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Long Term Analysis of Generation Adequacy of INPS

by

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ABSTRACT

This study evaluates the long-term generation adequacy of the Integrated Nepal Power System (INPS) at Hierarchical Level I (HL-I) using a Monte Carlo simulation-based probabilistic framework. The assessment considers seasonal variations, equipment outages, and multiple demand growth scenarios: Business-As-Usual (BAU), Medium, High, and Target growth. A separate Policy Intervention scenario incorporates electrification trends such as electric vehicles and electric cooking. Key reliability indices—Loss of Load Expectation (LOLE) and Expected Energy Not Supplied (EENS)—are computed under varying dry-season generation assumptions (40% and 25%) to simulate hydrological constraints.

The results show that under a 40% dry-season generation assumption, the INPS maintains adequate reliability in BAU and Medium scenarios up to 2050, while the High and Target scenarios exhibit significant reliability deterioration from 2035 onward. Under a 25% dry-season scenario, even BAU cases face reliability issues in early years, and EENS rises sharply across all growth paths. For instance, by 2050, the High Growth scenario sees LOLE exceeding 157 days/year and EENS approaching 1.5 million MWh/year. In the Target scenario, reliability collapses completely, with LOLE surpassing 311 days/year and EENS exceeding 2.8 million MWh/year, even under 40% availability.

The Policy Intervention scenario, while aligning with electrification goals, leads to substantial increases in demand that exceed system capacity from 2030 onward, particularly under Medium and High trajectories. By 2050, LOLE reaches 363 days/year and EENS crosses 6 million MWh/year in the High scenario. These findings underscore the trade-off between electrification-driven demand growth and system adequacy, especially in dry seasons.

This analysis emphasizes that Nepal's generation adequacy remains stable only if dry-season capacity is maintained and growth remains moderate. To ensure long-term reliability, significant investments in storage, firm capacity, and timely project execution are critical. The study supports adaptive, scenario-driven planning to balance development ambitions with energy security.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ALGORITHMS

LIST OF ABBREVIATIONS

BAU	Business As Usual
EENS	Expected Energy Not Supplied
EIR	Energy Index of Reliability
FOR	Forced Outage Rate
GDP	Gross Domestic Product
HL-I	Hierarchical Level I (Generation Adequacy)
HL-II	Hierarchical Level II (Generation & Transmission Adequacy)
HL-III	Hierarchical Level III (Generation, Transmission & Distribution Adequacy)
INPS	Integrated Nepal Power System
LOEE	Loss of Energy Expectation
LOLE	Loss of Load Expectation
LOLP	Loss of Load Probability
MCS	Monte Carlo Simulation
MW	Megawatt
MWh	MegaWatthour
NEA	Nepal Electricity Authority
OLS	Ordinary Least Squares
PPA	Power Purchase Agreement
PPP	Public Private Partnership
R^2	Coefficient of Determination
SE	Standard Error
WECS	Water and Energy Commission Secretariat
kWh	Kilowatt-hour

CHAPTER ONE: INTRODUCTION

1.1 Background

INPS is the centralized power system network consisting of generators, transmission lines, substations, and electrical loads[1]. Nepal's electricity generation and capacity have seen significant growth, with NEA reporting a total installed capacity of 3157.182 MW, including substantial contributions from hydropower (both NEA and independent power producers) and solar energy. The NEA Power Trade Department also confirms this installed capacity, reflecting Nepal's increasing reliance on renewable energy sources [2, 3]. Nepal's electricity generation capacity is expanding significantly. Future projections indicate substantial growth, as over 11256.92 MW of hydro projects have applied for construction licenses, while additional capacities are under construction or at the survey stage [4]. Nepal's energy demand is projected to grow alongside its socioeconomic development, as indicated by rising peak load, energy sales, and electricity consumption trends[5], as shown in Figure 1.1.

Generation adequacy is also one of the most significant characteristics of power system reliability, ensuring the available generation capacity is sufficient to satisfy electricity demand at all times under both normal and unexpected circumstances.[8] A power system's primary function is to provide reliable and economical electricity, but achieving continuous availability is challenging due to random failures beyond engineers' control. Proper reserve capacity planning is crucial, as insufficient investment leads to frequent interruptions, while excessive investment results in high costs passed to consumers. Since exact methods for determining reserve capacity do not exist, probability theory provides a systematic approach to balancing reliability and economic efficiency [9]. Generation adequacy is evaluated on a hierarchical level to categorize power system reliability into HL-I, HL-II, and HL-III, each of which deals with different aspects of the power system. HL-I, or generation adequacy evaluation, considers only the generation capability and its sufficiency to serve the total system load without considering transmission or distribution limitations.[10] This assessment level is important for long-term capacity expansion and tends to apply probabilistic reliability measures like LOLE, LOEE, and LOLP to assess the risk implicated in supply deficiencies. However, generation adequacy does not necessarily ensure the delivery of power to consumers because transmission constraints could affect the electricity flow. HL-II extends the analysis to the transmission system, looking at whether the generated power can be efficiently transmitted to demand

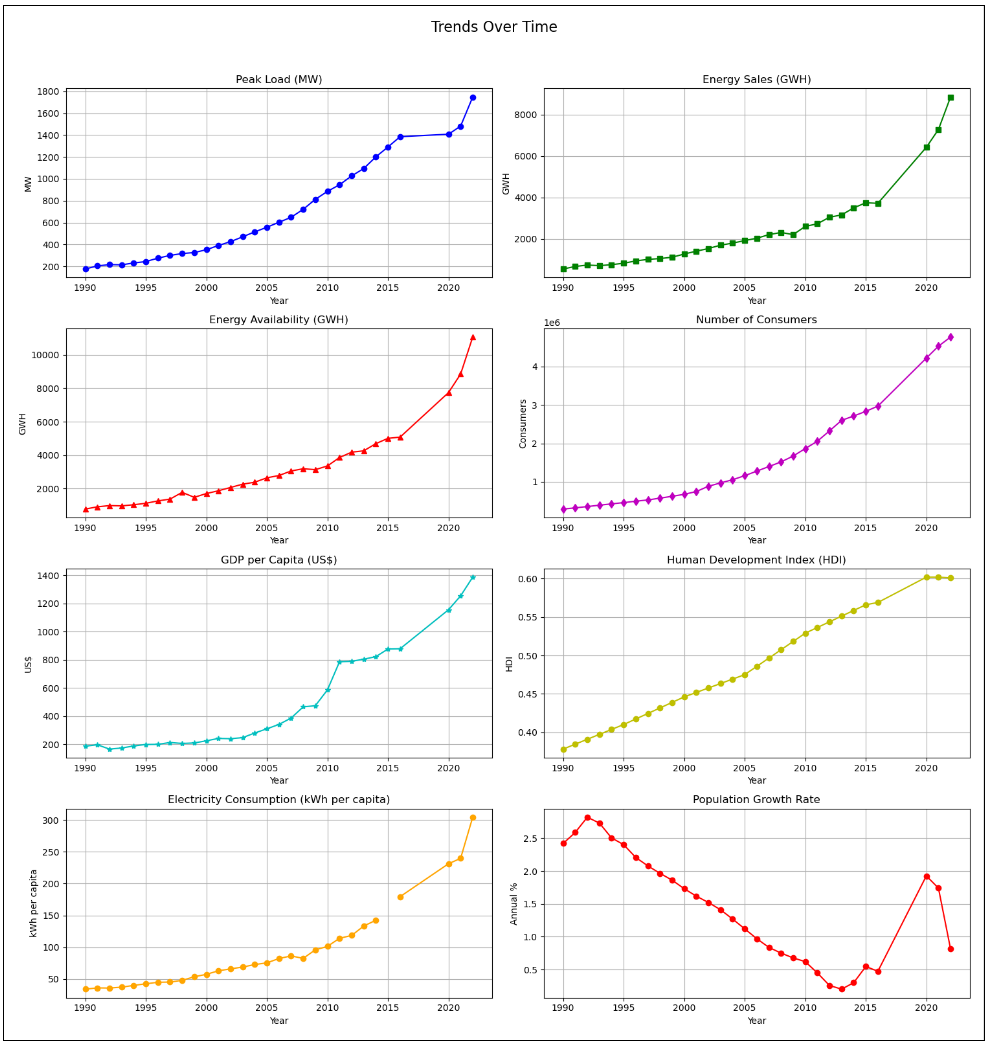


Figure 1.1: Trends in Peak Load, Energy Sales, Energy Availability, Number of Consumers, GDP per Capita, and HDI over Time [6, 7]

centers, thus addressing system-wide transmission bottlenecks and constraints. Beyond this, HL-III addresses the entire power system, i.e., generation, transmission, and distribution systems, to analyze reliability at a specific load point. This is the most sophisticated level, as it requires extensive modeling of local distribution networks to comprehend the probability and frequency of interruptions as seen by customers. Although HL-I analyses are mainly used for generation expansion planning, HL-II and HL-III assessments give more insight into system reliability but demand sophisticated network modeling and computational facilities. HL-I analysis of INPS is highlighted here, applying Monte Carlo Simulation methods to evaluate long-term generation adequacy against various growth scenarios to ensure that the system will be able to serve future electricity demand reliably.[11]

Traditional deterministic methods, such as Load Flow Analysis and N-1 Contingency Analysis, assume fixed values for generation, demand, and system components. While these methods are useful for short-term operational planning, they fail to capture the stochastic nature of power systems.

Table 1.1: Comparison of Deterministic vs. Probabilistic Methods in Power System Analysis

Aspect	**Deterministic Methods**	**Probabilistic (MCS) Methods**
Input Assumptions	Fixed values for demand, generation, and outages.	Considers variability and uncertainty in generation, demand, and outages.
Output	Single result (e.g., pass/fail or a worst-case scenario).	Distribution of results, providing probability-based risk analysis.
Consideration of Uncertainty	No consideration of randomness in demand, outages, or renewables.	Incorporates real-world uncertainties such as outages, load variation, and renewable fluctuations.
Suitability	Works well for deterministic planning (e.g., transmission planning, steady-state analysis).	Essential for reliability assessment, risk management, and generation adequacy studies.

1.2 Problem Statement

The **Transmission System Development Plan (TSDP, 2018)** outlines a comprehensive strategy for expanding Nepal's transmission infrastructure. However, it lacks probabilistic generation adequacy assessments, which are crucial for accurately predicting future power supply reliability.

The contingency analysis within the TSDP relies on the **WECS Electricity Demand Forecast Report (2014-2040)**, which has been identified to contain inaccurate load projections due to its reliance on deterministic forecasting methods. These methods fail to account for uncertainties in economic growth, leading to overestimations in previous planning frameworks.[12, 13]

Previous studies, such as those by **Chettry and N. Karki (2015)**, have primarily focused on short-term reliability assessments, leaving a gap in long-term generation adequacy evaluations.[9]

There is currently no existing study that evaluates Nepal's generation adequacy for the years 2030, 2035, 2040, and 2050 under various growth scenarios (BAU, High, Medium, and Target).

This gap in research highlights the need for a comprehensive analysis that incorporates probabilistic methods to better predict future power system reliability and ensure sustainable development of Nepal's power infrastructure.

1.3 Objectives

1.3.1 Main Objective

The main objective of this study is to perform a long-term generation adequacy assessment of Nepal's INPS using probabilistic methods, particularly Monte Carlo simulations, to evaluate whether the generation capacity will meet the projected electricity demand reliably under different growth scenarios.

1.3.2 Specific Objectives

The specific objectives of this research are as follows:

- To forecast Nepal's electricity demand for the years 2030, 2035, 2040, and 2050 based on economic and demographic growth scenarios using econometric models.

- To apply Monte Carlo simulation methods to evaluate the generation adequacy of Nepal's power system by assessing reliability indices such as LOLE, EENS, and EIR under different growth scenarios.

- To assess the impact of growing e-cooking and e-transport adoption and industrial boiler as policy intervention in Nepal on generation adequacy.

- This study addresses this gap by applying Monte Carlo simulations over multiple decades, incorporating industrial boiler electrification, e-transport, and e-cooking as policy interventions in load forecasting.

Each of the specific objectives will lead to a concrete output: demand forecasts, reliability indices, simulation results, and expansion recommendations. These outputs will contribute to achieving the overall objective of evaluating the adequacy of Nepal's power system in the face of future demand.

1.4 Scope and Limitations

1.4.1 Scope

This study focuses on evaluating the long-term generation adequacy of INPS using probabilistic methods, specifically Monte Carlo simulations. The analysis covers the years 2030, 2035, 2040, and 2050, assessing the system's capacity to meet electricity demand under various growth scenarios. The scope includes the impact of renewable energy sources (primarily hydropower and solar) on generation adequacy but does not account for transmission or distribution system limitations (HL I analysis).

1.4.2 Limitations

- The study only addresses generation adequacy and excludes transmission or distribution constraints.
- The accuracy of the results is dependent on the quality of demand forecasts and assumptions regarding the completion of planned hydropower projects.
- The study assumes that the economic and demographic trends will continue as projected, which may not account for sudden changes in these factors.
-The value of EENS is based on the assumption that the daily peak load persists throughout the entire day, which leads to an overestimation of the EENS value.
-This thesis provides insights into the behavior of generation and load; however, the accuracy of the EENS calculation is likely overestimated.
-The calculation is based on peak load forecasting but lacks consideration of energy forecasting. Future studies could adopt energy-based forecasting to provide deeper insights from an energy perspective.

1.4.3 Assumptions

- The analysis assumes that Nepal's renewable energy capacity, particularly hydropower, will remain the primary source of electricity generation.
- Future demand forecasts are based on historical trends and may not fully reflect unexpected shifts in economic or population growth.

1.5 Report Organization

This report is organized into the following chapters:

- **Chapter 1: Introduction** – Provides the background, problem statement, objectives, scope, and limitations of the study.
- **Chapter 2: Literature Review** – Reviews relevant literature on generation adequacy and identifies the research gaps in the context of Nepal's power system.Explains the key concepts of power system reliability, generation adequacy, and the methods used for assessment, including Monte Carlo simulations.
- **Chapter 4: Methodology** – Describes the methodology used to evaluate generation adequacy, including demand forecasting models and simulation techniques.
- **Chapter 5: Results and Discussion** – Presents the findings of the simulation, evaluates the results, and discusses their implications for Nepal's power system.
- **Chapter 6: Conclusion** – Summarizes the conclusions and offers recommendations for future energy infrastructure planning to ensure reliable power supply in Nepal.

CHAPTER TWO: LITERATURE REVIEW

2.1 Power System Reliability and Generation Adequacy

Power system reliability is classified into two key aspects: *adequacy* and *security*. Adequacy ensures that the system has sufficient generation and transmission capacity to meet demand, whereas security pertains to the system's ability to respond to disturbances [11].

Generation adequacy is a fundamental aspect of power system reliability, ensuring that sufficient generation capacity is available to meet electricity demand under both normal and stressed conditions. INPS is currently undergoing significant transformation, necessitating a robust generation adequacy assessment to guide long-term energy planning.

Generation adequacy, which falls under (HL-I), evaluates whether the available generation capacity is sufficient to meet electricity demand under normal and stressed conditions. It is commonly assessed using reliability indices such as LOLE and EENS.

2.1.1 Hierarchical Levels of Reliability Assessment

Billinton and Allan [10] introduced the *Hierarchical Level (HL) framework*, which categorizes power system reliability into three levels:

- **HL-I (Generation Adequacy)** – Evaluates only the sufficiency of generation resources to meet demand.
- **HL-II (Composite System Reliability)** – Considers both generation and transmission constraints.
- **HL-III (Load Point Reliability)** – Incorporates generation, transmission, and distribution system reliability at the consumer level.

Figure 2.1 summarizes the hierarchical level of adequacy assessment while Figure 2.2 explains the HL-1 model.

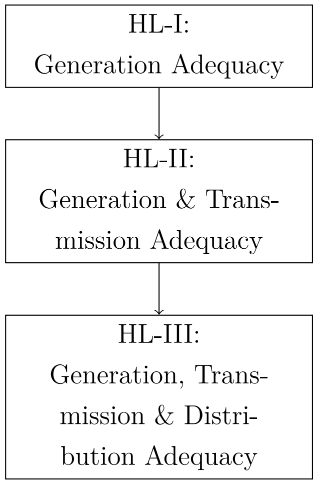


Figure 2.1: Classification of HL-1, HL-2, and HL-3 Reliability

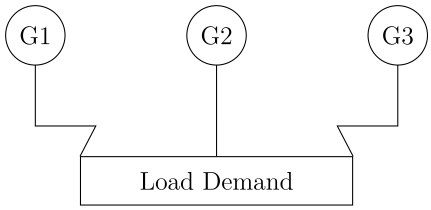


Figure 2.2: Model for HL-1 Analysis

This study focuses on **HL-I generation adequacy**, which is crucial for long-term capacity expansion and investment planning in Nepal.

2.1.2 Reliability Indices for Power System Adequacy

The following key reliability indices are used to evaluate generation adequacy[11]:

- **Loss of Load Expectation (LOLE)**
  - LOLE measures the expected number of days per year when electricity demand exceeds available generation, leading to a loss-of-load event .
  - Mathematically, it is given by:

$$LOLE = \sum_{i=1}^{N} P(C_i < D) \tag{2.1}$$

  - Where:

        * $P(C_i < D)$ represents the probability of available generation capacity C_i being insufficient to meet demand D.

        * N is the number of periods (e.g., days in a year).

    - A higher LOLE value indicates a greater risk of electricity shortages, guiding system planners on the need for reserve capacity.

- **Loss of Energy Expectation (LOEE)**

    - LOEE measures the total energy deficit caused by supply shortages over a specified period.

    - It is given by:

$$LOEE = \sum_{t=1}^{T} \max(0, D_t - C_t) \tag{2.2}$$

    - Where:

        * D_t is the demand at time t,

        * C_t is the available generation capacity at time t,

        * T represents the total analyzed period.

    - LOEE quantifies the severity of energy shortages, making it a key metric in capacity planning and investment decision-making.

- **Expected Energy Not Supplied (EENS)**

    - EENS estimates the expected amount of unserved energy, considering both the probability and magnitude of demand-supply imbalances .

    - It is defined as:

$$EENS = \sum_{i=1}^{N} x_i C_i \Delta t \tag{2.3}$$

    - Where:

        * x_i is the probability of a loss-of-load event at time step i,

        * C_i is the curtailed energy (MWh),

        * Δt represents the time interval.

    – EENS is expressed in megawatt-hours (MWh) and plays a crucial role in determining the economic impact of power shortages.

- **Energy Index of Reliability (EIR)**

    – EIR is a dimensionless reliability index that measures the proportion of total demand that is successfully met.

    – It is given by:

$$EIR = 1 - \frac{EENS}{E_D} \tag{2.4}$$

    – Where:

        * $EENS$ represents the expected unserved energy (MWh),

        * E_D is the total energy demand (MWh) over the analysis period.

    – EIR ranges from 0 to 1, where values closer to 1 indicate a highly reliable power system.

2.1.3 How These Metrics Quantify Power System Adequacy

LOLE, LOEE, EENS, and EIR provide quantitative insights into system adequacy. Their role in power system planning includes:

- **LOLE:** Indicates the likelihood of electricity shortages, aiding in capacity reserve planning.

- **LOEE:** Measures the total unserved energy, guiding investment in peak generation and energy storage.

- **EENS:** Helps evaluate the economic impact of supply shortages and supports cost-benefit analysis for expansion projects.

- **EIR:** Provides a normalized measure of reliability, allowing comparisons across different systems and planning scenarios.

A well-planned power system aims to minimize LOLE, LOEE, and EENS, while maximizing EIR, ensuring a secure, cost-effective, and resilient electricity supply.

Reliability indices such as LOLE, LOEE, EENS, and EIR provide a quantitative framework for assessing power system adequacy. Their application enables power system planners to evaluate the risk of generation inadequacy and optimize decisions regarding capacity expansion, demand-side management, and energy storage solutions [14]. These indices are critical in ensuring a sustainable, reliable, and secure electricity supply.

2.2 Introduction to Econometric Load Forecasting

Econometric modeling is a widely used approach in electricity demand forecasting, particularly for long-term projections. It establishes a statistical relationship between electricity consumption and economic, demographic, and environmental factors. Unlike traditional time-series models, econometric models incorporate *external economic drivers*, making them adaptable to policy changes, technological advancements, and structural shifts in energy demand [15].

The core assumption of econometric models is that **electricity demand (D)** is influenced by key macroeconomic variables such as[16]:

- **GDP** – Economic growth typically leads to increased electricity consumption.
- **Population Growth (POP)** – More people imply higher energy demand in residential and commercial sectors.
- **Electrification Rate (E)** – Measures the expansion of electricity access.
- **Electricity Price (P)** – Higher prices may reduce demand due to elasticity.
- **Temperature and Climate (T)** – Seasonal variations influence heating and cooling needs .

Mathematically, the general form of an econometric load forecasting model is given as:

$$D_t = f(GDP_t, POP_t, E_t, P_t, T_t) + \epsilon_t \tag{2.5}$$

where:

- D_t = Electricity demand at time t,
- $f()$ = Functional relationship between demand and independent variables,
- ϵ_t = Error term capturing unobserved factors.

Linear Regression Model

A simple linear econometric model expresses demand as[17]:

$$D_t = \beta_0 + \beta_1 GDP_t + \beta_2 POP_t + \beta_3 E_t + \beta_4 P_t + \beta_5 T_t + \epsilon_t \tag{2.6}$$

where:

- β_0 = Intercept term,
- $\beta_1, \beta_2, \ldots, \beta_5$ = Regression coefficients capturing the influence of each independent variable,
- ϵ_t = Random error term.

2.2.1 Estimation Techniques in Econometric Forecasting

The parameters (β_i, α_i) in econometric models are estimated using **statistical regression techniques**, primarily:

- **OLS** – Minimizes the sum of squared residuals to ensure best linear unbiased estimates.
- **Autoregressive Distributed Lag (ARDL) Models** – Used when demand is influenced by past values, incorporating **lagged variables**.
- **Cointegration Analysis** – Applied when variables exhibit **long-term equilibrium relationships** despite short-term fluctuations.

The model's accuracy is validated using:

- **R-Squared** (R^2) – Measures the model's goodness-of-fit.

- **Durbin-Watson Statistic** – Tests for autocorrelation in residuals.
- **Forecast Error Metrics (MAE, RMSE)** – Evaluate predictive accuracy.

2.2.2 Application of Econometric Models in Long-Term Load Forecasting

Econometric models are useful for forecasting load under multiple economic growth scenarios:

- **BAU** – Assumes historical trends continue.
- **High Growth Scenario** – Accounts for rapid industrialization and electrification.
- **Medium Growth Scenario** – Assumes moderate economic and population growth.
- **Target Scenario** – Includes policy-driven renewable energy expansion and energy efficiency improvements.

Using the estimated econometric model, electricity demand projections for **2030, 2035, 2040, and 2050** are generated under these scenarios.

2.2.3 Advantages and Limitations of Econometric Load Forecasting

Advantages

- Incorporates economic and demographic drivers, improving long-term forecasting accuracy.
- Allows scenario-based analysis under different policy and economic conditions.
- Captures elasticities of demand, aiding in tariff and energy policy formulation.

Limitations

- Requires high-quality historical data, which may be unavailable in developing regions.
- Assumes stable economic relationships, which may shift due to policy changes or technological advancements.

- May underestimate short-term fluctuations compared to time-series models like ARIMA.[18]

2.3 Monte Carlo Simulation for Power System Analysis

MCS is a probabilistic method used to analyze complex systems with uncertainty by performing repeated random sampling. It is widely applied in power system reliability and adequacy assessments to evaluate how random failures of generation units, fluctuations in demand, and variability in renewable generation affect system performance.

Unlike deterministic approaches, which assume fixed inputs and produce a single outcome, MCS generates a distribution of possible outcomes, allowing a deeper understanding of risk, variability, and probability of failure in power system operations.

2.3.1 Overview of Monte Carlo Simulation

The basic steps in Monte Carlo Simulation for power system analysis are:

1. **Random State Sampling:** Each generating unit is modeled with a probability of being operational or in outage, based on its FOR. A random number generator determines whether a unit is available in a given time step.

2. **System State Evaluation:** The available generation capacity is computed for each simulation run. The **available power is compared with system demand** to determine **if a load curtailment occurs**.

3. **Computation of Reliability Indices:** The simulation runs multiple times (e.g., 10,000 to 100,000 iterations) to estimate:

    - **LOLE**

    - **EENS**

    - **LOEE**

4. **Statistical Analysis:** The results from multiple simulations are aggregated to compute probability distributions, mean values, and confidence intervals for reliability indices.

Monte Carlo Simulation is preferred because:

- It accounts for random outages and load variations, which are crucial for long-term planning.
- It models renewable energy uncertainty, a key factor in modern power systems.
- It provides statistical confidence intervals, offering insights into worst-case and expected scenarios.
- It supports risk-based decision-making, which is crucial for energy policy and planning.

2.3.2 Applications of Monte Carlo Simulation in Generation Adequacy Assessments

Monte Carlo Simulation has been extensively applied in generation adequacy studies to evaluate whether a power system has sufficient capacity to meet demand under various conditions [19].

Reliability Indices Calculation

MCS is used to compute power system reliability metrics such as:

- **LOLE**

$$LOLE = \sum_{i=1}^{N} P(C_i < D) \tag{2.7}$$

- **EENS**

$$EENS = \sum_{i=1}^{N} x_i C_i \Delta t \tag{2.8}$$

- **LOEE**

$$LOEE = \sum_{t=1}^{T} \max(0, D_t - C_t) \tag{2.9}$$

Generation Expansion Planning

Energy policymakers use **Monte Carlo-based reliability assessments** to evaluate:

- **Future Generation Scenarios:** What happens if demand grows faster than expected? What level of reserve margin is required to maintain reliability?

- **Impact of Generator Outages:** How do aging power plants affect system reliability? What is the impact of planned maintenance schedules?

- **Cross-Border Electricity Trade:** Can imported electricity from neighboring countries enhance reliability? How do transmission line failures impact generation adequacy?

2.3.3 Probabilistic Methods in Generation Adequacy Analysis

Probabilistic methods, particularly MCS, have become the industry standard for generation adequacy assessment. Billinton & Karki [20, 21] demonstrated the effectiveness of MCS techniques in modeling stochastic variations in generation outages and demand fluctuations. Compared to deterministic methods, MCS provides a more comprehensive evaluation of power system risks by incorporating uncertainties such as:

- **FOR** of generating units

- **Seasonal and annual demand fluctuations**

Reliability indices such as LOLE and EENS have been widely used to quantify supply shortages [22].

2.3.4 Wind and Renewable Energy Integration in Generation Adequacy

The role of renewable energy sources (RES) in power system adequacy has gained prominence in recent years. Billinton et al. [11] emphasized that the variability and intermittency of wind power require advanced probabilistic models for reliability assessments. Shi and Lo [14] introduced MCS combined with the Frequency & Duration method to analyze the impact of wind power on system reliability.

Key findings from wind energy reliability studies include:

- **Energy storage (hydropower, batteries) plays a crucial role** in mitigating wind power variability.

- **Hybrid renewable models (solar-hydro) are essential** for improving Nepal's long-term energy security.

Nepal's hydropower-dominant system faces seasonal fluctuations and needs energy mixing for reliability.

2.4 Generation Adequacy Studies in Nepal

Several studies have assessed the adequacy of Nepal's *INPS*:

- Chetry and Karki (2015) conducted a short-term reliability analysis of INPS, highlighting significant LOLE and EENS values due to hydropower seasonality [9].

- The Transmission System Development Plan (TSDP, 2018) provides a roadmap for expanding Nepal's transmission infrastructure but lacks probabilistic generation adequacy assessments [12].

- The Electricity Demand Forecast Report (2014-2040) projected load growth but relied on deterministic forecasting methods, which do not fully capture uncertainties in economic growth and electrification trends[13].

Unlike these studies, the current research uses an econometric forecasting model, which integrates economic and demographic factors to enhance demand projections.

CHAPTER THREE: METHODOLOGY

3.1 Overall Process

The study uses the Non-Sequential Monte Carlo Method to analyze generation adequacy only (HL-I level). It employs a state sampling method to randomly assign generator outages based on the Forced Outage Rate (FOR) and computes LOLE and EENS. The general workflow is shown in Algorithm 1.

Algorithm 1 Generation Adequacy Simulation

```
1: Start
2: Forecast Load Data
3: Input Generation Capacity & FOR
4: Monte Carlo Simulation
5: Compute LOLE & EENS
6: Analyze Results
7: End
```

3.2 Load Forecasting

3.2.1 Peak Load Forecast

The correlation heatmap was analyzed to identify highly correlated parameters. Due to multicollinearity, only the most representative variables were retained. Ultimately, "GDP per capita" and "Population" were selected as the strongest variables, as they effectively capture economic and demographic influences while minimizing redundancy. This ensures a more robust and interpretable analysis.

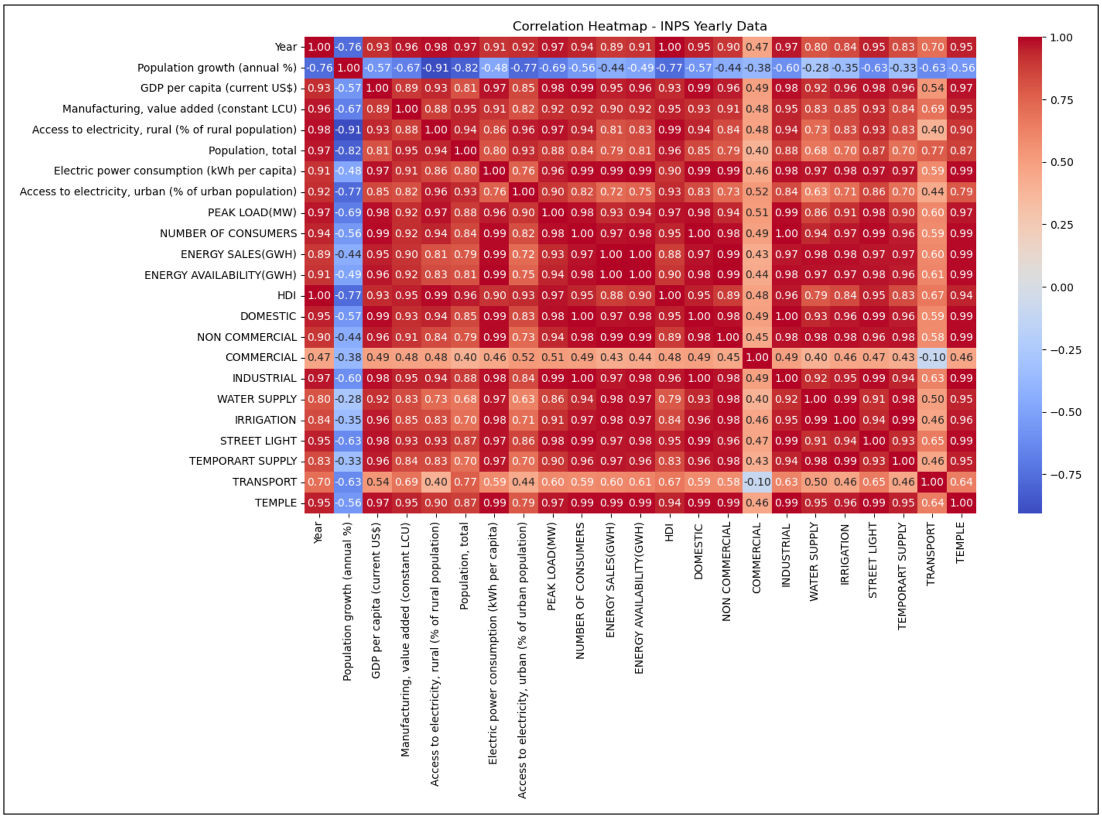


Figure 3.1: Correlation Heatmap of Different Parameters & Peak Load

The peak load forecast is based on a multiple linear regression model, where GDP per capita and population are used as independent variables. The general form of the regression equation is:

$$P_t = \beta_0 + \beta_1 X_1(t) + \beta_2 X_2(t) + \epsilon_t \tag{3.1}$$

where:

- P_t = Peak Load (MW) at time t
- β_0 = Intercept term
- β_1, β_2 = Regression coefficients
- $X_1(t)$ = GDP per capita at time t
- $X_2(t)$ = Population at time t

- ϵ_t = Error term

Using the estimated regression coefficients from the OLS model, the peak load for future years is calculated as:

$$P_{\text{future}} = \beta_0 + \beta_1 \cdot \text{GDP}_{\text{future}} + \beta_2 \cdot \text{Population}_{\text{future}} \tag{3.2}$$

To account for system losses, a 15% adjustment is applied. This final adjusted peak load projection is used for long-term power system planning.

3.3 Peak Forecasting with Policy Intervention

This section outlines the approach used to incorporate policy interventions in load forecasting, specifically focusing on the effects of electric vehicle (EV) adoption and electric cooking demand on future peak electricity load projections in Nepal. The methodology describes the base data, key assumptions, and how both **e-mobility** and **electric cooking** are incorporated into the model.

3.3.1 Base Data for EV Adoption, Electric Cooking Demand & Industrial Boiler

The base data used for forecasting includes the number of vehicles registered in 2023, with specific values for internal combustion engine (ICE) vehicles and electric vehicles (EVs) across various categories. Additionally, the demand for electricity from electric cooking is incorporated based on assumptions from national data.

Base Data for EVs (2023)

The following table summarizes the number of ICE vehicles and EVs in various categories, which forms the foundation for the future load forecast:

Source: Department of Transport Management (DoTM), 2024.

These values are used in the model to forecast the additional electricity load due to the growing adoption of electric cooking. These projections reflect the shift from biomass and LPG cooking to electric cooking, driven by policy efforts and household electrification initiatives.

Vehicle Type	ICEs (Internal Combustion Engines)	EVs (Electric Vehicles)
Motorcycle	4,266,566	18,004
Three Wheelers	92,476	67,569
Car/Jeep/Van	322,119	12,571
Microbus	11,715	2,032
Minibus	18,740	102
Bus	64,647	102
Truck/Mini truck	144,501	0
Pick up	90,512	0
Tractor	184,282	0
Others	9,019	0
Total	**5,204,577**	**100,278**

Table 3.1: Base Data for EV Adoption in 2023

3.3.2 Key Assumptions

The following assumptions were made to model the future electricity demand:

1. **Growth Scenarios**:
   - **BAU**: Assumes a steady increase in the adoption of EVs and electric cooking based on existing trends and policies.
   - **Medium**: Assumes moderate growth due to stronger incentives, infrastructure development, and public awareness of the benefits of EVs and electric cooking.
   - **High**: Assumes rapid growth driven by aggressive government policies, technological advancements, and a national shift toward clean energy.
2. **Electric Vehicle Growth**: Future EV adoption rates were projected based on historical growth patterns and the number of vehicles registered in 2023. This includes estimating future EV adoption in different vehicle categories (motorcycles, three-wheelers, cars, buses, etc.) using a compound annual growth rate (CAGR) model.
3. **Electric Cooking Adoption**: The growth in electric cooking adoption is based on national data regarding appliance imports and electricity access. The model assumes a continued increase in the adoption of electric stoves, particularly in urban areas, driven by government incentives and the rising cost of LPG.

4. **Electricity Demand Per EV**: The electricity demand per EV is estimated based on data from EV charging stations. This is calculated as follows:

$$\text{Energy Used Per EV} = \frac{\text{Charging Station Energy Used}}{\text{Current EV Count}} \tag{3.3}$$

   where:

   - Charging Station Energy Used: 2,663,363.19 kWh for 51 stations
   - Current EV Count: 100,278 EVs in 2023

   This results in an average energy consumption of approximately **26.6 kWh/EV/-day**.

5. **Electric Cooking Demand**: The electricity demand for electric cooking is forecasted by multiplying the number of households expected to adopt electric cooking technologies by the average energy consumption of these appliances (which is sourced from the 2023 electricity demand projections in the cooking sector).

3.3.3 Incorporating E-Mobility and Electric Cooking as Policy Intervention in Load Forecasting

Incorporating Electric Mobility (E-Mobility)

Electric mobility (EVs) is incorporated into the forecasting model by following these steps:

1. **Future EV Projections**: Using the base data for 2023 and growth scenarios (BAU, Medium, High), the future number of EVs for each vehicle type (motorcycles, cars, buses, etc.) is projected up to 2050. The growth rate for each vehicle category is based on GDP and population growth, as well as the adoption of cleaner technologies in the transport sector.

2. **Electricity Demand from EVs**: The electricity demand from EVs is calculated by multiplying the projected number of EVs by the average daily energy consumption per vehicle (**26.6 kWh/EV/day**). This value is then converted from kWh/day to MW for peak load forecasting, using the following conversion:

$$\text{Total Demand (MW)} = \frac{\text{Total Demand (kWh/day)}}{24 \times 1000} \tag{3.4}$$

The total demand for EVs is summed up for each year (2030, 2035, 2040, 2050) under each growth scenario.

Incorporating Electric Cooking (E-Cooking) and Industrial Boiler

Electric cooking and Industrial Boiler is incorporated in the following steps:

1. **Electric Cooking Demand**: According to the report on *Electricity Demand Creation in Different Sectors* [23], electricity demand for residential and commercial electric cooking is projected as follows:

   - **Residential Electric Cooking Demand:**
     - **2030**: 0.144 TWh
     - **2040**: 4.322 TWh
     - **2050**: 11.018 TWh
   - **Commercial Electric Cooking Demand:**
     - **2030**: 332 GWh
     - **2040**: 4,700 GWh
     - **2050**: 20,052 GWh

2. **Boiler Demand**: The following values are used for industrial boiler demand under three growth scenarios: BAU, Electrification, and High Growth:

   - **2030**: (2,583, 2,045, 3,079) GWh
   - **2040**: (8,330, 8,642, 13,648) GWh
   - **2050**: (19,415, 26,481, 40,341) GWh

Following Load Factor are considered for the study:

- Residential Electric Cooking: 20%
- Commercial Electric Cooking: 50%

- Boiler: 60%
- E-Mobility: 50%

These values are converted to MW for the peak load forecast using the same conversion method as for EVs:

$$\text{Total Cooking Demand (MW)} = \frac{\text{Electric Cooking Demand (TWh)}}{1,000 \times 365} \tag{3.5}$$

3.4 Annual Load Curve Forecast

Figure 3.2 shows the annual load curve of 2023 and 2024, which exhibits the same pattern. The projected annual load curve for each future year and scenario is computed using a scaling factor based on the maximum observed peak demand in 2024.

$$\text{Scaling Factor} = \frac{\text{Projected Peak Demand for Year } Y}{\text{Max Peak Demand in 2024}} \tag{3.6}$$

Using this factor, the scaled peak demand values for each day are calculated as:

$$\text{Peak Demand}_Y(d) = \text{Peak Demand}_{2024}(d) \times \text{Scaling Factor} \tag{3.7}$$

where:

- d represents the ranked day index.
- $\text{Peak Demand}_Y(d)$ is the forecasted peak demand for a given future year Y.
- $\text{Peak Demand}_{2024}(d)$ is the historical peak demand from 2024 data.

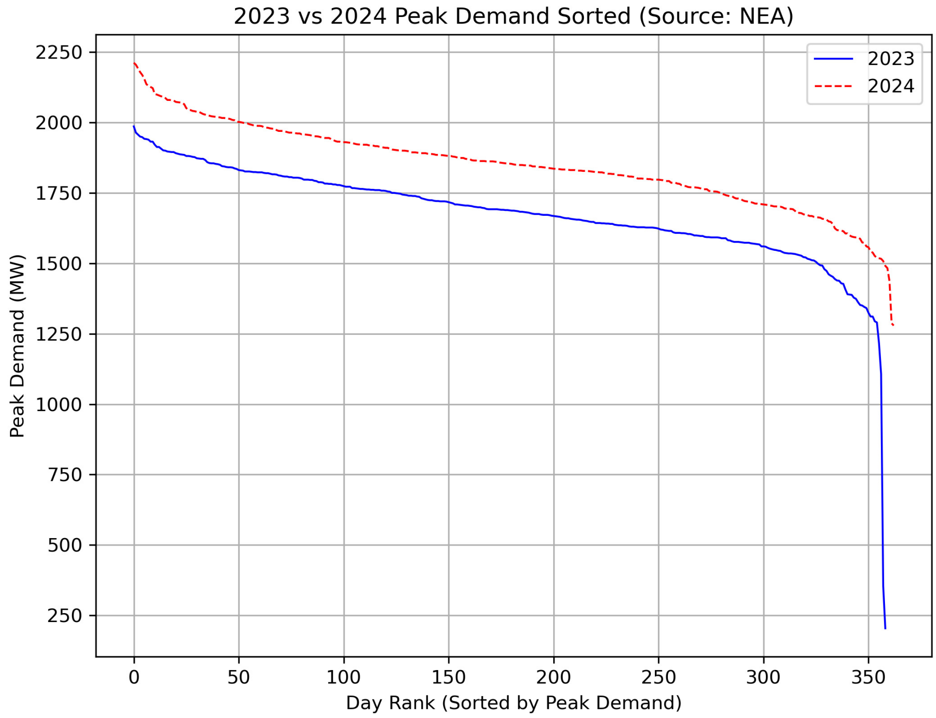


Figure 3.2: 2023-2024 Annual Load Curve

3.5 Generation Capacity of INPS

The 5-Year Plan outlines Nepal's strategy to expand electricity generation, strengthen transmission infrastructure, and ensure financial sustainability in the power sector. The plan prioritizes scaling up hydropower projects, including storage and run-of-river plants, to meet growing domestic demand and support cross-border electricity trade, particularly with India.

In terms of financing, the plan promotes public-private partnerships (PPP), foreign direct investment (FDI), and domestic bank financing as key funding sources. It encourages private sector participation in power generation while introducing investment incentives and policy reforms to attract long-term capital.

Table 3.2 presents the current status and installed capacity of various power projects in Nepal, categorizing them by operational, under-construction, and licensed projects, with a total projected capacity for future development.

Status	**Capacity (MW)**
NEA PPA Operational (2024)	2,495
Under Construction (Financial Closure)	3,905
Under Construction (Without Financial Closure)	3,899
Hydro Connected Capacity	3,241
PV Connected Capacity	107
Hydro Construction License Approved	10,054
PV Construction License Approved	77
Hydro Construction License Applied	11,256
PV Construction License Applied	60
Hydro Survey License Approved	8,041
PV Survey License Approved	3,643
Hydro Survey License Applied	3,643
PV Survey License Applied	717
Government Bank Studied	3,641

Table 3.2: Hydro and PV Project Status and Capacity

3.6 Monte Carlo Simulation

MCS involves multiple iterations of state sampling, generation availability computation, and load curtailment analysis. The MCS iteratively determines the adequacy of the system.

Algorithm 2 Monte Carlo Simulation for Generation Adequacy

Initialize: Set $LOLE \leftarrow 0$, $LOEE \leftarrow 0$, $EENS \leftarrow 0$, N_{sim} (number of simulations), and N_{days} (days in a year).
Load generator data: Capacity (C_i) and Forced Outage Rate (FOR_i).
Load daily peak demand data (D_t).
Define seasonal hydropower capacity factors.
for $sim \leftarrow 1$ to N_{sim} **do**
    Initialize: Set available capacity vector $C_{\text{available}}(t) \leftarrow 0$ for all t.
    for each generator i **do**
        Generate uniform random number $U_i \in (0,1)$.
        if $U_i < FOR_i$ **then**
            Set generator i as down ($C_i = 0$).
        else
            Generator i is online. Compute seasonal adjusted capacity:
            $C_i^{\text{adj}} = C_i \times \text{Seasonal Factor}(t)$
        end if
        Update available capacity:
        $C_{\text{available}}(t) = C_{\text{available}}(t) + C_i^{\text{adj}}$ for all t.
    end for
    Compute daily Loss of Load Probability (LOLP):
    for each day t **do**
        if $C_{\text{available}}(t) < D_t$ **then**
            Increment LOLE: $LOLE = LOLE + 1$.
            Compute daily energy shortfall:
            $LOEE = LOEE + (D_t - C_{\text{available}}(t))$.
        end if
    end for
end for
Compute Reliability Indices:
$LOLE = \frac{LOLE}{N_{sim}}$
$LOEE = \frac{LOEE}{N_{sim}}$
$EENS = LOEE$
Compute total energy demand: $E_D = \sum_{t=1}^{N_{days}} D_t$
Compute Energy Index of Reliability (EIR):
$EIR = 1 - \frac{EENS}{E_D}$

3.7 Generation Model

The Forced Outage Rate (FOR) for existing generation plants is taken from the NEA Report. For future plants, the FOR value is assumed to be 0.02. The following assumptions are made about generation modeling:

- **By 2030:** Generation capacity will include operational projects and those under construction with financial closure.

- **By 2035:** Generation capacity will include operational projects and those under construction with and without financial closure.

- **By 2040:** Generation capacity will include operational projects and those under construction with and without financial closure, and 90% of Construction License approved & 80% of Construction License applied.

- **By 2050:** Generation capacity will include operational projects and those under construction with and without financial closure, and 90% of Construction License approved & 80% of Construction License applied, and 60% of survey license approved and 50% of survey license applied.

This phased approach ensures a structured and scalable expansion of the generation capacity over time.

3.8 Monte Carlo Reliability Assessment for Generation Adequacy

Monte Carlo simulation is employed to assess the LOLE, LOEE, and EIR for different years and scenarios.

3.8.1 Input Data Preparation

The simulation requires the following datasets:

- **Generation Data:** Installed generation capacity and the FOR for each project.

- **Load Data:** Peak demand requirement sorted seasonally for different years and demand growth scenarios.

Seasonal variations in hydropower availability are considered using predefined seasonal capacity factors.

Season	Months	Capacity Factor
Dry	January, February, March	0.25/0.40
Pre-Monsoon	April, May	0.70
Monsoon	June, July, August, September	0.90
Post-Monsoon	October, November	0.70
Dry	December	0.25/40

Table 3.3: Seasonal Hydropower Capacity Factors and Corresponding Months

3.8.2 Monte Carlo Simulation Process

The Monte Carlo simulation runs for 1,00,000 iterations to model random outages of generators and their impact on system reliability. The key steps are outlined in Algorithm 2.

3.8.3 Simulation Scenarios

The analysis is performed for different future years (2030, 2035, 2040, 2050) under the following demand growth scenarios:

- **BAU**
- **Medium Growth**
- **High Growth**
- **Target Scenario**

CHAPTER FOUR:RESULTS AND DISCUSSION

4.1 Peak Load Forecast Analysis

The peak load forecast is based on multiple linear regression models, incorporating GDP per capita and population as independent variables. The results provide insights into future electricity demand trends under different growth trajectories.

Figure 4.1 illustrates the historical peak load alongside projections under various economic growth scenarios. Figure 4.2 compares the actual vs predicted peak load values for 2019–2024, demonstrating the model's accuracy.

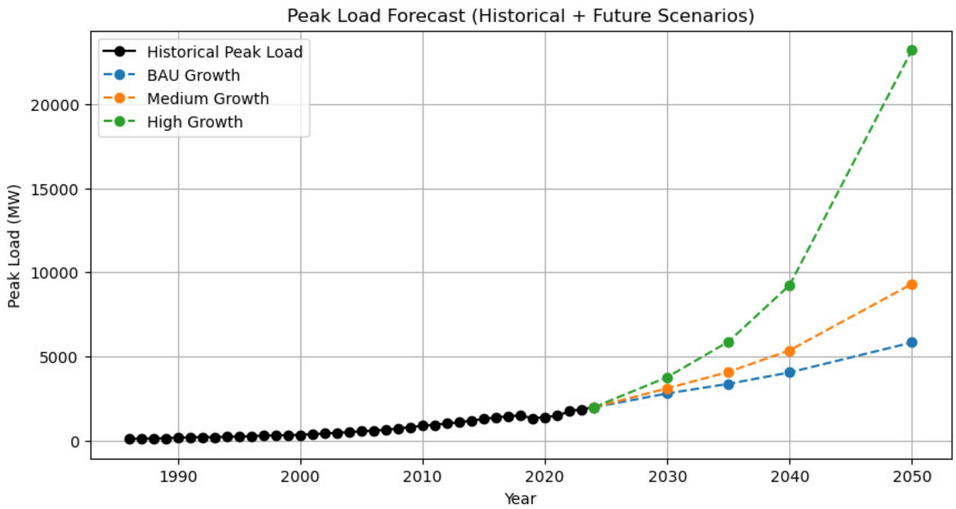


Figure 4.1: Historical and Forecasted Peak Load under Different Growth Scenarios

4.1.1 Regression Model Performance

The OLS regression model achieved a high coefficient of determination ($R^2 = 0.986$), indicating strong explanatory power. Table 4.1 summarizes the key regression metrics.

4.1.2 Projected Peak Load under Growth Scenarios

Table 4.2 presents the peak load estimates for Business-as-Usual (BAU), Medium, and High Growth Scenarios. The projections highlight a steady increase in peak demand over time, with substantial differences based on economic expansion rates.

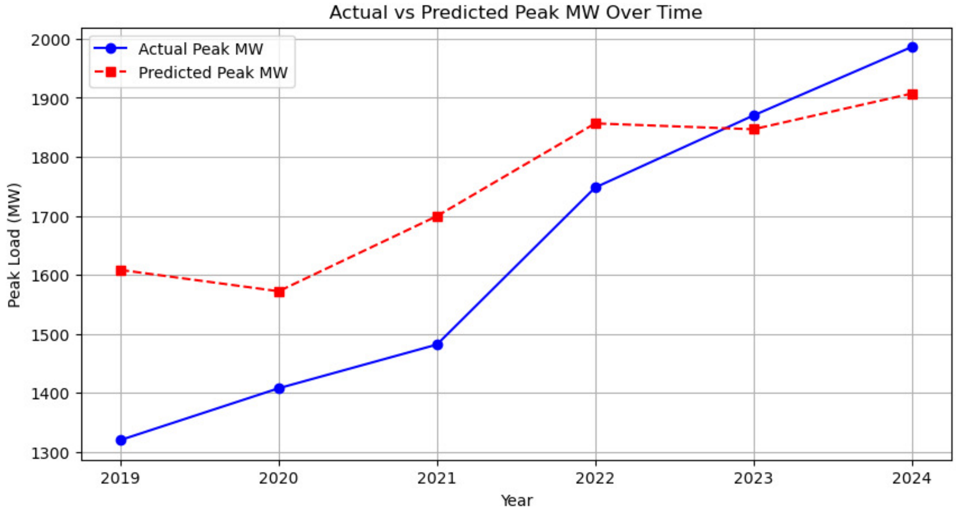


Figure 4.2: Comparison of Actual vs Predicted Peak Load for 2019–2024

Table 4.1: OLS Regression Summary

Metric	Value
R-squared	0.986
Adjusted R-squared	0.985
F-statistic	1031
P-value (Prob F-stat)	2.24e-28
GDP per Capita Coefficient	1.1182
Population Coefficient	3.371e-05
Durbin-Watson Statistic	1.050

4.1.3 Target Growth Scenario Based on Per Capita Consumption

In addition to GDP-driven scenarios, a target growth scenario was derived from per capita electricity consumption levels observed in other economies. A separate linear regression model was used to predict peak demand based on historical data of Electric Power Consumption (kWh per capita). The model equation is:

Table 4.2: Predicted Peak Load (MW) under Different Growth Scenarios

Year	BAU	Medium	High
2030	2,808	3,110	3,776
2035	3,377	4,084	5,884
2040	4,056	5,368	9,241
2050	5,834	9,313	23,205

$$\text{PEAK LOAD(MW)} = 6.5326 \times \text{Electric Power Consumption (kWh per capita)} + 33.2713 \tag{4.1}$$

The R^2 value of 0.9415 indicates a strong correlation, supporting the model's reliability for long-term projections.

Per Capita Consumption (kWh)	Target Country/Income Level	Predicted Peak Load (MW)
1,500	2035 Target	11,306
2,500	2040 Target	18,819
4,000	2050 Target	30,088

Table 4.3: Predicted Peak Load (MW) Based on Per Capita Consumption Targets

4.1.4 Final Comparison of Growth Scenarios

Table 4.4 consolidates the BAU, Medium, High, and Target projections, providing a holistic view of future energy demand.

Table 4.4: Final Peak Load Summary: BAU, Medium, High, and Target Scenarios

Year	BAU	Medium	High	Target
2030	2,808	3,110	3,776	-
2035	3,377	4,084	5,884	11,306
2040	4,055	5,368	9,241	18,819
2050	5,834	9,313	23,205	30,088

4.2 Key Findings and Implications

- The BAU scenario predicts a gradual rise in demand, whereas the High Growth scenario suggests a fourfold increase in peak demand by 2050.
- The target-based projections show a demand surge exceeding 30,088 MW for 2050 target.
- The per capita consumption model aligns with economic benchmarks, indicating that achieving upper-middle-income status by 2040 would require over 18,819 MW capacity.
- The strong R^2 values (0.986 for GDP-population regression and 0.9415 for per capita consumption) validate the models as reliable tools for energy planning.

4.3 Comparison of Real Peak Demand vs. Forecasts

The analysis compares the real recorded peak demand from 2015 to 2024 with the forecasts from both the WECS Report (2017) and our OLS-based model.

4.3.1 Real Peak Demand Data (2015-2024)

Table 4.5 presents the real peak demand recorded over the past decade.

Table 4.5: Real Peak Demand Data (2015-2024)

Year	Peak Demand (MW)
2015	1291.1
2016	1385.3
2017	1444.1
2018	1508.16
2019	1320.28
2020	1408
2021	1482
2022	1748
2023	1870
2024	1986

4.3.2 Comparison of Peak Demand Forecasts

Table 4.6 compares the real peak demand, our model's forecast, and WECS's projections[13].

Table 4.6: Comparison of Real Peak Demand vs. Forecasts (MW)

Year	Real Peak Demand	Our BAU Forecast	WECS BAU Forecast	WECS High Growth Forecast
2020	1408	-	3384	3794
2024	1980	1900	5787	7366
2030	-	2808.40	8937	13296
2035	-	3377.58	13242	23588
2040	-	4055.98	19151	42228

4.3.3 Visualization of Forecast Accuracy

Figure 4.3 compares real peak demand and forecasts.

4.3.4 WECS Overestimation and Its Implications

From Table 4.6, WECS significantly overestimates demand:

- In 2020, WECS projected 3384 MW (BAU scenario), whereas the real peak was only 1408 MW, showing an overestimation of 140%.

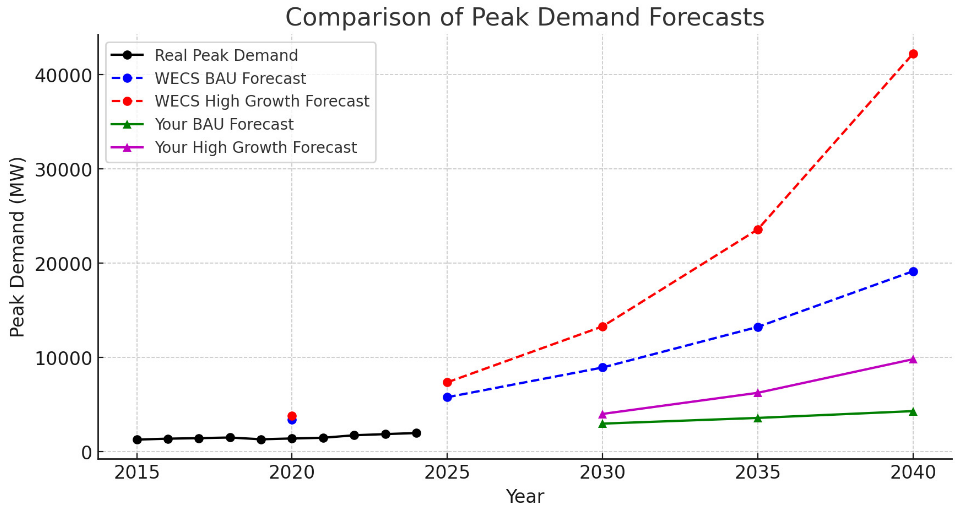


Figure 4.3: Comparison of Peak Demand Forecasts

- By 2025, WECS forecasts demand at 5787 MW (BAU) and 7366 MW (High Growth). Our OLS model suggests 2150 MW, aligning better with real trends.
- For 2040, WECS forecasts 19151 MW (BAU), while our model estimates 4055 MW, implying a potential 4x overestimation.

Need for Real-Time Forecasting: Our research integrates GDP per capita, population growth, and real economic trends to provide a more realistic forecasting model.

4.4 Why Scenario-Based Forecasting is Important

- If Nepal follows gradual development, the BAU scenario gives a conservative but accurate projection.
- If economic growth accelerates, the High Growth scenario provides a roadmap for additional infrastructure planning.
- If government policies (electric vehicle adoption, industrialization) change, the Medium Growth scenario captures potential demand shifts.

4.4.1 Future Work

Further improvements can be made by:

- Applying machine learning models for more accurate trend detection.

- Incorporating electric vehicle penetration, industrial expansion, and policy changes in the forecasting model.

- Developing a real-time forecasting dashboard for policymakers to monitor demand growth.

Our OLS-based forecasting model, incorporating GDP per capita and population trends, provides a realistic and adaptable method for peak demand estimation. Compared to the WECS model, which significantly overestimates demand, our research presents a more precise and data-driven approach to energy planning. Policymakers should adopt flexible, real-time data integration to ensure energy security without economic inefficiencies.

4.5 Peak Forecast with Policy Intervention

The load forecasting model incorporating electric vehicle (EV) adoption, electric cooking and electric boiler as policy intervention for demand has provided projections for the peak electricity demand (in MW) under three growth scenarios: Business As Usual (BAU), Medium, and High. The projections are presented for the years 2030, 2035, 2040, and 2050.

Year	BAU	Medium	High
2030	4,168	4,760	5,189
2035	8,242	9,442	10,909
2040	12,426	14,623	17,609
2050	25,616	30,667	41,739

4.5.1 Discussion

The projections indicate a significant increase in peak electricity demand over the coming decades across all three growth scenarios.

In the **Business As Usual (BAU)** scenario, the peak demand is expected to rise from 4,168 MW in 2030 to 25,616 MW by 2050. This reflects the gradual adoption of electric vehicles, electric cooking, and electric boilers under existing policy trends and limited additional interventions.

The **Medium** growth scenario shows a more substantial increase, with peak demand growing from 4,760 MW in 2030 to 30,667 MW by 2050. This scenario assumes stronger policy support and infrastructure development, leading to higher penetration of electric mobility and electric cooking technologies.

The **High** growth scenario projects the steepest rise in demand, from 5,189 MW in 2030 to a peak of 41,739 MW by 2050. This scenario reflects aggressive adoption of electrification technologies enabled by robust policy interventions, widespread behavioral change, and rapid technological advancement.

These projections underscore the transformative impact of electric vehicles, electric cooking, and electric boilers on electricity demand. The substantial rise in demand across all scenarios highlights the need for proactive planning in generation capacity, grid infrastructure, and energy resource management to ensure energy security and sustainability in the long term.

4.6 Annual Load Curve Forecast and Growth Scenarios

4.6.1 Historical Peak Demand Trends

To understand future demand patterns, the sorted peak load distributions for 2023 and 2024 were analyzed. The left panel of Figure 4.4 presents the sorted daily peak demand for 2023, while the right panel shows the corresponding 2024 daily peak demand profile.

4.6.2 Future Growth Scenarios and Peak Load Projections

The future peak load demand was projected under four distinct growth scenarios:

- Business-As-Usual (BAU) Growth: Assumes a continuation of historical trends.
- Medium Growth: Reflects moderate economic expansion and infrastructure development.
- High Growth: Represents rapid urbanization, industrialization, and increasing electricity usage.
- Growth Target Scenario: Derived from per capita electricity consumption targets, aligning with economic benchmarks such as Vietnam-level (2035), Upper-Middle-Income (2040), and High-Income (2050).

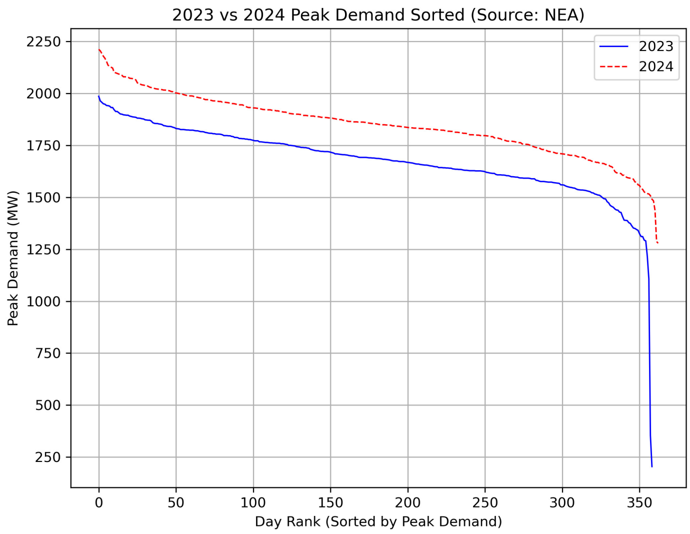


Figure 4.4: Historical Peak Demand Distribution for 2023 and 2024 (Source: NEA)

Figure 4.5 visualizes how each of these scenarios influences annual peak demand.

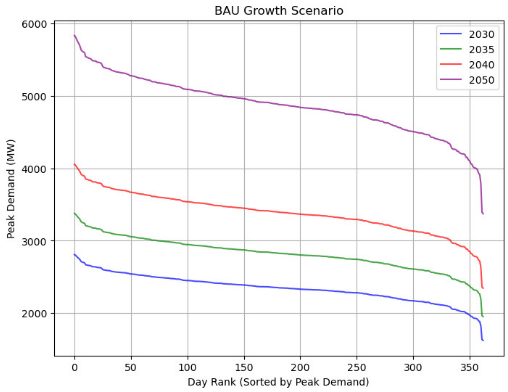
The projected peak demand for each future year is estimated using a scaling factor based on the observed peak demand in 2024. This allows for a direct comparison of the anticipated electricity demand under different growth scenarios. Figure 4.5 provides a detailed visualization of how electricity demand evolves from historical observations (2023, 2024) to future projections (2030, 2035, 2040, and 2050).

4.6.3 Annual Load Curve Forecast under Policy Intervention Scenario

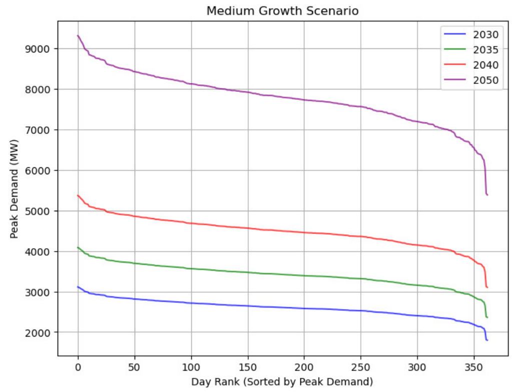
The projected peak demand under the policy intervention scenario is based on updated planning assumptions that include policy intervention for incentevizing e-cooking and e-mobility. Scaling factors derived from 2024 observations are used to forecast demand across multiple future years. Figure 4.6 illustrates the expected demand progression for BAU, Medium, and High growth conditions under this revised policy framework.

4.7 Reliability Under Different Scenarios

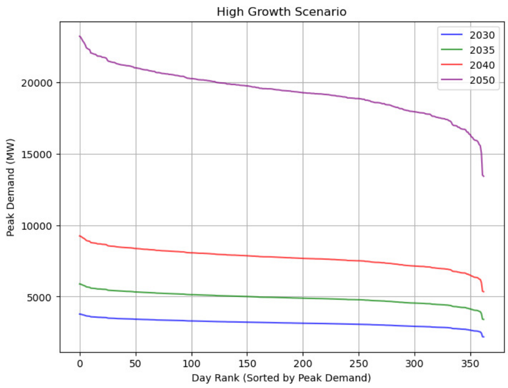
The comparison table for dry-season generation capacity is provided for both 25% and 40%, while the graph for 40% is shown exclusively in this section.



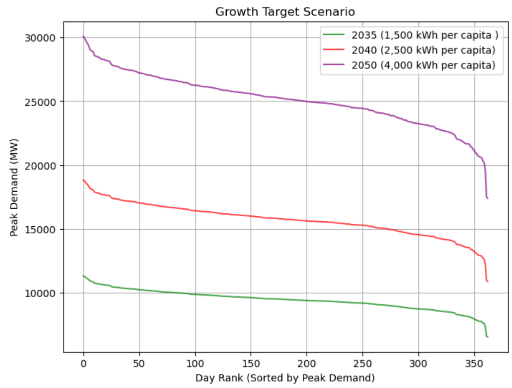
(a) BAU Growth Scenario



(b) Medium Growth Scenario



(c) High Growth Scenario

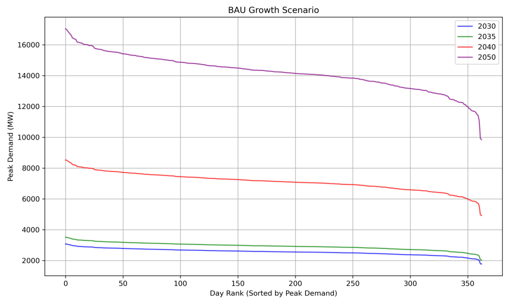


(d) Growth Target Scenario

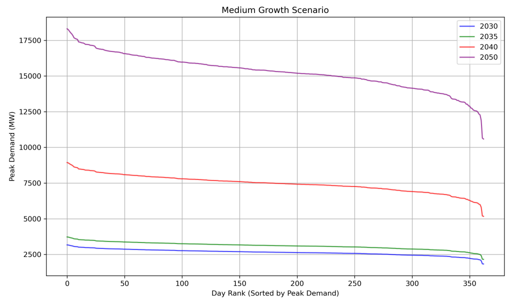
Figure 4.5: Comparison of Growth Scenarios

4.7.1 Capacity vs Peak Demand and EENS in 2030

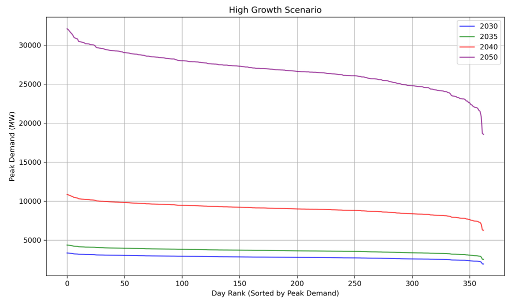
Under the BAU and Medium Growth scenarios, the available capacity generally meets the demand, with only minor shortages observed during the dry season when hydro capacity is reduced to 25%. The low Expected Energy Not Supplied (EENS) values—such as 64 MWh/year for BAU at 25% hydro capacity—indicate high system reliability, reflected by Energy Index of Reliability (EIR) values exceeding 0.92. In contrast, the High Growth scenario reveals significant seasonal shortages. EENS rises sharply to 33,143 MWh/year at 40% capacity and 160,330 MWh/year at 25% capacity. Correspondingly, the Loss of Load Expectation (LOLE) peaks between 109 and 121 days per year, underscoring the system's vulnerability during the dry season as shown in Figure 4.7.



(a) BAU Growth Scenario

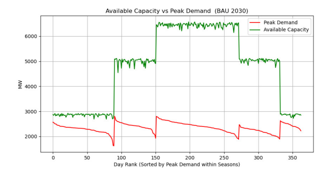


(b) Medium Growth Scenario

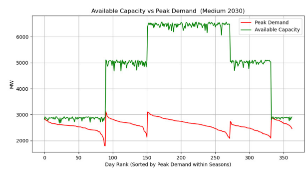


(c) High Growth Scenario

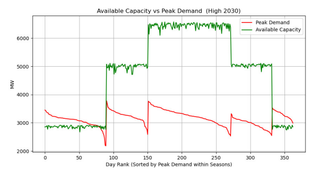
Figure 4.6: Comparison of Growth Scenarios under Policy Intervention



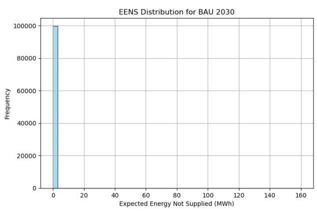
(a) BAU: Capacity vs Demand



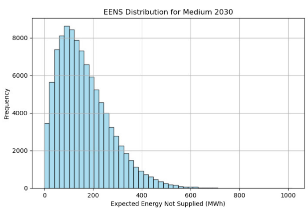
(b) Medium: Capacity vs Demand



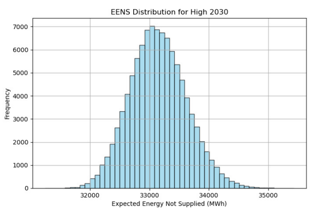
(c) High: Capacity vs Demand



(d) BAU: EENS Distribution



(e) Medium: EENS Distribution

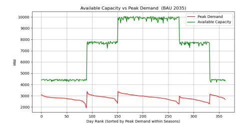


(f) High: EENS Distribution

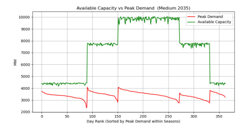
Figure 4.7: Comparison of Capacity vs Peak Demand and EENS Distribution for 2030 under different scenarios

4.7.2 Capacity vs Peak Demand and EENS in 2035

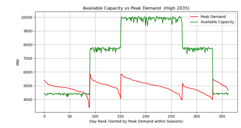
The available capacity and peak demand projections for 2035 under different growth scenarios are compared in Figure 4.8. Under the BAU and Medium Growthscenarios, system capacity is sufficient throughout the year when hydro generation is maintained at 40%. However, during the dry season, shortages begin to emerge when hydro capacity is reduced to 25%, with Expected Energy Not Supplied (EENS) ranging from 12,035 to 76,339 MWh/year. In the High Growth scenario, the system faces severe dry-season deficits, with EENS reaching 255,164 MWh/year and Loss of Load Expectation (LOLE) peaking at 121 days per year. This stands in stark contrast to the wet season, where there is often excess generation capacity.



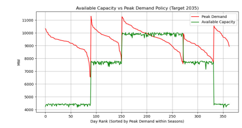
(a) BAU: Capacity vs Demand



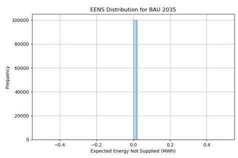
(b) Medium: Capacity vs Demand



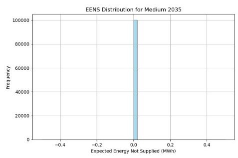
(c) High: Capacity vs Demand



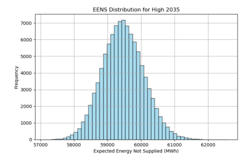
(d) Target: Capacity vs Demand



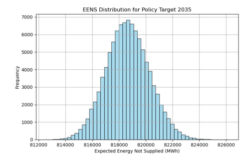
(e) BAU: EENS Distribution



(f) Medium: EENS Distribution



(g) High: EENS Distribution

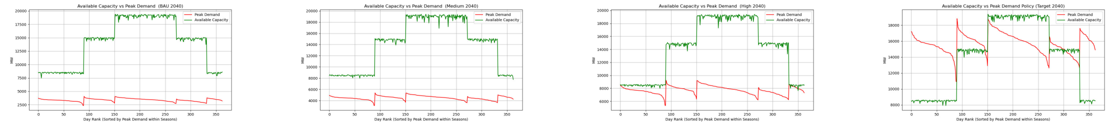


(h) Target: EENS Distribution

Figure 4.8: Comparison of Capacity vs Peak Demand and EENS Distribution for 2035 under Different Scenarios

4.7.3 Capacity vs Peak Demand and EENS in 2040

The available capacity and peak demand projections for 2040 under different growth scenarios are illustrated in Figure 4.9.Under the BAU and Medium Growth scenarios, there is no Expected Energy Not Supplied (EENS) at 40% hydro capacity, while only negligible shortages occur at 25% capacity—for instance, Medium Growth sees an EENS of just 8.7 MWh/year. In contrast, the High Growth scenario experiences significant dry-season shortages, with EENS reaching 282,915 MWh/year and Loss of Load Expectation (LOLE) rising to 120.7 days per year, indicating considerable stress on system limits.

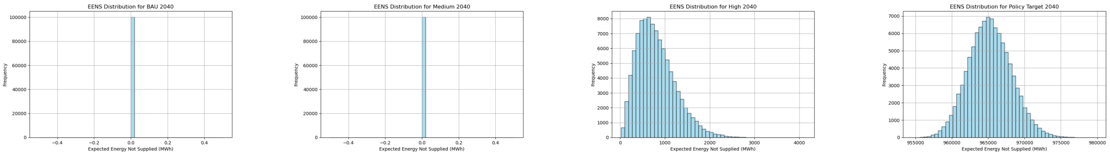


(a) BAU: Capacity vs Demand

(b) Medium: Capacity vs Demand

(c) High: Capacity vs Demand

(d) Target: Capacity vs Demand



(e) BAU: EENS Distribution

(f) Medium: EENS Distribution

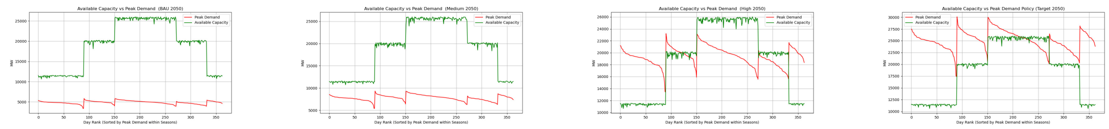
(g) High: EENS Distribution

(h) Target: EENS Distribution

Figure 4.9: Comparison of Capacity vs Peak Demand and EENS Distribution for 2040 under Different Scenarios

4.7.4 Capacity vs Peak Demand and EENS in 2050

The available capacity and peak demand projections for 2050 under different growth scenarios are illustrated in Figure 4.10. Under the BAU and Medium Growth scenarios, system capacity is adequate at 40%, with zero Expected Energy Not Supplied (EENS). However, Medium Growth shows minor dry-season risk at 25% hydro capacity, with EENS reaching 77,292 MWh/year. In the High Growth scenario, the system faces critical deficits, with EENS reaching 1.49 million MWh/year and Loss of Load Expectation (LOLE) rising to 157.6 days per year, highlighting the need for significant infrastructure expansion.

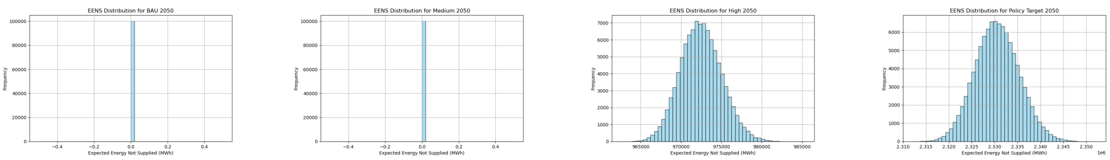


(a) BAU: Capacity vs Demand

(b) Medium: Capacity vs Demand

(c) High: Capacity vs Demand

(d) Target: Capacity vs Demand



(e) BAU: EENS Distribution

(f) Medium: EENS Distribution

(g) High: EENS Distribution

(h) Target: EENS Distribution

Figure 4.10: Comparison of Capacity vs Peak Demand and EENS Distribution for 2050 under Different Scenarios

The table 4.7 presents the summary of LOLE, LOEE & EIR for all years and scenarios for generation of 40% during dry season and table 4.8 presents for 25% generation during dry season.

Table 4.7: Monte Carlo Simulation Results for Different Scenarios and Years with 40% Generation During Dry Season

Year	Scenario	LOLE (days/year)	SE_LOLE	EENS (MWh/year)	SE_EENS	EIR	SE_EIR
2030	BAU	0.00	0.000	0	0.007	1.0000	8.35×10^{-9}
2030	Medium	3.54	0.005	164	0.342	0.9998	3.63×10^{-7}
2030	High	109.88	0.003	33,144	1.511	0.9710	1.32×10^{-6}
2035	BAU	0.00	0.000	0	0.000	1.0000	0
2035	Medium	0.00	0.000	0	0.000	1.0000	0
2035	High	112.26	0.003	59,460	1.958	0.9667	1.10×10^{-6}
2035	Target	293.90	0.007	818,646	5.115	0.7611	1.49×10^{-6}
2040	BAU	0.00	0.000	0	0.000	1.0000	0
2040	Medium	0.00	0.000	0	0.000	1.0000	0
2040	High	5.12	0.005	807	1.365	0.9997	4.87×10^{-7}
2040	Target	209.21	0.006	965,240	9.355	0.8308	1.64×10^{-6}
2050	BAU	0.00	0.000	0	0.000	1.0000	0
2050	Medium	0.00	0.000	0	0.000	1.0000	0
2050	High	157.56	0.007	972,456	8.109	0.8618	1.15×10^{-6}
2050	Target	311.89	0.007	2,330,542	15.320	0.7445	1.68×10^{-6}

Table 4.8: Monte Carlo Simulation Results for Different Scenarios and Years with 25% Generation During Dry Season

Year	Scenario	LOLE (days/year)	SE_LOLE	EENS (MWh/year)	SE_EENS	EIR	SE_EIR
2030	BAU	118.98	0.000	64,021	0.976	0.9248	1.15×10^{-6}
2030	Medium	120.29	0.002	93,905	0.983	0.9004	1.04×10^{-6}
2030	High	121.00	0.000	160,330	0.985	0.8599	8.60×10^{-7}
2035	BAU	80.19	0.006	12,035	1.047	0.9882	1.02×10^{-6}
2035	Medium	117.94	0.001	76,339	1.255	0.9383	1.01×10^{-6}
2035	High	121.00	0.000	255,164	1.267	0.8570	7.10×10^{-7}
2035	Target	293.92	0.007	1,017,991	4.872	0.7030	1.42×10^{-6}
2040	BAU	0.00	0.000	0	0.000	1.0000	0
2040	Medium	0.11	0.001	9	0.110	1.0000	6.76×10^{-8}
2040	High	120.69	0.002	282,915	3.207	0.8990	1.14×10^{-6}
2040	Target	209.21	0.006	1,348,979	8.479	0.7635	1.49×10^{-6}
2050	BAU	0.00	0.000	0	0.000	1.0000	0
2050	Medium	108.45	0.004	77,292	3.422	0.9726	1.21×10^{-6}
2050	High	157.56	0.007	1,488,309	6.780	0.7884	9.64×10^{-7}
2050	Target	311.88	0.007	2,846,387	14.643	0.6879	1.61×10^{-6}

4.8 Discussion of Monte Carlo Simulation Results

The Monte Carlo simulation results in Tables 4.7 and 4.8 reveal the impact of generation availability during the dry season (40% and 25%) on system reliability indicators such as LOLE , EENS , and EIR . Results vary significantly across scenarios (BAU, Medium, High, Target) and planning years (2030, 2035, 2040, 2050).

4.8.1 BAU (Business-As-Usual) Scenario

2030: With 40% dry season generation, the system shows excellent reliability (LOLE = 0.00 days/year), whereas at 25% generation, LOLE increases significantly to 118.98 days/year, EENS reaches 64,021 MWh/year, and EIR drops to 0.9248.
2035, 2040, and 2050: Under both 40% and 25% generation assumptions, LOLE is 0.00 days/year, EENS is 0, and EIR is 1.0000, indicating perfect reliability. This suggests that the BAU scenario can maintain high reliability from 2035 onwards even under reduced generation availability.

4.8.2 Medium Growth Scenario

2030: LOLE is 3.54 days/year at 40% generation, and increases to 120.29 days/year under 25% generation. EENS increases from 164 MWh/year to 93,905 MWh/year, and EIR drops from 0.9998 to 0.9004.
2035: No load loss under 40% generation (LOLE = 0.00), but under 25% generation, LOLE rises to 117.94 days/year, EENS is 76,339 MWh/year, and EIR drops to 0.9383.
2040: Both generation assumptions maintain perfect reliability, with negligible LOLE and EENS, and EIR = 1.0000.
2050: While 40% generation maintains zero LOLE and EENS, the 25% generation assumption results in LOLE of 108.45 days/year, EENS of 77,292 MWh/year, and a drop in EIR to 0.9726. This highlights potential long-term reliability risks without capacity expansion.

4.8.3 High Growth Scenario

2030: LOLE is already high at 109.88 days/year (40%) and worsens to 121.00 days/year (25%). EENS increases from 33,144 to 160,330 MWh/year and EIR drops from 0.9710 to 0.8599.
2035: LOLE increases from 112.26 (40%) to 121.00 days/year (25%), with EENS increasing from 59,460 to 255,164 MWh/year, and EIR falling from 0.9667 to 0.8570.
2040: Reliability improves with 40% generation (LOLE = 5.12 days/year, EENS = 807 MWh/year, EIR = 0.9997), but degrades under 25% (LOLE = 120.69, EENS = 282,915 MWh/year, EIR = 0.8990).
2050: LOLE remains at 157.56 days/year in both cases, but EENS nearly doubles

from 972,456 (40%) to 1,488,309 MWh/year (25%), and EIR drops from 0.8618 to 0.7884.

4.8.4 Target Growth Scenario

2035: LOLE is 293.90 days/year at 40%, increasing slightly to 293.92 at 25%. EENS increases from 818,646 to 1,017,991 MWh/year, and EIR drops from 0.7611 to 0.7030.
2040: LOLE is 209.21 days/year in both cases, but EENS increases from 965,240 (40%) to 1,348,979 MWh/year (25%), and EIR declines from 0.8308 to 0.7635.
2050: LOLE remains high at 311.89 days/year (40%) and 311.88 (25%). EENS increases from 2.33 million to 2.85 million MWh/year, and EIR decreases from 0.7445 to 0.6879, highlighting severe reliability issues under this scenario.

4.8.5 Key Takeaways

- **BAU Scenario:** Reliability remains excellent in all years under 40% dry season generation. Under 25%, significant reliability issues are seen only in 2030, which are resolved from 2035 onwards, indicating the system's resilience under BAU conditions with time.

- **Medium Growth Scenario:** High reliability is maintained with 40% generation, but under 25%, LOLE and EENS rise significantly from 2030 to 2050, particularly in 2050. This indicates the need for moderate capacity expansion to ensure reliability if dry season output drops.

- **High Growth Scenario:** System reliability declines substantially over time, especially under 25% generation. By 2050, EENS reaches nearly 1.5 million MWh/year and EIR drops below 0.80, calling for urgent generation capacity expansion and diversification.

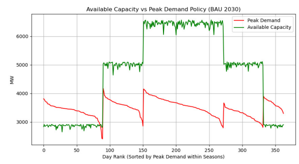
- **Target Growth Scenario:** The most critical scenario. Even at 40% generation, the system shows extreme unreliability by 2035. At 25%, reliability metrics worsen further, with LOLE nearing 312 days/year and EENS approaching 2.85 million MWh/year by 2050. This suggests a near-collapse scenario requiring immediate and massive investments in new generation, storage, and grid infrastructure.

- **Impact of Generation Availability:** Across all scenarios and years, reducing generation availability during the dry season from 40% to 25% significantly worsens reliability metrics. This highlights the importance of ensuring firm capacity during the dry season through storage, diversification, or demand-side management.

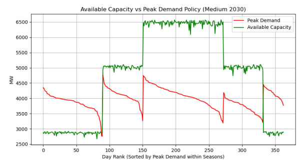
4.9 Reliability Under Policy Intervention Scenario

4.9.1 Capacity vs Peak Demand and EENS in 2030 under the Policy Intervention Scenario

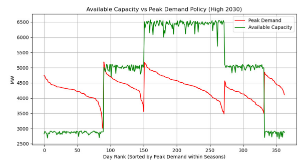
The available capacity and peak demand projections, along with the Expected Energy Not Supplied (EENS) distributions from 2030 to 2050 under the Policy Intervention Scenario, are shown from Figure 4.11 to Figure 4.14. These plots illustrate the adequacy of the system across BAU, Medium, and High growth scenarios.



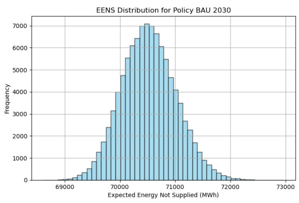
(a) BAU: Capacity vs Demand



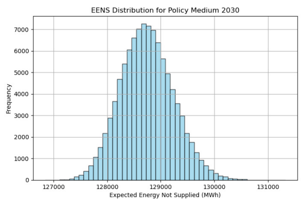
(b) Medium: Capacity vs Demand



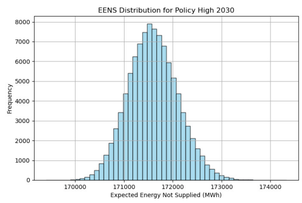
(c) High: Capacity vs Demand



(d) BAU: EENS Distribution



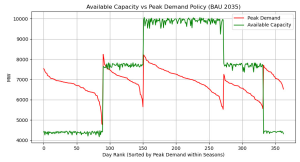
(e) Medium: EENS Distribution



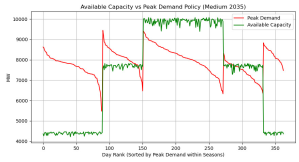
(f) High: EENS Distribution

Figure 4.11: Comparison of Capacity vs Peak Demand and EENS for 2030 under the Policy Intervention Scenario

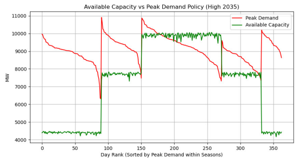
4.9.2 Capacity vs Peak Demand and EENS in 2035 under the Policy Intervention Scenario



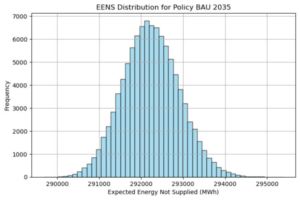
(a) BAU: Capacity vs Demand



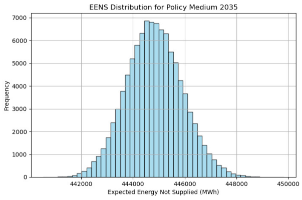
(b) Medium: Capacity vs Demand



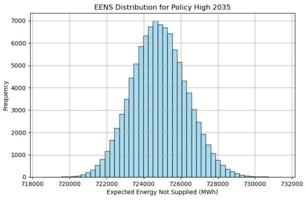
(c) High: Capacity vs Demand



(d) BAU: EENS Distribution



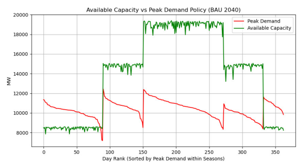
(e) Medium: EENS Distribution



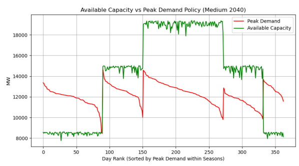
(f) High: EENS Distribution

Figure 4.12: Comparison of Capacity vs Peak Demand and EENS for 2035 under the Policy Intervention Scenario

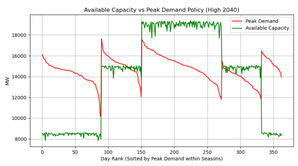
4.9.3 Capacity vs Peak Demand and EENS in 2040 under the Policy Intervention Scenario



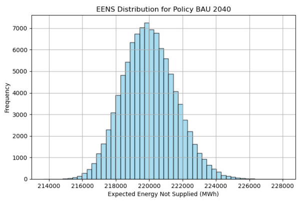
(a) BAU: Capacity vs Demand



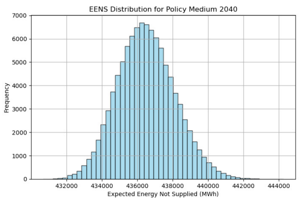
(b) Medium: Capacity vs Demand



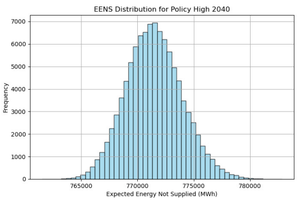
(c) High: Capacity vs Demand



(d) BAU: EENS Distribution



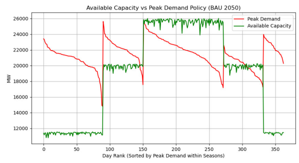
(e) Medium: EENS Distribution



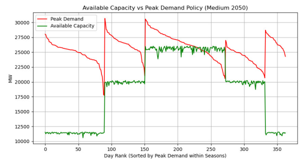
(f) High: EENS Distribution

Figure 4.13: Comparison of Capacity vs Peak Demand and EENS for 2040 under the Policy Intervention Scenario

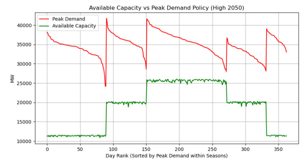
4.9.4 Capacity vs Peak Demand and EENS in 2050 under the Policy Intervention Scenario



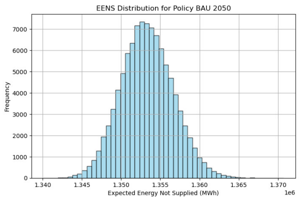
(a) BAU: Capacity vs Demand



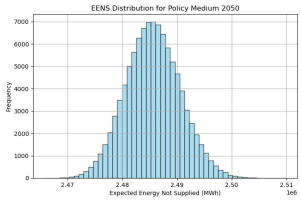
(b) Medium: Capacity vs Demand



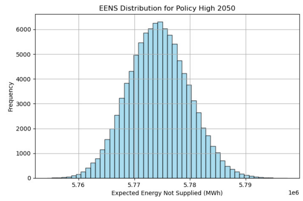
(c) High: Capacity vs Demand



(d) BAU: EENS Distribution



(e) Medium: EENS Distribution



(f) High: EENS Distribution

Figure 4.14: Comparison of Capacity vs Peak Demand and EENS for 2050 under the Policy Intervention Scenario

Incorporating e-cooking, e-transport and industrial boiler into the system during the Policy Intervention Scenarios (2030–2050) exacerbates dry-season gaps. By 2030, Expected Energy Not Supplied (EENS) spikes to 301,571 MWh/year under High Growth with 25% hydro capacity. By 2050, High Growth faces 363 days per year of Loss of Load Expectation (LOLE) and 6.29 million MWh/year of EENS, underscoring the need for diversified generation sources. In the Target Scenarios (2035–2050), the per-capita consumption targets (ranging from 1,500 to 4,000 kWh) put further strain on the

The Monte Carlo simulation results for the Policy Intervention scenario, based on LOLE, EENS, and EIR across different growth scenarios and years, are summarized in Table 4.9 and 4.10. These values represent the reliability and system adequacy under the proposed policy intervention measures.

Table 4.9: Monte Carlo Simulation Results for Different Scenarios and Years under Policy Intervention with 40% Generation During Dry Season

Year	Scenario	LOLE (days/year)	SE_LOLE	EENS (MWh/year)	SE_EENS	EIR	SE_EIR
2030	BAU	117.01	0.00188	70,523	1.56	0.9442	1.23×10^{-6}
2030	Medium	119.10	0.00096	128,741	1.57	0.9108	1.09×10^{-6}
2030	High	122.93	0.00219	171,597	1.62	0.8909	1.03×10^{-6}
2035	BAU	125.10	0.00353	292,234	2.14	0.8830	8.57×10^{-7}
2035	Medium	191.74	0.00674	444,824	3.42	0.8446	1.20×10^{-6}
2035	High	268.87	0.00700	724,833	4.71	0.7808	1.42×10^{-6}
2040	BAU	117.43	0.00164	220,000	5.06	0.9416	1.34×10^{-6}
2040	Medium	120.11	0.00261	436,508	5.16	0.9015	1.16×10^{-6}
2040	High	168.26	0.00734	771,467	7.91	0.8555	1.48×10^{-6}
2050	BAU	213.30	0.00526	1,353,316	10.55	0.8257	1.36×10^{-6}
2050	Medium	323.61	0.00560	2,485,598	15.79	0.7326	1.70×10^{-6}
2050	High	363.00	0.00000	5,774,344	17.28	0.5436	1.37×10^{-6}

Table 4.10: Monte Carlo Simulation Results for Different Scenarios and Years under Policy Intervention with 25% Generation During Dry Season

Year	Scenario	LOLE (days/year)	SE_LOLE	EENS (MWh/year)	SE_EENS	EIR	SE_EIR
2030	BAU	121.00	0.00000	199,412	0.99	0.8422	7.82×10^{-7}
2030	Medium	121.02	0.00048	258,505	0.99	0.8208	6.83×10^{-7}
2030	High	122.93	0.00218	301,572	1.05	0.8083	6.69×10^{-7}
2035	BAU	125.10	0.00353	491,568	1.45	0.8032	5.80×10^{-7}
2035	Medium	191.75	0.00672	644,153	3.05	0.7749	1.07×10^{-6}
2035	High	268.88	0.00702	924,169	4.41	0.7205	1.33×10^{-6}
2040	BAU	121.00	0.00000	600,791	3.20	0.8405	8.49×10^{-7}
2040	Medium	121.24	0.00144	820,153	3.26	0.8150	7.36×10^{-7}
2040	High	168.24	0.00731	1,155,193	6.81	0.7836	1.28×10^{-6}
2050	BAU	213.29	0.00529	1,869,144	9.56	0.7593	1.23×10^{-6}
2050	Medium	323.61	0.00562	3,001,433	15.11	0.6771	1.63×10^{-6}
2050	High	363.00	0.00000	6,290,193	16.73	0.5028	1.32×10^{-6}

Results Discussion

The simulation results demonstrate clear trends in system reliability under two policy intervention strategies: 25% and 40% generation availability during the dry season.

In **2030**, the 40% generation scenario outperforms the 25% case across all demand growth scenarios. LOLE values are slightly lower in the 40% case (117.01 to 122.93 days/year) compared to the 25% case (121.00 to 122.93 days/year). The EENS under the 40% scenario is significantly reduced—for instance, in the BAU scenario, EENS is 70,523 MWh (40%) versus 199,412 MWh (25%). Correspondingly, the EIR is higher in the 40% case, indicating greater system adequacy.

By **2035**, both policies see increased LOLE and EENS due to rising demand, yet the 40% policy maintains a performance advantage. In the High scenario, EENS is 724,833 MWh in the 40% case versus 924,169 MWh in the 25% case. EIRs decline more steeply in the 25% scenario, dropping to 0.7205 compared to 0.7808 in the 40% case.

In **2040**, the difference in system adequacy becomes more pronounced. While LOLE values under BAU and Medium scenarios remain close (approximately 120–121 days/year) across both policies, the 25% case shows much higher EENS, such as 820,153 MWh for the Medium scenario versus 436,508 MWh under 40%. EIRs continue to reflect this gap, favoring the 40% scenario.

By **2050**, system stress intensifies. Under the Medium scenario, EENS reaches 3,001,433 MWh (25%) compared to 2,485,598 MWh (40%), and EIR drops to 0.6771 versus 0.7326. Under the High scenario, the 25% policy results in the lowest EIR of 0.5028 and the highest EENS of 6,290,193 MWh, indicating severe inadequacy. In contrast, the 40% case moderates these values slightly, with EENS at 5,774,344 MWh and EIR at 0.5436.

These results highlight the differing impacts of policy choices on system reliability metrics across time and demand scenarios.

4.10 Standard Error vs No of Simulations

Monte Carlo simulations were performed with varying numbers of iterations to assess reliability metrics. The variation of the standard error (SE) of LOLE, LOEE, and EIR with increasing simulations is shown in Figures 4.15, 4.16, and 4.17, respectively. As the number of simulations increases, all standard errors decrease sharply, demonstrating stabilization beyond 100,000 simulations. The SE of LOLE decreases from 0.0626 at 1,000 simulations to 0.0051 at 150,000 simulations, the SE of LOEE decreases from over 100 to 20, and the SE of EIR decreases from over 1 to around 0.2. These results justify 100,000 simulations as a reasonable stopping criterion, ensuring reliable and computationally efficient estimations.

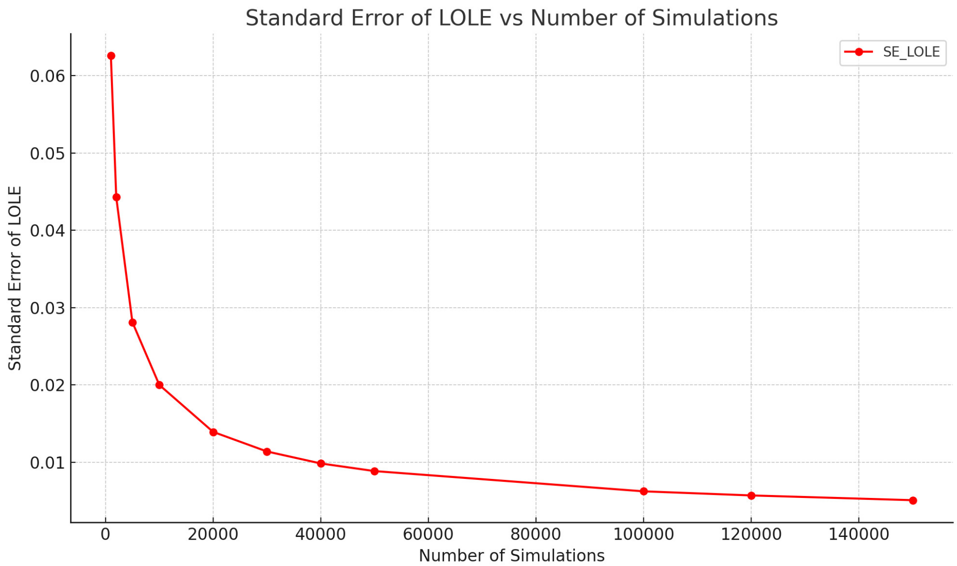


Figure 4.15: Standard Error of LOLE vs Number of Simulations

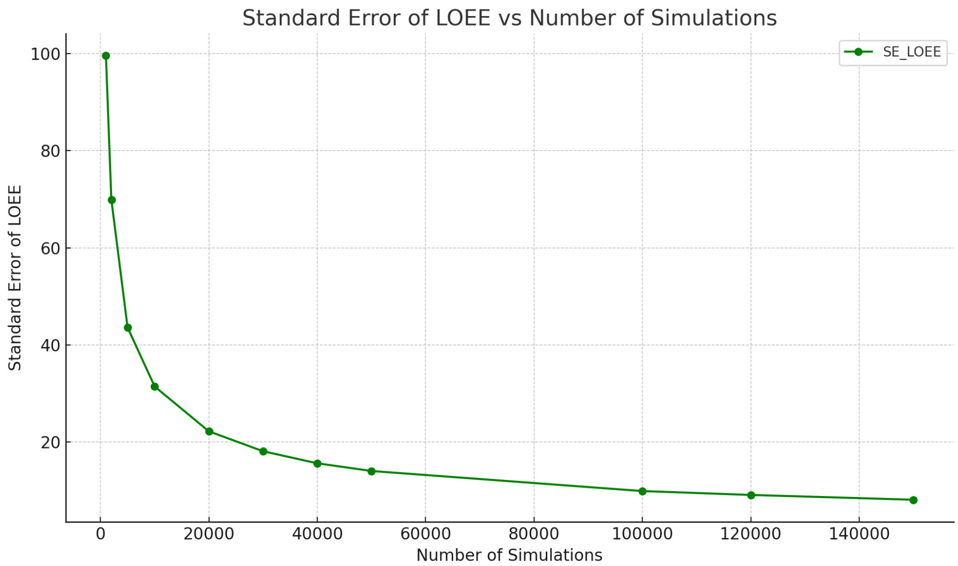


Figure 4.16: Standard Error of LOEE vs Number of Simulations

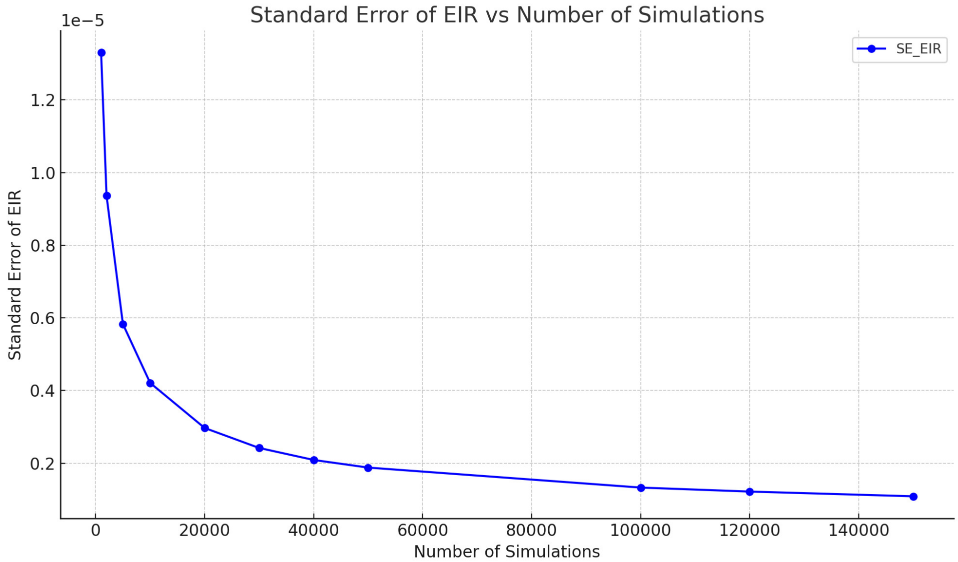


Figure 4.17: Standard Error of EIR vs Number of Simulations

These plots confirm that beyond 100,000 simulations, the standard errors stabilize, ensuring reliable and computationally efficient estimations for the assessment of the power system's reliability.

4.11 Discussion

A sensitivity analysis was conducted to evaluate the impact of implementing policy interventions targeting electrification in e-cooking and e-transport on system reliability under different growth scenarios. The Monte Carlo simulations indicate that these interventions, while beneficial for enhancing electrification, lead to a decrease in system reliability as they increase the overall electricity demand. The results are compared between the scenarios with and without policy intervention in Table 4.11 and 4.12.

Table 4.11: Comparison of Monte Carlo Simulation Results under No Policy Intervention and Policy Intervention Scenarios (40% Generation in Dry Season)

Year	Scenario	Without*			With*		
		LOLE	EENS (MWh)	EIR	LOLE	EENS (MWh)	EIR
2030	BAU	0.00	0	1.0000	117.01	70,523	0.9442
2030	Medium	3.54	164	0.9998	119.10	128,741	0.9108
2030	High	109.88	33,144	0.9710	122.93	171,597	0.8909
2035	BAU	0.00	0	1.0000	125.10	292,234	0.8830
2035	Medium	0.00	0	1.0000	191.74	444,824	0.8446
2035	High	112.26	59,460	0.9667	268.87	724,833	0.7808
2035	Target	293.90	818,646	0.7611	–	–	–
2040	BAU	0.00	0	1.0000	117.43	220,000	0.9416
2040	Medium	0.00	0	1.0000	120.11	436,508	0.9015
2040	High	5.12	807	0.9997	168.26	771,467	0.8555
2040	Target	209.21	965,240	0.8308	–	–	–
2050	BAU	0.00	0	1.0000	213.30	1,353,316	0.8257
2050	Medium	0.00	0	1.0000	323.61	2,485,598	0.7326
2050	High	157.56	972,456	0.8618	363.00	5,774,344	0.5436
2050	Target	311.89	2,330,542	0.7445	–	–	–

Note: With* indicates results under a policy intervention scenario ; Without* corresponds to no policy intervention.

Table 4.12: Comparison of Monte Carlo Simulation Results under No Policy Intervention and Policy Intervention Scenarios (25% Generation in Dry Season)

Year	**Scenario**	**Without***			**With***		
		LOLE	EENS (MWh)	EIR	LOLE	EENS (MWh)	EIR
2030	BAU	118.98	64,021	0.9248	117.01	70,523	0.9442
2030	Medium	120.29	93,905	0.9004	119.10	128,741	0.9108
2030	High	121.00	160,330	0.8599	122.93	171,597	0.8909
2035	BAU	80.19	12,035	0.9882	125.10	292,234	0.8830
2035	Medium	117.94	76,339	0.9383	191.74	444,824	0.8446
2035	High	121.00	255,164	0.8570	268.87	724,833	0.7808
2035	Target	293.92	1,017,991	0.7030	–	–	–
2040	BAU	0.00	0	1.0000	117.43	220,000	0.9416
2040	Medium	0.11	9	1.0000	120.11	436,508	0.9015
2040	High	120.69	282,915	0.8990	168.26	771,467	0.8555
2040	Target	209.21	1,348,979	0.7635	–	–	–
2050	BAU	0.00	0	1.0000	213.30	1,353,316	0.8257
2050	Medium	108.45	77,292	0.9726	323.61	2,485,598	0.7326
2050	High	157.56	1,488,309	0.7884	363.00	5,774,344	0.5436
2050	Target	311.88	2,846,387	0.6879	–	–	–

CHAPTER FIVE: CONCLUSION

5.1 Conclusion

This study has successfully addressed its primary objectives by forecasting Nepal's electricity demand and evaluating generation adequacy under various economic and policy scenarios. The findings align with the research objectives and offer valuable insights for Nepal's energy planning landscape.

The econometric models used for demand forecasting, incorporating GDP per capita and population growth, projected Nepal's electricity demand up to 2050. The forecasts indicated significant variations across different scenarios. Under the BAU scenario, demand is projected to grow gradually, reaching 5,834 MW by 2050. In contrast, the High Growth scenario anticipates a rapid surge in demand, exceeding 23,205 MW by 2050. The Target-Based scenario, which aligns with per capita consumption benchmarks under the assumption that Nepal achieves high-income status, projects a demand of 30,088 MW by 2050. The high correlation coefficients obtained from the regression models ($R^2 = 0.986$ for GDP-population regression and 0.9415 for per capita consumption) validate the robustness of these forecasting models.

System reliability was assessed using Monte Carlo simulations, which analyzed key reliability indices such as LOLE, EENS, and EIR. Under the BAU scenario, the results indicated high system reliability with LOLE approximately equal to 0 days per year and an EIR close to 1.0, largely due to moderate demand growth. However, the High Growth scenario revealed increasing reliability risks, with LOLE reaching 157.56 days per year and EIR declining to 0.8618 by 2050. The Target-Based scenario showed severe inadequacy, with LOLE exceeding 300 days per year and EIR falling below 0.75, underscoring the urgent need for capacity expansion. The simulations further demonstrated that reducing dry-season generation availability from 40% to 25% significantly worsens reliability metrics, highlighting the critical role of firm capacity during periods of low hydropower availability.

The study also evaluated the impact of policy interventions such as electric cooking (e-cooking) and electric transport (e-transport) on electricity demand and system reliability. These electrification policies substantially increase peak demand, with projections showing up to 41,739 MW under the High Growth scenario by 2050.

The Monte Carlo simulation results under these policy interventions revealed a significant deterioration in reliability, with LOLE rising to 363 days per year and EIR dropping to 0.5436 by 2050. These findings indicate that while such policies contribute to decarbonization goals, they must be accompanied by strategic investments in generation capacity and grid infrastructure to maintain system adequacy.

Lastly, a comparative analysis with existing forecasts, particularly the WECS (2017) projections, revealed substantial overestimations—up to 140% higher than actual demand in 2020. In contrast, the data-driven and scenario-based methodology adopted in this study provides a more accurate, flexible, and realistic framework for long-term energy planning in Nepal.

5.2 Recommendation

- **Enhance Load Forecasting Models (WECS & Government):** Our study demonstrates that traditional load forecasts often overestimate or underestimate demand due to rigid assumptions. We recommend WECS adopt a scenario-based econometric forecasting approach, integrating GDP per capita, population trends, and sector-wise consumption analysis. Our methodology, validated with real demand data ($R^2 = 0.986$), offers a more accurate and adaptable framework for predicting Nepal's electricity needs. Additionally, real-time data monitoring and periodic forecast updates should be institutionalized to align with economic and electrification trends.

- **Manage Seasonal Energy Imbalance:** Nepal's seasonal hydropower surplus in the wet season and deficit in the dry season must be addressed through:

  - Energy storage solutions such as pumped storage hydropower and battery storage to store excess energy for dry months.

  - Expanding regional power trade agreements to export surplus electricity and secure imports when needed.

  - A diversified generation mix, integrating solar and wind energy to balance dry-season shortages.

- **Ensure Policy & Investment Readiness:** Timely execution of planned projects is critical to maintaining reliability beyond 2035. Nepal must:

- Develop a structured investment roadmap to avoid delays in key projects.

- Encourage PPPs in the development of energy infrastructure.

- Establish strong regulatory frameworks for electricity pricing and cross-border trade policies.

By implementing these measures, Nepal can achieve a sustainable, resilient, and balanced power system, ensuring energy security and economic growth in the coming decades.

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APPENDIX A: LIST OF POWER PLANTS IN INPS

NEA and Its Subsidiary Power Plants in Different Stages

Table A.1: NEA and Its Subsidiary Power Plants in Different Stages

S.No.	Power Plants	Capacity (MW)	Category
1.0	Kaligandaki A	144	Major Hydropower Stations
2.0	Middle Marsyangdi	70	Major Hydropower Stations
3.0	Marsyangdi	69	Major Hydropower Stations
4.0	Kulekhani I	60	Major Hydropower Stations
5.0	Upper Trishuli 3A HEP	60	Major Hydropower Stations
6.0	Kulekhani II	32	Major Hydropower Stations
7.0	Chameliya	30	Major Hydropower Stations
8.0	Trishuli	24	Major Hydropower Stations
9.0	Gandak	15	Major Hydropower Stations
10.0	Devighat	15	Major Hydropower Stations
11.0	Modi Khola	14.8	Major Hydropower Stations
12.0	Kulekhani III HEP	14	Major Hydropower Stations
13.0	Sunkoshi	10.5	Major Hydropower Stations
14.0	Puwa Khola	6.2	Major Hydropower Stations

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S.No.	Power Plants	Capacity (MW)	Category
nan	Sub Total	564.5	Major Hydropower Stations
15.0	Chatara	3.2	Small Hydropower Plants
16.0	Panauti	2.4	Small Hydropower Plants
17.0	Tatopani	2	Small Hydropower Plants
18.0	Seti (Pokhara)	1.5	Small Hydropower Plants
19.0	Tinau	1.024	Small Hydropower Plants
20.0	Fewa	1	Small Hydropower Plants
21.0	Sundarijal	0.97	Small Hydropower Plants
22.0	Pharping	0.5	Small Hydropower Plants
23.0	Gamgad	0.4	Small Hydropower Plants
24.0	Khandbari	0.25	Small Hydropower Plants
25.0	Jomsom	0.24	Small Hydropower Plants
26.0	Phidim	0.24	Small Hydropower Plants
27.0	Baglung	0.2	Small Hydropower Plants
28.0	Surnaiyagad	0.2	Small Hydropower Plants
29.0	Doti	0.2	Small Hydropower Plants

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S.No.	Power Plants	Capacity (MW)	Category
30.0	Ramechhap	0.15	Small Hydropower Plants
31.0	Terhathum	0.1	Small Hydropower Plants
nan	Sub Total	14.574	Small Hydropower Plants
nan	Total	593.648	Total Hydropowers
32.0	Kalikot	0.5	Small Hydropower Plants (Isolated)
33.0	Heldung (Humla)	0.5	Small Hydropower Plants (Isolated)
34.0	Achham	0.4	Small Hydropower Plants (Isolated)
35.0	Jhupra (Surkhet)	0.345	Small Hydropower Plants (Isolated)
36.0	Darchula	0.3	Small Hydropower Plants (Isolated)
37.0	Bhojpur	0.25	Small Hydropower Plants (Isolated)
38.0	Dhankuta	0.24	Small Hydropower Plants (Isolated)
39.0	Jumla	0.2	Small Hydropower Plants (Isolated)
40.0	Syapruadaha (Rukum)	0.2	Small Hydropower Plants (Isolated)
41.0	Bajura	0.2	Small Hydropower Plants (Isolated)
42.0	Bajhang	0.2	Small Hydropower Plants (Isolated)
43.0	Dolpa	0.2	Small Hydropower Plants (Isolated)
44.0	Chaurjahari (Rukum)	0.15	Small Hydropower Plants (Isolated)

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S.No.	Power Plants	Capacity (MW)	Category
45.0	Arughat (Gorkha)	0.15	Small Hydropower Plants (Isolated)
46.0	Taplejung	0.125	Small Hydropower Plants (Isolated)
47.0	Okhaldhunga	0.125	Small Hydropower Plants (Isolated)
48.0	Rupalag (Dadedhura)	0.1	Small Hydropower Plants (Isolated)
nan	Total	4.185	Small Hydropower Plants (Isolated)
49.0	Duhabi Multifuel	39	Thermal Power Plants
50.0	Hetauda Diesel	14.41	Thermal Power Plants
nan	Total	53.41	Thermal Power Plants
nan	nan	583.16	Total Hydro (NEA)
nan	nan	578.624	Total Major Hydro - Grid Connected
nan	nan	4.536	Total Small Hydro - Isolated
nan	nan	492.9	Total Hydro (NEA Subsidiary)
nan	nan	1914.772	Total Hydro (IPPs)
nan	nan	2990.832	Total Hydro (Nepal)
nan	nan	53.41	Total Thermal (NEA)
nan	nan	6	Total Bagasse (IPPs)
nan	nan	106.94	Total Solar (Nepal)
nan	nan	25	Total Solar (NEA)
nan	nan	81.94	Total Solar (IPPs)
nan	nan	3152.646	Total Installed Capacity - Grid Connected
nan	nan	3157.182	Total Installed Capacity
nan	Power Plants	Capacity(MW)	Category

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S.No.	Power Plants	Capacity (MW)	Category
51.0	Tanahu	140	Under Construction Capacity (KW) - NEA Subsidiary
52.0	Rasuwagadi	111	Under Construction Capacity (KW) - NEA Subsidiary
53.0	Madhya Bhotekoshi	102	Under Construction Capacity (KW) - NEA Subsidiary
54.0	Sanjen	42.5	Under Construction Capacity (KW) - NEA Subsidiary
55.0	Rahuganga	40	Under Construction Capacity (KW) - NEA Subsidiary
56.0	Upper Trishuli 3B	37	Under Construction Capacity (KW) - NEA Subsidiary
57.0	Upper Sanjen	14.8	Under Construction Capacity (KW) - NEA Subsidiary
58.0	Tamakoshi-V	94.8	Under Construction Capacity (KW) - NEA Subsidiary
59.0	Upper Modi 'A'	42	Under Construction Capacity (KW) - NEA Subsidiary
60.0	Upper Modi	18.2	Under Construction Capacity (KW) - NEA Subsidiary
nan	Total	642.3	Under Construction Capacity (KW) - NEA Subsidiary

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S.No.	Power Plants	Capacity (MW)	Category
nan	nan	nan	nan
nan	nan	nan	nan
nan	Power Plants	Capacity(MW)	Category
61.0	Upper Arun	1061	Planned and Proposed Capacity (KW)
62.0	Uttar Ganga Storage	828	Planned and Proposed Capacity (KW)
63.0	Dudhkoshi Storage	635	Planned and Proposed Capacity (KW)
64.0	Chainpur Seti	210	Planned and Proposed Capacity (KW)
65.0	Aadhikhola Storage	180	Planned and Proposed Capacity (KW)
66.0	Begnas Rupa Pump Storage	150	Planned and Proposed Capacity (KW)
nan	Total	3064	Planned and Proposed Capacity (KW)

Table A.2: NEA PPA & Operational Power Plants

S.No.	Project	Capacity (MW)
1	Upper Tamakoshi	456.0
2	Solo Khola (Dudkoshi)	86.0
3	Likhu-1	77.0
4	Middle Tamor	73.0
5	Nilgiri Khola-2 Cascade	71.0
6	Khimti Khola	60.0
7	Super Dordi 'Kha'	54.0
8	Likhu-2	52.465
9	Likhu-IV	52.4
10	Upper Marsyangdi"A"	50.0
11	Upper Bhotekoshi Khola	45.0
12	Super Madi	44.0

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S.No.	Project	Capacity (MW)
13	Mistri Khola	42.0
14	Upper Chameliya	40.0
15	Upper Kalangagad	38.46
16	Upper Balephi A	36.0
17	Nyadi	30.0
18	Likhu Khola A	29.04
19	Lower Likhu	28.1
20	Dordi Khola	27.0
21	UpperMadi	25.0
22	Kabeli B-1	25.0
23	Singati Khola	25.0
24	Upper Dordi A	25.0
25	Solu Khola	23.5
26	Upper Chaku A	22.2
27	Chilime	22.1
28	Tallo Hewa Khola	22.1
29	Mai Khola	22.0
30	Bagmati Khola Small	22.0
31	Lower Modi	20.0
32	Upper Solu	19.8
33	Middle Modi	18.0
34	Kalangagad	15.33
35	Hewa KholaA	14.9
36	Maya Khola	14.9
37	Upper Sanjen	14.8
38	Upper Mailun	14.3
39	Ghar Khola	14.0
40	ThapaKhola	13.6
41	Madkyu Khola	13.0
42	Jhimruk Khola	12.0
43	Upper Khimti	12.0
44	Dordi-1 Khola	12.0
45	Namarjun Madi	11.88
46	Lower Khare	11.0

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S.No.	Project	Capacity (MW)
47	Upper Sanigad	10.7
48	Down Piluwa	10.3
49	Lower Modi 1	10.0
50	Makarigad	10.0
51	Mithila Solar PV Electric Project	10.0
52	Solar PV Project (1033), Nainapur, Banke, Block-2	10.0
53	Solar PV Project (1032), Nainapur, Banke, Block-1	10.0
54	Saurya Bidyut Project, Shivasakti	10.0
55	Upper Mai Khola	9.98
56	Kabeli B-1 Cascade	9.94
57	Iwa Khola	9.9
58	Upper Ingwa khola	9.7
59	Sipring Khola	9.658
60	Super Mai 'A'	9.6
61	Mai Beni	9.51
62	Mid Solu Khola	9.5
63	Andhi Khola	9.4
64	Super Chepe	9.05
65	Rudi Khola A	8.8
66	Chepe Khola Small	8.63
67	Naugadh gad Khola	8.5
68	Upper Hewa Khola Srrall	8.5
69	Butwal Solar Project	8.5
70	Ankhu Khola -1	8.4
71	Mai sana Cascade	8.0
72	Upper Naugad Gad	8.0
73	Taksar Pikhuwa	8.0
74	Super Mai	7.8
75	Jogmai	7.6
76	Indrawati - III	7.5
77	Upper Khorunga	7.5
78	Upper Midim	7.5

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S.No.	Project	Capacity (MW)
79	Yambling Khola	7.27
80	Mai Cascade	7.0
81	Molung Khola	7.0
82	Upper Mardi	7.0
83	Upper Khimti II	7.0
84	Upper Suri	7.0
85	Chepe kholaA	7.0
86	Grid Connected Sola r Project, Morang	6.8
87	Rudi Khola B	6.6
88	Sapsup Khola	6.6
89	Suri Khola	6.4
90	Lower Jogmai	6.2
91	DaraudiKholaA	6.0
92	Upper Phawa	5.8
93	UpperMaiC	5.1
94	Tadi Khola (Thaprek)	5.0
95	Mailung Khola	5.0
96	Upper Hugdi Khola	5.0
97	Pikhuwa Khola	5.0
98	Ghalemdi Khola	5.0
99	Ghatte Khola	5.0
100	Rukumgad	5.0
101	Belchautara Solar Project	5.0
102	Grid Connected Solar PV Project (VGF)	5.0
103	Lower Tadi	4.993
104	Richet Khola	4.98
105	Puwa - 2	4.96
106	Siuri Khola	4.95
107	Phawa Khola	4.95
108	Mardi Khola	4.8
109	Padam Khola	4.8
110	Upper Piluwa Khola 2	4.72
111	UpperChirkhwa	4.7

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S.No.	Project	Capacity (MW)
112	Upper Machha KLoIa Small	4.55
113	Mai Khola	4.5
114	Bijayapur 2 Khola Small	4.5
115	Hewa Khola	4.455
116	Bijayapur-1	4.41
117	Radhi Khola	4.4
118	Tungun-Thosne	4.36
119	Baramchi Khola	4.2
120	Khudi Khola	4.0
121	Sabha Khola	4.0
122	PuwaKhoIa-1	4.0
123	SardiKhola	4.0
124	Upper Chhyangdi Khola	4.0
125	Chandranigahpur Solar Project	4.0
126	Som RadhaKrishna Solar Farm Project(VGF)	4.0
127	Super Mai Cascade	3.8
128	DwariKhola	3.75
129	Charanawati Khola	3.52
130	SetiKhola	3.5
131	Kapadi Gad	3.33
132	Gelun	3.2
133	Piluwa Khola Small	3.0
134	Chaku Khola	3.0
135	Bhairab Kunda	3.0
136	Upper Puwa -1	3.0
137	Midim Karapu	3.0
138	Upper Rawa	3.0
139	Dhalkebar Solar Project	3.0
140	Indushankar Chini Udhyog Ltd.	3.0
141	Everest Sugar and Chemical Industries Ltd.	3.0
142	Chake Khola	2.83
143	Sunkoshi Small	2.5

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S.No.	Project	Capacity (MW)
144	Daram KholaA	2.5
145	Ridi Khola	2.4
146	Upper Syange Khola	2.4
147	Jiri Khola Small	2.2
148	Chhandi	2.0
149	Jhyadi Khola	2.0
150	KhaniKhola	2.0
151	Grid Connected Solar Project, Nawal-parasi	2.0
152	Middle Chaku	1.8
153	Lower Chaku Khola	1.8
154	Thoppal Khola	1.65
155	Theule Khola	1.5
156	Dhalkebar Solar Project	1.0
157	Simara Solar Project	1.0
158	Saiti Khola	0.999
159	Suspa Bukhari	0.998
160	Lower Chhote Khola	0.997
161	Hadi Khola Sunkoshi A	0.997
162	Pati Khola Small	0.996
163	MiyaKhola	0.996
164	Jeuligad	0.996
165	Pheme Khola	0.995
166	Chhote Khola	0.993
167	Upper Hadi Khola	0.991
168	Lower Piluwa Small	0.99
169	Seti-II	0.979
170	Ghatte Khola Small	0.97
171	Bishnu Priya Sola Farm Project	0.96
172	Sisne Khola Small	0.75
173	Solar	0.6804
174	Dhunge-Jiri	0.6
175	Belkhu	0.518
176	Rairang Khola	0.5

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S.No.	Project	Capacity (MW)
177	Sali Nadi	0.25
178	Syange Khola	0.183
179	Midim Khola	0.1
180	Sobuwa KhoIa-2 MHP	0.09
181	Leguwa Khola	0.04
182	SyauriBhumey	0.023

List of Power Plants with Approved Construction Licenses

Table A.3: List of Power Plants with Approved Construction Licenses

S.No.	Project	Capacity (MW)	Type
1	Arun 3	900.0	Hydro
2	Tila-1 Hydropower Project	440.0	Hydro
3	Tila-2 Hydropower Project	420.0	Hydro
4	Budhi Gandaki HEP	341.0	Hydro
5	Upper Tamor	285.0	Hydro
6	Budhi Gandaki Kha	260.0	Hydro
7	Upper Trishuli-1	216.0	Hydro
8	Bajhang Upper Seti HEP	216.0	Hydro
9	Chainpur Seti HEP	210.0	Hydro
10	Super Tamor HEP	166.0	Hydro
11	Kaligandki Gorge	164.0	Hydro
12	Lapche Khola	160.0	Hydro
13	Tanahu HEP	140.0	Hydro
14	Lower Manang Marsyangdi	139.2	Hydro
15	Upper Marsyangdi 1	138.0	Hydro
16	Manang Marsyangdi	135.0	Hydro
17	Budhi Gandaki Ka	130.0	Hydro
18	Tamor Mewa	128.0	Hydro
19	Rasuwa Bhotekoshi	120.0	Hydro
20	Jagdulla HEP	106.0	Hydro
21	Madhya Bhotekoshi	102.0	Hydro

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S.No.	Project	Capacity (MW)	Type
22	Upper Trishui-2 HPP	102.0	Hydro
23	Super Trishuli	100.0	Hydro
24	Tamakoshi V	99.8	Hydro
25	Isuwa Khola Hydropower Project	97.2	Hydro
26	Landruk Modi HEP	86.59	Hydro
27	Chameliya (Chhetigad)	85.0	Hydro
28	Lower Solu Hydropower Project	82.0	Hydro
29	Budhi Gandaki Prok Khola HEP	81.0	Hydro
30	Sanjen Khola	78.0	Hydro
31	Ghunsa Khola HEP	77.5	Hydro
32	Middle Mewa HPP	73.5	Hydro
33	Simbuwa Khola HEP	70.3	Hydro
34	Dudhkoshi-2 (Jaleswar) HPP	70.0	Hydro
35	Dudh khola HEP	65.0	Hydro
36	Bhotekoshi 5 HEP	62.0	Hydro
37	Tiplyang Kaligandaki HEP	58.0	Hydro
38	Nupche Likhu HEP	57.5	Hydro
39	Myagdi Khola Hydropower Project	57.3	Hydro
40	Himchuli Dordi HEP	57.0	Hydro
41	Jum Khola HEP	56.0	Hydro
42	Lower Apsuwa HEP	54.0	Hydro
43	Middle Kaligandaki	53.539	Hydro
44	Upper Myagdi-I HEP	53.5	Hydro
45	Upper Lapche Khola	52.0	Hydro
46	Mewa Khola Hydropower project	50.0	Hydro
47	Marsyangdi Besi	50.0	Hydro
48	Dana Khola HEP	49.95	Hydro
49	Khimti II	48.8	Hydro
50	Upper Rahughat	48.5	Hydro
51	Chujung Khola HEP	48.0	Hydro
52	Upper Balephi	46.0	Hydro
53	Kasuwa Khola HPP	45.0	Hydro

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S.No.	Project	Capacity (MW)	Type
54	Sani Bheri HEP	44.52	Hydro
55	Chilun Khola HEP	43.2	Hydro
56	Upper Nyasim Khola	43.0	Hydro
57	Upper Madi 0 HEP	43.0	Hydro
58	Ankhu Khola	42.9	Hydro
59	Upper Modi A	42.0	Hydro
60	Super Lower Bagmati HEP	41.86	Hydro
61	Sankhuwa Khola HEP	41.061	Hydro
62	Super Nyadi Hydropower Project	40.27	Hydro
63	Isuwa Khola PRoR Cascade HEP	40.1	Hydro
64	Khani Khola - 1	40.0	Hydro
65	Rahughat	40.0	Hydro
66	Bhotekoshi 1 HEP	40.0	Hydro
67	Lapche- Tamakoshi HEP	40.0	Hydro
68	Upper Sankhuwa Khola HEP	40.0	Hydro
69	Balephi Khola HEP	40.0	Hydro
70	Kalika Kaligandaki HEP	38.16	Hydro
71	Upper Ankhu Khola	38.0	Hydro
72	Kabeli-A	37.6	Hydro
73	Tamor Khola-5 HEP	37.5	Hydro
74	Upper Trishuli 3B	37.0	Hydro
75	Upper Myagdi	37.0	Hydro
76	Rahughat Mangale	37.0	Hydro
77	Brahmayani HEP	36.52	Hydro
78	Nyasim HEP	35.0	Hydro
79	Karuwa Seti HEP	32.0	Hydro
80	Upper Mewa Khola -A HEP	31.92	Hydro
81	Yaru Khola HEP	30.59	Hydro
82	Upper Dudh Khola HPP	30.4	Hydro
83	Khani Khola (Dolakha)	30.0	Hydro
84	Likhu Khola HPP	30.0	Hydro
85	Hongu Khola I HEP	30.0	Hydro
86	Palun khola 1 HEP	30.0	Hydro

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S.No.	Project	Capacity (MW)	Type
87	Mathillo Kabeli HEP	28.1	Hydro
88	Upper Khudi	26.0	Hydro
89	Super Aankhu Khola Hydropower Project	25.4	Hydro
90	Durbang Myagdi Khola	25.0	Hydro
91	Ilep Tatopani Khola HEP	25.0	Hydro
92	Bajra Madi Hydropower Project	24.8	Hydro
93	Luja Khola HEP	24.8	Hydro
94	Badigad Khola HEP	24.6	Hydro
95	Dobhan Khola HEP	24.5	Hydro
96	Khare Hydropower Project	24.1	Hydro
97	Madme Khola HPP	24.0	Hydro
98	Super Seti HPP	24.0	Hydro
99	Super Melamchi HEP	23.6	Hydro
100	Mewa khola HEP	23.0	Hydro
101	Middle Hongu Khola B HEP	22.9	Hydro
102	Mathillo Thulo Khola A HEP	22.5	Hydro
103	Balephi A	22.14	Hydro
104	Setikhola HEP	22.0	Hydro
105	Madhya Hongu Khola -A HPP	22.0	Hydro
106	Rolwaling Khola HEP	22.0	Hydro
107	Kabeli-3 Cascade HEP	21.93	Hydro
108	Nyadi-Phidi HPP	21.4	Hydro
109	Thulo Khola Hydropower Project	21.3	Hydro
110	Jaldigad	21.0	Hydro
111	Aayu Malun Khola HEP	21.0	Hydro
112	Palun Khola Small HEP	21.0	Hydro
113	Suti Khola HEP	21.0	Hydro
114	Langtang Khola Small Hydropower Project	20.0	Hydro
115	Sagu Khola HEP	20.0	Hydro
116	Lower Balephi	20.0	Hydro
117	Upper Seti HEP	20.0	Hydro

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S.No.	Project	Capacity (MW)	Type
118	Kunban Khola HEP	20.0	Hydro
119	Akhu Khola-2 HEP	20.0	Hydro
120	Tatopani khola HEP	19.0	Hydro
121	Dordi Dudh Khola Small HEP	19.0	Hydro
122	Upper Modi HPP Cascade Project	18.2	Hydro
123	Rauje Khola HPP	18.0	Hydro
124	Upper Maiwa HPP	17.85	Hydro
125	Chhahare Khola	17.5	Hydro
126	Upper Mailung B HEP	17.0	Hydro
127	Thuligad Khola Small PRoR HEP	17.0	Hydro
128	Liping Khola	16.26	Hydro
129	Ruru Banchu - 1	16.0	Hydro
130	Machhe Khola HEP	16.0	Hydro
131	Middle Trishuli Ganga nadi	15.625	Hydro
132	Irkhuwa Khola-B HPP	15.524	Hydro
133	Upper Brahmayeni HEP	15.15	Hydro
134	Sabha Khola-B HPP	15.1	Hydro
135	Upper Kabeli-2 HEP	15.0	Hydro
136	Phalakhu Khola HPP	14.7	Hydro
137	Mudi Khola Hydropower Project	14.7	Hydro
138	Upper Irkhuwa HPP	14.5	Hydro
139	Budum HEP	14.5	Hydro
140	Lower Irkhuwa Khola	14.15	Hydro
141	Upper Sunigad HEP	14.0	Hydro
142	Sisuwa Khola HEP	13.5	Hydro
143	Midim 1 HEP	13.424	Hydro
144	Middle Mailung (cascade) HEP	13.0	Hydro
145	Lower Nyadi HEP	12.6	Hydro
146	Ruru Banchu Khola- 2	12.0	Hydro
147	Super Kabeli Khola HEP	12.0	Hydro
148	Mistri Khola-2 HEP	12.0	Hydro

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S.No.	Project	Capacity (MW)	Type
149	Sunigad	11.05	Hydro
150	Upper Tadi	11.0	Hydro
151	Sabha Khola A	10.4	Hydro
152	Siddhi Khola	10.0	Hydro
153	Madya Super Daraundi HPP	10.0	Hydro
154	Upper Sagu HEP	10.0	Hydro
155	Daraudi Nadi HEP	9.84	Hydro
156	Upper Daraudi-C HEP	9.82	Hydro
157	Daram Khola HEP	9.6	Hydro
158	Lower Dudhkunda Hydropower Project	9.48	Hydro
159	Siwakhola HEP	9.3	Hydro
160	Upper Daraudi Hydropower Project	9.2	Hydro
161	Super Ghalemdi HEP	9.14	Hydro
162	Sona Khola HEP	9.0	Hydro
163	Khimti Ghwang Khola HEP	9.0	Hydro
164	Dudhpokhari Chepe HEP	8.836	Hydro
165	ChulepuKhola Hydropower Project	8.52	Hydro
166	Upper Daraudi B Small HEP	8.3	Hydro
167	Upper Deumai Khola Small HEP	8.3	Hydro
168	Tadi Ghyamphedi HEP	8.0	Hydro
169	Chino Khola HEP	7.9	Hydro
170	Upper Piluwa-1 HEP	7.7	Hydro
171	Jurimba Khola Small Hydropower Project	7.63	Hydro
172	Lower Hewa Khola-A HPP	7.3	Hydro
173	Shyam Khola HEP	7.25	Hydro
174	Lower Tawakhola HEP	7.1	Hydro
175	Menchet Khola HPP	7.0	Hydro
176	Hidi Khola HEP	6.82	Hydro
177	Garchyang Khola	6.6	Hydro

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S.No.	Project	Capacity (MW)	Type
178	Rawa Khola HPP	6.5	Hydro
179	Darkhola Small HEP	6.5	Hydro
180	Malta Bagmati Small HEP	6.5	Hydro
181	Upper Mailung -A	6.42	Hydro
182	Sabha Khola C HEP (Cascade)	6.3	Hydro
183	Lower Khani-B HEP	6.2	Hydro
184	Lower Bhim Khola HEP	6.05	Hydro
185	Upper Chauri Khola	6.0	Hydro
186	Buku Khola	6.0	Hydro
187	Nyam Nyam	6.0	Hydro
188	Rele Khola	6.0	Hydro
189	Super Hewa HPP	6.0	Hydro
190	Upper Junbesi Khola HEP	5.875	Hydro
191	Lower Khorunga	5.5	Hydro
192	Sagu khola 1 HPP	5.5	Hydro
193	Middle Tadi HPP	5.5	Hydro
194	Bagar Khola HEP	5.5	Hydro
195	Rawa Khola HEP	5.4	Hydro
196	Jhyaku Khola HPP	5.243	Hydro
197	Junbeshi	5.2	Hydro
198	Jogmai Cascade	5.2	Hydro
199	Tadi Khola	5.0	Hydro
200	Chauri Khola	5.0	Hydro
201	Phalakhu Khola HPP	5.0	Hydro
202	Lankhuwa Khola	5.0	Hydro
203	Buku-Kapati Hydropower Project	5.0	Hydro
204	Hewa A Small HEP	5.0	Hydro
205	Sangu Khola HPP	5.0	Hydro
206	Sepli Khola HEP	5.0	Hydro
207	Upper Piluwa Hills Small HP Project	4.99	Hydro
208	Bhim Khola Small HEP	4.96	Hydro

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S.No.	Project	Capacity (MW)	Type
209	Upper Piluwa 3 HPP	4.95	Hydro
210	Miwaje Khola HEP	4.95	Hydro
211	Upper Pikhuwa Khola HEP	4.9	Hydro
212	Khorunga Khola	4.8	Hydro
213	Middle Midim	4.8	Hydro
214	Syalque Khola Small HEP	4.8	Hydro
215	Super Iwa Khola HEP	4.795	Hydro
216	Syano Khola HEP	4.75	Hydro
217	Lower Thulo Khola HEP (RoR Cascade)	4.75	Hydro
218	Super Machha Khola HEP	4.6	Hydro
219	Middle Daram Khola-B HPP	4.5	Hydro
220	Tallo Indrawati HEP	4.5	Hydro
221	Upper Bhurundi Khola- A Small HEP	4.5	Hydro
222	Gasali Khola Small HEP	4.5	Hydro
223	Pegu Khola Small Hydropower Project	4.35	Hydro
224	Lohare Khola	4.2	Hydro
225	Pikhuwa Pashupati HEP	4.1	Hydro
226	Kisedi Khola Small HEP	4.1	Hydro
227	Lower Chirkhuwa	4.06	Hydro
228	Rupse Khola	4.0	Hydro
229	Upper Lohore SHP	4.0	Hydro
230	Lower Mid Rawa Khola HEP	4.0	Hydro
231	Upper Bhurundi Khola SHP	3.75	Hydro
232	Devdhunga Chaku Khola HEP	3.56	Hydro
233	Phedi Khola (Thumlung) Small HPP	3.52	Hydro
234	Lower Tara Khola HPP	3.5	Hydro
235	Sinkos Khola HEP	3.45	Hydro
236	Tinau Khola HPP	3.44	Hydro
237	Syarpu HEP	3.3	Hydro

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S.No.	Project	Capacity (MW)	Type
238	Sano Milti Khola SHP	3.0	Hydro
239	Middle Daram Khola-A HPP	3.0	Hydro
240	Tadi Khola Cascade	3.0	Hydro
241	Kalinchok Small HEP	3.0	Hydro
242	Upper Sardi HEP	2.9	Hydro
243	Bhalaudi Khola HEP	2.645	Hydro
244	Salankhu Khola	2.5	Hydro
245	Saptang Khola HPP	2.5	Hydro
246	Mid Rawa Khola HEP	2.5	Hydro
247	Upper Parajuli Khola	2.15	Hydro
248	Arun Khola 2 HEP	2.0	Hydro
249	Thaligad Small HPP	2.0	Hydro
250	Chepe Khola Cascade Hydropower Project	2.0	Hydro
251	Chisang Khola -A Small HEP	1.8	Hydro
252	Middle Tara Khola SHP	1.7	Hydro
253	Upper Gaddi Gad	1.55	Hydro
254	Istul Khola HPP	1.506	Hydro
255	Dharamnagar Solar Farm Project - II Kapilbastu	15.0	Solar
256	Grid Connected Solar PV Project, Ganeshpur, Kapilbastu	10.0	Solar
257	Mithila 2 Solar PV Project, Dhanusa	10.0	Solar
258	Dharamnagar Solar Farm Project	10.0	Solar
259	Bhrikuti Solar Power Project	9.0	Solar
260	Grid-Connected Solar Power Project, Duhabi, 33 kV S/S	8.0	Solar
261	Jira Bhawani Sedawa PV Project	7.7	Solar
262	Baigundhara Solar PV project	5.0	Solar
263	DDB Saurya Vidyut Aayojana	2.3	Solar

List of Power Plants with Applied Construction Licenses

Table A.4: List of Power Plants with Applied Construction Licenses

S.No.	Project	Capacity (MW)	Type
1	Mugu Karnali Storage HEP	1902.0	Hydro
2	Upper Arun HEP	1063.36	Hydro
3	Uttarganga Storage Hydropower Project	828.0	Hydro
4	Upper Marsyangdi -2	600.0	Hydro
5	Dudhkoshi Storage HEP	600.0	Hydro
6	Phukot Karnali HEP	480.0	Hydro
7	Kimathanka Arun HEP	454.0	Hydro
8	Betan Karnali HEP	439.0	Hydro
9	Nalsyau Gad Storage HEP	417.0	Hydro
10	Humla Karnali 2 HEP	335.0	Hydro
11	Upper Bheri PROR HEP	325.0	Hydro
12	Lantang Khola Reservoir HEP	310.0	Hydro
13	Upper Mugu Karnali HEP	306.0	Hydro
14	Bheri-1 HEP	270.0	Hydro
15	Humla Karnali 1 HEP	235.0	Hydro
16	Surke Dudhkoshi HEP	188.0	Hydro
17	Adhikhola Storage HEP	180.0	Hydro
18	Dudhkoshi-6 HEP	171.0	Hydro
19	Mugu Karnali HEP	159.62	Hydro
20	Begnas- Rupa Storage HEP	150.0	Hydro
21	Namlan Khola HEP	135.0	Hydro
22	Lower Barun Khola HPP	132.0	Hydro
23	Lower Seti (Tanahu) HEP	126.0	Hydro
24	Upper Chuwa Lurupya Khola PRoR HEP	110.2	Hydro
25	Chuwa Khola Cascade HPP	98.17	Hydro
26	Budhi Gandaki Nadi HEP	91.15	Hydro
27	Rolwaling Khola HEP	88.0	Hydro
28	Upper Tamor A HEP	72.0	Hydro

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S.No.	Project	Capacity (MW)	Type
29	Dudhkoshi Storage (with Dam - Toe Powerhouse) Hydropower Pro	70.0	Hydro
30	Seti Nadi-3 HEP	65.0	Hydro
31	Nar Khola HEP	58.9	Hydro
32	Sani Bheri 3 HEP	46.72	Hydro
33	Chunchet Syar Khola HEP	45.0	Hydro
34	Bakan Khola HEP	44.0	Hydro
35	Ghunsa-Tamor HEP	43.0	Hydro
36	Mathillo Simbuwa Khola HEP	40.03	Hydro
37	Ikhuwa Khola HEP	40.0	Hydro
38	Upper Apsuwa HEP	35.15	Hydro
39	Middle Chameliya HEP	35.0	Hydro
40	Myardi Khola	30.0	Hydro
41	Myagdi Khola A HEP	30.0	Hydro
42	Hongu Khola HEP	28.9	Hydro
43	Upper Trishuli-I Cascade HEP	24.6	Hydro
44	Super Inkhu Khola HEP	24.41	Hydro
45	Upper Inkhu Khola HEP	24.22	Hydro
46	Upper Ruru Banchu Khola HEP	23.9	Hydro
47	Apsuwa I HEP	23.0	Hydro
48	Upper Nyasem A HEP	21.0	Hydro
49	Supreme Middle Seti HEP	18.0	Hydro
50	Irkhuwa Khola Ka HEP	15.0	Hydro
51	Upper Seti-1 HEP	13.0	Hydro
52	Upper Mudi HEP	12.73	Hydro
53	Maygdi Khola- B HEP	12.5	Hydro
54	Dhaula Khola HEP	10.8	Hydro
55	Mathillo Chhum Chhum Gad HEP	10.0	Hydro
56	Tawa Khola HEP	9.96	Hydro
57	Nimrung Khola HEP	9.8	Hydro
58	Lower Inkhu HEP	9.8	Hydro

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S.No.	Project	Capacity (MW)	Type
59	Tirija Khola HEP	9.71	Hydro
60	Super Sabha Khola A HPP	9.55	Hydro
61	Nisi Khola HEP	8.8	Hydro
62	Middle Likhu Small HEP	8.6	Hydro
63	Paara Malun PRoR HEP	8.53	Hydro
64	Lower Kalanga Gad HEP	8.0	Hydro
65	Taksu Khola HEP	7.1	Hydro
66	Middle Molung Khola Small HEP	6.0	Hydro
67	Lower Melamchi HEP	4.96	Hydro
68	Upper Melamchi HEP	4.95	Hydro
69	Chhomron Khola Small HEP	4.894	Hydro
70	Api Naugad HEP	4.84	Hydro
71	Lapa Khola Hydropower Project	4.72	Hydro
72	Super Most Iwa HEP	4.6	Hydro
73	Manahari Khola HEP	4.5	Hydro
74	Chyandi Khola HEP	4.2	Hydro
75	Upper Most Iwa Khola HEP	4.1	Hydro
76	Super Sabha Khola Small Hydropower Project	4.1	Hydro
77	Lower Rupse Khola HEP	1.86	Hydro
78	Lodo Khola Sana HEP	1.6	Hydro
79	Garjan Khola Small HPP	0.9	Hydro
80	Elun Khola	0.485	Hydro
81	Grid Connected Solar PV Project, Lamahi	10.0	Solar
82	Grid Connected Solar Electricity Project Part-2 Ganeshpur, K	10.0	Solar
83	Grid Connected Solar PV Project, Lamahi 1	10.0	Solar
84	Arga Saurya Vidyut Aayojana, Arghakhachi	10.0	Solar
85	Gandak Solar PV Project	5.8	Solar
86	Solar PV Project, Dhalkebar	5.0	Solar

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S.No.	Project	Capacity (MW)	Type
87	Grid-Connected Solar Power Project, Lahan , 33 kV S/S	4.0	Solar
88	Jhupra Saurya Vidyut Project, Surkhet	2.0	Solar
89	Madhya Marsyangdi Solar Electricity Project, Lamjung	1.6	Solar
90	Grid Connected Solar PV Project, Birendranagar Surkhet	1.2	Solar

List of Power Plants with Approved Survey Licenses

Table A.5: List of Power Plants with Approved Survey Licenses

S.No.	Project	Capacity (MW)	Type
1	Upper Karnali HEP	900.0	Hydro
2	West Seti Hydropower Project	750.0	Hydro
3	Sunkoshi - 3 Storage Hydropower Project	683.0	Hydro
4	Lower Arun Hydropower Project	679.0	Hydro
5	Tamakoshi 3 PRoR Hydropower Project	650.0	Hydro
6	Arun 4 PRoR HEP	490.2	Hydro
7	Syarpu Lake Pump Storage Hydroelectric Project	334.0	Hydro
8	Mathillo Marsyangdi -2 Hydropower Project	327.0	Hydro
9	Mathillo Budigandaki Hydropower Project	203.0	Hydro
10	Tamor Storage	200.0	Hydro
11	Ghunsa Khola HEP	155.82	Hydro
12	Super Humla Karnali Nadi HEP	152.725	Hydro
13	Jagdulla A HEP	120.6	Hydro

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S.No.	Project	Capacity (MW)	Type
14	Dudhkoshi V HEP	110.0	Hydro
15	Upper Barunkhola HEP	109.5	Hydro
16	Jilli Chumli Khola Hydropower Project	100.0	Hydro
17	Budhigandaki Prok-1 HEP	93.0	Hydro
18	Marsyangdi River PRoR Hydropower Project	90.0	Hydro
19	Upper Sani Bheri PRoR HEP	90.0	Hydro
20	Super Chuwa Khola Hydropower Project (PRoR)	80.0	Hydro
21	Tribeni Bheri Nadi PRoR Hydropower Project	78.0	Hydro
22	Pelma Khola PRoR HPP	75.0	Hydro
23	Malumela - Seti Nadi PRoR Hydropower Project	72.0	Hydro
24	Tapowan Seti PRoR Hydroelectric Project	72.0	Hydro
25	Jawa Tila PRoR Hydroelectric Project	70.37	Hydro
26	Mimiban Khola PRoR Hydropower Project	70.0	Hydro
27	Bichhya Kuwadi Khola HEP	70.0	Hydro
28	Lower Loti Karnali PRoR Hydropower Project	61.0	Hydro
29	Mugu Khola HEP	57.0	Hydro
30	Maakali Seti PRoR Cascade Hydroelectric Project	54.0	Hydro
31	Ghatganga PRoR Hydroelectric Project	51.5	Hydro
32	Upper Chhujung HEP	50.5	Hydro
33	Marsyangdi - 7 Hydropower Project	50.0	Hydro
34	Super Seti Hydropower Project	46.0	Hydro

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S.No.	Project	Capacity (MW)	Type
35	Saldim Khola HEP	45.0	Hydro
36	Super Dona Khola HEP	42.75	Hydro
37	Ranma Khola HPP	36.6	Hydro
38	Likhu Khola HEP	36.0	Hydro
39	Syanban Khola Hydropower Project	31.5	Hydro
40	Middle Ghunsa HEP	30.24	Hydro
41	Sani Bheri 3 PRoR Cascade HEP	30.0	Hydro
42	Trishuli Galchhi Hydropower Project	30.0	Hydro
43	Tejo Thogam Khola HPP	29.0	Hydro
44	Bhimdang Hydropower Project	25.11	Hydro
45	Induwa Khola PRoR HEP	24.921	Hydro
46	Mathillo Pelma Khola Hydroelectric project	24.8	Hydro
47	Mathillo Langtang HEP	24.35	Hydro
48	Lurupya Khola PRoR HEP	21.1	Hydro
49	Lower Badigad HEP	16.69	Hydro
50	Super Kalanga Khola Hydropower Project	16.0	Hydro
51	Middle Iwa Khola Hydropower Project	15.0	Hydro
52	Daraudi/Marsyangdi PRoR Hydropower Project	14.9	Hydro
53	Aayu Chhatigad HEP	13.942	Hydro
54	Bhabil -1 PRoR Hydropower Project	13.86	Hydro
55	Chaudhabis Hydropower Project	13.0	Hydro
56	Mathillo Yaru Khola PRoR Hydropower Project	13.0	Hydro
57	Mathillo Chhumchhum Gad Hydropower Project	10.0	Hydro
58	Isuwa Cascade-3	9.95	Hydro

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S.No.	Project	Capacity (MW)	Type
59	Isuwa PRoR Cascade -2 Hydropower Project	9.95	Hydro
60	Kabeli-3 Hydropower Project	9.85	Hydro
61	Super Thulo Khola Hydropower Project	9.83	Hydro
62	Luja Khola Cascade HEP	9.8	Hydro
63	Seti Khola Cascade Hydropower Project	9.8	Hydro
64	Super Ikhuwa Khola Hydropower Project	9.732	Hydro
65	Lagan Khola (Bramhayani - A) HEP	9.7	Hydro
66	Rudrawati Badigaad Hydropower Project	9.6	Hydro
67	Lungri khola PROR HPP	9.6	Hydro
68	Upper Ikhuwa Khola Hydropower Project	9.6	Hydro
69	Super Siwa Khola Hydropower Project	9.6	Hydro
70	Ghatte Khola Hydroelectric Project	9.54	Hydro
71	Taksar Pikhuwa Cascade Hydropower Project	9.5	Hydro
72	Mathillo Baddigad Khola Hydropower Project	9.485	Hydro
73	Super Daraudi Khola E Hydropower Project	9.413	Hydro
74	Panchpokhari Khola PRoR Hydropower Project	9.03	Hydro
75	Sabha A Hydropower Project	9.0	Hydro
76	Lower Chepe Khola HPP	8.74	Hydro
77	Mathillo DudhKunda Hydropower Project	8.52	Hydro

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S.No.	Project	Capacity (MW)	Type
78	Upper Sisne Khola Hydropower Project	8.5	Hydro
79	Mathillo Siwa Khola PRoR Hydropower Project	8.18	Hydro
80	Lower Ingwa Khola Hydropower Project	8.0	Hydro
81	Super Daraudi - Pau Khola Hydropower Project	7.0	Hydro
82	Pikhuwa Khola HPP	6.7	Hydro
83	Lower Mewa Khola Hydropower Project	6.63	Hydro
84	Upper Taksu Small HEP	6.3	Hydro
85	Tallo Likhu Cascade Hydropower Project	6.0	Hydro
86	Sisne Khola Small Hydropower Project	5.9	Hydro
87	Upper Dovan Khola Hydropower Project	5.2	Hydro
88	Super Palung HEP	5.0	Hydro
89	Super Irkhuwa Khola HEP	5.0	Hydro
90	Mathillo Maya Khola Hydropower Project	5.0	Hydro
91	Chadaha Khola HEP	4.5	Hydro
92	Salleri Chialsa Hydropower Project	4.0	Hydro
93	Phedi Khola HEP	3.5	Hydro
94	Sirsagad Small HEP	2.5	Hydro
95	250MW Grid connected Solar Project in Kohalpur and Banganga	250.0	Solar
96	Godawari - Attariya Solar Electricity Project	40.0	Solar
97	Bhurigau Solar PV, Project	40.0	Solar

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S.No.	Project	Capacity (MW)	Type
98	Kohalpur Solar PV Project	40.0	Solar
99	Pahalmanpur Solar Electricity Project	30.0	Solar
100	Kapilvastu 30 MW Solar Project	30.0	Solar
101	Nepalgunj Solar PV Project	25.0	Solar
102	Gulariya Solar PV Project	25.0	Solar
103	Dullu Malika Saurya Vidyut Aayojana, Dailekh	15.0	Solar
104	Pratappur Solar PV Project	10.0	Solar
105	Jhimruk On Grid Solar Project	10.0	Solar
106	Lalbandhi Solar PV Project	10.0	Solar
107	Solududhakuna Solar PV Project	10.0	Solar
108	Solar PV Plant Block 2, Kailali	10.0	Solar
109	Solar PV Plant, Block-1, Kailali	10.0	Solar
110	Attariya Solar PV Plant Part 1	10.0	Solar
111	Attariya Solar PV Plant Part 2	10.0	Solar
112	Shantinagar Solar Project	10.0	Solar
113	Lamahi Saurya Vidyut Aayojana	10.0	Solar
114	Bheri Solar Power Plant	10.0	Solar
115	Parwat Saurya Vidyut Aayojana	10.0	Solar
116	Parwat Saurya Vidyut Aayojana - 2	10.0	Solar
117	N - Saurya Vidyut Aayojana	10.0	Solar
118	Kharbang Saurya Vidyut Aayojana	10.0	Solar
119	Kharbang Saurya Vidyut Aayojana - 2	10.0	Solar
120	Udayapur On Grid Saurya Vidyut Aayojana	10.0	Solar
121	Subha Solar PV Project	9.9	Solar
122	Duhabi Solar Farm	8.0	Solar
123	Tulsi Saurya Vidyut Aayojana, Dang	7.5	Solar

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S.No.	Project	Capacity (MW)	Type
124	Mithila Solar Project	5.0	Solar
125	Utkrishta Attariya Saurya Vidyut Aayojana	5.0	Solar
126	Gami Solar Energy Project	3.0	Solar
127	Juropani Saurya Urja Pariyojana	1.0	Solar

List of Power Plants with Applied Survey Licenses

Table A.6: List of Power Plants with Applied Survey Licenses

Column 1	Column 2	Column 3	Column 4
1	Budhi Gandaki Hydropower Project	1200.0	Hydro
2	Dudhkoshi - 9 Hydropower Project	166.0	Hydro
3	Ghunsa Khola Hydropower Project	155.82	Hydro
4	Bheri - 8 Hydroelectric Project	140.0	Hydro
5	Suli Gad Hydropower Project	120.0	Hydro
6	Lower Trishuli Hydropower Project	117.72	Hydro
7	Tom Dogar Hydropower Project	107.0	Hydro
8	Phoksundo Khola Hydropower Project	92.1	Hydro
9	Lower Magic Karnali PROR HEP	92.0	Hydro
10	Hilsa Karnali HydroelectricProject	80.3	Hydro
11	Lower Magic Karnali PRoR Hydropower Project	76.5	Hydro
12	Ghustung Khola Hydropower Project	75.0	Hydro
13	Tarap Khola HEP	72.0	Hydro

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Column 1	Column 2	Column 3	Column 4
14	Upper Jagdulla Hydropower Project	65.0	Hydro
15	Upper Jagdulla Hydroelectric Project	62.75	Hydro
16	Chhimdi - Kawadi Khola Hydropower Project	54.0	Hydro
17	Super Nilgiri Khola Peakng Hydropower Project	49.0	Hydro
18	Rukum Sani Bheri Hydropower Project	45.0	Hydro
19	Super Budhi Gandaki HEP	40.4	Hydro
20	Bheri 8 Cascade Hydropower Project	40.0	Hydro
21	Gidi Khola Hydropower Project	27.3	Hydro
22	Sunkoshi Marin Cascade Hydropower Project	24.8	Hydro
23	Lower Pelma Khola PRoR HEP	23.75	Hydro
24	Sani Bheri - 2 Hydropower Project	23.37	Hydro
25	Sani Bheri (Syarpu) Hydropower Project	23.25	Hydro
26	Thuli Bheri - A Hydropower Project	21.881	Hydro
27	Middle Rolwaling Hydropower Project	21.485	Hydro
28	Syar Khola Hydropower Project	21.0	Hydro
29	Lower Hima Nadi Hydropower Project	20.969	Hydro
30	Lower Chameliya HEP	20.0	Hydro
31	Dudhkoshi - 10 Hydropower Project	20.0	Hydro
32	Chaldi Khola Storage Hydropower Project	19.37	Hydro

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Column 1	Column 2	Column 3	Column 4
33	Likhu - 4 "A" Cascade Hydropower Project	12.5	Hydro
34	Super Sunigad Hydropower Project	12.0	Hydro
35	Lower Nyasem Cascade Hydroelectric Project	10.0	Hydro
36	Dudh Pokhari Bhalu Khola Hydropower Project	10.0	Hydro
37	Majaine Khola Hydropower Project	10.0	Hydro
38	Super Sisne Khola B Hydropower Project	10.0	Hydro
39	Super Sisne Majaine Khola A Hydropower Project	10.0	Hydro
40	Super Sisne Khola C hydropower Project	10.0	Hydro
41	Siwa and Saju Khola Hydropower Project	10.0	Hydro
42	Kalangagad A Hydropower Project	9.81	Hydro
43	Nwagad Hydroelectric Project	9.68	Hydro
44	Super Sankhuwa Hydropower Project	9.62	Hydro
45	Lower Seti (Bajhang) Hydropower Project	9.6	Hydro
46	Dogaria Gad Hydroelectric Project	9.561	Hydro
47	Madhya Madi Hydropower Project	9.5	Hydro
48	Lungri Khola A Hydropower Project	9.5	Hydro
49	Trishuli Khola Small HydroelectricProject	9.5	Hydro

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Column 1	Column 2	Column 3	Column 4
50	Chyamni Khola Hydropower Project	9.5	Hydro
51	Tila Karnali Hydropower Project	9.5	Hydro
52	Kimron Khola Hydropower Project	9.4	Hydro
53	Upper Lungri Hydropower Project	9.3	Hydro
54	Tallo Rukumgad Hydropower Project	9.144	Hydro
55	Tap Khola HPP	8.724	Hydro
56	Sadhu Khola Hydropower Project	8.3	Hydro
57	Supreme Sisne Khola Hydroelectric Project	8.2	Hydro
58	Super Machha Khola A HEP	8.0	Hydro
59	Super Manang Small Hydropower Project	8.0	Hydro
60	Nisi Khola Hydropower Project	7.81	Hydro
61	Gupche Khola Hydropower Project	7.5	Hydro
62	Lowa Hydropower Project	7.39	Hydro
63	Bakan Piling Hydropower Project	7.0	Hydro
64	MaiwaTatha Bhute Khola HPP	6.13	Hydro
65	Lower Rukumgad Hydropower Project	5.25	Hydro
66	Ragagad Hydroelectric Project	5.0	Hydro
67	Lower Chujung Hydropwer Project	5.0	Hydro
68	Dudh Marsyangdi Hydropower Project	5.0	Hydro
69	Nupche Khola Hydropower Project	5.0	Hydro
70	Super Malung Khola Hydropower Project	5.0	Hydro

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Column 1	Column 2	Column 3	Column 4
71	Suligad PRoR Hydropower Project	5.0	Hydro
72	Bhalu Khola Hydroelectric Project	5.0	Hydro
73	Bhurundi Khola Cascade Hydropower Project	5.0	Hydro
74	Super Juli Odar Khola HEP	5.0	Hydro
75	Landan Khola Hydropower Project	5.0	Hydro
76	Yanwa Khola Hydroelectric Project	4.99	Hydro
77	Lower Ranggad Hydropower Project	4.99	Hydro
78	Bhalu Khola Hydropower Project	4.99	Hydro
79	Ramailo Likhu Jalavidyut Aayojana	4.976	Hydro
80	Middle Tatopani Khola Hydroelectric Project	4.97	Hydro
81	Kauley Khola Hydropower Project	4.96	Hydro
82	Sisuwa Khola - A Hydropower Project	4.95	Hydro
83	Yangdeli Khola Hydropower Project	4.95	Hydro
84	Tamakoshi Khimti Hydropower Project	4.95	Hydro
85	Chameliya Khola Hydropower Project	4.94	Hydro
86	Hilsa Karnali Hydropower Project	4.92	Hydro
87	Dudh Khola 1 HPP	4.9	Hydro
88	Middle Kalangagad Hydropower Project	4.9	Hydro

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Column 1	Column 2	Column 3	Column 4
89	Syangdi Khola Hydropower Project	4.9	Hydro
90	Bichchhya Khola Hydropower Project	4.9	Hydro
91	Super Khimti Hydropower Project	4.9	Hydro
92	Supreme Kabeli Khola Hydropower Project	4.85	Hydro
93	Manggala Myagdi Cascade Hydropower Project	4.81	Hydro
94	Lower Pelma Khola	Uttar Ganga Nadi Hydropower Project	4.8
Hydro			
95	Super Sunigad Hydropower Project	4.8	Hydro
96	Mathillo Lankhuwa Khola Hydropower Project	4.8	Hydro
97	Lower Sunigad Hydropower Project	4.8	Hydro
98	Upper Sisuwa Khola Hydropower Project	4.77	Hydro
99	Leksuwa Khola PRoR Hydropower Project	4.7	Hydro
100	Upper Lankhuwa Khola Hydropower Project	4.66	Hydro
101	Super Likhu Small Hydropower Project	4.6	Hydro
102	Koluwa Khola Hydroelectric Project	4.55	Hydro
103	Upper Kasuwa Hydropower Project	4.5	Hydro

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Column 1	Column 2	Column 3	Column 4
104	Mathillo Rukumgad Hydropower Project	4.45	Hydro
105	Bamdan Khola Small Hydropower Project (second application)	4.23	Hydro
106	Rauje Khola Hydropower Project	4.23	Hydro
107	Machha Khola-A HPP	4.0	Hydro
108	Upper Larcha Khola Hydropower Project	3.7	Hydro
109	Nupche Likhu Cascade Hydropower Project	3.3	Hydro
110	Yanwa Hydropower Project	2.66	Hydro
111	Kiche Khola Small Hydropower Project	2.5	Hydro
112	Nenwa Khola Hydropower Project	2.48	Hydro
113	Kuntun Khola Peaking RoR Hydropower Project	2.3	Hydro
114	Khorunga-Tangmaya Khola HPP	2.0	Hydro
115	Sailun Khola Hydropower Project	1.74	Hydro
116	Liping Cascade Small Hydropower Project	1.55	Hydro
117	Nepalgunj Solar PV Project	100.0	Solar
118	Jhapa Saurya Vidyut Aayojana	100.0	Solar
119	Rolpa PV Project	50.0	Solar
120	Arghakhachi PV Project	50.0	Solar
121	Grid Connected Saurya Vidyut Aayojana Rolpa	50.0	Solar
122	Dhalkebar Solar Power Project	50.0	Solar
123	Palpa Solar PV Project	50.0	Solar
124	Rapti Dobhan Solar PV Project	30.0	Solar
125	Palpa Dambak Solar PV Project	25.0	Solar
126	Barju Solar PV Project	20.0	Solar
127	Loharpatti Solar PV Project	20.0	Solar

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Column 1	**Column 2**	**Column 3**	**Column 4**
128	Sitalpati Solar PV Project	10.0	Solar
129	Bharavnath Solar PV Project	10.0	Solar
130	Nawalpur Helio Solar Aayojana	10.0	Solar
131	Lahan Helio Solar Aayojana	10.0	Solar
132	Pokhariya Solar PV Project	10.0	Solar
133	Rakathum Solar PV Project	10.0	Solar
134	Amarapuri Solar PV Project	10.0	Solar
135	Baidehi Solar PV Project	10.0	Solar
136	Dhanushadham Solar PV Project	9.5	Solar
137	Baniyani Solar Power Project	9.5	Solar
138	Dhulabari Solar Photo-voltaic(PV) Project	9.5	Solar
139	Ganeshman Solar PV Project	9.5	Solar
140	Belauri Solar PV Project	9.0	Solar
141	Parwanipur Grid Connected Solar PV Project	8.0	Solar
142	Manpur Solar PV Project	5.0	Solar
143	Aurahi Solar PV Project	5.0	Solar
144	Maulapur Solar PV Project	5.0	Solar
145	Maulapur Solar PV Project	5.0	Solar
146	Saghutar Solar PV Project	5.0	Solar
147	Aurahi Solar PV Project	5.0	Solar
148	Banke Solar PV Project	5.0	Solar

RELATED CODES

0.1 Peak Load Forecasting Code

The following Python script was used for data analysis, trend visualization, correlation analysis, and peak load forecasting.

0.1.1 Data Loading and Trend Analysis

```
import pandas as pd
import matplotlib.pyplot as plt

file_path = "Annual_Peak&Parameter.xlsx"
xls = pd.ExcelFile(file_path)
df = pd.read_excel(xls, sheet_name='Sheet1')

# Ensure HDI is properly handled
df["HDI"] = pd.to_numeric(df["HDI"], errors="coerce")  # Convert to
    numeric, handle NaN
df = df.dropna(subset=["HDI"])  # Drop rows where HDI is NaN

# Create subplots
fig, axes = plt.subplots(nrows=4, ncols=2, figsize=(15, 16))
fig.suptitle("Trends␣Over␣Time", fontsize=16)

# Peak Load
axes[0, 0].plot(df["Year"], df["PEAK␣LOAD(MW)"], marker="o",
   linestyle="-", color='b')
axes[0, 0].set_title("Peak␣Load␣(MW)")
axes[0, 0].set_xlabel("Year")
axes[0, 0].set_ylabel("MW")
axes[0, 0].grid(True)

# Energy Sales
axes[0, 1].plot(df["Year"], df["ENERGY␣SALES(GWH)"], marker="s",
   linestyle="-", color='g')
axes[0, 1].set_title("Energy␣Sales␣(GWH)")
axes[0, 1].set_xlabel("Year")
axes[0, 1].set_ylabel("GWH")
axes[0, 1].grid(True)

plt.tight_layout(rect=[0, 0, 1, 0.96])
plt.show()
```

0.1.2 Sectoral Distribution of Consumers

```
# Trim whitespace from column names to avoid mismatches
df.columns = df.columns.str.strip()

# Select relevant columns
sectoral_columns = [
    "Year", "DOMESTIC", "NON␣COMMERCIAL", "COMMERCIAL", "INDUSTRIAL",
    "WATER␣SUPPLY", "IRRIGATION", "STREET␣LIGHT", "TEMPORART␣SUPPLY",
    "TRANSPORT", "TEMPLE"
]

df_sectoral = df[sectoral_columns]

# Ensure all values are numeric
df_sectoral.iloc[:, 1:] = df_sectoral.iloc[:, 1:].apply(pd.to_numeric, errors='coerce')

# Plot stacked bar chart
plt.figure(figsize=(14, 7))
df_sectoral.set_index("Year").plot(kind="bar", stacked=True, figsize=(14, 7), colormap="tab10")

plt.xlabel("Year")
plt.ylabel("Number␣of␣Consumers")
plt.title("Sectoral␣Distribution␣of␣Electricity␣Consumers␣Over␣Time␣(Stacked␣Bar)")
plt.legend(title="Sector", bbox_to_anchor=(1.05, 1), loc="upper␣left")
plt.grid(axis="y", linestyle="--", alpha=0.7)

plt.show()
```

0.1.3 Correlation Analysis

```
import seaborn as sns

# Step 1: Correlation Analysis (Yearly Data)
correlation_matrix = df.corr()
plt.figure(figsize=(14, 8))
sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation␣Heatmap␣-␣INPS␣Yearly␣Data")
plt.show()
```

0.1.4 Regression Model for Peak Load Forecasting

```
import numpy as np
import statsmodels.api as sm
from sklearn.linear_model import Ridge
from sklearn.metrics import mean_absolute_error, mean_squared_error

file_path = "Peak_Income.xlsx"  # Change if necessary
df = pd.read_excel(file_path)

# Rename columns for easier reference
df.columns = ["Year", "GDP_per_capita", "Population", "Peak_MW"]

# Split into training (up to 2018) and testing (2019-2024)
train = df[df["Year"] <= 2018]
test = df[(df["Year"] > 2018) & (df["Year"] <= 2024)]

# Define independent (X) and dependent (y) variables
X_train = train[["GDP_per_capita", "Population"]]
y_train = train["Peak_MW"]
X_test = test[["GDP_per_capita", "Population"]]
y_test = test["Peak_MW"]

# Fit the Ridge Regression model
model = Ridge(alpha=1.0)
model.fit(X_train, y_train)

# Predict on test data
y_pred = model.predict(X_test)

# OLS Regression Results using statsmodels
X_train_ols = sm.add_constant(X_train)  # Add intercept term
ols_model = sm.OLS(y_train, X_train_ols).fit()
print(ols_model.summary())

# Evaluate model performance
mae = mean_absolute_error(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
r2 = ols_model.rsquared
print(f"R ␣Score:␣{r2:.4f}")
print(f"MAE:␣{mae:.2f},␣RMSE:␣{rmse:.2f}")
```

0.1.5 Future Projections

```
# Future projections (2030, 2035, 2040, 2050)
years_future = [2030, 2035, 2040, 2050]
```

```python
gdp_growth_rates = {"BAU": 3.9, "Medium": 6, "High": 10}  # Growth
    Scenarios
pop_growth_rate = 1.08 / 100  # 1.08%

# Get the last known values from 2024
latest_gdp = df[df["Year"] == 2024]["GDP_per_capita"].values[0]
latest_pop = df[df["Year"] == 2024]["Population"].values[0]

# Predict Peak MW for different scenarios
predictions = {}

for scenario, gdp_growth in gdp_growth_rates.items():
    gdp_proj = [latest_gdp * ((1 + gdp_growth / 100) ** (year -
        2024)) for year in years_future]
    pop_proj = [latest_pop * ((1 + pop_growth_rate) ** (year -
        2024)) for year in years_future]

    # Create DataFrame for prediction
    future_data = pd.DataFrame({"GDP_per_capita": gdp_proj, "
        Population": pop_proj})

    # Predict Peak MW
    peak_mw_proj = model.predict(future_data)

    # Apply 15% system loss adjustment
    peak_mw_adj = peak_mw_proj / (1 - 0.15)

    predictions[scenario] = peak_mw_adj

# Display predictions
pred_df = pd.DataFrame(predictions, index=years_future)
pred_df.index.name = "Year"
print(pred_df)
```

This code was used to analyze past peak load trends, perform correlation analysis, develop regression models, and project future peak electricity demand under different economic growth scenarios.

0.2 Per Capita Power Consumption and Peak Load Forecasting

This section presents a linear regression analysis to estimate peak load based on per capita electricity consumption levels. The analysis provides projected peak demand for different consumption benchmarks, including Vietnam's consumption level, upper-middle-income, and high-income country benchmarks.

0.2.1 Python Code for Linear Regression Analysis

```
import pandas as pd
from scipy.stats import linregress

# Load the Excel file
try:
    df = pd.read_excel("Per_Capita_Power.xlsx")
except FileNotFoundError:
    print("Error:␣The␣file␣’Per_Capita_Power.xlsx’␣was␣not␣found.")
    exit()

# Drop rows with missing values
df = df.dropna()

# Extract the relevant columns
consumption = df["Electric␣power␣consumption␣(kWh␣per␣capita)"]
peak_load = df["PEAK␣LOAD(MW)"]

# Perform linear regression
slope, intercept, r_value, p_value, std_err = linregress(
   consumption, peak_load)

# Define the target consumption levels
vietnam_consumption = 2500
upper_middle_income_consumption = 3500
upper_income_consumption = 9000

# Predict the peak load for each target consumption level
vietnam_peak_load = slope * vietnam_consumption + intercept
upper_middle_income_peak_load = slope *
   upper_middle_income_consumption + intercept
upper_income_peak_load = slope * upper_income_consumption +
   intercept

# Print the results
print(f"Predicted␣peak␣load␣for␣Vietnam␣level␣(2500␣kWh):␣{
   vietnam_peak_load:.2f}␣MW")
print(f"Predicted␣peak␣load␣for␣Upper␣Middle␣Income␣level␣(3500␣kWh
   ):␣{upper_middle_income_peak_load:.2f}␣MW")
print(f"Predicted␣peak␣load␣for␣Upper␣Income␣level␣(9000␣kWh):␣{
   upper_income_peak_load:.2f}␣MW")
```

```
# Optional: Print the linear regression equation
print(f"\nLinear␣Regression␣Equation:")
print(f"PEAK␣LOAD(MW)␣=␣{slope:.4f}␣*␣Electric␣power␣consumption␣(
    kWh␣per␣capita)␣+␣{intercept:.4f}")

# Optional: print R squared value.
print(f"R-squared␣value:␣{r_value**2:.4f}")
```

0.3 Daily Peak Load Analysis and Forecasting

This section presents an analysis of historical daily peak demand for 2023 and 2024, along with future peak demand projections based on different economic growth scenarios. The dataset is used to scale future peak demand for 2030, 2035, 2040, and 2050, following Business-As-Usual (BAU), Medium Growth, High Growth, and Growth Target scenarios.

0.3.1 Python Code for Daily Peak Load Analysis

```
import pandas as pd
import matplotlib.pyplot as plt

# Load the Excel file
file_path = "Daily_Peak_22_25.xlsx"  # Update if necessary
df = pd.read_excel(file_path, engine="openpyxl")

# Remove trailing spaces in column names
df = df.rename(columns=lambda x: x.strip())

# Ensure 'Date' is in datetime format
df['Date'] = pd.to_datetime(df['Date'], errors='coerce')

# Extract 'Year' from the 'Date' column
df['Year'] = df['Date'].dt.year

# Select relevant columns
df = df[['Date', 'Year', 'Peak␣Demand␣(Requirement)␣(MW)']].dropna
    ()

# Filter and sort data for 2023 & 2024
df_2023 = df[df['Year'] == 2023].sort_values(by='Peak␣Demand␣(
    Requirement)␣(MW)', ascending=False).reset_index(drop=True)
df_2024 = df[df['Year'] == 2024].sort_values(by='Peak␣Demand␣(
    Requirement)␣(MW)', ascending=False).reset_index(drop=True)
```

```python
# Save 2023 & 2024 sorted data to CSV
df_2023.to_csv("Sorted_Peak_Demand_2023.csv", index=False)
df_2024.to_csv("Sorted_Peak_Demand_2024.csv", index=False)

# Get actual max peak demand for 2024
max_2024_peak = df_2024['Peak Demand (Requirement) (MW)'].max()

# Define projected peak values (from the table, including Growth
    Target)
peak_values = {
    2030: {"BAU": 2983, "Medium": 3305, "High": 4012, "Target":
        None},
    2035: {"BAU": 3588, "Medium": 4339, "High": 6252, "Target":
        16365},
    2040: {"BAU": 4309, "Medium": 5703, "High": 9818, "Target":
        22900},
    2050: {"BAU": 6199, "Medium": 9895, "High": 24655, "Target":
        58825}
}

# Dictionary to store scaled data for plotting
scaled_dfs = {scenario: pd.DataFrame() for scenario in ["BAU", "
    Medium", "High", "Target"]}

# Scale the 2024 data proportionally for each year & scenario
for scenario in ["BAU", "Medium", "High", "Target"]:
    for year, scenarios in peak_values.items():
        if scenarios[scenario] is not None:
            scaling_factor = scenarios[scenario] / max_2024_peak
            scaled_dfs[scenario][year] = df_2024['Peak Demand (
                Requirement) (MW)'] * scaling_factor

    # Save each scenario as a separate CSV file
    scaled_dfs[scenario].to_csv(f"Sorted_Peak_Demand_{scenario}.csv
        ", index=False)

# ---- PLOTTING ----
fig, axes = plt.subplots(3, 2, figsize=(14, 18))

scenario_titles = ["BAU Growth", "Medium Growth", "High Growth", "
    Growth Target"]
scenario_keys = ["BAU", "Medium", "High", "Target"]
colors = {2030: "b", 2035: "g", 2040: "r", 2050: "purple"}
```

```
# Updated Labels for Growth Target Scenario
growth_target_labels = {
    2035: "2035␣(2,500␣kWh␣per␣capita␣@␣Lower␣Middle␣Income␣like␣
       Vietnam)",
    2040: "2040␣(3,500␣kWh␣per␣capita␣@␣Upper␣Middle␣Income)",
    2050: "2050␣(3,500␣kWh␣per␣capita␣@␣High␣Income)"
}

# Plot 2023 & 2024 peak demand separately in Row 1
ax1 = axes[0, 0]
ax2 = axes[0, 1]

ax1.plot(df_2023['Peak␣Demand␣(Requirement)␣(MW)'], label="2023",
   linestyle='-', color="blue", linewidth=1)
ax2.plot(df_2024['Peak␣Demand␣(Requirement)␣(MW)'], label="2024",
   linestyle='--', color="red", linewidth=1)

ax1.set_title("2023␣Peak␣Demand␣Sorted␣(Source:␣NEA)")
ax2.set_title("2024␣Peak␣Demand␣Sorted␣(Source:␣NEA)")

for ax in [ax1, ax2]:
    ax.set_xlabel("Day␣Rank␣(Sorted␣by␣Peak␣Demand)")
    ax.set_ylabel("Peak␣Demand␣(MW)")
    ax.legend()
    ax.grid(True)

# Create subplots for different scenarios
for i, (ax, scenario) in enumerate(zip(axes[1], scenario_keys[:2]))
   :
    if scenario in scaled_dfs:
        for year in scaled_dfs[scenario].columns:
            ax.plot(scaled_dfs[scenario][year].sort_values(
               ascending=False).values,
                    label=f"{year}", linestyle='-', alpha=0.7,
                       color=colors[year])

    ax.set_title(scenario_titles[i])
    ax.set_xlabel("Day␣Rank␣(Sorted␣by␣Peak␣Demand)")
    ax.set_ylabel("Peak␣Demand␣(MW)")
    ax.legend()
    ax.grid(True)

# High Growth & Growth Target
ax_high = axes[2, 0]
ax_target = axes[2, 1]
```

```
if "High" in scaled_dfs:
    for year in scaled_dfs["High"].columns:
        ax_high.plot(scaled_dfs["High"][year].sort_values(ascending
            =False).values,
                     label=f"{year}", linestyle='-', alpha=0.7,
                        color=colors[year])

ax_high.set_title("High␣Growth␣Scenario")
ax_high.set_xlabel("Day␣Rank␣(Sorted␣by␣Peak␣Demand)")
ax_high.set_ylabel("Peak␣Demand␣(MW)")
ax_high.legend()
ax_high.grid(True)

if "Target" in scaled_dfs:
    for year in scaled_dfs["Target"].columns:
        ax_target.plot(scaled_dfs["Target"][year].sort_values(
            ascending=False).values,
                       label=growth_target_labels[year], linestyle=
                          '-', alpha=0.7, color=colors[year])

ax_target.set_title("Growth␣Target␣Scenario")
ax_target.set_xlabel("Day␣Rank␣(Sorted␣by␣Peak␣Demand)")
ax_target.set_ylabel("Peak␣Demand␣(MW)")
ax_target.legend()
ax_target.grid(True)

# Adjust layout and save image
plt.tight_layout()
image_filename = "Sorted_Peak_Demand_Comparison_Fixed.png"
plt.savefig(image_filename, dpi=300)
plt.show()

print(f"CSV␣files␣generated␣successfully.")
print(f"Image␣'{image_filename}'␣generated␣successfully.")
```

0.4 Monte Carlo Reliability Analysis

This section presents a Monte Carlo simulation approach to estimate power system reliability metrics, including Loss of Load Expectation (LOLE), Loss of Energy Expectation (LOEE), and Energy Index of Reliability (EIR). The methodology accounts for seasonal variations in capacity factors and the availability of generation units.

0.4.1 Python Code for Reliability Simulation

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import os

def monte_carlo_reliability(gen_file, load_file, num_simulations
    =100000):
    # Load Generation Data
    gen_data = pd.read_excel(gen_file)
    gen_data = gen_data[['Project', 'Capacity (MW)', 'FOR']].copy()
    gen_data['Availability'] = 1 - gen_data['FOR']

    # Load Peak Demand Data
    load_data = pd.read_csv(load_file)
    load_data['Date'] = pd.to_datetime(load_data['Date'])
    load_data['Month'] = load_data['Date'].dt.month

    # Seasonal Capacity Factors
    seasonal_capacity_factors = {
        "Winter": 0.25,
        "Pre-Monsoon": 0.70,
        "Monsoon": 0.9,
        "Post-Monsoon": 0.70
    }

    # Define seasons
    seasons = {
        "Winter_1": [1, 2, 3],
        "Pre-Monsoon": [4, 5],
        "Monsoon": [6, 7, 8, 9],
        "Post-Monsoon": [10, 11],
        "Winter_2": [12]
    }

    num_days = len(load_data)
    LOLE = 0
    LOEE = 0
    LOLE_list = []  # Store LOLE per simulation
    EENS_list = []  # Store LOEE per simulation

    # Precompute seasonal capacity factors
    seasonal_factors = np.ones(num_days)
    for season, months in seasons.items():
        idx = load_data['Month'].isin(months).values
```

```
    if "Winter" in season:
        seasonal_factors[idx] = seasonal_capacity_factors["
            Winter"]
    else:
        seasonal_factors[idx] = seasonal_capacity_factors[
            season]

# Convert load data to NumPy for efficiency
peak_demand = load_data['Peak Demand (Requirement) (MW)'].
    values

# Convert generator capacity and availability to NumPy arrays
gen_capacity = gen_data['Capacity (MW)'].values
gen_availability = gen_data['Availability'].values

# Monte Carlo Simulation
for _ in range(num_simulations):
    is_up_matrix = np.random.rand(len(gen_capacity), num_days)
        < gen_availability[:, None]
    available_capacity = np.sum(is_up_matrix * gen_capacity[:,
        None] * seasonal_factors, axis=0)

    daily_LOLP = (available_capacity < peak_demand)
    LOLE_sample = daily_LOLP.sum()  # LOLE for this simulation
    LOLE_list.append(LOLE_sample)  # Store for SE calculation

    daily_EENS = np.maximum(0, peak_demand - available_capacity
        ) * daily_LOLP
    LOEE_sample = daily_EENS.sum()  # LOEE for this simulation
    EENS_list.append(LOEE_sample)  # Store for SE calculation

    LOLE += LOLE_sample / num_simulations
    LOEE += LOEE_sample / num_simulations

# Energy Index of Reliability (EIR)
total_energy_demand = peak_demand.sum()
EIR_list = [1 - (loee / total_energy_demand) for loee in
    EENS_list]
EIR = 1 - (LOEE / total_energy_demand)

# Calculate Standard Error (SE) for LOLE, LOEE, and EIR
SE_LOLE = np.std(LOLE_list, ddof=1) / np.sqrt(num_simulations)
SE_LOEE = np.std(EENS_list, ddof=1) / np.sqrt(num_simulations)
SE_EIR = np.std(EIR_list, ddof=1) / np.sqrt(num_simulations)
```

```
    # Sorting Peak Demand by Subgroups
    sorted_load_data = load_data.copy()
    for season, months in seasons.items():
        subgroup_idx = sorted_load_data['Month'].isin(months)
        sorted_load_data.loc[subgroup_idx, 'Peak Demand (
           Requirement) (MW)'] = np.sort(
            sorted_load_data.loc[subgroup_idx, 'Peak Demand (
               Requirement) (MW)'].values
        )[::-1]

    return LOLE, SE_LOLE, LOEE, SE_LOEE, EIR, SE_EIR,
       sorted_load_data, available_capacity, EENS_list

# Define years and scenarios
years = [2030, 2035, 2040, 2050]
scenarios = ["BAU", "Medium", "High"]

# Dictionary to store results
results = []

for year in years:
    gen_file = f"For_{year}.xlsx"
    if not os.path.exists(gen_file):
        print(f"Skipping {gen_file} (File not found)")
        continue

    for scenario in scenarios:
        load_file = f"Annual_Peak_Demand_{scenario}_{year}
           _PolicyIntervention.csv"
        if not os.path.exists(load_file):
            print(f"Skipping {load_file} (File not found)")
            continue

        LOLE, SE_LOLE, LOEE, SE_LOEE, EIR, SE_EIR, sorted_load_data
           , available_capacity, EENS_list =
           monte_carlo_reliability(gen_file, load_file)

        # Append results
        results.append({
            "Year": year,
            "Scenario": scenario,
            "LOLE (days/year)": LOLE,
            "SE_LOLE": SE_LOLE,  # Standard Error for LOLE
            "LOEE (MWh/year)": LOEE,
            "SE_LOEE": SE_LOEE,  # Standard Error for LOEE
```

```
            "EIR": EIR,
            "SE_EIR": SE_EIR  # Standard Error for EIR
        })

        # Histogram of EENS Distribution
        plt.figure(figsize=(8, 5))
        plt.hist(EENS_list, bins=50, color='skyblue', edgecolor='
           black', alpha=0.7)
        plt.xlabel("Expected␣Energy␣Not␣Supplied␣(MWh)")
        plt.ylabel("Frequency")
        plt.title(f"EENS␣Distribution␣for␣{scenario}␣{year}")
        plt.grid(True)
        plt.savefig(f"EENS_Dist_{scenario}_{year}_PolicyInt.png")
        plt.close()

        # Time-Series of Available Capacity vs Load
        plt.figure(figsize=(10, 5))
        plt.plot(sorted_load_data.index, sorted_load_data['Peak␣
           Demand␣(Requirement)␣(MW)'], label="Peak␣Demand", color=
           'r')
        plt.plot(sorted_load_data.index, available_capacity, label=
           "Available␣Capacity", color='g')
        plt.xlabel("Day␣Rank␣(Sorted␣by␣Peak␣Demand␣within␣Seasons)
           ")
        plt.ylabel("MW")
        plt.title(f"Available␣Capacity␣vs␣Peak␣Demand␣({scenario}␣{
           year})")
        plt.legend()
        plt.grid(True)
        plt.savefig(f"Cap_vs_Demand_{scenario}_{year}_PolicyInt.png
           ")
        plt.close()

# Convert results to DataFrame and save
results_df = pd.DataFrame(results)
results_df.to_csv("
   Monte_Carlo_Reliability_Result_lakshPolicyIntervention.csv",
   index=False)

print("\nMonte␣Carlo␣Simulation␣Completed␣for␣All␣Scenarios␣&␣Years
   .")
print(results_df)
```

PUBLICATION

Conference paper

[IOEGC16] Editor Decision External Inbox ×

Suwarna Lingden <conference-noreply@ioe.edu.np> Wed, Apr 2, 12:09 AM (4 days ago)
to me, Upendra, Ashish, Dhiraj, Sochindra, Dinesh

pawan karki, Upendra Bhattarai, Ashish Oliya, Dhiraj Yadav, Sochindra Roy, Dinesh Ghimire:

We are pleased to inform you that your manuscript titled "Long Term Analysis of Generation Adequacy of INPS" submitted to 16th IOE Graduate Conference is **Accepted** for presentation in the Conference as well as inclusion in the Peer-Reviewed Proceedings. Please note that inclusion in hard copy proceedings is contingent upon your timely response to further edits, if any, during the publication process.

With Warm Regards,
IOEGC-16 Editorial Team

Dinesh Kumar Ghimire Wed, Apr 2, 4:44 AM (4 days ago)
to Suwarna, me, Upendra, Ashish, Dhiraj, Sochindra

Thank you so much for the great news!
Dinesh

Acceptance email for the paper titled "Long Term Analysis of Generation Adequacy of INPS" at the 16th IOE Graduate Conference.

Long Term Analysis of Generation Adequacy of INPS

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Abstract
The generation adequacy analysis determines how well a power system provides projected demand levels under random equipment failures. This analysis evaluates the INPS generation capacity to determine if it provides sufficient power to serve consumers despite unpredictable factors. The hierarchical reliability assessment begins at the HL-I level to evaluate generation capacity adequacy by disregarding transmission limitations. The methodology applies probabilistic calculations over deterministic methods to handle power system randomness by combining Loss of Load Expectation (LOLE) and Expected Energy Not Supplied (EENS) reliability metrics. Load forecasting is performed through econometric models using GDP per capita and population data. The modeling system includes projects from multiple development stages which operate at different time intervals. The representation of seasonal variations uses Annual load curves. Monte Carlo simulation is the primary analytical instrument that generates random generation state samples from Forced Outage Rates to determine available capacity against demand. Multiple economic growth scenarios are assessed through an iterative process that generates reliability indices consisting of LOLE and EENS to determine system adequacy.

Keywords
Energy Security, Generation Adequacy, Reliability Analysis, Monte Carlo Simulation, Loss of Load Expectation (LOLE), Integrated Nepal Power System (INPS), Nepal Electricity Authority (NEA), Power System Planning

1. Introduction

Nepal's electricity generation and capacity have seen significant growth, with the Nepal Electricity Authority (NEA) reporting a total installed capacity of 3157.182 MW, including significant contributions from hydropower (both the NEA and independent power producers) and solar energy [1]. The NEA Energy Trade Department also confirms this installed capacity, reflecting Nepal's increasing reliance on renewable energy sources [2]. Moreover, 11256.92 MW of hydro projects have applied for construction licenses, indicating strong future growth [3]. Nepal's energy demand is projected to grow alongside its socioeconomic development, as indicated by rising peak load, energy sales, and electricity consumption trends[4] as shown in Figure 1. The current installed capacity of Nepal's electricity generation is **3157.182 MW** [2], and future projections indicate substantial growth, with over **11256.92 MW** of hydro projects having applied for construction licenses, while additional capacities are under construction or at the survey stage [3]. The summary of the status of power plants is shown in Table 1.

A power system's primary function is to provide reliable and economical electricity, but achieving continuous availability is challenging due to random failures beyond engineers' control. Proper reserve capacity planning is crucial, as insufficient investment leads to frequent interruptions, while excessive investment results in high costs passed to consumers. Since exact methods for determining reserve capacity do not exist, probability theory provides a systematic approach to balancing reliability and economic efficiency [5]. The analysis of reliability is categorized into three hierarchical levels (HLs): HL-I (generation adequacy), HL-II (bulk transmission adequacy), and HL-III (distribution reliability) as summarized in Figure 2. HL-I analysis focuses on the sufficiency of generating capacity to meet demand, using probabilistic indices such as Loss of Load Expectation (LOLE), Loss of Energy Expectation (LOEE), and Frequency and Duration (F&D). There are no transmission constraints, and all generation reaches the load, as shown in Figure 3. Traditional deterministic approaches are increasingly replaced by probabilistic methods to reflect the stochastic nature of power systems [6].

Status	Capacity (MW)
NEA PPA Operational (2024)	2495.612
Under Construction (Financial Closure)	3905.724
Under Construction (Without Financial Closure)	3899.399
Hydro Connected Capacity	3241.584
Hydro Construction License Approved	10054.73
Hydro Construction License Applied	11256.92
Hydro Survey License Approved	8041.128
Hydro Survey License Applied	3643.05

Table 1: Hydropower Project Status and Capacity [3]

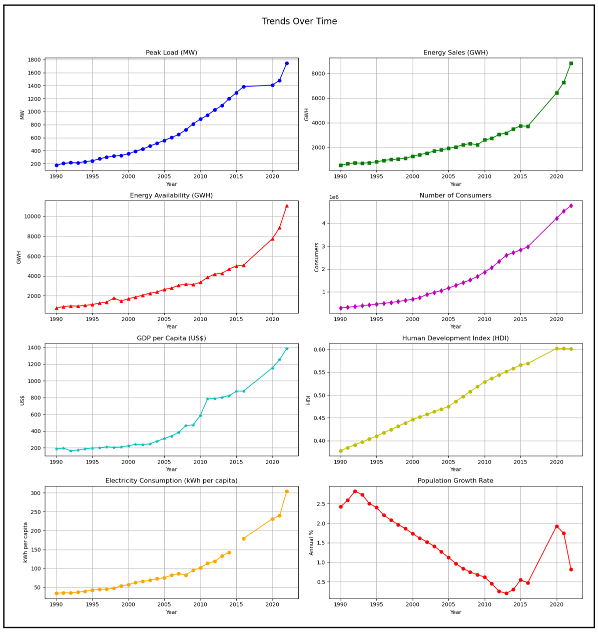

Figure 1: Trends in Peak Load, Energy Sales, Energy Availability, Number of Consumers, GDP per Capita, and HDI over Time [7, 8]

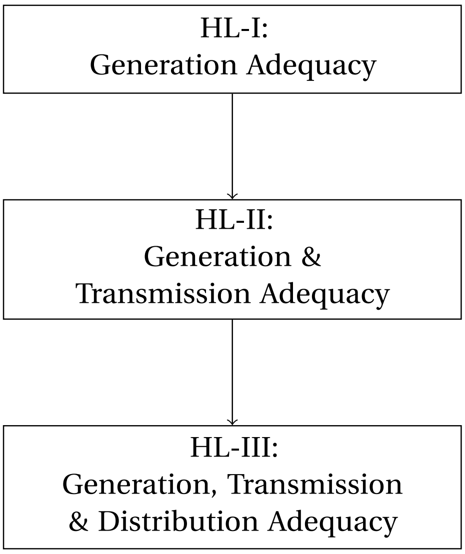

Figure 2: Classification of HL-1, HL-2, and HL-3 Reliability

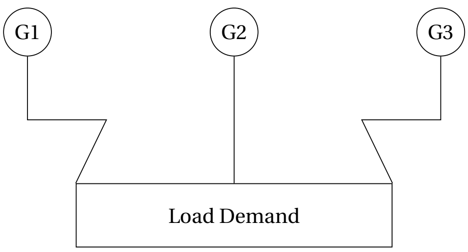

Figure 3: Model for HL-1 Analysis

2. Methodology

2.1 Overall Process

The study uses the Non-Sequential Monte Carlo Method to analyze generation adequacy only (HL-I level). It uses a state sampling method to randomly assign generator outages based on Forced Outage Rate (FOR) and computes Loss of Load Expectation (LOLE) and Expected Energy Not Supplied (EENS). The general workflow is shown in Algorithm 1.

Algorithm 1 Generation Adequacy Simulation

Start
Forecast Load Data
Input Generation Capacity & FOR
Monte Carlo Simulation
Compute LOLE & EENS
Analyze Results
End

- **FOR (Forced Outage Rate)** - Probability that a generator is unavailable due to forced outages.

$$FOR = \frac{\text{Forced Outage Hours}}{\text{Forced Outage Hours} + \text{Service Hours}} \tag{1}$$

where *Forced Outage Hours* is the total time the generator was out of service due to failures, and *Service Hours* is the total time the generator was operational.[9]

- **LOLE (Loss of Load Expectation)** - Expected number of days with load shedding.

$$LOLE = \sum_{i \in S} p_i T \tag{2}$$

where p_i is the probability of system state i leading to load loss, and T is the time period in days.[9]

- **LOEE (Loss of Energy Expectation)** - Total energy not supplied due to outages.

$$LOEE = \sum_{i \in S} p_i C_i T \tag{3}$$

where C_i is the amount of energy curtailed in state i.[9]

- **EENS (Expected Energy Not Supplied)** - Probability-weighted sum of unmet demand.

$$EENS = \sum_{i=1}^{N} x_i C_i \Delta t \tag{4}$$

where x_i represents the loss of load event at time step i, C_i is the curtailed energy, and Δt is the time interval.[9]

- **LOLP (Loss of Load Probability)** - Probability that available generation is insufficient.

$$LOLP = \sum_{i} \in S p_i \tag{5}$$

where S is the set of state of the system with load loss.[9]

2.2 Generation Model

The FOR value for the existing available generation plant is taken from the NEA Report. For unavailable data and future generation plants, the FOR value is assumed to be **0.02.** Seasonal variations in hydropower availability are modeled using predefined capacity factors: 90% during the monsoon (June–September), 40% in the dry months (January–March, December), and 70% in the pre-monsoon (April–May) and post-monsoon (October–November) periods. The following assumptions are made about generation modeling:

- **By 2030:** Generation capacity will include operational projects and those under construction with financial closure.
- **By 2035:** Additional capacity will come from projects currently under construction without financial closure.
- **By 2040:** Generation capacity will include operational projects and those under construction with and without financial closure, and 90% of construction licenses approved and 80% of construction licenses applied.
- **By 2050:** Generation capacity will include operational projects and construction projects without financial closure, and 90% of construction licenses approved and 80% of construction licenses applied, along with 60% of survey licenses approved and 50% of survey licenses applied.

This phased approach ensures a structured and scalable expansion of the generation capacity over time.

2.3 Load Forecasting

2.3.1 Peak Forecast using Econometric Model

The econometric model uses a multiple linear regression formula [10]:

$$D_t = \beta_0 + \beta_1 X_1(t) + \beta_2 X_2(t) + \cdots + \beta_n X_n(t) + \epsilon_t$$

Where:

- D_t: Electricity demand or peak load at time t.
- β_0: Intercept term.
- $\beta_1, \beta_2, \ldots, \beta_n$: Coefficients representing the impact of independent variables on demand.
- $X_1(t), X_2(t), \ldots, X_n(t)$: Independent variables such as GDP, population growth, electrification rate, etc.
- ϵ_t: Error term that accounts for unexplained variability.

2.3.2 Annual Load Curve Forecast

Figure 7 shows the annual load curve of 2023 and 2024, which exhibits the same pattern. Therefore, the projected annual load curve for each future year and scenario is computed using a scaling factor based on the maximum observed peak demand in 2024.

$$\text{Scaling Factor} = \frac{\text{Projected Peak Demand for Year } Y}{\text{Max Peak Demand in 2024}} \quad (6)$$

Using this factor, the scaled peak demand values for each day are calculated as:

$$\text{Peak Demand}_Y(d) = \text{Peak Demand}_{2024}(d) \times \text{Scaling Factor} \quad (7)$$

where:

- d represents the ranked day index (sorted from highest to lowest peak demand).
- $\text{Peak Demand}_Y(d)$ is the forecasted peak demand for a given future year Y.
- $\text{Peak Demand}_{2024}(d)$ is the historical peak demand from 2024 data.

2.4 Monte Carlo Simulation

Monte Carlo simulation (MCS) is widely used for power system reliability analysis, particularly to assess the adequacy of the generation. Unlike traditional deterministic methods, MCS models generation states probabilistically based on the Forced Outage Rate (FOR). The process involves multiple iterations of **state sampling**, generation availability computation, and load curtailment analysis. [11] The calculated reliability indices, such as LOLE (load loss expectation) and EENS (expected energy not supplied), provide a probabilistic measure of the adequacy of the system.[12] As shown in Algorithm 2, the Monte Carlo simulation iteratively determines the adequacy of the system.[13]

Algorithm 2 Monte Carlo Simulation for Generation Adequacy

1: **Initialize:** $D = 0, N = 0$
2: **for** each simulation iteration **do**
3:     Generate a uniform random number $U_1 \in (0,1)$
4:     **if** $U_1 < FOR$ **then**
5:         Unit 1 is in the down state ($C_1 = 0$)
6:     **else**
7:         Unit 1 operates at full capacity ($C_1 = 40$)
8:     **end if**
9:     **for** units $i = 2$ to 5 **do**
10:         Repeat steps 2–5 to determine C_i
11:     **end for**
12:     Compute total available capacity: $C = \sum_{i=1}^{5} C_i$
13:     Generate another uniform random number $U_2 \in (0,1)$
14:     Determine load level L using the cumulative probability function
15:     **if** $C < L$ **then**
16:         Increment D: $D = D + 1$
17:     **end if**
18:     Increment N: $N = N + 1$
19: **end for**
20: Compute LOLP: $LOLP = \frac{D}{N}$
21: Compute LOLE: $LOLE = LOLP \times 365$
22: Repeat steps until convergence criteria are met.

3. Result and Discussion

3.1 Peak Load Forecast

The correlation heatmap was analyzed to identify highly correlated parameters. Due to multicollinearity, only the most representative variables were retained. Ultimately, GDP per capita and population were selected as the most significant variables, as they effectively capture economic and demographic influences while minimizing redundancy. This ensures a more robust and interpretable analysis.

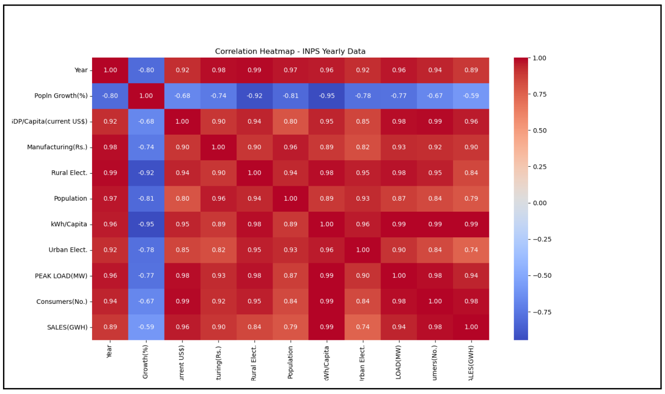

Figure 4: Correlation Heatmap of Different Parameters & Peak Load

The peak load forecast is based on a multiple linear regression model, where GDP per capita and population are used as independent variables. The general form of the regression equation is:

$$P_t = \beta_0 + \beta_1 X_1(t) + \beta_2 X_2(t) + \epsilon_t \tag{8}$$

where:

- P_t = Peak Load (MW) at time t
- β_0 = Intercept term
- β_1, β_2 = Regression coefficients
- $X_1(t)$ = GDP per capita at time t
- $X_2(t)$ = Population at time t
- ϵ_t = Error term

Using the estimated regression coefficients from the OLS model, the peak load for future years is calculated as:

$$P_{\text{future}} = \beta_0 + \beta_1 \cdot \text{GDP}_{\text{future}} + \beta_2 \cdot \text{Population}_{\text{future}} \tag{9}$$

where GDP and population are projected based on assumed growth rates:

$$\text{GDP}_{\text{future}} = \text{GDP}_{\text{current}} \times (1+g)^{(t-t_0)} \tag{10}$$

$$\text{Population}_{\text{future}} = \text{Population}_{\text{current}} \times (1+p)^{(t-t_0)} \tag{11}$$

where:

- g = Annual GDP growth rate
- p = Annual population growth rate
- t_0 = Base year (latest actual data year)
- t = Future year

To account for system losses, a 20% adjustment is applied. This final adjusted peak load projection is used for long-term power system planning.

The peak load forecast is estimated using a multiple linear regression model with GDP per capita and population as independent variables. Figure 5 shows the historical and forecasted peak load, while Figure 6 compares the actual vs. predicted peak load for 2019–2024.

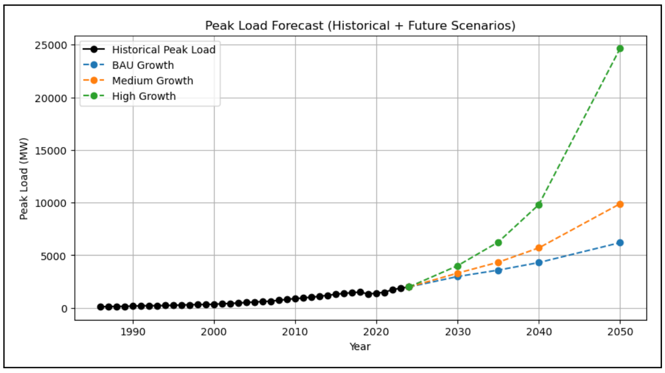

Figure 5: Historical and Forecasted Peak Load under Different Growth Scenarios

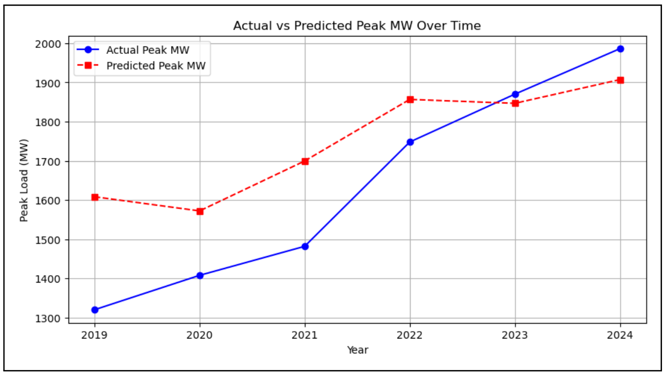

Figure 6: Comparison of Actual vs Predicted Peak Load for 2019–2024

Table 2 summarizes the Ordinary least-squares(OLS) regression model, which achieves an R^2 of 0.986, explaining 98.6% of the peak demand variance.

Table 2: OLS Regression Summary

Metric	Value
R-squared	0.986
Adjusted R-squared	0.985
F-statistic	1031
P-value (Prob F-stat)	2.24e-28
GDP per Capita Coefficient	1.1182
Population Coefficient	3.371e-05
Durbin-Watson	1.050

Table 3: Predicted Peak Load (MW) under Different Growth Scenarios

Year	BAU	Medium	High	Target
2030	2,983	3,305	4,012	-
2035	3,588	4,339	6,252	16,365
2040	4,309	5,703	9,818	22,900
2050	6,199	9,895	24,655	58,825

3.2 Annual Load Curve Forecast

The projected peak demand for each future year is computed using a scaling factor based on the maximum observed peak demand in 2024.

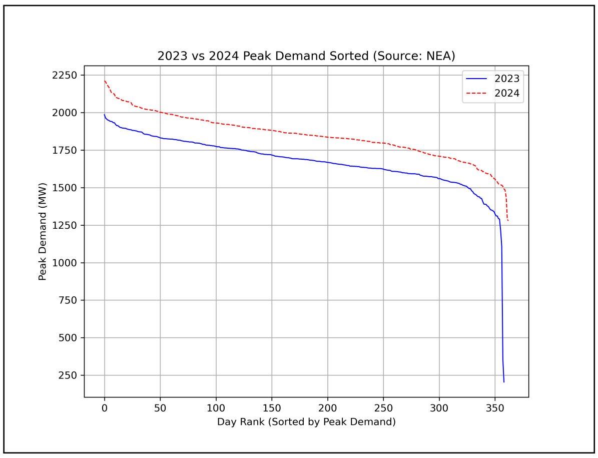

Figure 7: 2023-2024 Annual Load Curve

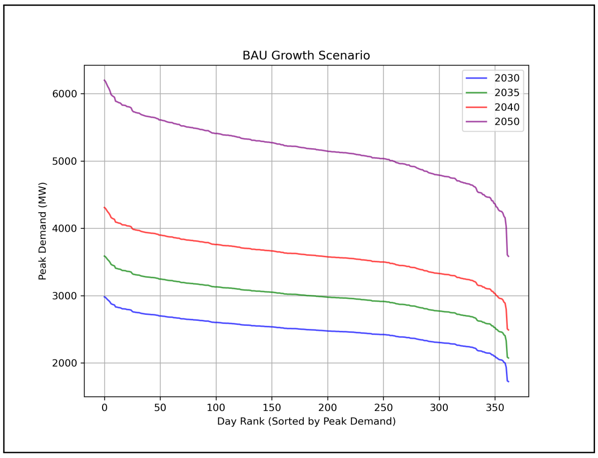

Figure 8: BAU Growth Scenario

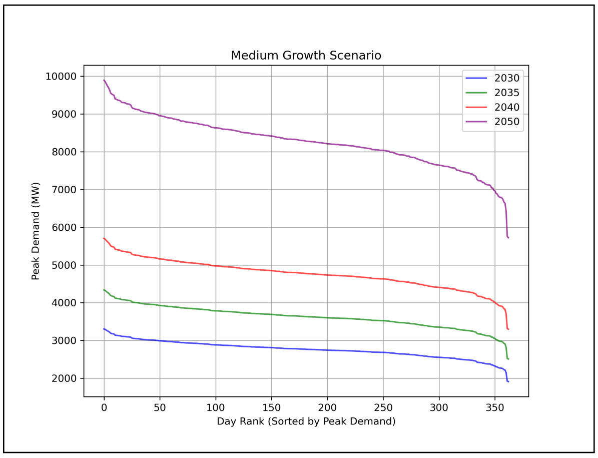

Figure 9: Medium Growth Scenario

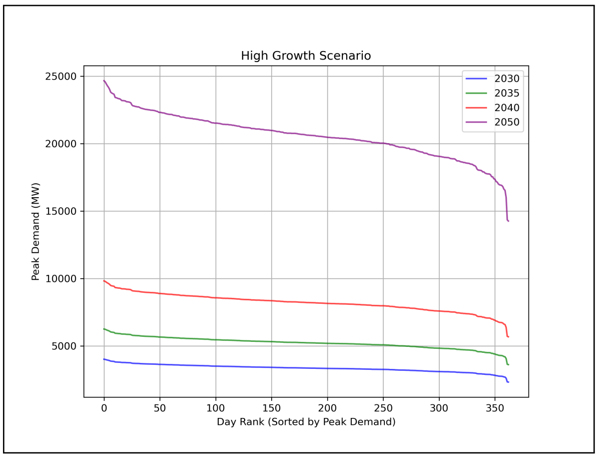

Figure 10: High Growth Scenario

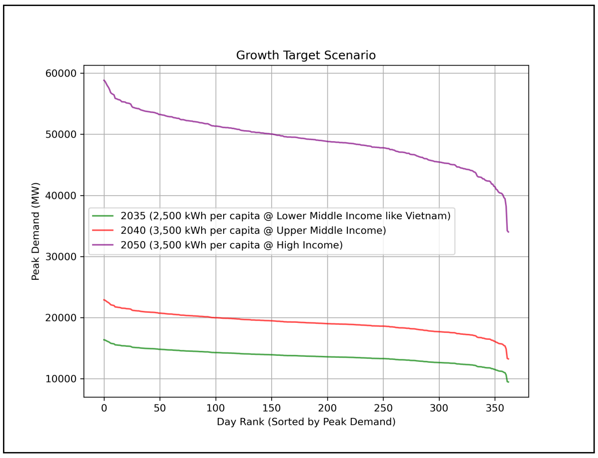

Figure 11: Growth Target Scenario

3.3 Reliability Under Different Scenarios

3.3.1 Capacity vs Peak Demand

The available capacity obtained after the Monte Carlo Simulation was compared with the peak demand in different scenarios, as shown in Figures 12 to 20 to assess the adequacy of the system.

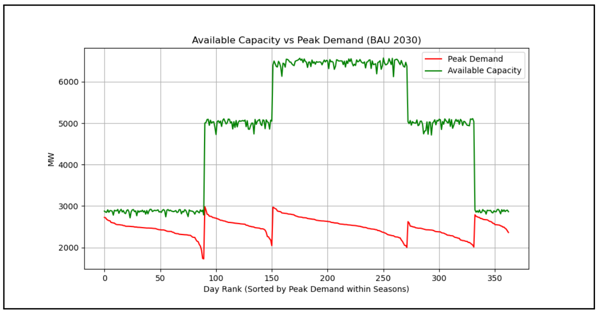

Figure 12: Comparison of Available Capacity vs. Peak Demand - BAU 2030

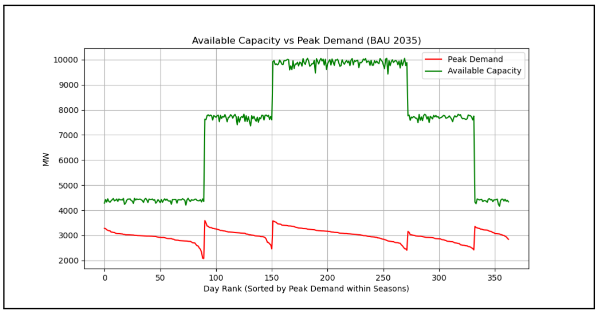

Figure 13: Comparison of Available Capacity vs. Peak Demand - BAU 2035

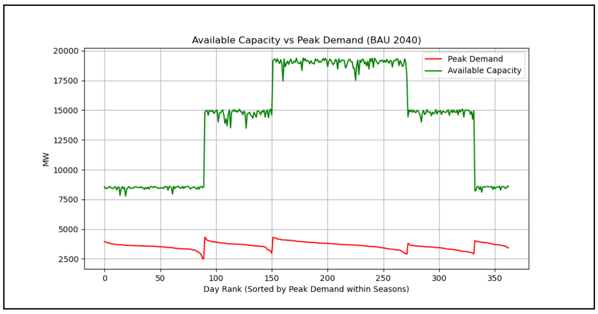

Figure 14: Comparison of Available Capacity vs. Peak Demand - BAU 2040

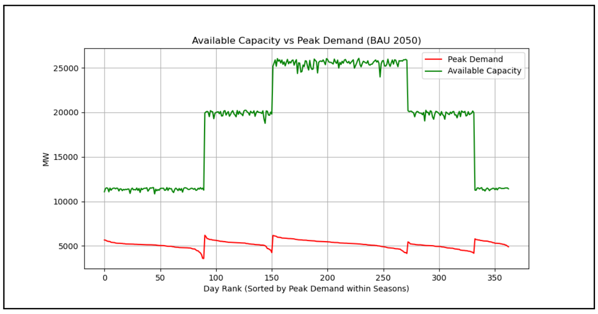

Figure 15: Comparison of Available Capacity vs. Peak Demand - BAU 2050

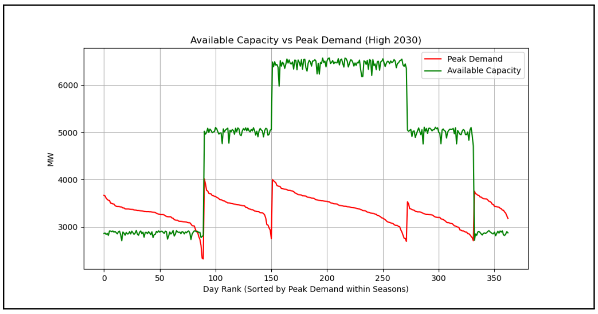

Figure 16: Comparison of Available Capacity vs. Peak Demand - High Growth 2030

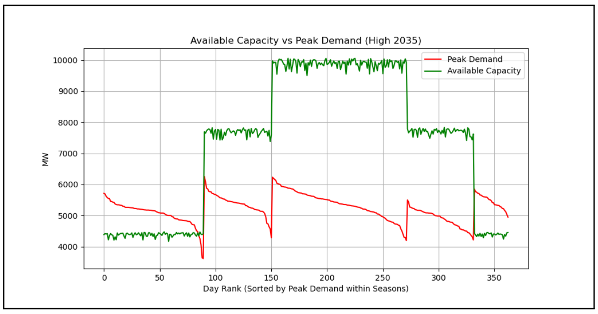

Figure 17: Comparison of Available Capacity vs. Peak Demand - High Growth 2035

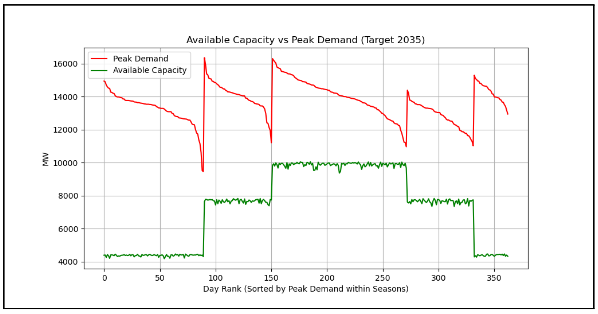

Figure 18: Comparison of Available Capacity vs. Peak Demand - Target Growth 2035

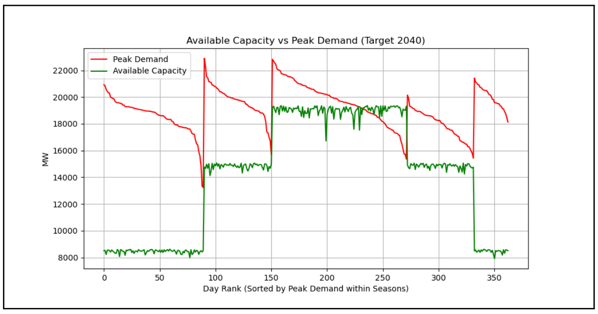

Figure 19: Comparison of Available Capacity vs. Peak Demand - Target Growth 2040

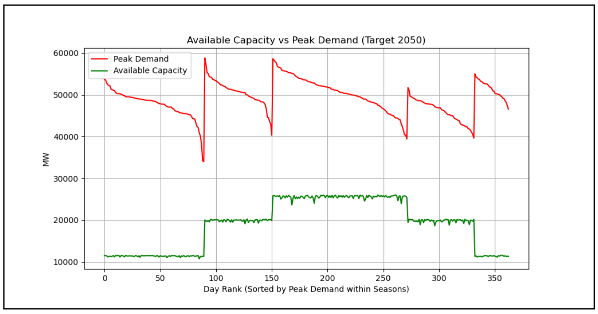

Figure 20: Comparison of Available Capacity vs. Peak Demand - Target Growth 2050

3.3.2 Expected Energy Not Supplied (EENS)

The Expected Energy Not Supplied (EENS) distribution under some sample demand growth scenarios is shown from Figures 21 to 35.

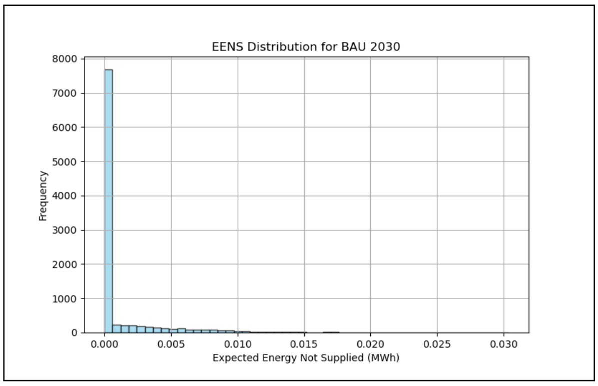

Figure 21: EENS Distribution - BAU 2030

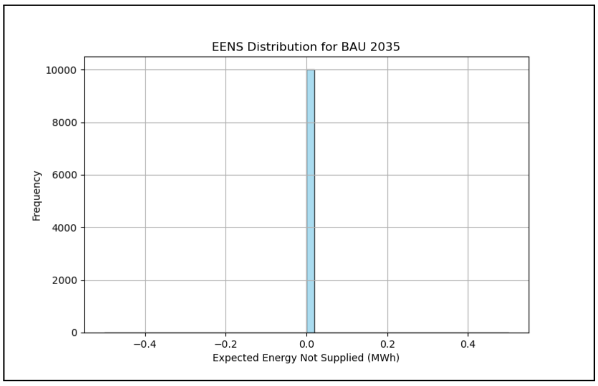

Figure 22: EENS Distribution - BAU 2035

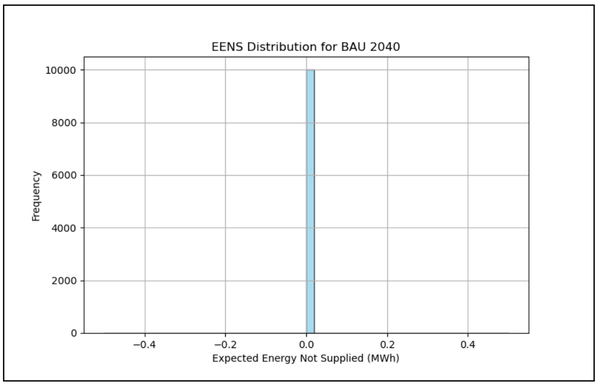

Figure 23: EENS Distribution - BAU 2040

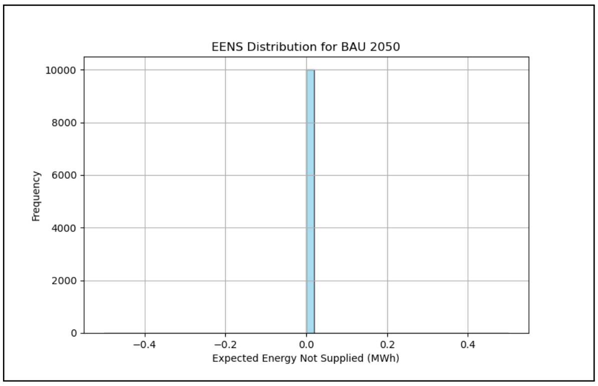

Figure 24: EENS Distribution - BAU 2050

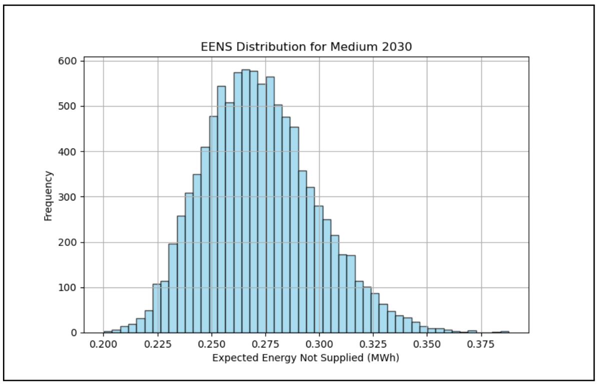

Figure 25: EENS Distribution - Medium 2030

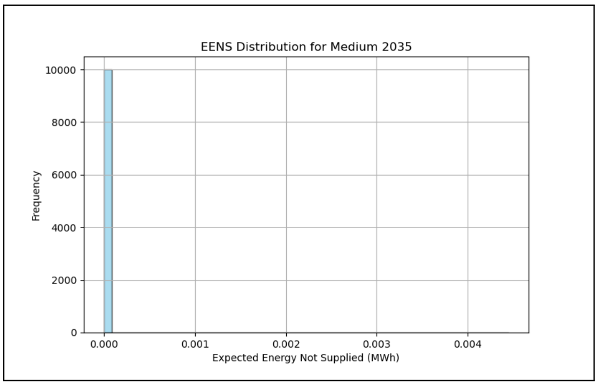

Figure 26: EENS Distribution - Medium 2035

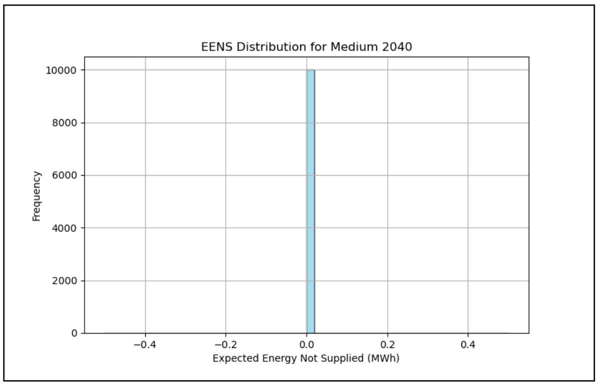

Figure 27: EENS Distribution - Medium 2040

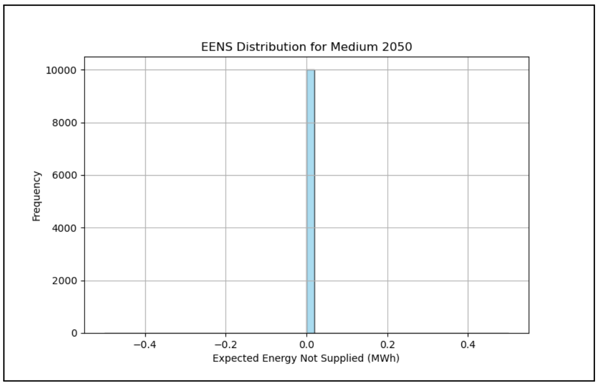

Figure 28: EENS Distribution - Medium 2050

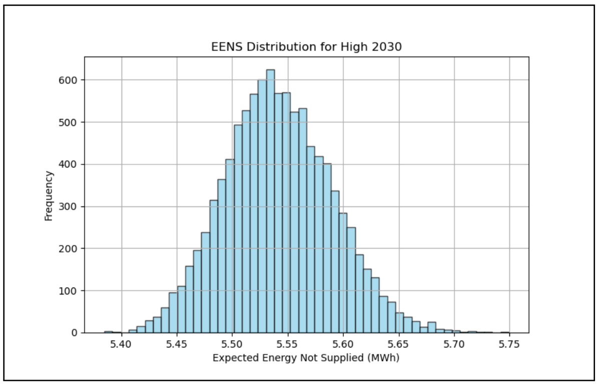

Figure 29: EENS Distribution - High 2030

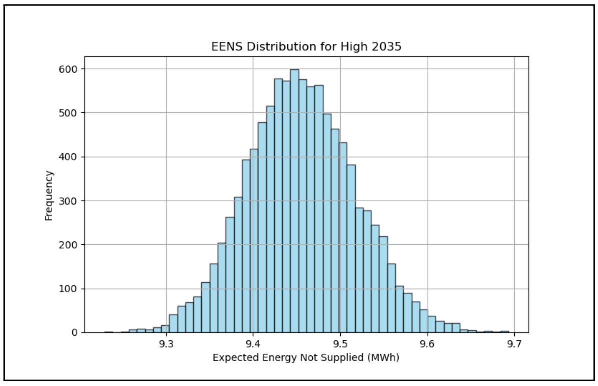

Figure 30: EENS Distribution - High 2035

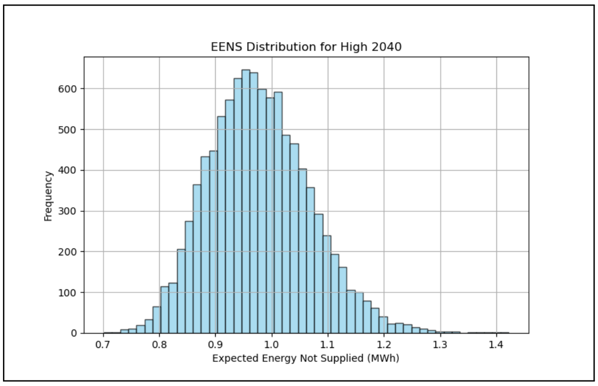

Figure 31: EENS Distribution - High 2040

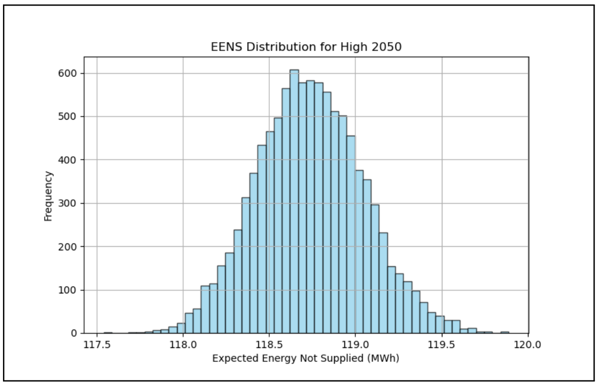

Figure 32: EENS Distribution - High 2050

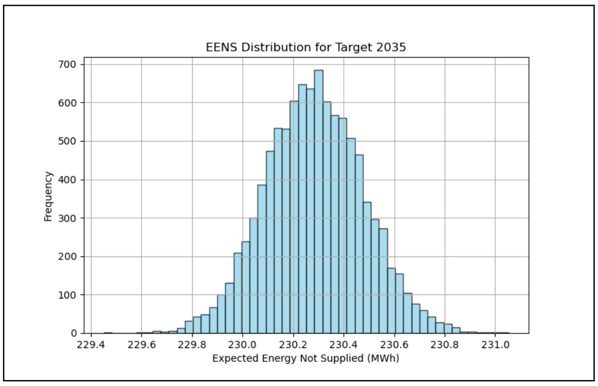

Figure 33: EENS Distribution - Target 2035

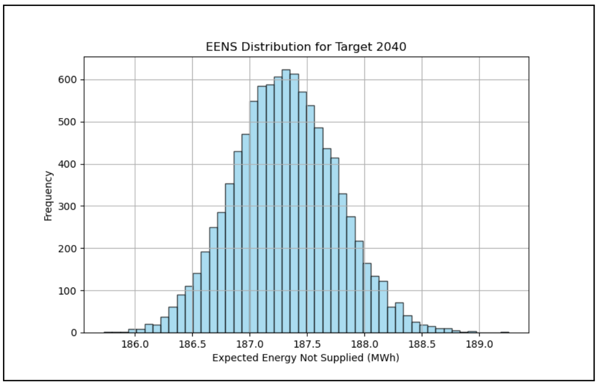

Figure 34: EENS Distribution - Target 2040

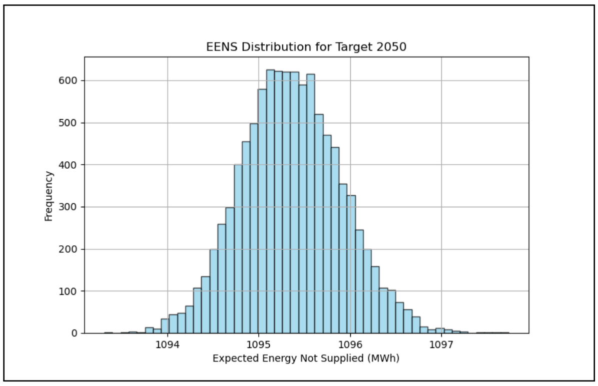

Figure 35: EENS Distribution - Target 2050

3.4 Reliability Metrics Summary

Table 4 presents a summary of Loss of Load Expectation (LOLE) and Expected Energy Not Supplied (EENS) for all scenarios. The results are obtained by using 100,000 simulations. Figure 36 shows that the standard error decreases from 0.02 at 10,000 simulations to 0.01 at 40,000 simulations, and with minimal reduction beyond 100,000, justifying its selection as the stopping point. Similarly, for the test data for the 2023 INPS load data & Major Hydropower, different numbers of simulations were plotted, and Figure 37 shows that after 100,000 simulations, the result is stable.

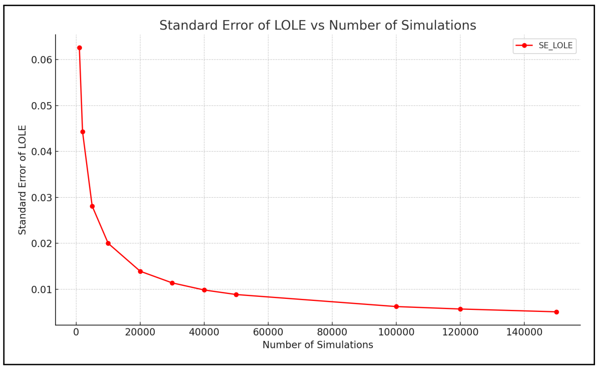

Figure 36: Standard Error vs No. of Simulations

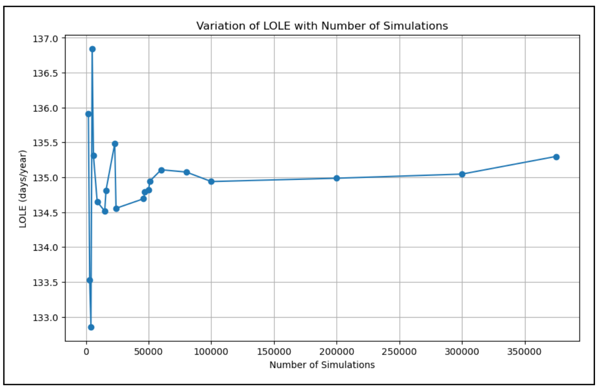

Figure 37: No. of Simulations vs LOLE

Table 4: Reliability Metrics for Different Scenarios

Year	Scenario	LOLE (days/year)	EENS (MWh/year)
2030	BAU	0.29488	12.5738
2030	Medium	27.50315	2726.5605
2030	High	115.341	55416.797
2035	BAU	0.0000	0.0000
2035	Medium	0.00052	0.0175
2035	High	116.21541	94552.9717
2035	Target	363.0000	2302847.403
2040	BAU	0.0000	0.0000
2040	Medium	0.0000	0.0000
2040	High	30.82378	9808.8051
2040	Target	325.15248	1873135.910
2050	BAU	0.0000	0.0000
2050	Medium	0.0000	0.0000
2050	High	197.43874	1187358.776
2050	Target	363.0000	10953555.880

3.5 Result Discussion

Reliability analysis demonstrates varying supply adequacy across different scenarios:

- In 2030, the BAU scenario experiences minimal reliability concerns with a LOLE of 0.29 days/year and EENS of 12.57 MWh/year. However, higher consumption scenarios, such as Medium and High, significantly increase shortages, reaching LOLE of 27.50 days/year and 115.34 days/year, respectively, with EENS peaking at 55,416.8 MWh/year.
- By 2035, the BAU and Medium scenarios maintain supply adequacy with near-zero LOLE. However, the High scenario leads to a significant reliability issue, with LOLE of 116.22 days/year and EENS of 94,552.97 MWh/year. The Target scenario results in extreme supply inadequacy, with LOLE of 363 days/year and EENS of 2.30 million MWh/year.
- In 2040, all BAU and Medium scenarios show no reliability concerns. However, the High scenario results in moderate shortages, with LOLE of 30.82 days/year and EENS of 9,808.81 MWh/year. The Target scenario leads to significant supply gaps, with LOLE of 325.15 days/year and EENS of 1.87 million MWh/year.
- By 2050, the BAU and Medium scenarios continue to meet demand without shortages. However, the High scenario experiences substantial deficits, with LOLE of 197.44 days/year and EENS of 1.18 million MWh/year. The Target scenario shows severe supply inadequacy, with LOLE of 363 days/year and EENS exceeding 10.95 million MWh/year.

4. Conclusion

The analysis of the adequacy of the Nepal Integrated Power System (INPS) reveals that under business as usual (BAU) and medium growth scenarios, the system maintains sufficient capacity with near zero LOLE and EENS from 2035 to 2050, ensuring a reliable power supply.

However, challenges arise in high-demand scenarios. In 2030, the high-growth scenario results in an LOLE of 115.34 days/year and an EENS of 55,416.80 MWh/year, indicating moderate supply concerns. By 2035, the Vietnam-level consumption target (2,500 kWh per capita) leads to severe reliability issues, with an LOLE of 363 days/year and an EENS of 2.30 million MWh/year. In 2040, the high-growth scenario yields an LOLE of 30.82 days/year and an EENS of 9,808.81 MWh/year, while the upper-middle-income target significantly increases LOLE to 325.15 days/year and EENS to 1.87 million MWh/year. By 2050, the high growth scenario results in an LOLE of 197.44 days/year and an EENS of 1.18 million MWh/year, while the high income target leads to critical supply inadequacy with an LOLE of 363 days/year and an EENS exceeding 10.95 million MWh/year. The results of econometric modeling that uses GDP per capita and population data ($R^2 = 0.986$) show that Nepal's power system has good reliability potential, but achieving economic goals alongside generation expansion will require detailed planning along with additional capacity installations.

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PLAGIARISM TEST REPORT

Pawan Karki

Long Term Analysis of Generation Adequacy of INPS

Tribhuvan University

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