Project Report

Evaluation of Distributed Solar PV and EV Hosting Capacity of Distribution Networks for Off-Grid Remote Communities in Canada

ECE 730 A01: Smart Grid Fundamentals

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Contents

1 Introduction

The world is switching to renewable and clean energy sources from fossil fuels to combat climate change, and with it, the architecture of power systems is evolving exponentially. One of the key elements in this transition is the widespread integration of distributed energy resources (DERs) including solar photovoltaic (PV) generations, wind turbines, and battery energy storage systems. However, high DERs penetration in low- and medium-voltage distribution networks can disrupt standard operations, causing voltage violations, reverse power flow, line overloads, and increased losses [1]. Similarly, large-scale adoption of electric vehicles (EVs) not only supports climate goals by promoting clean transportation system but also enhances operational efficiency of the power grid by providing ancillary services, and aiding in contingency management. Yet, large-scale EV integration to the grid introduces new complexities, including heightened electricity demand and new unique load profiles [2]. To maintain security and reliability of the distribution networks, distribution system operators (DSOs) assess the hosting capacity for DERs and EVs—i.e., the maximum amount of DER generations or EV loads capacity that can be integrated into a distribution network without violating any operational constraints. Early hosting capacity analysis methods primarily relied on simplified engineering models and deterministic approaches. However, the increasing complexity of distribution systems, along with the inherent uncertainties in DERs and EVs behavior, as well as varying system conditions, necessitates the adoption of more advanced and robust methodologies for hosting capacity estimation.

1.1 Motivation

PV generation is experiencing rapid global expansion and now plays a pivotal role in achieving worldwide carbon neutrality. In 2020, global PV installations rose by 18%, setting a record of 138 GW [3]. This momentum has fostered the proliferation of distributed PV systems within distribution networks, with rooftop PV—one of the most prevalent forms—projected to grow by 60%, reaching 96 GW by 2025 [3]. A parallel surge is evident in the global EV market as it advances the decarbonization of transportation sector. In 2022, global EV sales exceeded 10 million units [4], while in Canada, EV sales reached approximately 120,000 units (about 11.7% of total sales) [4]. To further support these transitions, the Canadian government aims to achieve a net-zero power system by 2035 and ensure that all new light-duty vehicle sales are zero-emission [5]. However, the participation of Canada's remote, off-grid communities—numbering 292 across its vast territory—is essential to successfully realize these objectives. Most of these communities depend on isolated, diesel-based power systems [6], as illustrated in Fig. 1. It is therefore critical to evaluate the readiness of these isolated grids for high penetrations of DERs and the associated EV charging loads. To address this issue, the initial step involves conducting a needs assessment to determine the extent of distributed PV generation and EV integration that can be accommodated without compromising system integrity—i.e., evaluating PV and EV hosting capacities. The goal of this course project is to propose a methodological framework for estimating PV and EV hosting capacities in the distribution systems of remote communities and to demonstrate its application through a case study.

1.2 Literature Review

Hosting capacity estimation for DERs and EVs can be conducted at various levels of the distribution network—node, feeder, substation, area, or even system-wide—based on voltage levels, load characteristics, and DER types. This field is evolving rapidly, driven by advancements in data analytics, machine learning, optimization algorithms, and computational capabilities. According to the existing literature, hosting capacity estimation techniques can be broadly classified into six categories: Deterministic, Stochastic, Streamlined, Time-series, Optimization-based, and Data-driven methods [1]. Each category has its own merits and limitations.

Deterministic approaches rely on prior data and use fixed or variable DER parameters, providing straightforward and computationally efficient analysis. However, they do not adequately account for uncertainties. For instance, [7] employs a deterministic, iterative snapshot power flow method to determine EV hosting capacity at the node level, considering bus voltage and line thermal limits as

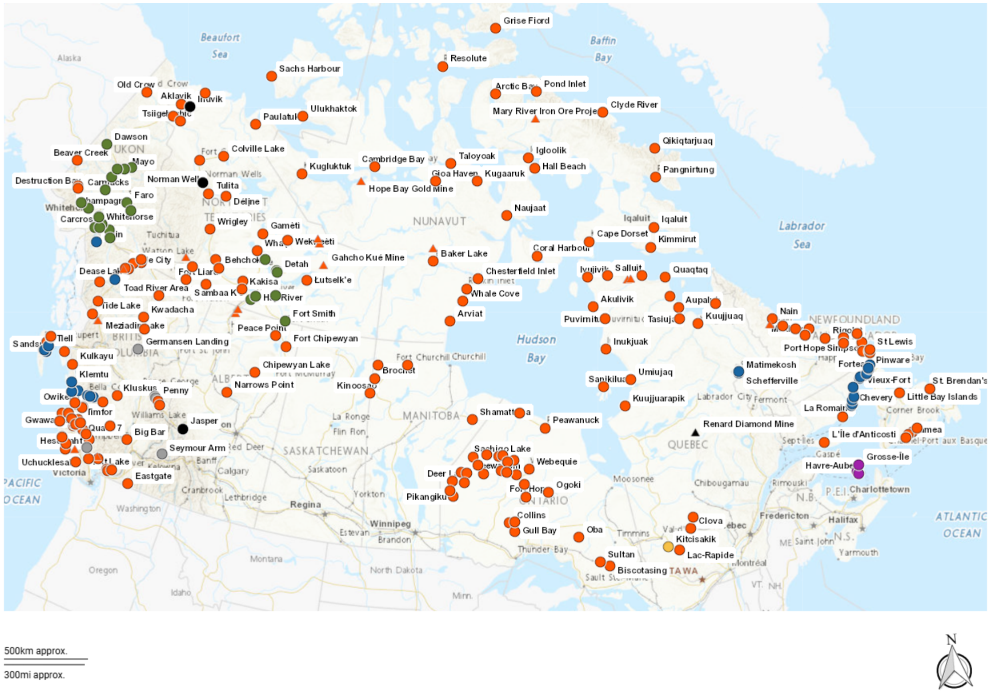


Figure 1: Off-grid remote communities in Canada [6]

performance indices. Although computationally simple, such methods may misrepresent real-world conditions due to their limited consideration of variability in load and generation.

Stochastic approaches incorporate uncertainties in load profiles and DER generation, leading to more realistic hosting capacity estimations. For example, [8] uses a Monte Carlo (MC)-based probabilistic power flow method to estimate PV hosting capacity for three distribution networks in Alberta, Canada, under different penetration levels considering considering bus voltage limits as the only performance index. Using probability distributions, this approach captures variability in generation and load more accurately. However, the computational complexity of stochastic methods is higher than that of deterministic ones.

Streamlined techniques estimate hosting capacity without simulating a large number of scenarios, thus reducing computational burden compared to stochastic methods. They can integrate other approaches, such as deterministic and optimization-based methods. For example, [9] presents a two-stage Optimal Power Flow (OPF)-based DER hosting capacity assessment technique. The first stage identifies optimal DER locations without operational constraints, while the second stage calculates the locational and total DER hosting capacity using a security-constrained OPF. Although streamlined methods are efficient, they rely on fixed assumptions and may not fully capture the uncertainties affecting realistic hosting capacity.

Time-series approaches improve upon deterministic techniques by incorporating temporal variations and high-resolution datasets that reflect fluctuating generation and load patterns. By considering time-varying uncertainties, these methods yield more realistic estimates. In [10], a Quasi-Static Time Series (QSTS) load flow method assesses EV hosting capacity, considering bus voltage limits and asset congestion as performance indices. While this approach captures time-varying conditions more accurately, it requires significant computational resources.

Optimization-based techniques explicitly formulate uncertainties and constraints as an optimization problem, allowing for systematic handling of multiple uncertainties, constraints, and objectives. For example, [11] employs a repeated Particle Swarm Optimization (PSO) algorithm to estimate PV hosting capacity, considering node voltages, line currents, transformer kVA, and reverse power flow limits as constraints. However, such optimization-based methods can be computationally demanding and depend on assumptions that may not perfectly reflect real-world scenarios.

Data-driven approaches leverage historical and measured data, often from smart meters or other monitoring devices, to create models for real-time hosting capacity estimation and forecasting. In [12], a

Spatial Temporal LSTM-based method provides real-time DER hosting capacity estimation. Despite the promise of data-driven solutions, they require substantial training data, often obtained from other hosting capacity estimation techniques, to ensure accurate and reliable performance.
In summary, each approach—deterministic, stochastic, streamlined, time-series, optimization-based, and data-driven—offers distinct advantages and faces inherent limitations. As research progresses and computational capabilities continue to grow, it is likely that future approaches will integrate and refine these methods, leading to more holistic, efficient, and data-driven solutions for DER and EV hosting capacity estimation.

1.3 Main Contributions

Upon reviewing the existing literature, it is evident that hosting capacity estimation are highly distribution network-specific. To advance this understanding, this course project adopts stochastic and time-series methods to jointly estimate the PV and EV hosting capacities of off-grid distribution networks in remote Canadian communities. As a case study, we focus on the Fort Chipewyan network in northern Alberta. The main contributions of this work are as follows:

- Develop a joint PV and EV hosting capacity estimation framework for distribution networks, integrating both stochastic and time-series techniques.
- Introduce a systematic approach to examine how PV penetration affects EV hosting capacity and, conversely, how EV integration influences the PV hosting capacity.
- Apply the proposed method to the Fort Chipewyan distribution network, demonstrating its applicability in a remote, off-grid Canadian community.

The remainder of this report is structured as follows: Section 2 outlines the methodology for hosting capacity estimation. Section 3 presents the use-case implementation in the Fort Chipewyan network. Section 4 discusses the effectiveness of the proposed approach and highlights key insights from the case study. Section 5 summarizes the main conclusions and suggests avenues for future work. Finally, Section 6 provides a link to the GitHub repository containing the dataset, source code, saved models, and results.

2 Methodology

We adopt a combination of stochastic analysis and QSTS simulation techniques to estimate the PV and EV hosting capacities of a distribution grid system. The stochastic approach, implemented via Monte Carlo (MC) simulations, addresses the inherent uncertainties associated with the location and generation of PV panels, EV charging loads' location, start times, and charging durations. The QSTS load flow analysis captures the time-varying nature of PV generation, EV charging demand, and residential loads, enabling a comprehensive assessment of their impact on grid hosting capacity. The overall methodology is illustrated in Fig. 2.
Before initiating the simulation, following tasks need to be carried out-

(i) *Network Modeling and Validation:* The distribution network model is built and validated in OpenDSS.

(ii) *Simulation Parameters:* The time step as well as time frame for simulation (e.g., specific days or months of a year) and the number of Monte Carlo runs to be conducted are defined.

The simulation process starts with random allocation of load profiles to customers. PV and EV hosting capacity of the distribution grid are analyzed separately.

2.1 Analysis of PV Hosting Capacity

PV hosting capacity estimation of a distribution grid at a fixed EV penetration level are executed in following manner-

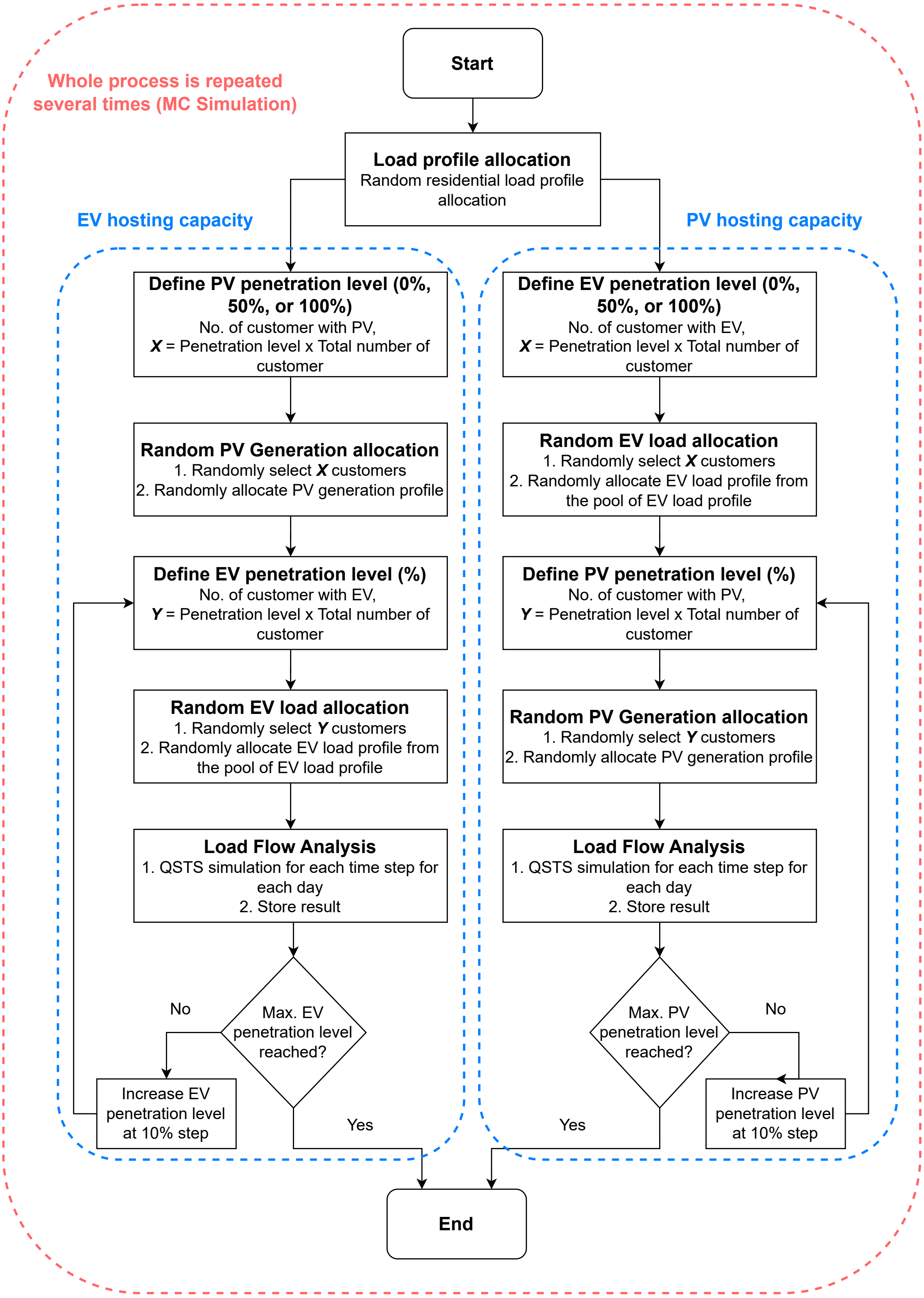


Figure 2: Overall methodology for estimating PV and EV hosting capacity of a distribution grid

(i) *Define EV Penetration Level:* A fixed EV penetration level (e.g., 0%, 50%, or 100%) is defined.

(ii) *Allocate EV Profiles:* The number of customers (denoted as X) with EV based on the penetration level is calculated, and EV charging load profiles are randomly allocated to these customers.

(iii) *Define PV Penetration Level:* PV penetration level starts with 0% and increments by 10% in successive simulations.

(iv) *Allocate PV Profiles:* For each PV penetration level, the number of customers (Y) with PV systems are calculated and their generation profiles are allocated randomly to these customers.

(v) *Load Flow Analysis:* Three-phase unbalanced load flow analysis for each time step are carried out and the results are stored.

The process is repeated by incrementing the PV penetration level in defined steps (10%) until it reaches 100%. This entire procedure is performed multiple times based on the specified number of MC runs to account for the uncertainties. Upon completing all MC runs for the current EV penetration level, the next EV penetration level is selected, and the entire PV hosting capacity estimation procedure is executed again.

2.2 Analysis of EV Hosting Capacity

The estimation of EV hosting capacity for a distribution grid at a fixed PV penetration level is conducted as follows:

(i) *Definition of PV Penetration Level:* The PV penetration level (e.g., 0%, 50%, or 100%) is defined.

(ii) *Allocation of PV Profiles:* PV generation profiles are randomly assigned to customers based on the specified PV penetration level.

(iii) *Definition of EV Penetration Level:* The EV penetration level is initialized at 0% and is incremented in steps of 10% for successive simulations.

(iv) *Allocation of EV Profiles:* For each EV penetration level, the number of EV-owning customers (Y) is calculated, and EV charging load profiles are randomly assigned from the available EV charging loads pool.

(v) *Load Flow Analysis:* Three-phase unbalanced load flow analysis is performed for each EV penetration level, and the results are stored.

The process is repeated by incrementing the EV penetration level in 10% steps until 100% is reached. To account for uncertainties, the entire procedure is repeated multiple times, as determined by the specified number of MC runs. Once all MC runs are completed for the current PV penetration level, the next PV penetration level is selected, and the entire EV hosting capacity estimation procedure is repeated.

2.3 Performance Metrics

The hosting capacity are assessed in terms of both voltage issues and asset congestion, measured using the following metrics:

- *Voltage Compliance:* The percentage of customers experiencing voltage levels outside the allowable range (0.95–1.05 p.u.).
- *Distribution Transformer Utilization:* The maximum daily utilization of transformers relative to their rated capacities.

In this study, we assume PV penetration level as the percentage of customers equipped with one solar PV system and EV penetration level as the percentage of customers owning one EV. The PV and EV hosting capacities of a distribution network are defined as the maximum penetration levels that do not result in asset congestion or voltage violations, thus maintaining network integrity. The AC power flow simulations are executed in OpenDSS [13] controlled through the *DSS-Python* [14] library in Python.

3 Case Study

Fort Chipewyan, as illustrated in Fig. 3, has been selected as the case study for this course project. It is an off-grid remote community located in northern Alberta, Canada, with a permanent population of approximately 1,000 residents. Accessibility to Fort Chipewyan is highly seasonal; during winter months, the community can be reached by its famous winter road. For the remainder of the year, access is limited to costly alternatives such as river barge transportation or air travel.

Figure 3: Fort Chipewyan remote community in northern Alberta (source: 3NE Fort Chip)

3.1 Distribution System of Fort Chipewyan

The electricity distribution network in Fort Chipewyan operates as a standalone microgrid operated and maintained by ATCO. This microgrid is entirely isolated from the Alberta Interconnected Electric System (AIES). A simplified single-line diagram of the system is depicted in Fig. 4. The microgrid includes four diesel generators, each with a capacity of 1.145 MW, supplying power at 4.16 kV. Additionally, it integrates two grid-scale solar PV farms with capacities of 600 kW and 2.2 MW, respectively, making it the largest off-grid solar farm in Canada to date [15]. The system also incorporates a grid-scale battery energy storage system with a capacity of 1.675 MWh. The distribution system operates at 25 kV in a three-phase configuration, with the residential zone located approximately 8 km from the diesel generation facility. The distribution system model has been developed and validated in *OpenDSS*. In all simulations and scenario studies, the tap positions of the distribution transformers are maintained one step above the nominal tap as a standard practice. Volt-watt control is implemented for the grid-scale PV solar farm system, while the grid-scale battery storage system operates in "Peak Shaving" mode. This network serves approximately 400 residential customers. Peak electricity demand occurs in January, reaching approximately 2.4 MW, while the lowest peak demand, 1.6 MW, is recorded in July, as per 2018 data. We have assumed $pf = 1$ for all residential customers in all the simulations for simplicity.

3.2 PV Generation Profiles

The global horizontal solar irradiance (GHI) data (kJ/m^2) for Fort Chipewyan in 2017 is collected from Natural Resources Canada [16]. This data is processed and converted into normalized PV generation potential compatible with *OpenDSS* for each day of the year. The PV generation potential for January and July is illustrated in Fig. 5a and Fig. 5b, respectively. It is evident that the PV generation potential in January (peak normalized PV generation potential is approx. 0.22) is significantly lower compared to July in Fort Chipewyan region. We considered various PV panel sizes (2 kW, 3 kW, 5 kW, and 8 kW), randomly assigned to customers with PV systems.

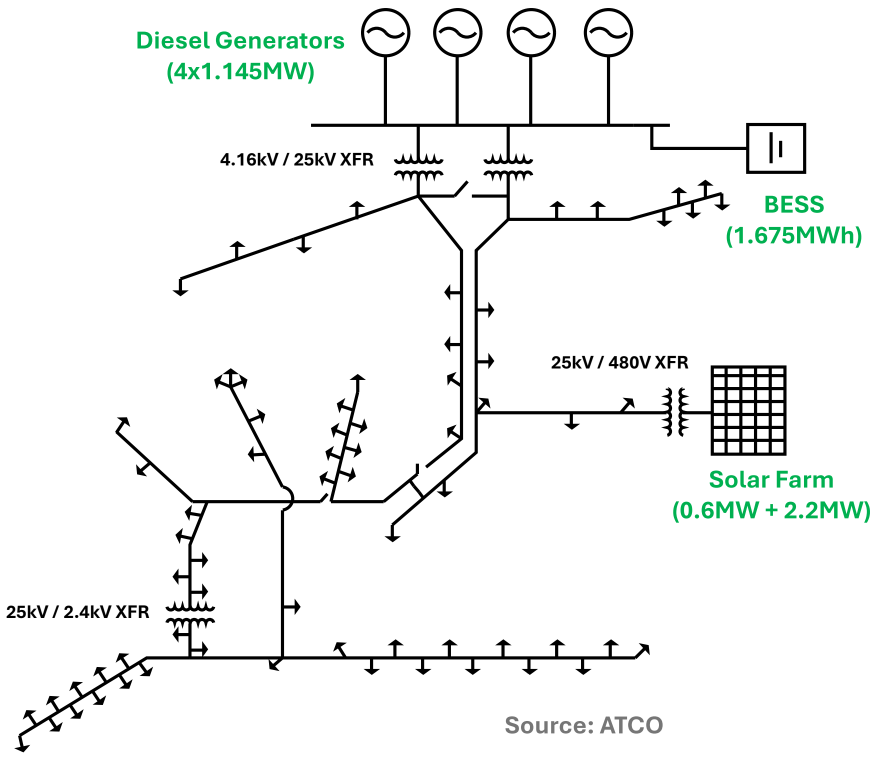


Figure 4: Distribution network at Fort Chipewyan community (source: ATCO)

3.3 EV Charging Demand Profiles

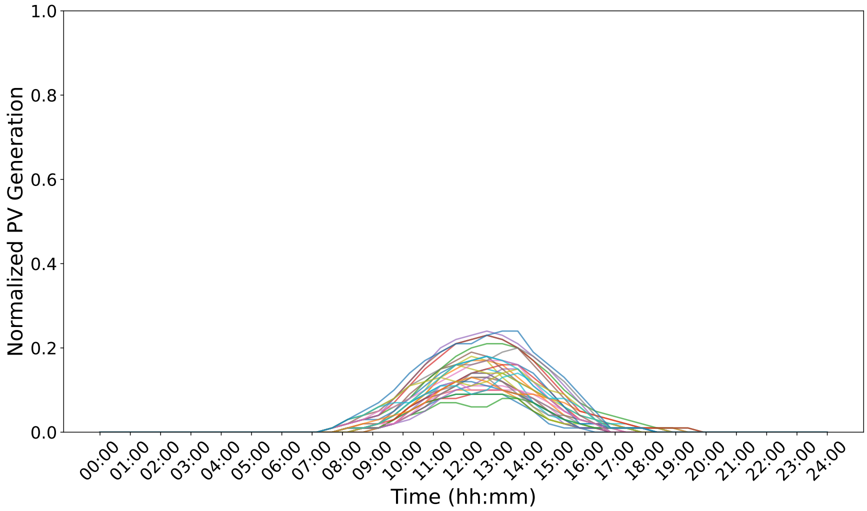
Residential EV charging session data is adopted from the Norwegian home EV charging dataset [17]. This dataset provides real-world EV charging sessions, documenting a total of 6,878 charging sessions registered by 97 user IDs, spanning from December 2018 to January 2020. The charging sessions include session-specific information such as user identifiers, plug-in time, plug-out time, and consumed energy. The probability distributions of charging start times and charging durations are shown in Fig. 6a and Fig. 6b, respectively. These distributions reveal that most EV charging sessions commence between 5:00 PM and 10:00 PM, with the majority of charging durations ranging from one to four hours.

The key criteria considered in this course project to model EV charging demand profiles are presented below.

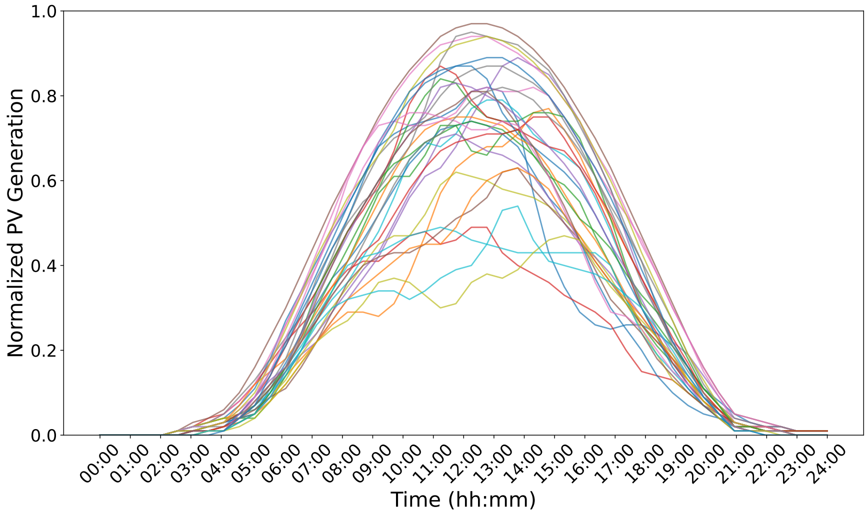
(i) *Charging start time and duration:* The most critical parameters characterizing a charging event are the charging 'start time' and 'duration', which represent the interval from the initiation to the completion of charging. For this study, it is assumed that EV charging patterns remain consistent across weekdays and weekends. Additionally, it is presumed that charging begins immediately upon plugging in the vehicle.

(ii) *EV charging power:* In North America, EV charging is classified into three levels based on power delivery [18]. Level 1 charging operates at 120V and provides up to 1.9 kW of power, suitable for basic home use. Level 2 charging, using 240V, delivers between 3.3 kW and 19.2 kW of power and is commonly used in homes, workplaces, and public charging stations. DC fast charging offers the highest power levels, typically ranging from 50 kW to over 350 kW. In this study, a charging power of 3.3 kW is considered for EVs, with the assumption that the charging power remains constant throughout the charging session.

(iii) *Power factor:* It is assumed that power factor is 1 throughout the charging session and no harmonic currents are injected by the chargers.



(a) PV generation potential for January, 2017.



(b) PV generation potential for July, 2017.

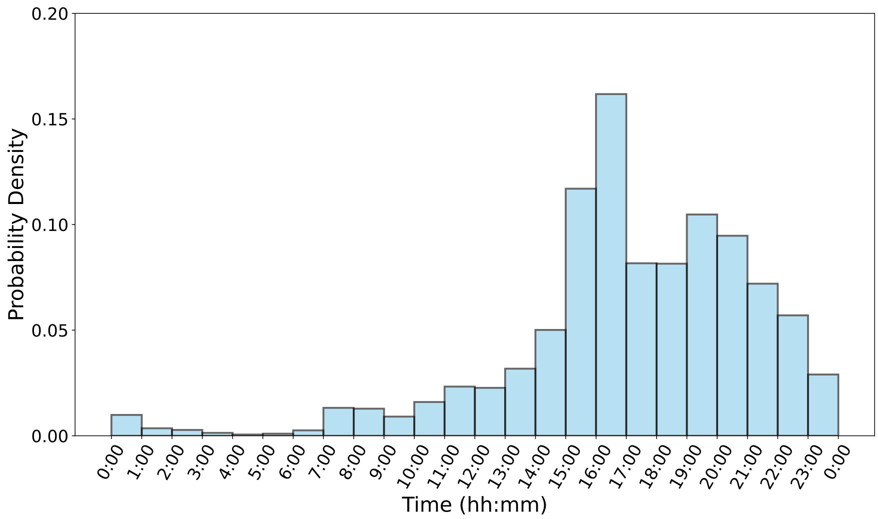
Figure 5: PV generation potential in Fort Chipewyan for (a) January, 2017 and (b) July, 2017.

(iv) *Uncoordinated charging:* It is assumed all the EV charging sessions are uncontrolled and EV starts drawing power at rated capacity as soon as it is plugged-in.

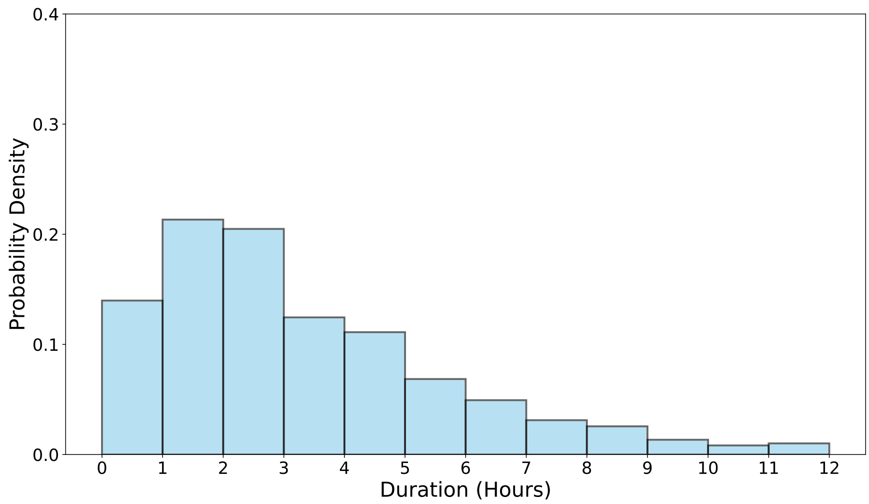
Using the probability distributions of charging start time and duration, along with the stated assumptions, a pool of 10,000 EV charging demand profiles are generated. A representative sample of 10 EV charging demand profiles is illustrated in Fig. 7.

3.4 Experiment

The distribution network model is developed and validated using OpenDSS [13]. OpenDSS (Open Distribution System Simulator) is an open-source software developed by EPRI for simulating and analyzing electric power distribution systems. It supports time-series simulations, load flow analysis, fault studies, and the integration of renewable energy resources, making it a versatile tool for grid planning, operation, and research. In this project, a half-hourly quasi-static time-series (QSTS) AC load flow simulation is conducted, corresponding to 48 time steps per day. To account for uncertainties in distributed PV generation and EV charging loads, 100 Monte Carlo (MC) simulations are performed for each scenario considering the available computational resources. For instance, with a fixed PV penetration level of 50%, the EV penetration level is varied from 0% to 100% in increments of 10%



(a) PDF for EV charging start time.



(b) PDF for EV charging duration.

Figure 6: Probability density functions for EV charging behavior: (a) start time and (b) duration.

and considering 100 MC simulations, the total number of power flow simulations with half-hourly load data for the month of January would be:

$$N_{\text{simulation steps}} = 100 \times 11 \times 48 \times 31 = 1,636,800$$

To estimate the PV and EV hosting capacity of the Fort Chipewyan distribution network, two distinct cases are analyzed:

(i) *PV hosting capacity estimation:* The month of July is chosen for PV hosting capacity estimation as it experiences the lowest electricity demand alongside the highest potential for PV generation. These conditions create a worst-case scenario for PV hosting capacity of the network (i.e., possibility of over voltage issues in the network). We have considered three EV penetration levels (0%, 50%, and 100%) to assess the impact of EV penetration on PV hosting capacity.

(ii) *EV Hosting Capacity Estimation:* The month of January is selected for EV hosting capacity estimation. It is the highest load month, which presents a worst-case scenario for EV hosting capacity estimation (i.e., possibility of low voltage issues in the network). In this case, we have considered three PV penetration levels (0%, 50%, and 100%) to determine the impact of PV penetration on EV hosting capacity. Since PV generation potential in January is low, its impact

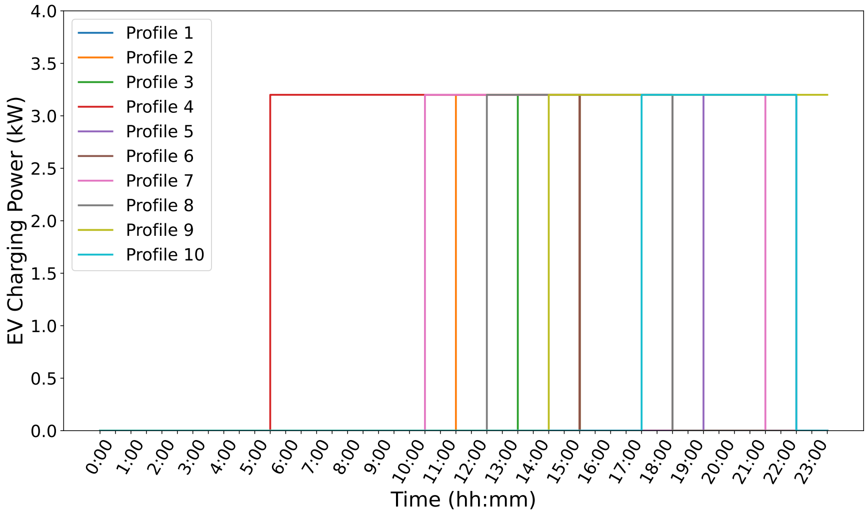


Figure 7: A sample of EV charging demand profiles

on EV hosting capacity may be negligible. To gain clearer insights into how PV penetration affects EV hosting capacity, we also present results for July, when PV generation potential is at its peak.

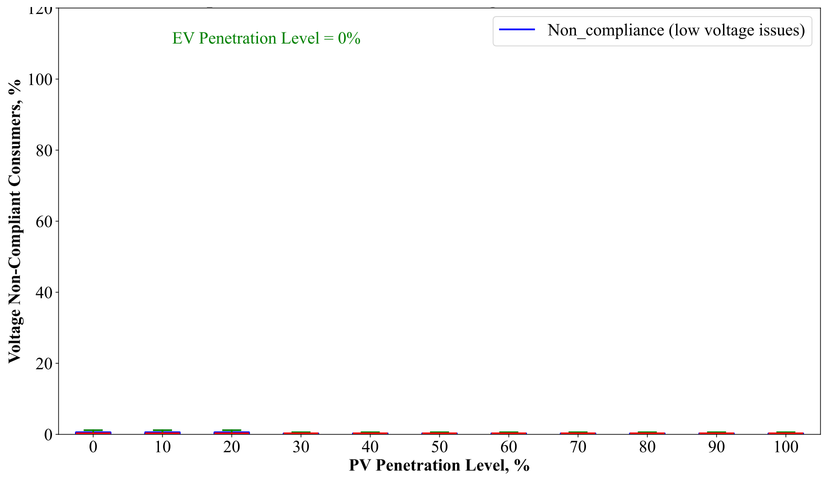
All simulations performed in OpenDSS are controlled through the `dss-python` library in Python [14].

3.5 Result and Analysis

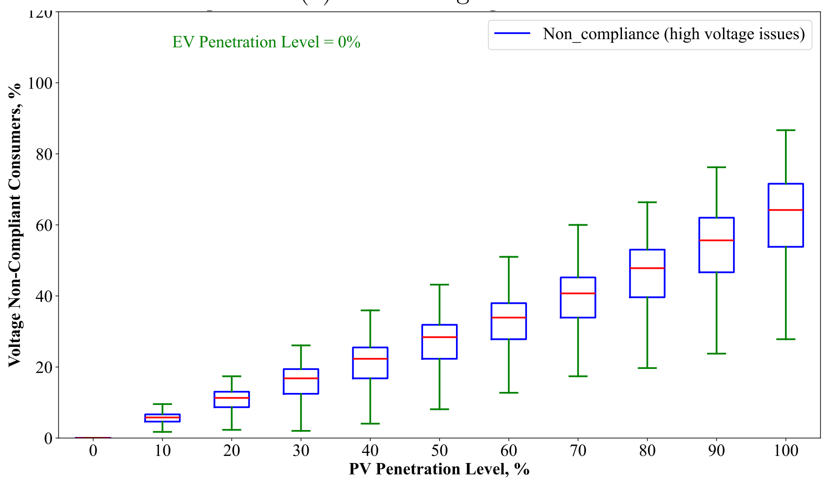
Since MC simulations are performed to account for the uncertainties in PV generation and EV charging loads, the results—such as the percentage of customers experiencing high or low voltage issues and the utilization levels of distribution transformers—are presented as probability distributions using box-and-whisker plots. This representation provides a clearer understanding of the range, variability, and likelihood of outcomes under different scenarios.

3.5.1 PV Hosting Capacity Estimation

The PV hosting capacity is first evaluated with the EV penetration level set to 0% (i.e., no EV loads) for the month of July. The percentage of customers experiencing low voltage and high voltage issues is shown in Fig. 8. It is evident that no customers face low voltage issues across all PV penetration levels. However, a small percentage of customers (approximately 5%) begin to experience high voltage issues at a PV penetration level of 10%, and this percentage increases at higher PV penetration levels. Percentage of customers experiencing high voltage issues reaches to approximately 80% at 100% PV penetration level. This trend arises because the existing grid-scale solar PV farm in Fort Chipewyan has a generation capacity of 2.8 MW, which far exceeds the peak load requirement for July (1.6 MW). Adding additional distributed PV systems to the network without local battery storage system causes these home PV generations to feed excess power back into the grid, leading to high voltage issues at the points of common coupling (PCC) on the LV side of the network. The distribution transformer utilization profile at 100% PV penetration is shown in Fig. 9, and no transformers exhibit overloading issues even at this penetration level. Consequently, in this scenario, the limiting performance metric is the LV bus voltage, and the PV hosting capacity is restricted to 10%.
The PV hosting capacity is also evaluated for the month of July with EV penetration levels fixed at 50% and 100%. Since the results for 100% EV penetration are similar to those for 50% EV penetration, only the results for 50% EV penetration are presented here in Fig. 10 and Fig. 11. The results indicate that a small percentage of customers begin to face high voltage issues at a PV penetration level of 10%, regardless of whether the EV penetration level is 50% or 100%. Additionally, some customers experience low voltage issues, although the percentage decreases slightly at higher PV penetration levels. These low voltage issues primarily result from the fixed EV penetration levels (50% and 100%).



(a) Low voltage issues



(b) High voltage issues

Figure 8: Percentage of customers facing low and high voltage issues with EV penetration fixed at 0% and varying PV penetration levels for the month of July.

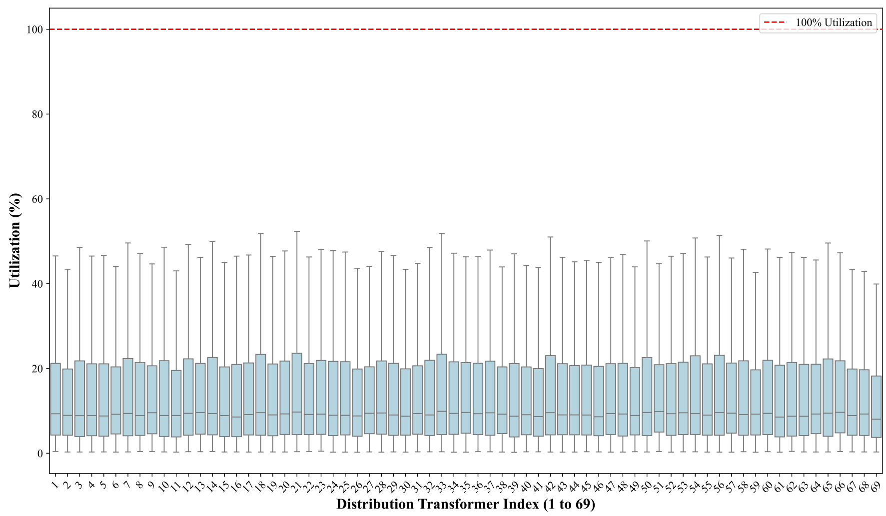
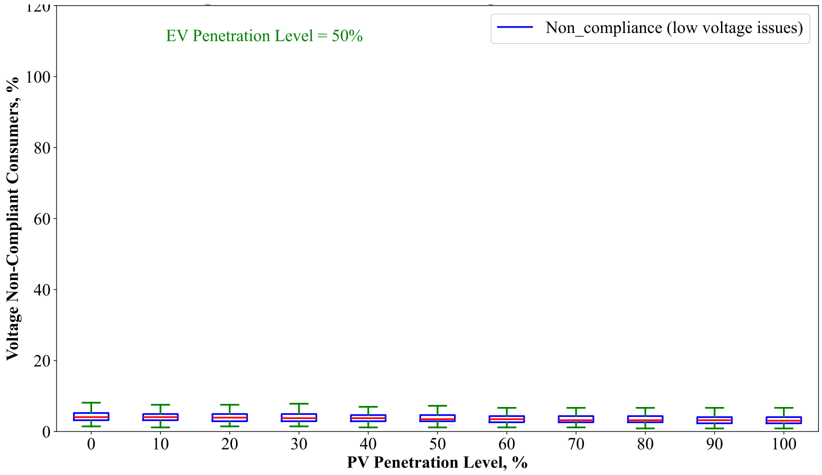
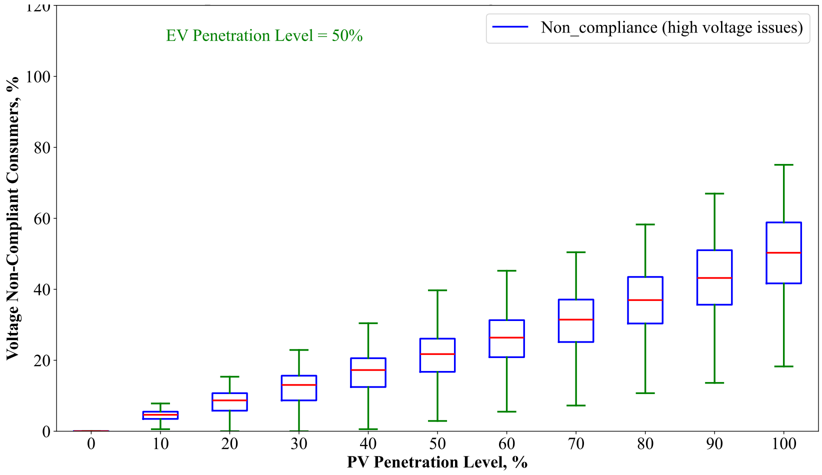


Figure 9: Utilization level of distribution transformers for 0% EV penetration and 100% PV penetration for the month of July

Furthermore, the distribution transformers continue to operate within their permissible utilization limits in all cases. Therefore, the limiting performance metric remains the LV bus voltage, and the PV hosting capacity is once again constrained to 10%. The minimal impact of EV penetration levels on PV hosting capacity is due to the mismatch between the peak times of PV generation and EV charging loads. The slight decreasing trend in the percentage of customers experiencing low voltage issues with increasing PV penetration suggests that aligning the EV load peak with the PV generation peak could significantly mitigate voltage issues, enhancing the network's ability to host higher levels of distributed PV generation.



(a) Low voltage issues



(b) High voltage issues

Figure 10: Percentage of customers facing low and high voltage issues with EV penetration fixed at 50% and varying PV penetration levels for the month of July.

3.5.2 EV Hosting Capacity Estimation

The EV hosting capacity of the network is first evaluated with the PV penetration level set to 0% (i.e., no distributed PV generation) for the month of January. The percentage of customers experiencing low voltage and high voltage issues is shown in Fig. 12. It is observed that approximately 5% of customers begin to experience low voltage issues at 30% EV penetration, with the percentage increasing at higher EV penetration levels. At 100% EV penetration level, percentage of customers facing low voltage issues reaches to approximately 35%. No customers face high voltage issues at any EV penetration level. The utilization levels of distribution transformers at 80% and 100% EV penetration are illustrated in Fig. 13. At 80% EV penetration, only one distribution transformer exhibits overloading during a few instances, whereas at 100% EV penetration, a significant number of transformers experience overloading. Therefore, in this scenario, the limiting performance metric is the LV bus voltage, and the EV hosting capacity of the network is restricted to 30%.

The EV hosting capacity is further evaluated with the PV penetration level fixed at 50% and 100% for the month of January. It is found that regardless of the PV penetration level, approximately

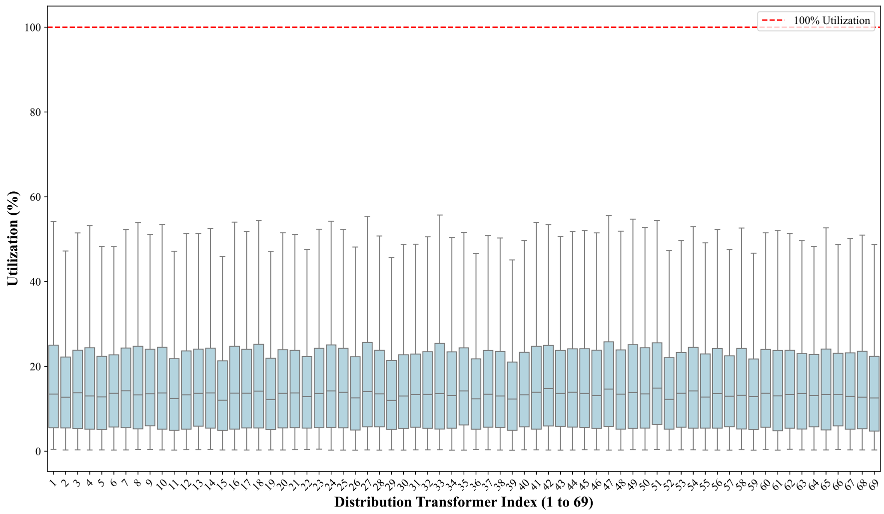
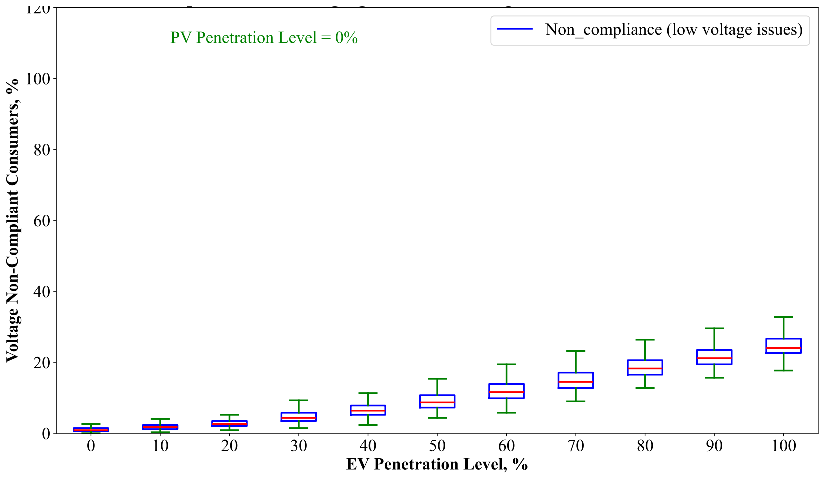
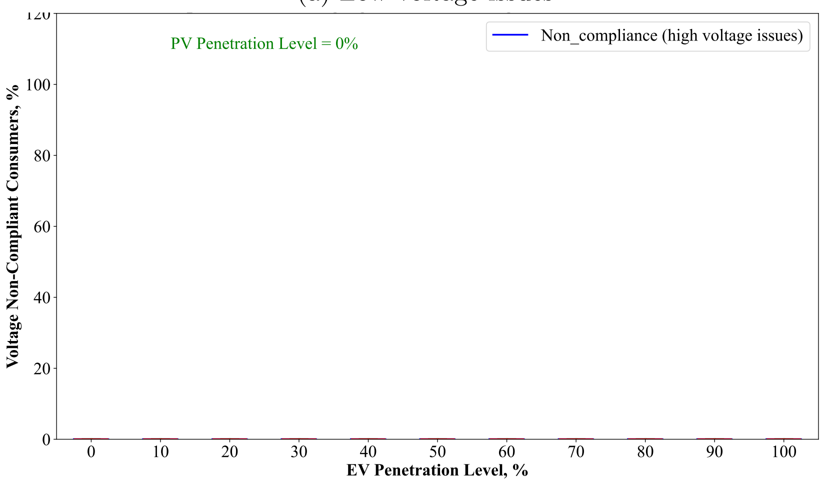


Figure 11: Utilization level of distribution transformers for 50% EV penetration and 100% PV penetration for the month of July



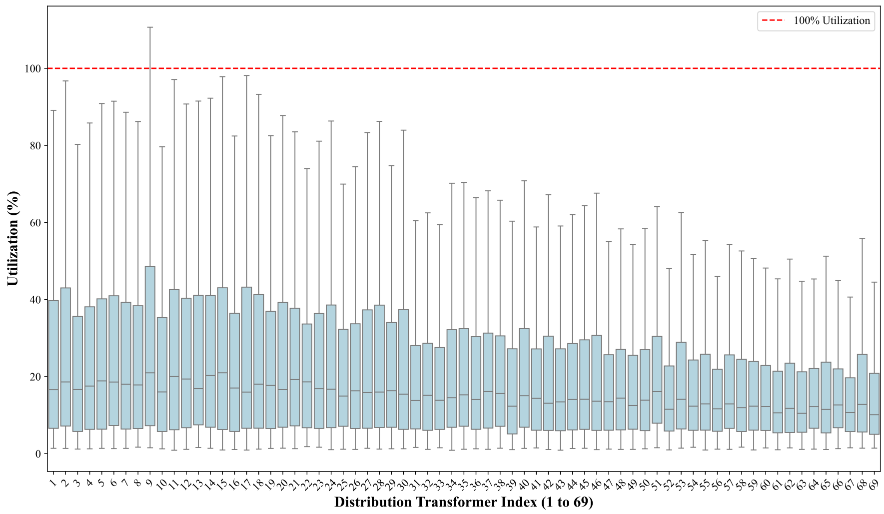
(a) Low voltage issues



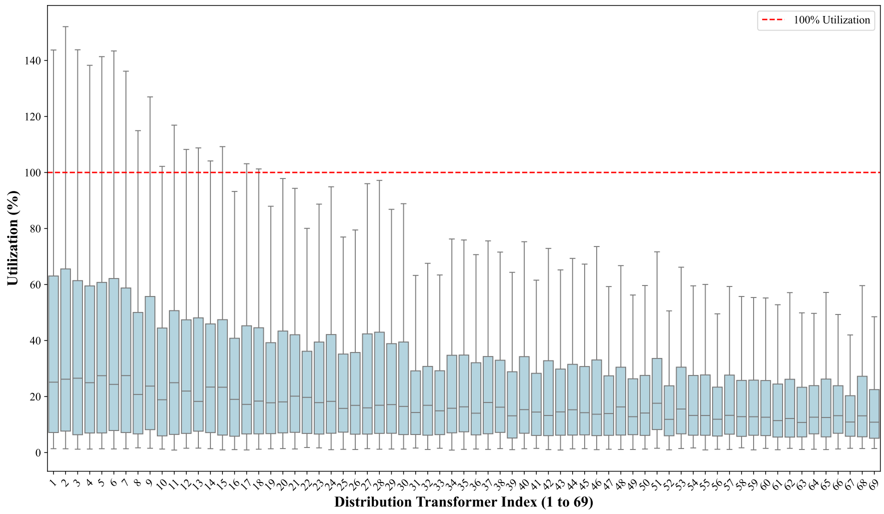
(b) High voltage issues

Figure 12: Percentage of customers facing low and high voltage issues with PV penetration fixed at 0% and varying EV penetration levels for the month of January.

5% of customers start experiencing low voltage issues at 30% EV penetration, with this percentage increasing at higher EV penetration levels. No high voltage issues are observed, even at 100% PV penetration. This is attributed to the low PV generation potential in the month of January in the Fort



(a) Utilization of distribution transformers for 80% EV penetration

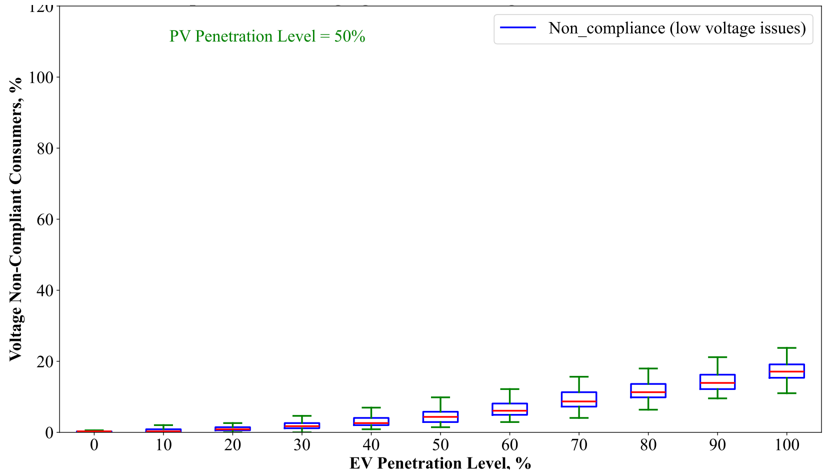


(b) Utilization of distribution transformers for 100% EV penetration

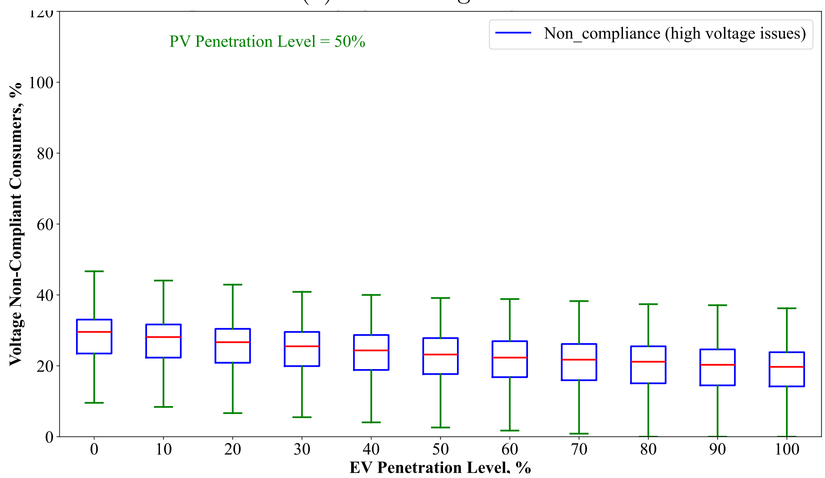
Figure 13: Utilization levels of distribution transformers for 0% PV penetration and varying EV penetration levels (80% and 100%) for the month of January.

Chipewyan region, which does not contribute to high voltage issues even at maximum PV penetration levels. The utilization levels of distribution transformers remain consistent with the case of 0% PV penetration. Thus, it is evident that the PV penetration level in January has negligible impact on the EV hosting capacity of the network.

To assess whether PV penetration has any impact on EV hosting capacity, the EV hosting capacity for the month of July (when PV generation potential is at its peak) is evaluated with the PV penetration level fixed at 50%. The percentage of customers experiencing low voltage and high voltage issues is shown in Fig. 14. It is observed that approximately 5% of customers begin to face low voltage issues at a higher EV penetration level (40%) compared to the January scenario (30%). However, with the PV penetration level fixed at 50%, about 30% of customers experience high voltage issues at 0% EV penetration. This percentage decreases gradually with increasing EV penetration levels. These results suggest that aligning the EV load peak with the PV generation peak could help mitigate voltage issues, thereby increasing both PV and EV hosting capacities. The utilization levels of distribution transformers remain consistent with the results obtained for January, indicating that transformer capacity is not a limiting factor in this scenario.



(a) Low voltage issues



(b) High voltage issues

Figure 14: Percentage of customers facing low and high voltage issues with PV penetration fixed at 50% and varying EV penetration levels for the month of July

4 Discussion

For both PV and EV hosting capacity estimations, the LV bus voltage (customer side) is identified as the limiting performance index for the Fort Chipewyan distribution network. The PV hosting capacity is determined to be 10%, while the EV hosting capacity is estimated at 30% for the Fort Chipewyan network. The limited PV hosting capacity is primarily attributed to the presence of a grid-scale solar PV farm with a capacity of 2.8 MW, which significantly exceeds the load demand for July, the month with the highest PV generation potential. Adding additional residential solar PV systems without local battery energy storage results in excess power being fed back into the grid, causing over voltage issues at the points of common coupling (PCC) on the LV side of the network. The impact of EV penetration on PV hosting capacity, and vice versa, is minimal. This is expected as PV generation peaks during midday, whereas EV charging load peaks typically occur in the evening, resulting in limited complementarity between their hosting capacities. However, at higher EV penetration levels, the percentage of customers experiencing low voltage issues decreases slightly with increasing PV penetration. Similarly, at higher PV penetration levels, the percentage of customers facing high voltage issues decreases slightly with increasing EV penetration. These observations suggest that aligning EV charging demand with PV generation peaks through demand response programs or other control strategies, or integrating battery energy storage systems to store excess PV generation for use during EV charging peaks, could significantly enhance both PV and EV hosting capacities of the network.

5 Conclusion

In this course project, we present a comprehensive framework to evaluate the joint PV and EV hosting capacities of distribution networks, leveraging both stochastic and time-series techniques. The proposed methodology is applied to the Fort Chipewyan distribution network, an off-grid remote community in northern Alberta, Canada. Our analysis reveals that the existing microgrid of the Fort Chipewyan community has limited hosting capacities for distributed PV generations and EV charging loads, posing significant challenges to their deep penetration. These findings emphasize the need for hosting capacity enhancement measures—such as network reinforcements, advanced control strategies, or energy storage solutions—before large-scale deployment of PVs and EVs can be realized in such remote communities. More broadly, the proposed methodology can be replicated across other off-grid communities in Canada, assisting stakeholders in strategically planning for cleaner energy adoption and supporting national goals toward net-zero emissions.

6 Dataset and Source Code Repository

The dataset, source code, saved models, dss files, and results can be accessed from the following Github repository.
Link: `https://github.com/MdTouhidulHaque/ECE730_Project`

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