

UNIVERSITY OF BAHRAIN

College of Engineering



**Department of Electrical and
Electronics Engineering**

IMPACTS AND MITIGATION OF THE ELECTRIC VEHICLES (EV) INTEGRATION ON BAHRAIN'S DISTRIBUTION NETWORK

A Thesis Submitted in Partial Fulfilment of the Requirements for
the M.Sc. Degree in Renewable Energy Engineering

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Abstract

The integration of electric vehicles (EVs) into power distribution networks presents both opportunities and challenges, particularly in regions with ambitious sustainability goals like Bahrain. This study evaluates the readiness of Bahrain's low-voltage distribution network to accommodate the growing demand for EV charging, addressing a significant research gap in the local context. It aims to assess the effects of EV charging on network performance and explore strategies to mitigate potential issues, and supporting Bahrain's transition to sustainable transportation. The research focuses on three objectives: modeling a typical distribution network in Bahrain, quantifying the impact of EV charging under various scenarios, and evaluating the effectiveness of indirect controlled charging as a mitigation strategy. Simulations using DIgSILENT PowerFactory assessed transformer loading, voltage violations, feeder loading, and power losses under different EV penetration levels, considering charger capacities of 7.6 kW and 11 kW. Complementing these simulations, a dataset of over 233 million transformer load readings was analyzed using Python to identify real-world load patterns, peak demands, and opportunities for charging optimization. Findings indicate that while Bahrain's network can handle upcoming EV penetration levels, higher penetration—particularly with 11 kW chargers—can lead to transformer overloading, voltage violations, and feeder loading issues. Indirect controlled charging strategies, such as off-peak charging between 2 AM and 8 AM, were shown to mitigate these impacts effectively. The developed impact matrix offers a practical tool for evaluating risks and planning interventions. These results contribute to informed policy-making and strategic planning, aligning with Bahrain's environmental goals and the global push for electrified transportation.

Dedication

This thesis is dedicated to my beloved parents. To my father, for his unwavering support, encouragement, and belief in my potential, and to my late mother, whose memory continues to inspire me every day. Her love and wisdom live on in every step I take, and this work is a reflection of her lasting influence on my life. Thank you both for shaping the person I am today.

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List of Abbreviations

AC	Alternating Current
ACB	Air Circuit Breaker
BEV	Battery Electric Vehicle
BSS	Battery Swapping Station
CBL	Customer Baseline Load
CPP	Critical Peak Pricing
CPT	Capacitive Power Transfer
DC	Direct Current
DSM	Demand-Side Management
DSO	Distribution System Operator
DPF	DIgSILENT PowerFactory
EM	Electric Motor
EMI	Electromagnetic Interference
EV	Electric Vehicle
EVCS	Electric Vehicle Charging Station
EVSE	Electric Vehicle Supply Equipment
FCEV	Fuel Cell Electric Vehicle
FCS	Fast Charging Station
HEV	Hybrid Electric Vehicle
HV	High Voltage
HRC	High Rupturing Capacity
ICE	Internal Combustion Engine
ICEV	Internal Combustion Engine Vehicle
IEC	International Electrotechnical Commission
IPT	Inductive Power Transfer
LV	Low Voltage

MVA	Mega Volt Ampere
OLPT	On-Line Inductive Power Transfer
PHEV	Plug-in Hybrid Electric Vehicle
PMPT	Permanent Magnet Coupling Power Transfer
PTR	Peak Time Rebate
RAPT	Resonant Antennae Power Transfer
RIPT	Resonant Inductive Power Transfer
RMS	Root Mean Square
RMU	Ring Main Unit
RTP	Real-Time Pricing
SoC	State of Charge
THD	Total Harmonic Distortion
TOU	Time-of-Use
TX	Transformer
V2G	Vehicle-to-Grid
VPP	Virtual Power Plant
VUF	Voltage Unbalance Factor
VUF	Voltage Unbalance Factor
WC	Wireless Charging
kVA	Kilo Volt Ampere

Chapter 1: Introduction

Chapter Overview:

This chapter introduces the context, objectives, and significance of the study on electric vehicle (EV) integration in Bahrain's distribution network. It begins with an overview of global trends in EV adoption, exploring the role of EVs in sustainable transportation and emission reduction efforts worldwide. This is followed by an examination of EV adoption in Bahrain, highlighting the country's environmental targets and the potential contributions of EVs to national sustainability goals. The chapter then formulates the problem addressed by this study, laying out the specific challenges that EV integration presents for Bahrain's distribution network. The research objectives and questions are defined to guide the study's focus, while the significance section emphasizes the study's potential impact on Bahrain's energy sector and policy-making. Finally, a brief thesis outline provides an overview of the remaining chapters, summarizing the structure of the work.

1.1 Electric Vehicles Globally

The urgent need to transition away from fossil fuels and mitigate climate change has catalyzed a global shift toward eco-friendly energy systems. This transformation relies on clean energy solutions, including renewable power, energy-efficient technologies, and sustainable transportation alternatives. Electric vehicles (EVs) are a key component of this shift, offering a path to decarbonize road transport, a sector responsible for around one-sixth of global emissions.

In recent years, the EV market has become one of the most dynamic areas of clean energy. Driven by advancements in battery range, vehicle performance, and model diversity, EV sales have surged worldwide. It is projected that in 2024, more than one in five new cars sold will be electric (IEA, 2024). Figure 1.1 illustrates this rapid growth trend, underscoring the increasing momentum toward grid connected EV adoption as countries enact policies to phase out gasoline-powered cars, invest in charging infrastructure, and incentivize EV purchases (IEA, 2024).

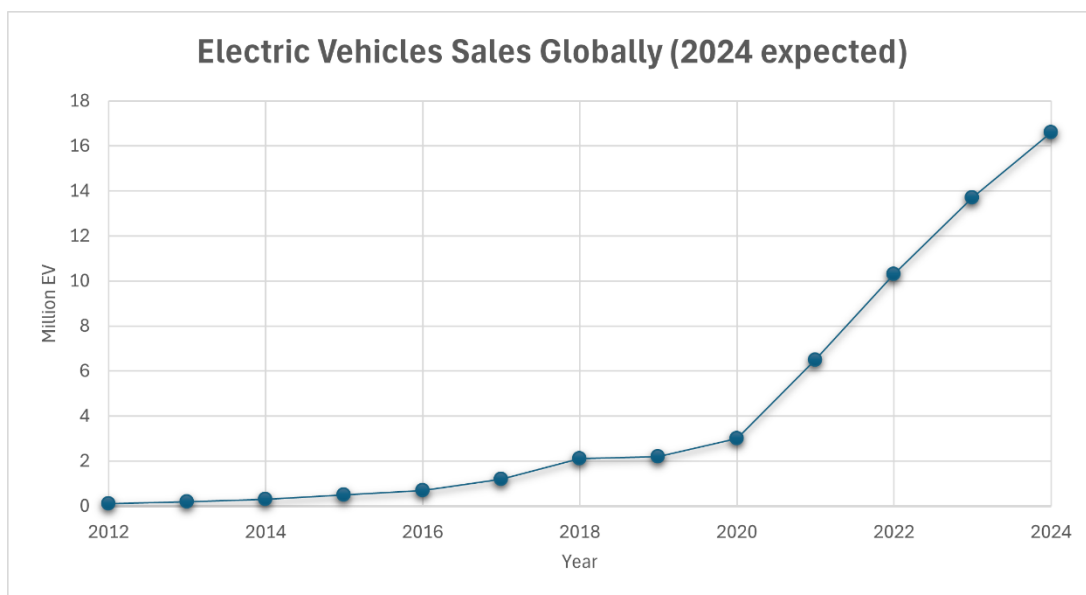


Figure 1.1 EVs Sales Globally

These global efforts highlight a collective commitment to reducing greenhouse gas emissions and addressing climate change. As nations transition toward EVs, the role of electric vehicles as a sustainable transportation solution continues to grow, demonstrating the potential for significant environmental benefits through reduced emissions and improved air quality.

1.2 Electric Vehicles in Bahrain

Bahrain relies heavily on petroleum as its primary energy source, making it a country with a substantial carbon footprint due to its main reliance on fossil fuels in the economy (IEA, 2021).

To address this, Bahrain has set ambitious environmental targets. Aiming for net-zero carbon by 2060 and a 30% reduction in carbon emissions by 2035 is a significant move toward tackling climate change and promoting sustainability (BNA, 2021). These targets reflect a significant commitment to addressing climate change and advancing sustainability.

The total number of vehicles in Bahrain is estimated to be around 750,000, yet battery electric vehicles (BEVs) currently account for less than 0.1% of this total (MIER, 2024). This minimal penetration of BEVs highlights the significant potential for growth in the EV sector as Bahrain moves toward its environmental targets.

Achieving net-zero carbon means balancing emitted greenhouse gases with their removal, effectively neutralizing the country's carbon footprint. In this context, the adoption of electric vehicles (EVs) is a key component of Bahrain's strategy. EVs, which run on electricity instead of fossil fuels, offer a sustainable alternative that can drastically reduce emissions from

the transportation sector—a major source of urban pollution and greenhouse gases.

Bahrain’s commitment to environmental targets aligns with the promotion of EVs as part of a broader shift toward sustainable transportation. By encouraging EV adoption, Bahrain aims to decrease its reliance on traditional fossil fuel vehicles, contributing to cleaner air and a healthier environment for its residents. These efforts not only support Bahrain’s national sustainability goals but also reflect the country’s alignment with global initiatives to reduce greenhouse gas emissions and improve air quality.

However, the growing adoption of EVs brings new challenges for Bahrain’s electricity distribution network, particularly in managing increased demand and ensuring grid stability. This study focuses on assessing the potential impacts of EV integration on Bahrain’s distribution network, identifying key areas of vulnerability, and proposing strategies to support a smooth transition to sustainable transportation.

1.3 Problem Formulation

The integration of electric vehicles (EVs) into Bahrain’s electric grid, expected to increase significantly over the next 10–15 years, poses new challenges for the nation’s distribution network. While EV adoption will grow gradually, the additional energy demand from EVs introduces risks of sharp load peaks, especially during evening hours and holiday periods when simultaneous charging is likely. Current distribution grids were not designed with EV charging in mind, and there is limited understanding of the potential impact of EV loads on urban distribution systems in Bahrain.

This knowledge gap is critical, as it concerns not only the average increase in demand but also extreme scenarios that could push the grid beyond safe operating limits. Without proper planning, EV integration could lead to grid stress, voltage violation, and overloaded transformers and feeders, resulting in costly capacity upgrades. Conversely, strategic planning and effective load management could mitigate these issues, offering opportunities to balance demand by shifting EV charging to off-peak times. Thus, addressing this uncertainty is essential to prepare Bahrain's distribution network for the evolving demands of EV integration.

1.4 Purpose and Aim

This thesis aims to explore the current state of electric car technology and analyze its potential effects on Bahrain's distribution grid. Additionally, the goal is to provide recommendations to lessen or mitigate the impact of electric vehicles (EVs) on the distribution system.

1.5 Research Objectives

The primary objective of this study is to investigate the impact of electric vehicle (EV) integration on Bahrain's distribution network and explore potential mitigation strategies. This research is driven by the need to understand how increasing EV adoption affects the stability, reliability, and efficiency of the distribution system and to develop methods for managing these effects. The specific objectives of this study are as follows:

1. **To model a typical Bahrain distribution network** – This objective involves developing a representative model of a distribution network in Bahrain, focusing on LV network. By modeling the existing network structure, this study establishes

a baseline for analyzing the impact of EV integration under realistic operating conditions.

2. **To quantify the impact of EV integration on the distribution network** – This objective focuses on assessing the effects of EV charging on transformer loading, voltage violation, LV feeder overload and power losses. The study aims to quantify these impacts under various EV penetration levels and charger power ratings, identifying potential risks of voltage violations and overloads as EV adoption increases.
3. **To investigate the opportunities for indirect control charging as a mitigation strategy** – This objective involves evaluating the potential of indirect control methods, such as Time of Use (TOU) pricing, to reduce peak demand and alleviate stress on the distribution network. The study uses load data analysis to determine if indirect control can effectively shift EV charging demand to off-peak periods, thereby minimizing its impact on network performance.

1.6 Research Questions

To address the challenges posed by electric vehicle (EV) integration on Bahrain's distribution network, this study seeks to answer the following research questions:

- 1- **What are the anticipated impacts of increasing EV penetration on the operational limits of a typical distribution network in Bahrain's grid, particularly concerning voltage violation, equipment overload and power losses?**

This question aims to identify how growing EV charging demand affects critical network components, focusing on voltage drop, equipment loading limits and power losses under various EV penetration levels.

2- How can the effects of EV integration on distribution network performance be quantified by simulating different transformer loading and simultaneous charging scenarios?

This question investigates how simulation results can be used to assess and measure the impact of EV charging on network performance, with an emphasis on identifying high-risk scenarios.

3- How can real-time and historical current values across multiple distribution transformers help in understanding load distribution patterns and peak demand behavior in the context of EV integration?

This question explores how analyzing the historical current values across transformers provides insight into the likelihood of demand surges and their timing, informing potential stress points in the network.

4- What opportunities exist for using indirect control strategies, such as Time of Use (TOU) pricing, to mitigate the risk of overload and voltage violations due to EV charging?

This question assesses the potential of indirect control methods, like TOU pricing, to shift EV charging demand away from peak periods, potentially minimizing grid stress

1.7 Significance

This research provides valuable insights for Bahrain's economy and, more specifically, for the Distribution System Operator (DSO). It focuses on understanding the consequences of the uncontrolled adoption of Electric Vehicles (EVs) and preparing for the inevitable changes to the distribution

network. By identifying potential impacts and recommending suitable remedial actions, this study addresses the critical challenges associated with the expected growth of EV usage in Bahrain. As one of the first studies to examine the effects of EV integration on Bahrain's distribution network, this research lays essential groundwork for informed decision-making, contributing to the resilience and sustainability of the national power infrastructure.

1.8 Thesis Outline

The thesis is organized into five chapters, beginning with Chapter 1, which introduces the research context, objectives, and significance of studying electric vehicle (EV) integration in Bahrain's distribution network, providing a global and local perspective on EV adoption and its challenges. Chapter 2 reviews the theoretical background and existing literature, focusing on EV technology, charging infrastructure, and the impact of large-scale EV integration on power distribution networks, along with potential mitigation strategies. Chapter 3 outlines the methodology used to simulate the impact of EV integration on the network and evaluate mitigation strategies through advanced modeling and data analysis. Chapter 4 presents the results and analysis, integrating findings from simulations and real-world data to assess network performance under various EV charging scenarios and explore the feasibility of indirect charging controls. Finally, Chapter 5 concludes the study with key insights, practical recommendations, and future research directions for optimizing EV integration into Bahrain's distribution network.

Chapter 2: Theoretical Background and Literature Review

Chapter Overview:

This chapter provides a comprehensive overview of the theoretical background and literature on electric vehicle (EV) technology, charging infrastructure, and their implications for power distribution networks. It begins by examining various EV types—hybrid, plug-in hybrid, battery electric, and fuel cell vehicles—highlighting their unique operational characteristics, environmental benefits, and potential for widespread adoption. The discussion then shifts to EV charging infrastructure, covering conductive and wireless technologies, battery swapping stations, and the standards and charging modes set by the International Electrotechnical Commission (IEC) to contextualize global practices. The chapter also explores the potential impact of large-scale EV integration on distribution networks, focusing on issues such as voltage fluctuations, phase imbalances, harmonic distortions, and increased power losses associated with higher EV penetration. Drawing from international studies, it underscores the importance of grid-ready solutions to manage peak demand, ensure power quality, and maintain reliability. The chapter concludes by reviewing strategic mitigation approaches—such as controlled charging, Time-of-Use (TOU) pricing, and Vehicle-to-Grid (V2G) integration—that enhance grid stability and support a seamless transition to an electrified transportation system.

An electric vehicle (EV) is a type of vehicle that operates, at least partially, using electricity. Examples include trams, metros, electric cars, electric trains, and trolleybuses. Typically, when the term "EV" is used, it commonly refers to private electric cars rather than other forms of electrified transportation, such as trams or metros. While most of these technologies are well-established and commonly used, private electric cars, in particular, have gained significant attention in recent years (Shaukat et al., 2018a). Although EV technology is not new and dates back to the 19th century, when it was powered by lead-acid batteries, it was not widely adopted due to the superior performance of fuel-powered cars, such as internal combustion engine vehicles (ICEVs), at that time (Ajanovic, 2015).

2.1 Types of Electric Vehicle

There are essentially four different kinds of electric vehicles: hybrid electric vehicles, plug-in hybrid electric vehicles, battery electric vehicles and fuel cell electric vehicles. All four varieties of electric vehicles use electricity for propulsion, but they differ in how they operate and their respective powertrains and electric range (Shaukat et al., 2018b). The basic structure of different EV types is shown in Figure 2.1 (Climate Council, 2022).

2.1.1 Hybrid Electric Vehicle

Hybrid electric vehicles (HEVs) are similar to regular cars but have a larger electric motor and battery. These batteries can be charged while braking or when the car is lightly loaded by the internal combustion engine (ICE). Usually, the battery and electric motor power the vehicle at slower speeds, while the ICE takes over at higher speeds. The electric motor can

also help the ICE during heavy loads, which improves the vehicle's performance and efficiency (Nour et al., 2020). HEVs produce fewer greenhouse gas emissions and use less fuel than regular cars. Since they don't charge from the electrical grid like electric cars, they don't affect the power system or provide electricity services. There are different types of HEVs, like series, parallel, or mild HEVs, which car makers use to reduce fuel usage, increase mileage, and improve performance (Tie & Tan, 2013). HEVs use regenerative braking to save energy, and their systems manage fuel use by balancing power between the ICE and electric motor based on factors like vehicle speed, driver input, battery charge, and motor speed (Un-Noor et al., 2017).

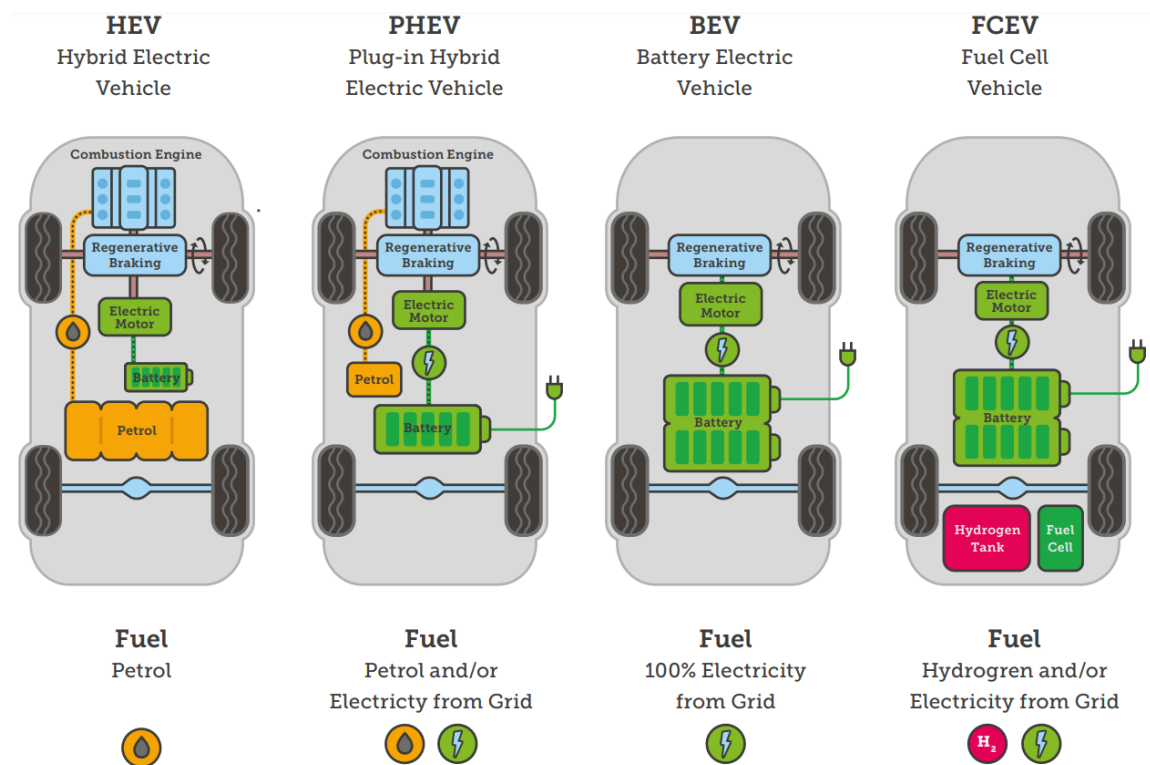


Figure 2.1 Types of EVs

2.1.2 Plug-in Hybrid Electric Vehicle

Plug-in hybrid electric vehicles (PHEVs) are similar to hybrid electric vehicles (HEVs), but they have larger batteries that can be charged through regenerative braking, the internal combustion engine (ICE), or an EV

charger from the distribution network (Tie & Tan, 2013). PHEVs have a stronger electric motor, a smaller ICE, and a larger battery compared to HEVs, enabling them to run entirely on electricity and produce no greenhouse gas emissions (Un-Noor et al., 2017). The battery size determines how far the vehicle can drive on electric power alone, with PHEVs usually having smaller batteries, which means they have fewer impacts on the electric power system and limited ability to provide electrical services.

2.1.3 Battery Electric Vehicle

Battery electric vehicles (BEVs) are anticipated to become the primary choice in the electric vehicle (EV) market due to improvements in battery technology and reduced costs. BEVs operate solely on an electric motor (EM) powered by a battery, eliminating the need for an internal combustion engine (ICE) (Nicoletti et al., 2020). The driving range of BEVs depends on the size of the battery, and there are different configurations available depending on the manufacturer (Tie & Tan, 2013). BEVs charge their batteries from the distribution network using EV chargers, and during deceleration and braking, the motor functions as a generator through regenerative braking (Nour et al., 2020). However, BEVs encounter challenges such as lengthy charging times and limited availability of public charging stations, although these issues may be resolved in the future with advancements in battery technology and the expansion of fast charging infrastructure (Alanazi, 2023). BEVs have the potential to offer electrical services and possess the largest battery capacity among EVs, which may strain the power system if not managed effectively. Nevertheless, BEVs provide advantages such as simplicity, environmental

friendliness, and strong torque output even at low speeds (Un-Noor et al., 2017).

2.1.4 Fuel Cell Electric Vehicle

Fuel cell electric vehicles (FCEVs), also called Fuel Cell Vehicles (FCVs), operate similarly to Battery Electric Vehicles (BEVs) with electric motors (EM), but instead of batteries, they use fuel cells (Kumar et al., 2023). These vehicles are fueled with hydrogen, which is converted by the fuel cell into electricity to power the motor. Hydrogen can be obtained from fossil fuels or through water electrolysis (Un-Noor et al., 2017). FCEVs have a quick refueling time like Internal Combustion Engine Vehicles (ICEVs) and can also use a combination of batteries and supercapacitors. Unlike BEVs, FCEVs do not need electric charging from the distribution system (Nour et al., 2020). They generate electricity through chemical reactions in fuel cells, using hydrogen as fuel and oxygen from the air. The electricity produced powers the motor, and any excess energy is stored in batteries or supercapacitors. FCEVs only emit water as a byproduct, making them environmentally friendly, and they can refuel as quickly as traditional vehicles at a gas pump, making them more attractive for adoption (Zhao et al., 2022).

2.2 Electric Vehicle Charging Infrastructure

Electric vehicle (EV) charging encompasses three main technologies: conductive charging, wireless charging (WC), and battery swapping (Habib, Khan, Abbas, & Tang, 2018). Conductive charging, currently the most common method, involves physical contact (i.e., cable) between the power supply and battery, whereas WC requires no physical contact. Although WC and battery swapping are still in the development phase, they

offer promising alternatives to conductive charging (Kumar et al., 2023). EVs comprise two primary components: the battery and the charging topology, with charging facilities categorized as on-board or off-board. Chargers can be unidirectional or bidirectional, with bidirectional systems enabling power flow in both directions. On-board chargers are limited in power due to weight, space, and cost restrictions. DC or AC systems can be used for EV charging, with different configurations denoted as 'modes' and the time required for a full charge varying accordingly (M. R. Khalid et al., 2021).

2.2.1 Conductive Charging

EV battery chargers are essential for the advancement of EVs, as their adoption and acceptance rely on the easy availability of charging stations or street chargers. Chargers are classified into on-board (inside the vehicle for slow charging) and off-board (external to the vehicle for fast charging) (Abraham et al., 2021). They can also be categorized as unidirectional or bidirectional. Unidirectional chargers have straightforward hardware and only support power flow from the grid to the EV. In contrast, bidirectional chargers allow power flow from the grid to the EV and can also send power from the EV battery back to the grid, building, or home (M. Khalid et al., 2022). Different topologies have been designed for single-phase and three-phase EV chargers, which generally include an AC/DC converter, power factor correction components, and a DC/DC converter (Shareef et al., 2016). Figure 2.3 summarizes EV charger classification.

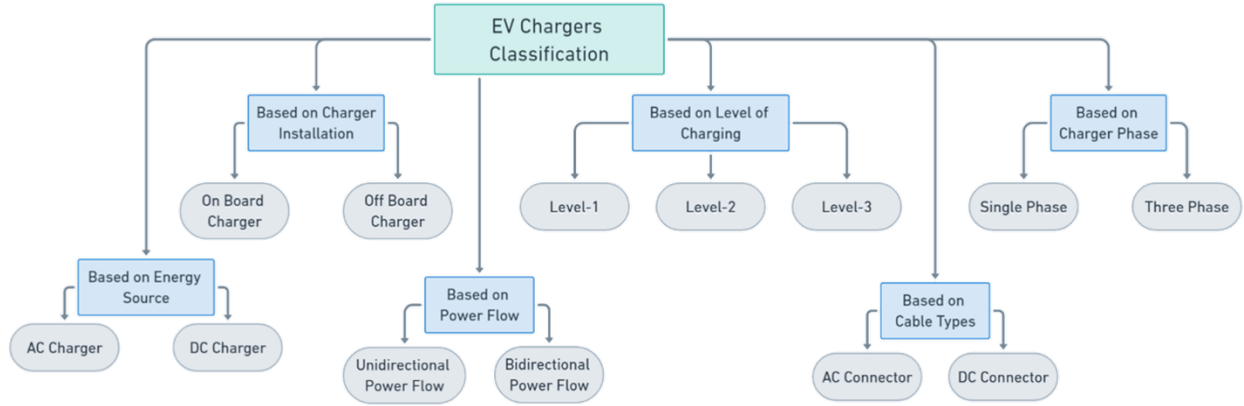


Figure 2.2 EV charger classification

The International Electrotechnical Commission (IEC) has set global standards for EV charging, specifically IEC-62196 and IEC-61851. These standards outline four modes of AC and DC charging for electric vehicles. Mode 1, used for slow charging at home, has a current limit between 8A and 16A depending on the country, and connects EVs to the grid using standard single-phase or three-phase power outlets with phase(s), neutral, and protective earth conductors. Mode 2, suitable for semi-fast charging at homes or public locations, allows a maximum current of 32A using similar outlets. Mode 3 can handle both slow and fast charging with a current range from 32A to 250A, connecting EVs to the grid through specific outlets equipped with EV Supply Equipment (EVSE), with cables that include an earth and control pilot for proper communication between the EV and the grid. Mode 4 supports ultra-fast charging using fixed EVSE with 600V DC power, permitting a maximum current of 400A through a connection cable that includes an earth and control pilot (Acharige et al., 2023). Table 2.1 provides a comparison of these four charging modes as defined by the IEC standards.

Table 2.1 EV charger modes

Charge Mode	Phase	Current (max)	Voltage (max)	Power (max)	Specific Connector
Mode 1	1- ϕ AC	16 A	230–240 V	3.8 kW	No
	3- ϕ AC	16 A	480 V	7.6 kW	No
Mode 2	1- ϕ AC	32 A	230–240 V	7.6 kW	No
	3- ϕ AC	32 A	480 V	15.3 kW	No
Mode 3	1- ϕ AC	32–250 A	230–240 V	60 kW	Yes
	3- ϕ AC	32–250 A	480 V	120 kW	Yes
Mode 4	DC	250–400 A	600–1000 V	400 kW	Yes

2.2.2 Wireless Charging

Wireless charging (WC) is gaining popularity due to its convenience. Unlike traditional wired charging, WC does not require plugs or cables, reducing the risk of sparks and shocks in wet or dirty environments and decreasing the chance of vandalism. Various WC technologies are being explored, each with different operating frequencies, efficiencies, and levels of electromagnetic interference (EMI) (Yang et al., 2018). Inductive power transfer (IPT) is a mature, contactless technology, although it is not completely wireless. Capacitive power transfer (CPT) is cost-effective and compact at low power levels but not suitable for high-power applications like EV charging. Permanent magnet coupling power transfer (PMPT) is inefficient and has other disadvantages. Resonant inductive power transfer (RIPT) and on-line inductive power transfer (OLPT) show potential but may face infrastructure challenges. Resonant antennae power transfer (RAPT) operates at MHz frequencies, which can pose health risks if not properly shielded, affecting range and performance (Musavi & Eberle, 2014). Personal vehicle wireless charging will not be implemented in the future, at least shortly, because of health, fire, safety issues, and alignment and range issues. Besides, the impossibly high costs

of embedding WC systems into the roads for charging moving vehicles present a significant challenge (V et al., 2023), (Kurs et al., 2007).

2.2.3 Battery Swapping

At a Battery Swapping Station (BSS), a depleted EV battery can be swiftly replaced with a fully charged one, typically within a few minutes. This approach is particularly advantageous for commercial vehicles, such as taxis, where time efficiency is crucial, and for electric buses with large-capacity batteries that require extended charging times. A BSS must maintain a substantial inventory of batteries, either owned by the station or rented from a third party. The key components of a BSS include a distribution transformer, AC/DC converters for charging the batteries, the batteries themselves, and the equipment necessary for the swapping process (Zheng et al., 2014). According to some research, BSS can deliver electrical services via vehicle-to-grid (V2G) mode by using bidirectional chargers. However, there are several challenges associated with this technology, including the huge space required for the BSS, expensive infrastructure costs, and the need for battery uniformity. That's why there are only about 30 battery swapping stations in Europe (Rematec, 2024).

2.3 Bahrain's Distribution Network

Electricity is generated at power plants and travels through a complex network which includes substations, transformers, and power lines connecting electricity producers and consumers. In an electrical power system, there are three primary stages for delivering electricity: Generation, Transmission, and Distribution. In Bahrain, generators produce electricity at 11kV, which can increase to 21kV. The transmission system operates at 33kV, 66kV, 220kV, and 400kV, while the distribution

system delivers electricity at 11kV, 415V (3-phase), and 230V (1-phase). The distribution system operator (DSO) in Bahrain is responsible for the distribution network starting from the 11kV termination on the primary substation 11kV bus bar to the customer meter. Figure 2.3 is a schematic diagram illustrating a typical section of Bahrain's electrical power system, highlighting the stages and voltage levels involved.

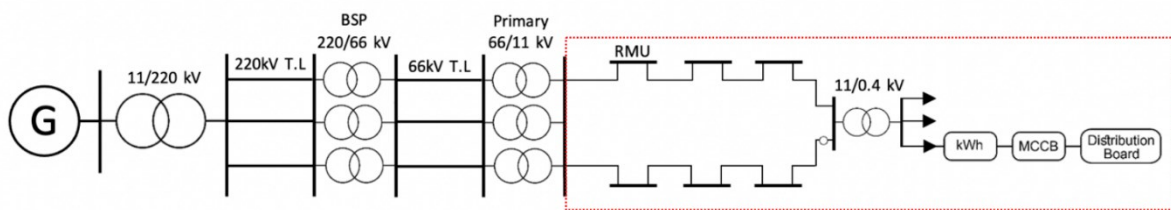


Figure 2.3 Bahrain's power system

Bahrain's distribution network is a vital part of the electrical power system, responsible for delivering electricity from primary substations to consumers. Distribution substations are integral components of this network, stepping down the voltage to levels suitable for consumer use through step-down transformers. The distribution system operator in Bahrain oversees the distribution network, starting from the 11kV termination on the primary bus bar to the customer meter.

In the distribution network, substations are often connected in a ring configuration using manual switches located within the ring main units (RMUs) of the distribution substations. Typically, distribution substations are fed from different feeders originating from primary substations. One of the switches in the RMU of a particular substation is kept in the 'OFF' position, creating an open point. This configuration ensures that some distribution substations are fed from one feeder and others from a different feeder, which helps restore the supply in case of a fault.

The main equipment involved in the distribution system, as shown in figure 2.4, includes distribution substations and feeders, which can be either overhead or underground cables. A typical distribution substation (11/0.4kV) feeds all customers and consists of distribution transformers, RMUs, and low voltage (LV) boards or air circuit breakers (ACBs). Currently, Bahrain uses 500kVA, 1000kVA, and 1500kVA distribution transformers in its secondary substations. Substations generally have 5-way, 7-way, or 10-way LV boards for multi-consumer connections and ACBs for single consumers with loads exceeding 340kVA.

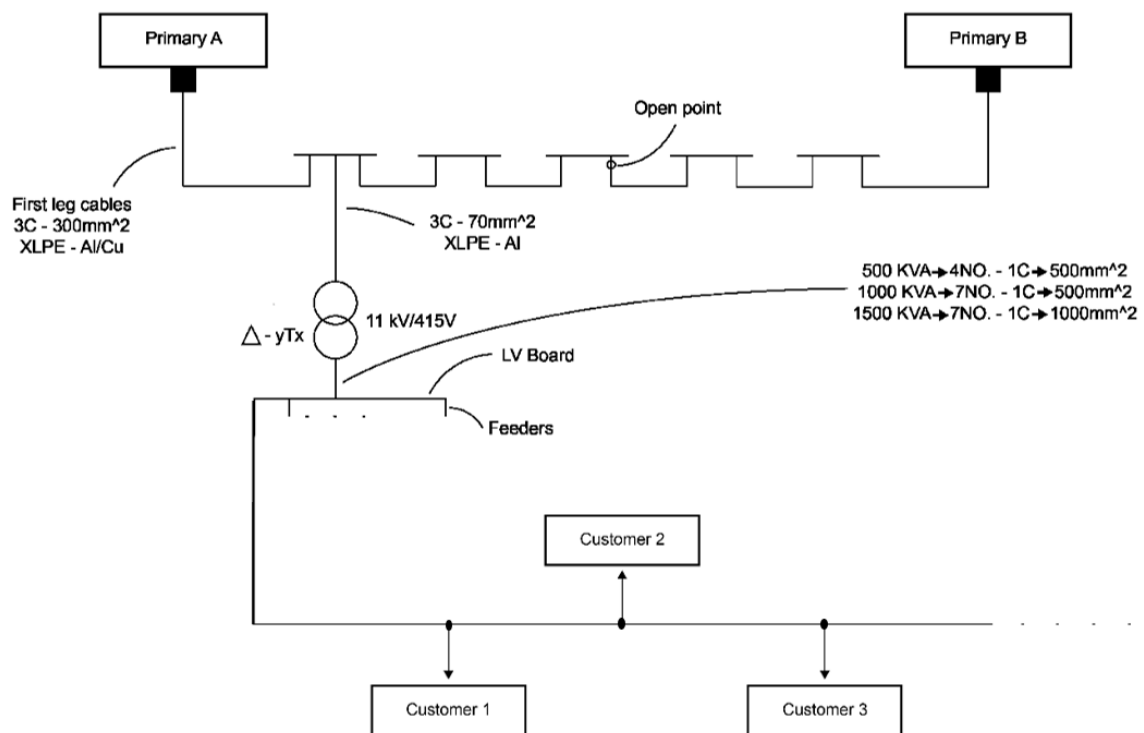


Figure 2.4 Typical Bahrain's distribution network

The primary purpose of an RMU is to link a substation to other substations via the busbar within the RMU and to protect the distribution transformer in the secondary substation from faults. An RMU typically includes multiple load break switches and a 630A circuit breaker to protect the transformer.

Distribution transformers in Bahrain have the following characteristics: they are 3-phase, 11kV/415V transformers with a vector group of Dyn11 (Δ -Y, with a phase displacement of 30° lead). These transformers are equipped with off-load tap changers. Typically, up to four transformers can be installed within a distribution substation in Bahrain.

2.3.1 System characteristics

The system characteristics as follow (Electricity and Water Authority, 2015):

11kV system:

- Nominal voltage: 11000 volt $\pm 6\%$, three phase, three wire.
- Frequency: 50 Hz $\pm 2\%$
- Neutral arrangement: The system neutral is connected to earth through a low resistance at the sending end station.
- Maximum prospective fault level: 20 kA (350 MVA) at 11 kV for a short time duration of 1 s. (Maximum)

LV system:

- Nominal voltage: 400/230 volt $\pm 6\%$, three phase, four wire.
- Frequency: 50 Hz. $\pm 2\%$
- Neutral arrangement: Solidly earthed. Installation earthing: “TT” system as per IEC 60364-3.
- Maximum prospective fault level: 50 kA (31 MVA) at 400 V and short time duration of 0.5 s (Maximum)

The distribution system operator (DSO) in Bahrain applies specific 11kV design policies for substation networks. If the first leg is made of

copper (Cu) conductors, the load up to the open point should not exceed 3MVA (150A), with a total ring connection accommodating up to 6MVA (300A). If the first leg is made of aluminum (Al) conductors, the load up to the open point should not exceed 2.5MVA (125A), with a total ring connection accommodating up to 5MVA (250A). A sub-network may require high-voltage (HV) reinforcement or rearrangement if a portion of it needs to support a higher load or to distribute the load to avoid overloading any feeder.

For LV customer side, the size of the cut-outs (C.O) or circuit breakers and LV cables to the customer (also known as service cable) depends on the customer demands as per table 2.2 (Electricity and Water Authority, 2015).

Table 2.2 Customers connection categorize

No.	KVA	Cable Size	C.O/C.B size
1	0 – 40	4×25mm ²	60A
2	41 – 70	4×70mm ²	100A
3	71 – 100	4×120mm ²	160A
4	101 – 170	4×240mm ²	250A
5	171 – 340	2×4×240mm ²	500A
6	341 – 500	4×1×500mm ²	800A
7	501 – 1000	7×1×500mm ²	1600A
8	1001 – 1500	7×1×1000mm ²	2500A

2.4 Impact of EV on Distribution Network

It is anticipated that unintended detrimental effects on the electrical system will result from the uncontrolled charging of EVs with high penetration levels. The effects of increasing peak demand, voltage variations exceeding the allowable limits, phase imbalance because of single-phase chargers, injection of harmonics, overloading power system equipment, and a rise in power system power losses are among the potential drawbacks (Habib, Khan, Abbas, Sang, et al., 2018) .

2.4.1 Factors behind the impact

The calculation of EV charging consequences is dependent on multiple conditions and involves numerous uncertainties that need to be taken into account (Ahmadian et al., 2020). The primary variables that have been the subject of numerous research include:

2.4.1.1 EV user behavior

User behavior of electric vehicles (EVs) is influenced by various factors such as location, charging time, and battery state of charge (SoC), all of which significantly affect the electrical system. Since EV charging times are unpredictable, it is challenging to forecast when multiple charging events will occur and if they will coincide with periods of high demand on the distribution network. Some studies model this data as a probability distribution, while others use surveys to determine typical home arrival times or estimate EV charging start times (Nour et al., 2020). Additionally, EV users charge at various locations, such as home, a friend's house, street chargers, or dedicated stations, and the type and location of the charger can have different effects on the distribution network. The SoC

at plug-in is also variable; some studies assume a fixed SoC, while others use a probability distribution, which affects the duration and intensity of charging (Nour et al., 2020).

(Y. Zhang et al., 2022) focuses on identifying key factors influencing user behavior, such as EVs, demand side response, and distributed generation. It highlights that EV and demand side response can significantly alter the peak-valley difference rate of the load curve, which is crucial for predicting future load changes. Moreover, the study shows that changes in user behavior due to economic and social transformations can significantly impact load characteristics, leading to the appearance of the "duck curve" in load profiles, which is vital for future grid planning. (Gonzalez Venegas et al., 2021) evaluates non-systematic plug-in behavior and its effect on grid integration. It shows that non-systematic plug-in behavior, where users do not charge their vehicles daily, can reduce the simultaneous charging impact and flexibility of the EV fleet, especially with large-battery EVs. (Lilhore et al., 2023) uses machine learning models to predict EV user behavior, focusing on energy consumption and session duration. The findings suggest that accurate predictions of these parameters are essential for smart charge scheduling and mitigating grid issues like overloading and harmonic distortions. (Demirci et al., 2023) provides a framework for evaluating EV driving and charging behaviors to enhance charge management. It emphasizes the importance of high-resolution data (time steps lower than ten minutes) for precise assessments and explores the potential of vehicle-to-grid (V2G) integration to support grid stability and renewable energy consumption.

2.4.1.2 EV charger type

The type of charger used for electric vehicles (EVs) can vary depending on the charging infrastructure and the EV model, with both single-phase and three-phase chargers being common. Additionally, EV chargers come in various power ratings and operate at different voltage levels. Fast chargers, in particular, are likely to cause a larger increase in peak demand compared to slow chargers.

2.4.1.3 Battery capacity

Electric vehicles (EVs) have a wide range of battery capacities as shown in Table 2.3 (EV database, 2024). Plug-in hybrid electric vehicles (PHEVs) typically have smaller battery capacities, while battery electric vehicles (BEVs) have larger battery capacities. EVs with higher battery capacities will consume more energy from the power grid. (Takagi & Ikeya, 2023) evaluates the impact of larger battery capacities and high-power quick chargers on peak load. It finds that increased battery capacity allows for more flexible charging but may lead to concentrated charging during specific times, such as before weekends, thereby impacting peak load management.

Table 2.3 BEV Battery Capacity

Vehicle	Year	Capacity	Range
Mini Cooper JCW	2024	49.2 kWh	290 km
Audi A6 Avant e-tron	2024	75.8 kWh	475 km
Opel Mokka Electric	2024	50.8 kWh	285 km
BYD ATTO 3	2022	60.5 kWh	330 km
Tesla Model 3	2023	57.5 kWh	420 km
Tesla Model Y	2022	57.5 kWh	350 km
BYD SEAL	2023	82.5 kWh	445 km

Kia Niro EV	2022	64.8 kWh	385 km
Hyundai Kona Electric	2023	65.4 kWh	390 km
Mercedes-Benz EQB 250+	2023	70.5 kWh	415 km
Mercedes-Benz EQS 450+	2024	118 kWh	690 km
Fiat 500e Hatchback	2020	37.3 kWh	235 km
Kia EV6 Long Range 2WD	2021	74 kWh	410 km
Kia EV3 Standard Range	2024	55 kWh	325 km
Hyundai IONIQ 5	2024	60 kWh	330 km
Toyota bZ4X FWD	2022	64 kWh	350 km
Nissan Leaf	2022	39 kWh	235 km
Kia EV9 AWD	2023	96 kWh	435 km
BMW i4 eDrive40	2024	81.3 kWh	515 km
Porsche Macan 4 Electric	2024	95 kWh	485 km
Jeep Avenger Electric	2023	50.8 kWh	310 km
Lexus RZ 450e	2023	64 kWh	350 km

2.4.1.4 Penetration level

The level of electric vehicle (EV) penetration is crucial for studying the impact on the power grid. Higher penetration levels mean more EVs are connected to the grid, which can significantly influence load demand patterns, peak demand, and overall energy consumption. Understanding the penetration level helps in accurately predicting and managing potential issues. Consequently, numerous studies have analyzed different levels of EV penetration, spanning from 10% to 100%. (Lezama et al., 2023) simulates the impact of local transactions and high EV penetration on the distribution network. They find that EV penetration increases the complexity of managing the grid, requiring careful consideration of voltage limits and line overloading to maintain stable operation. (Hungbo et al., 2022) uses a probabilistic approach to analyze the impact of various EV penetration levels (25%, 50%, 75%, 100%) on low-voltage grids. The

results show that higher penetration levels significantly increase transformer loading and can lead to voltage levels exceeding regulatory limits. Vehicle-to-grid (V2G) technology can mitigate some of these impacts.

2.4.1.5 Distribution Network

The status of the distribution system significantly affects the integration of electric vehicles (EVs) by determining its capacity to handle additional loads, maintain voltage levels, and manage power quality.

2.4.2 voltage violations and imbalance

Voltage violations are a major concern that limits the integration of large-scale EV charging into distribution networks. Charging EVs from the grid leads to voltage drops and deviations at the connection points. High levels of EV charging penetration can violate safe voltage regulatory limits on the network. Consequently, utilities in various countries are tasked with maintaining customer service voltage within acceptable ranges according to different grid specifications. For example, in the United Kingdom, utilities are required to maintain voltage within the declared range of 230V with a tolerance of -6% to +10%, resulting in an allowable voltage range of 216.2V to 253.0V (SP Energy Networks, 2024). Similarly, in the United States, the American National Standards Institute (ANSI) Standard C84.1 specifies that residential service voltage must remain within $\pm 5\%$ of the nominal 120V, resulting in a range of 114V to 126V (Idaho power, 2024). Additionally, voltage unbalance occurs in the electrical distribution system when phase voltages vary in amplitude or their phase shift relationship deviates from the normal 120 degrees. This imbalance is often caused by unevenly distributed single-phase loads and impedances.

Various studies have been conducted to investigate the impact of EV on distribution network voltage. (Soofi et al., 2022) investigated the voltage profile of distribution networks with high EV penetration and found that both fixed power and fixed current EV models can affect voltage levels, particularly under time-of-use pricing. A study on the impact of EV charging on low voltage network stability in Bhutan showed that even low penetration levels can trigger voltage violations, suggesting the need for voltage correction techniques (Chophel et al., 2020). Furthermore, (Mane et al., 2022) analyzed the impact of EV chargers on power grids, emphasizing the importance of phase symmetry and power factor considerations to manage voltage profiles. Moreover, (Hungbo et al., 2022) also confirmed significant voltage limit violations with increased EV penetration in low-voltage networks. (Helm et al., 2020) examined the effects of unbalanced EV charging on low-voltage grids, showing significant voltage unbalances that exceed allowable limits, especially in weak grids. (Sohail et al., 2022) investigated the effects of uncoordinated EV charging on a residential distribution network, finding poor power quality, low voltage levels, and increased transformer loading, emphasizing the need for coordinated charging strategies. (Schinke & Hirsch, 2019) assessed the combined impact of EV charging and photovoltaic generation on voltage volatility, using stochastic models and Monte Carlo simulations to quantify the effects on a test network. (Nalo et al., 2020) explored how different EV penetration levels affect voltage profiles and unbalance, showing that high penetration can lead to significant voltage variations. Lastly, (Jones et al., 2021) simulated the impacts of uncontrolled EV charging on distribution systems, finding modest voltage impacts but noticeable line loading increases and peak load time shifts.

2.4.3 Injection of harmonics

Sinusoidal waveforms with frequencies other than the fundamental power system frequency are known as harmonics. They usually originate from non-linear voltage/current characteristics of equipment. Elevated harmonic distortion can cause excessive heat in motors, premature failures, and insulation breakdown in wires, among other negative impacts on a distribution system (Cheng et al., 2018). Elevated temperatures during operation may also affect other pieces of equipment, leading to malfunctions and unexpected failures. Harmonics in the electrical system can also negatively impact critical analog circuits and force computers to restart (Megha et al., 2020).

Various studies have been conducted to investigate the impact of EV on distribution network harmonics. In (Rusan et al., 2022), simulations of harmonic power flows were performed to analyze the impact of an electric vehicle charging station (EVCS) on voltage harmonic distortion in a low voltage distribution network. The results indicated that power quality could deteriorate when considering the combined impact of EVCS and photovoltaics. (Singh & Howe, 2022) demonstrated tools and techniques utilities can use to predict the power quality impact of large EV charging facilities and emphasized the importance of system strength in determining the appropriate feeder for integrating an EV charging facility. Moreover, (Slangen et al., 2022) conducted a comprehensive analysis of the harmonic emissions of a fast charging station (FCS) under various supply voltage and operating conditions, developing a test setup to define charging parameters and supply voltage, resulting in a harmonic fingerprint of the FCS. (Sharma et al., 2022) assessed harmonic analysis and total harmonic distortion (THD) with increasing EV charging stations, using an LCL filter

at the rectifier end to reduce harmonics for the same number of charging cars. (Iqbal et al., 2021) estimated the current harmonic emission of EV charging loads at different voltage distortions using a stochastic EV load model and examined the impact of EV charging on distribution transformers. Furthermore, (Ahmed et al., 2021) evaluated the performance of the public distribution network in terms of the percentage increase in harmonic distortion due to EVCS penetration and analyzed the voltage profile as the EV load increased to determine the capacity of buses at certain THD levels, using MATLAB/Simulink to compare THD from both medium and low voltage sides for a distribution network branch of Qatar Electricity & Water Company (QEWCo). (Rodrigo & Priyanka, 2018) modeled a commonly available EV charger in MATLAB to study EV chargers and performed a comprehensive harmonic analysis on an LV distribution feeder with different EV penetration and load levels. Lastly, (Bosak et al., 2019) studied the effect of voltage and current harmonics on the low voltage network during EV charging, focusing on the impact on network performance.

2.4.4 Overloading equipment

Massive power transmission from the grid to the load is necessary for large-scale EV charging on the distribution network, and this could overburden the current network's transformers and cables. In (Barros et al., 2023), a comparative analysis was conducted to examine the effects of charging short-range and long-range electric vehicles on transformer lifespan, focusing on the hottest-spot temperature and the aging acceleration factor of transformers. (S. Mukherjee, 2023) explored the impact of EV charging on the service life of rural service transformers and highlighted the importance of transformer resiliency in addressing these

challenges. (Visakh et al., 2022) analyzed the effect of controlled EV charging on the internal temperature and aging rate of a distribution transformer, following the IEEE C57.91 standard guidelines. (Chacon & Gavela, 2022) proposed a technical analysis methodology to evaluate the impact of EV charging on distribution transformers, considering different levels of EV penetration in the distribution system. This methodology is based on stochastic models that represent consumer behavior randomness and multi-scenario investigations of battery charging behavior and their associated harmonic levels. In (Sonder et al., 2022), the authors developed an algorithm to estimate the energy consumption and demand of common EV models capable of rapid charging. This algorithm, implemented using the Deno runtime based on the JavaScript programming language, also analyzes the impact of chargers on the loading of distribution cables and substation transformers.

2.4.5 Rise power losses

Power loss is an inherent characteristic of a power line caused by the flow of current and is proportional to the square of the current's magnitude. Integrating high levels of EVs into the distribution system will increase power losses due to feeder overload and changes in feeder current. In (Pavličević & Mujović, 2022), a methodology is proposed to analyze the impact of reactive power from public electric vehicle charging stations (EVCSs) on two main indicators of the distribution system: globally, by assessing active power losses, and locally, by evaluating transformer aging. (Chaudhary et al., 2023) quantified and investigated the effects of deploying EVCS loads on voltage profiles, reliability, and power losses using the standard IEEE 33-bus Radial Distribution test system with the MATLAB programming interface. (Neagoe-Stefana et al., 2014) examined

the influence of charging a large number of electric vehicles on power losses and voltage levels in a radial low voltage network with 12 consumers, studying three scenarios: without EVs, with a 50% EV penetration rate, and with different charging time intervals.

2.5 EV impact: Around the World

2.5.1 Saudi Arabia

(Alquthami et al., 2022) conducted a case study using an actual distribution network model to assess the impact of electric vehicles (EVs) on Saudi Arabia's distribution network. The study's findings reveal that a 20% penetration of EVs results in a 3.4% increase in peak demand. Additionally, using real feeder data, the study illustrates the direct correlation between EV deployment and network load. For every 1% increase in EV deployment, daily demand on the distribution feeder rises by 0.1%, while peak demand and power losses grow by 0.2%.

2.5.2 Italy

(Mogos & Grillo, 2021) conducted an in-depth investigation into the impact of electric vehicle (EV) charging loads on distribution systems in Italy. The study found that as EV load penetration increases, both transformer loading and the Power Availability Ratio (PAR) also rise. This trend suggests that the distribution network may struggle to accommodate high levels of EV penetration in the future. A minor voltage drop was observed at the medium-voltage (MV) nodes, but the voltage remained within acceptable limits. The main conclusion drawn is that the studied network can safely handle EV load penetration without requiring significant upgrades until 2026.

2.5.3 Kuwait

In the study by (Abdullah et al., 2020), the impact of electric vehicle (EV) charging demand was assessed for the Ahmadi low-voltage (LV) residential network. The analysis revealed that high penetration of EV chargers in the residential area led to a 17% increase in nighttime power demand. However, even under the worst-case scenario of peak summer load, this increase did not exceed the network's power system limitations. The study also highlighted that the network's capacity for fast EV charging in residential areas is constrained by its physical characteristics. Specifically, the maximum demand that can be provided to all customers through an EV charging station (EVCS) is limited to 4 kW, restricting DC fast charging to centralized locations at the network's main buses.

2.5.4 Norway

(Lillebo et al., 2019) explored the impact of increasing electric vehicle (EV) penetration levels in a Norwegian distribution grid, utilizing real power measurements from household smart meters and performing load flow analyses with varying levels of EV integration. The study found that the grid had a high EV hosting capacity, as the majority of end-users (all but six) remained within the minimum voltage limits and below the nominal cable power ratings throughout the year, even with 100% EV penetration. However, the main transformer experienced overloading for 12 hours during this scenario, but this was deemed manageable due to the low outside temperatures during that time of year. When considering the limitations of all end-users in the system, the grid could accommodate 50% EV penetration in terms of voltage, and 20% penetration in terms of the rated power capacity of the weakest cable in the network.

2.5.5 Germany

(Draz et al., 2018) conducted an analysis on the impact of electric vehicles (EVs) on low-voltage (LV) grids in Berlin, examining both urban and suburban grid topologies. The study found that the effects of EVs on Berlin's LV grids are influenced by factors such as charging rates, grid location, expected EV penetration, charging concurrency, and charger harmonic emissions. The analysis showed that, provided EVs adhere to regulatory standards and maintain the proposed charging concurrency, LV grids could handle high EV penetration levels of 50% to 100% without requiring reinforcement. However, in suburban grids, a significant decline in power quality was observed due to uneven load distribution across three phases. In certain cases, the Voltage Unbalance Factor (VUF) exceeded the regulatory limit of 2% (as specified by EN 50160). To mitigate this issue, Stromnetz Berlin plans to implement phase selector techniques at each charging point. While the short-term impacts on suburban networks are expected to be minimal, the long-term integration of EVs into suburban grids presents a greater challenge compared to urban grids, which are better positioned to manage the anticipated effects.

2.5.6 Canada

(Awadallah et al., 2016) performed a study on the impact of electric vehicle (EV) charger loads on the capacity of distribution feeders and transformers in a residential neighborhood in Toronto, Canada. The study found that transformer and secondary conductor overloads are likely to occur due to EV charging, especially at higher EV penetration levels or with larger charger sizes. Despite these risks, the voltage at all nodes on the low-voltage feeders remained within the standard limit of $\pm 5\%$. Overload is more likely to affect the secondary drop lead, secondary feeder,

or both, and its likelihood decreases when the secondary drop lead is centrally located relative to household load. Ambient temperature was identified as a key factor influencing the system's ability to manage EV loads, with a higher risk of overload in the summer due to increased air conditioning usage and reduced system-current-carrying capacity at elevated temperatures. Chargers rated at 3.3 kW or lower are unlikely to cause overloading, while 6.6-kW chargers pose a moderate risk. Larger chargers, rated at 10 kW or higher, require system upgrades to be safely accommodated, as even a few EVs charging at this capacity could overwhelm the system components.

2.5.7 Switzerland

(Salah et al., 2015) studied the impact of electric vehicle (EV) charging loads on Swiss distribution substations under varying penetration levels and pricing regimes. The analysis of BKW's distribution substations revealed that under current tariff conditions and with an EV market penetration of 16%, there is no risk of substation overloads. However, at higher penetration levels, such as 50%, uncoordinated EV charging could lead to overloads in certain locations. The study also found that if regulatory conditions permit the use of dynamic electricity pricing and consumers adjust their charging behavior to minimize mobility costs, the frequency of substation overloads would be significantly reduced compared to static pricing scenarios.

2.5.8 EV impact: conclusion

The global integration of electric vehicles (EVs) into power distribution networks reveals diverse challenges and opportunities, shaped by regional grid characteristics, EV penetration levels, and charging

behaviors. Studies conducted across various countries highlight the nuanced effects of EV adoption on distribution systems, offering insights into the network's capacity to handle increased EV loads.

These findings underline the importance of tailored solutions for managing EV impacts on distribution networks. Proactive measures such as infrastructure upgrades, controlled charging strategies, and regulatory adaptations can ensure sustainable EV integration while maintaining grid stability. The lessons from these studies offer valuable guidance for Bahrain and other nations embarking on similar transitions.

2.6 EV Controlled Charging

Charging strategies for EVs can be broadly categorized into uncontrolled and controlled charging. Figure 2.5 shows the charging strategies.

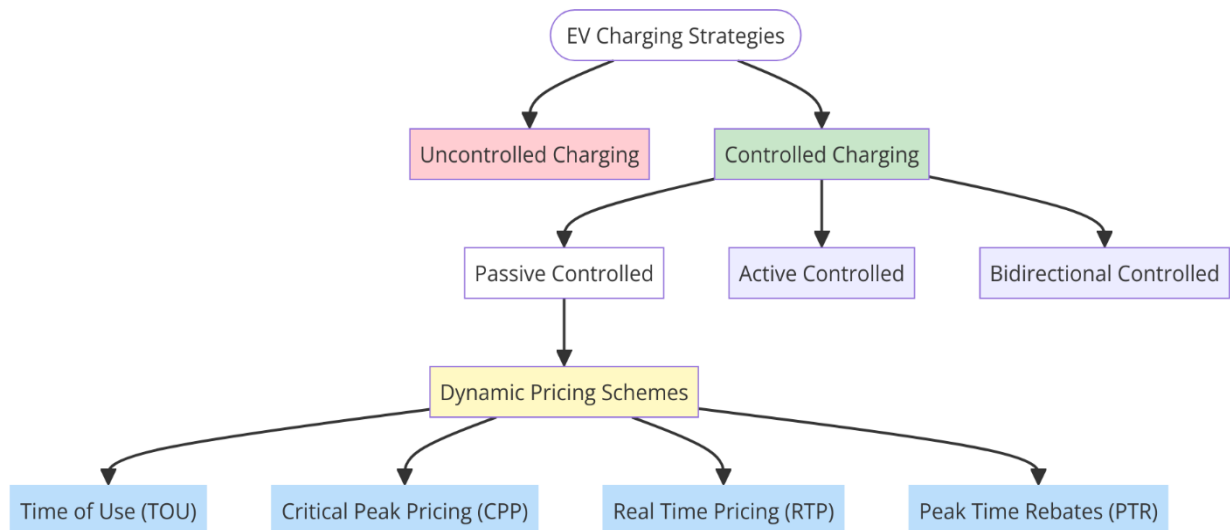


Figure 2.5 EV Charging Strategies

Uncontrolled charging refers to the scenario where electric vehicles (EVs) commence charging immediately upon connection to the power grid, without any scheduling or coordination from grid operators. This approach occurs during both off-peak and peak hours, directly impacting the grid's

stability (Kong & Karagiannidis, 2016). The simplicity of uncontrolled charging hides its potential risks, as it does not provide grid operators with user data or system insights. Large-scale uncontrolled charging can significantly affect

grid performance, highlighting the need for effective management strategies (Micari et al., 2017), (Saldanha et al., 2016).

In contrast, the controlled charging of electric vehicles (EVs) empowers both consumers and network operators to strategically schedule charging profiles, yielding significant technical and economic advantages. This approach is recognized as a specific form of demand-side management (DSM) for EVs (García-Villalobos et al., 2014). Controlled charging has received increasing attention in recent years due to its effectiveness in alleviating the negative impacts associated with uncontrolled charging practices. By facilitating a coordinated method of operation, this strategy allows grid operators to establish and oversee charging schedules that enhance power quality and mitigate risks of system destabilization (Wenzel et al., 2018). Moreover, controlled charging effectively addresses the charging needs of EV drivers while aligning with broader financial and operational goals (Seddig et al., 2017). The success of this method is closely linked to the existing infrastructure and its ability to accommodate necessary upgrades (Mousavi & Flynn, 2016). Controlled charging can be classified into three categories based on the employed control parameters: passive controlled, active controlled, and bidirectional charging (Solanke et al., 2020).

2.6.1 Active controlled charging

Active (direct) controlled charging methods are designed for real-time implementation, necessitating a control mechanism capable of providing long-term solutions. This approach is grounded in intelligent charging systems, which facilitate data exchange between electric vehicles (EVs) and charging stations, while ensuring connectivity with distribution system operators. Such systems empower operators to monitor, control, and regulate the remote utilization of charging devices, optimizing energy demand in the process (Cheng et al., 2015). The development of intelligent charging methods typically involves the constrained formulation of optimization problems that can be addressed through advanced optimization techniques or intelligent control systems (Galus et al., 2013). However, it is important to acknowledge that the establishment of these control mechanisms involves significant costs. These expenditures encompass the initial infrastructure investments required for smart charging stations, ongoing operational expenses, and the integration of sophisticated software and communication technologies (J. C. Mukherjee & Gupta, 2015).

2.6.2 Bidirectional charging

The capability of electric vehicles (EVs) to supply power to the distribution network positions them as valuable distributed energy storage devices. Bidirectional EV chargers facilitate the flow of electricity in both directions—allowing for charging from the grid to the vehicle and discharging from the vehicle to the grid (Saldaña et al., 2019). This dual functionality is encapsulated in the concept of Vehicle-to-Grid (V2G), which was pioneered by Amory Lovins and William Kempton. They envisioned a future where EVs would be ubiquitous, providing significant

electricity capacity that could serve as essential storage for the grid (Kempton & Letendre, 1997), (Kempton & Tomić, 2005). The fundamental premise of V2G is that during periods of high demand, parked EV batteries can inject power back into the grid, while they recharge during low-demand periods (Tan et al., 2014). This dynamic interaction not only enhances grid reliability but also illustrates the substantial potential impact of EVs on electrical utilities as they become more integrated into the distribution system (Habib, Khan, Abbas, & Tang, 2018).

Furthermore, the V2G concept paves the way for advanced integration and control mechanisms, particularly in conjunction with renewable energy sources and the emerging framework of virtual power plants (VPPs). VPPs represent a clustering model that enables the management of geographically dispersed electrical generation and demand as if they were a single entity from the perspective of the system operator. This approach mitigates financial risks associated with the individual participation of each distributed generator, thereby maximizing benefits for both distributed generator owners and system operators in the future (García-Villalobos et al., 2014), (Asmus, 2010).

Despite the promise that V2G technology holds for enhancing electrical services within the power system, several challenges and barriers remain. The complexity of V2G implementation necessitates significant infrastructure changes, including the deployment of bidirectional chargers and the establishment of continuous two-way communication between EVs and system operators or aggregators. Additionally, the frequent charging and discharging cycles associated with this technology may lead to battery degradation, potentially shortening the lifespan of EV batteries (Peterson et al., 2010).

2.6.3 Passive controlled charging

The passive controlled charging method, also known as decentralized or indirect control, focuses on understanding and leveraging consumer behavior and decision-making, typically at a lower cost compared to active control methods. In recent years, this approach has gained traction due to the evolving electricity market, which features adjustable pricing incentives designed to encourage optimal consumption patterns. As energy prices rise, consumers are increasingly motivated to shift their EV charging loads to off-peak hours when grid capacity is more readily available. This shift not only helps to prevent grid overload but also enhances the overall efficiency of the energy system (Solanke et al., 2020), (Tamor & Milačić, 2015).

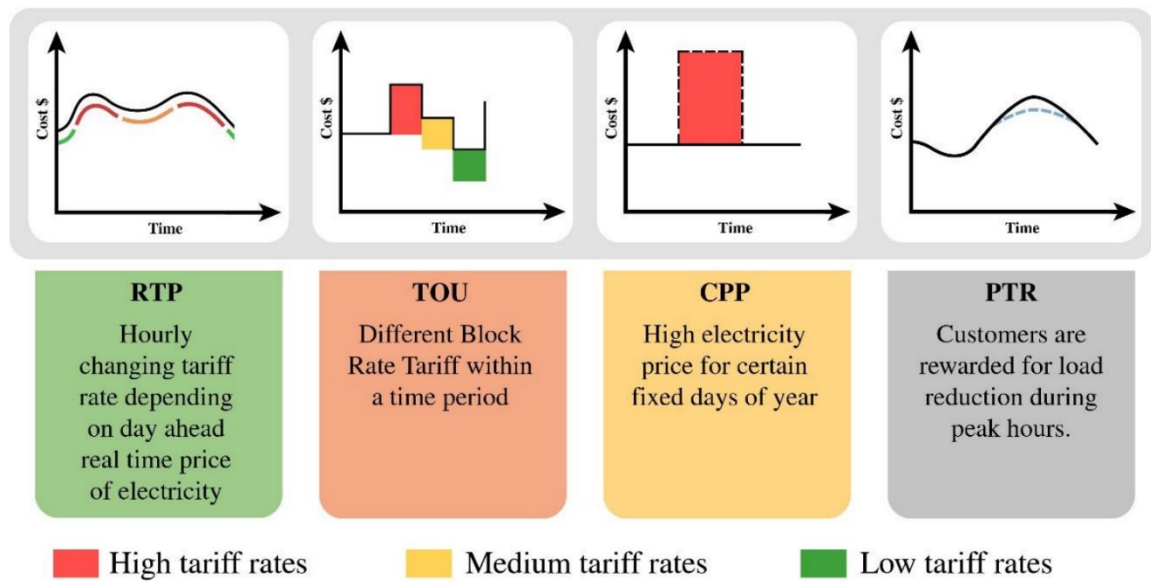


Figure 2.6 Dynamic Pricing Schemes

Various dynamic pricing schemes, such as Time-of-Use (TOU) rates, real-time pricing (RTP), critical peak pricing (CPP) and peak time rebate (PTR), can effectively facilitate this transition by incentivizing consumers to charge their vehicles during periods of lower demand as explained in Figure 2.6 (Amin et al., 2020). By aligning charging behavior with the

availability of excess capacity, passive controlled charging presents a cost-effective solution for managing energy consumption while supporting grid stability and sustainability (Yong et al., 2023).

2.6.3.1 Time-of-Use (TOU)

Time-of-Use (TOU) pricing is an adaptive tariff structure designed to incentivize consumers to adjust their electricity consumption from high-demand peak periods to lower-demand off-peak times. This model typically categorizes the day into three distinct segments: off-peak, mid-peak, and on-peak. Utilities announce TOU rates in advance, based on historical data, enabling consumers to plan their energy usage effectively (Dutta & Mitra, 2017), (Nazar et al., 2012). However, the structure of TOU pricing can present challenges, particularly when large fleets of electric vehicles (EVs) charge simultaneously during off-peak hours, potentially leading to a new peak in demand (De A. Bitencourt et al., 2017). Nonetheless, TOU pricing schemes have shown significant advantages for EV charging by facilitating load shifting from peak to non-peak hours. This strategy is especially pertinent in light of the increasing intermittent charging demands posed by EVs, which present substantial challenges for the current grid system's capacity and demand management (Phuangpornpitak & Tia, 2013), (Nicolson et al., 2017).

2.6.3.2 Critical Peak Pricing (CPP)

Critical Peak Pricing (CPP) is a demand response strategy designed to enhance the efficiency and economic viability of peak load management. It features a straightforward pricing structure. Unlike Time-of-Use (TOU) pricing, which relies on historical data, CPP is based on forecasting high-demand periods and is communicated to consumers with significantly

shorter notice (X. Zhang, 2014). This approach allows CPP to respond dynamically to current grid conditions, making it more effective in reducing peak load. CPP days are categorized into critical and non-critical days, with peak prices on critical days being substantially higher than those of TOU pricing (Park et al., 2015). While CPP typically features higher prices than TOU, its greater effectiveness in curbing peak demand underscores its importance in modern energy management strategies (Newsham & Bowker, 2010). Addressing potential challenges, such as the "payback phenomenon," is essential to ensure the sustained benefits of demand reduction in CPP schemes.

2.6.3.3 Real-Time Pricing (RTP)

Real-Time Pricing (RTP) is a dynamic pricing scheme characterized by frequent adjustments to electricity rates, typically occurring in intervals of hours or even minutes (Korolko & Sahinoglu, 2017). This adaptability allows prices to accurately reflect real-time market conditions and the actual costs of electricity supply. While RTP can enhance pricing efficiency and enable utilities to achieve desired load curves in a smart grid environment, it also introduces a degree of uncertainty and risk for consumers. The rapid fluctuations in rates may challenge customers, many of whom lack the knowledge to navigate this complex billing structure effectively. Additionally, existing infrastructure and automation systems in residential and commercial buildings may not be adequately equipped to support RTP (Amin et al., 2020), (Soltani et al., 2015).

2.6.3.4 Peak Time Rebate (PTR)

Peak Time Rebate (PTR) is a demand response pricing scheme where customers are rewarded with rebates for reducing their electricity

consumption during peak hours (Dutta & Mitra, 2017). Unlike other dynamic pricing schemes such as Real-Time Pricing (RTP), Critical Peak Pricing (CPP), or Time-of-Use (TOU), which increase rates during peak times to discourage high usage, PTR incentivizes customers by offering financial rewards for consuming less energy during these critical periods. Customers perceive this load reduction as a gain, whereas in other schemes, shifting load to off-peak hours is often seen as a loss (Mohajeryami et al., 2015). The cost-effectiveness of PTR largely depends on the accurate estimation of the Customer Baseline Load (CBL), which serves as a reference point for measuring load reduction. This requirement makes PTR more expensive for electricity providers to implement, as it demands precise and often complex CBL estimation techniques (Faruqui & Palmer, 2012).

2.7 Research contribution

This study contributes to the existing body of knowledge on electric vehicle (EV) integration by addressing specific gaps identified in the literature. While prior research has extensively examined the impact of EV penetration on distribution networks in various countries, limited attention has been given to the unique characteristics of Bahrain's network. This study bridges this gap by developing a detailed simulation and analysis framework tailored to Bahrain's distribution system, including actual transformer data. Additionally, the development of an impact matrix provides a practical tool for utilities to evaluate impacts and plan for EV adoption. By proposing and evaluating indirect controlled charging strategies, this research offers actionable solutions to mitigate potential network challenges, contributing to both academic discourse and practical grid management strategies.

Chapter 3: Methodology

Chapter Overview:

This chapter details the methodology used to evaluate the impact of electric vehicle (EV) integration on Bahrain's distribution network and explore potential mitigation strategies. The study models a representative low-voltage network, simulating various levels of EV penetration and transformer loading to analyze the effects on key parameters like voltage level, transformer loading, feeder overloads, and power losses. Using DIgSILENT PowerFactory, the simulations account for different EV charging scenarios, including 30%, 50%, 70%, and 100% simultaneous charging. Additionally, Python is used to analyze load data from 500 distribution transformers, focusing on peak loads, peak times, and daily load profiles to assess the feasibility of indirect control charging strategies, such as Time-of-Use (TOU) pricing. This approach aims to provide valuable insights into managing increased EV demand and ensuring network stability as EV adoption grows.

3.1 Introduction

The study focuses on modeling a typical Bahrain distribution network, simulating the effects of various levels of EV penetration, and exploring the potential of indirect control charging as a mitigation strategy. The primary objective of this study is to quantify the impact of EV charging on the electrical distribution network and to evaluate solutions to mitigate potential negative effects. To achieve this, three specific objectives are outlined:

1. **Modeling a typical Bahrain distribution network**, including a representative 1500 kVA distribution transformer supplying 50 households, with varying loading conditions to simulate different scenarios.
2. **Quantifying the impact of EV integration** on the network by analyzing the additional load imposed by EV charging and its effect on key parameters such as voltage violations, loading, and network losses.
3. **Investigating opportunities for indirect control charging**, such as Time of Use (TOU) pricing, to reduce peak loads and balance the additional demand caused by EVs, without direct intervention in consumer charging behavior.

The methodology is built around the available data, which is utilized to create accurate scenarios reflecting potential EV charging behaviors. Central to this analysis is load flow modeling under various conditions, which allows for a detailed examination of network performance across different levels of EV integration. The developed scenarios account for key impact factors discussed in Section 2.4.1, ensuring that each scenario

provides insights into the distribution network's capacity to manage increased EV demand.

This study assumes most EV charging will occur at home, as observed in a recent study conducted in Saudi Arabia (Almutairi et al., 2023), a country with similar residential energy usage patterns and infrastructure to Bahrain. From the grid impact perspective, dedicated charging stations require specialized infrastructure and planning thus eliminating the network penetration impact, in addition, charging at work or at commercial locations, being centralized, simplifies control to avoid the impact. However, home charging with the existing infrastructure represents the main concern. This makes residential charging the focal point of the analysis. Additionally, with Bahrain's smart meter infrastructure, indirect control measures, such as Time of Use (TOU) pricing, emerge as promising strategies for load management and network stability as EV adoption grows.

3.2 Objective 1: Modeling a Typical Bahrain Distribution Network

The first objective of this study is to model a typical Bahrain LV distribution network to establish a baseline for analyzing the impact of electric vehicle (EV) integration. This section outlines the methodology used to model a representative distribution transformer supplying a group of households, incorporating assumptions regarding network infrastructure, customer load characteristics, and the use of Python for generating deterministic household loads.

3.2.1 Network model

Transformer Capacity: As discussed in Section 2.3, three transformer sizes are typically used in Bahrain's distribution network. In this study, the 1500 kVA transformer is selected as it is the largest and can accommodate more electric vehicles (EVs), making it more significantly impacted by EV integration.

Household Load: All customers are from category 1 as per table 2.2, where in Bahrain, the majority of customers fall under this category (load range: 0-40 kVA).

Main LV Cable: A 240 mm² main LV cable serves 5 households.

Figure 3.1 represents the modeled network. For detailed descriptions of the network elements, including their models and parameter settings, refer to Appendix 1.

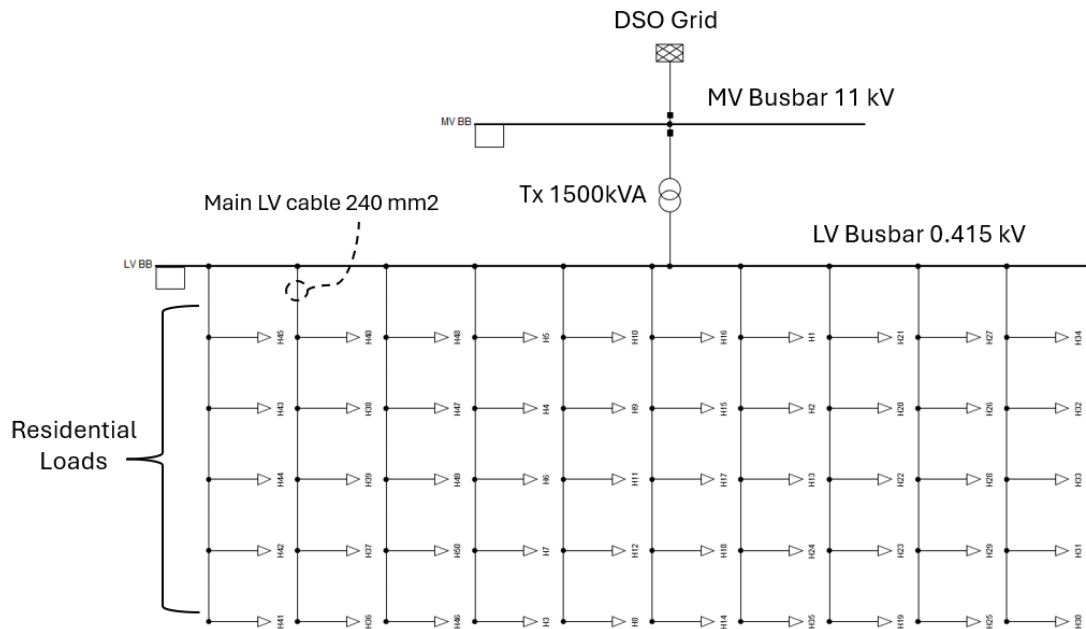


Figure 3.1 Network Under Study

3.2.2 Load Simulation Scenarios

To simulate household electricity demand, deterministic instantaneous loads for each of the 50 households are generated using Python. This approach ensures that each household's load is fixed at a particular value, representing a snapshot of demand at a specific moment in time. For each scenario, 1440 different load distributions will be generated to capture variability in household consumption while maintaining deterministic load values in each scenario.

- Scenario 1: 30% Loading: The total load of the 50 households results in the transformer operating at 30% of its rated capacity, simulating light demand.
- Scenario 2: 50% Loading: This scenario represents moderate demand, with the transformer operating at 50% of its capacity.
- Scenario 3: 80% Loading: The final scenario simulates high demand, with the transformer operating at 80% of its rated capacity, approaching its operational limits.

3.2.3 Assumptions

The following assumptions are made to ensure the model reflects realistic conditions:

Load Profiles: It is assumed that household loads will always include a space to accommodate EV charging, preventing overloading that could result in blown cutout fuses.

Cable Length and Configuration: The main low-voltage (LV) cable is assumed to be 250 meters in length. This length was selected to shed light on the worst-case scenario in the network, as it represents a challenging

condition for the system under study. The cable serves households via 25 mm² service connections, with each household connected at intervals of 50 meters.

3.3 Objective 2: Quantifying the Impact of EV Integration

The second objective of this study is to quantify the impact of electric vehicle (EV) integration on Bahrain's distribution network. This section outlines the methodology used to simulate the additional load introduced by EVs, assessing its effect on key network parameters.

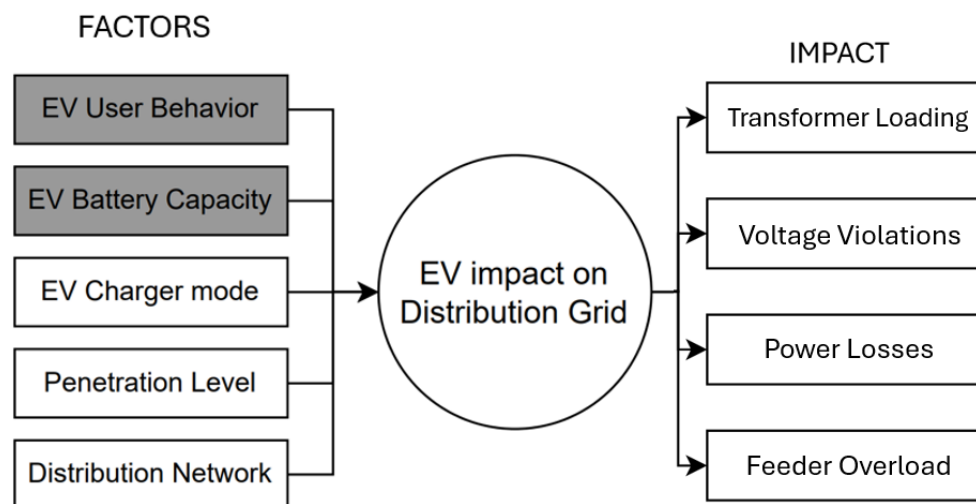


Figure 3.2 Factors Contributing to the Impact of EVs

In order to investigate the impact of electric vehicles (EVs) on the distribution grid, the contributing factors as shown in figure 3.2 must be analyzed. This research focuses primarily on the worst-case scenario by conducting simulations on deterministic scenarios. Consequently, EV user behavior and battery capacity will not be considered in this study, as analyzing user behavior requires a different type of study focused on behavioral patterns and preferences. Additionally, while battery capacity affects the charging duration, this study focuses on assessing the impact on

the distribution network using simultaneous charging scenarios, which represent a worst-case approach to evaluate the network's capacity and performance under maximum stress conditions.

3.3.1 EV charging load

In this study, a residential charger with a 3-phase connection and a power rating of 7.6 kW is considered. The choice of 3-phase chargers is justified because single-phase chargers can cause imbalances in the distribution network, as highlighted in relevant literature. Moreover, the majority of residential buildings in Bahrain are equipped with 3-phase connections, making this choice more appropriate for the region. In addition to the 7.6kW charger, an 11kW charger is also analyzed to account for a higher power demand scenario.

3.3.2 EV penetration level

From the perspective of EV impact on the distribution grid, simultaneous charging is more critical than overall penetration, especially when it coincides with high load periods on the grid. Therefore, this study develops various scenarios simultaneous charging percentages: 30%, 50%, 70%, and 100%. As shown in figure 3.3, figure 3.4, figure 3.5 and figure 3.6 respectively. Where the number of EVs calculated as the following equation:

$$\begin{aligned}
 & \text{Number of EVs} \\
 &= \text{Total Number of Households} \\
 &\times \text{simultaneous charging percentage}
 \end{aligned}$$

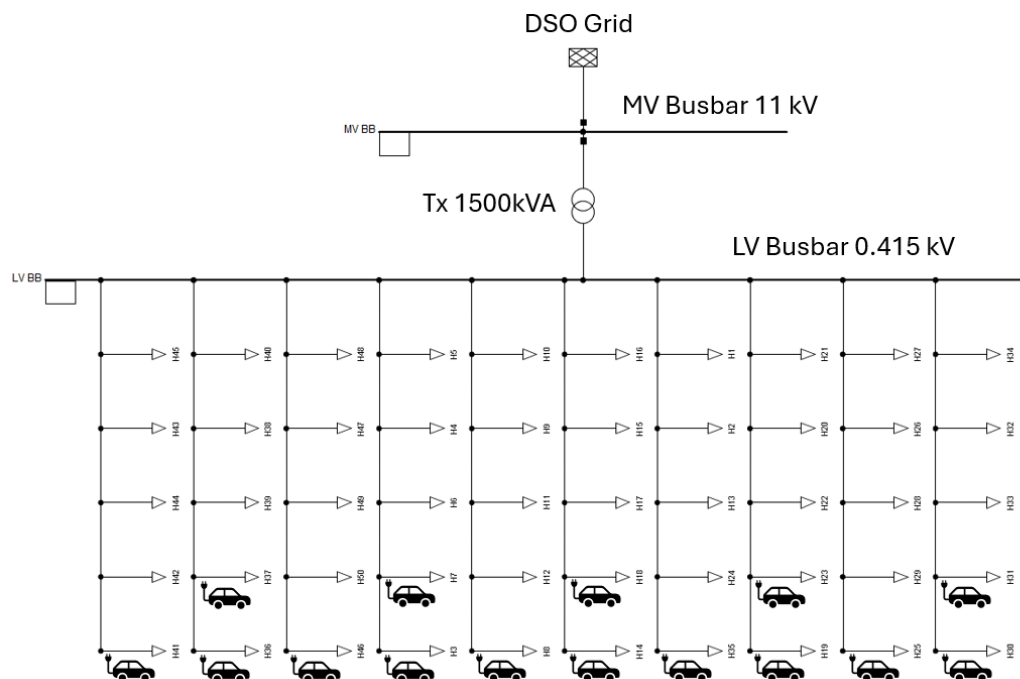


Figure 3.3 Network with 30% simultaneous EV charging

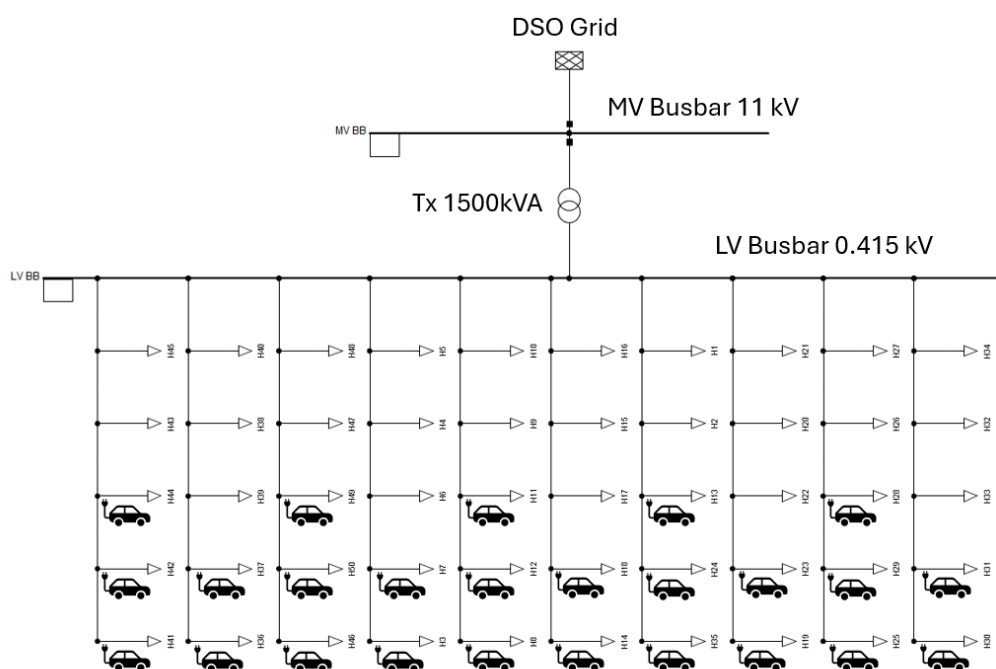


Figure 3.4 Network with 50% simultaneous EV charging

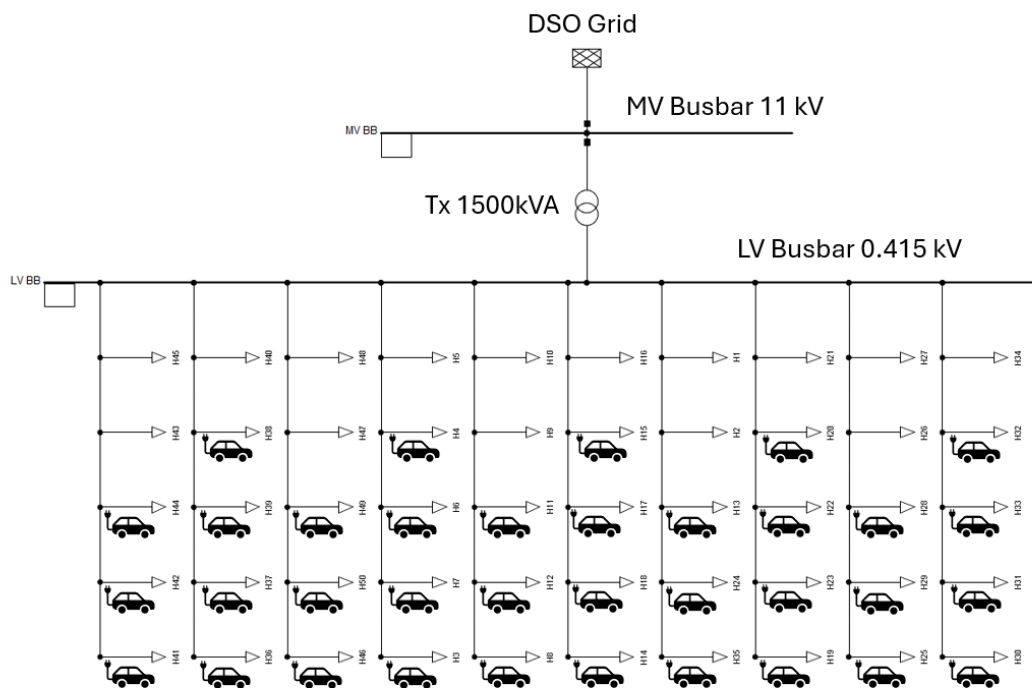


Figure 3.5 Network with 70% simultaneous EV charging

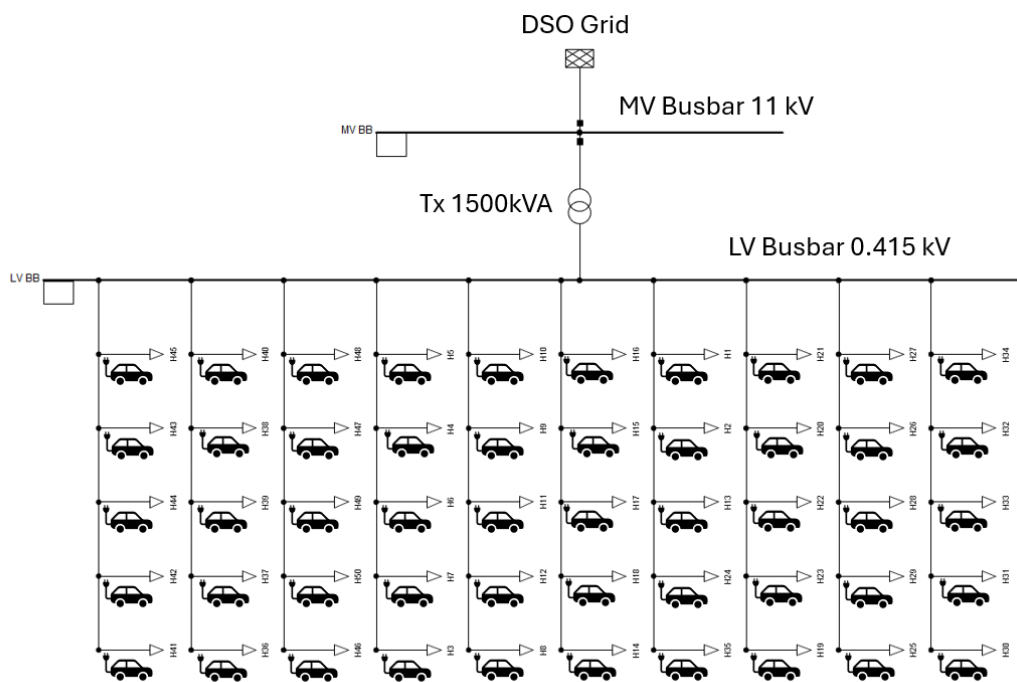


Figure 3.6 Network with 100% simultaneous EV charging

3.3.3 Key parameters for impact assessment

The impact of EV integration is assessed by analyzing several critical parameters that reflect the performance of the distribution transformer and network infrastructure:

3.3.3.1 Voltage violations

One of the primary concerns is the potential for voltage violations due to increased load from EV charging. In this study, voltage must remain above 0.94 per unit (pu) to ensure compliance with voltage regulation standards. Any voltage drop below this threshold will be considered a violation, indicating that the network is operating outside acceptable limits. In this study, the voltage reference is assumed to be the busbar of the RMU, which is considered to have a reference value of 11kV.

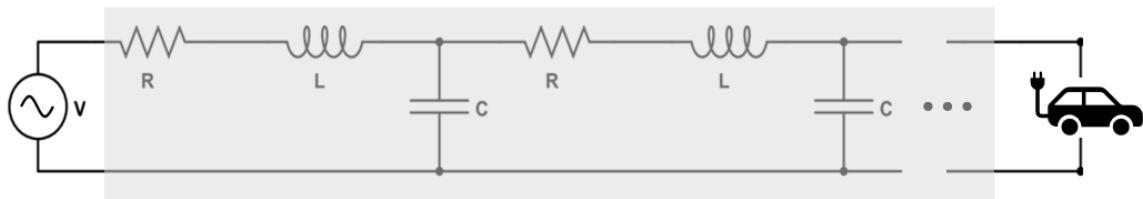


Figure 3.7 Cable Equivalent Circuit

The effect of electric vehicle (EV) charging is more significant when EVs are connected to households located farthest from the transformer. This is due to the fact that the longer the electrical path between the transformer and the load, the greater the voltage drop, as the resistance and reactance of the cable increase with length as shown in figure 3.7.

3.3.3.2 Transformer loading

The additional load introduced by EV charging will increase the stress on the transformer. The study will assess the extent to which the transformer approaches or exceeds its rated capacity under different EV

penetration levels and charger power scenarios (7.6 kW and 11 kW). Transformer overloading could lead to overheating and decreased lifespan if operating beyond safe limits for extended periods.

3.3.3.3 LV feeder overload

The low-voltage (LV) feeders, which distribute power to the households, are also critical components of the network. In this study, the LV feeder phases are protected by High Rupturing Capacity (HRC) fuses rated at 315A. Overloading these feeders can cause the fuses to blow, leading to service interruptions. The study will evaluate whether the increased load from EV integration causes the LV feeder currents to exceed the fuse ratings, triggering overload conditions.

3.3.3.4 Power Losses

The integration of EVs introduces higher current levels within the distribution network, which in turn leads to an increase in power losses. Power losses are a key indicator of network efficiency, as excessive losses can elevate operational costs and reduce overall network performance. In this study, power losses will be quantified under varying EV penetration levels and charging scenarios

3.3.4 Simulation software

The simulation in this study is carried out using an appropriate power system software package to accurately model and analyze the impact of electric vehicle (EV) integration on the distribution network. The 2023 version of PowerFactory, developed by DIgSILENT (DIgital SImuLation of Electrical NETworks), is the primary software tool used for the simulations. DIgSILENT PowerFactory (DPF) is widely recognized for its

ability to perform highly sophisticated and advanced analyses of electrical power systems. It is a powerful and versatile tool used in the investigation of generation, transmission, distribution, and industrial electrical networks.

3.3.5 Simulation procedure

The simulation procedure for objective 2 is illustrated in the flowchart of Figure 3.8. The process begins by modeling a typical low voltage (LV) distribution network in Bahrain. Three scenarios are considered for transformer (Tx) loading, representing 30%, 50%, and 80% of the transformer's rated capacity. Each loading scenario is used to evaluate the impact of integrating electric vehicle (EV) charging on the network. After establishing the base network loading scenarios, EV charging loads are added. Two types of EV chargers are analyzed: a 7.6 kW charger and an 11 kW charger, both with a three-phase connection to reflect the typical setup in Bahrain. These chargers are applied to the network under four simultaneous charging levels, where 30%, 50%, 70%, and 100% of the households are assumed to be charging EVs simultaneously. These levels represent different potential penetration rates of EVs in a neighborhood. For each charging level, the network's performance is analyzed by assessing key parameters such as voltage levels, transformer loading, power losses, and LV feeder overloads. This allows for a comprehensive evaluation of how the network responds to varying degrees of EV integration under different loading conditions.

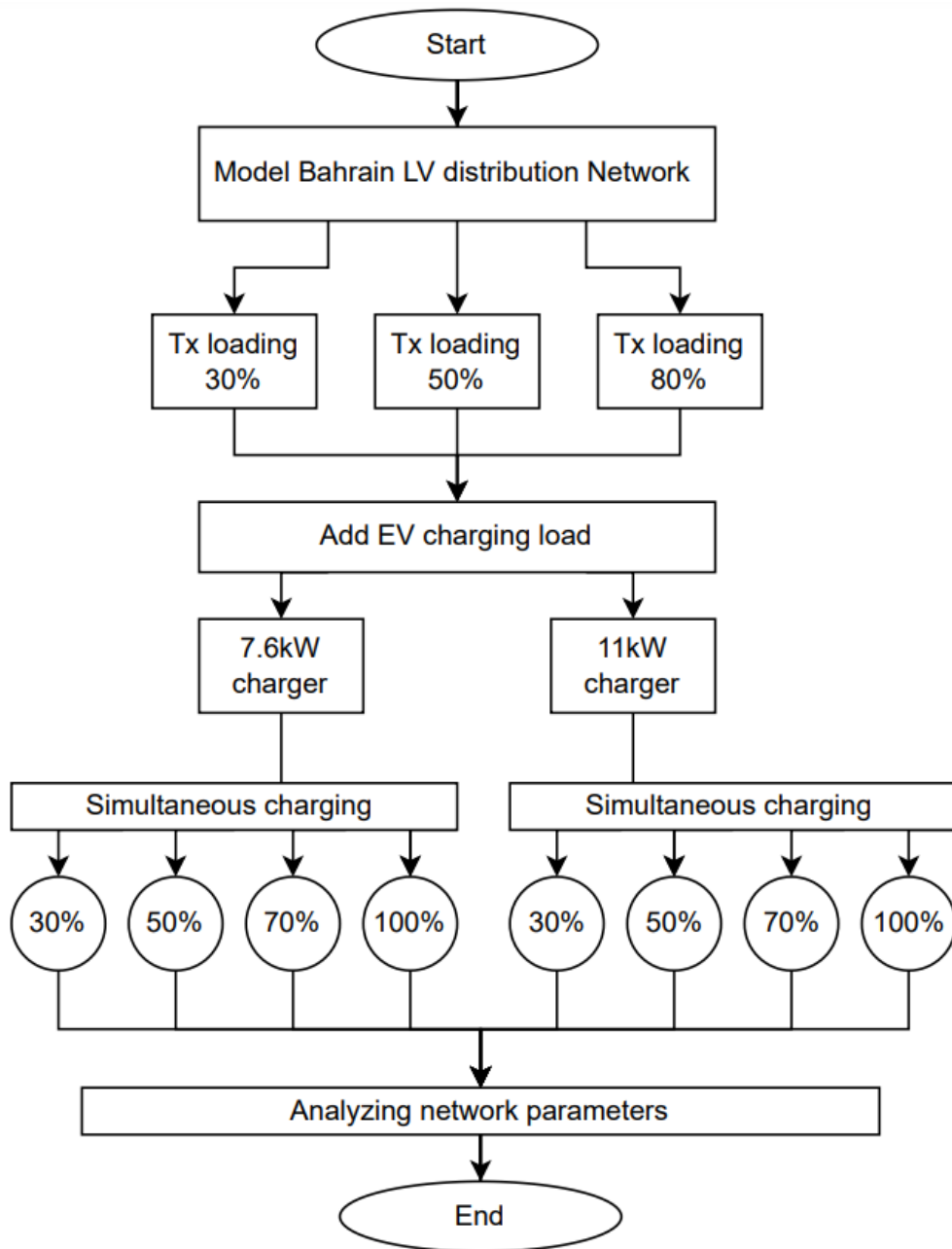


Figure 3.8 Imapct Assessment Process

3.4 Objective 3: Investigating Opportunities for Indirect Control Charging

The third objective of this study is to investigate the opportunity to use indirect control as a strategy to manage the impact of electric vehicle (EV) integration on Bahrain's distribution network. Indirect control strategies, such as shifting EV charging to off-peak periods, can potentially reduce the stress on the distribution transformers and LV feeders during peak demand periods. In this study, the effectiveness of indirect control will be assessed by analyzing the load profiles of 456 distribution transformers using Python.

3.4.1 Data collection and analysis approach

To assess the viability of indirect control, this study will analyze load data for 456 distribution transformers. The analysis will focus on the period from May till mid of November of 2024 that registered the highest peak load for Bahrain. This time period provides a representative sample of the most critical conditions under which indirect control strategies would be necessary.

The data will be analyzed using Python to generate the following insights:

- **Peak Load distribution:** The probability distribution of peak loads across the 456 transformers will be calculated. This will help identify the likelihood of transformers reaching high loading conditions.
- **Peak Time distribution:** The timing of the peak loads will also be analyzed to determine when peak demand typically

occurs throughout the day. This information is essential for understanding whether shifting EV charging can meaningfully reduce transformer loading during critical hours.

- **Average Load Profiles:** The average load on each transformer throughout the day will be analyzed to establish baseline conditions for evaluating the effectiveness of indirect control strategies.

The approach for analyzing the data is as follows:

- **Raw Data Collection:** the dataset comprises approximately 233 million values, representing transformer current readings recorded at one-minute intervals. This extensive dataset provides a comprehensive basis for analysis.
- **Data Cleaning:** the collected data undergoes preprocessing to ensure its quality and relevance. This step includes organizing the dataset and excluding entries from newly commissioned substations with zero load, focusing the analysis on active transformers.
- **Python Code Development:** a Python-based analytical framework is developed to process the cleaned dataset. This framework includes functionalities to calculate transformer loading metrics, detect trends, and perform statistical analysis to derive meaningful insights.
- **Graph Generation:** the analysis results are visualized through a series of graphs that illustrate loading patterns, peak demands, and peak time.

The following figure 3.9 summarizes the process.

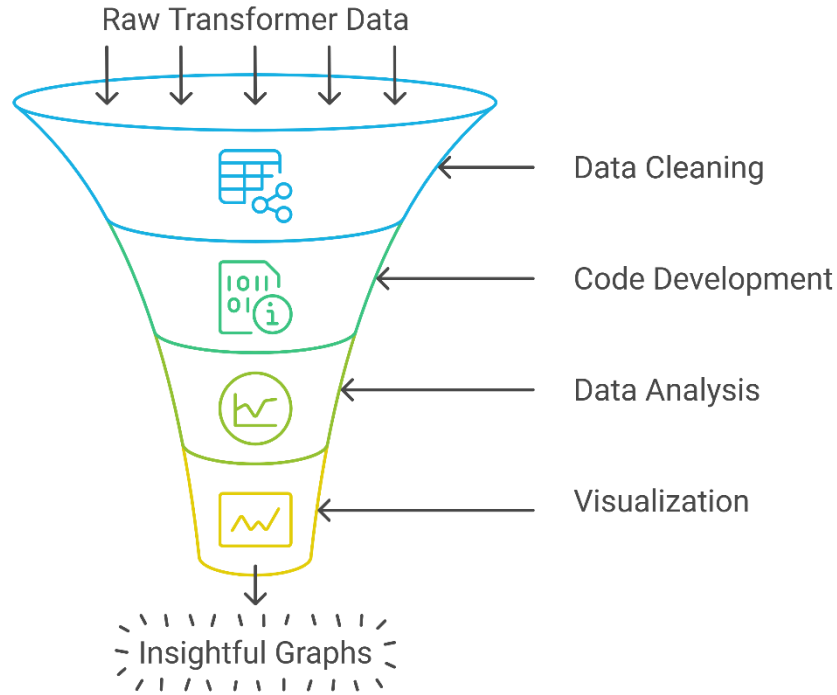


Figure 3.9 Data analysis approach funnel

3.4.2 Evaluating the effectiveness of indirect control

To evaluate the effectiveness of indirect controlled charging, it is essential to consider two key factors: (1) the range of the possible controlled load percentage, defined as the difference between the peak load percentage and the minimum load percentage of the transformer as shown in the equation below, and (2) the time period of the minimum load, which can be utilized for control purposes. These factors are critical to assess whether indirect control strategies can effectively mitigate the impact of electric vehicle (EV) charging on the distribution network.

$$\text{possible controlled load } (\Delta L) = L_{max} - L_{min}$$

The analysis begins with the investigation of the average transformer load for each hour, differentiated between weekdays and weekends, over the analyzed period. This aggregated analysis provides insights into

general loading patterns across multiple transformers, offering a macro-level view of the feasibility of applying a global indirect charging control strategy. By examining the range of the possible controlled load percentage across this dataset, the potential effectiveness of a unified, system-wide control approach can be assessed.

Following this, a more granular analysis is conducted by selecting random individual transformers for detailed evaluation. This micro-level analysis focuses on examining the specific characteristics of selected transformers, including their load profiles and minimum load timing. This helps to determine whether a targeted, transformer-specific indirect control strategy would be more effective.

Together, these analyses aim to provide a comprehensive understanding of the feasibility and effectiveness of indirect control strategies for EV charging. By combining insights from global and individual transformer perspectives, this methodology evaluates the potential to optimize transformer loading and mitigate overloading risks using indirect control mechanisms.

Chapter 4: Results and Analysis

Chapter Overview:

This chapter presents the results and analysis of the study. It consolidates findings from simulations and real-world transformer loading data to evaluate the network's performance under various EV charging scenarios. Key aspects such as transformer loading, voltage violations, LV feeder loading, power losses and simultaneous charging thresholds are analyzed using statistical methods and visual tools like heatmaps and impact matrices. Additionally, the chapter examines the potential of indirect controlled charging as a mitigation strategy, assessing its feasibility through load patterns and transformer-specific analyses. The insights derived from this chapter form the foundation for practical recommendations to optimize EV integration into the grid.

Following the simulations conducted using DIgSILENT PowerFactory software, the results are organized based on the rated power of EV chargers. The analysis is divided into two main sections: one for 7.6 kW chargers and the other for 11 kW chargers. Within each section, results are further categorized into three subsections corresponding to different transformer loading levels: 30%, 50%, and 80%. This structure allows for a detailed examination of how different charging power levels and loading conditions affect key parameters in Bahrain's distribution network, providing a comprehensive view of the network's response to EV integration under varying conditions.

4.1 Impact of 7.6kW EV chargers

4.1.1 30% loading scenarios

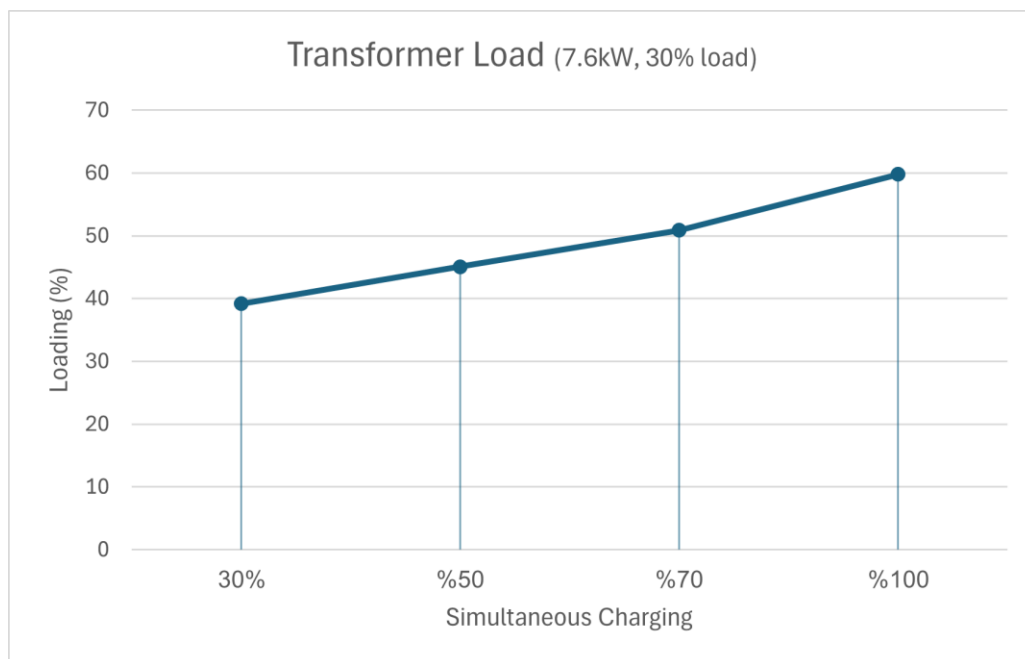


Figure 4.1 Transformer Loading with 30% Base Load and 7.6 kW EV Chargers

Figure 4.1 illustrates the impact of adding 7.6 kW electric vehicle (EV) chargers on a distribution transformer with an initial base load of 30%. The x-axis represents the percentage of EVs charging simultaneously, while the y-axis shows the resulting transformer loading as a percentage of

its rated capacity. As the percentage of simultaneous EV charging increases from 30% to 100%, the transformer load exhibits a steady upward trend. With 30% of EVs charging simultaneously, the transformer loading reaches approximately 40%, showing a modest increase from the initial base load. At 50% simultaneous charging, the loading rises to around 46%. As the simultaneous charging level further increases to 70% and 100%, the transformer loading continues to escalate, reaching 52% and nearly 60%, respectively.

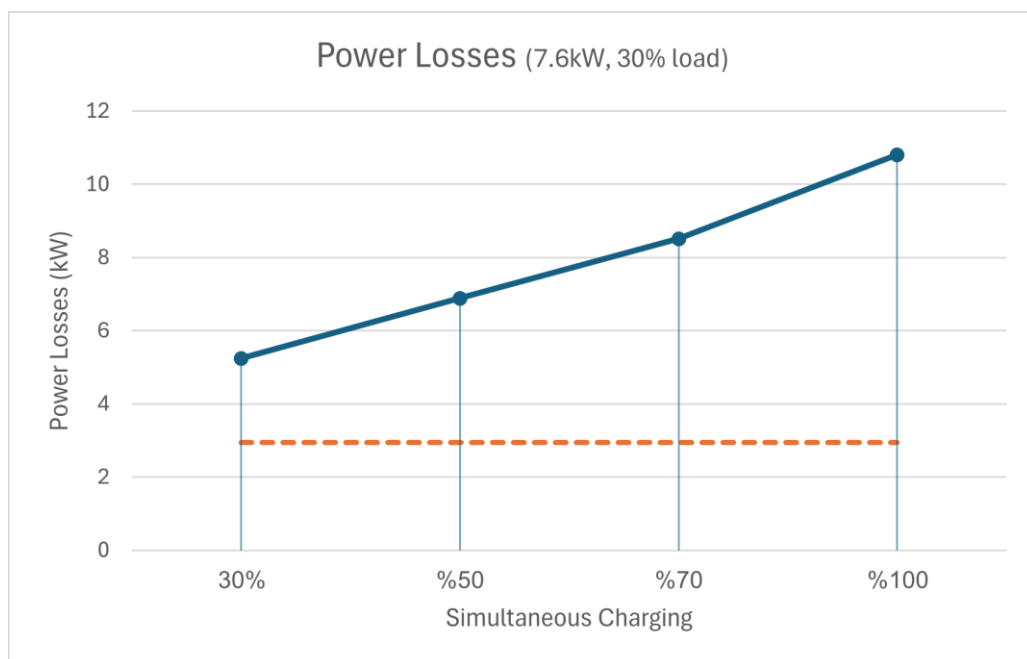


Figure 4.2 Power Losses with 30% Base Load and 7.6 kW EV Chargers

Figure 4.2 shows the power losses in the distribution network when electric vehicles (EVs) are added to a transformer with an initial base load of 30%. The blue line represents power losses as EV charging increases, while the orange dashed line indicates the baseline power losses without EV integration. The graph shows a clear upward trend in power losses as the percentage of simultaneous EV charging increases from 30% to 100%. At 30% simultaneous charging, power losses are approximately 5 kW, which is already above the baseline level of around 3 kW observed without EV charging. When 50% of the EVs are charging simultaneously, the losses

rise to about 7 kW. As the simultaneous charging level reaches 70% and 100%, the power losses further escalate to 9 kW and 11 kW, respectively.

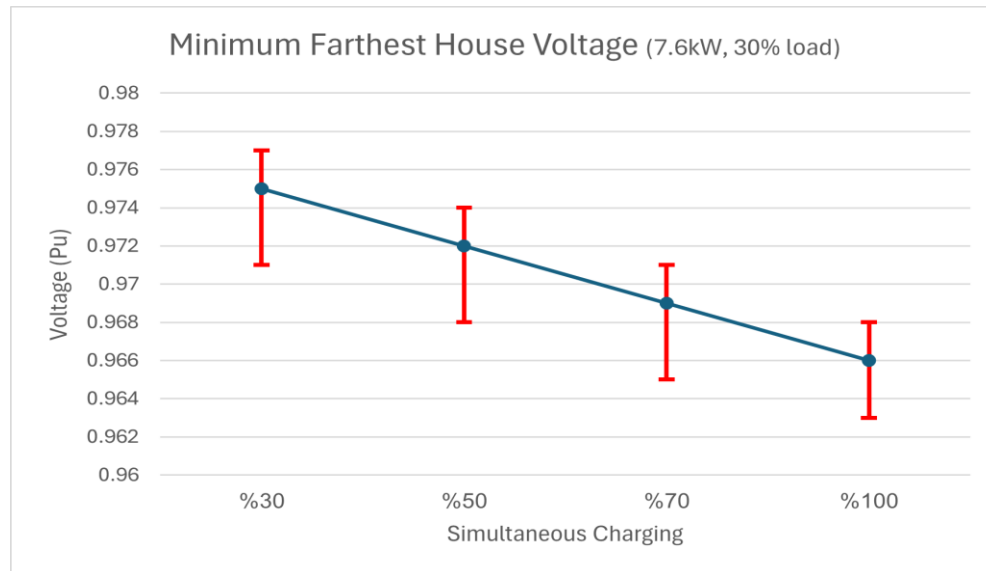


Figure 4.3 Minimum Voltage at the Farthest House with 30% Base Load and 7.6 kW EV Chargers

Figure 4.3 demonstrates the minimum voltage observed at the farthest house from the transformer as simultaneous electric vehicle (EV) charging levels increase, with an initial base load of 30%. The x-axis represents the percentage of EVs charging simultaneously, while the y-axis displays the voltage in per-unit (pu). The blue line indicates the average minimum voltage, and the red error bars show the range of the voltage values obtained from 1440 simulations conducted with different household load distributions, the error bars exclude low-likelihood values, which are instead presented separately in the detailed analysis for clarity and focus on significant results. The results indicate a clear decline in voltage levels at the farthest point on the network as simultaneous EV charging increases. At 30% simultaneous charging, the minimum voltage is around 0.976 pu. As the charging level rises to 50%, the voltage drops to approximately 0.973 pu. Further increases in simultaneous charging, to 70% and 100%, lead to minimum voltages of roughly 0.970 pu and 0.966 pu, respectively.

It is noteworthy that despite the observed decline, there were no voltage violations relative to the standard -6% minimum voltage limit (0.94 pu),

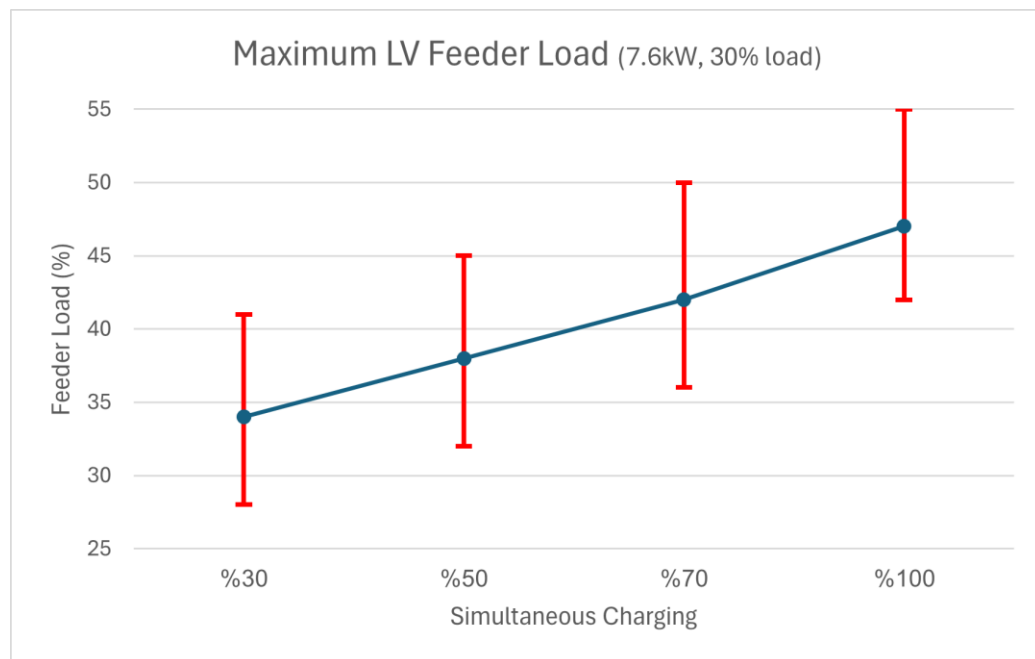


Figure 4.4 Maximum LV Feeder Load with 30% Base Load and 7.6 kW EV Chargers

Figure 4.4 displays the maximum load on the low-voltage (LV) feeder as the level of simultaneous electric vehicle (EV) charging increases, with an initial base load of 30% and a charger power rating of 7.6 kW. The x-axis represents the percentage of EVs charging simultaneously, while the y-axis displays the feeder load as a percentage of its rated capacity. The blue line indicates the average maximum feeder load, and the red error bars represent the range of values across 1440 simulations, each with different household load distributions. As simultaneous EV charging increases from 30% to 100%, there is a consistent rise in the maximum LV feeder load. At 30% simultaneous charging, the average maximum feeder load reaches around 34%, slightly above the base load level. When 50% of EVs are charging simultaneously, the maximum feeder load increases to approximately 37%. With further increments in simultaneous charging 70% and 100% the feeder load rises to about 43% and 47%, respectively.

A detailed analysis was conducted for each simultaneous charging scenario to explore the likelihood of impacts under different load distribution scenarios, focusing on voltage violations and feeder loading.

- **30% simultaneous charging:**

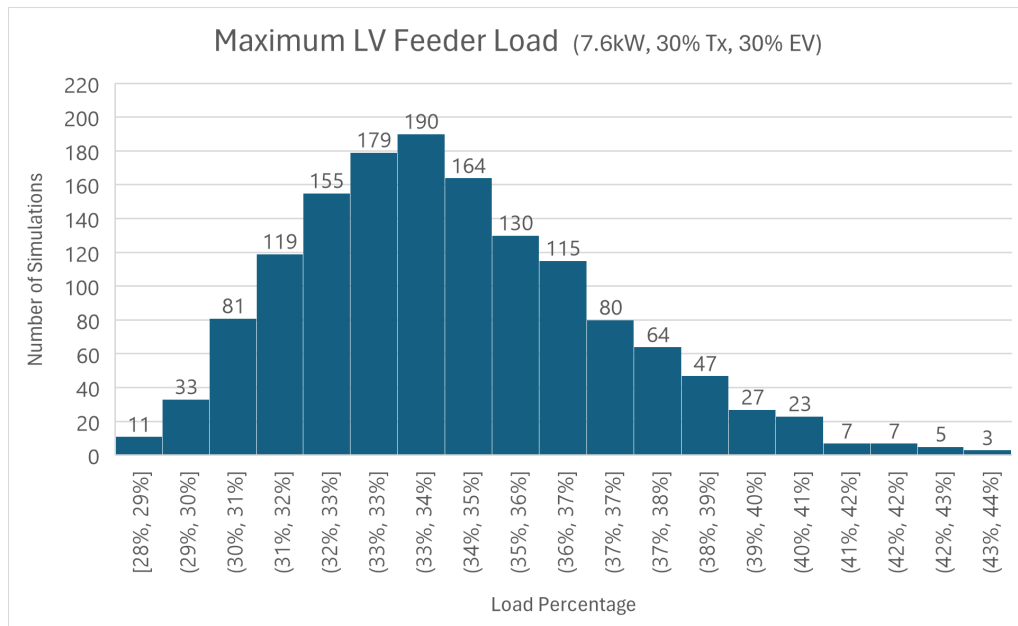


Figure 4.5 Distribution of Maximum LV Feeder Load for 30% EV Penetration (7.6 kW Chargers, 30% Transformer Load)

Figure 4.5 illustrates the distribution of maximum low-voltage (LV) feeder loads across 1440 simulations with 30% of electric vehicles (EVs) charging simultaneously. The x-axis represents the percentage of feeder load relative to its rated capacity, while the y-axis indicates the number of simulations corresponding to each load range. The majority of simulations resulted in maximum feeder loads between 33% and 35%, with the highest frequency observed in the 33%-34% range, accounting for 369 simulations. This suggests that for most scenarios, the feeder load increases moderately but remains below 40% of its rated capacity. The distribution is slightly right-skewed, with fewer simulations resulting in feeder loads exceeding 37%. Only a small number of simulations (e.g., 3 to 7) show maximum feeder loads reaching beyond 42%, indicating that extreme cases

are rare but possible under certain household load distributions. On the lower end, feeder loads below 30% are infrequent, with only 11 simulations recorded in the 28%-29% range. This variability across the distribution reflects the influence of different household load profiles and EV charging patterns on feeder performance.

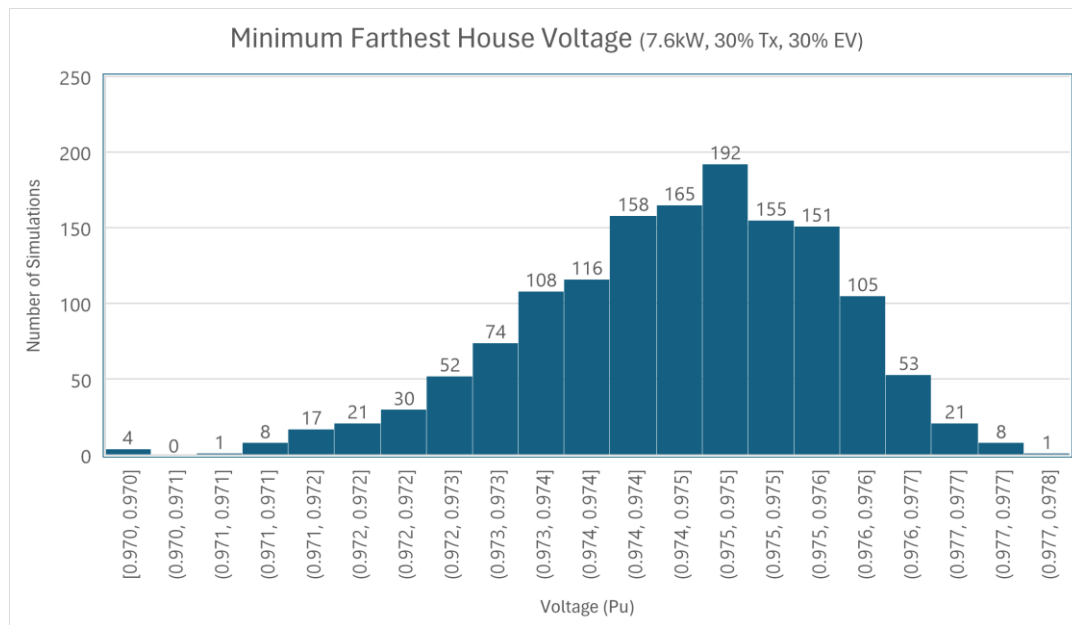


Figure 4.6 Distribution of Minimum Voltage at the Farthest House for 30% EV Penetration (7.6 kW Chargers, 30% Transformer Load)

Figure 4.6 shows that the most frequently observed minimum voltage range is 0.975 pu, with 192 simulations falling within this range. The majority of simulations are concentrated between 0.973–0.975 pu, collectively accounting for over 500 simulations. On the lower end, extreme cases are rare, with only 4 simulations in the 0.970 pu range, while on the higher end, only 1 simulation falls within the 0.977–0.978 pu range. The distribution highlights relatively stable voltage levels for most scenarios, with occasional deviations depending on household load distributions.

- **50% simultaneous charging:**

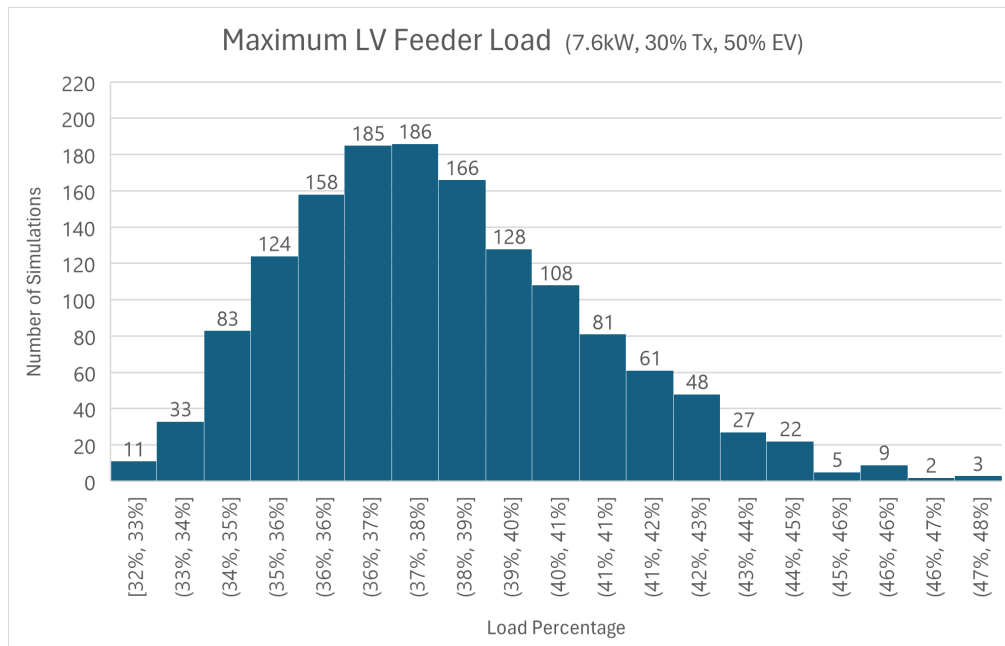


Figure 4.7 Distribution of Maximum LV Feeder Load for 50% EV Penetration (7.6 kW Chargers, 30% Transformer Load)

Figure 4.7 presents that the most frequent maximum LV feeder load falls within the range of 37%-38%, with 186 simulations, closely followed by 36%-37%, with 185 simulations. The majority of the simulations are distributed between 34%-39%, while lower loads below 34% are rare, with only 44 simulations. Higher loads above 42% are infrequent, with only 48 simulations in the 42%-43% range, and very few in the extreme ranges above 45%.

Figure 4.8 Highlights that the most frequent minimum voltage range is 0.972 pu, with 362 simulations, followed by 0.971 pu, with 164 simulations. The majority of simulations fall between 0.970–0.973 pu, collectively accounting for over 500 simulations. Lower voltage levels below 0.969 pu are rare, with only 4 simulations recorded in the 0.967–0.968 pu range. Higher voltage levels above 0.974 pu are similarly infrequent, with just 1 simulation in the 0.974–0.975 pu range.

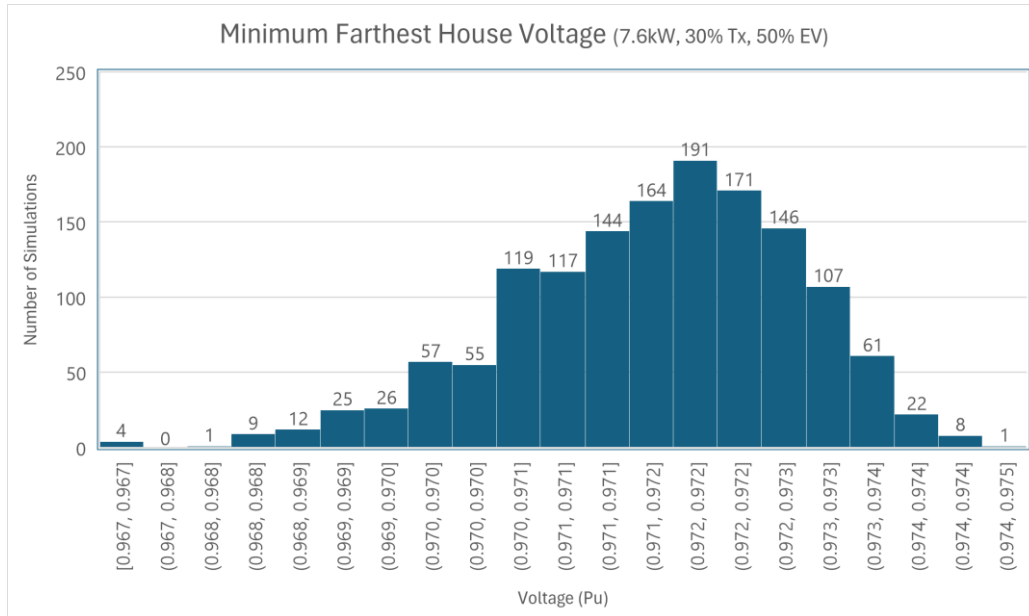


Figure 4.8 Distribution of Minimum Voltage at the Farthest House for 50% EV Penetration (7.6 kW Chargers, 30% Transformer Load)

- **70% simultaneous charging**

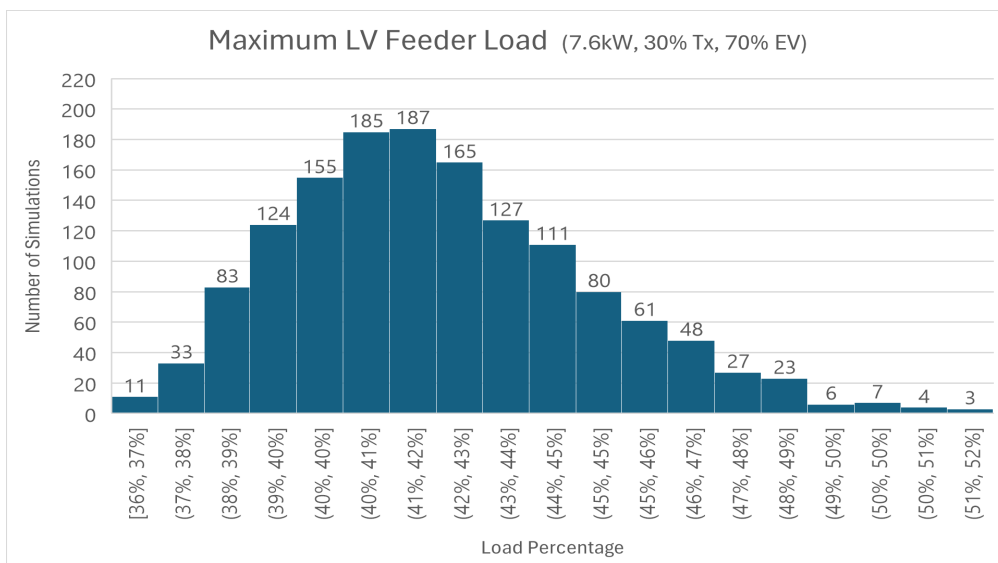


Figure 4.9 Distribution of Maximum LV Feeder Load for 70% EV Penetration (7.6 kW Chargers, 30% Transformer Load)

Figure 4.9 illustrates that the most frequent maximum LV feeder load falls within the range 41%-42%, with 187 simulations, closely followed by 40%-41%, with 185 simulations. The majority of simulations are concentrated between 39%-44%, representing the bulk of the results. Lower loads below 38% are infrequent, with only 33 simulations in the

37%-38% range, while higher loads above 47% are rare, with just 6 simulations recorded in the 49%-50% range.

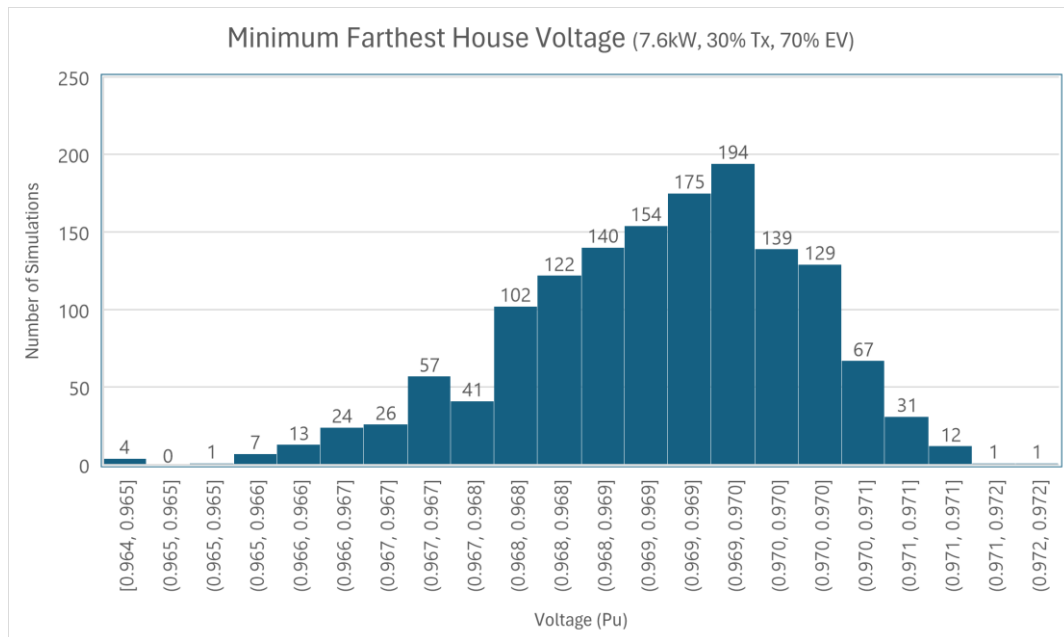


Figure 4.10 Distribution of Minimum Voltage at the Farthest House for 70% EV Penetration (7.6 kW Chargers, 30% Transformer Load)

Figure 4.10 highlights that the most frequent minimum voltage range is 0.968–0.969 pu, with 693 simulations, followed by 0.969–0.970 pu, with 469 simulations. The majority of simulations are concentrated between 0.968–0.970 pu, accounting for a significant proportion of the results. Lower voltage levels below 0.966 pu are infrequent, with only 7 simulations recorded in the 0.965–0.966 pu range and fewer as the voltage drops further. Higher voltage levels above 0.971 pu are rare, with only 14 simulations recorded in the 0.971–0.972 pu range.

- **100% simultaneous charging:**

Figure 4.11 indicates that the most frequent maximum feeder load occurs in the range 46% - 47%, with 197 simulations. The majority of simulations (approximately 954) fall between 44% - 49%, while higher

loads exceeding 53% are less frequent, with just 1 simulation in the extreme 58% - 59% range.

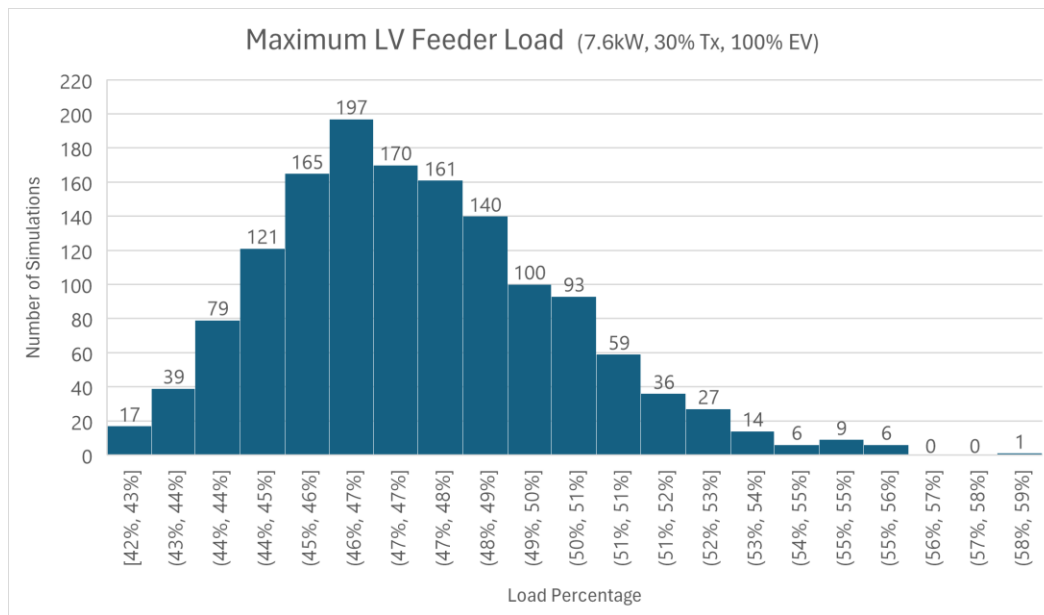


Figure 4.11 Distribution of Maximum LV Feeder Load for 100% EV Penetration (7.6 kW Chargers, 30% Transformer Load)

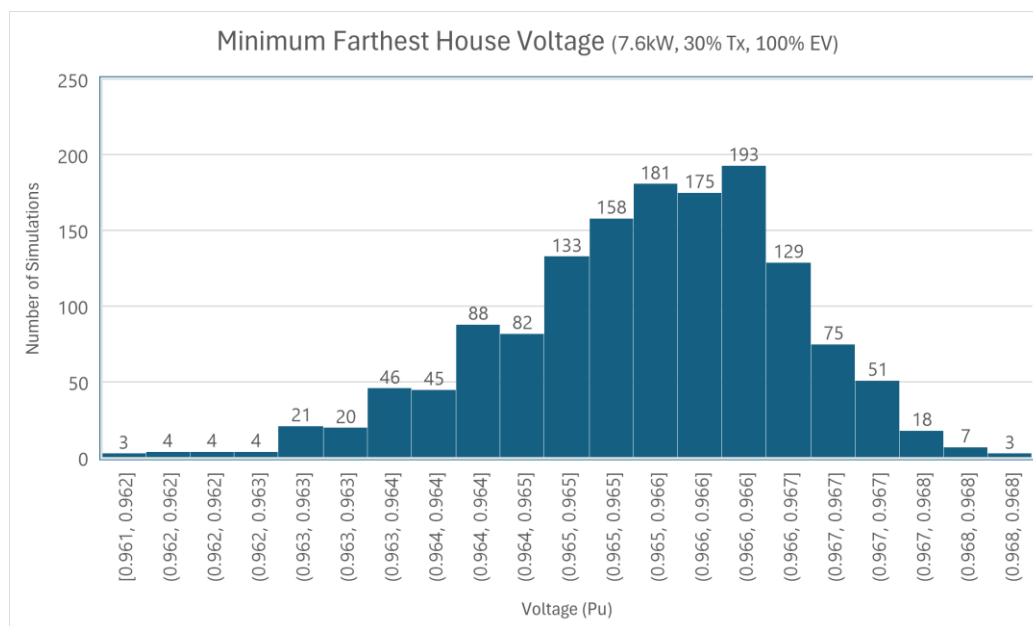


Figure 4.12 Distribution of Minimum Voltage at the Farthest House for 100% EV Penetration (7.6 kW Chargers, 30% Transformer Load)

Figure 4.12 shows that the most frequent minimum voltage range is 0.965–0.966 pu, with 840 simulations. The majority of simulations are concentrated between 0.964–0.967 pu, accounting for a significant

proportion of the results. Lower voltage levels below 0.963 pu are infrequent, with only 11 simulations recorded in the 0.961–0.962 pu range. Higher voltage levels above 0.967 pu decrease gradually, with just 10 simulations recorded in the 0.968 pu range.

4.1.2 50% loading scenarios

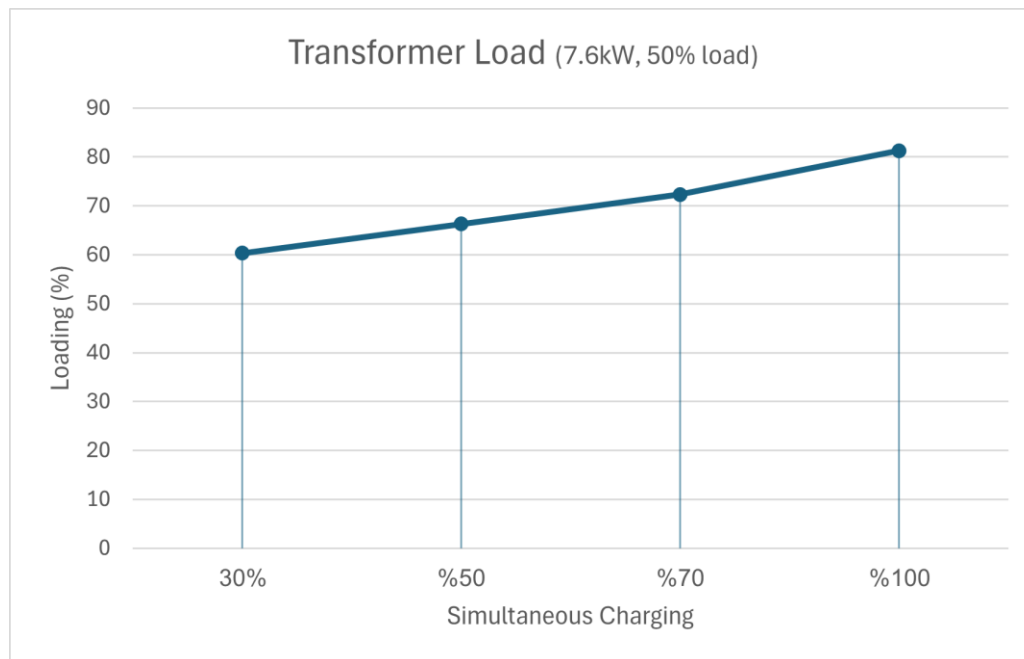


Figure 4.13 Transformer Loading with 50% Base Load and 7.6 kW EV Chargers

Figure 4.13 displays the transformer loading for a 50% base load scenario as EV penetration increases. At 30% simultaneous EV charging, the transformer load reaches approximately 61% of its capacity. This increases to 67% at 50% EV charging, 72% at 70% EV charging, and 81% under 100% simultaneous EV charging.

Figure 4.14 represents the increase in power losses as EV penetration rises for a 50% base load scenario. At 30% simultaneous EV charging, power losses reach approximately 12 kW, which is higher than the baseline losses without EVs (orange line). As EV charging increases, losses rise steadily to 14.5 kW at 50% charging, 17 kW at 70% charging, and 20 kW at 100% charging.

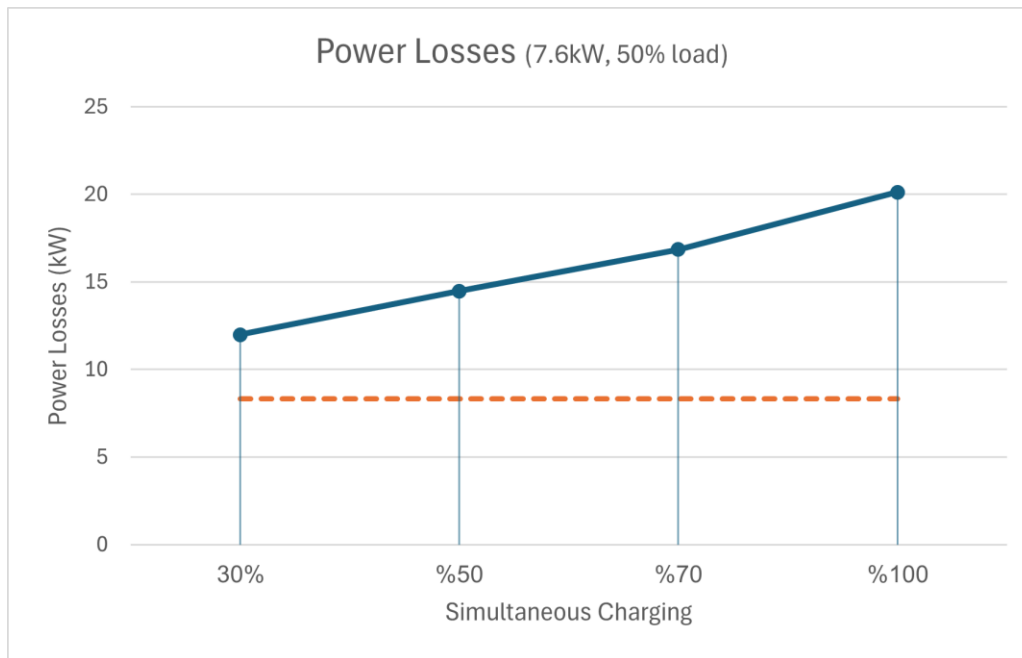


Figure 4.14 Power Losses with 50% Base Load and 7.6 kW EV Chargers

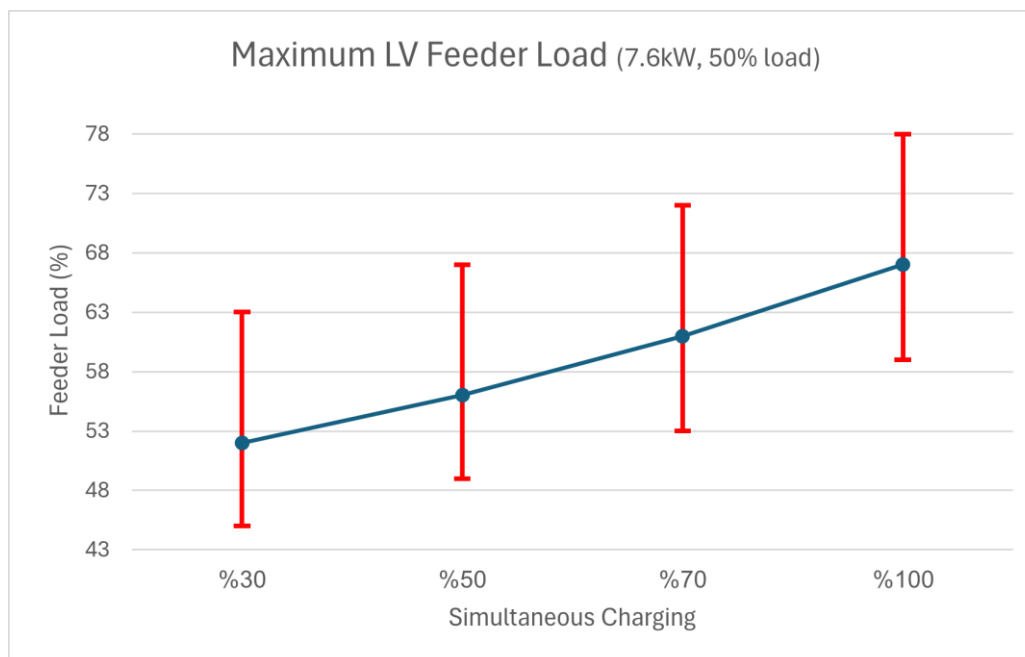


Figure 4.15 Maximum LV Feeder Load with 50% Base Load and 7.6 kW EV Chargers

Figure 4.15 demonstrates the maximum LV feeder load as EV penetration increases for a 50% base load scenario. At 30% simultaneous EV charging, the feeder load is approximately 52%, increasing to 56% at 50% EV charging, 61% at 70% EV charging, and 67% under 100% simultaneous EV charging. The maximum feeder load reached in this

scenario is 78%, as indicated by the upper bound of the bar at 100% EV charging.

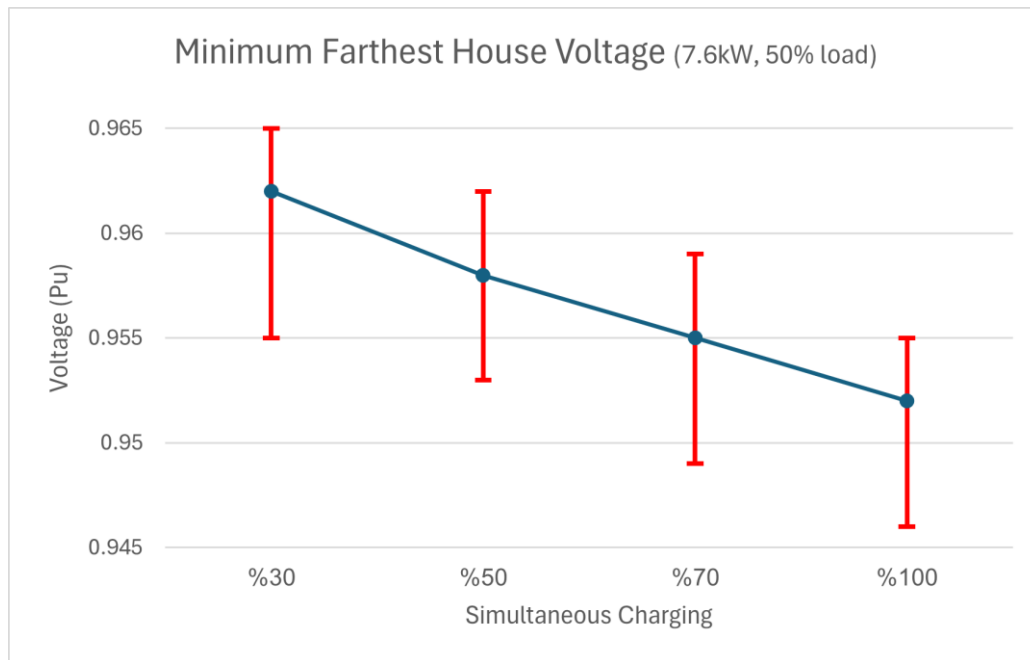


Figure 4.16 Minimum Voltage at the Farthest House with 50% Base Load and 7.6 kW EV Chargers

Figure 4.16 presents the minimum voltage at the farthest house as EV penetration increases for a 50% base load scenario. At 30% simultaneous EV charging, the minimum voltage is approximately 0.963 pu, decreasing steadily to 0.958 pu at 50% EV charging, 0.955 pu at 70% EV charging, and 0.952 pu under 100% simultaneous EV charging. The lowest voltage reached in this scenario is 0.946 pu, as indicated by the lower bound of the bar at 100% EV charging.

Detailed analysis for each simultaneous charging.

- **30% simultaneous charging:**

Figure 4.17 shows that the most frequent maximum feeder load range is 51%–52%, with 191 simulations. The majority of simulations are concentrated between 46%–59%, accounting for a significant proportion

of the results. Lower feeder load levels below 45% are infrequent, with only 6 simulations recorded in the 43%–45% range. Higher feeder load levels above 60% decrease gradually, with just 2 simulations recorded in the 66%–67% range and a single simulation in the 70%–71% range.

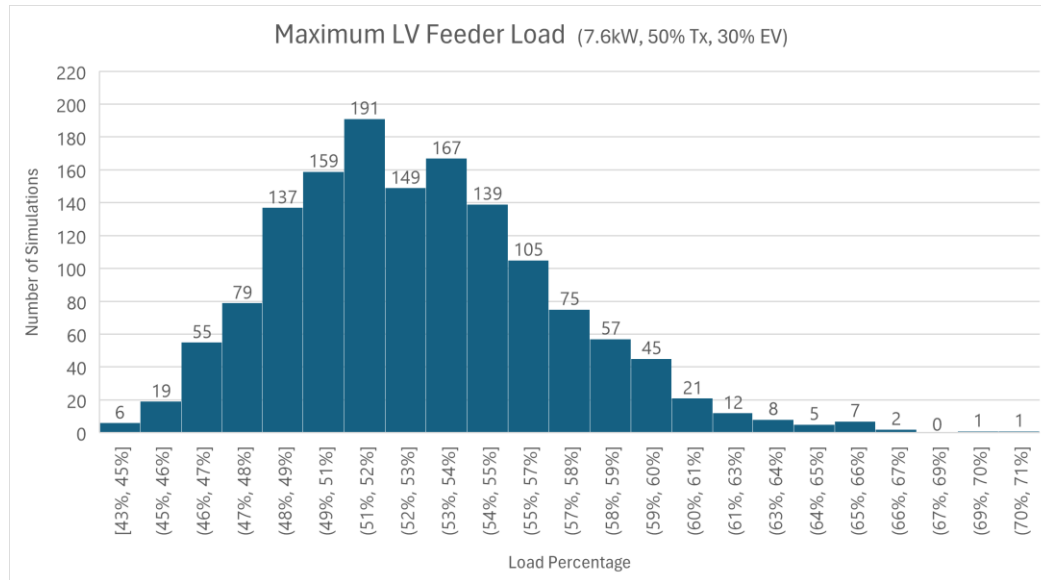


Figure 4.17 Distribution of Maximum LV Feeder Load for 30% EV Penetration (7.6 kW Chargers, 50% Transformer Load)

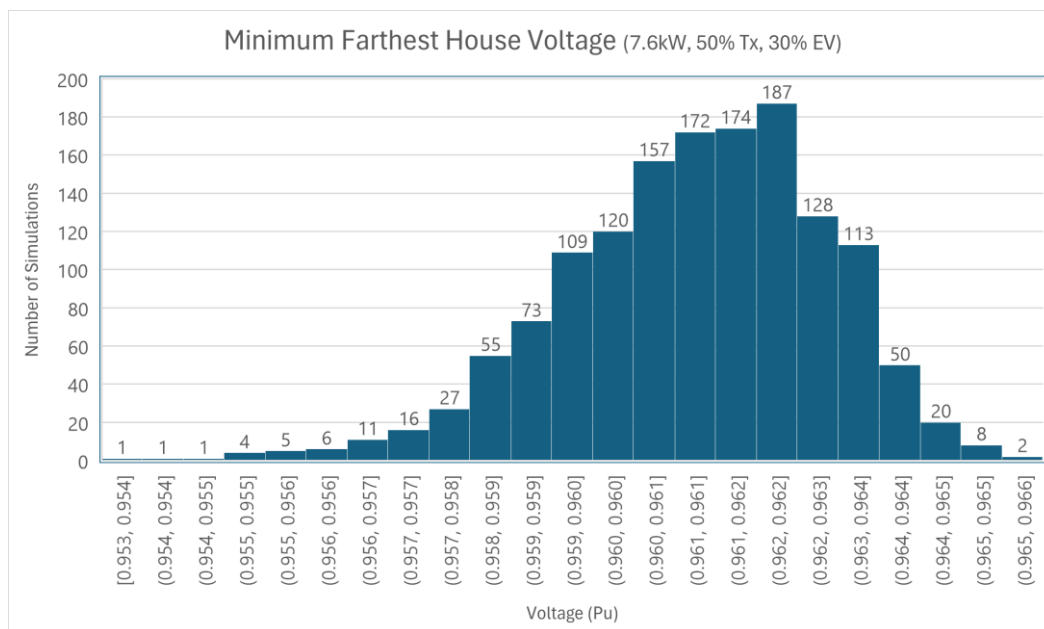


Figure 4.18 Distribution of Minimum Voltage at the Farthest House for 30% EV Penetration (7.6 kW Chargers, 50% Transformer Load)

Figure 4.18 illustrates that the most frequent minimum voltage range is 0.961–0.962 pu, with 533 simulations. The majority of simulations are

concentrated between 0.959–0.964 pu, accounting for a significant proportion of the results. Lower voltage levels below 0.956 pu are rare, with only 15 simulations recorded in the 0.955–0.956 pu range and fewer as the voltage drops further. Higher voltage levels above 0.964 pu decrease gradually, with just 2 simulations recorded in near the 0.966 pu range.

- **50% simultaneous charging:**

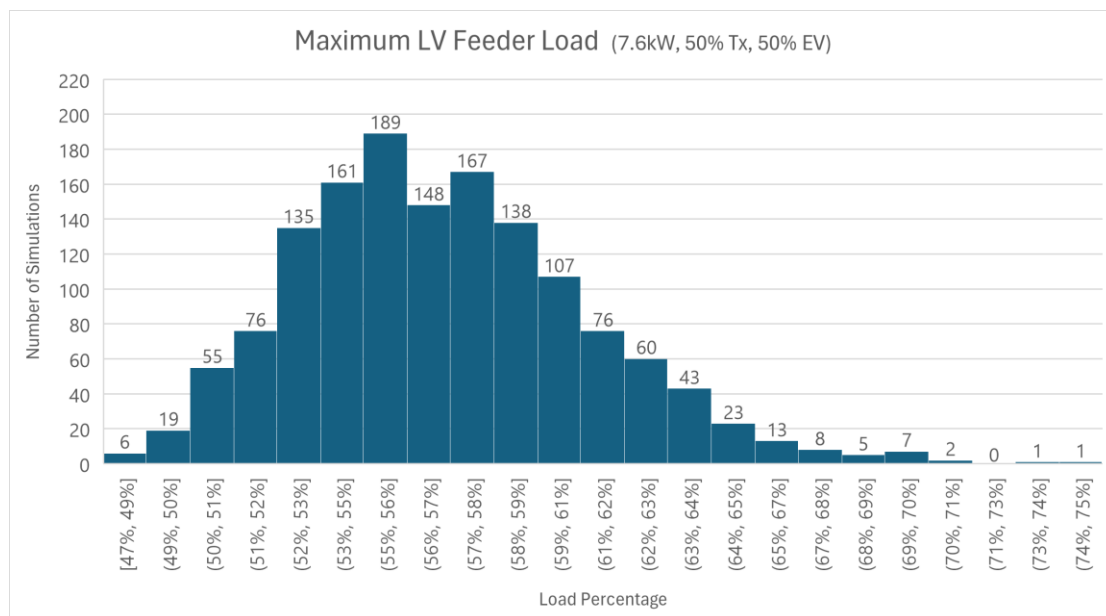


Figure 4.19 Distribution of Maximum LV Feeder Load for 50% EV Penetration (7.6 kW Chargers, 50% Transformer Load)

Figure 4.19 demonstrates that the most frequent maximum feeder load range is 55%–56%, with 189 simulations. The majority of simulations are concentrated between 50%–63%, accounting for a significant proportion of the results. Lower feeder load levels below 49% are infrequent, with only 6 simulations recorded in the 47%–49% range. Higher feeder load levels above 65% decrease gradually, with just 2 simulations recorded in the 70%–71% range and a single simulation in the 74%–75% range.

Figure 4.20 illustrates that the most frequent minimum voltage range is 0.958–0.959 pu, with 545 simulations. The majority of simulations are concentrated between 0.955–0.961 pu, accounting for a significant

proportion of the results. Lower voltage levels below 0.955 pu are rare, with only 19 simulations recorded in the 0.954 pu range and fewer as the voltage drops further. Higher voltage levels above 0.961 pu decrease gradually, with just 2 simulations recorded in the 0.962–0.963 pu range.

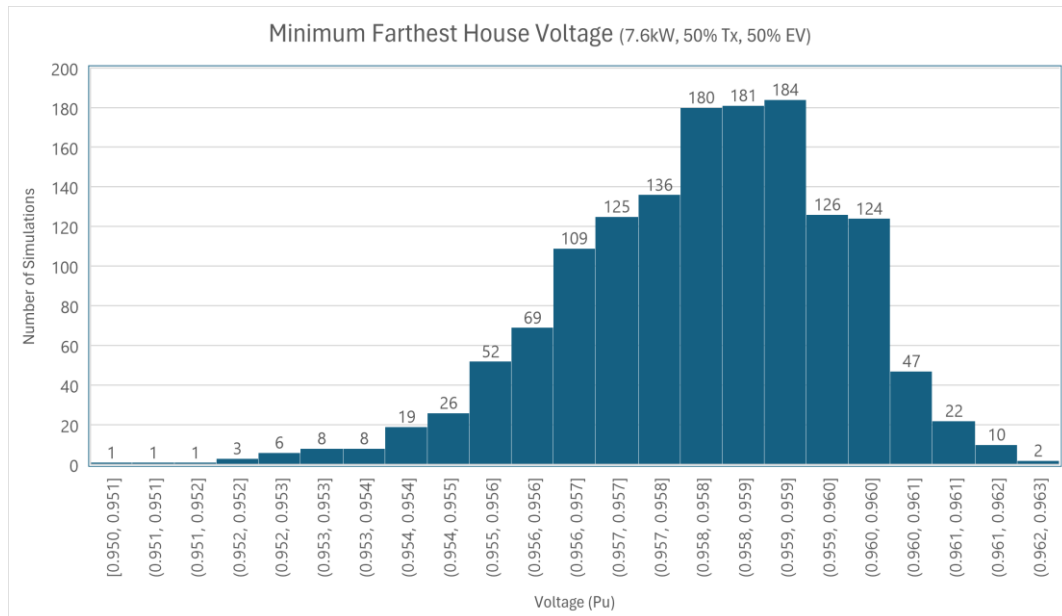


Figure 4.20 Distribution of Minimum Voltage at the Farthest House for 50% EV Penetration (7.6 kW Chargers, 50% Transformer Load)

- **70% simultaneous charging:**

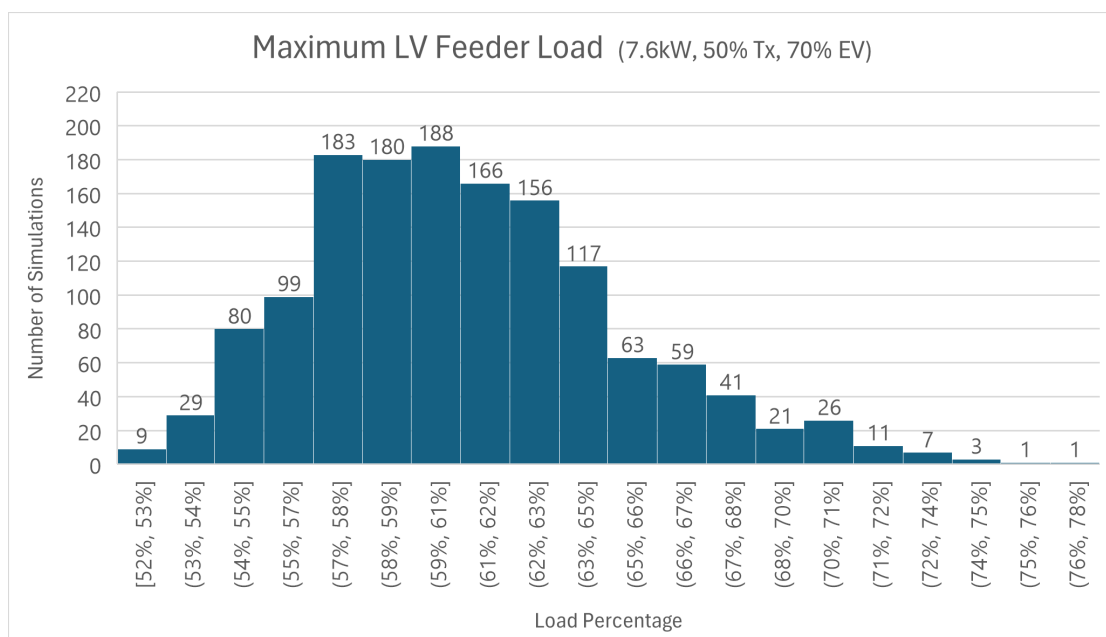


Figure 4.21 Distribution of Maximum LV Feeder Load for 70% EV Penetration (7.6 kW Chargers, 50% Transformer Load)

Figure 4.21 highlights that the most frequent maximum feeder load range is 59%–61%, with 188 simulations. The majority of simulations are concentrated between 54%–67%, accounting for a significant proportion of the results. Lower feeder load levels below 54% are rare, with only 9 simulations recorded in the 52%–53% range. Higher feeder load levels above 68% decrease gradually, with 11 simulations in the 71%–72% range and just 1 simulation recorded in the 76%–78% range.

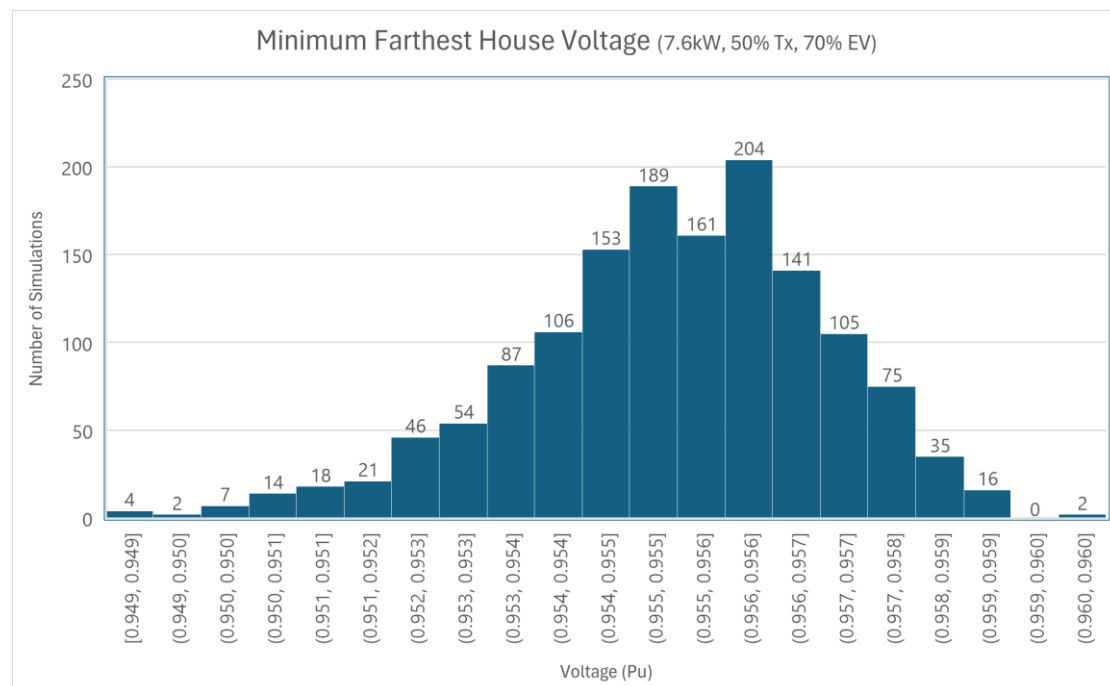


Figure 4.22 Distribution of Minimum Voltage at the Farthest House for 70% EV Penetration (7.6 kW Chargers, 50% Transformer Load)

Figure 4.22 illustrates that the most frequent minimum voltage range is 0.956 pu, with 204 simulations. The majority of simulations are concentrated between 0.953–0.958 pu, accounting for a significant proportion of the results. Lower voltage levels below 0.951 pu are rare, with only 27 simulations recorded in the ranges below 0.951 pu. Higher voltage levels above 0.958 pu decrease gradually, with 16 simulations in the 0.959 pu range and just 2 simulations recorded in the 0.960 pu range.

- **100% simultaneous charging:**

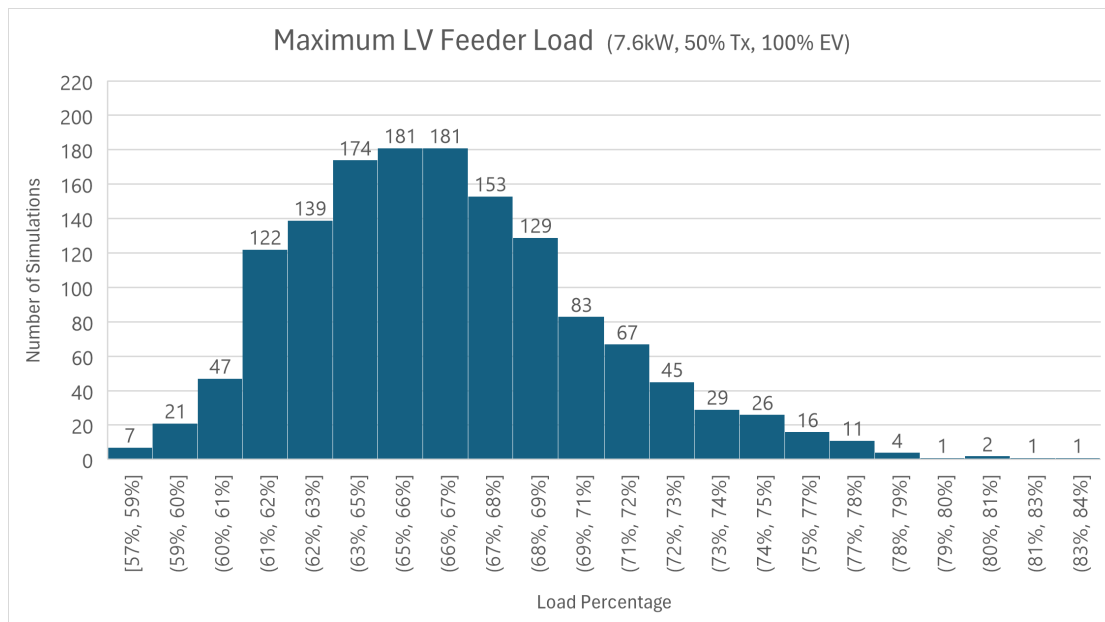


Figure 4.23 Distribution of Maximum LV Feeder Load for 100% EV Penetration (7.6 kW Chargers, 50% Transformer Load)

Figure 4.23 shows that the most frequent maximum feeder load ranges are 65%–66%, and 66%–67% with 181 simulations. The majority of simulations are concentrated between 61%–72%, accounting for a significant proportion of the results. Lower feeder load levels below 60% are rare, with only 7 simulations recorded in the 57%–59% range. Higher feeder load levels above 73% decrease gradually, with 11 simulations in the 77%–78% range and fewer as the feeder load increases, culminating in a single simulation in the 83%–84% range.

Figure 4.24 demonstrates that the most frequent minimum voltage range is 0.952 pu, with 187 simulations. The majority of simulations are concentrated between 0.949–0.954 pu, accounting for a significant proportion of the results. Lower voltage levels below 0.948 pu are rare, with only 3 simulations recorded in the 0.945–0.946 pu range. Higher voltage levels above 0.955 pu decrease gradually, with just 11 simulations recorded in the 0.955–0.956 pu range.

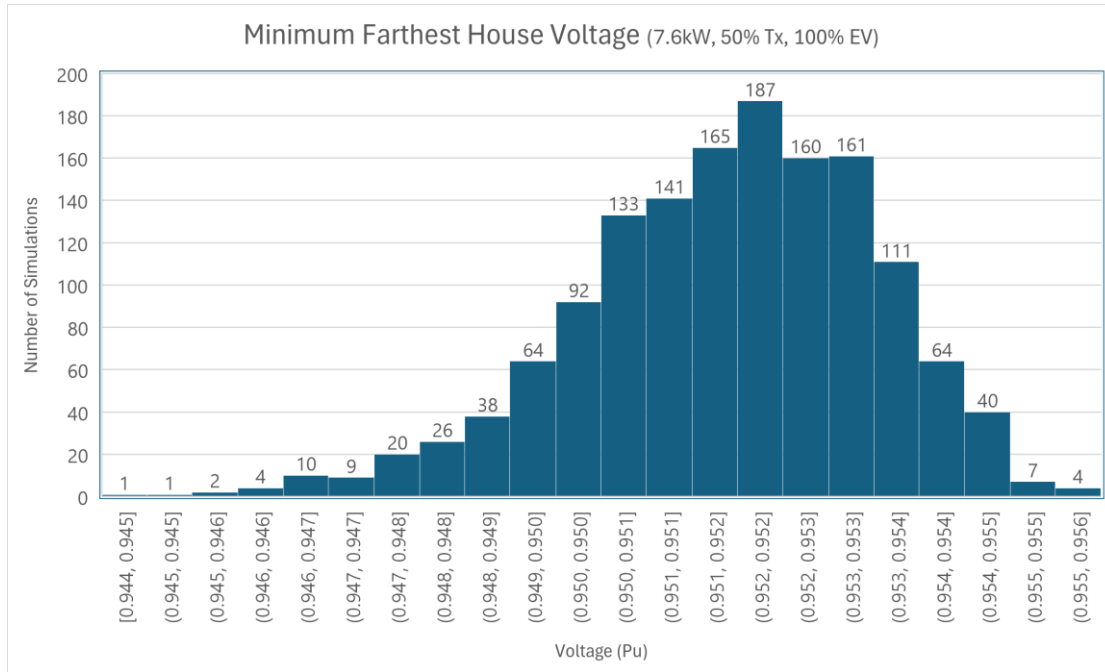


Figure 4.24 Distribution of Minimum Voltage at the Farthest House for 100% EV Penetration (7.6 kW Chargers, 50% Transformer Load)

4.1.3 80% loading scenarios

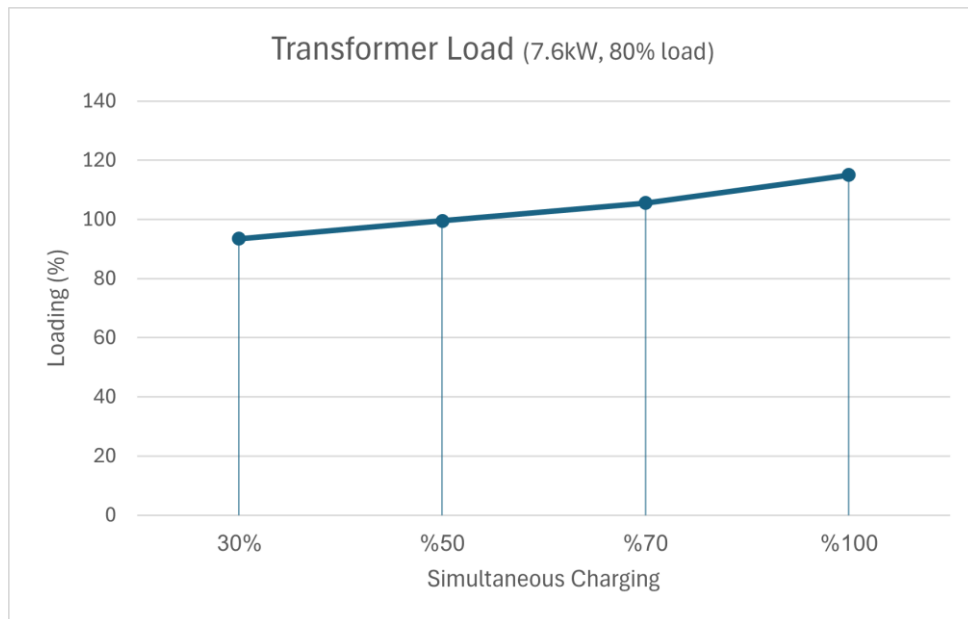


Figure 4.25 Transformer Loading with 80% Base Load and 7.6 kW EV Chargers

For the 80% base load scenario, Figure 4.25 depicts the transformer load under varying levels of simultaneous EV charging (30%, 50%, 70%, and 100%) with 7.6 kW chargers. The initial transformer load starts at 80% due to the base load and increases steadily as EV charging penetration rises.

Notably, at 50% simultaneous charging, the transformer load reaches near 100%, marking the limit of the transformer's capacity. At 100% simultaneous charging, the transformer load exceeds 115%, indicating a significant overloading condition. This underscores the critical need for load management strategies when high base loads are combined with substantial EV integration.

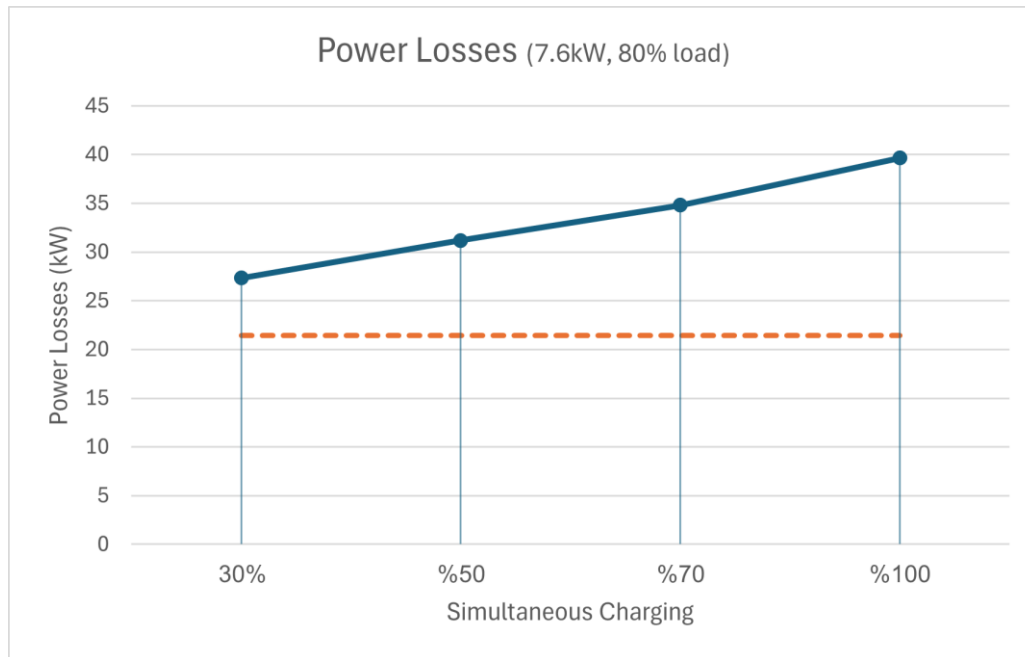


Figure 4.26 Power Losses with 80% Base Load and 7.6 kW EV Chargers

Figure 4.26 illustrates the power losses under varying levels of simultaneous EV charging with 7.6 kW chargers. The power losses increase progressively with higher charging penetration, starting from approximately 27 kW at 30% charging and reaching nearly 40 kW at 100% charging. The orange dashed line represents the baseline power losses without EV charging, which is around 21 kW.

Figure 4.27 demonstrates the maximum LV feeder load under varying levels of simultaneous EV charging. The maximum feeder load increases steadily from approximately 77% at 30% EV penetration to around 90% at 100% simultaneous charging. Notably, the maximum value observed in

this scenario approaches 99%, indicating that the feeder load is nearing its capacity under these conditions.

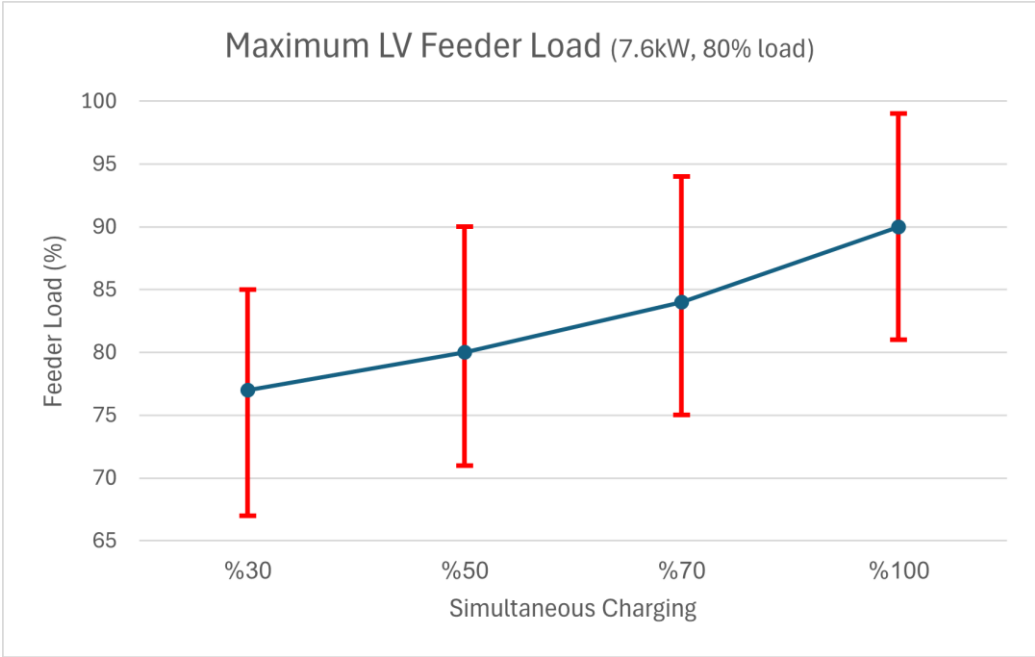


Figure 4.27 Maximum LV Feeder Load with 80% Base Load and 7.6 kW EV Chargers

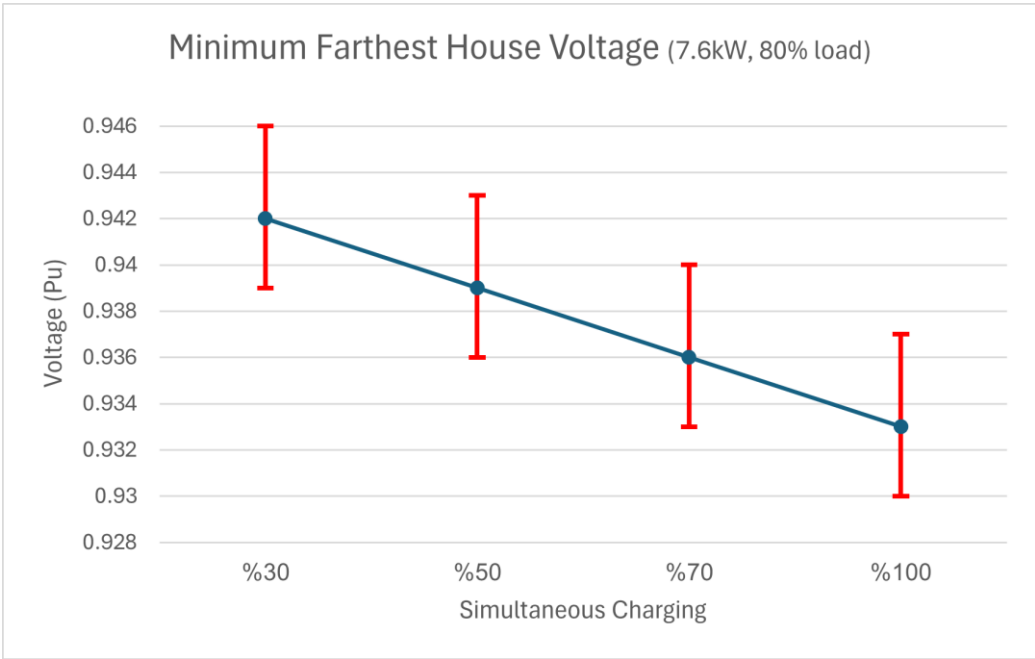


Figure 4.28 Minimum Voltage at the Farthest House with 80% Base Load and 7.6 kW EV Chargers

Figure 4.28 presents the minimum farthest house voltage under varying levels of simultaneous EV charging. The minimum voltage

decreases consistently from approximately 0.942 pu at 30% EV penetration to around 0.933 pu at 100% simultaneous charging. Notably, the voltage drops below the limit of 0.94 pu starting from 50% simultaneous charging, indicating an increased likelihood of voltage violations as the charging levels exceed 30%.

Detailed analysis for each simultaneous charging.

- **30% simultaneous charging:**

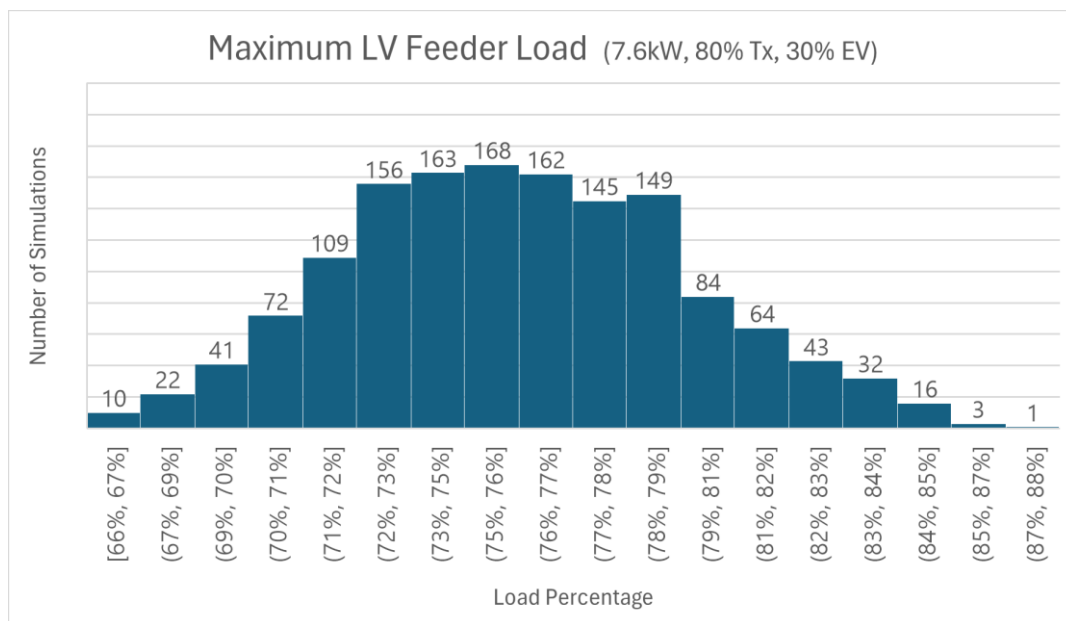


Figure 4.29 Distribution of Maximum LV Feeder Load for 30% EV Penetration (7.6 kW Chargers, 80% Transformer Load)

Figure 4.29 highlights that the most frequent maximum feeder load range is 75%–76%, with 168 simulations. The majority of simulations are concentrated between 70%–81%, accounting for a significant proportion of the results. Lower feeder load levels below 70% are rare, with only 10 simulations recorded in the 66%–67% range. Higher feeder load levels above 81% gradually decrease, with just 1 simulation recorded in the 87%–88% range.

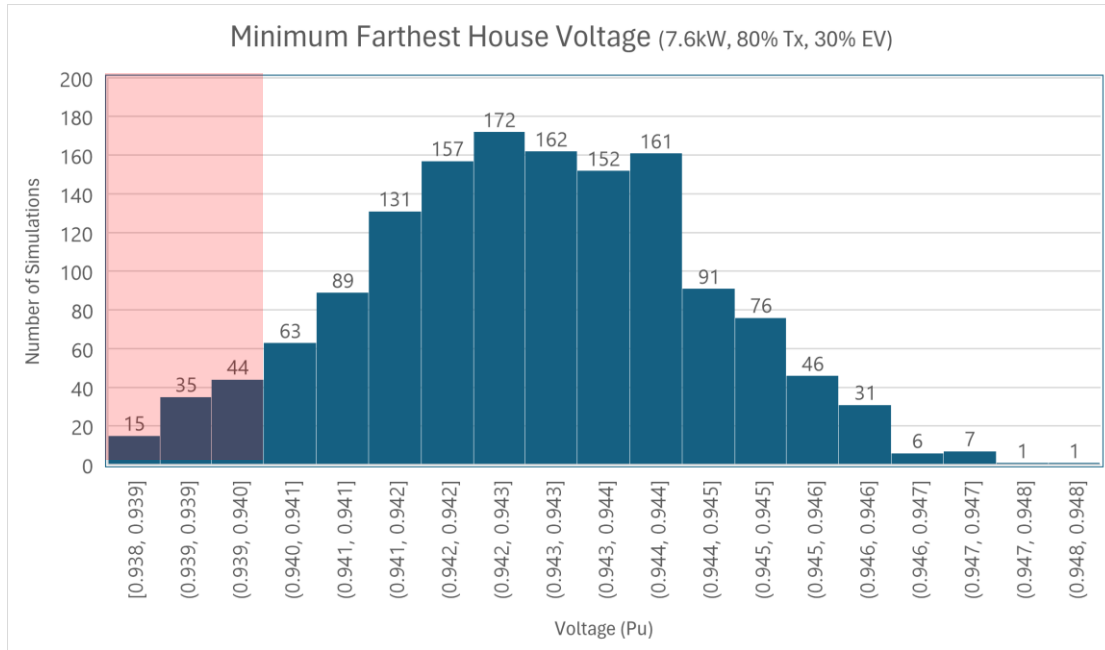


Figure 4.30 Distribution of Minimum Voltage at the Farthest House for 30% EV Penetration (7.6 kW Chargers, 80% Transformer Load)

Figure 4.30 illustrates that the most frequent minimum voltage range is 0.942–0.943 pu, with 491 simulations. The majority of simulations are concentrated between 0.940–0.945 pu, accounting for a significant proportion of the results. Lower voltage levels below 0.940 pu are rare, with only 94 simulations recorded (approximately 6.5%), as indicated in the shaded area. Higher voltage levels above 0.946 pu gradually decrease, with just 2 simulations recorded in the 0.947–0.948 pu range.

- **50% simultaneous charging:**

Figure 4.31 demonstrates that the most frequent maximum LV feeder load range is 79%–80%, with 167 simulations. The majority of simulations are concentrated between 74%–86%, accounting for a significant portion of the results. Lower feeder load levels below 73% are rare, with only 10 simulations recorded in the 70%–72% range. Higher feeder load levels above 86% decrease gradually, with just 1 simulation recorded in the 91%–92% range.

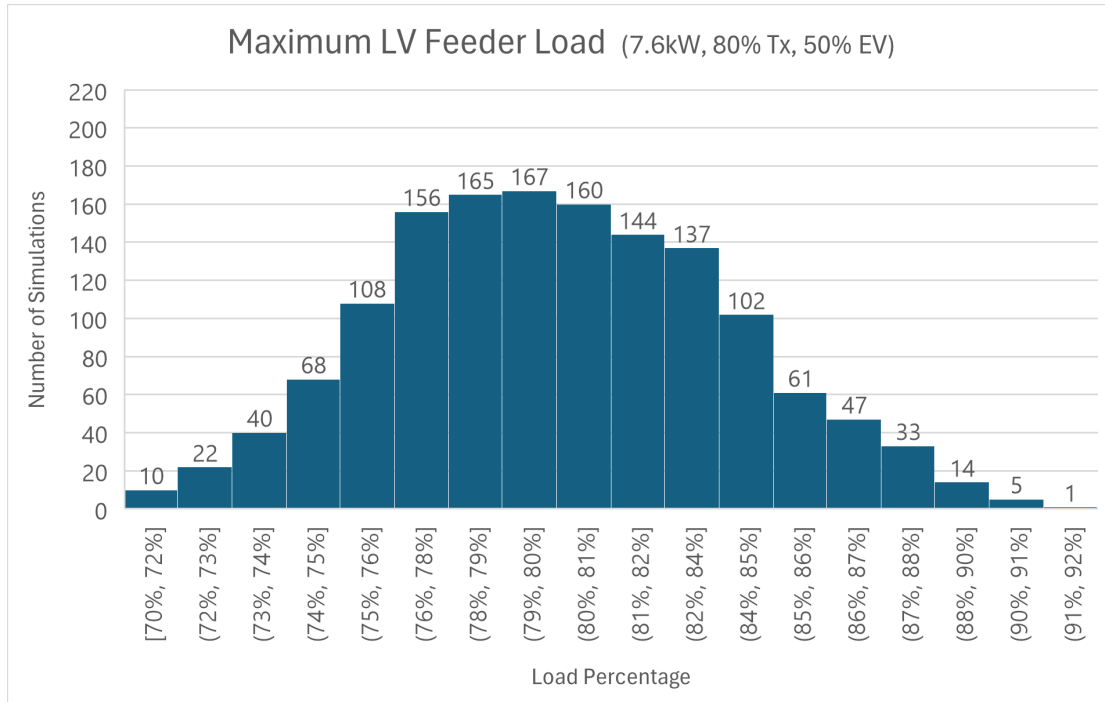


Figure 4.31 Distribution of Maximum LV Feeder Load for 50% EV Penetration (7.6 kW Chargers, 80% Transformer Load)

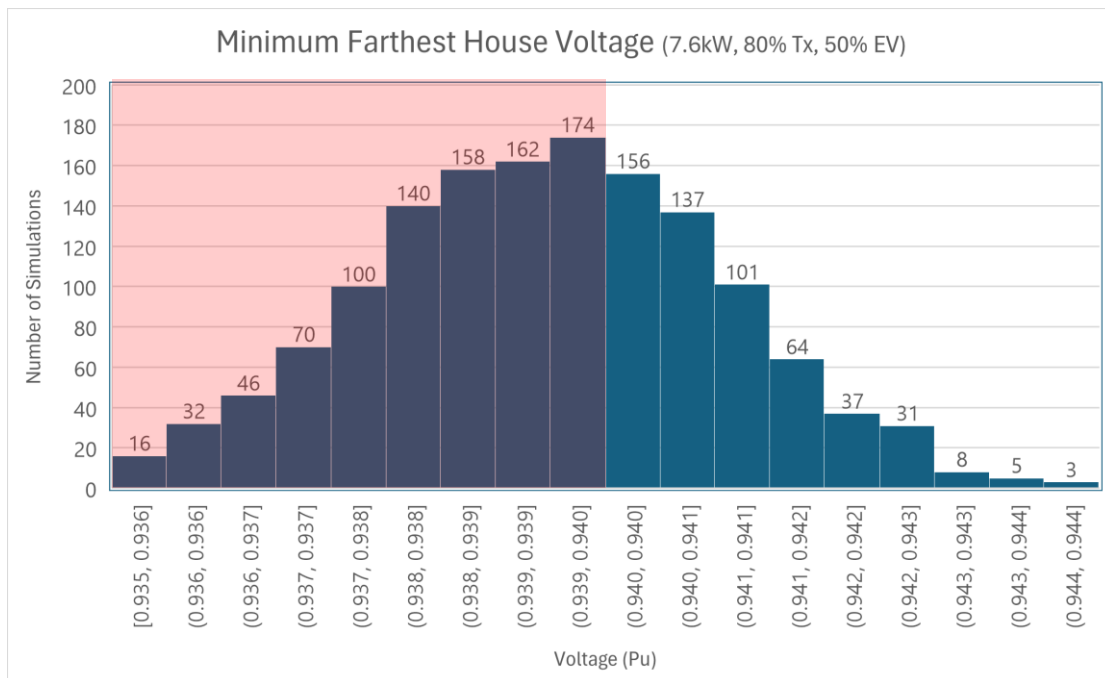


Figure 4.32 Distribution of Minimum Voltage at the Farthest House for 50% EV Penetration (7.6 kW Chargers, 80% Transformer Load)

Figure 4.32 shows that the most frequent minimum voltage range is 0.939–0.940 pu, with 492 simulations. The majority of simulations are concentrated between 0.937–0.941 pu, accounting for a significant

proportion of the results. Lower voltage levels below 0.94 pu are frequent, which represent voltage violations according to standard limits with 898 simulations recorded (around 62%). Higher voltage levels above 0.941 pu gradually decrease, with just 3 simulations recorded in the 0.944 pu range.

- **70% simultaneous charging:**

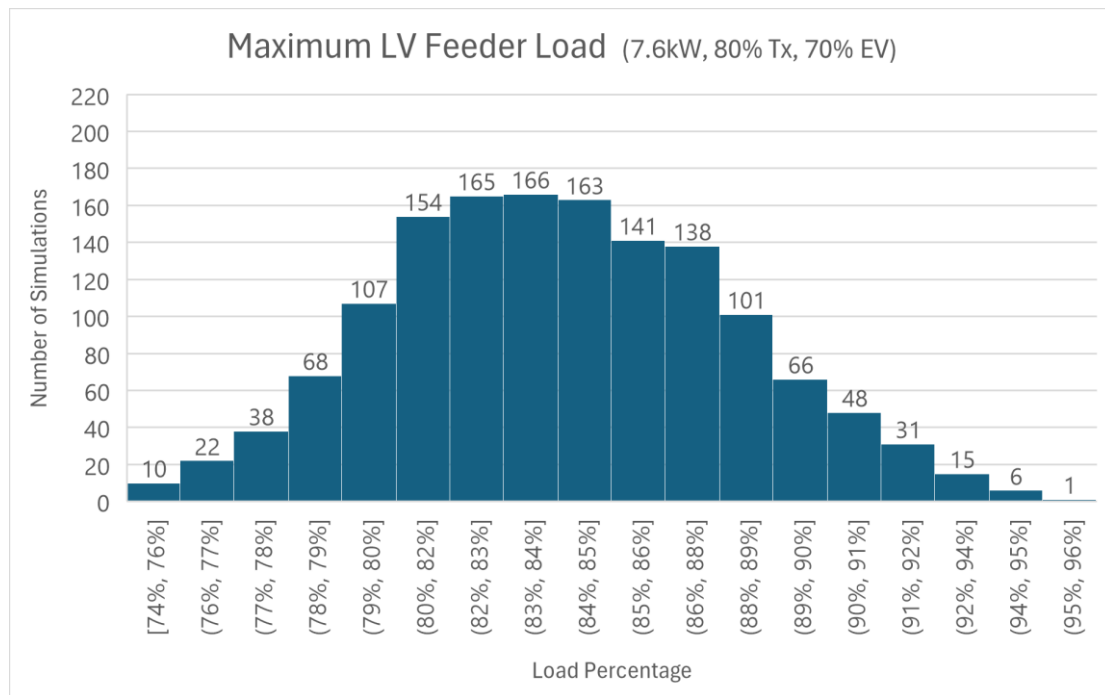


Figure 4.33 Distribution of Maximum LV Feeder Load for 70% EV Penetration (7.6 kW Chargers, 80% Transformer Load)

Figure 4.33 presents that the most frequent maximum feeder load range is 83%–84%, with 166 simulations. The majority of simulations are concentrated between 78%–90%, encompassing a significant proportion of the results. Lower feeder load levels below 77% are infrequent, with only 10 simulations recorded in the 74%–76% range. Higher feeder load levels above 90% gradually decrease, with just 1 simulation recorded in the 95%–96% range.

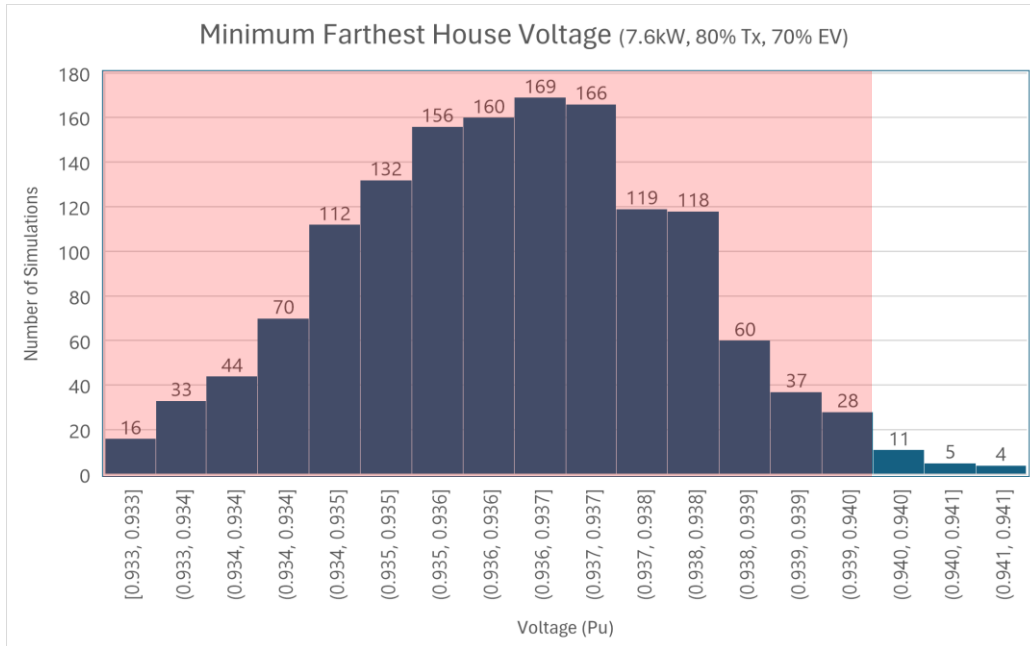


Figure 4.34 Distribution of Minimum Voltage at the Farthest House for 70% EV Penetration (7.6 kW Chargers, 80% Transformer Load)

Figure 4.34 illustrates that the majority of the simulations fall below 0.94 pu, highlighting a significant occurrence of voltage levels under the acceptable limit.

- **100% simultaneous charging:**

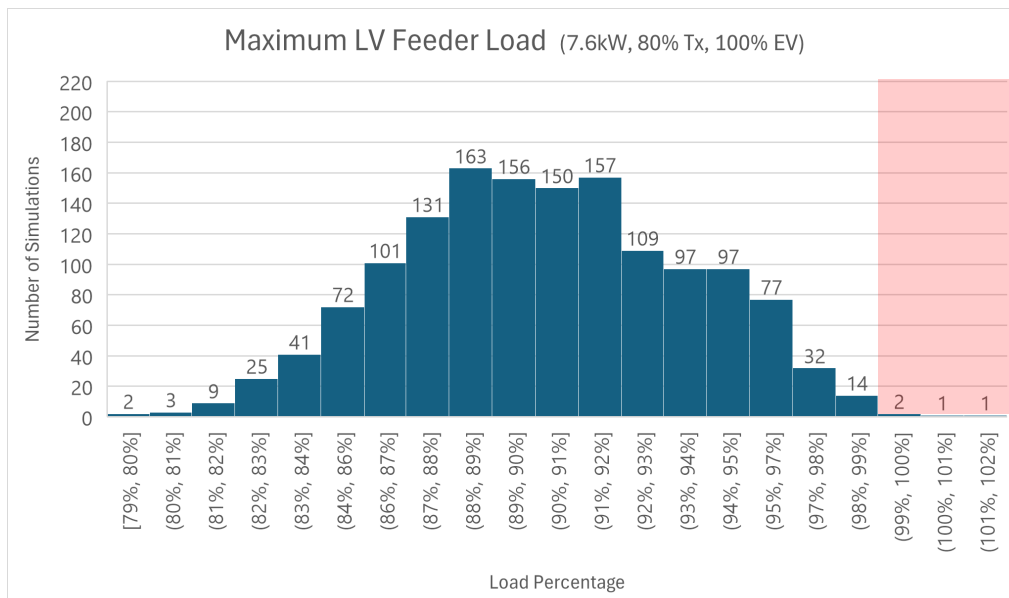


Figure 4.35 Distribution of Maximum LV Feeder Load for 100% EV Penetration (7.6 kW Chargers, 80% Transformer Load)

Figure 4.35 presents that the most frequent maximum LV feeder load range is 88%–89%, with 163 simulations. The majority of simulations are concentrated between 84%–97%, accounting for a significant proportion of the results. Higher load levels above 97% become increasingly rare, with only 14 simulations recorded in the 98%–99% range, and just 1 simulation observed in the 101%–102% range, indicating an overload condition. Lower load levels below 83% are also infrequent, with only 2 simulations recorded in the 79%–80% range.

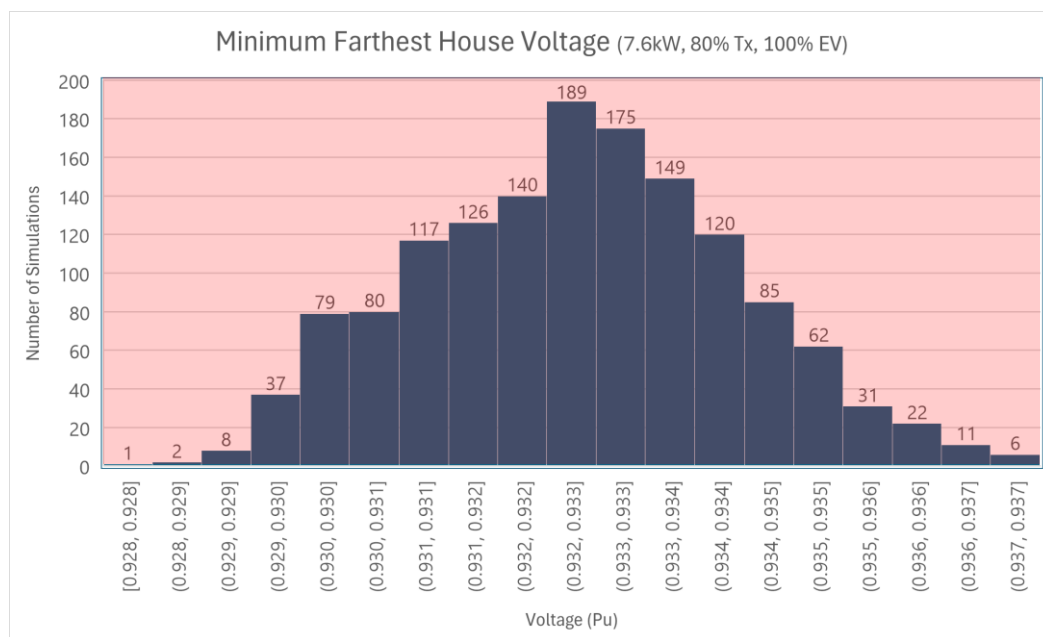


Figure 4.36 Distribution of Minimum Voltage at the Farthest House for 100% EV Penetration (7.6 kW Chargers, 80% Transformer Load)

Figure 4.36 shows that for the 7.6 kW, 80% transformer loading, and 100% EV scenario, all simulations resulted in voltages below the 0.94 pu limit, indicating consistent voltage violations under these conditions.

4.2 Impact of 11kW EV chargers

The following section explores the impact of 11 kW chargers on the distribution network under similar conditions, providing insight into the increased challenges posed by higher charging capacities.

4.2.1 30% loading scenarios

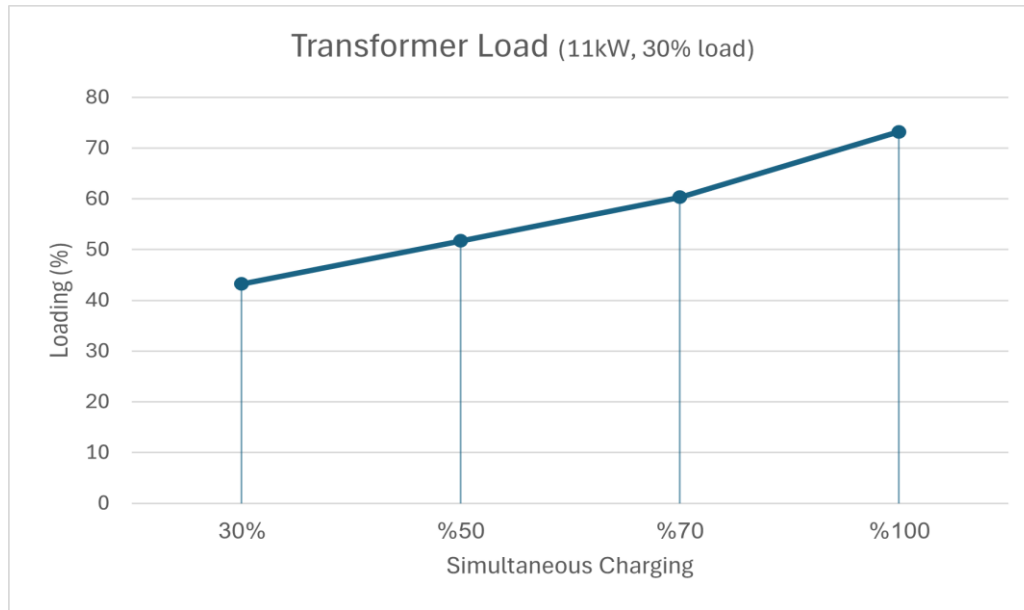


Figure 4.37 Transformer Loading with 30% Base Load and 11 kW EV Chargers

Figure 4.37 demonstrates the transformer load under the 11 kW charger condition for a 30% base load. As simultaneous EV charging increases from 30% to 100%, the transformer load rises linearly, starting at approximately 42% and reaching nearly 71%. This indicates that the transformer is operating well within its capacity, with no signs of overloading in this base load scenario. The results suggest that at lower base loads, the integration of 11 kW chargers has a manageable impact on transformer utilization.

Figure 4.38 highlights the power losses under varying levels of simultaneous EV charging with 11 kW chargers at a 30% base load. The power losses increase progressively with higher charging penetration, starting from approximately 6.5 kW at 30% charging and reaching nearly 16 kW at 100% charging. The orange dashed line represents the baseline power losses without EV charging, which is around 3 kW.

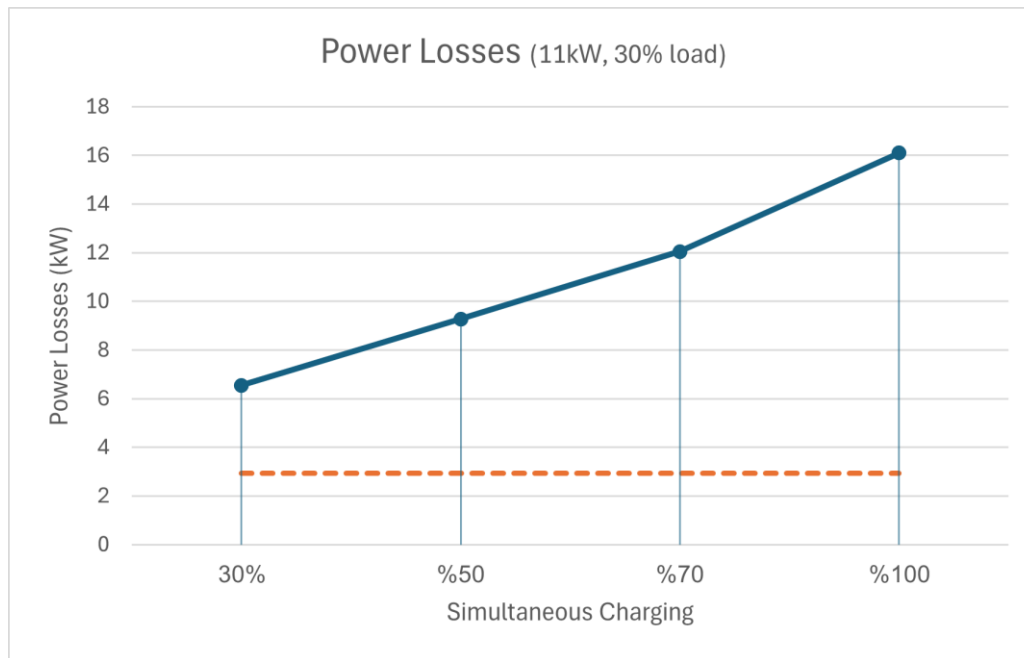


Figure 4.38 Power Losses with 30% Base Load and 11 kW EV Chargers

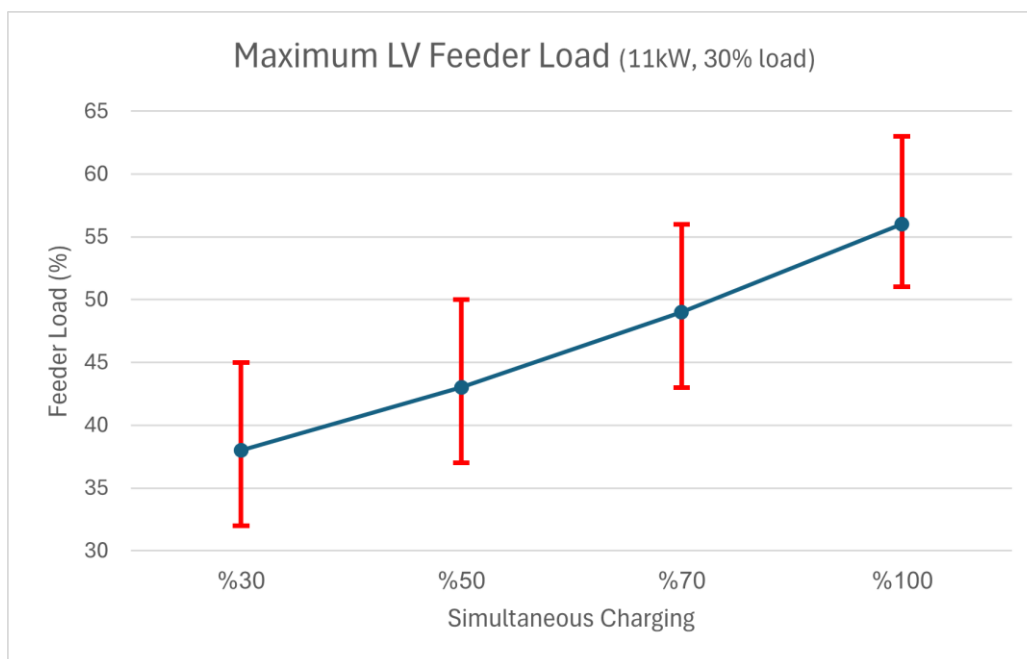


Figure 4.39 Maximum LV Feeder Load with 30% Base Load and 11 kW EV Chargers

Figure 4.39 presents the maximum LV feeder load under varying levels of simultaneous EV charging with 11 kW chargers at a 30% base load. The feeder load increases steadily, starting from approximately 38% at 30% charging and reaching nearly 56% at 100% charging. The

maximum loading of the LV feeder under these conditions remains within the acceptable limits.

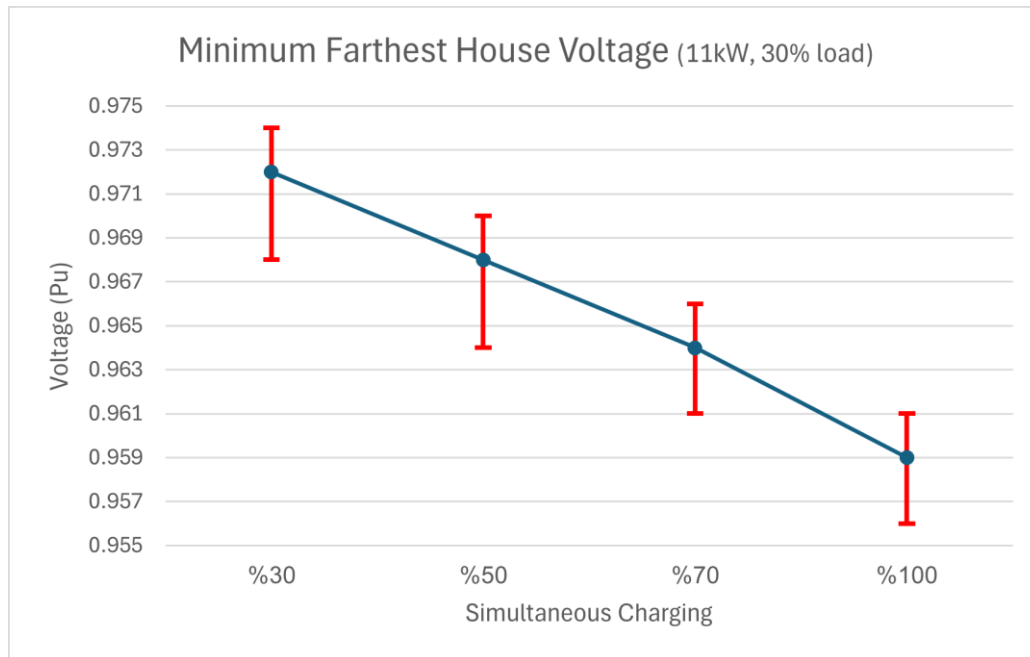


Figure 4.40 Minimum Voltage at the Farthest House with 30% Base Load and 11 kW EV Chargers

Figure 4.40 depicts the minimum voltage at the farthest house under varying levels of simultaneous EV charging with 11 kW chargers and a 30% base load. The voltage decreases progressively with higher charging penetration, starting at approximately 0.972 pu at 30% charging and dropping to 0.959 pu at 100% charging. All voltage levels remain above the acceptable limit of 0.94 pu in this scenario.

Detailed analysis for each simultaneous charging.

- **30% simultaneous charging:**

Figure 4.41 shows the maximum LV feeder load distribution for the scenario with 11 kW chargers, 30% transformer base load, and 30% EV penetration. The most frequent load range is between 37%–38%, with 196 simulations recorded. The majority of simulations fall within the range of 33%–42%, indicating that under these conditions, the LV feeder load

remains relatively moderate. Higher load levels, exceeding 43%, are rare, with only a few simulations reaching up to 48%.

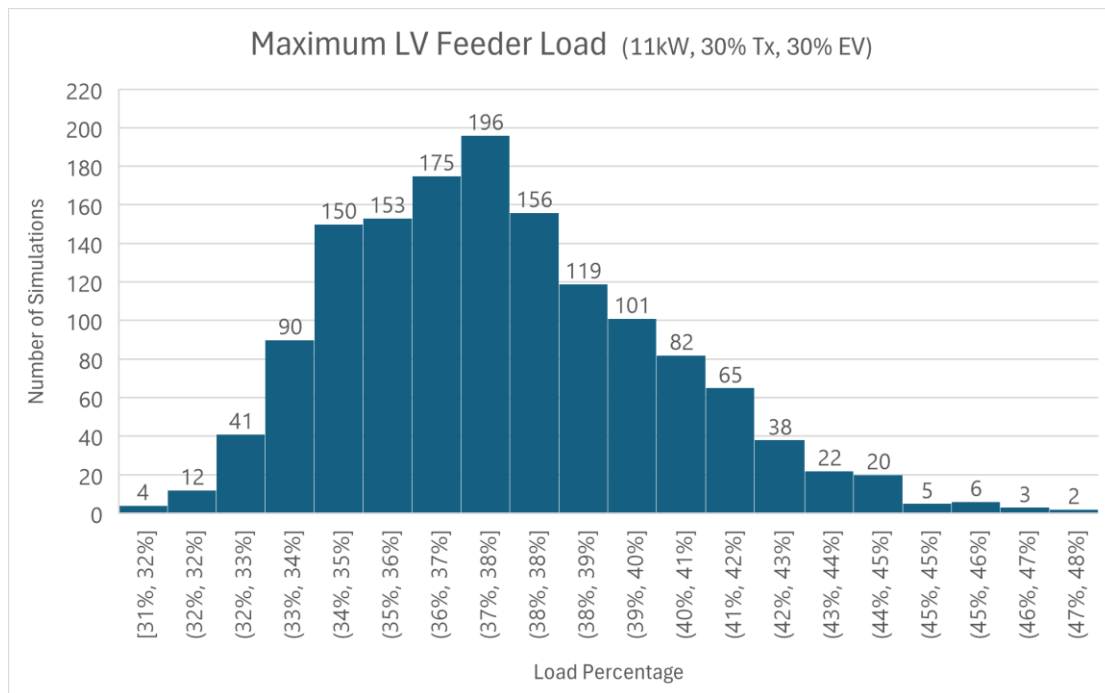


Figure 4.41 Distribution of Maximum LV Feeder Load for 30% EV Penetration (11kW Chargers, 30% Transformer Load)

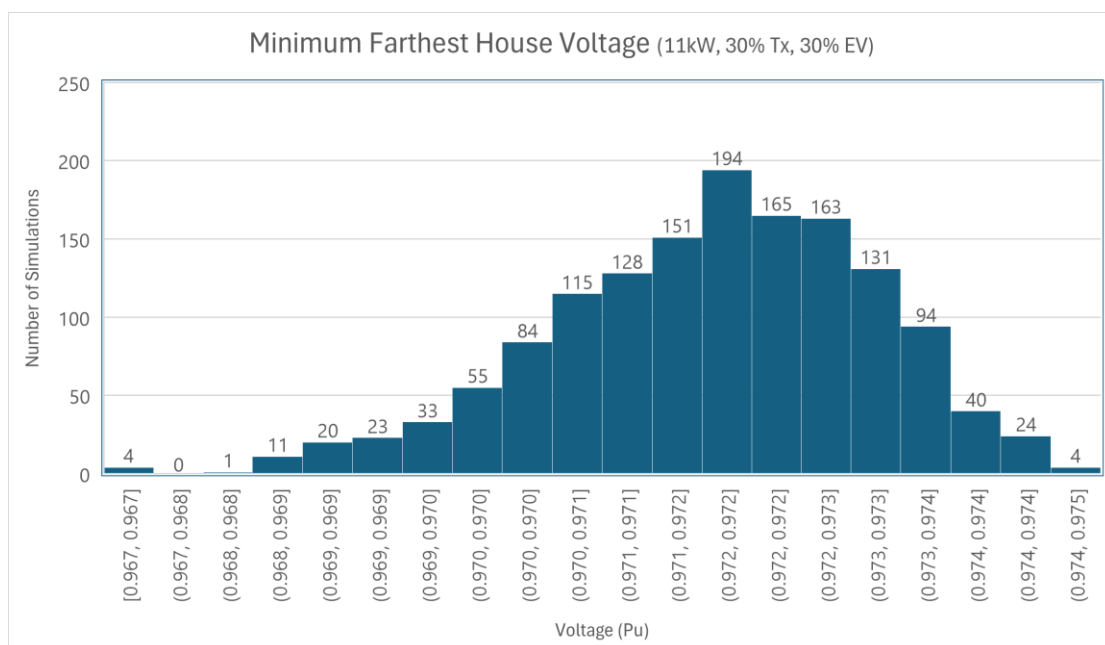


Figure 4.42 Distribution of Minimum Voltage at the Farthest House for 30% EV Penetration (11 kW Chargers, 30% Transformer Load)

In figure 4.42, the most frequent voltage range is 0.972 pu, with 194 simulations recorded. The majority of the simulations are concentrated between 0.970–0.974 pu, demonstrating a stable voltage profile under these conditions.

- **50% simultaneous charging:**

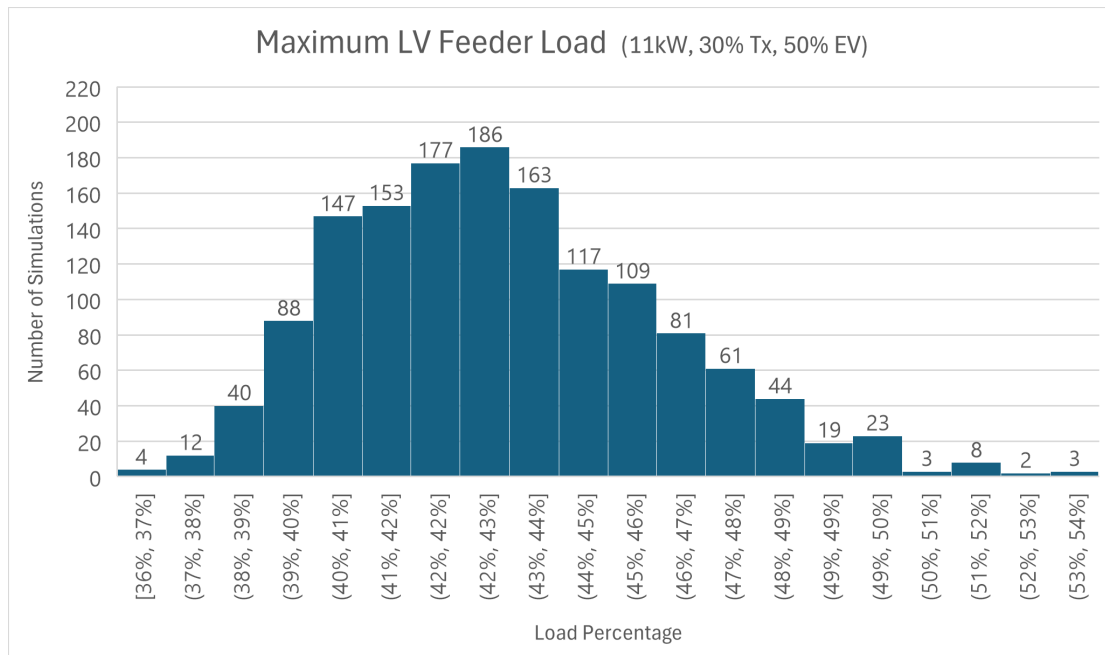


Figure 4.43 Distribution of Maximum LV Feeder Load for 50% EV Penetration (11kW Chargers, 30% Transformer Load)

Figure 4.43 demonstrates that the most frequent maximum feeder load range is 42%–43%, with 186 simulations. The majority of simulations fall between 39%–48%, encompassing a substantial portion of the results. Lower feeder load levels below 39% are infrequent. Higher feeder load levels above 49% gradually decrease, with just 3 simulations recorded in the 52%–54% range.

In figure 4.44, the majority of simulations fall between 0.966–0.969 pu, indicating a relatively consistent voltage performance under these

conditions. Voltage levels below 0.965 pu are rare, with only a small number of simulations, such as 26 simulations in the 0.964–0.965 pu range.

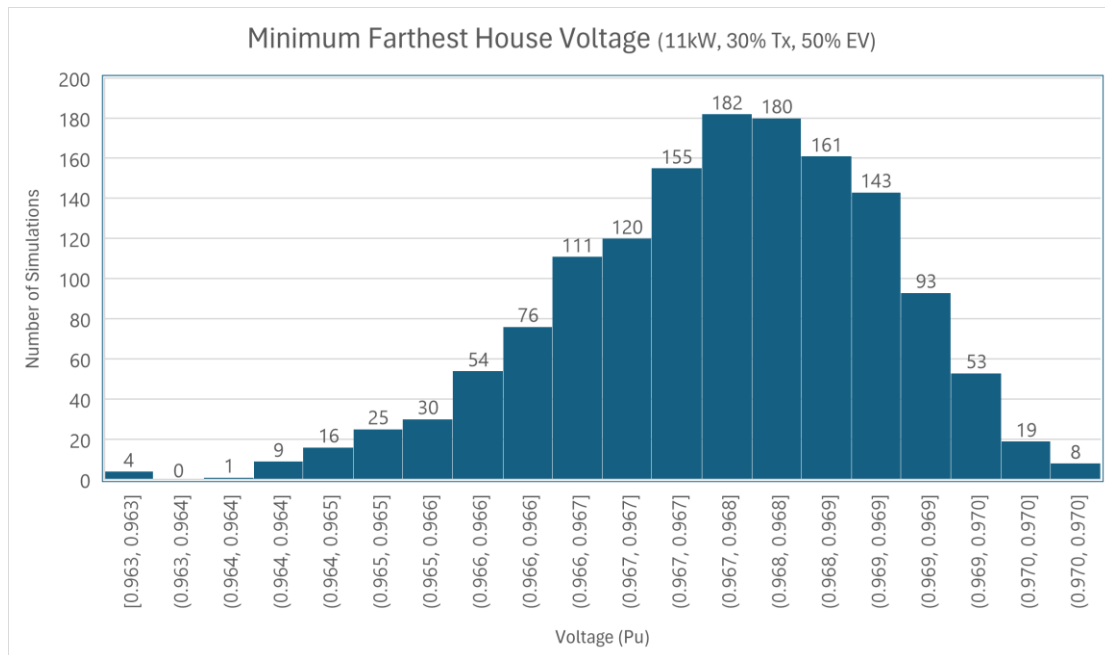


Figure 4.44 Distribution of Minimum Voltage at the Farthest House for 50% EV Penetration (11 kW Chargers, 30% Transformer Load)

- **70% simultaneous charging:**

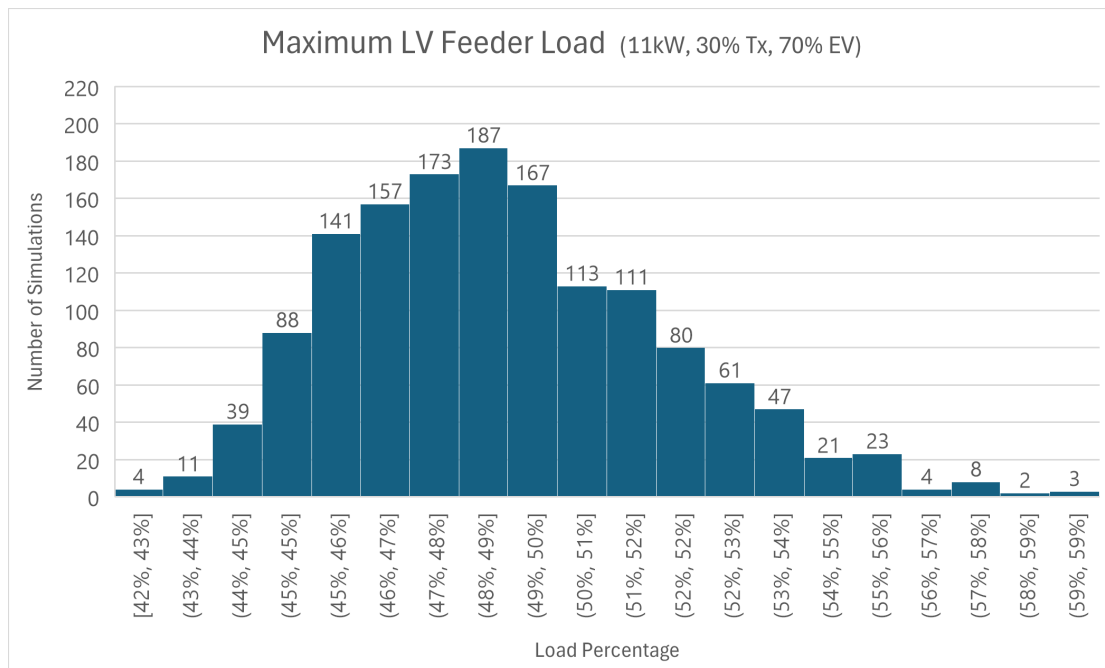


Figure 4.45 Distribution of Maximum LV Feeder Load for 70% EV Penetration (11kW Chargers, 30% Transformer Load)

Figure 4.45 demonstrates that the most frequent maximum feeder load range is 48%–49%, with 187 simulations. The majority of simulations fall between 45%–53%, encompassing a substantial portion of the results. Lower feeder load levels below 44% are infrequent. Higher feeder load levels above 50% gradually decrease, with just 3 simulations recorded in the 59% range.

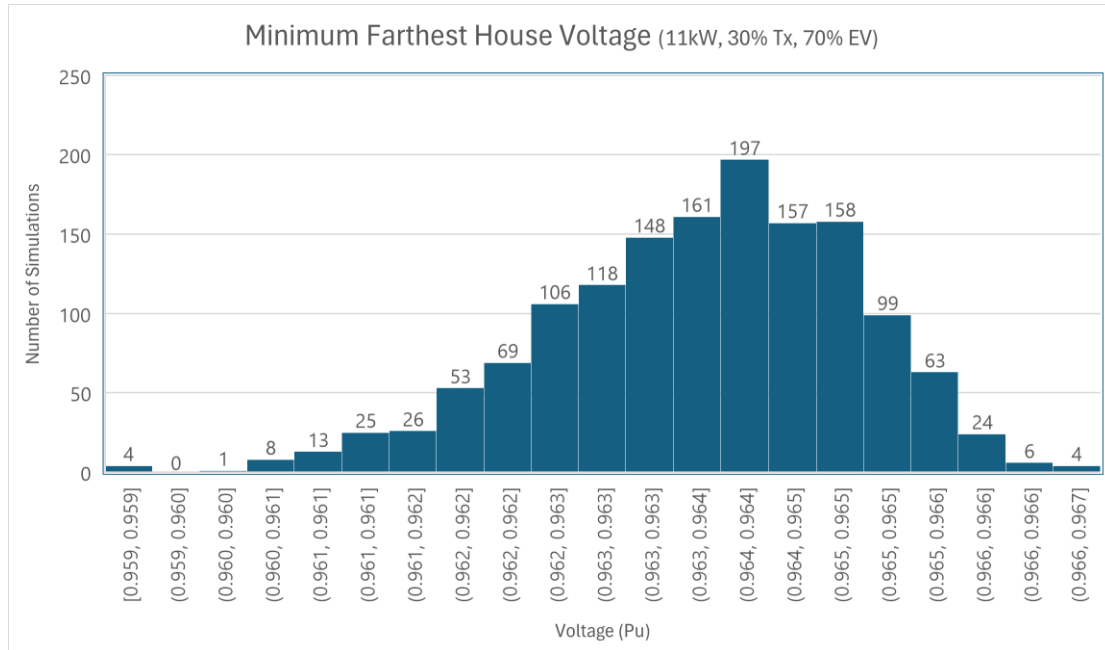


Figure 4.46 Distribution of Minimum Voltage at the Farthest House for 70% EV Penetration (11kW Chargers, 30% Transformer Load)

In figure 4.46, most simulations are clustered within the 0.962–0.966 pu range, showcasing stable voltage behavior under these conditions. Lower voltage levels, particularly below 0.961 pu, are uncommon, with minimal occurrences where only 13 simulations observed.

- **100% simultaneous charging:**

In Figure 4.47, the most frequent maximum LV feeder load falls within the range of 55%–56%, recorded in 193 simulations. The majority of simulations are concentrated between 52%–60%, accounting for a substantial portion of the results. Lower feeder load levels below 52% are

less common. Higher load levels above 58% gradually diminish, with just 1 simulation reaching the 67% range.

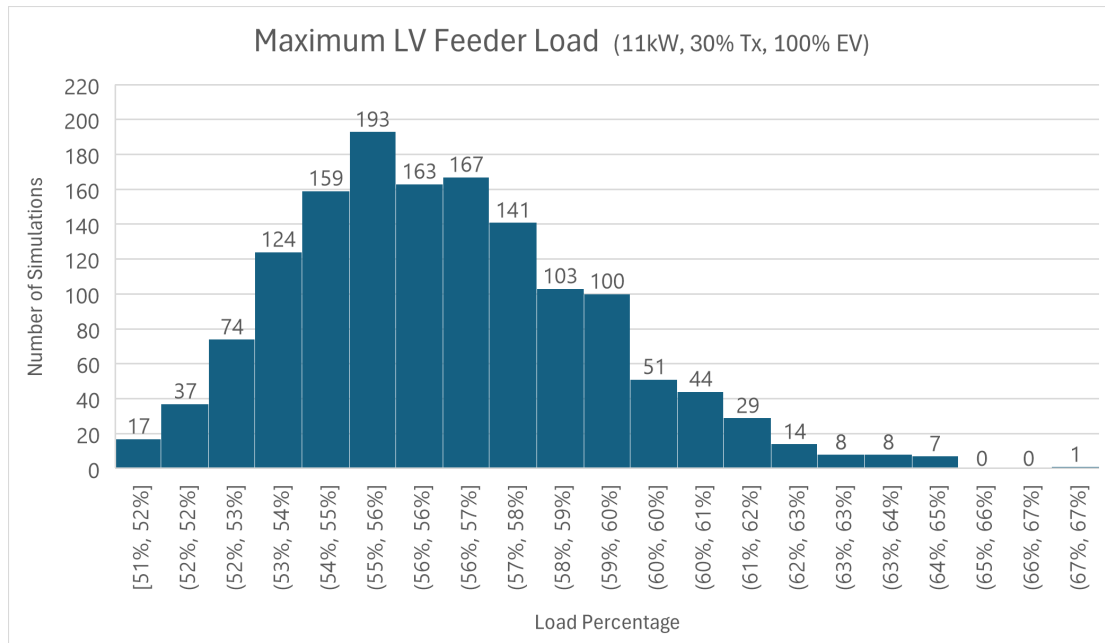


Figure 4.47 Distribution of Maximum LV Feeder Load for 100% EV Penetration (11kW Chargers, 30% Transformer Load)

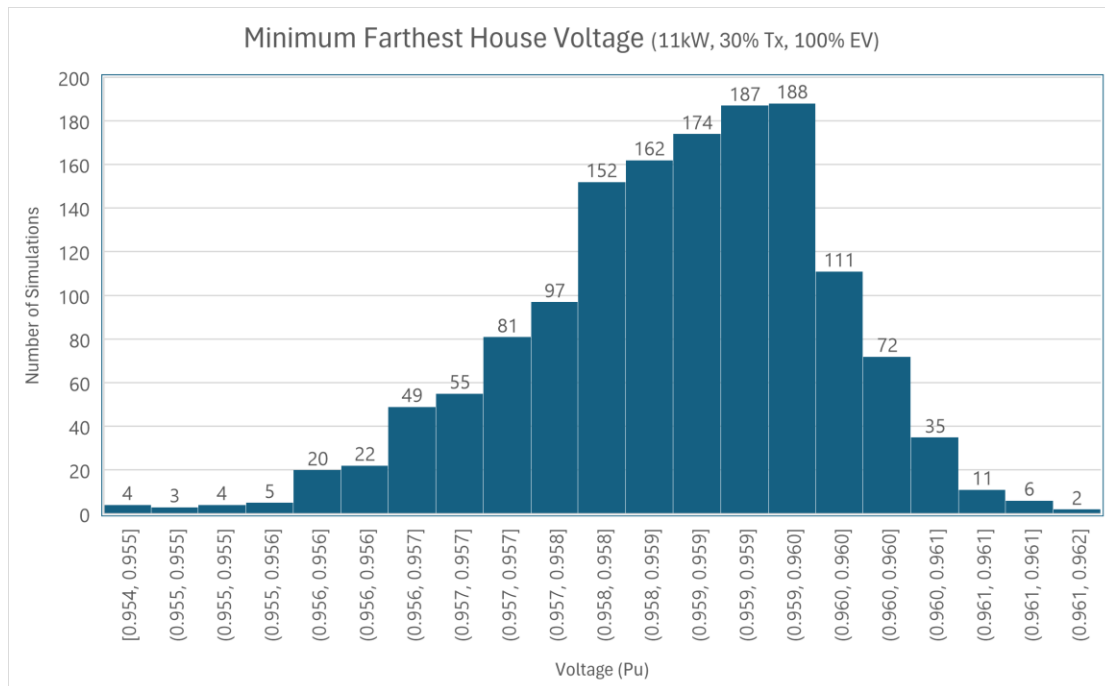


Figure 4.48 Distribution of Minimum Voltage at the Farthest House for 100% EV Penetration (11 kW Chargers, 30% Transformer Load)

In Figure 4.48, the voltage distribution is predominantly clustered between 0.957–0.960 pu. Voltage levels below 0.955 pu are relatively rare,

with only 4 simulations. Higher voltage levels above 0.961 pu are also infrequent.

4.2.2 50% loading scenarios

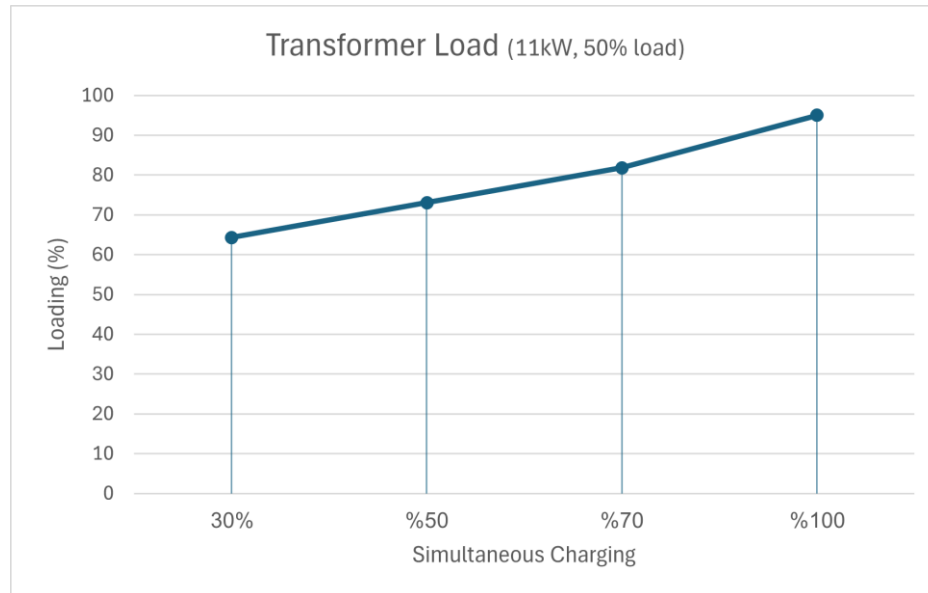


Figure 4.49 Transformer Loading with 50% Base Load and 11 kW EV Chargers

Figure 4.49 illustrates the transformer load under the 11 kW charger condition for a 50% base load scenario. As simultaneous EV charging penetration increases from 30% to 100%, the transformer load steadily rises, starting from approximately 65% and peaking at nearly 95%. This indicates that while the transformer approaches its higher capacity limit at 100% simultaneous charging, it remains within acceptable operating conditions.

Figure 4.48 highlights the trend of increasing power losses as simultaneous EV charging penetration rises under the 11 kW charger condition at a 50% base load. The power losses start at approximately 14 kW at 30% charging and reach close to 27 kW at full (100%) charging. The baseline losses, represented by the orange dashed line which is 8.5 kW.

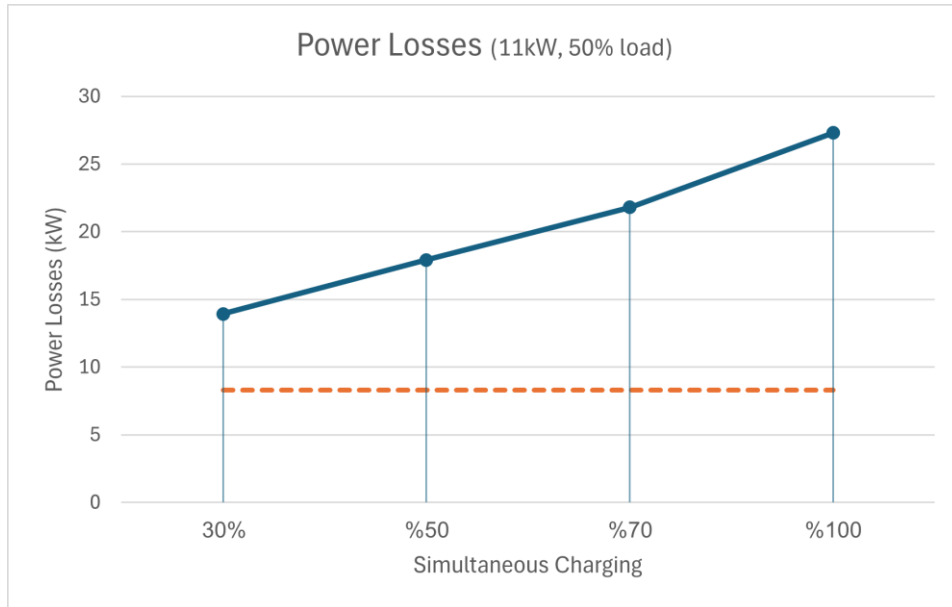


Figure 4.50 Power Losses with 50% Base Load and 11 kW EV Chargers

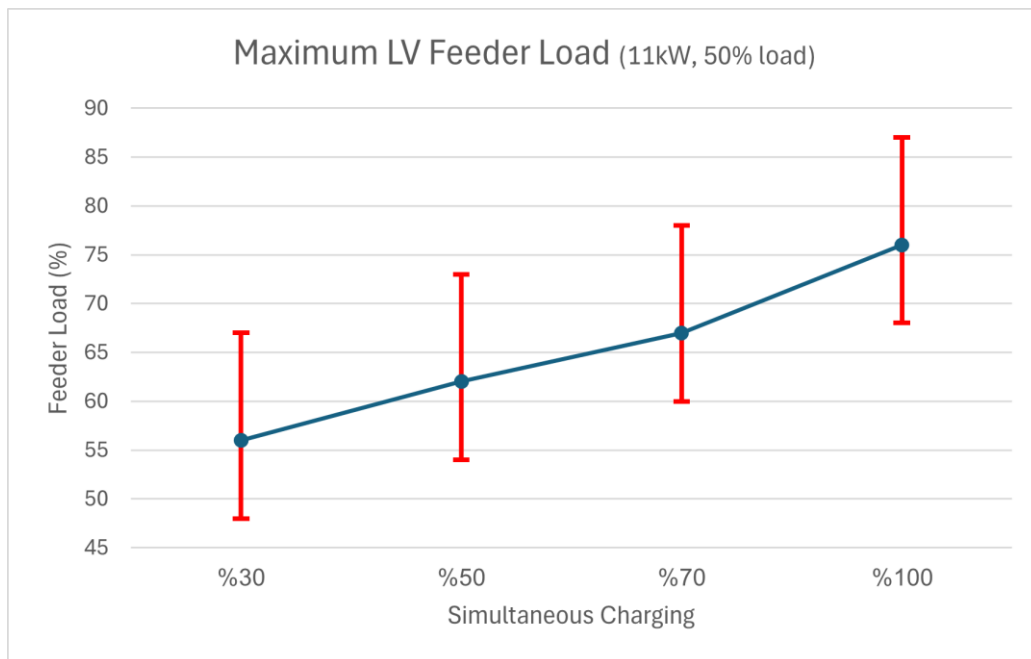


Figure 4.51 Maximum LV Feeder Load with 50% Base Load and 11 kW EV Chargers

Figure 4.51 displays the maximum LV feeder load under the 11 kW charger condition with a 50% base load. At 30% charging, the average load is around 56%, while at 100% charging, it approaches 76%. Notably, the maximum loading reached in this scenario is less than 93% that even with higher penetration of EV charging, the feeder operates within acceptable limits without exceeding critical thresholds.

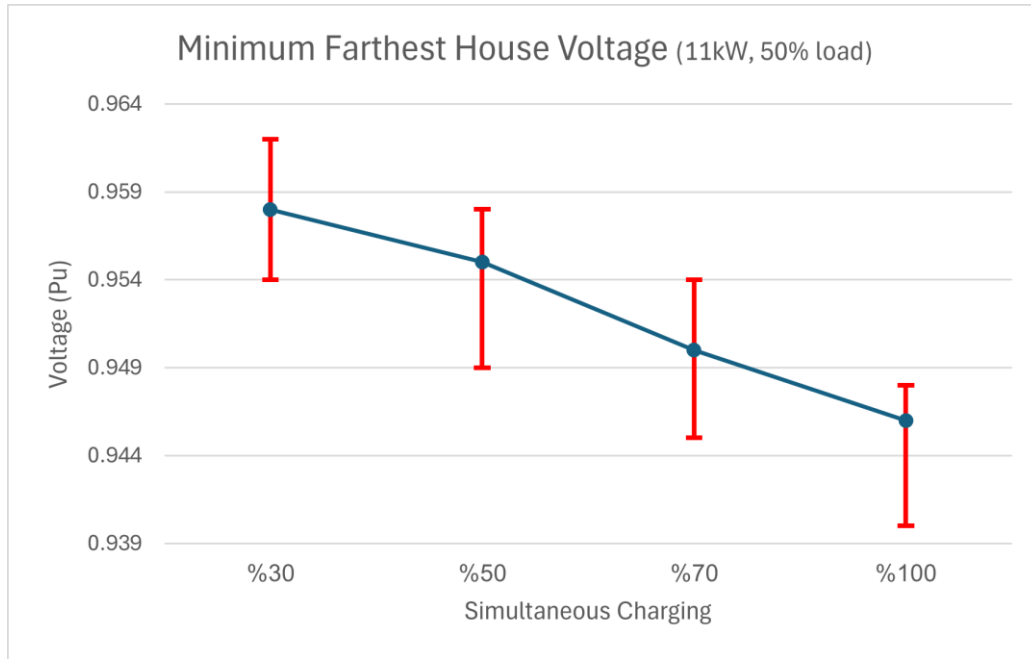


Figure 4.52 Minimum Voltage at the Farthest House with 50% Base Load and 11 kW EV Chargers

Figure 4.52 presents the minimum voltage observed at the farthest house under the 11 kW charger condition with a 50% base load. The voltage consistently decreases as simultaneous EV charging increases from 30% to 100%. At 30% charging, the voltage is approximately 0.958 pu, but it drops to around 0.946 pu at 100% charging. There is a likelihood that the voltage could drop below 0.94 pu under these conditions.

Detailed analysis for each simultaneous charging.

- **30% simultaneous charging:**

Figure 4.53 shows that the most frequent maximum LV feeder load range is 53%–54%, occurring in 188 simulations. The majority of simulations are clustered between 49%–61%, representing a substantial portion of the results. Higher load levels above 61% are progressively less frequent, with only 12 simulations recorded in the 65%–66% range, and just 1 simulation observed in the 74%–75% range. Similarly, lower load

levels below 49% are relatively rare, with only 3 simulations recorded in the 45%–47% range.

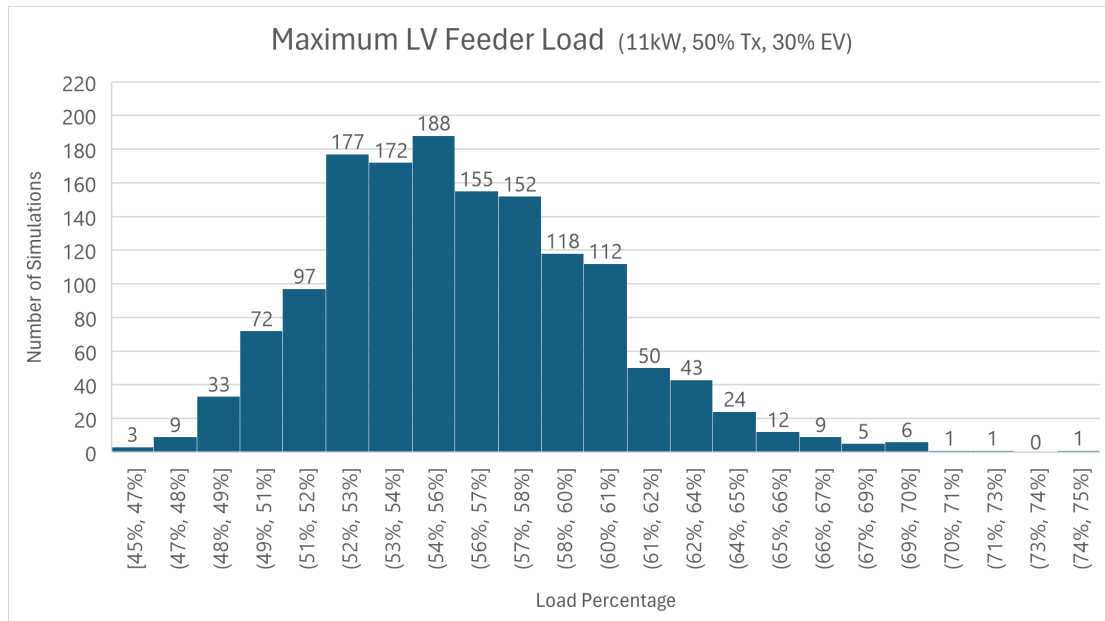


Figure 4.53 Distribution of Maximum LV Feeder Load for 30% EV Penetration (11kW Chargers, 50% Transformer Load)

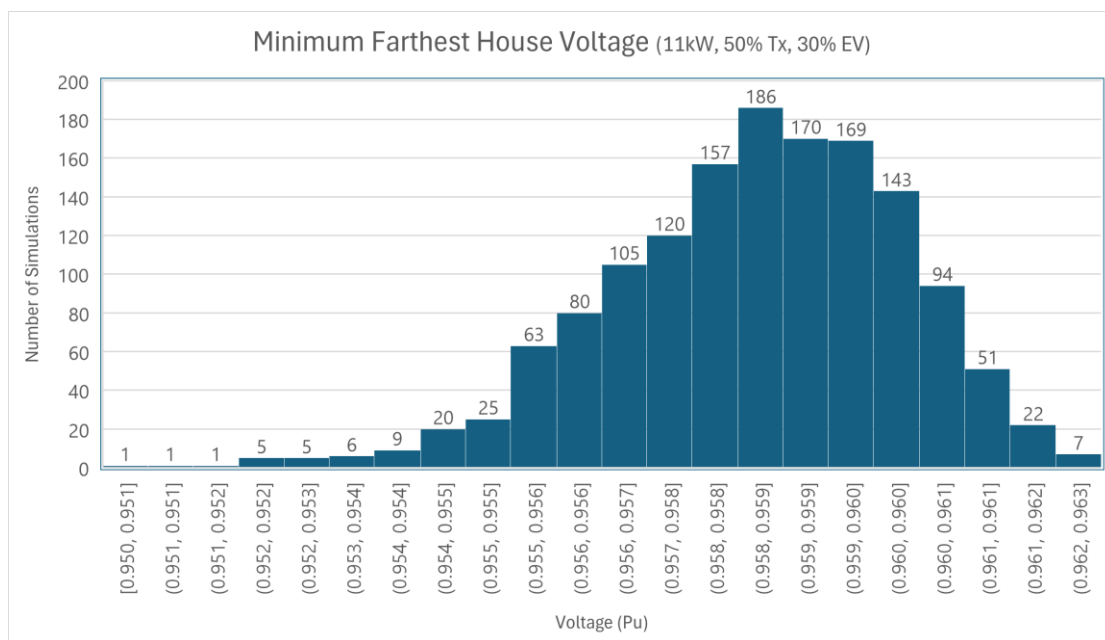


Figure 4.54 Distribution of Maximum LV Feeder Load for 30% EV Penetration (11kW Chargers, 30% Transformer Load)

Figure 4.54 reveals that the most frequent voltage range for the majority of simulations are concentrated between 0.955–0.961 pu,

representing the bulk of the results. Voltage levels below 0.954 pu are rare, with only 1 simulation recorded below 0.951 pu.

- **50% simultaneous charging:**

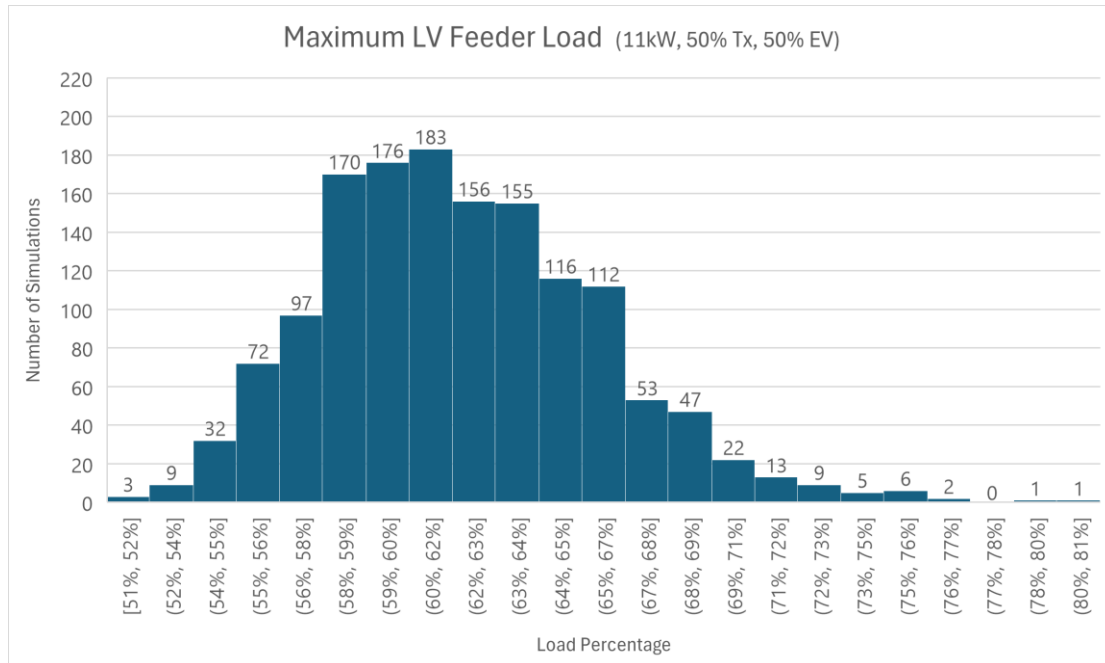


Figure 4.55 Distribution of Maximum LV Feeder Load for 50% EV Penetration (11kW Chargers, 50% Transformer Load)

Figure 4.55 presents that the most frequent maximum feeder load range is 60%–62%, with 183 simulations. The majority of simulations are concentrated between 55%–68%, encompassing a significant proportion of the results. Lower feeder load levels below 54% are infrequent. Higher feeder load levels above 69% gradually decrease, with just 1 simulation recorded in the 80%–81% range.

Figure 4.56 illustrates that the majority of simulations are concentrated between 0.951–0.957 pu, covering a significant portion of the results. Lower voltage levels below 0.950 pu are infrequent, with only 2 simulations recorded below 0.947 pu range. Higher voltage levels above 0.956 pu are infrequent.

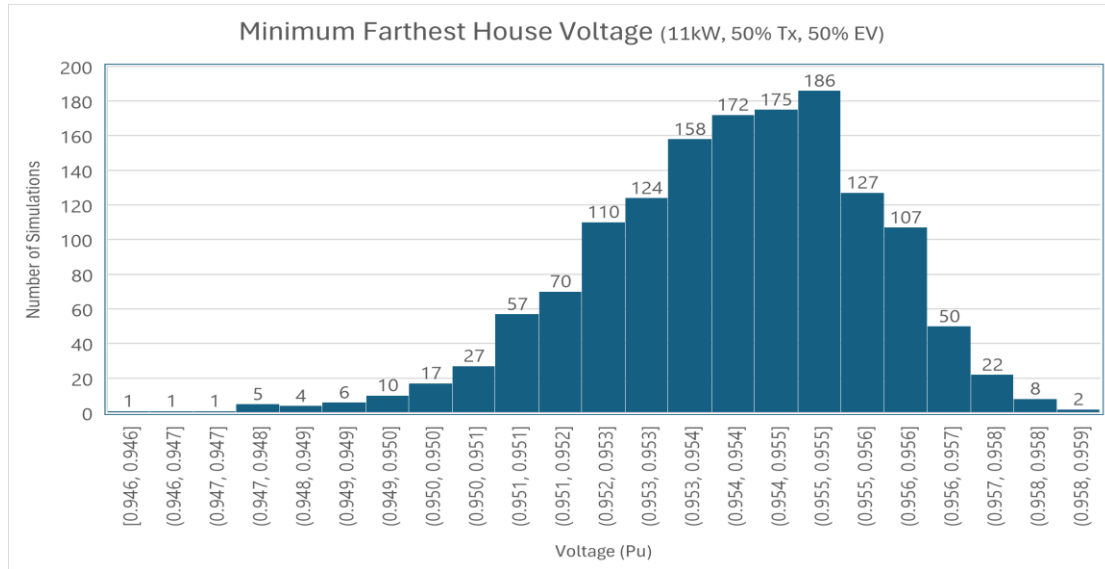


Figure 4.56 Distribution of Minimum Voltage at the Farthest House for 50% EV Penetration (11 kW Chargers, 50% Transformer Load)

- **70% simultaneous charging:**

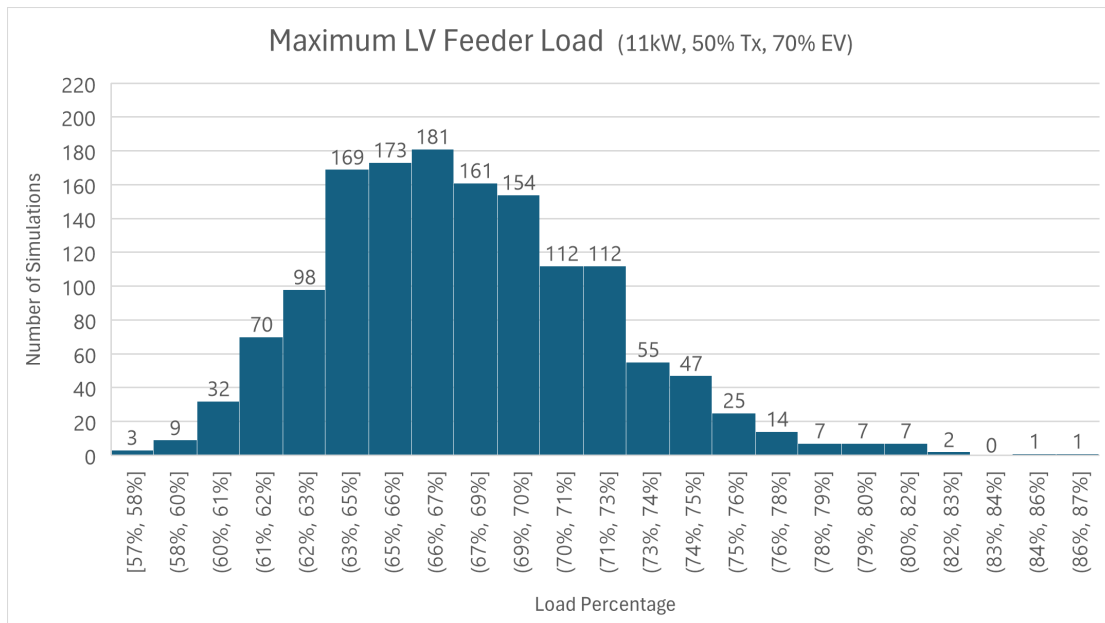


Figure 4.57 Distribution of Maximum LV Feeder Load for 70% EV Penetration (11kW Chargers, 50% Transformer Load)

Figure 4.57 indicates that the most frequent maximum LV feeder load range is 66%–67%, with 181 simulations recorded. A significant portion of simulations falls between 61%–75%. Load levels above 70% decrease in frequency, with only 1 simulation in the 86%–87%. Similarly, load levels below 57% are rare.

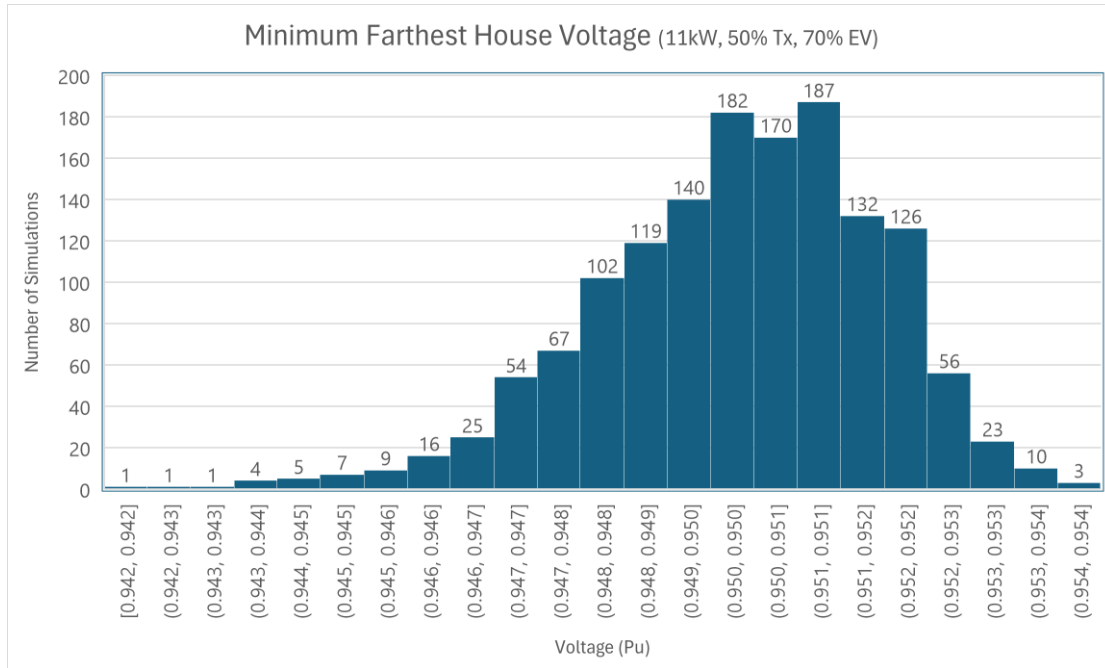


Figure 4.58 Distribution of Minimum Voltage at the Farthest House for 70% EV Penetration (11 kW Chargers, 50% Transformer Load)

Figure 4.58 represents that the majority of simulations are concentrated between 0.947–0.953 pu, encompassing a significant portion of the results. Lower voltage levels below 0.947 pu are infrequent, with only 5 simulations recorded in the 0.943–0.944 pu range and one instance reaching as low as 0.942 pu. Higher voltage levels above 0.952 pu are less common, with a gradual decline in occurrences.

- **100% simultaneous charging:**

Figure 4.59 indicates that the most frequent maximum LV feeder load range is between 74%–75%, with 177 simulations. The majority of the results are concentrated between 70%–81%, representing a significant portion of the simulations. Lower load levels below 70% are less common. Conversely, higher load levels above 81% gradually decrease in frequency, with only 2 simulations recorded in the 89%–91% range and 1 simulation reaching 92%–93%, indicating an approaching limit to feeder capacity.

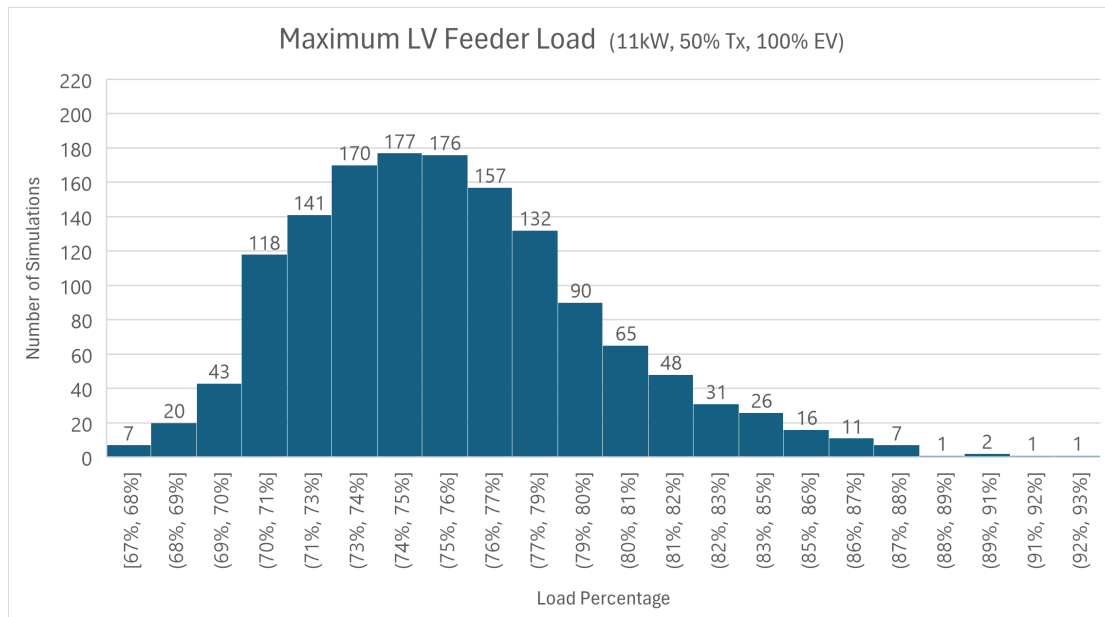


Figure 4.59 Distribution of Maximum LV Feeder Load for 100% EV Penetration (11kW Chargers, 50% Transformer Load)

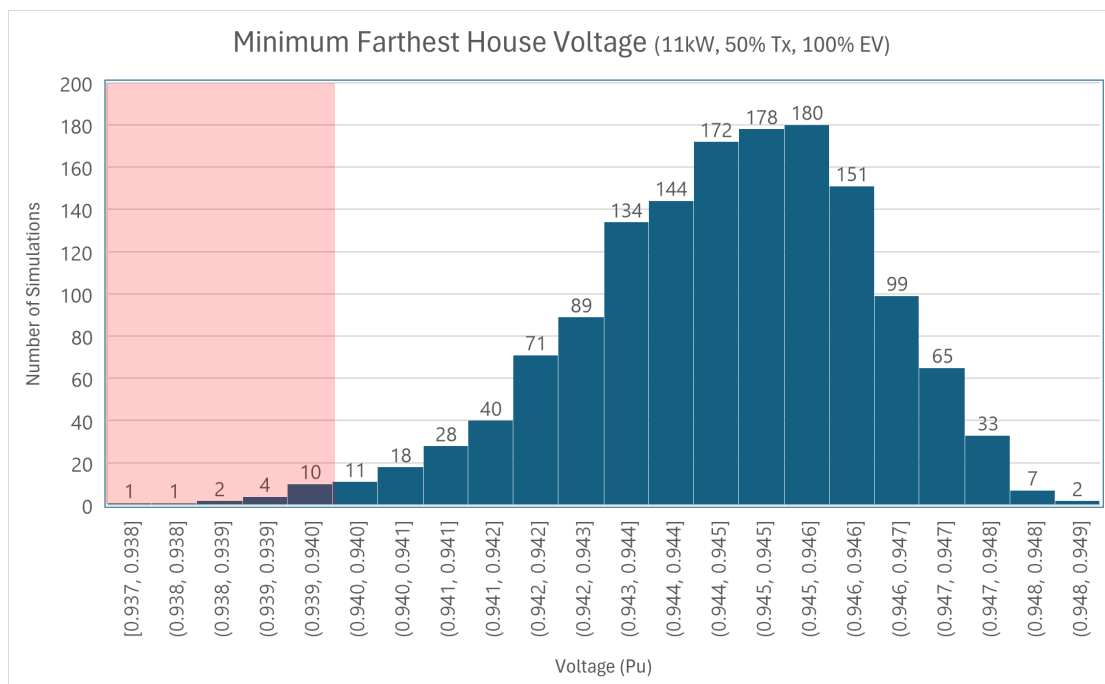


Figure 4.60 Distribution of Minimum Voltage at the Farthest House for 100% EV Penetration (11 kW Chargers, 50% Transformer Load)

Figure 4.60 demonstrates that the majority of simulations are concentrated between 0.942–0.947 pu, accounting for a significant portion of the results. Lower voltage levels below 0.943 pu are less frequent, with only 18 simulations recorded below 0.940 pu (the acceptable limit). Higher voltage levels above 0.947 pu are uncommon.

4.2.3 80% loading scenarios

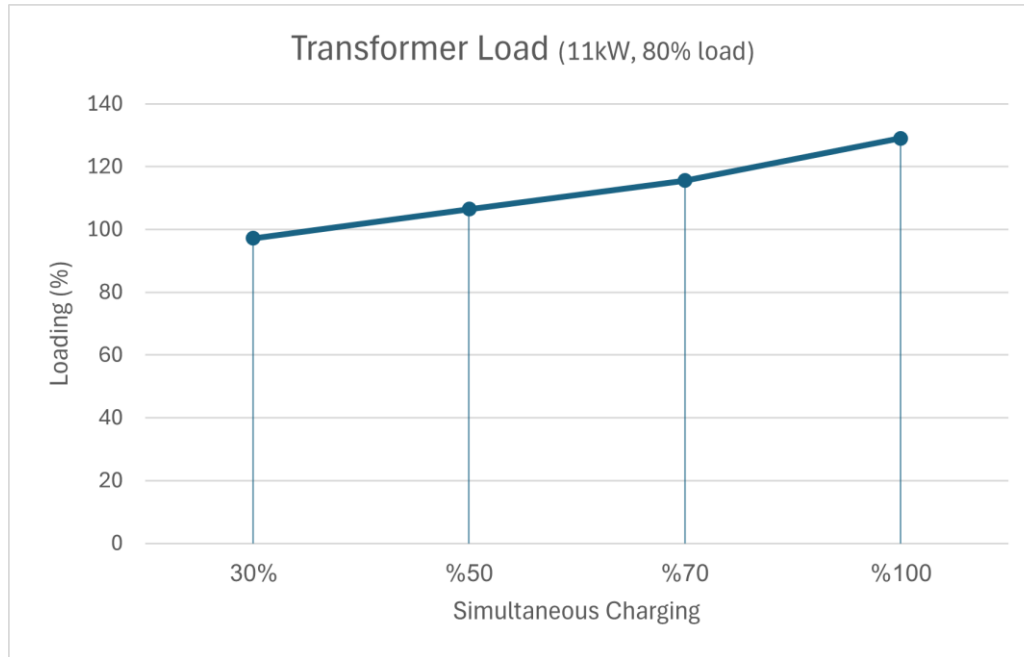


Figure 4.61 Transformer Loading with 80% Base Load and 11 kW EV Chargers

Figure 4.61 displays the transformer load under the condition of 11kW chargers with an 80% base load. The transformer experiences a consistent increase in loading as simultaneous EV charging rises from 30% to 100%. At 30% charging, the transformer is already operating at approximately 97% of its capacity, escalating to over 120% at full charging penetration. This indicates that the transformer is significantly overloaded under these conditions, highlighting the need for mitigation measures to handle such high EV charging scenarios effectively.

Figure 4.62 highlights the power losses under the condition of 11 kW chargers with an 80% base load. Power losses increase progressively with the rise in simultaneous EV charging penetration, starting from approximately 30 kW at 30% charging and climbing to nearly 50 kW at full charging penetration. The orange dashed line indicates the baseline power losses without EV charging, which is around 21 kW.

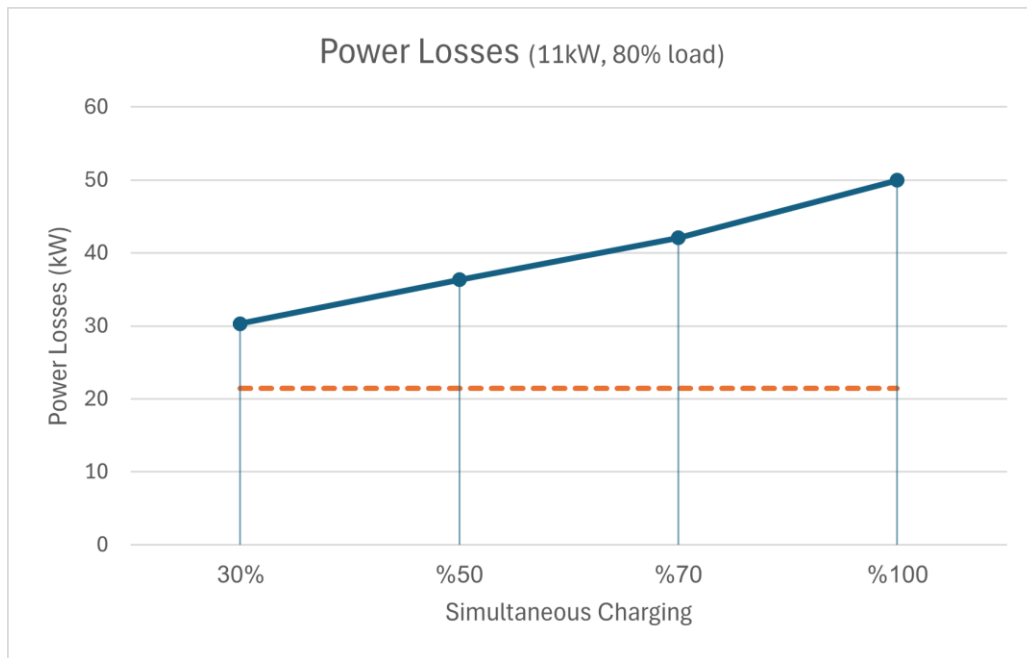


Figure 4.62 Power Losses with 100% Base Load and 11 kW EV Chargers

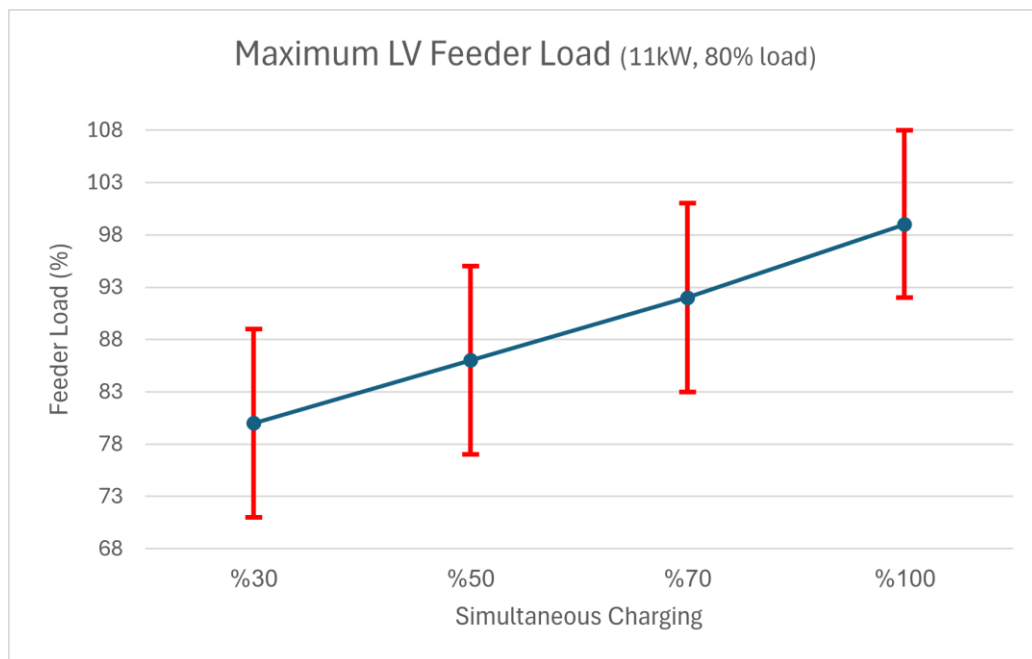


Figure 4.63 Maximum LV Feeder Load with 100% Base Load and 11 kW EV Chargers

Figure 4.63 depicts the maximum LV feeder load under the condition of 11 kW chargers with an 80% base load. As the simultaneous EV charging increases from 30% to 100%, the feeder load rises steadily, starting at approximately 80% and reaching around 100%. These results

indicate that with an 80% base load, the LV feeder is likely to experience overloading at higher EV charging penetration levels.

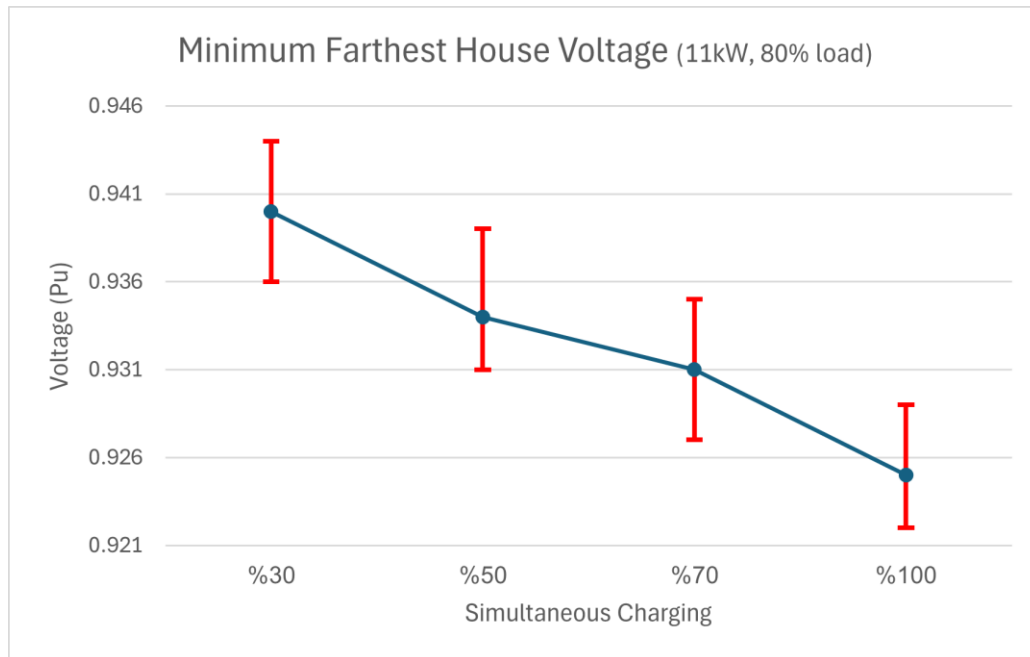


Figure 4.64 Minimum Voltage at the Farthest House with 100% Base Load and 11 kW EV Chargers

Figure 4.64 illustrates the minimum voltage at the farthest house under the condition of 11 kW chargers with an 80% base load. As simultaneous EV charging increases from 30% to 100%, the voltage decreases steadily, starting at approximately 0.94 pu and dropping below 0.926 pu. These results show that under high base load and charging conditions, the voltage is consistently below acceptable margins, raising significant concerns about voltage limits.

Detailed analysis for each simultaneous charging.

- **30% simultaneous charging:**

Figure 4.65 shows that the most frequent maximum LV feeder load range is between 79%–80%, with 180 simulations. The majority of the results are concentrated between 72%–88%, encompassing a significant

portion of the simulations. Lower load levels below 72% are less common, with only 5 simulations recorded in the 69%–70% range. Conversely, higher load levels above 88% show a gradual decline, with just 1 simulation observed in the 92%–93% range.

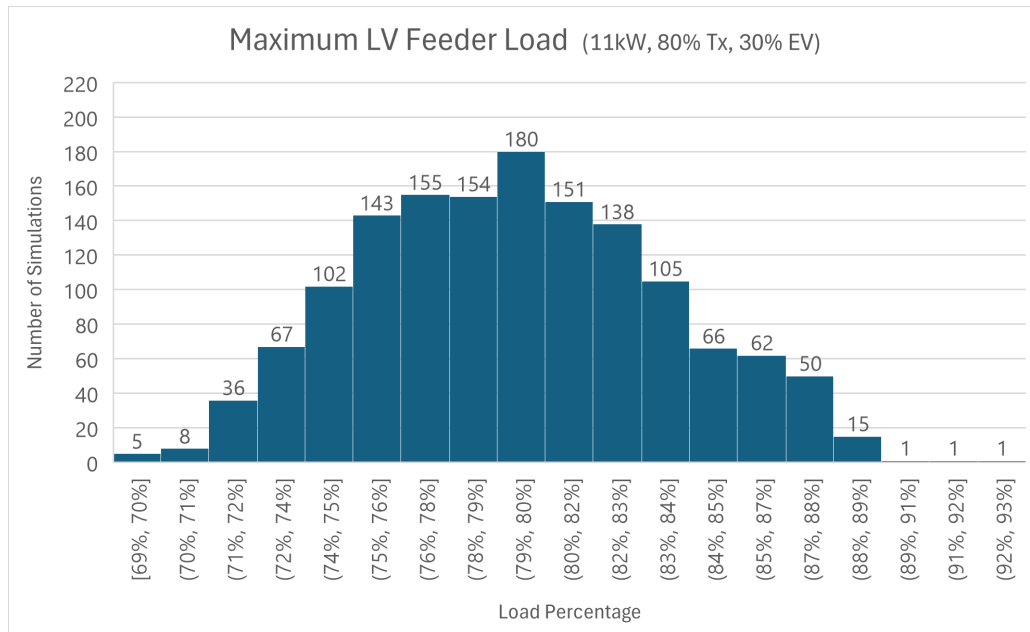


Figure 4.65 Distribution of Maximum LV Feeder Load for 30% EV Penetration (11 kW Chargers, 80% Transformer Load)

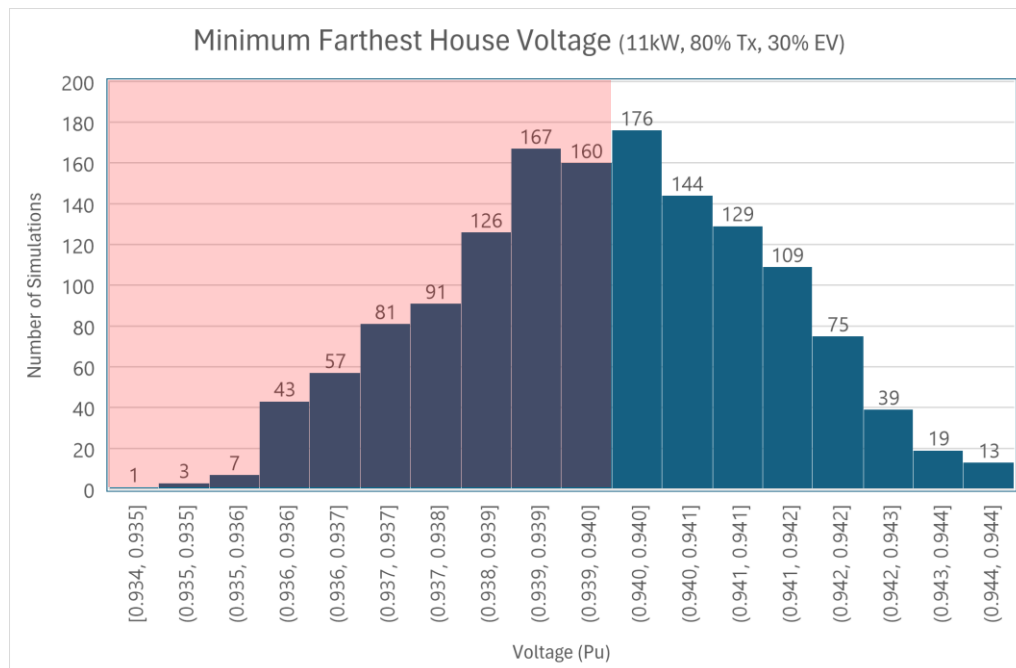


Figure 4.66 Distribution of Minimum Voltage at the Farthest House for 30% EV Penetration (11 kW Chargers, 80% Transformer Load)

Figure 4.66 demonstrates that the majority of the simulations are concentrated between 0.938–0.940 pu, representing a significant proportion of the results. Lower voltage levels below 0.94 pu likely to occur, with a likelihood of approximately 51%, where 736 simulations recorded. Higher voltage levels above 0.942 pu are rare.

- **50% simultaneous charging:**

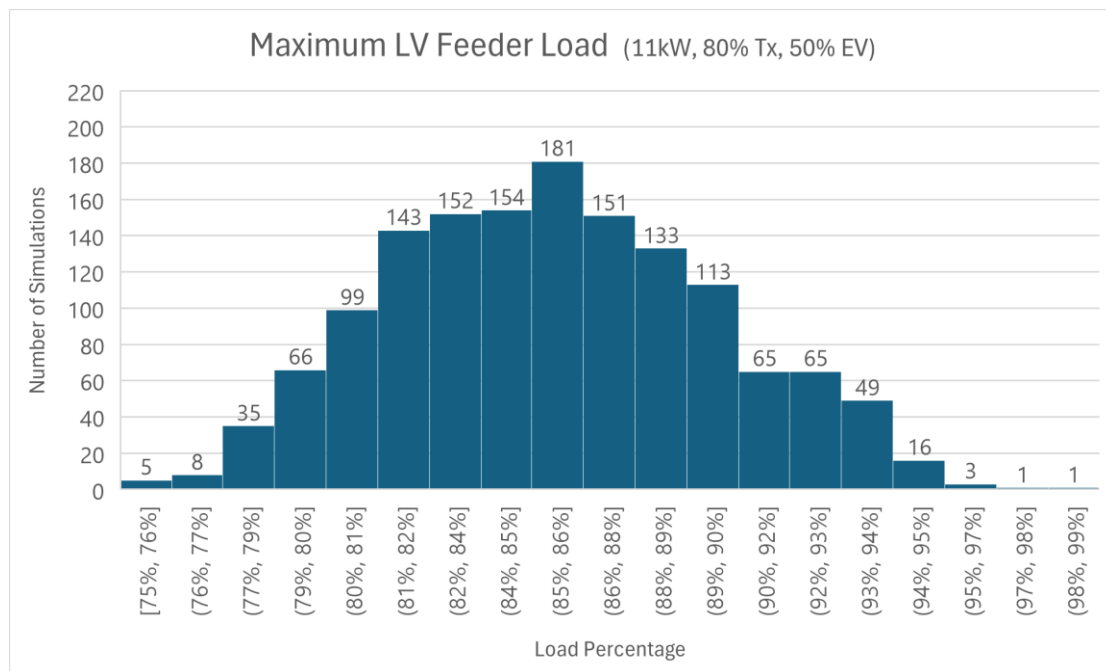


Figure 4.67 Distribution of Maximum LV Feeder Load for 50% EV Penetration (11kW Chargers, 80% Transformer Load)

Figure 4.67 reveals that the most common maximum LV feeder load range falls between 85%–86%, with 181 simulations recorded. A substantial portion of the simulations is clustered between 79%–94%, representing the majority of the results. Load levels below 79% occur infrequently, with just 5 simulations observed in the 75%–76% range. Similarly, higher load levels exceeding 94% become progressively rarer, with 3 instances noted in the 95%–97% range and a single occurrence reaching 98%–99%, signaling a potential approach to the feeder's capacity limit.

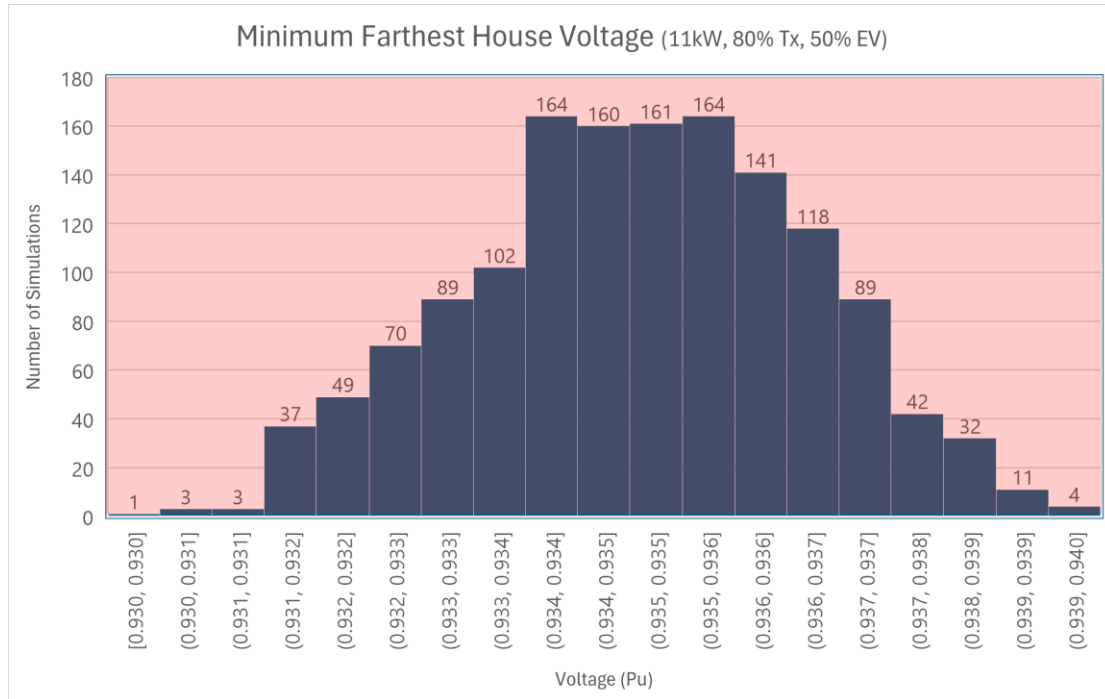


Figure 4.68 Distribution of Minimum Voltage at the Farthest House for 50% EV Penetration (11 kW Chargers, 80% Transformer Load)

Figure 4.68 highlights that in the 11 kW, 80% transformer loading, and 50% EV penetration scenario, every simulation yielded voltage levels below the 0.94 pu threshold, signifying consistent violations of the acceptable voltage limit under these operating conditions.

- **70% simultaneous charging:**

Figure 4.69 shows that the most common maximum LV feeder load range is between 91%–92%, occurring in 178 simulations. The majority of the results are clustered between 85%–100%, encompassing a substantial portion of the data. Lower load levels below 85% are relatively uncommon, while higher load levels above 100% show a gradual decline. Notably, only 4 simulations fall within the 101%–103% range, and a single instance each is observed at 103%–104% and 104%–105%, signaling that the feeder is exceeding its capacity limits.

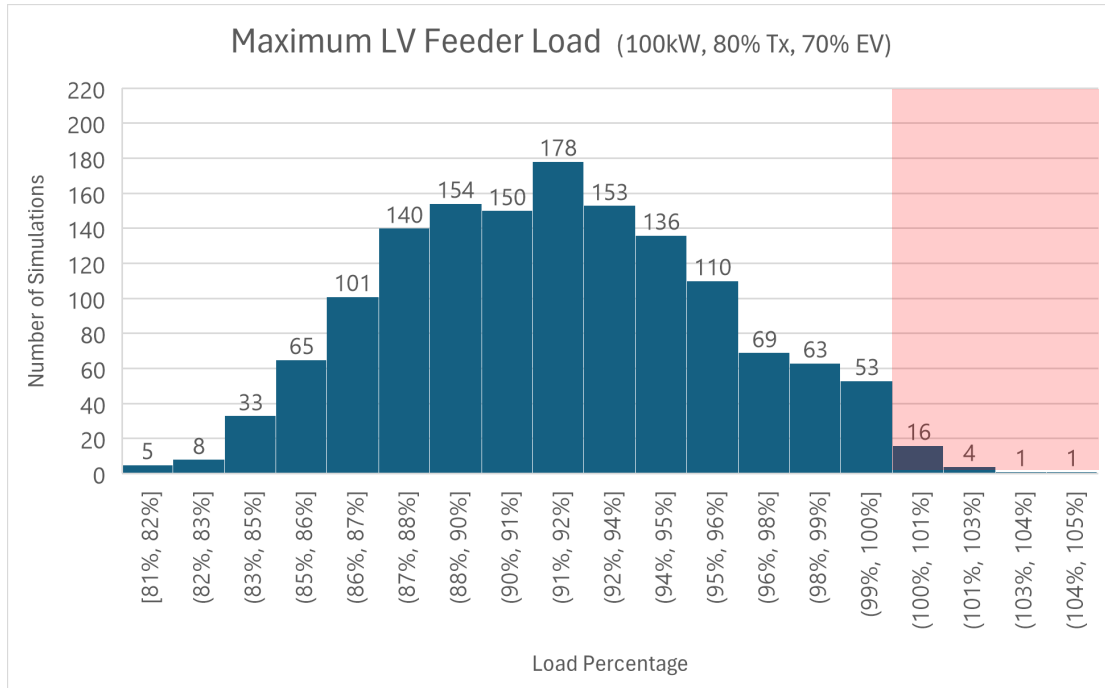


Figure 4.69 Distribution of Maximum LV Feeder Load for 70% EV Penetration (11kW Chargers, 80% Transformer Load)

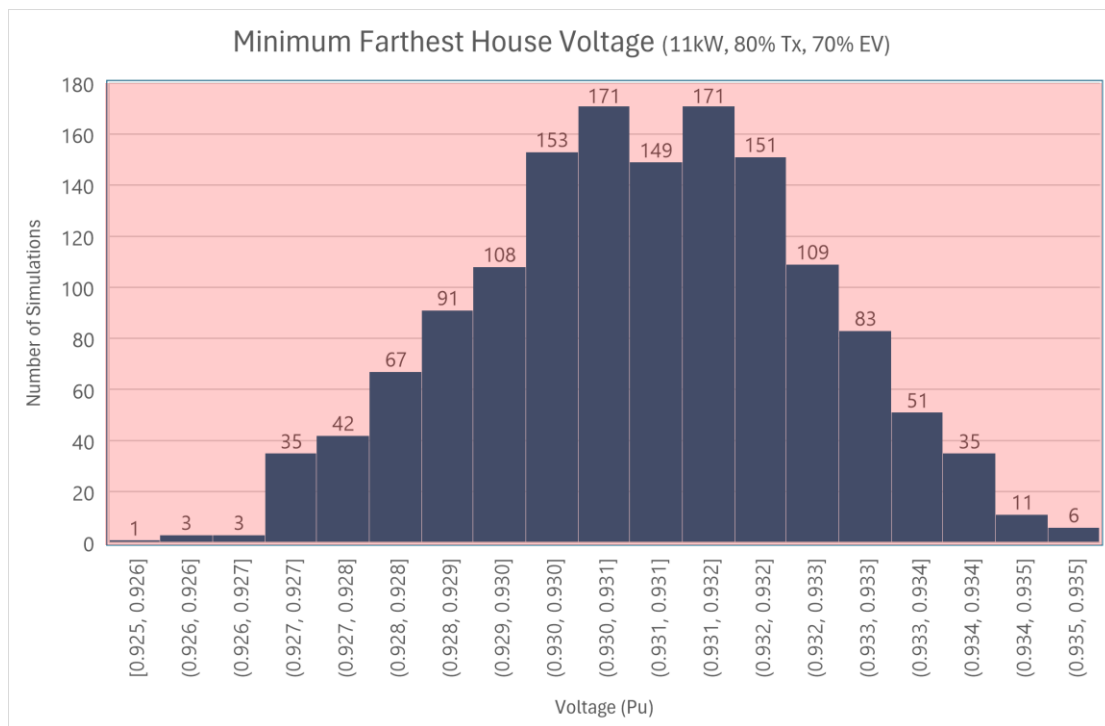


Figure 4.70 Distribution of Minimum Voltage at the Farthest House for 70% EV Penetration (11 kW Chargers, 80% Transformer Load)

Figure 4.70 reveals that under the 11 kW, 80% transformer loading, and 70% EV scenario, all simulations produced voltages falling below the

0.94 pu threshold. This consistent occurrence highlights a persistent issue of voltage violations under the given conditions.

- 100% simultaneous charging:**

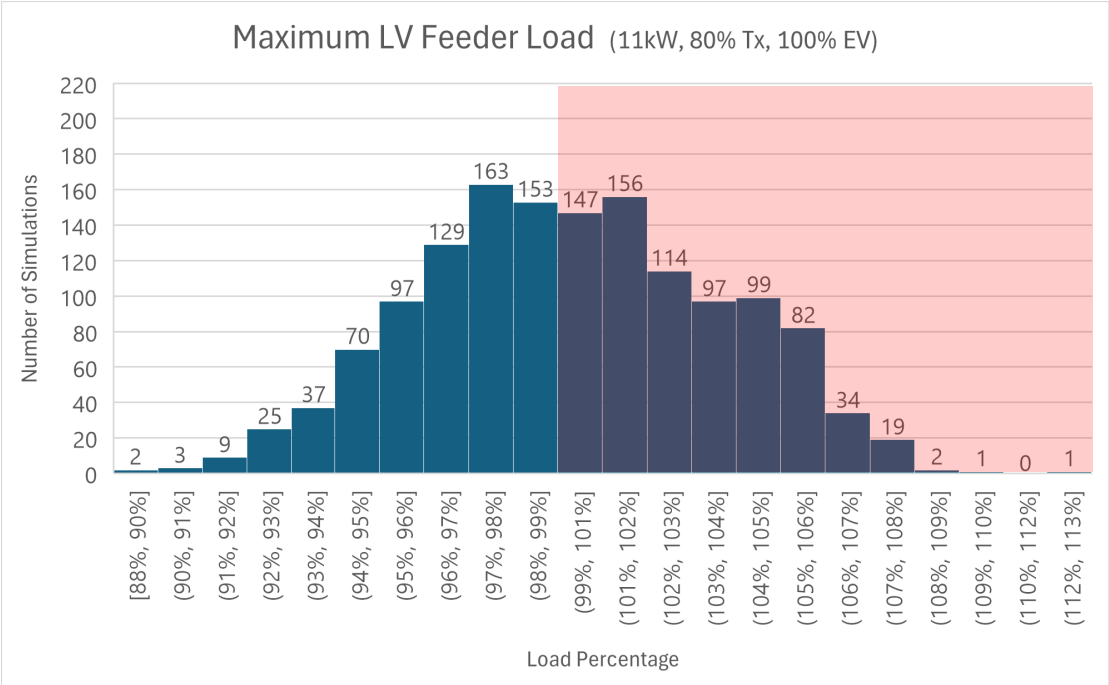


Figure 4.71 Distribution of Maximum LV Feeder Load for 100% EV Penetration (11kW Chargers, 80% Transformer Load)

Figure 4.71 demonstrates that for the 11 kW, 80% transformer loading, and 100% EV scenario, most results are concentrated between 94%–106%, accounting for a significant portion of the data. Load levels above the permissible limit of 100% occur in 752 simulations, representing a 52% probability of overload under these conditions.

Figure 4.72 reveals that under the 11 kW, 80% transformer loading, and 100% EV scenario, all simulations resulted in voltages below the acceptable limit of 0.94 pu. Furthermore, the voltage violations extend to deep limits, with some simulations reaching as low as 0.920 pu. This indicates a significant inability of the system to sustain voltage levels within acceptable thresholds, emphasizing the severity of the voltage violations under these conditions.

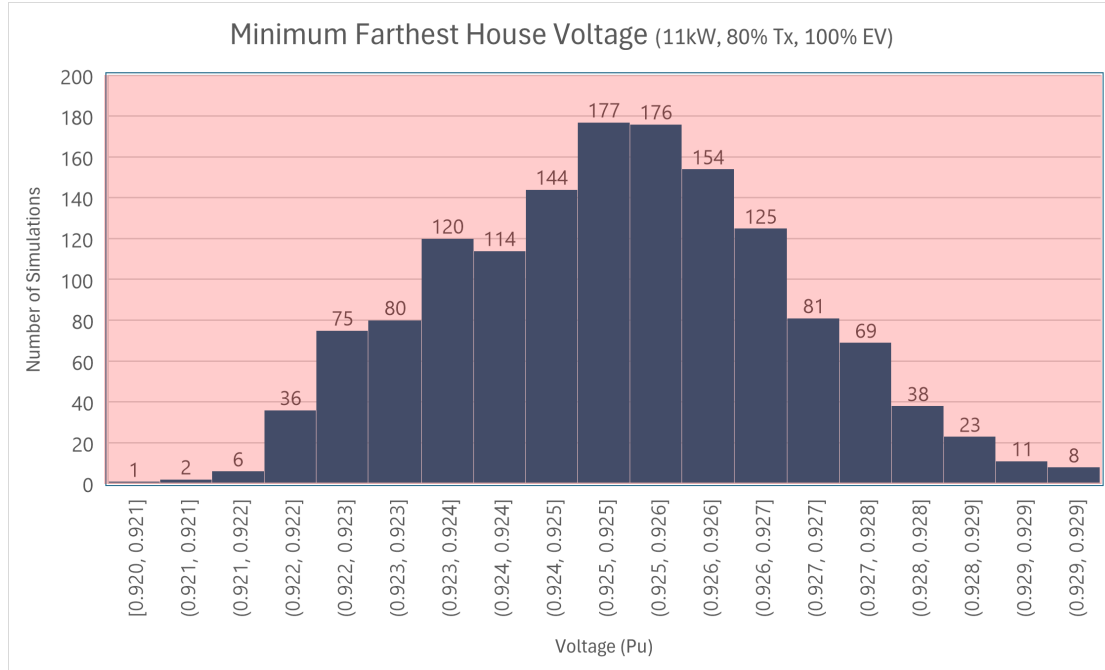


Figure 4.72 Distribution of Maximum LV Feeder Load for 100% EV Penetration (11kW Chargers, 80% Transformer Load)

4.3 Impact Summary

This section aims to integrate the insights obtained from the analysis of individual scenarios into a comprehensive assessment of the impact of EV charging on the distribution network. To achieve this, impact matrices will be developed for both 7.6 kW and 11 kW chargers. These matrices will systematically consolidate the findings across different transformer load percentages and simultaneous charging percentages, offering a holistic representation of the overall impact under varying operational conditions.

It is important to highlight that these results are based on a worst-case scenario, where the distribution cable is assumed to operate at its maximum allowable length, and the houses are distributed at the farthest possible distances from the distribution substation. This consideration ensures that the findings represent the most challenging conditions for the network, providing a conservative assessment of the impact of EV charging integration.

Simultaneous Charging	100%										
	90%										
	80%										
	70%										
	60%										
	50%										
	40%										
	30%										
	20%										
	10%										
7.6kW		10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Transformer Load											

Figure 4.73 Impact matrix for 7.6 kW EV charger

Simultaneous Charging	100%										
	90%										
	80%										
	70%										
	60%										
	50%										
	40%										
	30%										
	20%										
	10%										
11kW		10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Transformer Load											

Figure 4.74 Impact matrix for 11 kW EV charger

Figures 4.73 and 4.74 presents an impact matrix for 7.6 kW and 11 kW chargers, summarizing the effects of varying transformer load percentages (X-axis) and simultaneous EV charging percentages (Y-axis)

on the low-voltage (LV) network. The color coding in the matrix conveys the severity of the impact:

- **Dark Red:** Represents scenarios where the transformer loading exceeds its limit, indicating critical network performance issues and significant violations.
- **Light Red:** Denotes conditions where either voltage violations or feeder overloads occur with a likelihood exceeding 20%. While the transformer loading remains within acceptable limits, the impact is significant and affects parts of the network.
- **Yellow:** Highlights situations where either voltage violations or feeder overloads occur, but with a likelihood of less than 20%. These conditions indicate a lower risk of impact compared to light red but still require monitoring.
- **Light Green:** Indicates scenarios where the transformer load exceeds 85% of its capacity but remains within safe operational limits, with no violations or overloading observed, but the conditions signal a warning for potential future issues.
- **Dark Green:** Denotes stable and safe operating conditions, with no observable impacts on the LV network. This represents optimal performance with ample operational margin

The impact matrix assesses EV integration on the low-voltage network, highlighting risks like overloading or voltage violations and aiding proactive planning. Its color-coded zones provide insights for targeted mitigation strategies, ensuring a reliable transition to EV adoption. Linking these findings to actual transformer loading data helps utilities understand their infrastructure's current and future state. The next section builds on this by analyzing distribution transformer loading in detail.

4.4 Transformer Loading Analysis

This section addresses the third objective of this research, focusing on the analysis of real transformer loading data to evaluate the current state of the distribution network and its readiness for EV integration. By leveraging actual operational data from distribution transformers, this section bridges the gap between modeled scenarios and real-world conditions.

The analysis involves examining the historical loading patterns of transformers, identifying peak demand periods, and assessing how current load levels compare to the thresholds established in the impact matrices. This evaluation will provide insights into which transformers are already operating near their capacity and are most vulnerable to the additional load imposed by EV charging.

4.4.1 Peak Load

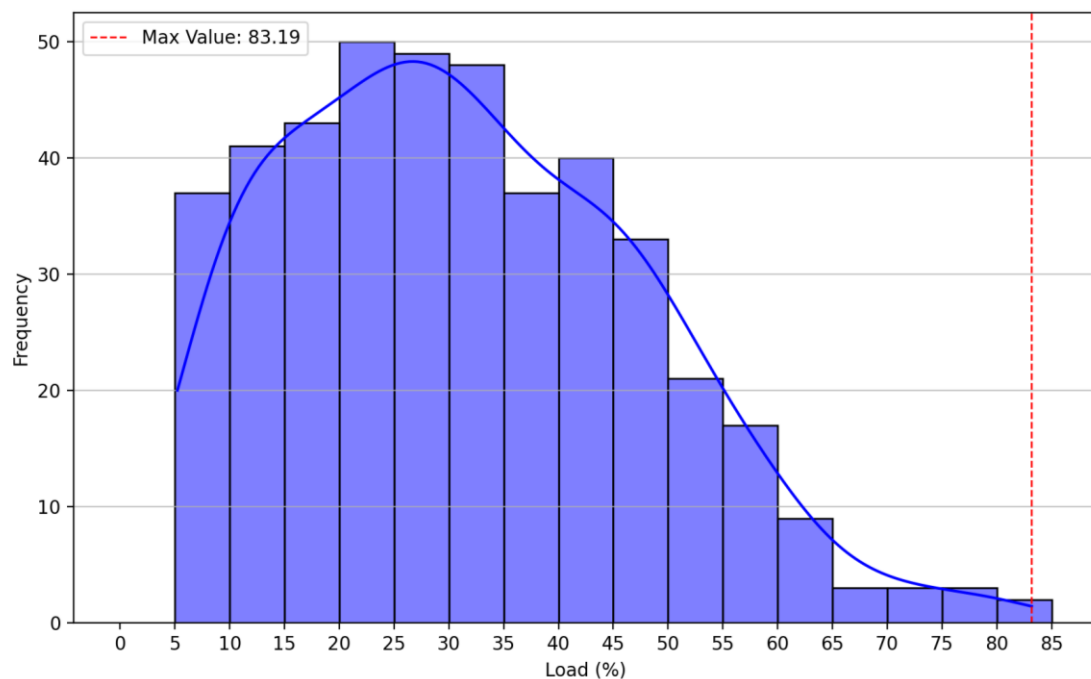


Figure 4.75 Transformers peak load distribution

Figure 4.75 represents the distribution of maximum transformer load percentages collected from a random sample of distribution transformers during the period from May to November 2024. The histogram shows the frequency distribution of maximum load values, with the data points ranging from approximately 5% to 83.19%. The red dashed line indicates the highest recorded load within the dataset at 83.19%. The distribution is positively skewed, with most transformers operating at lower load levels. The peak frequency occurs in the range of 20%–40% load, highlighting that the majority of the transformers are operating well below their rated capacity.

4.4.2 Peak Time

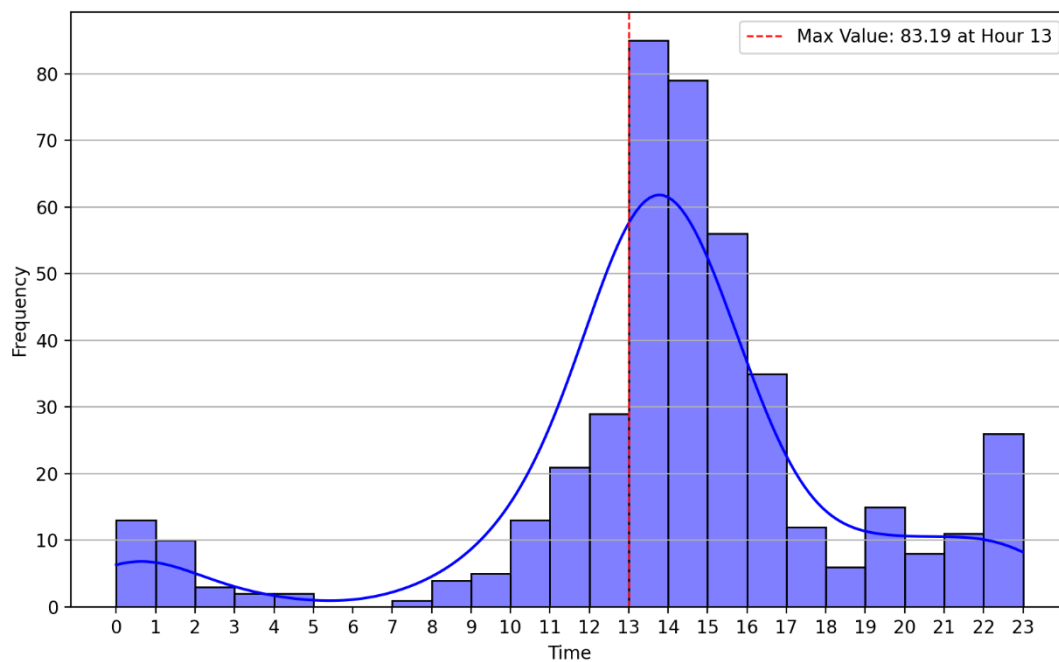


Figure 4.76 Transformers peak time distribution

Figure 4.76 represents the distribution of the peak time for the maximum load values identified in the previous figure. It highlights the timing of peak load occurrences, with a notable concentration around hour 13, as indicated by the red dashed line marking the maximum value of 83.19%. Also, the histogram illustrates that the largest concentration of

peak load occurrences is observed between hours 13 and 17, indicating that these hours represent the most critical period for transformer loading. This distribution provides useful insights into the general trend of peak load timings, which could aid in understanding transformer loading behavior during critical periods.

However, it is important to note that this analysis is based on maximum load values, which might occur only once a year, limiting its accuracy in reflecting daily operational patterns. For a more comprehensive and accurate understanding, it is necessary to analyze the load pattern over an entire day. This approach will offer a better representation of the typical load profile and will be addressed in detail in the subsequent section.

4.4.3 Loading Heat map

Figures 4.77-4.81 provide a visual representation of the frequency of transformer loading across various devices, illustrating the range and intensity of load values. Each column corresponds to a specific transformer, while the rows represent different loading ranges. The color intensity indicates the frequency of occurrences within each loading range, with darker shades representing higher frequencies.

This analysis is critical for understanding how often transformers operate within specific loading ranges and identifying whether peak load conditions persist over time or occur sporadically. Transformers with darker areas in higher loading ranges indicate sustained high loads, which may require intervention to prevent overloading or prolonged stress. Conversely, lighter areas in higher ranges suggest that peak loads are transient.

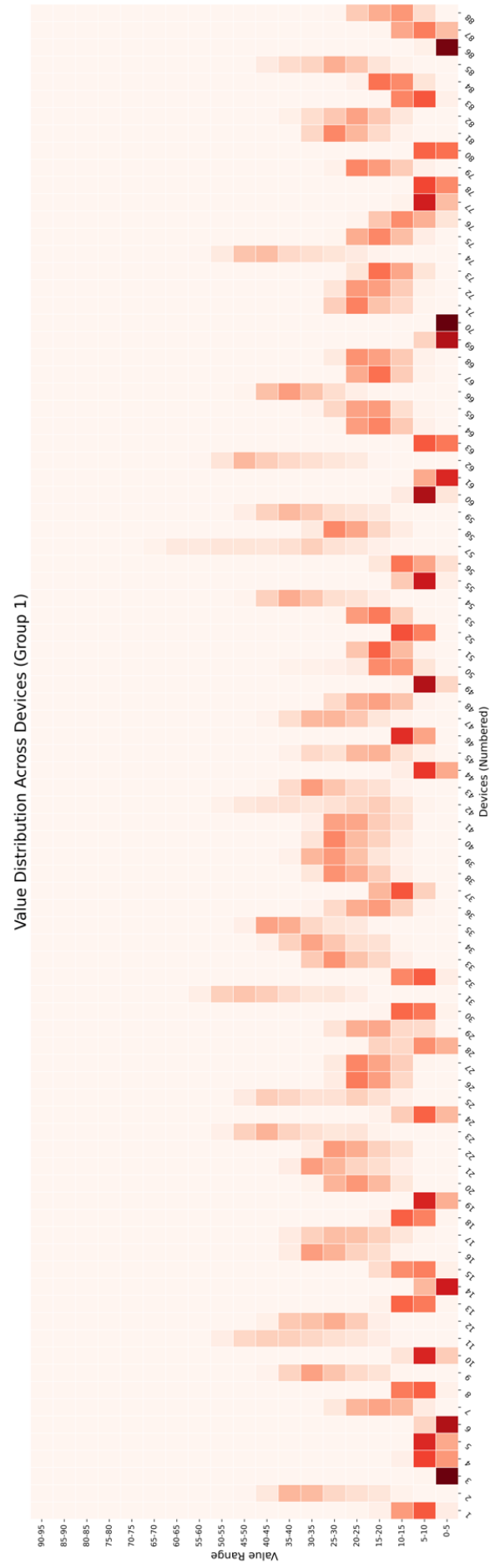


Figure 4.77 Transformers load heat map group 1

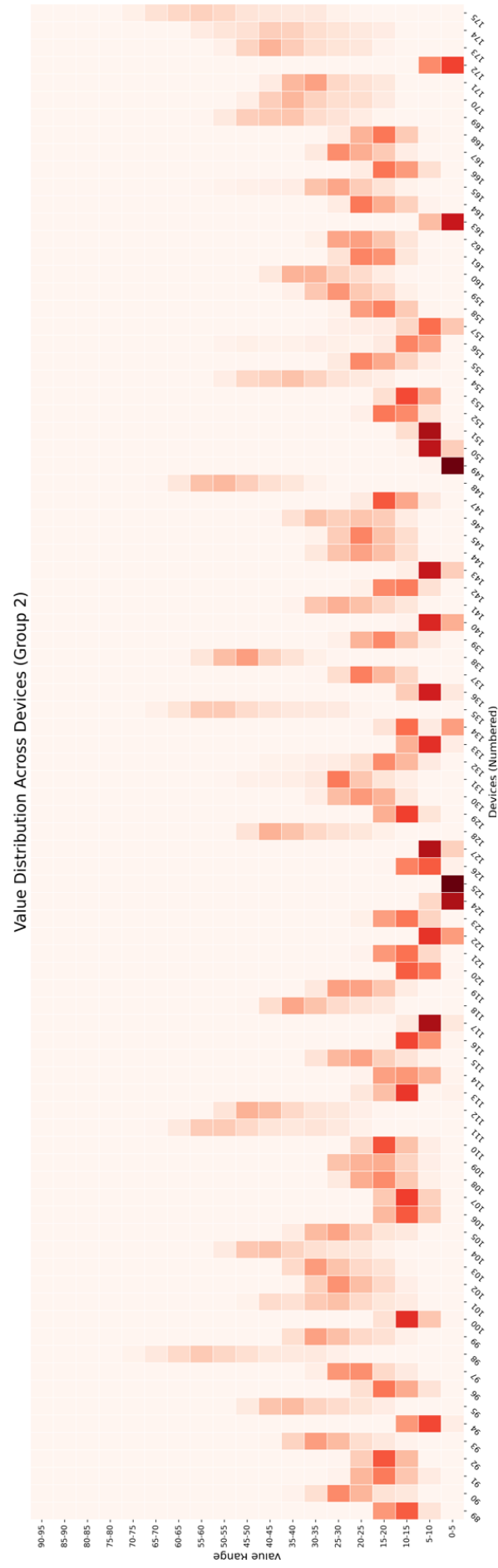


Figure 4.78 Transformers load heat map group 2

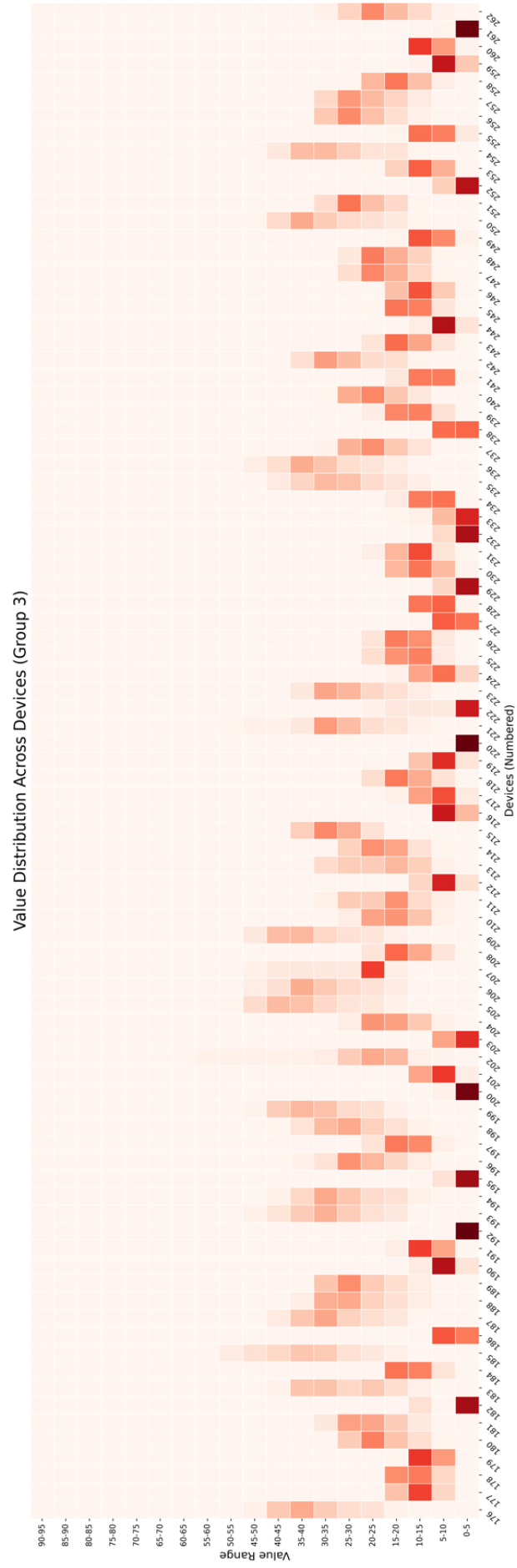


Figure 4.79 Transformers load heat map group 3

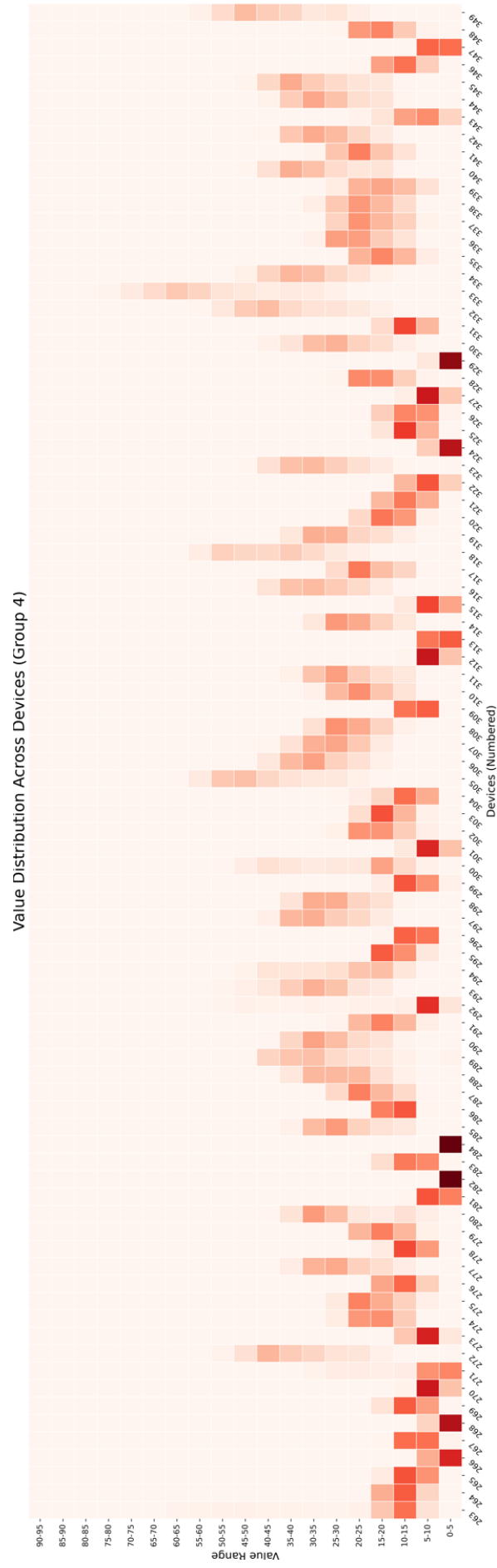


Figure 4.80 Transformers load heat map group 4

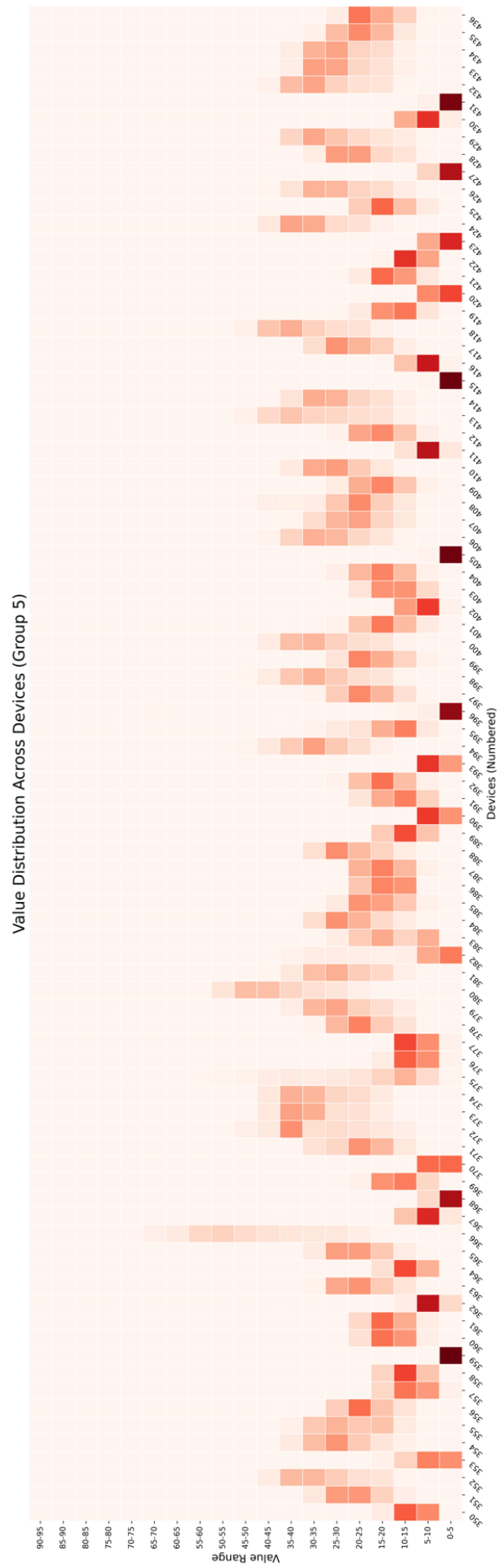


Figure 4.81 Transformers load heat map group 5

4.4.4 Load Pattern

The load pattern analysis is a crucial step in evaluating the potential for implementing indirect charging control strategies for electric vehicles. By examining the hourly distribution of transformer loading, we gain valuable insights into the typical load behavior across different times of the day. This approach helps identify peak load periods and low-demand times, which are essential for assessing the feasibility and effectiveness of indirect charging control. The analysis distinguishes between weekdays and weekends and categorizes transformers based on their loading levels, identifying transformers that exceeded 30% loading at any point during the entire study period (May–November 2024), providing a comprehensive understanding of load patterns and their implications for control strategies. The below figures 4.82 - 4.88 represent the load pattern for each month.

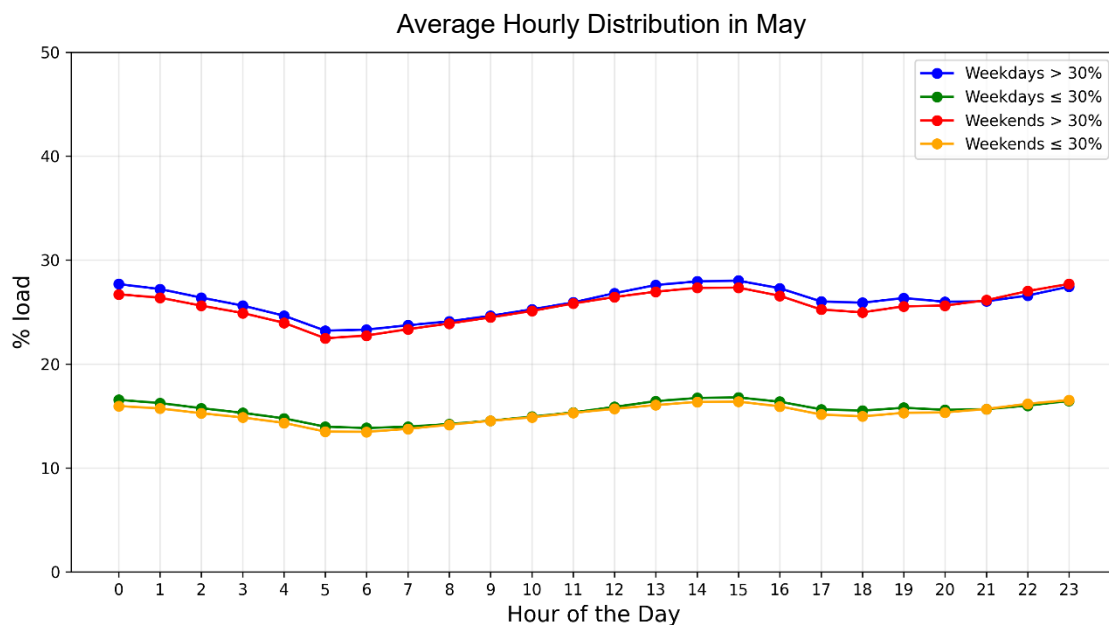


Figure 4.82 Transformers load pattern in May 2024

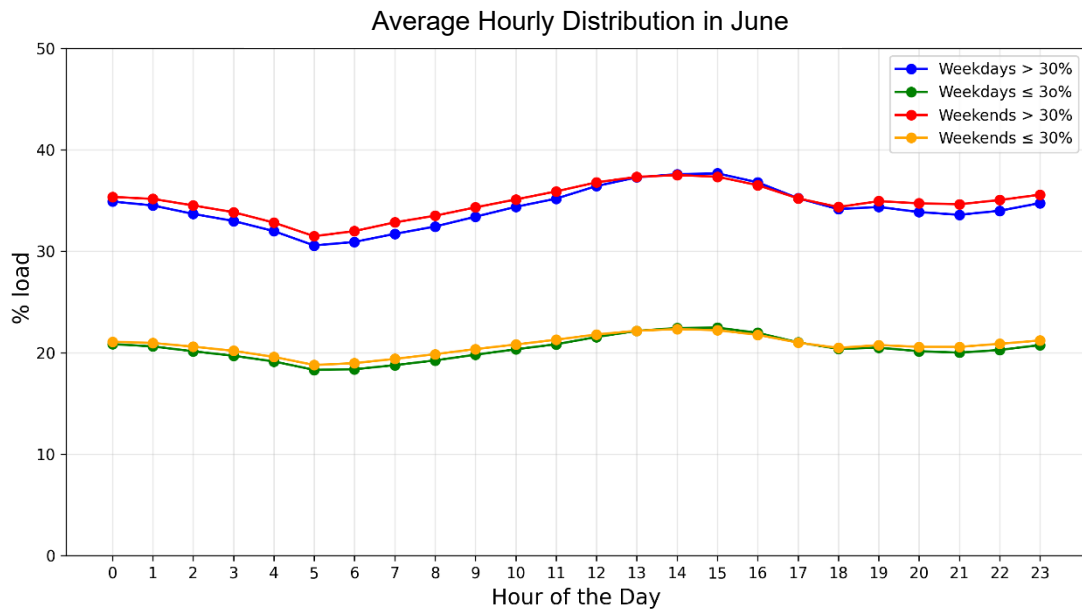


Figure 4.83 Transformers load pattern in June 2024

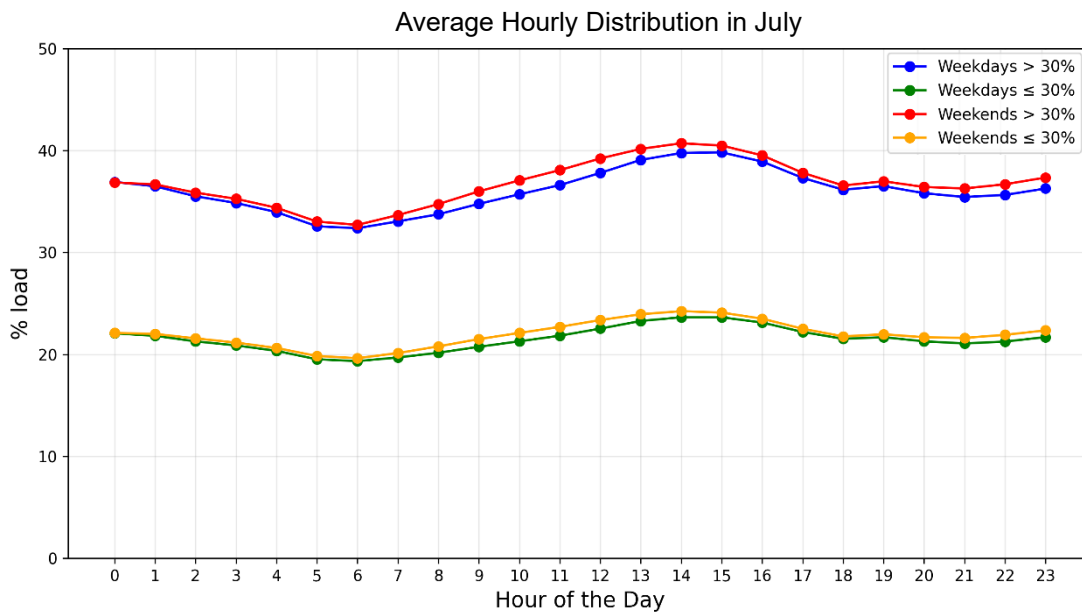


Figure 4.84 Transformers load pattern in July 2024

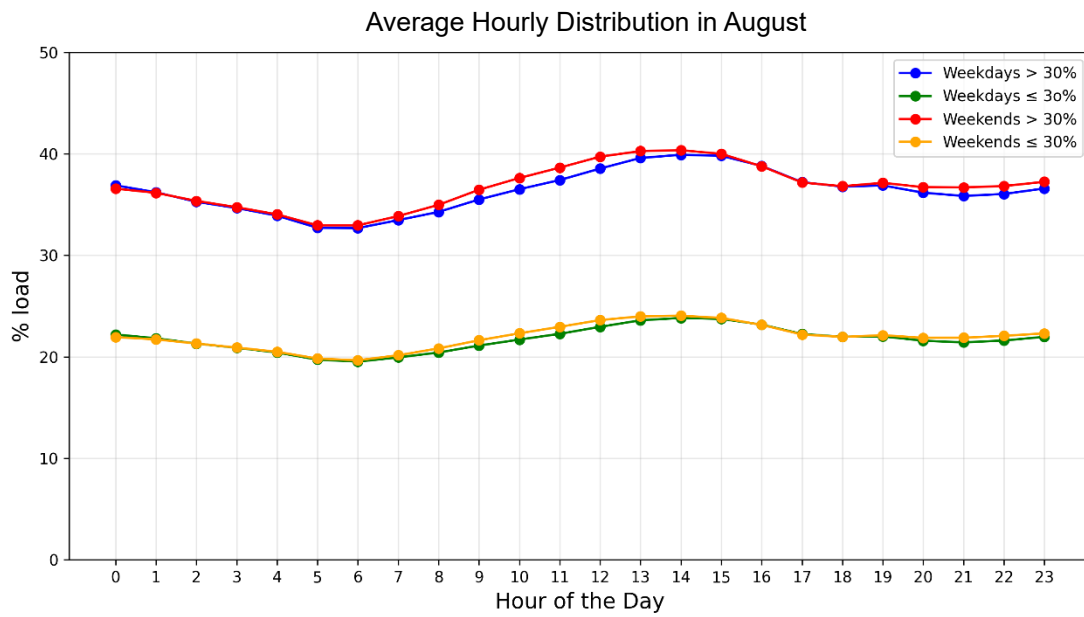


Figure 4.85 Transformers load pattern in August 2024

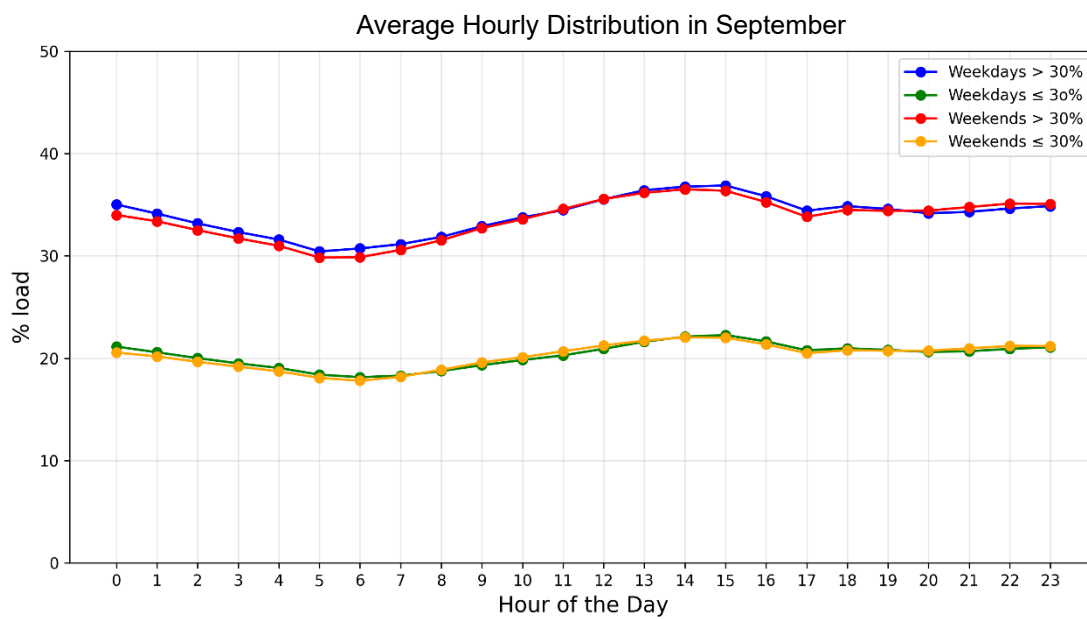


Figure 4.86 Transformers load pattern in September 2024

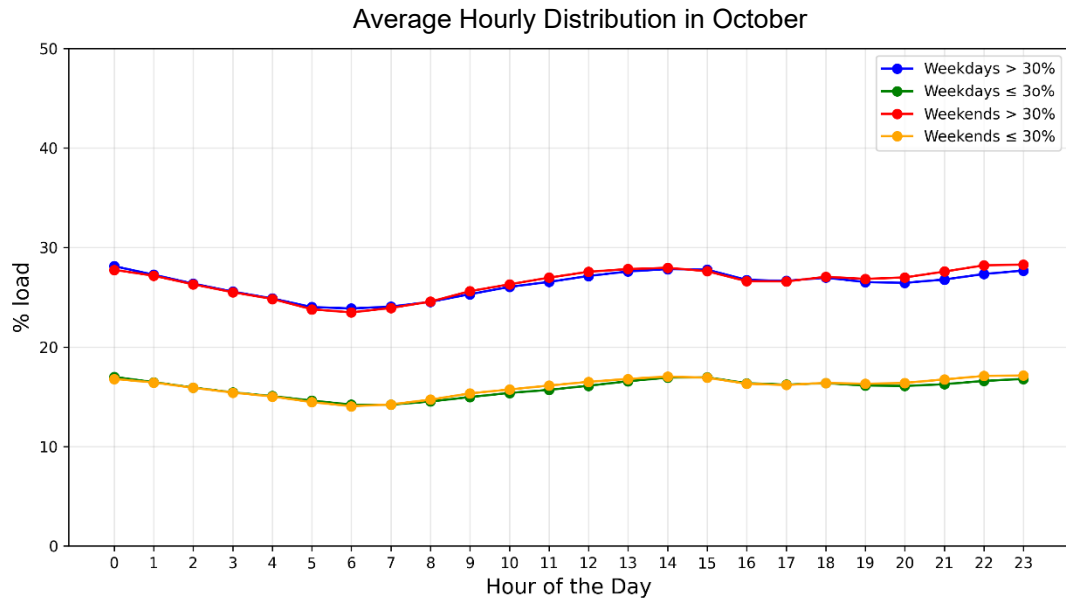


Figure 4.87 Transformers load pattern in October 2024

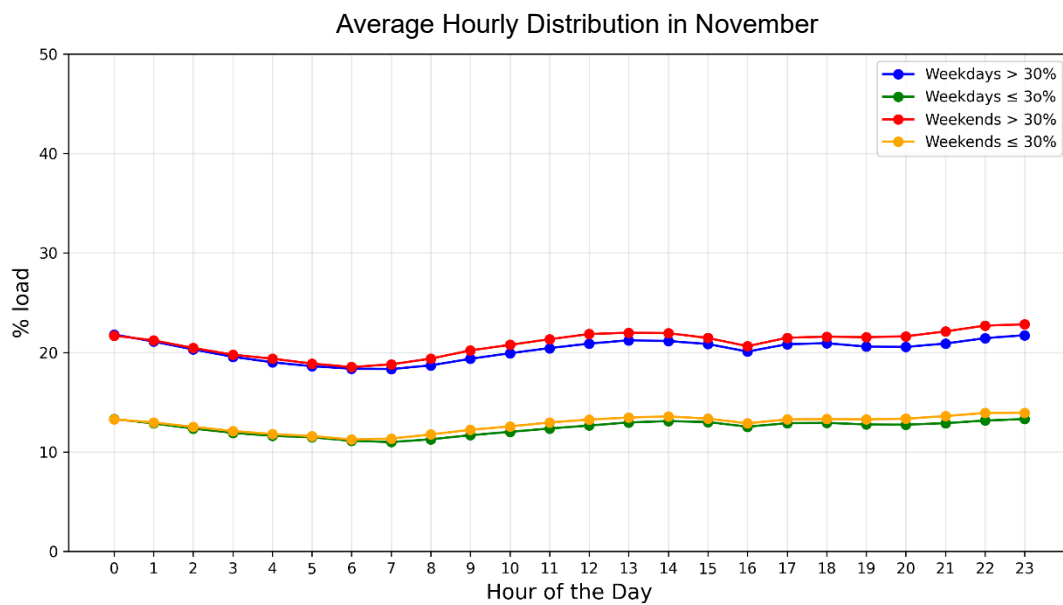


Figure 4.88 Transformers load pattern in November 2024

After conducting a thorough analysis of the load pattern figures for the months of May through November, several key observations were identified. Firstly, the load patterns for weekdays and weekends demonstrate a similar overall trend, with only a slight increase in load observed during weekends. This increase is consistent across the analyzed

months, reflecting the minor variations in usage patterns between workdays and rest days.

Secondly, the load pattern across the months exhibits significant uniformity, indicating that the general shape of the daily load curve remains consistent. However, as the overall load increases in certain months, the value of the ΔL (possible controlled load) also rises. This suggests a higher potential for flexibility in load management during months with increased overall demand. July stands out as the month with the highest observed load, with a ΔL of approximately 9%.

Lastly, the analysis points to the time window between 2 AM and 8 AM as the most suitable period for electric vehicle (EV) charging. During these hours, the load consistently remains at its lowest, providing an ideal opportunity to accommodate EV charging. This recommendation is strongly supported by the observed trends across all months and aligns with the goal of minimizing the impact of EV integration on the distribution network.

It is important to highlight that, based on the previously obtained impact matrix, a 10% reduction in transformer load can allow for approximately 30% additional simultaneous EV charging in the case of 7.6kW EV chargers. This observation underscores the significant potential of employing indirect charging control strategies to optimize transformer utilization. By strategically managing charging schedules, this approach not only accommodates a greater number of electric vehicles but also effectively mitigates the potential negative impacts on the distribution network. Furthermore, indirect controlled charging can be particularly beneficial during months with high transformer loads.

To validate the optimal timing for indirect controlled charging, five high-load transformers were randomly selected for further analysis. Figure 4.89 illustrates the load pattern for each transformer during the month of July. This approach allows a closer examination of individual transformer behavior to assess the feasibility of implementing targeted charging control. The lower load periods are observed during late-night hours, particularly between 2 AM and 8 AM, reinforcing the recommendation of this time window for EV charging.

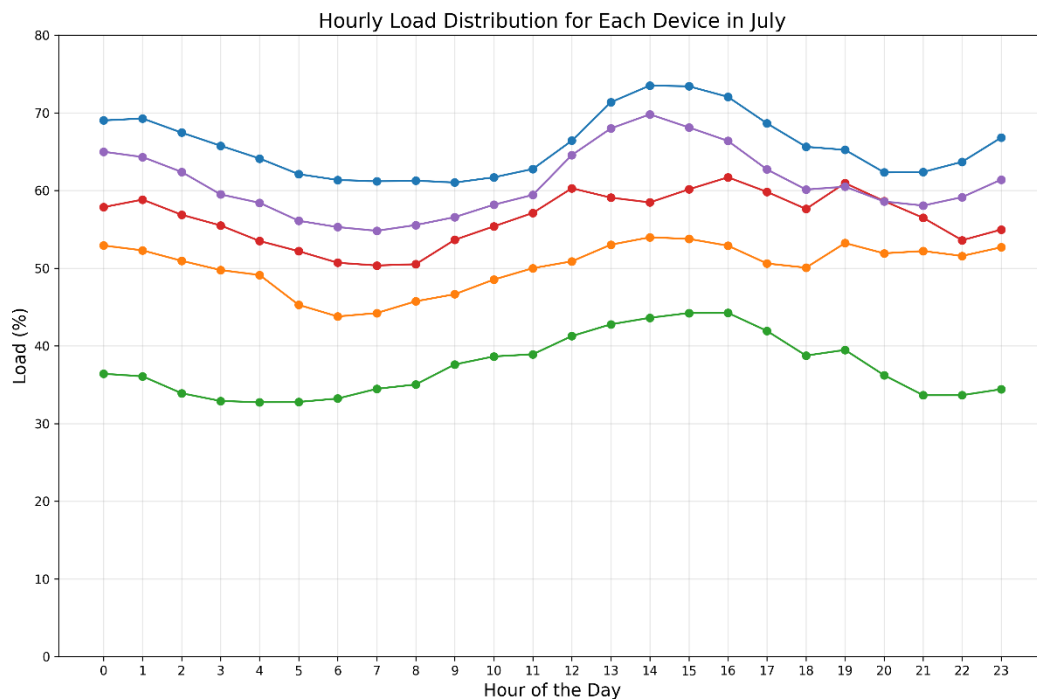


Figure 4.89 Individual Transformer load pattern of five transformers in July, 2024

Chapter 5: Conclusion and Recommendations

Chapter Overview:

This chapter concludes the thesis by summarizing the key findings, highlighting the practical implications of the research, and providing actionable recommendations for stakeholders to manage the integration of electric vehicles (EVs) into Bahrain's distribution network. The chapter also outlines the study's limitations, offering transparency about the assumptions and constraints of the analysis. Finally, future research directions are proposed, addressing emerging challenges

5.1 Conclusion

This thesis has comprehensively explored the impact of electric vehicle (EV) integration on Bahrain's low-voltage (LV) distribution network, addressing critical challenges associated with the increasing adoption of EVs. It aimed to assess the potential effects of various EV charging scenarios on transformer loading, voltage violations, feeder loading, and power losses, while evaluating mitigation strategies such as indirect controlled charging.

A key contribution of this thesis is the development of a robust methodology based on the available data. This methodology included the modeling of a representative LV network using DIgSILENT PowerFactory to simulate different EV penetration levels and charging scenarios. The study analyzed varying transformer base loads (30%, 50%, and 80%) and simultaneous charging percentages (30%, 50%, 70%, and 100%) for two charger capacities (7.6 kW and 11 kW). The results provided a comprehensive understanding of network performance under diverse conditions, including worst-case scenarios such as maximum cable lengths and distant consumer locations.

In addition, this research proposed an impact matrix as a critical tool to evaluate the effects of EV charging under different loading and charging conditions. The matrix offers a clear and intuitive representation of the potential risks to the network, identifying areas with voltage violations, feeder and transformer overloading, and operational margins. It serves as a valuable framework for utilities and policymakers to assess and plan for the challenges posed by EV integration.

Complementing the simulations, this thesis analyzed real-world transformer loading data, comprising approximately 233 million readings from 456 transformers. The data provided insights into load patterns, peak demand periods, and transformers operating near their capacity limits. By examining these patterns across weekdays and weekends and categorizing transformers based on loading levels, the study identified critical periods and conditions for potential intervention.

The thesis also assessed the effectiveness of indirect controlled charging strategies, such as Time-of-Use (TOU) pricing, by analyzing hourly load profiles. The findings highlighted the potential of shifting EV charging to off-peak periods, particularly between 2 AM and 8 AM, to alleviate transformer loading and mitigate voltage violations.

In summary, this thesis not only provides valuable insights into the readiness of Bahrain's distribution network for EV integration but also offers practical tools and methodologies for proactive planning. The conclusions and recommendations drawn from this research inform utility companies, policymakers, and stakeholders, contributing to a sustainable and resilient transition to electrified transportation.

5.2 Recommendations

Based on the findings of this research, it is expected that there will be no significant impact on Bahrain's distribution network in the immediate future or during the early stages of electric vehicle (EV) penetration. The current penetration levels remain low, and the network is capable of accommodating the anticipated demand in the upcoming years. However, regular monitoring of transformer loading and feeder performance is essential to ensure the network continues to operate within acceptable

limits as EV adoption increases. The following recommendations are proposed:

5.2.1 Establish Regular Monitoring Systems

Develop and implement a comprehensive monitoring framework to track transformer and feeder loading levels. Regular monitoring will provide early warning of potential stress points as EV penetration grows, enabling proactive intervention.

5.2.2 Implement Controlled Charging Strategies

While the network is currently capable of managing the upcoming penetration levels, controlled charging strategies such as Time-of-Use (TOU) pricing should be developed and introduced gradually. These strategies will prepare the network for higher penetration levels and ensure stability in the long term.

5.2.3 Utilize the Impact Matrix for Planning

Use the developed impact matrix as a planning tool to anticipate future challenges and prioritize infrastructure investments. The matrix provides clear thresholds for distribution transformer under varying EV penetration scenarios.

5.3 Limitations

While this study provides valuable insights into the integration of electric vehicles (EVs) into Bahrain's distribution network, several limitations should be acknowledged to contextualize the findings and inform future research.

- 1- Simulation Limitations:** The low-voltage (LV) network modeled in this study relies on theoretical data for network elements such as transformers, cables, and loads. While these assumptions ensure a standardized approach to evaluating the impact of EV integration, real-world conditions may differ due to environmental conditions, aging infrastructure, or local operational practices.
- 2- Data Scope and Quality:** Transformer loading data was collected from a sample of 456 distribution transformers, which is considered a sufficient representation of Bahrain's network. However, certain cases or anomalies may affect the observed load patterns. For instance, localized events, such as transformer outages or temporary shifts in consumer behavior, could introduce variations that were not captured in the dataset.
- 3- Impact of Technological Advancements:** Advancements in EV charging technologies and grid systems could significantly alter the observed impacts. Furthermore, future changes in consumer load patterns driven by emerging technologies like renewable energy integration or home energy storage systems may render the findings less applicable over time.
- 4- Controlled Charging Assumptions:** The evaluation of indirect controlled charging strategies in this study is based on the assumption of full consumer compliance with charging schedules. However, real-world implementation is subject to human behavior, variability in charging needs, and the enforcement of policies or incentives. These factors may influence the effectiveness and feasibility of controlled charging strategies as a mitigation measure for EV integration impacts.

5.4 Future Research Directions

1- Integration of Renewable Energy Sources

Investigate the potential for integrating renewable energy sources, such as solar and wind, with EV charging infrastructure. Research should focus on optimizing the interaction between renewable generation and EV loads to reduce reliance on the main grid and enhance sustainability.

2- Harmonic Analysis

Conduct studies on the harmonic distortions introduced by EV chargers, especially with high penetration levels. Harmonic analysis should evaluate the potential impact on power quality, equipment lifespan, and mitigation strategies, such as harmonic filters or improved charger designs.

3- Vehicle-to-Grid (V2G) Technology

Explore the feasibility and benefits of implementing V2G technology in Bahrain's distribution network. This includes assessing the ability of EVs to provide ancillary services, such as voltage support and load balancing, while evaluating the infrastructure and policy requirements for V2G adoption.

4- EV User Behavior Analysis

Investigate the impact of user behavior on EV charging patterns and the effectiveness of indirect controlled charging strategies. This research should consider socio-economic factors, charging preferences, and compliance with controlled charging incentives or policies.

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Appendix 1: Simulation and Network Setup

Load Flow simulation: The Quasi-Dynamic Simulation method was employed in this study to analyze the impact of EV integration on the distribution network. This approach involved conducting multiple load flow calculations over a 24-hour period, with a time step of one minute, resulting in a total of 1440 simulations. The simulation accounted for variations in the active power of residential loads, which were treated as the primary variable. The load flow analysis itself was performed using the Newton-Raphson method. Table A shows the network elements with their associated models and settings.

Table A: Network Parameter

#	Element	Model	Setting
1	DSO Grid	Infinite Bus	$V_{nominal} = 11kV$ $f = 50Hz$ X/R neglected
2	Distribution Transformer	Two winding transformer model	$S_{rated} = 1500kVA$ $V_{HV} = 11kV$ $V_{LV} = 0.415kV$ $Z = 4.5\%$ $P_{no\ load\ Losses} = 1600W$ $P_{copper\ Losses} = 6250W$ $P_{Eddy\ current\ Losses} = 3200W$ $P_{stray\ Losses} = 1580W$ Cooling Type: ONAN Vector Group = Dyn11 off Load Tap = 3 (Normal)

3	LV Feeder	π -model (TypLne)	<i>Type: Underground</i> <i>Conductor: Aluminum</i> <i>Cross section Area = 240mm²</i> $R = 0.124 \Omega/km$ $X = 0.093 \Omega/km$ β : negligible $I_n = 315 A$ <i>Length: 250m</i>
4	Residential Load	Constant power (P, cos θ)	<i>Load type: AC</i> <i>Connection: 3 – phase</i> $P = X kW$ $pf = 0.8$ lagging X: variable with 1440 values
5	EV charger	Constant power (P, cos θ)	<i>Load type: AC</i> <i>Connection: 3 – phase</i> $P = 7.6$ and $11 kW$ $pf = 0.85$ lagging

المخلص

يمثل دمج المركبات الكهربائية في شبكات توزيع الكهرباء تحدياً كبيراً، خاصة في البلدان ذات الأهداف الطموحة لتحقيق الاستدامة مثل مملكة البحرين. تهدف هذه الدراسة إلى تقييم جاهزية شبكة التوزيع ذات الجهد المنخفض في البحرين لاستيعاب الطلب المتزايد على شحن المركبات الكهربائية. تسعى الدراسة إلى تقييم تأثير شحن المركبات الكهربائية على أداء الشبكة واستكشاف استراتيجيات التخفيف من هذه الآثار، بما يدعم انتقال البحرين إلى نظام نقل مستدام.

تركز الدراسة على ثلاثة أهداف رئيسية: نمذجة شبكة توزيع الكهرباء ذات الجهد المنخفض في البحرين، قياس تأثير شحن المركبات الكهربائية في سيناريوهات مختلفة، وتقييم فاعلية التحكم غير المباشر لشحن المركبات كاستراتيجية للتخفيف من التأثيرات المحتملة. تم إجراء محاكاة باستخدام برنامج (DigSILENT PowerFactory) لتحليل أحمال المحولات، هبوط الجهد، أحمال المغذيات، وخسائر القدرة الكهربائية، في ظل مستويات تواجد مختلفة للمركبات الكهربائية وسيناريوهات شحن متنوعة (7.6 كيلوواط و 11 كيلوواط). كما تم تحليل قاعدة بيانات تضم أكثر من 233 مليون قراءة لأحمال المحولات باستخدام برنامج (Python) لدراسة أنماط الأحمال الحقيقية، وأوقات الذروة، وفرص تحسين الشحن.

أظهرت النتائج أن شبكة البحرين يمكنها استيعاب مستويات التواجد للمركبات الكهربائية في المستقبل القريب، لكن في مستويات التواجد الأعلى، خاصة مع شواحن بقوة 11 كيلوواط، قد تؤدي إلى تحميل زائد للمحولات، وهبوط للجهد، وزيادة تحميل المغذيات. أثبتت استراتيجيات التحكم غير المباشر، مثل شحن المركبات في أوقات انخفاض الأحمال بين الساعة 2 صباحاً و 8 صباحاً، فعاليتها في التخفيف من هذه الآثار. كما تم تطوير مصفوفة لتأثير المركبات على الشبكة لتقييم المخاطر والتخطيط الفعال. تسهم هذه النتائج في صياغة السياسات والتخطيط الاستراتيجي بما يتماشى مع أهداف البحرين البيئية والتحول العالمي نحو النقل الكهربائي.

جامعة البحرين

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الكهربائية والالكترونية



كلية الهندسة

التأثيرات والحلول لدمج المركبات الكهربائية في شبكة توزيع الكهرباء في مملكة البحرين

أطروحة مقدمة كجزء من متطلبات الحصول على درجة الماجستير
في هندسة الطاقة المتجددة

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