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Reliability Analysis of Dhalkebar's Grid Considering Solar PV Converter Reliabilities

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CERTIFICATE OF APPROVAL

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ABSTRACT

Nepal is expanding its renewable energy, mainly through hydropower and increasingly solar PV, to meet its climate goals and to participate more in regional electricity markets. As solar PV becomes a bigger part of the power system, power electronic converters play a crucial role. They connect solar power to the grid, help keep voltage and frequency stable, and provide important functions like reactive power support and fault handling. However, many traditional studies on power system reliability do not consider how reliable these converters are, leaving gaps in understanding the full picture, especially as more renewable energy is added.

This study fills that gap by using an established system reliability assessment method and adding converter reliability into the analysis for a part of Nepal's national grid. Converter reliability was evaluated based on the established FIDES approach, then linked to the overall system model with machine learning tools like Random Forest and Support Vector Regression. These techniques helped capture the complex relationships between individual converter performance and the system's reliability. Finally, system reliability measures such as Loss of Load Expectation (LOLE) and Expected Energy Not Supplied (EENS) were calculated through Monte Carlo simulation. The results show that including converter reliability gives a more realistic view of system performance and highlights how important converters are in assessing the power system's ability to meet demand.

Overall, the adapted approach offers a practical pathway for enhancing reliability studies in grids with increasing contributions from converter-based renewable technologies.

Keywords: Power Converters, Power System Reliability, Monte Carlo Simulation, Machine Learning

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LIST OF ABBREVIATIONS

EENS	Expected Energy Not Served
FOR	Forced Outage Rate
LOLE	Loss of Load Expectation
GWH	Giga Watthour
kV	kilo Volt
λ	Failure Rate
μ	Repair Rate
IEEE	Institute of Electrical and Electronics Engineers
MTTF	Mean Time to Failure
MTTR	Mean Time to Repair
MW	Mega Watt
MWH	Mega Watthour
kV	Kilovolt
yr.	Year
RES	Renewable Energy Source
PV	Photovoltaic
WT	Wind Turbine
SVM	Support Vector Machine
RMSE	Root Mean Squared Error
SVR	Support Vector Regression
RF	Random Forests
ML	Machine Learning
MCS	Monte Carlo Simulation
MATLAB	Matrix Laboratory
HEPP	Hydro Electric Power Plant
IPP	Independent Power Producer
INPS	Integrated Nepal Power System

CHAPTER ONE: INTRODUCTION

1.1 Background

Global energy systems are undergoing rapid transformation driven by decarbonization goals, expanding renewable energy portfolios, rising power demand, and increasing digitalization of the electric grid. Among renewable technologies, solar photovoltaic (PV) systems have seen accelerated growth due to declining costs, modular deployment, and suitability for distributed as well as utility-scale applications. A defining characteristic of modern renewable generation is that nearly all such sources interface with the grid through power electronic converters, which perform functions essential for operational compatibility—DC–AC conversion, maximum power extraction, voltage regulation, and grid support. As renewable penetration grows, these converter-interfaced units increasingly shape the operational behaviour, stability margins, and reliability attributes of the power system.

Similar trends are emerging in Nepal, where the contribution of solar PV plants to the generation mix is growing as part of broader strategies to diversify supply, reduce import dependence, and support future regional energy trading. Unlike conventional rotating machines, these renewable technologies rely fundamentally on power electronic converters, which serve as the essential interface between variable, intermittent sources and the electricity grid. The ability of such converters to perform efficient, stable, and uninterrupted power conversion is therefore central to the operational dependability of renewable-rich systems. In practical terms, electricity produced by PV arrays or other renewable sources can reach the grid or the load only if the converters remain functional, making converter reliability a critical determinant of system adequacy.

Figure 1.1: Converters as the interface

Despite this increasing dependence on power electronic interfaces, converter reliability has not yet been explicitly incorporated into Nepal's power system reliability and adequacy assessment practices. Existing national or academic studies often rely on simplified assumptions in which converter failures are assigned a fixed, constant failure rate, typically borrowed from generic databases or averaged field statistics. However, a power converter is not a simple, monolithic device. It is a complex electrothermal system composed of semiconductor switches, capacitors, drivers, control modules, sensors, and protection elements—each of which can degrade differently under varying environmental and operational stresses. Solar inverters in Nepal operate under diverse ambient temperatures, diurnal thermal cycling, humidity variations, and dust accumulation. Under such non-uniform and stress-dependent conditions, treating converter failure rates as static values may obscure the underlying physics of degradation and lead to inaccurate adequacy estimates [1].

A growing body of international research reports that power electronic converters represent one of the most failure-prone elements in renewable energy systems. Field studies and reliability analyses show that converter failure rates often exceed those of other major subsystems, with dominant degradation mechanisms linked to thermal cycling, semiconductor stress, capacitor aging, and environmental conditions [2, 3, 4, 5]. These works consistently demonstrate that converter reliability is highly sensitive to operating temperature, mission profiles, switching dynamics, and local climatic stressors, underscoring the need for time and condition dependent reliability modeling, particularly in systems with high penetration of inverter-interfaced generation.

At the same time, advances in reliability engineering have led to frameworks such as the FIDES methodology, which provides stress-oriented reliability prediction for electronic systems by accounting for mission profiles, thermal effects, environmental categories, and component-specific degradation mechanisms [6]. Such approaches offer the potential to represent converter behavior more accurately, especially in locations where environmental variability is high and real-world performance differs from manufacturer-provided nominal failure rates.

1.1.1 Reliability Concepts

To motivate the present research, it is also important to clarify the reliability terminology and indices commonly used in system planning. In the field of electrical power systems, the concept of reliability, as defined in classical reliability theory Billinton and Allan, 1970 or 1996 edition [7, 8], represents the probability that the system performs its intended function of supplying electricity continuously and adequately under specified conditions for a defined period. As introduced in the pioneering work of Billinton and Allan [9] and expanded in their later edition [8], reliability is fundamentally a probabilistic measure of system performance that captures the random nature of component failures and restorations. It means the likelihood that a system or a part of it will keep working properly without breaking down, while unreliability represents the complementary probability of failure [7, 9, 8]. According to the hierarchical classification of reliability evaluation introduced by Billinton and Allan [9, 8], system studies are generally categorized as HL-I, HL-II, and HL-III, representing generation-only, composite generation–transmission, and composite generation–transmission–distribution analyses, respectively. These definitions have been widely adopted and refined in subsequent works.

From a system-level perspective, power system reliability encompasses two broad aspects [9, 8]:

1. Adequacy, referring to the ability of the generation and transmission system to meet the total demand at all times under normal operating conditions; and

2. Security, referring how well a system can handle and stay stable when unexpected problems happen, like faults or unexpected equipment outages, without service interruption.

This research focuses exclusively on system adequacy, corresponding to Hierarchical Level I (HL-I) reliability classification as defined by Billinton and Allan [9, 8]. At the component level, reliability is governed by stochastic parameters—most notably the failure rate (λ) and repair rate (μ). The corresponding time-based indicators are the Mean Time to Failure (MTTF) and Mean Time to Repair (MTTR), which represent the expected operating and restoration durations of a component, respectively. These parameters are interrelated through $\lambda = 1/\mathrm{MTTF}$ and $\mu = 1/\mathrm{MTTR}$. The balance between these two rates defines the steady-state availability (A) and unavailability (U) of a component, given by $\mathrm{A} = \mu/(\lambda+\mu)$ and $\mathrm{U} = \lambda/(\lambda+\mu)$ [7, 9, 8, 10].

For generating units, IEEE Std 762-2006 [10] defines the Forced Outage Rate (FOR) as the fraction of total time that a unit is unavailable due to unplanned or forced outages. Outages are generally categorized as planned, associated with scheduled maintenance, or forced, resulting from unexpected equipment failures, control errors, or protection malfunctions [7, 8, 9, 10]. The forced outage rate (FOR), together with the associated measures of availability and unavailability, forms the statistical foundation for estimating the likelihood of generation shortfall events in adequacy studies.

System adequacy indices extend these component-level measures to the aggregate level. LOLE quantifies the expected number of hours or days per year when the available generation is insufficient to serve the load, while EENS expresses the corresponding energy deficit in megawatt-hours per year. These indices provide both a temporal and an energetic perspective on supply shortfalls and are standard planning criteria for generation adequacy studies [7, 9, 8].

1.2 Problem Statement

Modern power systems are undergoing a paradigm shift from conventional synchronous machines toward converter-interfaced renewable generation. This transformation has introduced new operational challenges related to reliability, availability, and maintenance of power electronic converters that form the interface between renewable sources and the grid [1, 5]. Existing reliability assessments at both system and component levels often rely on simplified statistical assumptions, commonly the exponential model with a constant failure rate (λ), which neglect the time-dependent degradation and environmental stress factors that significantly influence converter lifetime [11, 12]. As a result, such models tend to underestimate risk during long-term operation and fail to capture realistic trends.

Field investigations by Fischer et al. [11, 2] have shown that power converters represent one of the dominant causes of downtime in renewable energy installations, accounting for a substantial portion of lost production hours. However, these studies largely provide empirical failure statistics without embedding them into system-level adequacy or reliability frameworks. Similarly, most analytical models incorporate converter reliability using fixed failure rates [1]. While useful for preliminary analyzes, such constant-parameter models fail to represent mission-profile variations in temperature, humidity, electrical stress, and duty cycle that prevail under real operating conditions [1, 13, 3].

Furthermore, national and regional power system reliability assessments, such as those conducted for Nepal, typically consider generation adequacy and network reliability at an aggregate level, omitting the converter's role as a reliability-limiting component. Nepal's unique environmental context, characterized by strong seasonal temperature gradients and monsoon-induced humidity, exacerbates thermal-mechanical and electrochemical stresses within converter components. Ignoring these context-specific degradation drivers can lead to optimistic reliability indices (LOLE, EENS) and, consequently, unrealistic investment or operation planning.

The FIDES methodology [6] provides a detailed and physics-based approach to model reliability of electronic components, accounting for quality factors, environmental influences, operating profiles, and life-cycle parameters. Despite its robustness, the FIDES framework has seen limited application in the power system domain, particularly in the context of renewable converter reliability and system reliability studies [13, 4, 1].

Machine learning (ML) involves a variety of computer algorithms designed to improve automatically through experience and data usage. A core area within this field is regression analysis, which focuses on predicting a continuous numerical value rather than a category. In this direction, Zhang et al. incorporated regression-based ML tools to establish mappings between stress-dependent converter failure rates and system reliability indices [1]. Their results showed that supervised learning models—such as nonlinear regression and kernel-based estimators—can effectively capture the dependence of converter aging processes on thermal cycles, switching patterns, and environmental variations. While the present study does not employ ML algorithms directly for real-time prediction or prognostics, it adopts the same modelling philosophy demonstrated by Zhang et al. —namely, that stress-informed, data-supported parameter estimation improves the realism of converter reliability representation [1]. In this thesis, the converter failure parameters are obtained through the FIDES-based electrothermal stress analysis, which provides time-dependent and condition-correlated reliability indicators analogous in purpose to ML-based regression outputs. These stress-derived component-level parameters are then integrated into a hierarchical reliability evaluation to quantify system-level adequacy indices (LOLE, EENS). By aligning with the data-driven mapping framework used by Zhang et al., this study ensures that converter ageing behaviour is consistently and realistically embedded into power-system reliability assessment.

Therefore, a clear need exists to:

1. Adopt a FIDES-based reliability modeling framework that evaluates converter reliability under realistic mission profiles representative of Nepal's environmental and operational conditions.

2. Integrate converter reliability models into power system adequacy analysis, linking converter availability to indices such as LOLE and EENS.

3. Quantify the deviation between the reliability indices (EENS, LOLE) to demonstrate the impact of converter reliability on Nepal's system-level metrics.

Addressing these gaps will provide a scientifically grounded understanding of converter reliability in renewable-rich grids, inform future maintenance strategies, and contribute to more reliable and sustainable energy systems for Nepal and similar developing power networks.

1.3 Objectives

The main objectives of the research are, by adapting and adopting established methodologies,

1. To formulate power converter reliabilities

2. To analyze reliability of Dhalkebar's Grid considering solar PV converter reliabilities

3. To map converter level reliability into system level reliability using ML regression techniques

1.4 Scope

The study focuses on an area grid with a peak demand of 110 MW supplied through 126 MVA of upstream feeders, integrated with distributed PV plants of 1 MW, 3 MW, and 10 MW capacities. The reliability assessment is performed using a chronological probabilistic framework adapted from Zhang et al. (2021). For each hour of the year, the model evaluates all combinations of feeder and converter availability through state enumeration, using component FORs and failure rates to compute the hourly available capacity, unserved load, and corresponding reliability indices.

The scope of this dissertation is the following:

1. Converter Reliability Modeling

2. Reliability of Power System Using Monte Carlo Simulation

3. Reliability Modeling using ML Regression

1.5 Limitations

The limitations of this dissertation are the following:

1. The main focus is on the reliability impact of power converters while the components are considered independent

2. Failure events that depend on each other, like cascading failures, are not included in this analysis

3. The FIDES-aligned device modeling provides improved physical realism at the component level; however, because system-level mapping is aggregated, short-term operational phenomena (voltage/line constraints, re-dispatch) are not captured. Results should therefore be interpreted as adequacy-level risk indicators rather than operational security assessments.

This is consistent with the research objective: to evaluate how converter reliability assumptions alter planning-level adequacy outcomes.

1.6 Thesis Organization

The dissertation is organized into five chapters. This section enlists a brief outline of each chapter and its contents.

- This chapter describes the importance of converter reliability and presents basic reliability concepts. The problem statement is described and followed by specifying the scope, objectives and limitations of the thesis work.

- Chapter 2 provides the literature review on the field of reliability analysis, converter reliability, importance of converter reliability in the system-level analyzes and prior research works.

- Chapter 3 lays the research design and methodology. An overall methodological framework to perform set of tasks to achieve the thesis objective are discussed.

- Chapter 4 presents the modeling and simulation approach and displays the results. Each results also discusses the implications of the results followed by the related discussions.

- Chapter 5 concludes the findings of this study.

CHAPTER TWO: LITERATURE REVIEW

The total installed capacity of the Integrated Nepal Power System (INPS) is 3,586.726 MW. Within this mix, the Nepal Electricity Authority (NEA) operates 25 MW of grid-connected solar PV capacity, while Independent Power Producers (IPPs) contribute 116.94 MW, resulting in a combined operational solar PV capacity of 141.94 MW [14]. Furthermore, a total of 59 MW of solar PV projects is currently under construction, and an additional 199.2 MW of solar PV capacity is represented by multiple projects at various stages of planning and development [14]. It is foreseeable that there will be a huge penetration of solar PV converters in the INPS.

Power converter reliability has been a subject of extensive investigation over the past two decades. Yang et al. [15] conducted one of the earliest large-scale industrial surveys to identify common failure modes in power electronic converters, revealing that capacitors, semiconductor devices, and control circuits account for the majority of failures. Similarly, authors in [2] and [11] analyzed field data from wind turbines, concluding that converters contribute most of total system downtime. These studies underscored the importance of converter reliability in renewable energy systems and motivated subsequent research into predictive and physics-based reliability models.

Traditional reliability assessment often uses the exponential distribution with a constant failure rate (λ), which simplifies calculations but fails to reflect the wear-out and environmental stress mechanisms that dominate converter failures [12]. To address this limitation, several authors proposed alternative approaches such as the Weibull distribution and physics-of-failure (PoF) models. Authors in [5] introduced a hierarchical method to propagate component-level reliability data up to converter and system-level indices, while [1] modeled converter failure impacts on power system reliability through Monte Carlo simulations. Fides Guide 2004 [6] captures stress-dependent failure dynamics, such as those found in photovoltaic (PV) converters. This methodology accounts for environmental factors like ambient temperature and irradiation profiles, which significantly influence converter lifetime predictions. Authors in [3] applied the FIDES methodology to photovoltaic (PV) converters, demonstrating its advantage in capturing stress-dependent failure dynamics. Their analysis revealed that environmental factors such as ambient temperature and irradiation profiles significantly influence converter lifetime predictions. Authors in [13] and subsequent works expanded on this by comparing FIDES results with MIL-HDBK-217F and IEC-62380 models, concluding that FIDES provided more realistic lifetime estimations for converters exposed to variable field conditions. Moreover, authors in [16] formulated converter reliability prediction guidelines, emphasizing electrothermal coupling and mission-profile-based lifetime evaluation of IGBTs and capacitors. Recent studies such as [11, 2, 16, 4, 5, 1] highlight the necessity of transitioning from constant to dynamic failure-rate models to improve reliability projections in converter-dominated systems. Incorporating such models into system adequacy analysis (e.g., LOLE and EENS computation) is expected to yield more accurate and risk-aware planning outcomes. However, very few publications have applied FIDES-based reliability modeling at the system level, and almost none have considered its implementation in Nepal's power grid. This research therefore identifies a critical opportunity to integrate FIDES-based reliability models into converter-centric power system adequacy frameworks.

CHAPTER THREE: METHODOLOGY

This chapter discusses the research workflow, which starts with data collection, continues with the methodological framework, adaptation for real system application, and ends with tools and software section.

3.1 Data Collection

For this research, several key data parameters are essential. These include solar photovoltaic (PV) integration into the system, hourly generation, supply and load data, as well as the capacity and outage information of the incomers. Such data provide critical insights into the supply capabilities within the grid, enabling a comprehensive assessment of the system's overall capacity. These datasets were obtained from the respective substation office. Additionally, the computation of the forced outage rate for all incomers is necessary to evaluate system reliability, as this parameter directly influences reliability indices. Furthermore, reliability modeling of power converters yields vital data on the converters' reliability and availability. Hourly solar irradiance and ambient temperature data were acquired from the Department of Hydrology and Meteorology. The reliability analysis of the system covers a one-year period, spanning from March 14, 2024, to March 13, 2025.

Figure 3.1: Control room

3.2 Approach

This study applies the methodological framework presented by Zhang et al. [1] to integrate converter and device-level reliability behavior into a real power system adequacy study. This study focuses on the 33 kV and 11 kV power network supplied by the Dhalkebar Substation, hereafter referred to as the Dhalkebar's grid. In the system, there are two incomers from 132 kV side, through 132/33 kV 63 MVA transformers. The 33 kV busbar serves 7 outgiong feeders and two 33/11 kV 16.6 MVA transformers. Two 10 MW and 3 MW solar PV plants inject power into the 33 kV busbar. Through the two 33/11 kV transformers, the power is fed to 11 kV bus, which is also fed by a 1 MW solar PV plant. Seven feeders emerge from the 11 kV bus to serve the demand of the station load, industrial load, Lalgadh, Godar, Mahendranagar and Dhalkebar. Dhalkebar Grid Division is located at Dhalkebar. This division supervises, maintains, and operates seven substations namely at Chapur, Dhalkebar, Lahan, Mirchaiya, Rupani, Tingla, and Nawalpur. This division carries out maintenance and operation of 132 kV and above voltage level transmission lines in Saptari, Siraha, Dhanusa, Sindhuli, Ramechhap, Mohattari, Sarlahi, Rautahat and Bara districts. This division also operates and maintains the Nepal portion of the Dhalkebar-Muzaffarpur 400 kV double circuit transmission line [17].

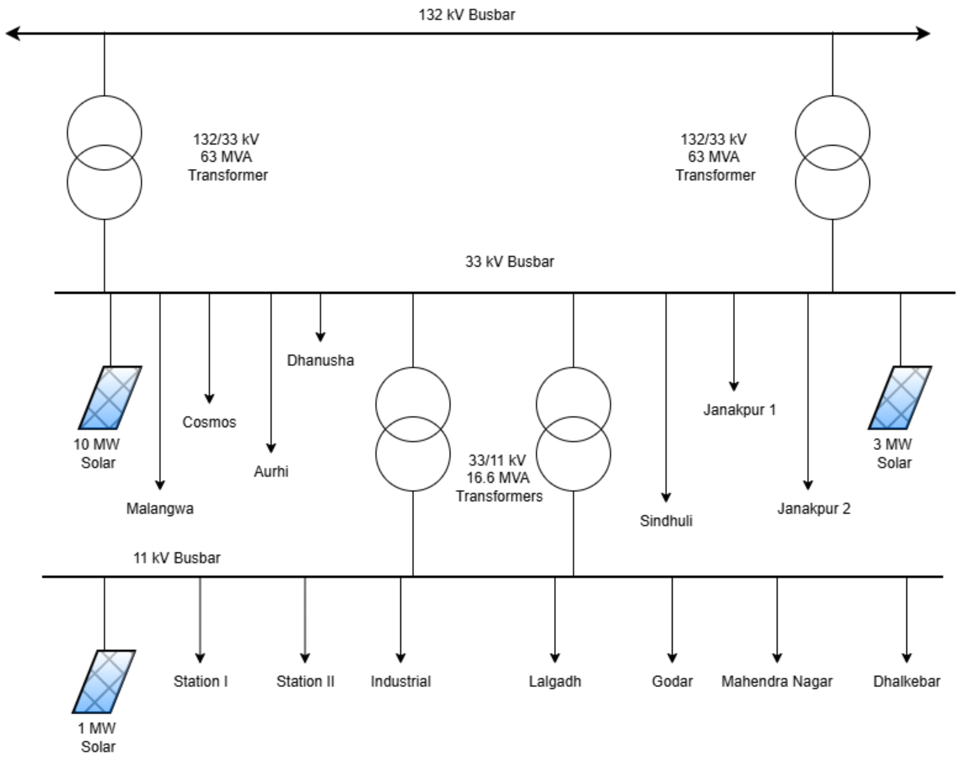


Figure 3.2: SLD of the system under consideration

Here, that methodological idea is adapted and implemented for a real converter-integrated power system, focusing on component/device-level realism at the bottom layer and adequacy analysis at the system layer. Following Zhang et al.'s reliability modeling concept, converter components are treated as stress-dependent elements. As the present study focuses on adequacy evaluation, only generation and load data are considered in the reliability assessment. System-level modifications are therefore confined to the evaluation of adequacy indices (LOLE and EENS) through non-sequential Monte Carlo Simulation, representing a planning-oriented adaptation of the hierarchical framework proposed by Zhang et al [1].

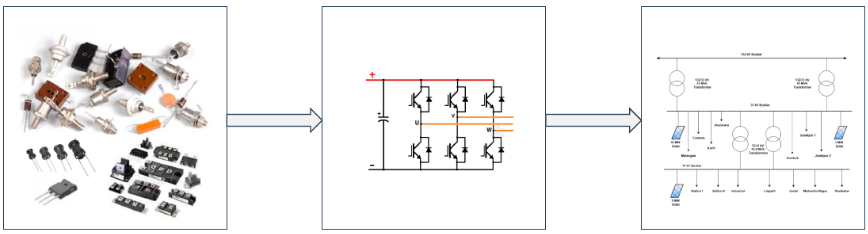
3.3 Conceptual Framework

The analytical process follows three interconnected layers:

1. Component/Device Layer: In the basic level, the reliability of each converter components, like power semiconductor devices, is represented through stress-dependent failure rates. These parameters are derived from environmental and operational mission profiles. The formulation philosophy is aligned with reliability standards referenced by Zhang et al. [1].

2. Converter Layer: Component reliability models are combined to evaluate overall converter availability. This aggregation uses established reliability modeling techniques, as described in [1]. The resulting converter availability data serve as stochastic inputs to the system-level adequacy model.

3. System Layer (Adequacy Study): At the top level, the system model evaluates how converter availability affects the overall generation adequacy of the grid. The adequacy assessment is performed through probabilistic simulation based on the hierarchical structure introduced by Zhang et al., with adequacy indices Loss of Load Expectation (LOLE) and Expected Energy Not Supplied (EENS).



Device Layer Converter Layer System Layer

Figure 3.3: Adapted approach

3.4 Adaptation for Real System Application

For this study, the hierarchical methodology is applied to the real Nepalese power system context. Component and converter data are parameterized using realistic mission profiles derived from regional environmental records and actual operating

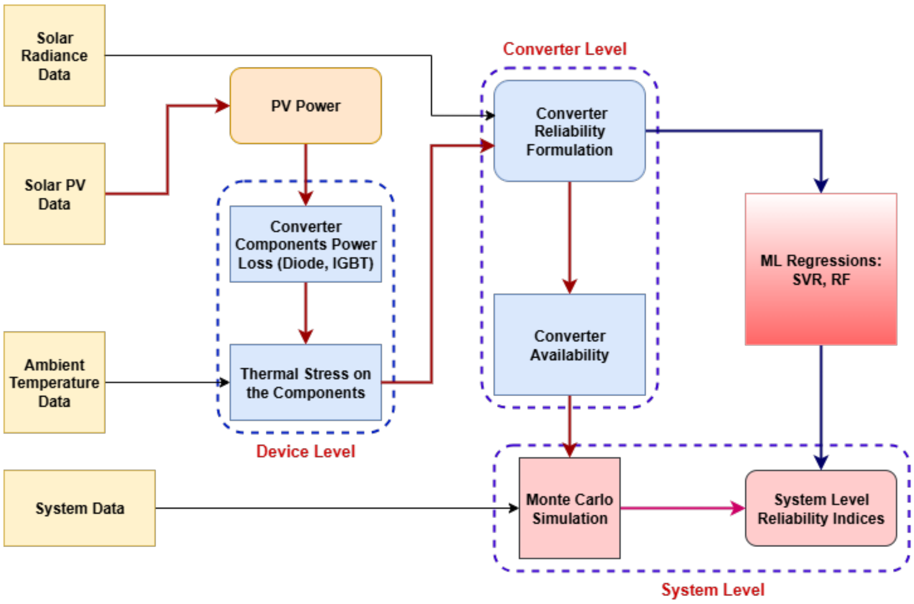


Figure 3.4: Flowchart of the proposed work

conditions. The system-level adequacy simulation incorporates these converter reliability parameters as part of the generation availability model. This adaptation allows investigation of how converter reliability variations, driven by Nepal's environmental stresses, affect adequacy indicators.

In summary, this adapted methodology applies Zhang et al.'s hierarchical reliability concept to a real converter- integrated system, emphasizing adequacy analysis with time- dependent converter reliability inputs.

3.5 Tools and Software

3.5.1 MATLAB Environment

MATLAB is a high-level programming environment widely used for numerical computing, data analysis, and algorithm development. It provides an interactive platform that integrates computation, visualization, and programming in a user-friendly manner. MATLAB's extensive built-in functions and toolboxes make it a preferred choice for researchers and engineers dealing with complex mathematical modeling and simulations. Its capability to handle matrix operations efficiently and visualize data dynamically enhances the ease of exploring various computational problems. The device-level failure rate computation, converter reliability estimation, and system-level reliability estimation are done using this software.

3.5.2 Monte Carlo Simulation in Power System Studies

Overview of Monte Carlo Simulation

Monte Carlo Simulation (MCS) is a probabilistic numerical technique used to analyze systems influenced by uncertainty and random behavior. Instead of relying on deterministic assumptions, MCS evaluates a large number of possible outcomes by producing random samples based on the statistical characteristics of input variables. The collective behavior of these samples enables the estimation of the likelihood of different system states, making the method well-suited for complex systems where direct analytical solutions are impractical or highly approximated.

In power system studies, uncertainties arise from multiple sources, including variable generation, fluctuating demand, and random component failures. MCS provides a systematic framework to model these behaviors by treating system inputs as probability distributions rather than fixed values. Through repeated sampling and statistical aggregation, MCS enables the evaluation of system adequacy, reserve requirements, and loss-of-supply risks across a wide range of operational conditions.

Sequential Monte Carlo Simulation

Sequential Monte Carlo Simulation models the chronological behavior of a system by simulating state transitions in time order. In power system reliability analysis, this means that component up-time and down-time durations are generated using distributions such as exponential or Weibull models, and system states are evaluated as they evolve over time. While this approach preserves temporal dependency and allows analysis of time-correlated events, it requires long simulation periods and significant computational effort to obtain stable adequacy estimates, especially for large-scale systems.

Non-Sequential Monte Carlo Simulation

Non-Sequential Monte Carlo Simulation (NS-MCS) does not simulate the system chronologically. Instead, it generates independent system state samples without considering the sequence of state transitions. Each sample represents a random snapshot of the entire system's condition, where component availability is modeled using probability values derived from reliability parameters such as forced outage rates and operational states. Since adequacy assessment at any moment relies on the overall state rather than failure history, temporal dependency is omitted by design, significantly reducing simulation complexity and runtime.

NS-MCS is particularly effective for power system adequacy studies because the objective is to assess whether the system has sufficient generation capacity to meet demand at any given random state, rather than analyzing how failures propagate over time. By performing numerous independent state evaluations, NS-MCS computes adequacy indices such as the probability of capacity deficiency, expected unserved energy, and loss-of-load risks using direct statistical averaging. This approach improves computational efficiency while maintaining estimation accuracy for long-term system-level adequacy evaluation.

Application in Power System Adequacy Assessment

In generation adequacy studies, NS-MCS is used to evaluate whether the available supply capacity is sufficient to meet the load requirement under random operating conditions. For every generated system state, total generation availability is compared against the system load. If the available capacity is lower than the required load, the sample is marked as a loss-of-supply condition, and the magnitude of deficiency is recorded. The accumulated sample statistics are then used to quantify system adequacy performance across the study period.

State sampling continues until adequacy index estimates converge within acceptable stability limits. Common adequacy indicators derived through this process include:

- Probability of generation capacity shortfall,
- Expected frequency of insufficient supply states,
- Estimated magnitude of unserved energy across all deficiency samples,
- System adequacy margins under uncertainty.

The non-sequential nature of the simulation allows these metrics to be obtained without tracking chronological state transitions, offering a fast yet statistically meaningful method for long-term adequacy evaluation.

Advantages of Non-Sequential MCS in Adequacy Studies

The major benefits of NS-MCS for adequacy analysis include:

1. **Computational efficiency**: independent state evaluation avoids long failure timeline generation,

2. **Scalability**: suitable for large systems with many independent reliability parameters,

3. **Statistical robustness**: adequacy indices can be computed directly from random snapshots,

4. **Simplified modeling**: relies on component availability probabilities rather than time-dependent transitions,

5. **Effective convergence**: stable adequacy metrics are achieved with fewer simulation constraints.

Due to these attributes, NS-MCS forms a practical and widely adoptable strategy for assessing generation adequacy, capacity sufficiency, and long-term supply reliability under random system conditions.

3.5.3 Power System Adequacy and Reliability Indices

Loss of Load Expectation (LOLE)

Loss of Load Expectation (LOLE) is a probabilistic index that estimates the duration within a defined evaluation period during which the available generation capacity is expected to be insufficient to meet the system load. LOLE does not measure how large the supply deficit is, but rather how often and for how long the system may fail to fully serve the demand. In long-term adequacy studies, LOLE is typically expressed in units such as hours/year or days/year, representing the statistically expected time span of potential load curtailment due to capacity deficiency.

A lower LOLE value indicates a more adequate generation reserve margin, implying that the system has a higher probability of meeting the load requirement at any arbitrary operating condition. LOLE is widely used by system planners to evaluate whether installed capacity provides sufficient assurance against expected loss-of-supply states under uncertainty.

Expected Energy Not Served (EENS)

Expected Energy Not Served (EENS) is a quantitative index that measures the magnitude of unserved electrical energy when generation capacity falls short of the system load. Unlike LOLE, which tracks the duration of loss-of-supply conditions, EENS accumulates the total energy deficit across all inadequate system states. It reflects the integral impact of supply insufficiency by averaging the unserved energy from a large set of simulated system state samples.

In non-sequential Monte Carlo adequacy analysis, EENS is computed by recording the energy shortage for each deficiency sample and then calculating the statistical mean of all recorded deficits. The final index is expressed in energy units such as MWh/year, representing the estimated amount of electricity demand that the system does not meet when generation sources are unavailable or there is not enough capacity to meet the load.

A smaller EENS value reflects better system availability and capacity planning, meaning that even if capacity shortage conditions occur, their aggregated impact on total unserved energy remains limited.

Relationship Between LOLE and EENS

Although LOLE and EENS both assess adequacy, they capture different dimensions of reliability risk:

- LOLE measures the **expected time duration** of capacity shortfall events,
- EENS measures the **expected volume of unserved energy** during those events.

A system may experience occasional short inadequacy periods (moderate LOLE) with small deficits (low EENS), or infrequent but severe capacity failures (low LOLE and high EENS). Therefore, evaluating both indices jointly provides a more informative adequacy perspective compared to relying on a single metric.

Use of LOLE and EENS in Monte Carlo Adequacy Evaluation

In Monte Carlo based adequacy studies, the computation process follows a direct logical evaluation of random system state samples:

1. For each generated state, the total available generation is compared against the system load,
2. If the generation meets or exceeds the load, the sample is considered reliable,

3. If generation is lower than the load, the sample is marked as a *capacity deficiency state*,

4. Duration of deficiency samples contributes to LOLE estimation,

5. The energy gap in each deficiency sample contributes to the EENS evaluation.

By aggregating thousands of independent state evaluations, LOLE is calculated as the fraction of unsupplied states multiplied by the total evaluation period length, while EENS is derived as the statistical average of all energy deficit values scaled to the analysis time horizon.

Interpretation for System Planning

Since power system adequacy evaluation focuses on long-term capacity and reserve sufficiency, LOLE and EENS serve the following planning purposes:

- **LOLE** provides a criterion for sizing installed generation reserve levels to maintain acceptable continuity margins,

- **EENS** quantifies expected service risk in energy terms, supporting economic and operational decisions such as redundancy investment, capacity expansion, and supply security trade-off assessments,

- Together, these indices support risk-aware grid planning under stochastic generation and random component availability conditions.

Because both indices are expectation-based rather than actual failure records, they provide statistically meaningful reliability insights even when evaluated without sequential failure timelines.

3.5.4 Python and Scikit-Learn in Google Colab

Python has emerged as one of the leading programming languages in scientific computing and machine learning due to its simplicity and extensive ecosystem of libraries. Scikit-learn is a powerful Python library specifically designed for machine learning tasks, offering a range of supervised and unsupervised learning algorithms. Google Colab provides an accessible cloud-based environment for Python programming, allowing users to write and execute code through web browsers without requiring local setup. It supports collaborative work and offers free computational resources, including GPUs, which are particularly beneficial for training machine learning models efficiently. Machine learning regression methods, including SVR and Random Forest, are used to build a reliability relationship between the converter and the overall power system levels, as demonstrated by Zhang et al. [1].

3.5.5 Machine Learning Regression Methods

Regression analysis is a fundamental task in machine learning, aimed at modeling the relationship between input variables and continuous output targets. This work focuses on two popular regression techniques: Support Vector Regression (SVR) and Random Forest Regression.

Support Vector Regression

Support Vector Regression is an extension of the Support Vector Machine algorithm, adapted for regression problems. The SVR works by finding a function that approximates the data within a specified margin of tolerance, known as the epsilon-insensitive tube. The model attempts to balance complexity and prediction accuracy by minimizing the coefficients of the regression function while allowing certain deviations controlled by slack variables. SVR is particularly effective for capturing non-linear relationships by employing kernel functions, enabling it to fit complex datasets without overfitting.

Random Forest Regression

Random Forest Regression is an ensemble learning method that constructs multiple decision trees during training and outputs the average prediction of individual trees to improve generalization. By combining a large number of trees, it reduces the risk of overfitting and enhances the prediction accuracy. Each tree in the forest is built from a random subset of the training data and features, promoting diversity among the trees. Random Forests are well-suited for handling high-dimensional datasets and capturing complex, non-linear interactions between variables.

3.5.6 Model Training and Evaluation

The data set was divided into training and testing subsets using an 80:20 ratio, where 80% of the data were used to train the regression models, and the remaining 20% was reserved for independent testing. Both Support Vector Regression (SVR) and Random Forest (RF) models were trained on the training set with hyperparameters optimized via grid search and cross-validation.

Model performance was evaluated on the test set using Root Mean Square Error (RMSE) and the coefficient of determination (R^2) as primary metrics. RMSE measures the average magnitude of prediction errors, while R^2 indicates the proportion of variance in the dependent variable explained by the model. Comparative analysis of these metrics allowed for the assessment of each model's predictive accuracy and robustness in mapping reliability from converter to system levels.

3.6 Mathematical Formulation

The mathematical framework used in this study is adapted from Zhang et al. [1]. For methodological completeness, the core equations are reproduced, while the original mathematical structure and variable notations are preserved for consistency with prior literature. All environmental and operational parameters are replaced with Nepal-specific mission profile data.

The PV system includes a DC–DC boost converter and a DC–AC inverter. The losses in the DC to DC converter stage components are given by

$$P_{pv\_boost\_IGBT} = R_{DS(on)} \cdot I_{in}^2 + \frac{1}{2} V_{out} I_{in} (E_{on} + E_{off}) f_s \tag{3.1}$$

$$P_{pv\_boost\_diode} = I_{out}^2 r_F + I_{pv} V_{F0} \tag{3.2}$$

$$P_{pv\_boost\_inductor} = I_{in}^2 r_{es} \tag{3.3}$$

Here, $R_{DS(on)}$ is the IGBT on-state resistance, f_s denotes the switching frequency, r_F denotes the diode resistance, V_F is the forward voltage drop of diode, and r_{es} is the equivalent inductor resistance.

The total semiconductor losses in the PV converters consist of conduction and switching losses. The conduction losses for the diode and IGBT are expressed as

$$P_{pv\_diode\_con} = I_{pv} V_{F0} \left(\frac{1}{2\pi} - \frac{M \cos\varphi}{8} \right) + I_{pv}^2 r_F \left(\frac{1}{8} - \frac{M}{3\pi} \cos\varphi \right) \tag{3.4}$$

$$P_{pv\_IGBT\_con} = I_{pv} V_{CE0} \left(\frac{1}{2\pi} + \frac{M \cos\varphi}{8} \right) + I_{pv}^2 r_{CE} \left(\frac{1}{8} + \frac{M}{3\pi} \cos\varphi \right) \tag{3.5}$$

where I_{pv} is the device current, V_{CE0} and V_{F0} are the threshold voltage drops of the IGBT and diode, respectively, r_{CE} and r_F are their corresponding resistances, M is the modulation index, and $\cos\phi$ is the power factor.

Switching losses are calculated using

$$P_{pv\_IGBT\_SW} = \frac{1}{\pi} f_{SW} (E_{on} + E_{off}) \frac{I_{pv} V_{DC}}{V_{ref\_IGBT} I_{ref\_IGBT}} \tag{3.6}$$

$$P_{pv\_diode\_SW} = \frac{1}{\pi} f_{sw} E_{rec} \frac{I_{pv} V_{DC}}{V_{ref\_diode} I_{ref\_diode}} \tag{3.7}$$

where E_{on} and E_{off} are the IGBT switching energies, E_{rec} is the diode reverse-recovery energy, and (V_{ref}, I_{ref}) denote reference commutation conditions.

The total losses for each device are obtained by summing conduction and switching losses:

$$P_{loss\_IGBT} = P_{pv\_IGBT\_con} + P_{pv\_IGBT\_sw} \tag{3.8}$$

$$P_{loss\_diode} = P_{pv\_diode\_con} + P_{pv\_diode\_sw} \tag{3.9}$$

Given the converter topology, the total converter power loss is computed as

$$P_{pv\_conv\_loss} = \sum_{n=1}^{n_D} P_{loss\_diode} + \sum_{n=1}^{n_G} P_{loss\_IGBT} \tag{3.10}$$

where n_D and n_G denote the number of diodes and IGBTs.

The way a component responds to heat plays a major role in how fast it deteriorates over time. Using $P_{pv\_conv\_loss}$ and hourly ambient temperature, the junction temperatures of the IGBT and diode are estimated as

$$T_{j\_IGBT} = T_c + R_{sa\_IGBT} P_{pv\_conv\_loss} + R_{jh\_IGBT} P_{loss\_IGBT} \tag{3.11}$$

$$T_{j\_diode} = T_c + R_{sa\_diode} P_{pv\_conv\_loss} + R_{jh\_diode} P_{loss\_diode} \tag{3.12}$$

where T_c is the surrounding (ambient) temperature, and R_{sa} and R_{jh} are the thermal resistances from sink to ambient and junction to sink.

The thermal stress factors for the IGBT and diode are then obtained from

$$\pi_{T\_IGBT} = \exp\left[1925\left(\frac{1}{298} - \frac{1}{T_{j,IGBT} + 273}\right)\right] \tag{3.13}$$

$$\pi_{T\_diode} = \exp\left[3091\left(\frac{1}{298} - \frac{1}{T_{j\_diode} + 273}\right)\right]. \tag{3.14}$$

Similarly, the temperature cycling factor is given by

$$\pi_{TCi} = \gamma \left(\frac{12 N_s}{t(i)} \right) f(\Delta T_b) \cdot \exp \left[1414 \left(\frac{1}{313} - \frac{1}{T_{b,max} + 273} \right) \right] \tag{3.15}$$

with γ and $f(\Delta T_b)$ defined specifically for each device type.

Finally, the probability of failure for component j at time t is expressed as

$$\lambda_{j,t} = \sum_{i=1}^{N_s} (\lambda_{0Th} \pi_{Tj,t} + \lambda_{0tc} \pi_{TCj,t}) \pi_{ln} \pi_{Pm} \pi_{Pr} \tag{3.16}$$

where λ_{0Th} and λ_{0TC} are the base thermal and cycling failure rates, π_{In} is the overstress factor, π_{Pm} is the quality factor, and π_{Pr} represents reliability control and aging considerations.

The PV converter reliability results are shown below. Here,N_m is the total number of devices in the converter, and $\lambda_{m,t}$ is the failure rate of component m at given time t.

$$R_{pv\_conv(t)} = e^{-\left(\sum_{m=1}^{Nm} \lambda_{m,t} \right) t} \tag{3.17}$$

CHAPTER FOUR: RESULTS AND DISCUSSION

The reliability evaluation of the 110 MW peak load system, supplied through 126 MVA of incoming feeders and integrated with locally available PV capacities (1 MW, 3 MW, and 10 MW), was conducted under two defined scenarios:

1. Scenario I: Incoming feeders and locally available PV plants collectively feeding the load demand.

2. Scenario II: Same as Scenario I, but incorporating converter failure rates in the reliability estimation.

In order to create a comprehensive reliability representation for hybrid grid–PV systems, these scenarios show a progressive layering of system complexity.

4.1 Solar PV Converter Reliabilities

The PV converter reliabilities are obtained using the FIDES approach, considering PV generation, ambient temperature, power losses in converter components, thermal stress factor, overstress factor and temperature cycling factor. First, hourly solar generation data are collected, and with hourly stress variables such as power loss, temperature rise, and ambient temperature, the temperature cycling factor is calculated along with the thermal stress factor. The converters used in existing PV systems are for 1 MW, 0.25 MW, 1.045 MW, and 4.5 MW capacities. The failure rate of the converters for each hour is computed. With this, the average failure rates for the converters used in the PV systems are computed. The analysis of power converters used in those PV systems yielded average annual failure rates ranging between 1.9899e-04 per hr to 3.0351e-04 per hr, depending on the converter capacity and duty profile. The average failure rates obtained for the converters for the year are shown in Table 4.1. A comparison with converter related failure data from wind

Table 4.1: Average failure rates of the converters

Converter Size (MW)	Average Failure Rate (per hr.)
1	2.3073e-04
0.25	2.4323e-04
1.045	1.9899e-04
4.5	3.0351e-04

turbine systems (reported between 0.12 and 0.39 failures per turbine per year) [2] indicates that the converter failure rates observed in the present PV systems are relatively higher, consistent with expectations considering the more thermally and environmentally demanding operating conditions of PV converters.

Converter failure rates were calculated because converters are the main power-handling stage where real-time electrical and thermal stresses accumulate and lead to unexpected outages. Unlike PV modules that degrade slowly, converters contain active switches, capacitors, and cooling interfaces that experience continuous power losses, heat build-up, temperature gradients, and repeated heating–cooling cycles. These stresses vary over time due to changing sunlight, converter control actions (e.g., MPPT), and grid disturbances, causing components to wear unevenly rather than fail at fixed schedules. By computing the failure rate (λ), the study converts these complex stress effects into one measurable value that represents how often failures are expected to occur in practice, helping explain the added outage risk seen in the results.

4.2 Reliability Analysis

For reliability analysis, it is important to compute failure rates for the incomers. The MTTF, MTTR, and FOR obtained on the basis of actual operational data are summarized in table 4.2 below: These results highlight that while feeders demonstrate longer operating times between failures, PV plants exhibit relatively higher forced outage risks, mainly driven by environmental stress and converter component fatigue. To emphasize why power converters matter in system reliability, the traditional system indicators EENS and LOLE are calculated for both cases. Through the use of non-sequential MCS, the reliability of the system is analyzed, considering solar PV converter reliabilities.

Table 4.2: MTTF, MTTR, and FOR Computation

S.N.	Supply Source	MTTF (hours)	MTTR (hours)	FOR
1	Feeder 1	168.461538	0.541666667	0.003215373
2	Feeder 2	461.052632	24.4745614	0.053084094
3	Solar 1 MW	105.08	4.41	0.0403
4	Solar 3 MW	144.90	1.98	0.0135
5	Solar 10 MW	20.99	1.96	0.0855

1. Scenario I: Reliability analysis takes into account grid power supplies as well as power supplied by locally accessible solar PV. It excludes the reliability of power converters.

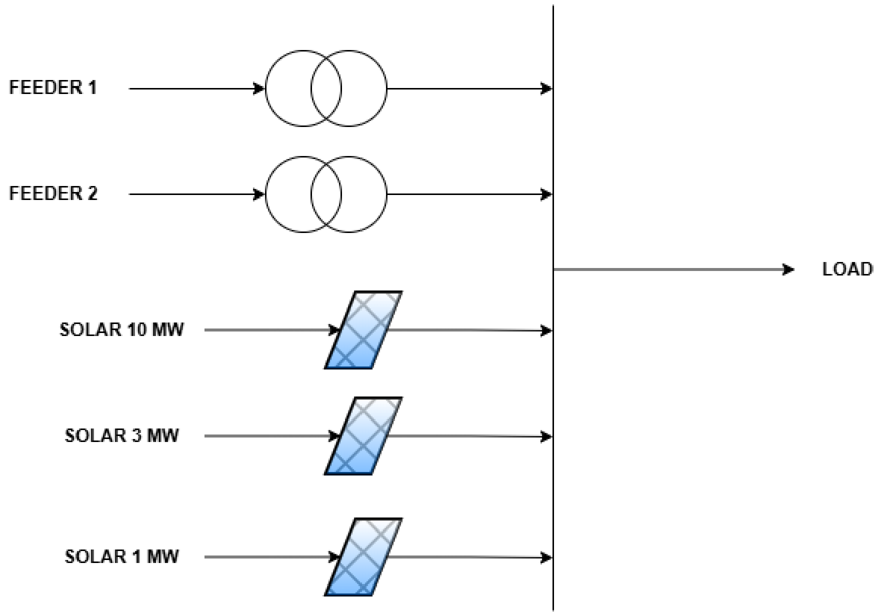


Figure 4.1: Scenario I

The reliability metrics obtained for this situation are LOLE = 1.2026 days/yr., and EENS = 2242.8424 MWh/yr.

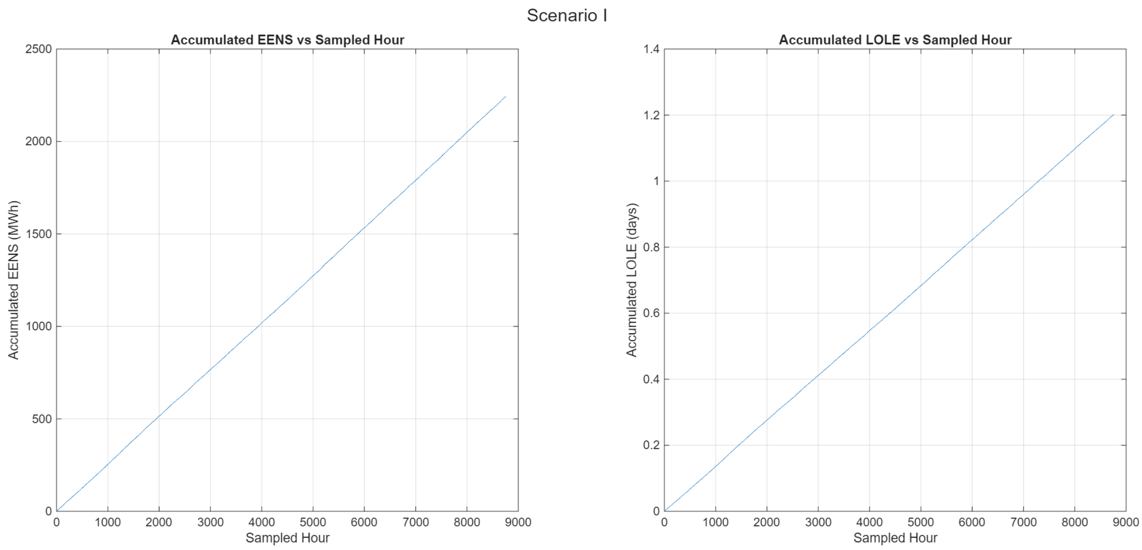


Figure 4.2: Plots of accumulated EENS and accumulated LOLE for Scenario I

2. Scenario II: Reliability analysis takes into account grid power supplies as well as power supplied by locally accessible solar PV.

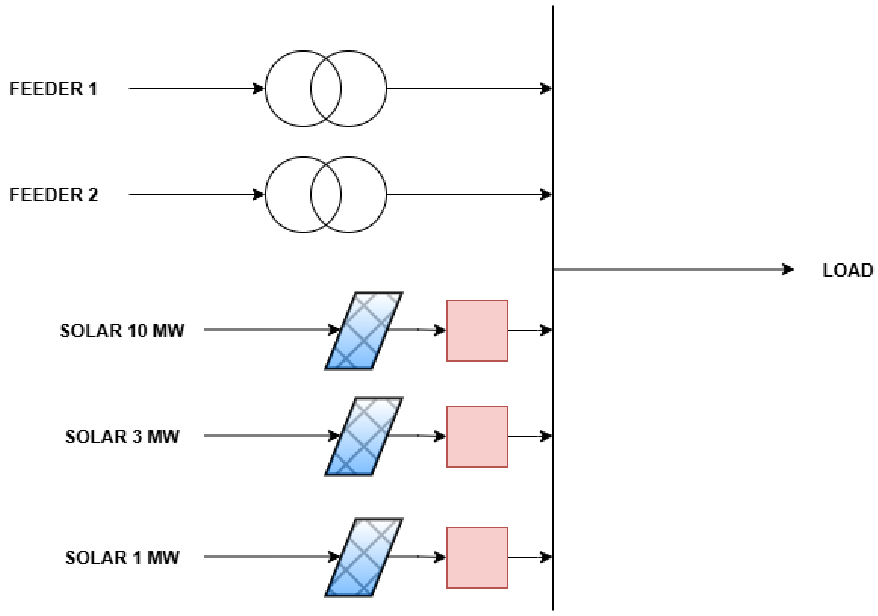


Figure 4.3: Scenario II

The reliability metrics obtained for this situation are LOLE = 1.2486 days/yr., and EENS = 2290.7308 MWh/yr.

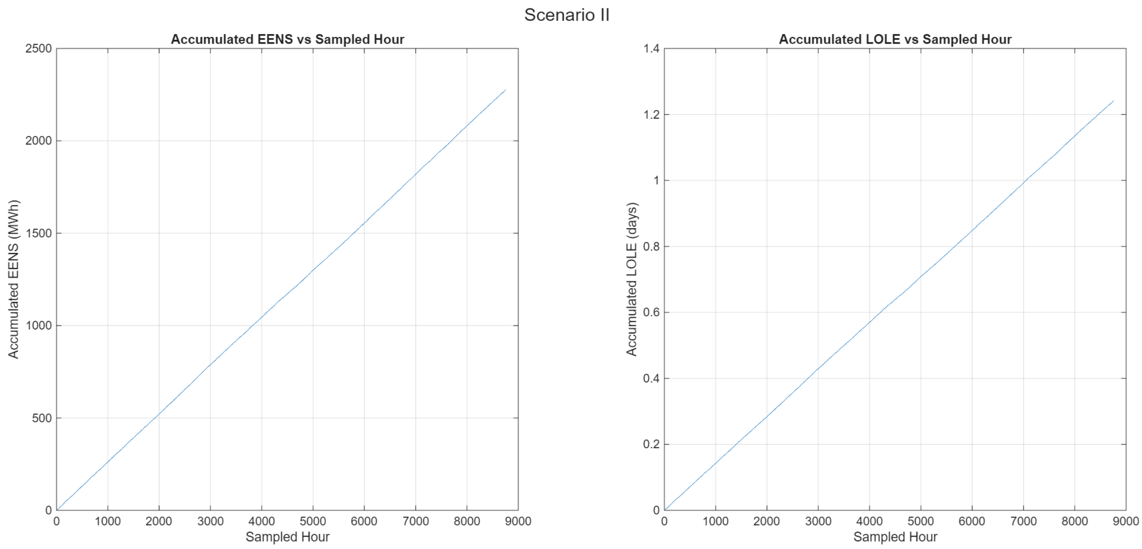


Figure 4.4: Plots of accumulated EENS and accumulated LOLE for Scenario II

The estimated reliability measures for the system for the two scenarios are summarized in Table 4.3. The increase in both LOLE and EENS values demonstrates

Table 4.3: Reliability Analysis Results

Scenario	Incomers	LOLE (days/yr.)	EENS (MWh/yr.)
I	Feeders + PV	1.2026	2242.8424
II	Feeders + PV (with converter reliability)	1.2486	2290.7308

that while the addition of distributed PV capacity marginally enhances local energy availability, the converter reliability limitations introduce additional outage risks. These findings stress the importance of component-level reliability integration for realistic grid adequacy evaluation. A change of approximately 0.046 days/yr. in LOLE and 47.8884 MWh/yr. in EENS between Scenarios I and II, though modest, is significant in financial and operational terms for systems of this scale. This translates into potential annual energy shortfall costs and reserve margin adjustments that utilities must consider in generation scheduling.

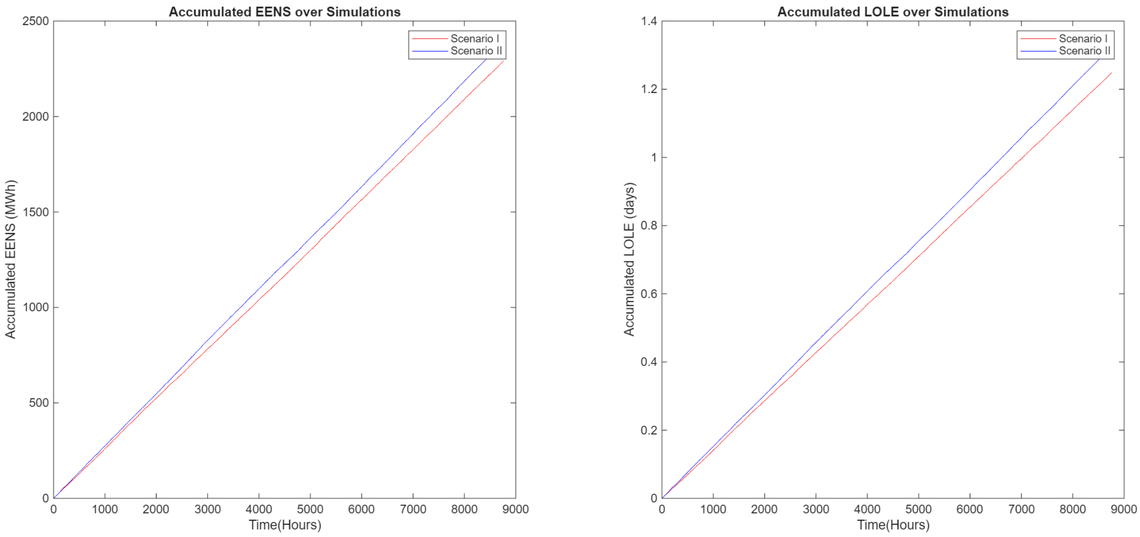


Figure 4.5: Plots of LOLE and EENS for the scenarios

The plots of accumulated LOLE and accumulated EENS for the scenarios over the simulations are depicted in Figure 4.5.

4.3 ML Regression Based Reliability Modeling

To support scalability, regression models based on Support Vector Regression (SVR) and Random Forest (RF) were developed to map device-level reliability parameters to system-level outcomes.80% of the reliability data is used for training and the remaining 20% is used for testing. Root mean squared error and R squared values are evaluated for their comparison and evaluation of the models. The regression program is done and executed in Python 3.11.13 using Google Colab. The results obtained are shown in Table 4.4.

Table 4.4: Results of ML Regression

Model	RMSE	R Squared
SVR	0.0328	0.9283
RF	0.0336	0.9249

Figure 4.6 shows actual vs predicted values of EENS obtained using SVR and RF. The maximum deviation (absolute value) between the actual vs predicted values is 0.1376 for SVR and 0.1440 for RF regression.

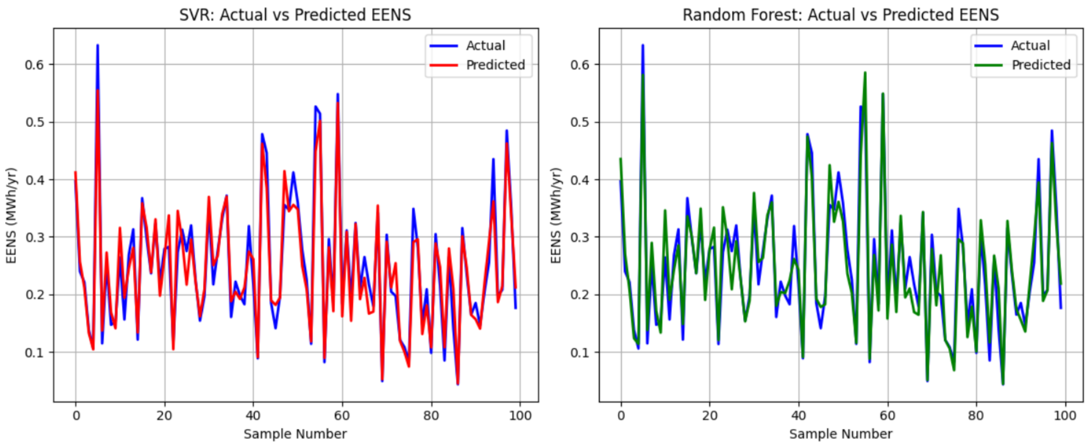


Figure 4.6: Actual vs Predicted EENS

These results confirm the suitability of both ML techniques for predictive reliability assessment and data-driven system planning, offering flexibility for systems with evolving configurations.

CHAPTER FIVE: CONCLUSION

This study aimed to evaluate the adequacy of a solar photovoltaic (PV) integrated system with a specific focus on integrating power converter reliabilities, which are critical components affecting overall system performance and uptime. Integrating converter-level data into system-level reliability models provided more accurate estimations compared to traditional approaches that assume ideal converter performance.

By understanding converter wear-out behaviors and mean time to failure, power producers can right-size spare inventories, optimize replacement intervals, and minimize revenue losses from unplanned outages. Moreover, incorporating converter reliability into lifetime energy yield models enables more accurate financial projections and risk-adjusted investment decisions, turning reliability insights into measurable economic advantage.

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This is to formally confirm that the authors listed herein presented their research paper entitled **"Reliability Analysis of Dhalkebar's Grid Considering Solar PV Converter Reliabilities"** during the 4th University Scholar Conference: Engineering, Innovation and Advancements (USC 2025), convened on November 18–19, 2025, at Kathmandu University, Dhulikhel, Nepal.

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