per foot of conductor as reported in two sources. First, two of the three IOUs with representative feeders reported costs of $95/ft and $80/ft for overhead and underground line re-conductoring, respectively. The overhead costs include replacing supporting structures to bear additional conductor weight. Second, an NREL cost study reported low, medium, and high costs of $130/ft, $173/ft, and $258/ft, respectively.

We use the preceding cost information to estimate costs based on four re-conductoring "steps" that depend on the ampacity difference between the original and replaced conductor. Each step reflects a 15% increase in conductor ampacity. We assume that the lower cost applies to the first step, and the highest cost to the fourth step. Underground cables are upgraded in a single step, so we use the $80/ft reported by the utility. Finally, we use a 50% cost adder for copper conductors assuming that all costs are for aluminum conductors. Feeder level results are escalated to the aggregate IOU level using the scaling factors described earlier in this manuscript (Table 5.9).

Table 5.9 Feeder-level and aggregate costs for line loading by scenario and cluster

	Feeder Costs (million $2017)		Aggregate Costs for All IOUs (million $2017)	
Cluster	**High Electrification**	**Boundary**	**High Electrification**	**Boundary**
1				
2				
3		$0.396		$297.0
4	$0.271	$0.412	$147.4	$223.8
5		$0.973		$306.5
6				

Re-conductoring was only required for clusters 3, 4 and 5 and for the High Electrification and the

Boundary scenarios. We estimate about $150 million in upgrade costs for feeders in cluster 4 in the High Electrification scenario, and roughly $820 million in investments for the Boundary scenario. These investment values correspond to approximate annualized costs of $12.5 million for the High Electrification scenario and $70 million for the Boundary scenario.

It is important to acknowledge that this linear segment-by-segment upgrade method is just one of the ways in which utilities address real line loading issues in their systems. Our assessment uses individual segment upgrades, usually called an "incremental line upgrade", largely due to data availability and resource constraints. Another example of an incremental upgrade not employed in this study is adding phases to a single-phase circuit to increase its capacity. Furthermore, in some situations, poles will need to be replaced along supporting structures and conductors in a "major line upgrade". In some cases these methods will be insufficient and utilities may be required to build additional feeder sections and reconfigure feeders to offload affected circuits. Regulators, utilities, and/or other stakeholders should consider sponsoring a more detailed line-loading study under different DER adoption pathways.

Energy losses

Distribution system energy losses is energy that a utility procured, but could not deliver to end-use customers. Estimating the cost of these losses entails using an average wholesale market delivery cost to value the energy losses first reported in Table 5.5. We use the generation and transmission costs—reported in dollars per MWh— from the SUFG to monetize energy losses under each scenario relative to the base case (see Table 5.10). The cost of energy-related losses in the High PV and High PV and Storage scenarios are identical and there is no difference between the Base case and Storage scenario.

Table 5.10 Changes in the cost of energy losses relative to the base case

	2025		2040	
Scenario	**Wholesale Electricity Cost Assumption (¢/kWh)**	**Cost of Energy Losses (million $2017)**	**Wholesale Electricity Cost Assumption (¢/kWh)**	**Cost of Energy Losses (million $2017)**
High Electrification	4.23¢	$0.15	5.40¢	$2.69
High PV	4.05¢	-$0.91	5.21¢	-$2.34
High PV and Storage	4.05¢	-$0.91	5.21¢	-$2.34
Storage	4.16¢	$0	5.32¢	$0
Boundary	4.31¢	-$0.57	6.05¢	$12.55

By 2025, the economic impact of energy losses under increased DER adoption in energy losses is modest, ranging from an additional cost of $150,000/year in the High Electrification scenario to savings of almost $1 million per year in the two High PV scenarios. The economic impact becomes more over the long-term. The High PV scenarios save over $2 million in distribution-related energy losses compared to the Base case, while the Boundary scenario has an additional $12.5 million in energy loss-related costs compared to the Base case.

5.2.4 Economic impact of DER adoption

Tables 5.11 and 5.12 shows the incremental combined economic impact of increased DER adoption relative to the Base case. Costs are reported by scenario and for the three segments of the power system: generation, transmission, and distribution. Table 5.11 reports the absolute cost changes. Table 5.12 shows cost changes in cents per kWh; In this case, we divide the absolute costs reported in Table 5.11 by forecasted retail sales.

Table 5.11 Overall economic impact of DER adoption by scenario and power system segment relative to the base case (million $2017)

	2025 Annual Cost Change Relative to Base				2040 Annual Cost Change Relative to Base			
Scenario	**Gen.**	**Trans.**	**Dist.**	**Total**	**Gen.**	**Trans.**	**Dist.**	**Total**
High Electrification	$79.1	$15.8	$10.7	$105.6	$204.0	$91.3	$25.9	$321.2
High PV	-$242.4	-$32.4	$9.7	-$265.2	-$485.5	-$71.9	$8.2	-$549.2
High PV and Storage	-$242.7	-$32.4	$9.7	-$265.5	-$481.6	-$70.6	$8.2	-$544.1
Storage	$1.7	$0.0	$10.6	$12.3	$2.6	$0.0	$10.6	$13.1
Boundary	-$18.6	$27.5	$10.0	$19.0	$759.7	$734.1	$94.1	$1,587.9

Table 5.12 Overall incremental economic impact of DER adoption by scenario and power system segment relative to the base case (2017 cents/kWh)

	2025 Annual Cost Change Relative to Base				2040 Annual Cost Change Relative to Base			
Scenario	**Gen.**	**Trans.**	**Dist.**	**Total**	**Gen.**	**Trans.**	**Dist.**	**Total**
High Electrification	0.11¢	0.02¢	0.01¢	0.14¢	0.25¢	0.11¢	0.03¢	0.39¢
High PV	-0.34¢	-0.04¢	0.01¢	-0.37¢	-0.64¢	-0.09¢	0.01¢	-0.72¢
High PV and Storage	-0.34¢	-0.04¢	0.01¢	-0.37¢	-0.63¢	-0.09¢	0.01¢	-0.72¢
Storage	0.00¢	0.00¢	0.01¢	0.02¢	0.00¢	0.00¢	0.01¢	0.02¢
Boundary	-0.03¢	0.04¢	0.01¢	0.03¢	0.96¢	0.93¢	0.12¢	2.01¢

There are relatively modest economic impacts of DER adoption for all scenarios in the short term. Over the long term, impacts range from ~$550 million in savings for the High PV scenarios to $1.6 billion in additional costs for the Boundary scenario, all relative to the Base case. The largest cost impacts are observed in the generation sector, with nearly 90% of the cost savings occurring in this segment for the High PV scenarios. Distribution-related cost impacts from DER adoption are generally the smallest among the power system segments studied, ranging 1% to 10% of the overall cost change under any given scenario.

Finally, the rate impacts of these incremental costs are reported in Table 5.13. This assessment employs the SUFG ratemaking model using the existing rate base and the incremental cost changes reported in Table 5.11. In contrast to the incremental costs reported earlier, average rates increase for all scenarios in the long term. In the High PV scenarios this is due to the reduction in sales that needs to be compensated with higher rates for utilities to recover their fixed costs. In the other scenarios this is compounded with the need for incremental generation and transmission infrastructure to meet increased peak demand. Overall, the average changes in rates are relatively modest in the non-Boundary scenarios.

Table 5.13 Impact of DER adoption on electricity rates by scenario and customer type (2017 cents/kWh)

	2025 Rate Change Relative to Base				2040 Rate Change Relative to Base			
Scenario	**Residential**	**Commercial**	**Industrial**	**Average**	**Residential**	**Commercial**	**Industrial**	**Average**
High Electrification	0.25¢	0.24¢	0.19¢	0.22¢	-0.03¢	0.05¢	0.14¢	0.06¢
High PV	-0.06¢	-0.10¢	-0.19¢	-0.13¢	1.01¢	0.73¢	0.23¢	0.59¢
High PV and Storage	-0.06¢	-0.10¢	-0.19¢	-0.13¢	1.00¢	0.71¢	0.22¢	0.58¢
Storage	0.00¢	0.00¢	0.00¢	0.00¢	0.05¢	0.05¢	0.01¢	0.03¢
Boundary	0.52¢	0.47¢	0.18¢	0.35¢	1.88¢	1.96¢	1.46¢	1.70¢

5.3 Reliability impacts of increased DER adoption

This section details an assessment of the impact of customer-sited battery storage on reliability and resilience from both the system's and the customer's perspectives. Reliability from the customer's perspective may differ from the utility's or system's perspective given that, with DER adoption, utility outages may not lead to end-use interruption from the customer perspective. In this report we focus on system level impacts, but in this section we also highlight the changes in reliability experienced by customers who own DER.

We focus solely on battery storage, because we found no evidence in the literature and practice that the other DER technologies (e.g., PV systems without batteries, EV charging) had any meaningful impact on reliability metrics from the customers' perspective. The metrics for measuring reliability are described in Section 3.2 and include SAIFI, SAIDI, and CAIDI from the perspective of average customers as well as customers who adopted batteries. We examine the number of customers impacted by longer duration, severe interruptions (i.e., 24 hours or longer) as one metric for system resilience. We start by providing an overview of historical power outages for IOU customers by cluster. Next, we explain assumptions about the batteries, including adoption levels and modes of operation. We conclude by detailing the impacts of different battery adoption and operations assumptions on a trio of reliability metrics and one resilience metric—the ability to avoid longer duration power interruptions.

5.3.1 Outage characteristics

Examining historical 2014-2018 outage data from the five IOUs provided a baseline with which to estimate the impacts of battery storage deployed at customer sites. The IOUs each provided a dataset containing details of historical outages from 2014-2018. Each row of data includes details of an outage that impacted a certain number of customers on a particular circuit as well as the start and end times—thus allowing us to calculate the duration of each interruption. Other key details of the outages were whether the outage occurred during a major event day (MED), whether the outage was planned, and the cause of the outage. Planned outages are initiated by the utility in order to perform equipment replacement that can only be completed on a de-energized circuit.

The first step in examining outage information was to clean the data, which involved removing outliers and applying consistent rules for which outages to include and how to characterize them. This analysis includes only sustained outages, defined as any interruption lasting five minutes or longer. We excluded five outages with reported durations of over 10 days. We also removed a small percentage of outages containing data inconsistencies (e.g. negative durations).

Figure 5.6 shows a histogram of the number of interruptions of each duration for the five IOUs from 2014-2018, excluding MEDs and truncated at 1,000 minutes (16.7 hours). Each outage represented by the histogram impact a different number of customers. The shape of the histogram is typical of outage duration distributions, with a long tail to the right. The tail extends to nearly 9 days, but the outages less than 1,000 minutes represent greater than 99 percent of all non-MED outages. Quartiles are indicated by the red lines. The median duration was 84 minutes and three quarters of all outages had a duration of 154 minutes or less. When MEDs were included in the distribution (Figure A.1, Appendix), the median increased to 92 minutes and the 75th percentile to 187 minutes. Interestingly, more than 10 percent of outages lasted longer than one day if MEDs were included.

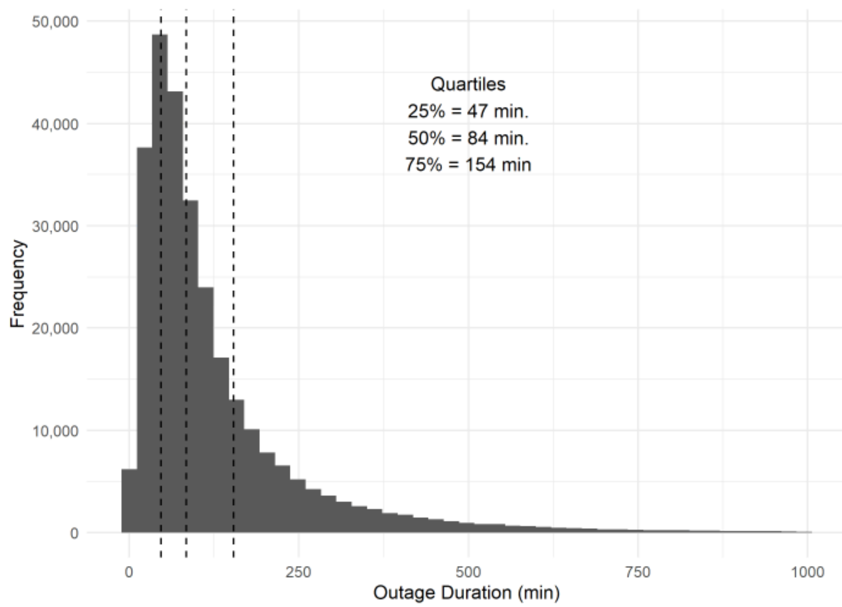

Figure 5.6 Frequency of outages by duration (truncated at 1,000 minutes) (2014-2018)

Outage cause descriptions in the datasets varied by utility. Utilities categorize their outages with cause codes of varying detail: the number of different codes ranges from 10 to 115. We categorized all outages into seven higher-level cause categories to ensure that outages were categorized consistently and at a level that would allow for meaningful assessment and comparison. The seven categories include:

- *Equipment Failure*: outage cause description indicated failure of a specific component or equipment in general
- *Loss of Supply*: unexpected loss of generation or power supply
- *Planned*: outage initiated to allow for planned system maintenance or infrastructure replacement

- *Public*: outage caused by actions of the general public (e.g., vehicle accidents, vandalism, contractors accidentally damaging cables)
- *Vegetation*: trees or other vegetation came into contact with conductors, poles, or other utility equipment to cause an outage
- *Other*: outages with cause descriptions that did not number enough to merit a separate category. Some of the larger subcategories included outages caused overloads, foreign objects, and load management
- *Unknown*: no cause given or cause unknown

Each outage in the dataset had a field that indicated the circuit impacted. We were also provided with a set of characteristics for each circuit, including the number and mix of customers served. This dataset was used to create the six clusters described in Section 4.2. Using these two sources of data, it was possible to map outage causes to detailed information about the characteristics of these circuits. Approximately 86% of outages occurred on circuits included in the characteristics file.

Figure 5.8 shows average annual customer minutes interrupted (CMI) by outage cause category and cluster. We are interested in understanding how outages in major event days compare to outages in days with no major events. Then, in Figure 5.7 outages without major event days are presented in the left panel and outages that only include MEDs are presented in the right panel.

Most outages are caused by either vegetation or equipment failure. Cluster 3, characterized as relatively dense suburban residential with mostly overhead lines, has the highest average annual CMI. Cluster 6, composed of circuits that were relatively shorter, more heavily industrialized, and with a significant amount of underground components, has the lowest CMI. Cluster 5 has the largest proportion of underground circuit length (67%) and, not surprisingly, shows the lowest portion of CMI due to vegetation aside from Cluster 6, which has the second highest proportion of underground circuit length (39%). In major event days the majority of the outages are caused by equipment failure and vegetation, with increased intensity due to inclement weather.

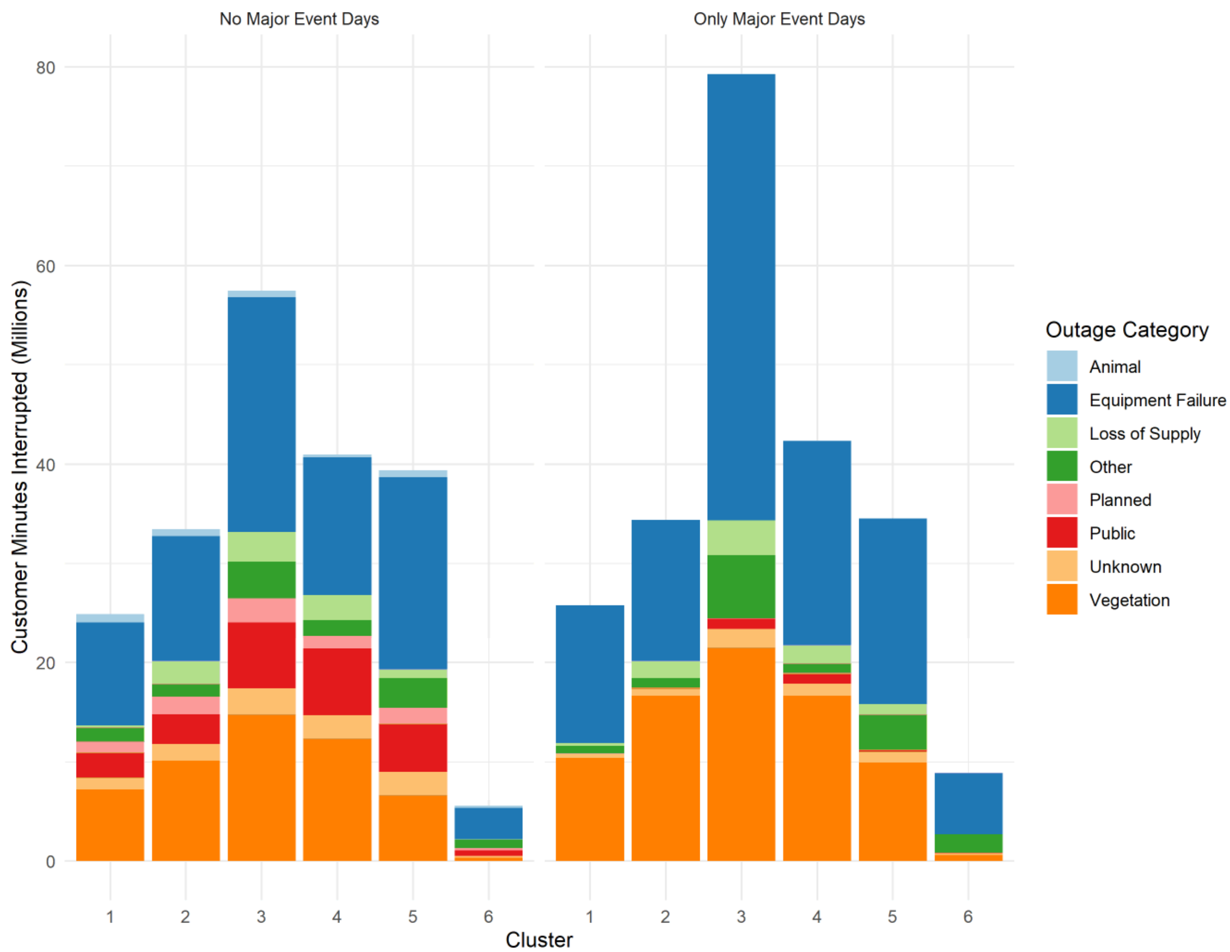

Figure 5.7 Average annual CMI by MED and outage category (2014-2018)

Figure 5.8 shows the number of customer outages by outage cause category[8]. The number of non-MED annual customer outages was higher than the number of MED-only customer outages for all clusters. Overall, the number of non-MED customer outages was approximately four times higher than the number of MED-only outages. When analyzed in combination with the CMI reported in Figure 5.7, it appears that outages on major event days tend to last longer than those that occurred during 'blue sky' conditions and result in more CMI per outage.

[8] Note that a "customer outage" is different from an "outage" in that an outage can impact multiple customers, whereas a customer outage refers to one customer experiencing one interruption. Thus, an outage that impacts 10 customers equates to ten customer outages.

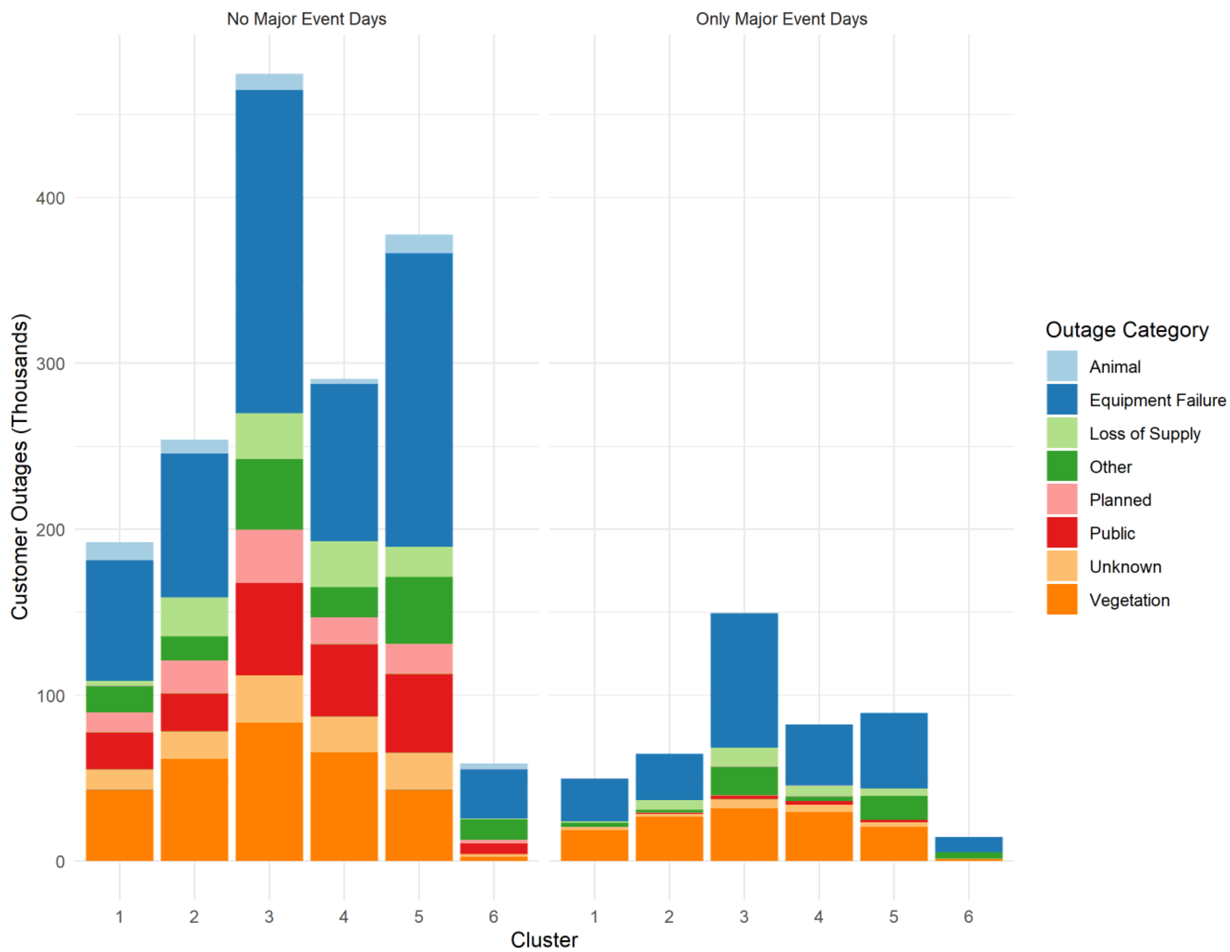

Figure 5.8 Average annual customer outages by MED and outage category (2014-2018)

One reason for the difference in outage totals between clusters is due to the number of customers in each cluster. Figure 5.9 shows the number of customers by type and cluster. The total number of customers ranges from close to 600,000 for Clusters 3 and 5 to only 100,000 for Cluster 6. Residential customers make up a large percentage of the customer totals for each cluster. However, these portions do not account for differences in aggregate battery installed capacity; residential installed capacity was only 25 percent and 15 percent for Clusters 1 and 6, respectively (see Section 4.2.3)

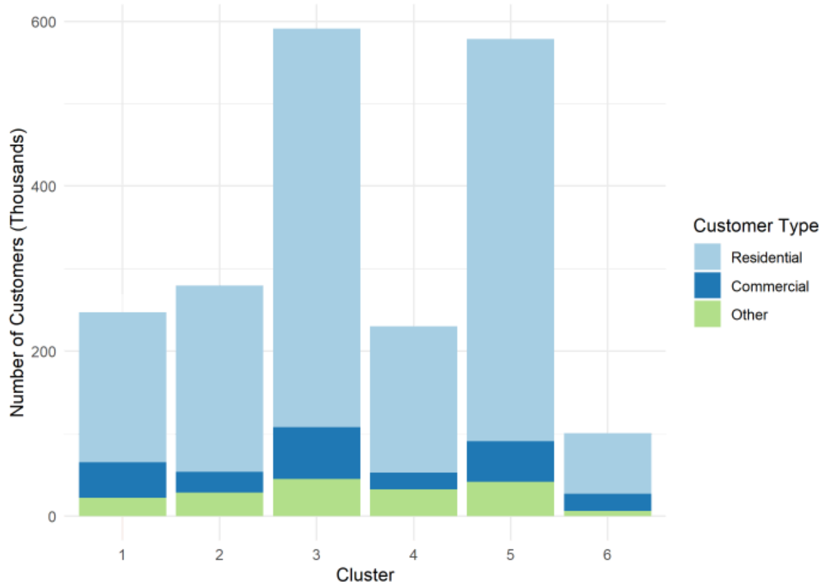

Figure 5.9 Number of customers by type and cluster

5.3.2 Battery storage characteristics

A set of assumptions regarding battery characteristics, penetration levels, and modes of operation are necessary to model the impacts of battery storage systems on reliability and resilience. The battery characteristics were first detailed in Section 4.3 and are listed again below in Table 5.14. PV system characteristics are also listed, as some of the models assumed that batteries are integrated with PV arrays. Size and capacity assumptions for both types of systems are generally the same as described earlier. However, the reliability/resilience analysis only uses generalized customer type, so there was no variation in the size of the PV or battery systems based on customer size.

Table 5.14 Assumed size for rooftop PV and battery storage systems

DER Technology	Residential	Commercial	Industrial
Rooftop PV	• 8 kW	• 16 kW	N/A
Battery storage	• 7 kW max discharge capacity • 12 kWh storage capacity • 90% roundtrip efficiency • 25% maximum discharge level	• 14 kW max discharge capacity • 38 kWh storage capacity (0.1% of average annual kWh consumption) • 90% roundtrip efficiency • 25% maximum discharge level	N/A

It is important to clarify that this analysis is not based on the six adoption *scenarios* outlined in Section 2, but on the three adoption *levels* for battery storage as indicated below:

- BAU: 0.01% of total customers adopt
- High: 1% of total customers adopt

- Very High: 5% of total customers adopt

These adoption levels were for customers across all clusters, but the actual numbers of customers adopting varied by cluster according to the assumptions outlined in Section 4.3. Figure 5.10 shows the penetration of battery storage among residential and commercial customers by cluster. Residential adoption at the High level ranges from negligible levels for Cluster 6 to roughly 3.5 percent for Cluster 4; the Very High level ranges from less than 0.5% in Cluster 6 to nearly 5% in Cluster 4. As indicated earlier, circuits in Cluster 4 are relatively long, rural, and residential. Commercial adoption was contained to Clusters 1 and 6 at the High level and Clusters 1, 4, and 6 at the Very High level. It is worth noting that adoption levels employed in the reliability analysis reflect year 2040 adoption developed for the power flow analysis (Section 5.1). We apply these adoption levels with 2014-2018 outage data, because resource and time constraints prevented us from projecting outages into the future.

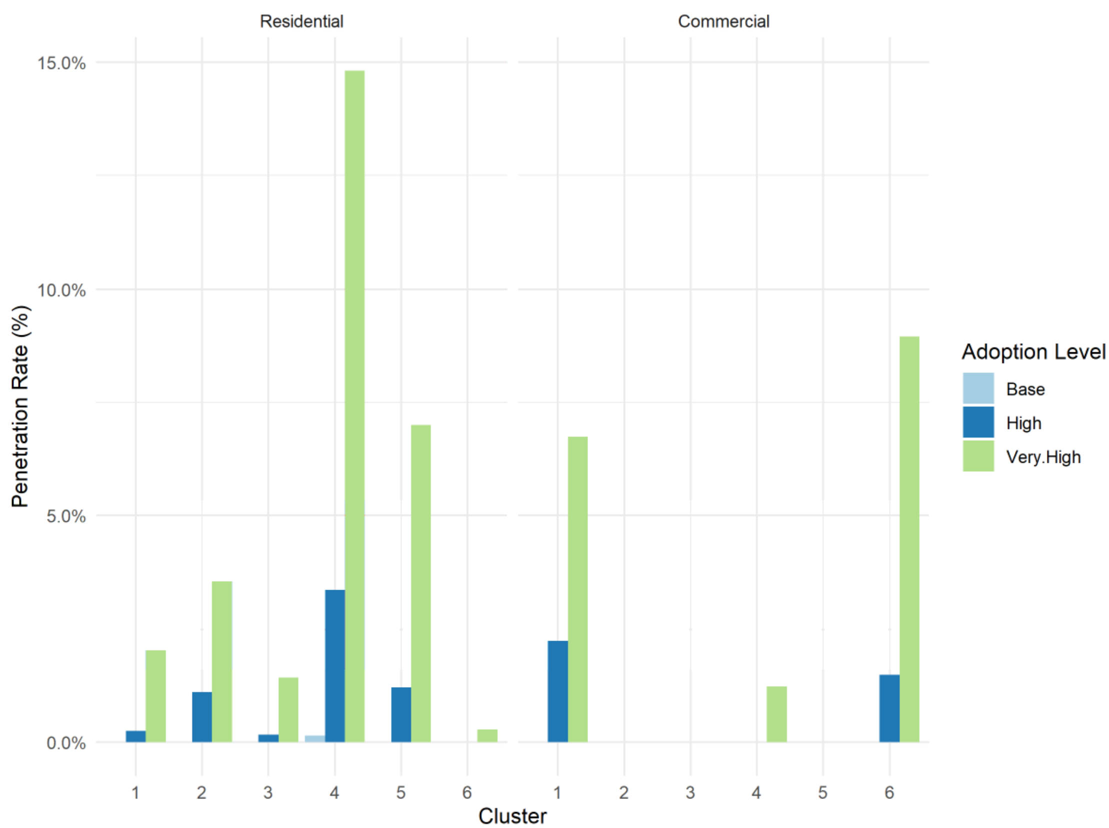

Figure 5.10 Battery storage penetration by customer type and cluster

This analysis assumes that the customer can operate the battery using one of five modes of operation. The modes of operation are purely illustrative and this report does not make any assumptions about policies for encouraging or discouraging one mode of operation over another—or for promoting adoption of DERs in general. The modes of operation are explained in more detail below and Figure 5.11 shows the available charge for mitigating outages by hour of the day for the first four modes.

In the "Full" mode, the battery is only used during interruptions and does not discharge otherwise. The red line in the figure shows that in any hour of the day that an outage could occur, the battery is fully charged and ready to provide its full capacity to the customer premise if an outage occurs. The “Half” mode is similar to the “Full” mode, but a battery only has half of the storage capacity. The green line in the figure shows that the battery has 6 kWh at all hours of the day. This mode of operation functions as a sensitivity analysis of the assumed storage capacity in mitigating the given set of outages.

In the “PV” mode, each battery is assumed to be coupled with a PV system. The PV system primarily provides power for the residence or commercial facility—with excess generation going toward charging the battery during the day. When onsite demand is higher than PV generation, the battery discharges to provide the net demand. The battery continues discharging to supply onsite power until it reaches 25% of capacity, at which point the rest is saved to mitigate nighttime outages and the customer draws power from the grid until PV generation begins on the following day. The purple line in Figure 5.11 shows the available storage capacity for this mode of operation during the summer. The battery remains at its minimum 25% charge until around 9 am, when the PV system generates more electricity than the household uses. The battery reaches its maximum capacity at 1 pm and remains at this level until early evening, when net demand is higher than PV output. The battery continues discharging until it reaches 25% charge around 10 pm. If an outage occurs, the PV system stops generating electricity and the battery supplies power to the customer until it no longer has charge.

The “Peak Times” mode makes the battery charge from the grid and offset demand at the residence or facility during system peak hours of 12 pm to 5 pm. For this analysis, the system peak was defined as hours where load was 90% of the all-time system peak. The light blue line in Figure 5.11 shows the battery charge during summer for this mode of operation. The battery is at full capacity in the morning and begins discharging at noon. It continues discharging until it reaches 25 percent capacity between 4 pm and 5 pm. At 5 pm, it recharges from the grid. When an outage occurs, the battery supplies electricity to the customer until it no longer has charge. While this analysis does not make any assumptions about policy or pricing structures for compelling this (or any) mode of operation, this charge/discharge pattern does reflect one possible way that customer-sited batteries could be operated to mitigate peak demand.

Finally, the “Islanding” mode of operation assumes—similar to the “PV” mode—that each battery storage system works in conjunction with a PV system. The difference for this mode of operation is that the battery can continue to recharge from the PV system during an outage, whereas the PV mode assumes that the PV system does not operate during the outage. Then, the charge profile for a battery operating in Islanding mode is contingent on outage timing.

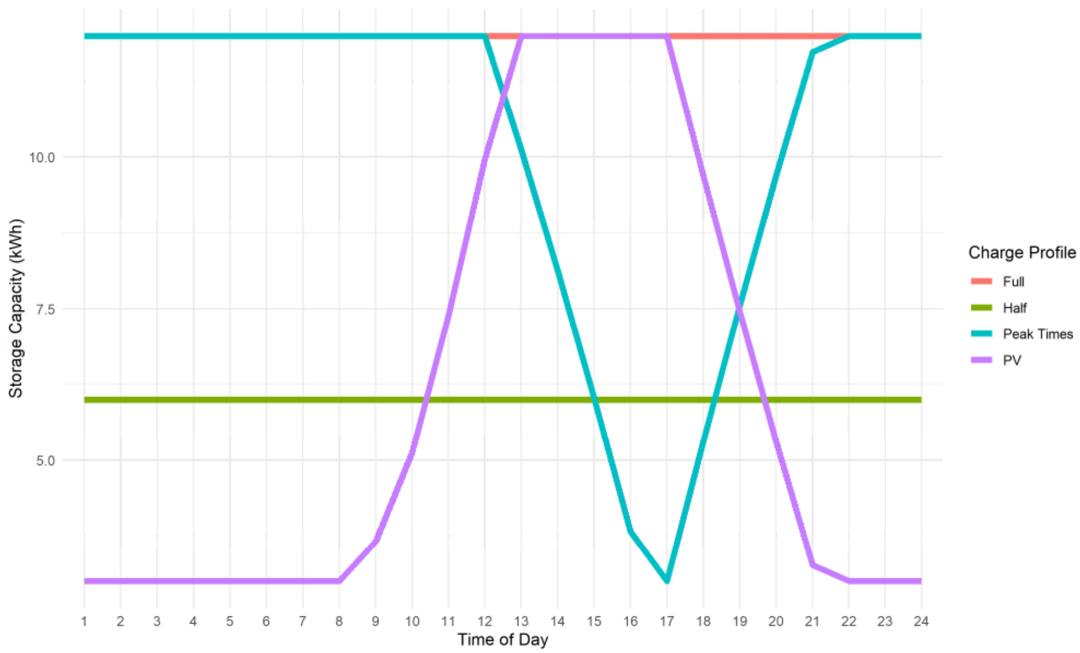

Figure 5.11 Residential storage capacity in summer, by hour of day and operation mode

Batteries are able to eliminate outages of certain durations and reduce outages of longer durations under each mode of operation and set of adoption assumptions. The simulation proceeds systematically through each outage in the dataset. For each outage, we assume that the number of residential and commercial customers impacted was proportional to the overall mix of customer types on the affected circuit, as the outage dataset only provided a total number of customers interrupted and not the number of customers affected by type. Each combination of customer type, season, outage onset hour, and mode of operation was associated with a battery storage capacity that could reduce or eliminate the outage for the percentage of customers that had adopted battery storage systems on that cluster. We reduced the duration of the outage according to the available storage capacity—for the portion of affected customers who would have adopted batteries. If the duration was reduced to zero with a battery, then the number of customers affected by the outage was reduced proportionally. Reducing the outage duration for a portion of the customers in turn reduced the number of customer minutes interrupted for the outage. The next section provides the results of the analysis.

5.3.3 Outage mitigation results

This analysis measures reliability impacts of DER adoption in terms of changes in SAIDI, SAIFI, and CAIDI, which were described in Section 3.2. This analysis examines impacts under two conditions: with MEDs and without MEDs. The reliability metrics are calculated at the cluster level, such that the number of customers N_T in the denominator of the SAIDI and SAIFI equations is equal to the total number of customers in the cluster (calculated by summing the number of customers on each circuit in the cluster). Table 5.15 shows the baseline levels of the metrics for reliability with and without MEDs for each cluster. The table shows some differences when comparing reliability metrics with and without MEDs, but the general trends are the same: reliability metrics for Clusters 1-3 are relatively similar; reliability metrics for Cluster 4 —particularly for SAIDI and SAIFI, are significantly higher than other clusters; reliability metrics for Clusters 5 and 6 are relatively low, which indicates above-average reliability.

Table 5.15 Base case reliability metrics (with and without major event days) by cluster

	Base Case Reliability Metrics (without MEDs)			Base Case Reliability Metrics (with MEDs)		
Cluster	**SAIDI**	**SAIFI**	**CAIDI**	**SAIDI**	**SAIFI**	**CAIDI**
CL1	1.68	0.77	2.17	3.41	0.96	3.56
CL2	1.99	0.91	2.19	4.03	1.12	3.59
CL3	1.62	0.80	2.02	3.85	1.04	3.71
CL4	2.97	1.26	2.35	6.03	1.58	3.81
CL5	1.13	0.65	1.74	2.13	0.79	2.69
CL6	0.92	0.58	1.58	2.39	0.71	3.34

Figure 5.12 shows the improvements in SAIDI without MEDs included by mode of operation, adoption level, and cluster (SAIFI changes are very similar, hence not reported). A portion of residential and commercial customers assumed to have installed batteries will have their outages mitigated—as explained earlier. These reductions for particular customers lead to reductions in the total number of customers affected and customer minutes interrupted for each cluster, which in turn reduce cluster-level SAIDI and SAIFI calculations.

Battery adoption levels have more impact on reliability metrics than mode of operation. Cluster 4 has the largest residential battery adoption at 3.5% and 15% for High and Very High levels, respectively. Subsequently, it shows the greatest improvements in SAIDI, ranging from 2%-2.5%for the High level and 9.0%-11.5%for Very High level. The results show that the mode of operation has a modest impact on reliability metrics compared to the battery penetration level. Even a battery with half of the capacity performs relatively well compared to the Full mode. For example, Very High adoption levels in "Half" mode in Cluster 4 improved SAIDI by 9.8% compared to 11.5% for "Full" mode. Doubling the storage capacity led only to a ~15% improvement in reliability metrics.

There are significant differences in reliability impact metrics across clusters. Using the "Full" mode of operation as an example, Cluster 4 had the greatest reduction in SAIDI for High and Very High adoption levels at 2.5% and 11.5%, respectively. Cluster 5 showed a SAIDI reduction of 1% for High adoption and nearly 6% for Very High. Cluster 3 had the lowest impacts, with negligible improvements at the High level and a 1.1% SAIDI reduction at the Very High level. The results appear to be driven by battery adoption assumptions as Cluster 4 has the highest residential adoption and reliability improvement. Clusters 6 and 1 had the highest levels of commercial storage adoption, with negligible commercial adoption for Clusters 2, 3, and 5. Cluster 3 had low residential adoption and negligible commercial adoption and subsequently showed the lowest reliability improvements.

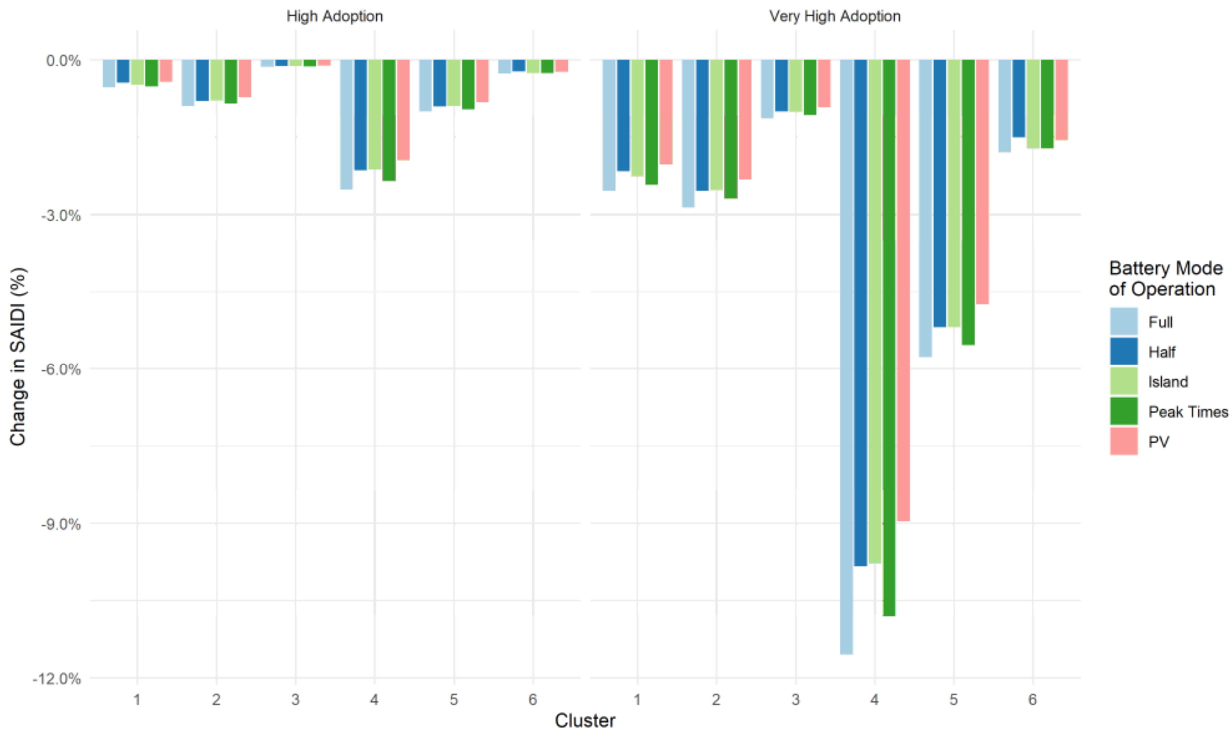

Figure 5.12 SAIDI improvements relative to BAU adoption level by mode of operation – without MEDs

A reason for the comparable performance between modes is likely due to the shape of the statistical distribution of outages in the dataset. As reported in Section 5.3.1, roughly 75 percent of outages are less than two and a half hours. Thus, given the assumptions for average battery capacity (12 kWh for residential and 38 kWh for commercial), using a battery with half of the capacity appears to improve reliability almost as well. In addition, using the battery during the day in tandem with PV, or to reduce peak time demand from the grid, appears to reduce reliability improvements only slightly compared to having a full battery dedicated only to function as a backup power system.

Figure 5.13 shows the results for reliability improvements with MEDs included. The figure displays only the results for SAIDI, as the improvements to SAIFI were larger than those for SAIDI. The SAIDI improvements were more modest across the board, as the pool of outages was larger with the MED outages included, which were longer on average than outage dataset that does not include MEDs. For example, Cluster 4 showed improvements without MEDs of 9.0% for PV and 11.5% for Full, whereas improvements, with MEDs included, were only 6.5% for PV and 9.2% for Full. SAIFI improved more than SAIDI when including MEDs—generally by 20 to 40% in relation to the percent improvement in SAIDI.

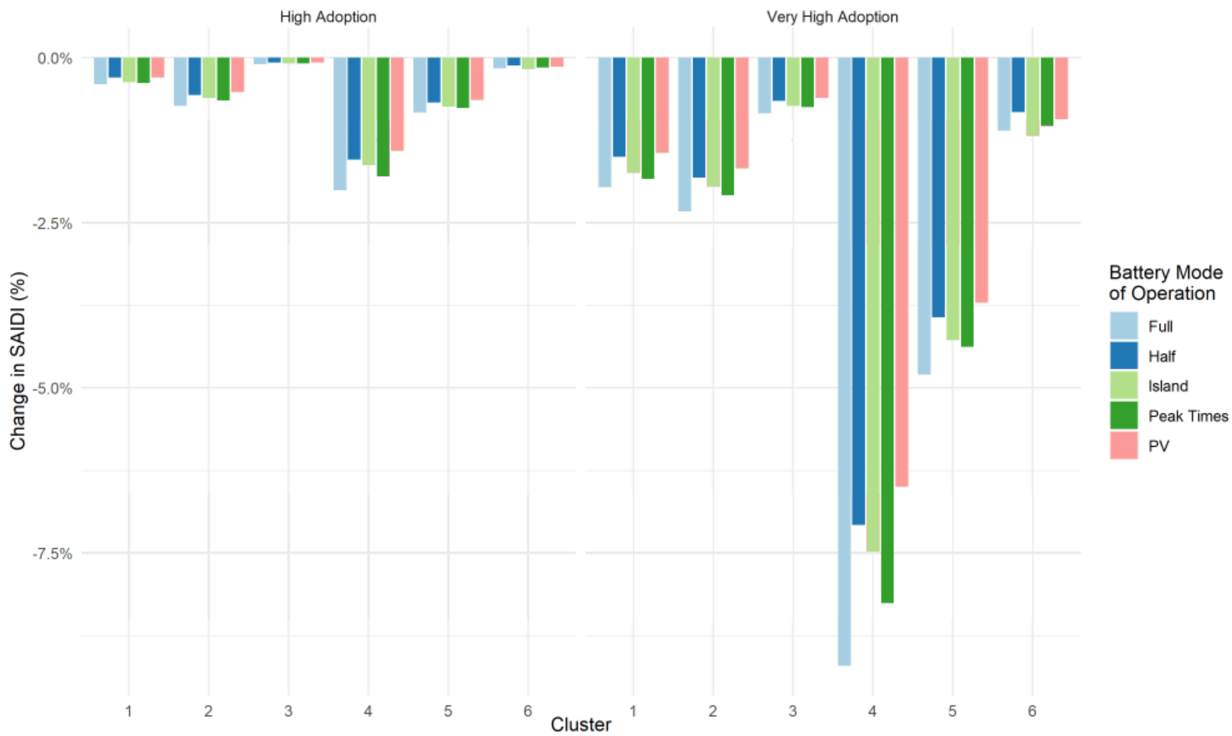

Figure 5.13 SAIDI improvements relative to BAU adoption level by mode of operation – with MEDs

The metrics thus far have shown the reliability impacts from a system-wide perspective. However, in reality, only those customers who installed a battery storage system would benefit from the outage reductions and the remaining customers would not. Figure 5.15 shows the impacts without MEDs to total outage time, outage frequency, and average outage duration for *battery owners only* using the Full mode of operation. It follows that these metrics would translate to cluster-level SAIDI, SAIFI, and CAIDI if all customers in that cluster had batteries. The figure shows that reliability impacts without MEDs to total outage time (equivalent to SAIDI) and outage frequency (equivalent to SAIFI) are very similar, with approximately 90% improvements for each metric in each cluster. Average outage time (equivalent CAIDI) shows increases approaching 30% for Clusters 3 and 6. This counter-intuitive finding is related to the fact shorter duration outages were mitigated by the use of batteries while longer duration outages were still present thus driving up the *average* duration of outages.

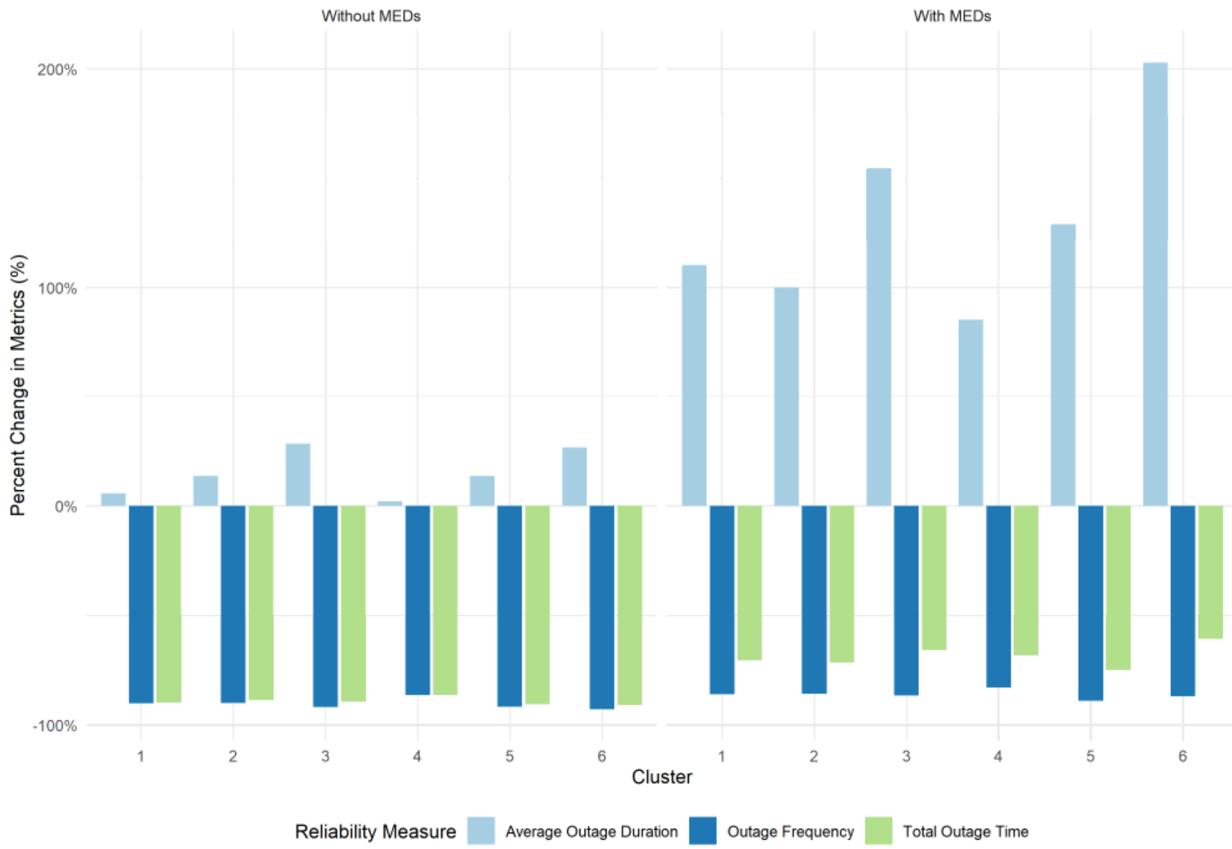

Figure 5.14 Reliability changes relative to the base case for battery storage adopters under full battery mode (with and without MEDs included)

Reliability metric improvements—when MEDs are included—are significant, but more modest when compared to the reliability metrics improvements when MEDs are not included (see Figure 5.14 and Figure A.2, Appendix A). The average outage durations (CAIDI) when MEDs are included is substantially higher relative CAIDI when MEDs are not included—between 100 and 200 percent, depending on the cluster. The results suggest that installing a standard-sized battery can reduce customers' total annual outage durations and frequencies by a significant amount. Overall, we expect significant improvement for the customers that adopt these technologies, but modest system-level reliability improvements across the IOU's distribution systems (see Table 5.16 and Figure A.3, Appendix A).

Table 5.16 Reliability metrics under different behind-the-meter battery storage adoption levels

		Behind-the-meter Battery Storage Adoption Levels			
		BAU	**High**	**Very High**	**Theoretical Limit**
Without MED	**SAIDI**	1.66	1.64	1.58	0.18
	SAIFI	0.81	0.80	0.77	0.08
	CAIDI	2.00	2.00	2.00	2.32
With MED	**SAIDI**	3.09	3.07	2.97	0.96
	SAIFI	0.90	0.89	0.86	0.12
	CAIDI	2.94	2.95	2.97	6.80

5.3.4 Resilience assessment

As discussed earlier, we develop an initial metric of system resilience—the ability to avoid longer-duration (greater than 24 hours) power interruptions. Figure 5.15 shows a histogram of customer-outages lasting longer than 24 hours (1,440 minutes) that occurred for the five IOUs between 2014 and 2018. Recall that a customer-outage is defined as one customer experiencing one outage. The histogram is truncated at 4,000 minutes (2.8 days) to focus on the portion of the histogram with most of the data points. The total number outages in the final dataset lasting longer than 24 hours was 7,612, representing 192,607 customer-outages over the 5-year period.

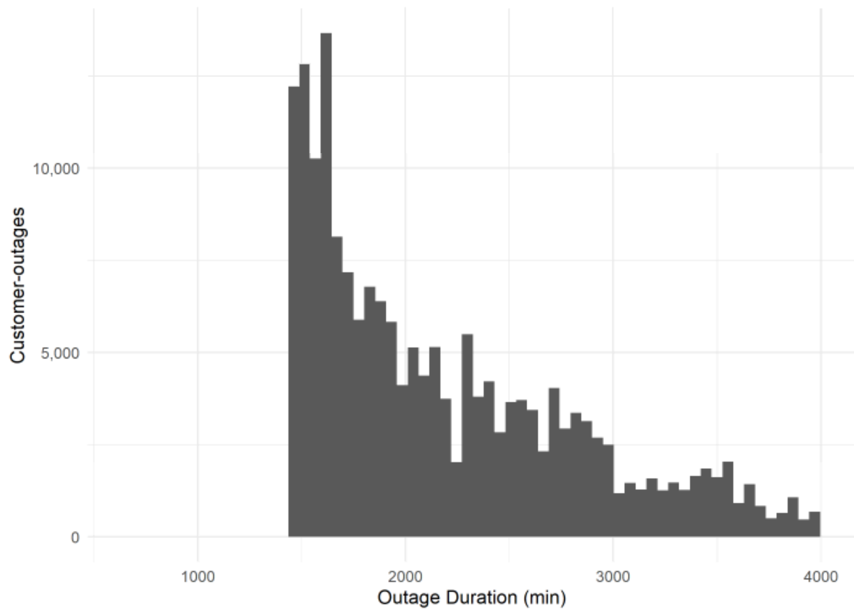

Figure 5.15 Histogram of customer-outages lasting longer than 24 hours (2014-2018)

We follow the same simulated outage mitigation procedure described in Section 5.3.3 to assess the impact of battery storage adoption on the set of long-duration outages. Each of the 7,612 long-duration outages in the dataset is broken down into three outages: (1) a shorter outage affecting the subset of residential customers on the specified circuit who adopted battery storage; (2) another shorter outage affecting the subset of commercial customers who adopted battery storage; and (3) an outage of the original duration, but affecting fewer customers (i.e. the original number of customers affected minus the residential and commercial customers with batteries).

Figure 5.16 shows a histogram representing the impact of the Very High level of battery adoption—operated in Full mode—on the set of long-duration outages (truncated at 4,000 minutes for the figure). The transparent bars outlined in blue represent the histogram of mitigated outages. The graph shows that a number of the outages have shifted left, to durations shorter than 1,440 minutes. It also shows blue bars that are below the original grey level, indicating the mitigated customer-outages (which shifted to shorter durations). The total number of long-duration customer-outages reduces slightly – to 188,879—representing a modest decrease of 2 percent.

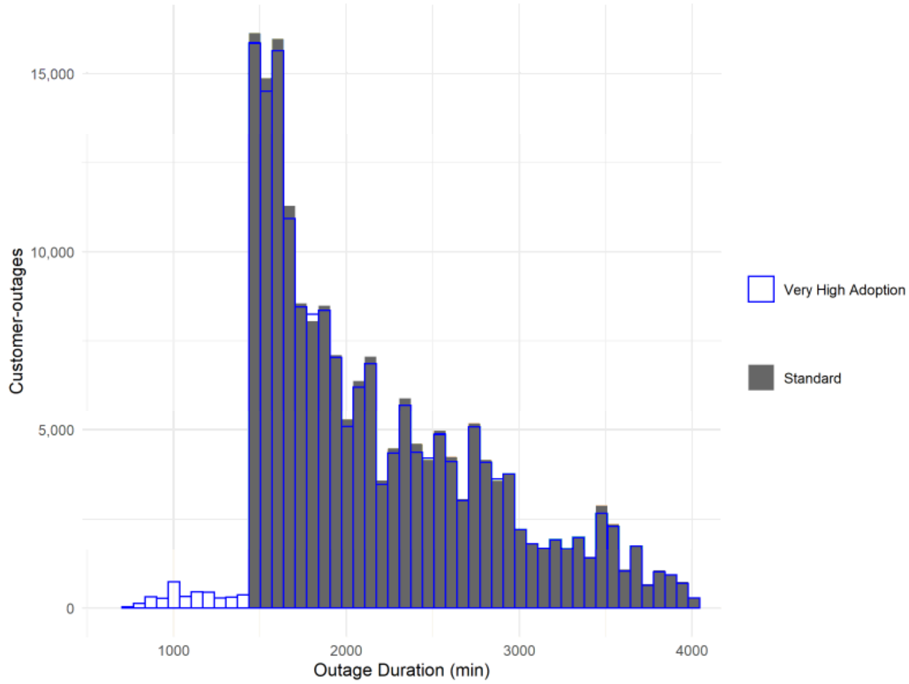

Figure 5.16 Histogram of customer-outages with and without mitigation from Very High level of battery adoption, operated in Full mode (2014-2018)

Using this framework, we examine an illustrative example of the impact on long-duration outages of battery adoption by every residential and commercial customers (Figure 5.17, truncated at 4,000 minutes). Apart from residential and commercial customers, circuits could also contain industrial, agricultural, and/or other customer types. Thus, having all residential and commercial customers adopt battery storage would still leave some customers on each circuit without a battery system. The transparent bars outlined in green in Figure 5.18 represent the histogram of mitigated outages; the grey bars represent the original unmitigated long-duration outages. The graph shows a larger number of customer-outages have shifted left, to durations shorter than 1,440 minutes. The total number of long-duration customer-outages reduces more significantly to 114,831, representing a 40% decrease. This illustrative example shows that even widespread adoption of relatively large battery storage systems would still leave 60% of long-duration outages unmitigated.

The results of this resilience assessment indicate that customer-sited battery storage systems could have an impact on mitigating outages lasting longer than 24 hours. The long tail to right on the duration histogram means that high adoption levels would be needed to shift a substantial portion of customer-outage durations below the somewhat arbitrary threshold of 24 hours. The ability of batteries to mitigate outages longer than 24 hours could be further enhanced by other measures that a customer could take. For example, our approach does not include changing customer behaviors, which could include reducing or eliminating discretionary power consumption (e.g. television) during outages when the battery was providing power. This type of behavior would allow customers to extend the length of time they would be able to power essential electrical appliances, including refrigeration, cell phone chargers, etc. Further research should be conducted to explore how integrating battery storage with other mitigation measures could significantly enhance distribution system resilience.

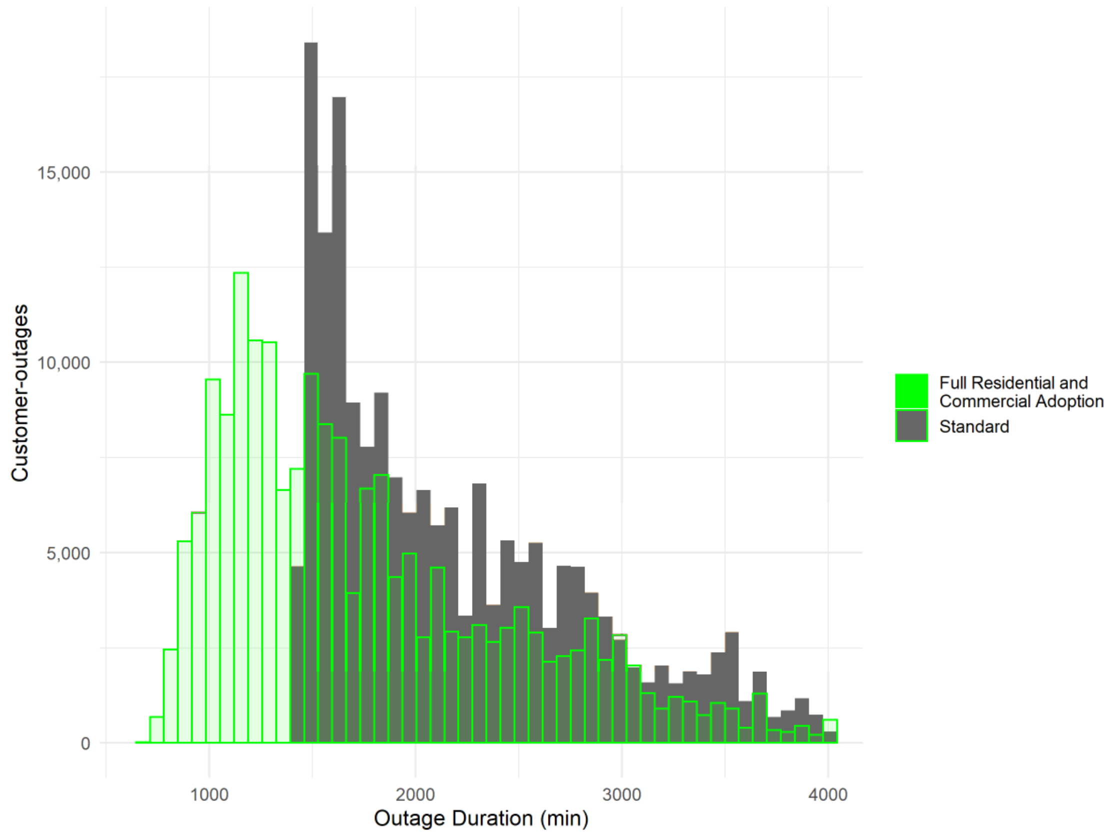

Figure 5.17 Illustrative histogram of customer-outages with and without mitigation from 100% battery adoption for residential and commercial customers, operated in Full mode (2014-2018)

These results account only for the infrastructure requirements to maintain resource adequacy and operational standards, but not the costs of interruptions to customers. For commercial customers, these costs include net revenue losses, equipment damage, and response costs; for residential customers, the costs are primarily due to inconvenience (Sullivan et al., 2018). Over the last few decades, researchers have used survey-based approaches to measure costs of interruptions lasting 24 hours or less. The Interruption Cost Estimation (ICE) Calculator is an interactive online tool for estimating interruption costs using the data from 34 customer interruption cost studies that used similar, survey-based methodologies. Other monetization methods, including the use of regional economic models, could be useful for determining the economic impacts of avoiding longer duration power interruptions as well as the indirect effects to the broader economy (Larsen et al., 2019; Zamuda et al., 2019). Proper accounting of the economic impacts from avoiding power interruptions can help utilities, regulators, and other stakeholders weigh the cost of integrating DERs against these types if benefits. Future research could involve efforts by Indiana IOUs—and their partners—to monetize the customer benefits of reliability and resilience improvements using the ICE Calculator metadata, new customer interruption cost studies, and/or regional economic modeling.

6. Conclusion

In 2019, the Indiana General Assembly enacted House Enrolled Act No. 1278 to explore the impact that fuel transitions and emerging technologies may have on the state's power system. The Act created the 21st Century Energy Policy Development Task Force, whose work will be informed by a comprehensive study of the impacts of fuel transitions and emerging technologies across Indiana. The preceding analysis explores the impacts of emerging technologies that could be deployed in Indiana IOU distribution systems by 2025 and 2040.

We develop six adoption scenarios that combine deployment levels of rooftop solar, electric vehicle charging, and battery storage—collectively referred to as DER—in residential and commercial customers connected to Indiana IOU systems. Five of the adoption scenarios implement a mix of expected and optimistic deployment of these resources, while a sixth scenario is developed as a stress-test with very high adoption levels. For example, rooftop PV adoption by 2040 ranges from 820 MW in the Base case to almost 6.5 GW in the Boundary scenario.

This study develops and employs an empirical framework that measures the impact of emerging distributed technologies on the power system for the six scenarios. The framework measures both the economic value and the reliability impact of DER:

- The economic value of DER is assessed by developing capacity expansion and power flow analysis of the generation and distribution segments, respectively, under future hourly demand assumptions based on the six adoption scenarios. The assessment of generation energy and capacity impacts uses State Utility Forecasting Group (SUFG) modeling platform to simulate optimal production and expansion costs. The assessment of distribution impacts employs the industry-standard Cymdist distribution power flow model with an array of strategies to upgrade feeders to address voltage, line loading, and energy losses issues. A simplified model for transmission expansion measures the economic impact of DER on three power system segments.
- The reliability impact of DER adoption is measured using a pioneering method first developed for this study. We use a data set of over half a million of historical outages across the five Indiana IOUs to inform this measurement. The method simulates the impact of different levels of behind-the-meter battery storage adoption, with several operational strategies, to reduce the frequency and duration of outages from the customer's perspective. This analysis is complemented with an assessment of the impacts of DER on reducing long-duration (more than 24 hours) interruptions as an initial measure of resilience impacts on the distribution system.

This study uses statistical techniques to classify over 2,800 feeders across Indiana into one of six groups that represent different types of feeders based on their customer mix, length, reliability, and other variables. Representative feeders from each group are selected to run power flow analyses for DER impacts on distribution systems, which can then be extrapolated to produce state-wide results.

Results for the distribution system power flow simulations show that voltage violations are relatively rare. Only 159 out of 3,456 simulated hours exhibit voltage violations of the ANSI optimal range levels, generally spanning a relatively small fraction of load nodes in a feeder. The majority of voltage issues arise only in the Boundary case and the violations are relatively small in magnitude. Voltage violations can be mitigated at a very low cost using a combination of smart inverters in future rooftop PV systems and voltage adjustments in the feeder heads. Line loading issues are minimal, with only eight simulation hours showing loading levels above 100% of capacity in about 3% of segments for feeders in clusters 3, 4, and 5. Line loading issues are addressed by upgrading conductors with relatively low costs given the few affected segments. Line losses are ~4%-10% higher than the Base case in the High Electrification and Boundary scenarios and 11% lower than the Base case in the High PV and High PV and Storage scenarios. Energy losses are not mitigated in this analysis, but monetized using the wholesale generation power costs that are output by the SUFG model.

Customer-sited battery storage systems can achieve multiple objectives related to improved reliability/resilience. When sized and operated appropriately, batteries can be used behind-the-meter for peak shaving or mitigating the PV 'duck curve' although their ability to mitigate power interruptions is limited. Reliability and resilience improvements are driven more by battery adoption levels than by mode of operation. We study battery storage adoption levels of 0.01% of customers (BAU), 1% of customers (high), 5% of customers (very high), and 100% of residential and commercial customers (theoretical limit). This analysis assumes that the battery discharge could only be consumed behind the meter. It is possible that larger system-wide benefits could be achieved if customer-sited batteries could discharge power back to the grid under direction from utility operations staff.

We estimate that the economic impact on power system investment and operation of increased DER adoption within the IOU service territories will be between -$265 million to +$105 million and -$550 million to +$1.6 billion in 2025 and 2040 relative to the Base case, respectively. In general, scenarios with high adoption of rooftop solar result in system-wide savings, while scenarios with high adoption and charging of electric vehicles result in large peaks that require substantial new generation capacity and higher system costs. The economic impacts of DER in the power system are concentrated in the generation segment, with about 80% of the cost impacts. The impact on the distribution segment is at most 0.12 ¢/kWh by 2040 in the Boundary scenario, while the impacts in generation can reach close to 1 ¢/kWh by 2040 in the same scenario. It is important to note that the results only account for the infrastructure requirements to maintain resource adequacy and operational standards—they do not account for avoided costs of power interruptions to customers.

This report is one of the first manuscripts to estimate the economic impact of increased adoption of distributed technologies across the different segments of the power system—generation, transmission, and distribution—using a forward-looking simulation framework. This study is also novel in that it develops an empirically-based estimation of the impact of behind-the-meter battery storage adoption on reliability indices from the customer and grid operators' perspective. This report identifies a number of future research opportunities including:

- The investigation of impacts to secondary distribution networks.
- More targeted upgrade assessments for representative feeders that consider a wider range of expansion options to integrated DER.

- Estimating the economic value of avoiding power interruptions due to DER adoption.
- A more thorough examination of the impacts of DER adoption on transmission expansion using an optimization model with explicit transmission representation.
- Development and implementation of additional methods to measure and mitigate impacts on distribution system resilience, including integration of battery storage with demand management processes.

The framework developed for this report can serve as a blueprint for utilities, policymakers, and other stakeholders who may be interested in conducting more targeted and expansive technology adoption impact studies.

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Appendix A. Additional results

The following results complement the cluster-level analysis for voltage violations in section 5.1.1 and reliability results from section 5.3

Table A.1 Number of nodes with voltage violations of the optimal range by simulation hour for Cluster 1

Year	Scenario	Cluster	Load Day Type	Simulation Time	Hour of Day	Number of nodes with high voltage violations	Number of nodes with no violations	Number of nodes with low voltage violations	Percent nodes with high voltage violations	Percent nodes with low voltage violations
2040	Boundary	CL1	max	22874400	18	0	436	6	0.0%	1.4%
2040	Boundary	CL1	max	22878000	19	0	435	7	0.0%	1.6%
2040	Boundary	CL1	max	22881600	20	0	441	1	0.0%	0.2%
2040	Boundary	CL1	min	9712800	10	1	441	0	0.2%	0.0%
2040	Boundary	CL1	min	9716400	11	1	441	0	0.2%	0.0%
2040	Boundary	CL1	min	9720000	12	1	441	0	0.2%	0.0%
2040	Boundary	CL1	min	9723600	13	1	441	0	0.2%	0.0%
2040	Boundary	CL1	min	9727200	14	0	441	1	0.0%	0.2%
2040	Boundary	CL1	min	9730800	15	0	441	1	0.0%	0.2%

Table A.2 Number of nodes with voltage violations of the optimal range by simulation hour for Cluster 2

Year	Scenario	Cluster	Load Day Type	Simulation Time	Hour of Day	Number of nodes with high voltage violations	Number of nodes with no violations	Number of nodes with low voltage violations	Percent nodes with high voltage violations	Percent nodes with low voltage violations
2025	HighElec	CL2	max	23032800	14	0	623	1	0%	0%
2025	HighElec	CL2	max	23036400	15	0	623	1	0%	0%
2040	Base	CL2	max	23032800	14	0	619	5	0%	1%
2040	Base	CL2	max	23036400	15	0	619	5	0%	1%
2040	Base	CL2	max	23040000	16	0	623	1	0%	0%
2040	Boundary	CL2	max	22874400	18	0	370	254	0%	41%
2040	Boundary	CL2	max	22878000	19	0	432	192	0%	31%
2040	Boundary	CL2	max	22881600	20	0	613	11	0%	2%
2040	Boundary	CL2	min	7149600	18	0	605	19	0%	3%

2040	Boundary	CL2	min	7153200	19	0	602	22	0%	4%
2040	HighElec	CL2	max	23032800	14	0	613	11	0%	2%
2040	HighElec	CL2	max	23036400	15	0	613	11	0%	2%
2040	HighElec	CL2	max	23040000	16	0	618	6	0%	1%
2040	HighPV	CL2	max	22874400	18	0	620	4	0%	1%
2040	HighPV	CL2	max	22878000	19	0	623	1	0%	0%
2040	HighPVSto	CL2	max	22874400	18	0	620	4	0%	1%
2040	HighPVSto	CL2	max	22878000	19	0	623	1	0%	0%
2040	Storage	CL2	max	23032800	14	0	619	5	0%	1%
2040	Storage	CL2	max	23036400	15	0	619	5	0%	1%
2040	Storage	CL2	max	23040000	16	0	623	1	0%	0%

Table A.3 Number of nodes with voltage violations of the optimal range by simulation hour for Cluster 3

Year	Scenario	Cluster	Load Day Type	Simulation Time	Hour of Day	Number of nodes with high voltage violations	Number of nodes with no violations	Number of nodes with low voltage violations	Percent nodes with high voltage violations	Percent nodes with low voltage violations
2040	Boundary	CL3	max	22856400	13	274	311	0	46.8%	0.0%
2040	HighPV	CL3	max	22852800	12	272	313	0	46.5%	0.0%
2040	HighPVSto	CL3	max	22852800	12	272	313	0	46.5%	0.0%
2040	Boundary	CL3	max	22860000	14	264	321	0	45.1%	0.0%
2025	Boundary	CL3	max	23022000	11	164	421	0	28.0%	0.0%
2025	Base	CL3	max	23018400	10	162	423	0	27.7%	0.0%
2025	HighElec	CL3	max	23018400	10	162	423	0	27.7%	0.0%
2025	Storage	CL3	max	23018400	10	162	423	0	27.7%	0.0%
2025	Base	CL3	max	23050800	19	153	432	0	26.2%	0.0%
2025	HighPV	CL3	max	23050800	19	153	432	0	26.2%	0.0%
2025	HighPVSto	CL3	max	23050800	19	153	432	0	26.2%	0.0%
2025	Storage	CL3	max	23050800	19	153	432	0	26.2%	0.0%
2025	HighElec	CL3	max	23050800	19	152	433	0	26.0%	0.0%
2025	Boundary	CL3	max	23050800	19	140	445	0	23.9%	0.0%
2040	HighPV	CL3	max	22856400	13	134	451	0	22.9%	0.0%
2040	HighPVSto	CL3	max	22856400	13	134	451	0	22.9%	0.0%

2025	HighPV	CL3	max	23022000	11	131	454	0	22.4%	0.0%
2025	HighPVSto	CL3	max	23022000	11	131	454	0	22.4%	0.0%
2040	Boundary	CL3	min	7124400	11	99	486	0	16.9%	0.0%
2040	Boundary	CL3	min	7131600	13	99	486	0	16.9%	0.0%
2040	Boundary	CL3	min	7135200	14	98	487	0	16.8%	0.0%
2040	Boundary	CL3	min	7120800	10	95	490	0	16.2%	0.0%
2040	Base	CL3	max	23018400	10	88	497	0	15.0%	0.0%
2040	HighElec	CL3	max	23018400	10	88	497	0	15.0%	0.0%
2040	Storage	CL3	max	23018400	10	88	497	0	15.0%	0.0%
2040	Boundary	CL3	max	22867200	16	81	504	0	13.8%	0.0%
2040	HighPV	CL3	max	22860000	14	81	504	0	13.8%	0.0%
2040	HighPVSto	CL3	max	22860000	14	81	504	0	13.8%	0.0%
2040	Base	CL3	max	23050800	19	74	511	0	12.6%	0.0%
2040	Storage	CL3	max	23050800	19	74	511	0	12.6%	0.0%
2025	Boundary	CL3	max	23025600	12	73	512	0	12.5%	0.0%
2040	Boundary	CL3	min	7128000	12	69	516	0	11.8%	0.0%
2040	Boundary	CL3	max	22852800	12	66	519	0	11.3%	0.0%
2040	Boundary	CL3	max	22849200	11	63	522	0	10.8%	0.0%
2040	HighElec	CL3	max	23050800	19	63	522	0	10.8%	0.0%
2040	Boundary	CL3	max	22885200	21	59	526	0	10.1%	0.0%
2025	Base	CL3	max	23047200	18	52	533	0	8.9%	0.0%
2025	HighElec	CL3	max	23047200	18	52	533	0	8.9%	0.0%
2025	HighPV	CL3	max	23047200	18	52	533	0	8.9%	0.0%
2025	HighPVSto	CL3	max	23047200	18	52	533	0	8.9%	0.0%
2025	Storage	CL3	max	23047200	18	52	533	0	8.9%	0.0%
2025	Boundary	CL3	max	23047200	18	50	535	0	8.5%	0.0%
2025	Base	CL3	max	23022000	11	37	548	0	6.3%	0.0%
2025	HighElec	CL3	max	23022000	11	37	548	0	6.3%	0.0%
2025	Storage	CL3	max	23022000	11	37	548	0	6.3%	0.0%
2040	HighPV	CL3	max	22881600	20	31	554	0	5.3%	0.0%
2040	HighPVSto	CL3	max	22881600	20	31	554	0	5.3%	0.0%
2025	HighPV	CL3	max	23025600	12	19	566	0	3.2%	0.0%

2025	HighPVSto	CL3	max	23025600	12	19	566	0	3.2%	0.0%
2025	Boundary	CL3	max	23043600	17	16	569	0	2.7%	0.0%
2040	Base	CL3	max	23047200	18	16	569	0	2.7%	0.0%
2040	Storage	CL3	max	23047200	18	16	569	0	2.7%	0.0%
2040	Boundary	CL3	max	22870800	17	15	570	0	2.6%	0.0%
2025	HighPV	CL3	max	23043600	17	13	572	0	2.2%	0.0%
2025	HighPVSto	CL3	max	23043600	17	13	572	0	2.2%	0.0%
2040	HighPV	CL3	max	22867200	16	5	580	0	0.9%	0.0%
2040	HighPVSto	CL3	max	22867200	16	5	580	0	0.9%	0.0%
2025	Boundary	CL3	max	23029200	13	4	581	0	0.7%	0.0%
2025	Base	CL3	max	23043600	17	3	582	0	0.5%	0.0%
2025	Storage	CL3	max	23043600	17	3	582	0	0.5%	0.0%
2040	Boundary	CL3	max	22845600	10	3	582	0	0.5%	0.0%
2040	HighPV	CL3	max	22849200	11	3	582	0	0.5%	0.0%
2040	HighPVSto	CL3	max	22849200	11	3	582	0	0.5%	0.0%
2025	HighElec	CL3	max	23043600	17	2	583	0	0.3%	0.0%
2040	Base	CL3	max	23022000	11	2	583	0	0.3%	0.0%
2040	HighElec	CL3	max	23022000	11	2	583	0	0.3%	0.0%
2040	Storage	CL3	max	23022000	11	2	583	0	0.3%	0.0%

Table A.4 Number of nodes with voltage violations of the optimal range by simulation hour for Cluster 4

Year	Scenario	Cluster	Load Day Type	Simulation Time	Hour of Day	Number of nodes with high voltage violations	Number of nodes with no violations	Number of nodes with low voltage violations	Percent nodes with high voltage violations	Percent nodes with low voltage violations
2040	Boundary	CL4	max	22874400	18	0	734	877	0%	54%
2040	Boundary	CL4	max	22878000	19	0	747	864	0%	54%
2040	HighElec	CL4	max	23032800	14	0	836	775	0%	48%
2040	HighElec	CL4	max	23036400	15	0	891	720	0%	45%
2040	Base	CL4	max	23036400	15	0	1206	405	0%	25%
2040	Storage	CL4	max	23036400	15	0	1206	405	0%	25%
2040	HighPV	CL4	max	22874400	18	0	1232	379	0%	24%
2040	HighPVSto	CL4	max	22874400	18	0	1232	379	0%	24%

2040	Base	CL4	max	23032800	14	0	1238	373	0%	23%
2040	Storage	CL4	max	23032800	14	0	1238	373	0%	23%
2040	HighElec	CL4	max	23040000	16	0	1251	360	0%	22%
2025	Boundary	CL4	max	22874400	18	0	1268	343	0%	21%
2040	Boundary	CL4	max	22881600	20	0	1279	332	0%	21%
2040	HighPV	CL4	max	22878000	19	0	1298	313	0%	19%
2040	HighPVSto	CL4	max	22878000	19	0	1298	313	0%	19%
2040	Boundary	CL4	min	7149600	18	0	1313	298	0%	18%
2040	Base	CL4	max	23040000	16	0	1314	297	0%	18%
2040	Storage	CL4	max	23040000	16	0	1314	297	0%	18%
2040	Boundary	CL4	min	7153200	19	0	1330	281	0%	17%
2025	HighElec	CL4	max	23036400	15	0	1403	208	0%	13%
2025	Base	CL4	max	23032800	14	0	1417	194	0%	12%
2025	Storage	CL4	max	23032800	14	0	1417	194	0%	12%
2025	HighElec	CL4	max	23032800	14	0	1426	185	0%	11%
2025	Boundary	CL4	max	22878000	19	0	1429	182	0%	11%
2025	Base	CL4	max	23036400	15	0	1455	156	0%	10%
2025	Storage	CL4	max	23036400	15	0	1455	156	0%	10%
2025	HighElec	CL4	max	23040000	16	0	1457	154	0%	10%
2040	HighElec	CL4	max	23043600	17	0	1472	139	0%	9%
2025	Base	CL4	max	23040000	16	0	1473	138	0%	9%
2025	Storage	CL4	max	23040000	16	0	1473	138	0%	9%
2040	Base	CL4	max	23029200	13	0	1473	138	0%	9%
2040	HighElec	CL4	max	23029200	13	0	1473	138	0%	9%
2040	HighPV	CL4	max	22881600	20	0	1473	138	0%	9%
2040	HighPVSto	CL4	max	22881600	20	0	1473	138	0%	9%
2040	Storage	CL4	max	23029200	13	0	1473	138	0%	9%
2025	Base	CL4	max	23029200	13	0	1474	137	0%	9%
2025	HighElec	CL4	max	23029200	13	0	1474	137	0%	9%
2025	HighPV	CL4	max	22874400	18	0	1474	137	0%	9%
2025	HighPVSto	CL4	max	22874400	18	0	1474	137	0%	9%
2025	Storage	CL4	max	23029200	13	0	1474	137	0%	9%

2040	Base	CL4	max	23043600	17	0	1474	137	0%	9%
2040	HighElec	CL4	max	23047200	18	0	1474	137	0%	9%
2040	Storage	CL4	max	23043600	17	0	1474	137	0%	9%
2040	HighPV	CL4	max	22863600	15	0	1526	85	0%	5%
2040	HighPVSto	CL4	max	22863600	15	0	1526	85	0%	5%
2040	Base	CL4	max	23025600	12	0	1528	83	0%	5%
2040	HighElec	CL4	max	23025600	12	0	1528	83	0%	5%
2040	Storage	CL4	max	23025600	12	0	1528	83	0%	5%
2025	Boundary	CL4	max	22881600	20	0	1538	73	0%	5%
2040	Boundary	CL4	max	22863600	15	0	1559	52	0%	3%
2040	Base	CL4	max	23047200	18	0	1600	11	0%	1%
2040	Storage	CL4	max	23047200	18	0	1600	11	0%	1%
2025	HighPV	CL4	max	22863600	15	0	1609	2	0%	0%
2025	HighPVSto	CL4	max	22863600	15	0	1609	2	0%	0%

Table A.5 Number of nodes with voltage violations of the optimal range by simulation hour for Cluster 5

Year	Scenario	Cluster	Load Day Type	Simulation Time	Hour of Day	Number of nodes with high voltage violations	Number of nodes with no violations	Number of nodes with low voltage violations	Percent nodes with high voltage violations	Percent nodes with low voltage violations
2040	Boundary	CL5	max	22874400	18	0	389	119	0%	23%
2040	Boundary	CL5	max	22878000	19	0	396	112	0%	22%
2040	Boundary	CL5	min	7120800	10	215	293	0	42%	0%
2040	Boundary	CL5	min	7124400	11	340	168	0	67%	0%
2040	Boundary	CL5	min	7128000	12	51	457	0	10%	0%
2040	Boundary	CL5	min	7131600	13	396	112	0	78%	0%
2040	Boundary	CL5	min	7135200	14	327	181	0	64%	0%
2040	Boundary	CL5	min	7138800	15	31	477	0	6%	0%

Table A.6 Number of nodes with voltage violations of the optimal range by simulation hour for Cluster 6

Year	Scenario	Cluster	Load Day Type	Simulation Time	Hour of Day	Number of nodes with high voltage violations	Number of nodes with no violations	Number of nodes with low voltage violations	Percent nodes with high voltage violations	Percent nodes with low voltage violations
2040	Boundary	CL6	min	12153600	16	1	237	0	0.4%	0

Table A.7 Total incremental transmission costs by scenario and year

	Simulation Year	
Adoption Scenario	**2025**	**2037**
1 Base	1,077,613,431	1,457,049,154
2 High Electrification	1,093,451,837	1,548,299,883
3 High PV	1,045,216,453	1,385,144,937
4 High PV and Storage	1,045,218,128	1,386,399,530
5 Storage	1,077,614,894	1,457,043,925
6 Boundary	1,105,144,637	2,191,110,968

Table A.8 Line upgrades for cluster 3, Boundary scenario, year 2040

Cluster	Length(ft)	Line	Line Type	Loading	Material	New Ampacity	New Size	New Type
3	51	2107973_2108_OH	Overhead Line	113.1	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
3	52	1349839_2108_OH	Overhead Line	111	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
3	158	1956950_2108_OH	Overhead Line	113.1	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
3	121	2258992_2108_OH	Overhead Line	111	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
3	247	1804292_2108_OH	Overhead Line	104.1	ALUMINIUM	645	556.5 kcmil	AAC DAHLIA 556.5 KCMIL
3	98	1198047_2108_OH	Overhead Line	112.4	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
3	128	1500660_2108_OH	Overhead Line	119.3	ALUMINIUM_ALLOY	200	1 AWG	AAAC 1 AWG
3	116	1980686_2108_OH	Overhead Line	103.5	ALUMINIUM_ALLOY	200	1 AWG	AAAC 1 AWG
3	58	1197568_2108_OH	Overhead Line	119.3	ALUMINIUM_ALLOY	200	1 AWG	AAAC 1 AWG
3	134	2283272_2108_OH	Overhead Line	101	ALUMINIUM_ALLOY	200	1 AWG	AAAC 1 AWG
3	92	1373954_2108_OH	Overhead Line	109.4	ALUMINIUM_ALLOY	200	1 AWG	AAAC 1 AWG
3	73	1349597_2108_OH	Overhead Line	104.1	ALUMINIUM	645	556.5 kcmil	AAC DAHLIA 556.5 KCMIL
3	80	1956400_2108_OH	Overhead Line	104.1	ALUMINIUM	645	556.5 kcmil	AAC DAHLIA 556.5 KCMIL
3	87	1980711_2108_OH	Overhead Line	109.4	ALUMINIUM_ALLOY	200	1 AWG	AAAC 1 AWG
3	107	2107409_2108_OH	Overhead Line	113.1	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
3	204	2107615_2108_OH	Overhead Line	104.1	ALUMINIUM	645	556.5 kcmil	AAC DAHLIA 556.5 KCMIL
3	55	1222320_2108_OH	Overhead Line	109.4	ALUMINIUM_ALLOY	200	1 AWG	AAAC 1 AWG
3	78	1980317_2108_OH	Overhead Line	101	ALUMINIUM_ALLOY	200	1 AWG	AAAC 1 AWG
3	103	1501183_2108_OH	Overhead Line	111	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
3	82	1652450_2108_OH	Overhead Line	119.3	ALUMINIUM_ALLOY	200	1 AWG	AAAC 1 AWG
3	136	1501186_2108_OH	Overhead Line	104.1	ALUMINIUM	645	556.5 kcmil	AAC DAHLIA 556.5 KCMIL
3	254	1501372_2108_OH	Overhead Line	104.1	ALUMINIUM	645	556.5 kcmil	AAC DAHLIA 556.5 KCMIL
3	50	1349642_2108_OH	Overhead Line	111	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
3	139	1349641_2108_OH	Overhead Line	100.1	ALUMINIUM	645	556.5 kcmil	AAC DAHLIA 556.5 KCMIL
3	95	1804287_2108_OH	Overhead Line	112.4	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
3	96	1804286_2108_OH	Overhead Line	112.4	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
3	220	1198053_2108_OH	Overhead Line	104.1	ALUMINIUM	645	556.5 kcmil	AAC DAHLIA 556.5 KCMIL
3	100	1652939_2108_OH	Overhead Line	112.4	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
3	151	1350232_2108_OH	Overhead Line	111	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL

3	173	1350230_2108_OH	Overhead Line	113.1	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
3	96	1350231_2108_OH	Overhead Line	113.1	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL

cluster	Phases	Previous Ampacity	Previous Size	Previous Type	Ratio	Steps	Unit Cost ($/ft)	Total Cost ($)
3	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.316	2	130	6630
3	ABC	570	397.5 kcmil	397.5_KCMIL_AL_BR	0.316	2	130	6760
3	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.316	2	130	20540
3	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.316	2	130	15730
3	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.132	1	95	23465
3	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.316	2	130	12740
3	C	128	2 AWG	#2_AAAC_BR	0.563	1	95	12160
3	A	128	2 AWG	#2_AAAC_BR	0.563	1	95	11020
3	C	128	2 AWG	#2_AAAC_BR	0.563	1	95	5510
3	A	128	2 AWG	#2_AAAC_BR	0.563	1	95	12730
3	A	128	2 AWG	#2_AAAC_BR	0.563	1	95	8740
3	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.132	1	95	6935
3	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.132	1	95	7600
3	A	128	2 AWG	#2_AAAC_BR	0.563	1	95	8265
3	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.316	2	130	13910
3	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.132	1	95	19380
3	A	128	2 AWG	#2_AAAC_BR	0.563	1	95	5225
3	A	128	2 AWG	#2_AAAC_BR	0.563	1	95	7410
3	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.316	2	130	13390
3	C	128	2 AWG	#2_AAAC_BR	0.563	1	95	7790
3	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.132	1	95	12920
3	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.132	1	95	24130
3	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.316	2	130	6500
3	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.132	1	95	13205
3	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.316	2	130	12350
3	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.316	2	130	12480

3	ABC		570	397.5 kcmil	397.5_KCMIL_AL_PE	0.132	1	95	20900
3	ABC		570	397.5 kcmil	397.5_KCMIL_AL_PE	0.316	2	130	13000
3	ABC		570	397.5 kcmil	397.5_KCMIL_AL_PE	0.316	2	130	19630
3	ABC		570	397.5 kcmil	397.5_KCMIL_AL_PE	0.316	2	130	22490
3	ABC		570	397.5 kcmil	397.5_KCMIL_AL_PE	0.316	2	130	12480

Table A.9 Line upgrades for cluster 4, Boundary scenario, year 2040

Cluster	Length(ft)	Line	Line Type	Loading	Material	New Ampacity	New Size	New Type
4	155.7	PRIOH36034657-17	Overhead Line	113.8	COPPER	180	4 AWG	CCC 4 A
4	173.5	PRIOH36034657-12	Overhead Line	105.7	COPPER	160	5 AWG	CCC 5 A
4	164	PRIOH36034657-19	Overhead Line	119.9	COPPER	180	4 AWG	CCC 4 A
4	163.6	PRIOH36034657-14	Overhead Line	109.6	COPPER	160	5 AWG	CCC 5 A
4	6.9	PRIOH36034657-13	Overhead Line	108.1	COPPER	160	5 AWG	CCC 5 A
4	11.9	PRIOH36034977	Overhead Line	122	COPPER	180	4 AWG	CCC 4 A
4	172.6	PRIOH36034669-2	Overhead Line	103.8	COPPER	160	5 AWG	CCC 5 A
4	301.9	PRIOH36034657-15	Overhead Line	112.1	COPPER	180	4 AWG	CCC 4 A
4	220.4	PRIOH36034657-20	Overhead Line	122	COPPER	180	4 AWG	CCC 4 A
4	239.6	PRIOH36034657-11	Overhead Line	102.7	COPPER	160	5 AWG	CCC 5 A
4	170.5	PRIOH36034657-16	Overhead Line	116.1	COPPER	180	4 AWG	CCC 4 A
4	393.8	PRIOH36034669-1	Overhead Line	101.3	COPPER	160	5 AWG	CCC 5 A
4	211.8	PRIOH36034657-18	Overhead Line	117.1	COPPER	180	4 AWG	CCC 4 A
4	39.8	PRIUG38005501	Cable	123.3	COPPER	475	450 kcmil	IEEE 600V-5KV NONSHIELDED 450KCMIL SR 1C CU
4	17.1	PRIUG38019283	Cable	123.3	COPPER	475	450 kcmil	IEEE 600V-5KV NONSHIELDED 450KCMIL SR 1C CU

cluster	Phases	Previous Ampacity	Previous Size	Previous Type	Ratio	Steps	Unit Cost ($/ft)	Total Cost ($)
4	A	140	26.248 kcmil	#6A-CW_BARE	0.286	2	195	30361.5
4	A	140	26.248 kcmil	#6A-CW_BARE	0.143	1	142.5	24723.75
4	A	140	26.248 kcmil	#6A-CW_BARE	0.286	2	195	31980
4	A	140	26.248 kcmil	#6A-CW_BARE	0.143	1	142.5	23313
4	A	140	26.248 kcmil	#6A-CW_BARE	0.143	1	142.5	983.25
4	A	140	26.248 kcmil	#6A-CW_BARE	0.286	2	195	2320.5
4	ABC	140	26.248 kcmil	#6A-CW_BARE	0.143	1	142.5	24595.5
4	A	140	26.248 kcmil	#6A-CW_BARE	0.286	2	195	58870.5
4	A	140	26.248 kcmil	#6A-CW_BARE	0.286	2	195	42978
4	A	140	26.248 kcmil	#6A-CW_BARE	0.143	1	142.5	34143
4	A	140	26.248 kcmil	#6A-CW_BARE	0.286	2	195	33247.5
4	ABC	140	26.248 kcmil	#6A-CW_BARE	0.143	1	142.5	56116.5
4	A	140	26.248 kcmil	#6A-CW_BARE	0.286	2	195	41301
4	ABC	382	350 kcmil	12KV_350CU_1/C_TAPE_SHIELD	0.243	2	120	4776
4	ABC	382	350 kcmil	12KV_350CU_1/C_TAPE_SHIELD	0.243	2	120	2052

Table A.10 Line upgrades for cluster 3, Boundary scenario, year 2040

Cluster	Length(ft)	Line	Line Type	Loading	Material	New Ampacity	New Size	New Type
5	198	2268221_2854_OH	Overhead Line	101.8	ALUMINIUM	645	556.5 kcmil	AAC DAHLIA 556.5 KCMIL
5	220	1813448_2854_OH	Overhead Line	130	ALUMINIUM	800	875.5 kcmil	AAC ANEMONE 874.5 KCMIL
5	194	1816870_2854_OH	Overhead Line	138.6	ALUMINIUM	800	875.5 kcmil	AAC ANEMONE 874.5 KCMIL
5	51	1661550_2854_OH	Overhead Line	119.9	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
5	97	1813574_2854_OH	Overhead Line	119.9	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
5	205	2116482_2854_OH	Overhead Line	119.9	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
5	223	2268149_2854_OH	Overhead Line	130	ALUMINIUM	800	875.5 kcmil	AAC ANEMONE 874.5 KCMIL
5	202	1509873_2854_OH	Overhead Line	119.9	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
5	192	1816645_2854_OH	Overhead Line	138.6	ALUMINIUM	800	875.5 kcmil	AAC ANEMONE 874.5 KCMIL
5	212	1513395_2854_OH	Overhead Line	130	ALUMINIUM	800	875.5 kcmil	AAC ANEMONE 874.5 KCMIL
5	195	1816689_2854_OH	Overhead Line	138.6	ALUMINIUM	800	875.5 kcmil	AAC ANEMONE 874.5 KCMIL

5	36	151080124_2854_OH	Overhead Line	119.9	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
5	203	1510149_2854_OH	Overhead Line	119.9	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
5	96	2271306_2854_OH	Overhead Line	138.6	ALUMINIUM	800	875.5 kcmil	AAC ANEMONE 874.5 KCMIL
5	188	2271307_2854_OH	Overhead Line	138.6	ALUMINIUM	800	875.5 kcmil	AAC ANEMONE 874.5 KCMIL
5	193	1510354_2854_OH	Overhead Line	122.4	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
5	44	1358439_2854_OH	Overhead Line	119.9	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
5	192	1510316_2854_OH	Overhead Line	119.9	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
5	97	2271305_2854_OH	Overhead Line	138.6	ALUMINIUM	800	875.5 kcmil	AAC ANEMONE 874.5 KCMIL
5	60	151570492_2854_OH	Overhead Line	119.9	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
5	156	2116518_2854_OH	Overhead Line	119.5	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
5	121	1813603_2854_OH	Overhead Line	122.4	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
5	99	1965598_2854_OH	Overhead Line	119.9	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
5	185	1965135_2854_OH	Overhead Line	119.9	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
5	203	2268150_2854_OH	Overhead Line	119.9	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
5	181	1210203_2854_OH	Overhead Line	138.6	ALUMINIUM	800	875.5 kcmil	AAC ANEMONE 874.5 KCMIL
5	96	1665149_2854_OH	Overhead Line	138.6	ALUMINIUM	800	875.5 kcmil	AAC ANEMONE 874.5 KCMIL
5	211	1510275_2854_OH	Overhead Line	130	ALUMINIUM	800	875.5 kcmil	AAC ANEMONE 874.5 KCMIL
5	182	1210246_2854_OH	Overhead Line	138.6	ALUMINIUM	800	875.5 kcmil	AAC ANEMONE 874.5 KCMIL
5	177	1210247_2854_OH	Overhead Line	138.6	ALUMINIUM	800	875.5 kcmil	AAC ANEMONE 874.5 KCMIL
5	192	1813209_2854_OH	Overhead Line	122.4	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
5	204	1661844_2854_OH	Overhead Line	119.9	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
5	95	1968614_2854_OH	Overhead Line	138.6	ALUMINIUM	800	875.5 kcmil	AAC ANEMONE 874.5 KCMIL
5	206	1358440_2854_OH	Overhead Line	119.9	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
5	97	1358486_2854_OH	Overhead Line	119.9	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
5	191	2116076_2854_OH	Overhead Line	119.9	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
5	191	2116075_2854_OH	Overhead Line	119.9	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
5	62	1510323_2854_OH	Overhead Line	119.9	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
5	209	1665083_2854_OH	Overhead Line	130	ALUMINIUM	800	875.5 kcmil	AAC ANEMONE 874.5 KCMIL
5	205	1206743_2854_OH	Overhead Line	119.9	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
5	100	1965204_2854_OH	Overhead Line	119.9	ALUMINIUM	750	715.5 kcmil	AAC NASTURTIUM 715.5 KCMIL
5	57	1362103_2854_UG	Cable	119.7	COPPER	695	2000 kcmil	ENERGYA 15KV IEC 500MM 3C CU UA

5	115	1816518_2854_UG	Cable	119.7	COPPER	695	2000 kcmil	ENERGYA 15KV IEC 500MM 3C CU UA

cluster	Phases	Previous Ampacity	Previous Size	Previous Type	Ratio	Steps	Unit Cost ($/ft)	Total Cost ($)
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_BR	0.132	1	95	18810
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.404	3	173	38060
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.404	3	173	33562
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.316	2	130	6630
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_BR	0.316	2	130	12610
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.316	2	130	26650
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.404	3	173	38579
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.316	2	130	26260
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.404	3	173	33216
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.404	3	173	36676
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.404	3	173	33735
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.316	2	130	4680
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.316	2	130	26390
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.404	3	173	16608
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.404	3	173	32524
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_BR	0.316	2	130	25090
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.316	2	130	5720
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_BR	0.316	2	130	24960
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.404	3	173	16781
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.316	2	130	7800
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_BR	0.316	2	130	20280
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_BR	0.316	2	130	15730
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_BR	0.316	2	130	12870
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.316	2	130	24050
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.316	2	130	26390
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.404	3	173	31313
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.404	3	173	16608

5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.404	3	173	36503
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.404	3	173	31486
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.404	3	173	30621
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_BR	0.316	2	130	24960
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.316	2	130	26520
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.404	3	173	16435
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.316	2	130	26780
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_BR	0.316	2	130	12610
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.316	2	130	24830
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.316	2	130	24830
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_BR	0.316	2	130	8060
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.404	3	173	36157
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_PE	0.316	2	130	26650
5	ABC	570	397.5 kcmil	397.5_KCMIL_AL_BR	0.316	2	130	13000
5	ABC	660	211.6 kcmil	3P_750_KCMIL_CU_15KV_QUAD	0.053	0	120	6840
5	ABC	660	211.6 kcmil	3P_750_KCMIL_CU_15KV_QUAD	0.053	0	120	13800

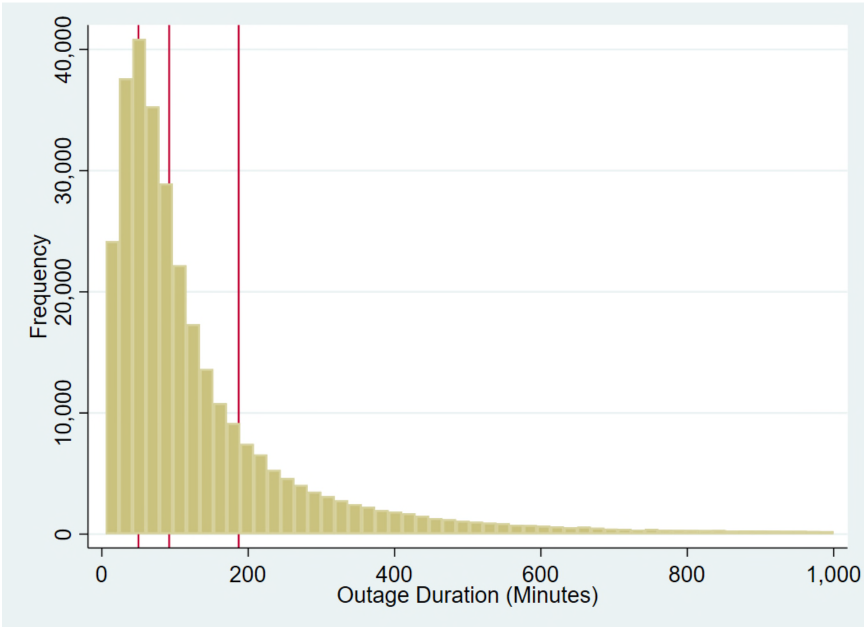

Figure A.1 Frequency of outages by duration including MEDs (truncated at 1,000 minutes) (2014-2018)

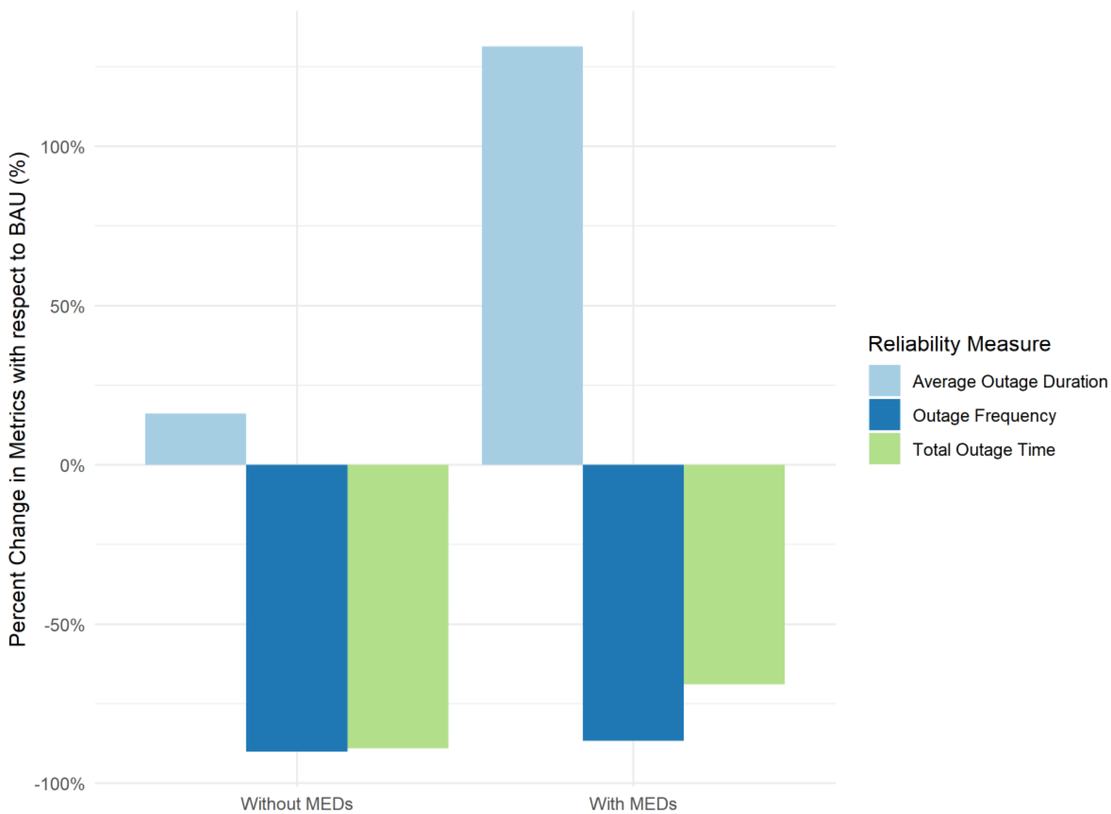

Figure A.2 State-wide reliability changes relative to the base case for battery storage adopters under full battery mode (with and without MEDs included)

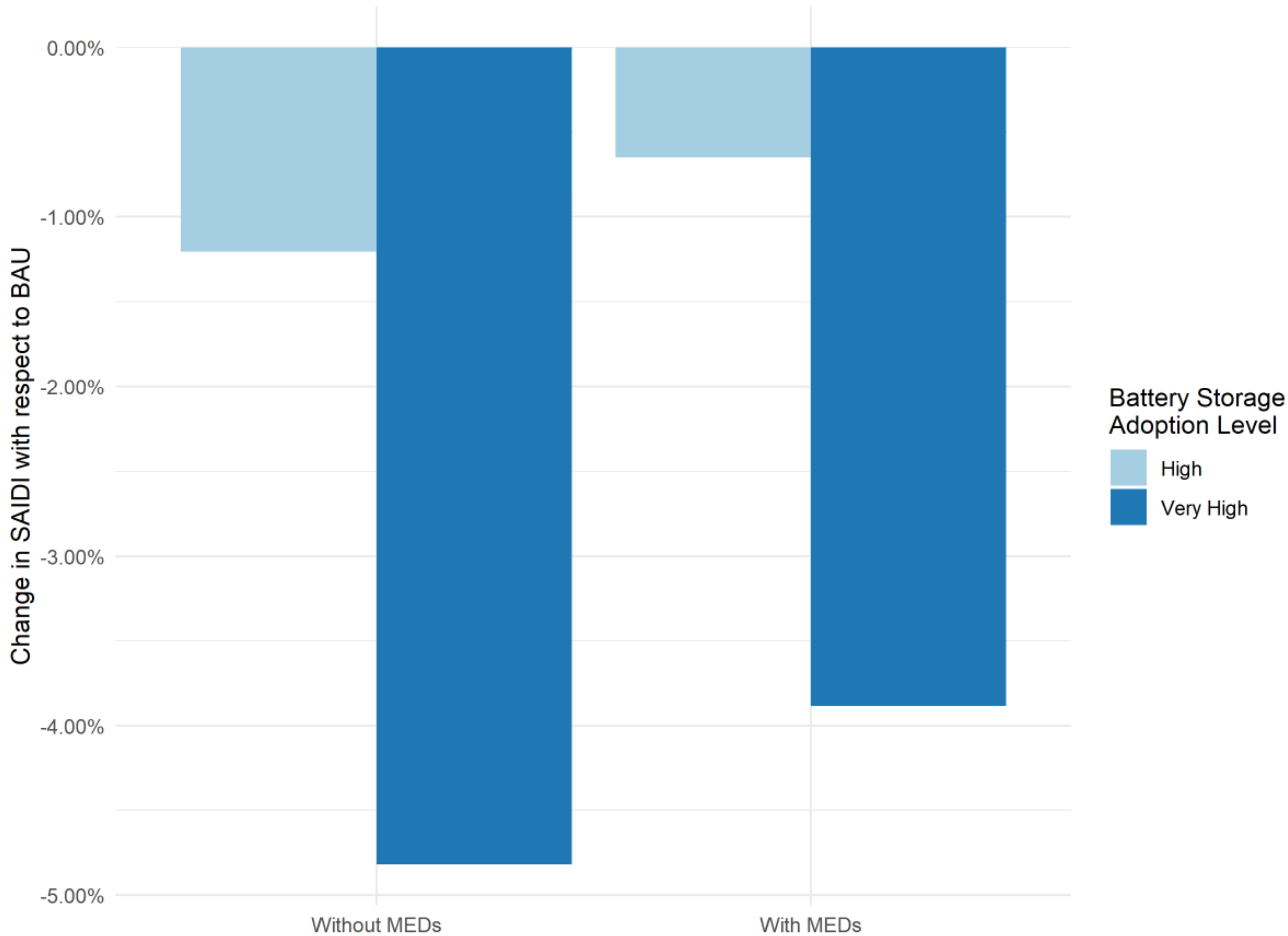

Figure A.3 Average state-wide SAIDI changes with respect to BAU with and without MEDs.

Appendix B. Technical Appendix

B.1. Feeder clustering methodology

This subsection reports the method used to preprocess the feeder dataset using Principal Component Analysis (PCA)

B.1.1. Transforming the data using PCA

Data transformation is a pre-processing step intended to extract useful information from an otherwise noisy and possibly redundant dataset. Outliers need to be identified and cleaned or removed to make sure the critical differences and similarities between feeders are evident and lead to better clustering. Reducing the complexity of the dataset leads to an improved and computationally tractable analysis of large datasets.

In the case of feeder metrics, potential correlation between parameters can hinder appropriate clustering. For example, the aggregate transformer capacity in a feeder and its peak demand may be highly correlated. Including both in the analysis may give inappropriate weight to these two parameters, preventing important information from other parameters to be considered.

We transformed the data employing Principal Component Analysis. PCA is a method designed to extract and display the systematic variation in a data set (Broderick and Williams, 2013). Technically speaking, PCA seeks to express the feeder metrics on a different basis, such that the variance across parameters is maximized and their covariance is minimized (Cale et al., 2014). As stated by Shlens (2005), "PCA provides a roadmap for how to reduce a complex data set to a lower dimension to reveal the sometimes hidden, simplified structure that often underlie it."[9]

The resulting data allows us to express each feeder as a combination of the transformed variables. For example, in Figure B.1, each dot represents a single feeder characterized by their first two standardized principal components. The condensation of data in several areas of the plot suggests how clusters can be formed, and the dots that are farther from the center (0, 0) are candidates for outliers.

[9] Technical details on the method are out of the scope of this study, but an accessible tutorial is available from Shlens (2005).

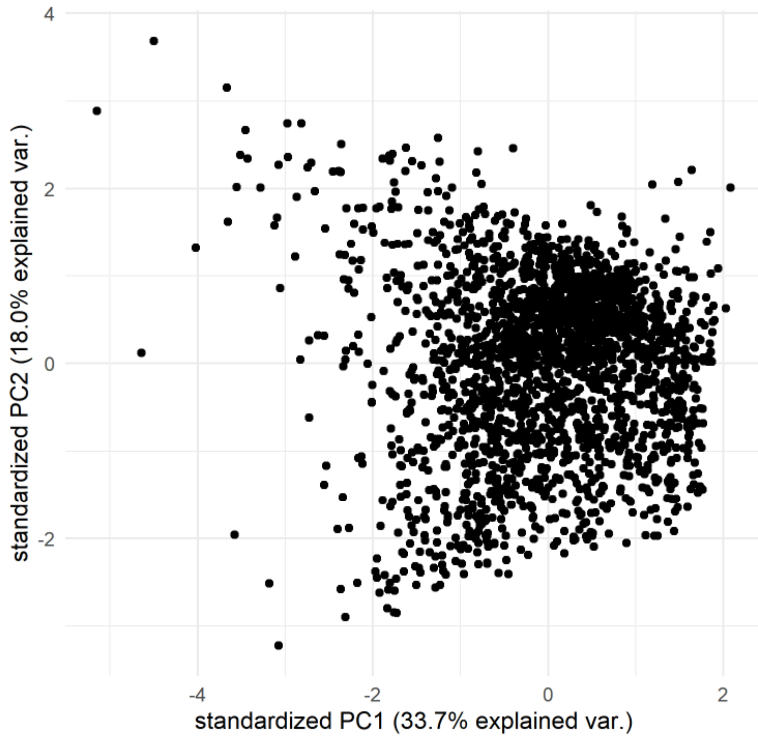

Figure B.1 Indiana feeder data expressed in its first two principal components

Sampling techniques are very sensitive to the presence or exclusion of outliers. A genuine outlier – a data point that is most likely wrong – should be excluded when possible to minimize distortion of the outcome. However, feeder metrics that are extreme may signal an unusual type of feeder whose properties should be captured by the clustering algorithm and not discarded.

This study employs the Mahalanobis distance (D^2) to identify outliers within the dataset (McLachlan, 1999). Outliers are usually analyzed within individual dimensions (for example, the 99th percentile of the number of poles for each feeder). However, a feeder with many poles could represent a long feeder with many customers, hence being a "typical" feeder from a multivariable perspective. The D^2 metric measures the "distance" between a point and the center of its distribution (Ruefer, 2016). In this case, it allows to measure the distance of a set of feeder parameters to their joint distribution, allowing the identification of true outliers that avoid the issue presented before.

The application of the D^2 method to the dataset did not remove a substantial number of data points. This is due, in part, to the cleaning described earlier, but also because we used a conservative threshold to classify outliers in order to preserve a reasonable amount of variation within the dataset. The final dataset used for determining feeder clusters was composed of 12 parameters representing over 2,250 feeders across the Indiana IOU service territories.

B.1.2. Determining the number of clusters

After the dataset is transformed, scaled, and cleaned of outliers, the next step is to classify these feeders according to common features and produce "representative" clusters of feeders. This clustering step was performed in two stages.

First, a clustering technique is applied iteratively and performance metrics are calculated for each iteration. These performance metrics identify the optimal number of clusters from a statistical perspective. We employ the Partitioning Around Medoids (PAM), which was used by (Cale et al., 2014) as a more robust method than the well-known k-means cluster algorithm. Second, we manually examine the clusters and iterate further to produce a final set of clusters. The definitive clusters can be represented by its two principal components by assigning the corresponding cluster to each dot in Figure B.1 (see Figure B.2 below). The figure shows clusters forming on the two left quadrants (purple and orange), two interior clusters closer to the center (green and blue), and two clusters in the right quadrants (red and yellow).

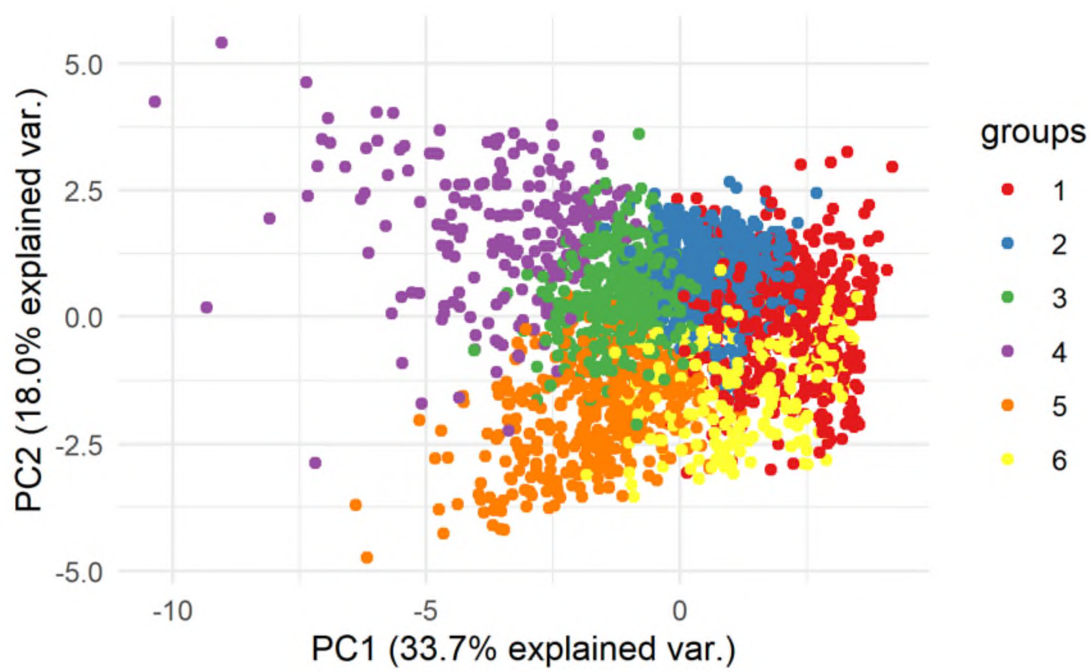

Figure B.2 Result of PAM algorithm on the first two principal components (PC1 and PC2, respectively).

B.1.3. Selecting representative feeders

We used again the D^2 distance defined in subsection B.1.1 to choose a representative feeder for each cluster, which will be then used for the power flow simulations in the next stage of the analysis. The D^2 distance identifies the center of the "cloud" of data points, and then reports the distance of each actual data point (in this case, feeder) to that center value. The feeders with the shortest distance to this median value are then the ones that most closely represent an average feeder within a cluster. This is the method used to select representative feeders for simulation.

B.2. Distribution system power flow simulation results

This appendix includes a deeper analysis of voltage violations for each individual cluster.

Cluster 1: 442 total nodes

The representative feeder for cluster 1 has less than seven nodes compromised on a few simulation hours, all of them in the Boundary scenario and the year 2040 (Table A.1, Appendix A). Low voltage issues exist on up to seven nodes over five hours, and high voltage issues on a single node over four additional hours. Cluster 1 is one of the least impacted feeders, probably due to its short length and its larger share of commercial customers which have a relatively high load factor.

Cluster 2: 624 total nodes

In year 2040, the representative feeder for cluster 2 has only low voltage issues (Table A.2, Appendix A). Most hour-scenario combinations have few nodes with voltage violations. However, there are two simulation hours in the Boundary scenario where 31% and 41% of nodes exhibit low voltage issues. These voltage issues occur at 6 pm and 7 pm on a maximum load day. A topology map of this feeder shows low voltage levels at the points farther from the source node, at times of the day when PV voltage support declines due to reduced production (Figure 5.2). In the figure, small dots represent nodes colored according to their voltage level in p.u., and yellow dots represent location of PV systems in this feeder.

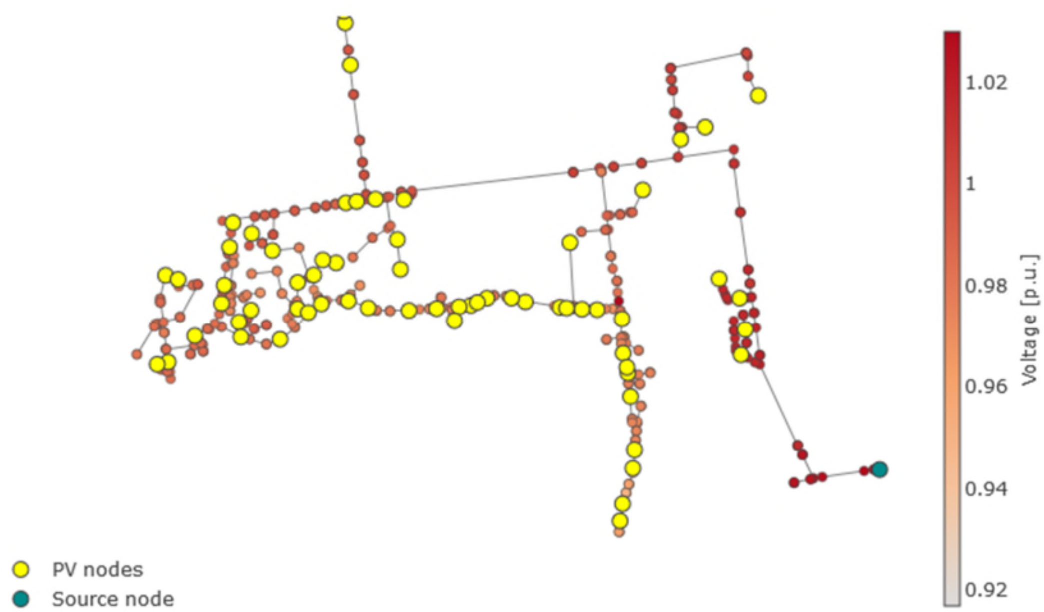

Figure B.3 Depiction of voltage levels for Cluster 2 in 2040 under the Boundary scenario

Cluster 3: 585 total nodes

The representative feeder for cluster 3 exhibited voltage issues during 67 simulation hours out of 576—the most recorded for all clusters (Table A.3, Appendix A). It should be noted that there are only high voltage anomalies in this cluster. About 20% of the nodes exhibited high voltage issues. The majority of these high voltage issues occurred in the middle of the day, which likely correlates with increased PV production and is expected with the Boundary and High PV scenarios.

However, further analysis of the high voltage anomalies reveal that the base voltage set point at the feeder header is set at 1.045 p.u. in the Cymdist feeder model submitted by the utility. The absolute minimum voltage in any node in this feeder is 0.982 p.u., which is high for a relatively long feeder. Even scenarios with low PV adoption including the 2025 Base scenario exhibit high voltage issues in over 15% of the nodes. Furthermore, this is the only feeder with a similar number of voltage violations in 2025 and 2040; voltage violations in other feeders happen almost exclusively in 2040. Our analysis suggests that about half of the responsibility for high voltage issues can be attributed to the current base voltage set point at feeder header, and the other half to DER adoption.

Cluster 4: 1,611 total nodes

The representative feeder for cluster 4 exhibited low voltage issues only, in about 50 simulation hours out of 576 (Table A.4, Appendix A). This feeder also exhibits the widest range of node voltages among clusters, most likely due to its length.

The low voltage issues appear to be correlated with high demand during the middle of the day. About half of the nodes have low voltage issues in the worst four simulation hours. These correspond to the Boundary scenario, at 6 pm and 7 pm; and to the High Electrification scenario, at 2 pm and 3 pm. The timing of the two worst hours in the Boundary scenario suggests that high PV adoption is indeed contributing to the improvement in low voltage issues exhibited in this feeder. Not surprisingly, the two worst simulation hours correspond to the High Electrification scenario, which has a high net demand due to electric vehicle charging. It is possible that, with lower PV adoption, these two hours in the High Electrification scenario would also exhibit the highest levels of voltage violations.

Cluster 5: 508 total nodes

The representative feeder for cluster 5 has only eight simulation hours out of 576 with voltage issues (Table A.5, Appendix A). However, this feeder is unique in that it exhibits *both* low and high voltage issues affecting a reasonably large number of nodes (20% of notes exhibited low voltage issues and 75% exhibited high voltage issues). However, all voltage issues in this feeder occur in the Boundary scenario.

This cluster has the highest PV adoption per customer node—more than double the next closest cluster. It is possible that higher PV adoption correlates to relatively more affluent residential customers, who are more likely to take advantage of PV incentives and be served by higher shares of underground circuits (Barbose et al., 2020). It follows that high voltage violations occur during very low load hours, which is when PV production can have the most significant impact on voltage increases. This suggests that most voltage issues in this feeder may be solved by smart inverters that can consume reactive power at specific times to prevent voltage increases.

Cluster 6: 238 total nodes

As with the feeder in cluster 1, the representative feeder in cluster 6 is essentially not impacted by DER adoption. There is a single simulation hour with voltage issues, which takes place on a single node out of the 238 nodes in the feeder (Table A.6, Appendix A). The relatively high share of industrial customers on nodes in cluster 6—who do not adopt DER in our study—as well as the relative short circuit length make feeders in this cluster less prone to develop voltage issues, even in the Boundary scenario.