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**Assessment of Generation Adequacy of Integrated Nepal Power System for Next
10 Years**

by
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ABSTRACT

Electricity is essential for everyday life and plays a crucial role in the development of any sector of a country. To ensure efficient and reliable supply, it is important to deliver electricity with good quality. The quality of electricity is measured by parameters such as voltage, frequency, reliability, and power loss. Among the key indicators of power system reliability are system security and adequacy. Power system adequacy refers to the ability of available generation to meet the electricity demand under normal conditions. It can be evaluated using two approaches: deterministic and probabilistic. In this thesis, generation adequacy assessment is done using analytical approach for the existing INPS, assuming that there is no failure in the transmission line. First, Capacity outage probability table of all seven provinces are evaluated for wet, dry and normal seasons separately because there is low generation in dry season as compare to normal season and there is always high generation in wet season resulting in variation in reserve margin in three different seasons. After that, all those COPT for respective seasons are combined to evaluate adequacy of INPS in different seasons. Reliability indices evaluated on different seasons are combined to get a LOLE and EENS of existing INPS. While doing the analysis, energy import during dry season is not considered to study the worst-case scenario. It is found that INPS has low reliability due to a lower reserve margin in the dry season. Furthermore, load forecasting is done for the next 10 years using two ML algorithms, LSTM and ANN-MLP, to identify system adequacy to meet the future load demand. It is found that LSTM can forecast with better accuracy compared to ANN-MLP. After forecasting peak load for next decade, adequacy assessment is done to identify whether expected generation-currently on construction phase-which is assumed to be connected to national grid in the period of next 10 years will be sufficient to meet the expected load demand. It is concluded that if the growth rate of consumers remains the same in the future as in the past, INPS will have acceptable reliability with low LOLE and EENS. However, if energy consumption increases rapidly, INPS will again lose reliability, and the system will not be adequate to supply the load demand.

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ABBREVIATIONS

ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
COPT	Capacity Outage Probability Table
EENS	Expected Energy Not Supplied
FOR	Forced Outage Rate
HLI	Hierarchy Level I
HLII	Hierarchy Level II
HLIII	Hierarchy Level III
INPS	Integrated Nepal Power System
LOLE	Loss of Load Expectation
LOLP	Loss of Load Probability
LSTM	Long Short Term Memory
MCS	Monte Carlo Simulation
MLP	Multilayer Perceptron
MW	Mega Watt
NEA	Nepal Electricity Authority
RBTS	Roy Billinton Test System
SARIMA	Seasonal Autoregressive Integrated Moving Average
SDA	Supply Demand Algorithm

CHAPTER 1. INTRODUCTION

1.1. Background

Electricity plays a vital role in our daily lives, powering everything from our homes to industries. It is generated from diverse sources, ranging from renewable like solar, wind and hydro to non-renewable such as coal and natural gas. Most of the power plants, which generates electricity, are often located far away from cities and towns where people live and work. So, we need transmission lines to carry electricity over long distances to where it's needed most. The whole system of generating electricity, moving it through these transmission lines, and then distributing it to the locations where it is required is called a power system.

Power system needs to provide reliable, efficient and economical supply of electrical energy to the consumers. A high degree of reliability ensures that electricity supply interruptions are minimized, as disruptions can significantly impact consumers. For instance, industrial operations may experience curtailment, leading to reduced production capacity and loss of potential profit. This affects both the industry directly and related sectors indirectly, such as commercial and domestic users. In commercial sector, interrupted power supply can disrupt daily operations. Also, in the domestic sector, power outages disrupt daily routines, impact household appliances, and compromise comfort and safety. Therefore, ensuring a stable and cost-effective power supply is crucial to mitigate these impacts and support economic activities across all sectors.

Reliability and economy are two major constrains in power systems. Ensuring reliability typically necessitates increased investment in infrastructure, maintenance, and capacity, which can strain economic resources. However, this increased investment can be costly and affect the overall economy. On the other hand, if financial resources are limited, it can lead to compromises in system reliability due to inadequate upgrades or maintenance. So, finding the right balance between these two factors is key to running a power system effectively. These facilities include the necessary generation systems to produce the required amount of energy, as well as the associated transmission to transmit required energy and distribution systems to deliver this energy to its consumers.

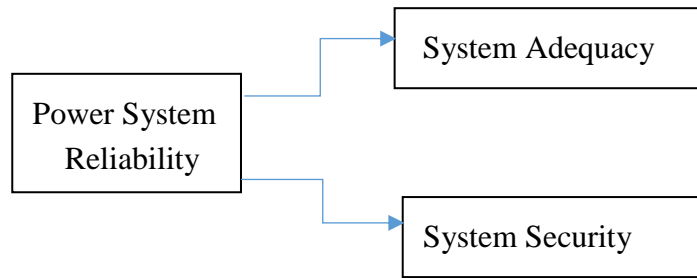


Figure 1.1: Division of Power System Reliability

System adequacy is evaluated under steady-state conditions, without considering the performance of the power system during disturbances.

Also, many disturbances like voltage, transient and dynamic instability can occur in the power system. The ability of the system to respond to these disturbances is known as power system security. This capability ensures the system remains stable and operational during and after such disruptions. Therefore, Power system reliability is the ability of power systems to meet the reliability and security of the system.

Modern power system networks are highly integrated, complex, and extensive. Analysing the entire network as a single entity in a realistic and exhaustive manner requires very powerful computer setups. Therefore, evaluating the whole network in one go is often impractical. To facilitate easier and faster calculations and analysis, the network can be divided into appropriate subsystems. This approach allows each subsystem to be evaluated separately, making the overall analysis more manageable and efficient.

Dividing the whole system based on its main functional zone is the best approach. Based on this, divisions are:

1. Generation System
2. Composite (Bulk power) system
3. Distribution system

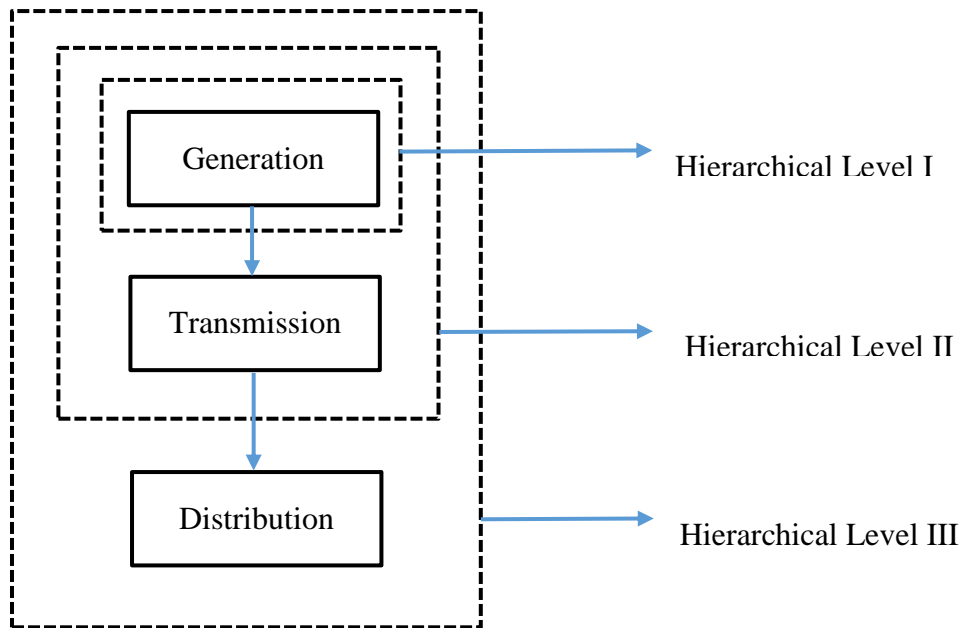


Figure 1.2: Hierarchical Levels

These functional zones can also be subdivided into many sub zones like individual generating stations, substations and protection systems. The concept of hierarchical order has been developed to provide a consistent method for identifying and grouping these functional zones. Hierarchical level I of Figure 1.2 refers to its generation only assuming that there is no any failure in transmission line. On this level, total generation connected to system without considering transmission system is evaluated to determine its adequacy to meet the total system load demand. Hierarchical level II refers to the combined system considering generation and transmission, also known as the bulk power system, and its capacity to supply energy to the bulk supply point. Likewise, Hierarchical level III refers to the entire system, including the distribution system along with the generation and transmission systems, and its ability to meet required energy demands of individual customers.

Adequacy assessment of power systems can be performed using any of two approaches, i.e. Deterministic or probabilistic techniques. Since system behaviour is stochastic with random failures of components, plants, and systems, the impact, frequency, and duration of these failures can vary yearly. Utilities typically records these events and produce performance measures. Early reliability evaluation methods, like percentage reserve criteria or single contingency evaluation, are deterministic and do not account for the system's stochastic nature, even though reliability of power system depends on it. Thus, using probabilistic techniques is more logical for accurately evaluating power

system reliability.

1.2. Problem Statement

Nepal Electricity Authority (NEA), under the supervision of the Government of Nepal, is the primary generator and distributor of electric power in the country. Over the years, the number of electricity consumers has steadily increased, reaching 5.46 million in the fiscal year 2023/24, a 6.33% rise from 5.14 million the previous year. Also, there is continuous rise in load demand which is due to several factors viz. the growth of industrial and commercial customers, the increased usage of domestic appliances, and import/export with India.

Recent years have also witnessed a notable increase in available generation, along with the extension of the transmission and distribution systems. Nepal entered an era of power surplus during the high flow seasons (wet season), enabling the country to export surplus electricity to India. This export of energy generation outside the country not only improves NEA's financial health but also helps significantly in boosting the foreign exchange reserves of the country.

Moreover, Nepal is creating a conducive environment for hydropower development and exploring the potential of expanding the power market to the BBIN (Bangladesh, Bhutan, India, Nepal) in the near future. To sustain large-scale energy exports to foreign countries in the future, it is essential to ensure sufficient energy production to meet both domestic and foreign demand.

At the consumer level, power quality and reliability are crucial factors. Therefore, Generation Adequacy Assessment is a vital process to determine if the adequacy of the INPS is within allowable limits to meet the required load demand during low generation period or not. Additionally, it provides insights into whether the future generation capacity of the INPS will adequately meet both national and overall demand with a high degree of reliability. Thus, conducting a thorough Generation Adequacy Assessment of the INPS is imperative.

1.3. Objective

The objective of this dissertation is to conduct a Generation Adequacy Assessment of the INPS to determine if the existing generation is adequate to meet the present load

demand with a high degree of reliability. Furthermore, it aims to assess whether the planned generation expansion will be sufficient to meet the increased load demand in next 10 years.

1.4. Scope

The Scope of this research includes:

- Evaluation of the COPT using existing generating stations and the load duration curve for different seasons.
- Evaluation of reliability indices (LOLP, LOLE, and EENS) of the existing system.
- Forecasting of peak load demand up to the year 2034 AD.
- Evaluation of the COPT table for the year 2034 AD considering existing generating stations, generating stations expected to be in operation and the forecasted load duration curve.
- Evaluation of reliability indices (LOLP, LOLE, and EENS) for the INPS system in the year 2034 AD.

1.5. Assumptions and Limitations

The research work has the following assumptions and limitations:

- Reliability indices of power system is evaluated using analytical techniques and not by using simulation technique.
- System security, one of two factors for evaluating overall system reliability is not evaluated.
- The HL1 reliability is evaluated under the assumption that the transmission line of the INPS is fully reliable.
- The failure rate and forced outage rate for the INPS is assumed to be 0.02. Considering the resiliency of the system, the assumed FOR might not be enough. However, evaluating FOR requires significant effort and is out of scope of this research
- Power plants under construction is assumed to be completed and connected to the grid in next 10 years.
- Peak load forecast up to 2034 AD is done using two machine learning algorithms i.e. LSTM and ANN MLP.

CHAPTER 2. LITERATURE REVIEW

2.1. Introduction

This research reviews a variety of research papers focused on evaluating power system reliability and assessment of generation adequacy. Additionally, it explores a range of literature on different methodologies for load forecasting.

In [1], the authors present a novel methodology for assessing power system reliability by integrating generation, transmission, transformation, and distribution. The approach uses the minimal cut-set method and Monte Carlo Simulation (MCS) to evaluate both the generation-transmission system and the substation system, linking these to the distribution system's reliability through hierarchical indices. Tested on the IEEE RTS-79 and IEEE RBTS, 6 bus systems, the method demonstrates how the grid's reliability affects the entire power system, offering enhanced insights for planning and operation.

In the study conducted by Lin Cheng, et al. titled "An extended minimal cut set algorithm applied into overall power system reliability assessment" [2] the author introduces an innovative approach for evaluating the system reliability. The methodology features an extended minimal cut-set method to analyse the correlations among switch outages and an idealized substation model derived from a reliability parameter matrix and expected contingency set. This comprehensive approach provides a more accurate reliability index, capturing system interactions and dependencies that traditional methods overlook. The findings offer valuable insights for enhancing system reliability and aiding planners and managers.

In paper by Dogan Urgan and Chanan Singh [3], a novel approach is introduced for evaluating power system reliability indices. The study combines MSC with a Multi-label Radial Basis Function classifier to assess system reliability without the need for optimal power flow analysis except during the training phase. This method enhances computational efficiency and reliability index accuracy by allowing the classification of composite power system states into multiple classes. Applied to the IEEE Reliability Test System (IEEE-RTS-79) at various load levels, the MLRBF algorithm demonstrates high classification accuracy and significantly reduced computation time.

In the study titled "Generation System Adequacy Assessment Using Analytical Technique" authored by Joe Oteng-Adjei et al. [4], an analytical approach is utilized to

evaluate the adequacy of generation systems, focusing on the Ghanaian power system. The research employs a recursive technique to construct the Capacity Outage Probability Table (COPT) as a representation of the generation model. It assesses Loss of Load Probability (LOLP) and Loss of Load Expectation (LOLE) indices, investigating how changes in system peak affect these metrics. The study develops a specialized Generation System Adequacy Assessment program validated against the Roy Billinton Test System (RBTS), highlighting critical implications for Ghana's future energy planning beyond 2021.

In paper [5] by Vladislav Oboskalov et al., compare the traditional Monte-Carlo Simulation (MCS) with a more efficient Supplied Demand Algorithm (SDA) for calculating Generation Adequacy Indices (GAI). Developed using C# and VBA, the methods use data on generation mix, system demand, and load probabilities. The results show that the SDA reduces computational time without compromising accuracy, offering a practical alternative for GAI calculations in complex power systems.

The paper [6] explores how wind power's unpredictability affects electric power systems. The authors propose a way to predict wind power output using an ARIMA model with MCMC-based Bayesian estimation and a quantum genetic algorithm to calculate the most accurate prediction intervals. They then assess system reliability through sequential Monte Carlo simulation on the IEEE-RTS79 test system. Their approach effectively captures wind power uncertainty and shows better performance compared to traditional methods like genetic algorithms and particle swarm optimization, offering valuable insights for power generation planning.

The paper [7] by Tamer Ahmed Farrag and Ehab E. Elattar presents an optimized Stacked LSTM Network (SLSTMN) for long-term load forecasting (LTLF). Using a Genetic Algorithm (GA) to fine-tune the model's architecture and hyper parameters, the authors test hundreds of configurations. The model is evaluated on the South Australia State (SA) power system dataset (2005–2016), considering daily load, temperature, weekdays, months, and holidays. The SLSTMN achieves high accuracy, with an error rate around 1%, outperforming other models and demonstrating its effectiveness for reliable power system planning.

In Paper [8] by K C Rupesh, G Renushree et.al presents a load forecasting system using machine learning techniques, focusing on the Long Short-Term Memory (LSTM)

model. The system integrates data collection, pre-processing, model training, and user interaction, with a React front-end and a Flask backend for seamless communication with the ML model. Visualizations like line graphs help illustrate load patterns, while interpolation and extrapolation techniques enhance forecasting accuracy. The LSTM model is compared with the XGBoost model and shows superior accuracy, highlighting its effectiveness in load forecasting for energy management.

In paper [9] by Battula Harish et.al. compare different deep learning models for short-term and medium-term load forecasting using Austria's electrical load time series data. The study finds that MLP performs best for single timestamp ahead prediction (STAP), while ID-CNN excels in multiple timestamps ahead prediction (MTAP).

2.2. Overview of Generation in Nepal

The Generation Directorate of the Nepal Electricity Authority (NEA), led by the Deputy Managing Director, is responsible for the development, optimal operation, and maintenance of NEA's power plants. This Directorate oversees two thermal power plants and twenty hydroelectric power plants, managing a crucial segment of Nepal's electricity generation, transmission, and distribution infrastructure.

As a vertically integrated institution, NEA is tasked with every aspect of electricity management in Nepal, from generation to transmission and distribution. The total installed capacity of NEA's hydropower plants has reached 573.62 MW, while its thermal power plants contribute an additional 53.41 MW. This robust infrastructure supports NEA's mission to meet the country's energy demands effectively.

A notable achievement for NEA has been its success in selling 700 MW of electricity through the Indian Energy Exchange Limited (IEX) and bilateral contracts [10]. This accomplishment involves energy generated from a diverse array of plants, including Kaligandaki 'A', Middle-Marsyangdi, Marsyangdi, Trishuli, Devighat, and Chilime, along with contributions from independent power projects such as Likhu IV, Solu, Lower Modi, and Kabeli B-I. This milestone signifies a significant advancement in the development of Nepal's power sector.

In the fiscal year 2080/81 (2023/24), NEA's total power generation amounted to 2,911GWh, representing a slight decrease from the 2,930GWh generated in FY 2079/80

(2022/23). This reduction was primarily due to diminished rainfall and lower river discharge compared to the previous year.

Regarding energy supply and demand, NEA experienced significant increases in energy purchases in FY 2023/24. The Authority acquired 6,564GWh of energy from Independent Power Producers (IPPs) and 2,597GWh from its own subsidiaries, reflecting increases of 28.25% and 4.37%, respectively, from the previous fiscal year. Additionally, the amount of energy imported from India grew slightly by 3.38% to reach 1,895GWh. Overall, the total available generation in the system increased by 12.91% to 13,966GWh, up from 12,369GWh in FY 2022/23. NEA and its subsidiaries contributed 39.43% of this total energy, while energy imports from the external grid and purchases from nation's independent power producers accounted for 13.57% and 47.00%, respectively. The share of domestic generation in the total available energy slightly increased from 85.18% in FY 2022/23 to 86.43% in FY 2023/24.

On the domestic front, electricity consumption increased to 10,243GWh in FY 2023/24, reflecting a 9.46% rise from 9,358GWh in FY 2022/23. During the same period, electricity exports to India soared to 1,946GWh, marking a 44.57% increase from the previous year's 1,346GWh. Nepal became a net exporter of electricity in FY 2023/24, with exports surpassing imports by 51GWh, compared to a net import of 487GWh in FY 2022/23.

Under the Engineering Services Directorate (ESD), Nepal Electricity Authority (NEA) has been advancing several key hydropower projects at various stages of development. In FY 2023/24, NEA continued to prioritize the development of strategic storage-type and pumped storage hydropower projects to meet the growing energy demands and enhance energy security. Notable projects identified and advanced during the fiscal year include the Upper Mustang Storage Project, Jawa Tila Hydropower Project (73 MW), Bharbhung Hydroelectric Project, and Begnas Rupa Pump Storage HEP. Furthermore, detailed studies are ongoing for projects such as the Chainpur Seti HEP (210 MW), Aandhi Khola Storage HEP, and Syapru Lake Pump Storage Project (332 MW).

NEA also executed a memorandum of understanding (MoU) with Indian Sutlej Jalvidyut Nigam (SJVN) for the establishment of a joint venture for the development

of the Arun 4 Hydropower Project with total capacity of 490.2 MW. The fourth Nepal-Bangladesh Joint Steering Committee (JSC) meeting enabled signing of an agreement between the two governments for the development of the Sunkoshi III HEP (683 MW) as a joint venture company.

To further bolster energy capacity, NEA has facilitated private sector participation through Power Purchase Agreements (PPAs). In FY 2023/24, 29 new projects developed by IPPs were commissioned, adding a total installed capacity of 520 MW. This expansion increased the total number of operational IPP-owned projects to 165, with a cumulative installed capacity of 2,543 MW, including 478 MW from NEA's subsidiary projects. Additionally, 132 IPP projects with a total capacity of 3,450 MW are under construction, while 115 projects at various stages of development are expected to contribute an additional 2,900 MW.

For the future years, NEA has accorded high priority to the development of large-scale projects like the Dudhkoshi Reservoir, Upper Arun, Chainpur Seti, Tamakoshi V, and Upper and Lower Modi Hydropower Projects with an installation capacity of 635 MW, 1063 MW, 210 MW, 99.8 MW and 61.8 MW respectively. Collaborative efforts with international partners continue to drive the development of significant projects like Arun 4 HEP and Sunkoshi III HEP. These initiatives aim to enhance Nepal's energy self-sufficiency, meet increasing domestic demand, and expand cross-border electricity trade opportunities.

2.3. Generation Adequacy Assessment Techniques

2.3.1. Deterministic approach

The deterministic approach in power system planning and operations relies on predefined, fixed criteria to maintain system reliability and efficiency. This method has been essential in establishing design, planning, and operating standards over many years. For example, generating capacity is often planned by setting the installed capacity to match the expected maximum demand along with fixed safety margin. Similarly, operating capacity is ensured by maintaining spinning reserves that can cover the expected load demand plus the capacity of the largest generating units. In network capacity planning, the (N-1) or (N-2) redundancy criterion is frequently used, where

the minimum number of circuits is built based on the peak demand of the load to ensure redundancy.

Despite their effectiveness in addressing random failures, these deterministic criteria have inherent limitations. This method fails to incorporate the inherent uncertainty associated with system operations, fluctuations in consumer demand, and the likelihood of unexpected component failures. By assuming that system parameters and demands are known and unchanging, deterministic methods oversimplify the complexities and uncertainties present in power systems.

2.3.2. Probabilistic approach

Utilizing a probabilistic technique for risk assessment is logical due to the stochastic nature of system behaviour [5]. Component failure, plants, and systems occur randomly, with their frequency, duration, and impact varying annually. This variability is well-understood and expected. Typically, utilities document these events as they happen and develop a range of performance measures. These metrics, which range from restricted to comprehensive, include things like system availability, anticipated unsupplied energy, incident frequency, and interruption duration.

On probabilistic approach, there are two most used general assessment techniques i.e. Analytical technique and Simulation technique.

2.3.3. Analytical technique

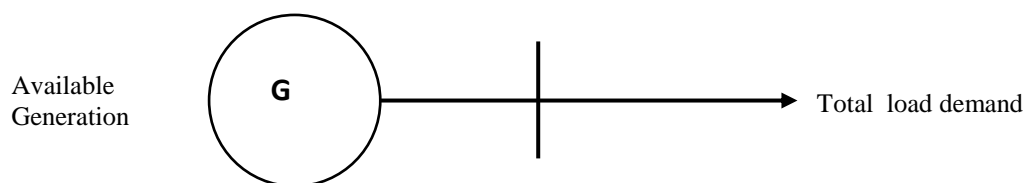


Figure 2.1: Conventional System Model

Figure 2.1 shows the conventional system representation model. However, the main problem with this model is that it measures the total system adequacy of the generation and doesn't show generation deficiencies at specific load points.

Generation model is combined with load model to generate a risk model. The reliability indices usually don't consider transmission constraints and transmission reliabilities, but these can be included if needed and reliability indices obtained through this are overall system adequacy indices

Currently, the evaluation of probability of loss of load or loss of load expectation method is the most popular probabilistic approach to evaluate the adequacy of a generation system. The basic method for evaluating generation adequacy is the same across different techniques. It has three parts, as shown in Figure 2.2.

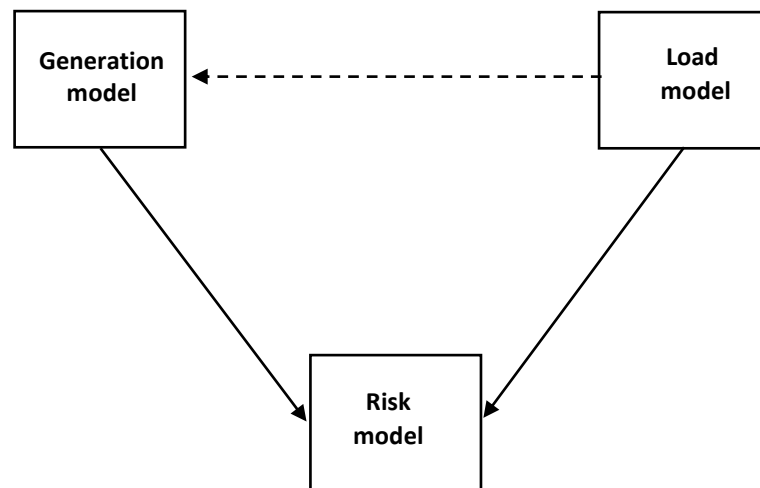


Figure 2.2: Conceptual task in generating capacity reliability evaluation [13]

In many analytical techniques, array format are used to represent the generating model and its capacity in/capacity out probability. This representation is known as the Capacity Outage Probability Table (COPT). Additionally, the Load Duration Curve (LDC) is used to model the load. The LDC is generated by arranging load data of particular period in descending order.

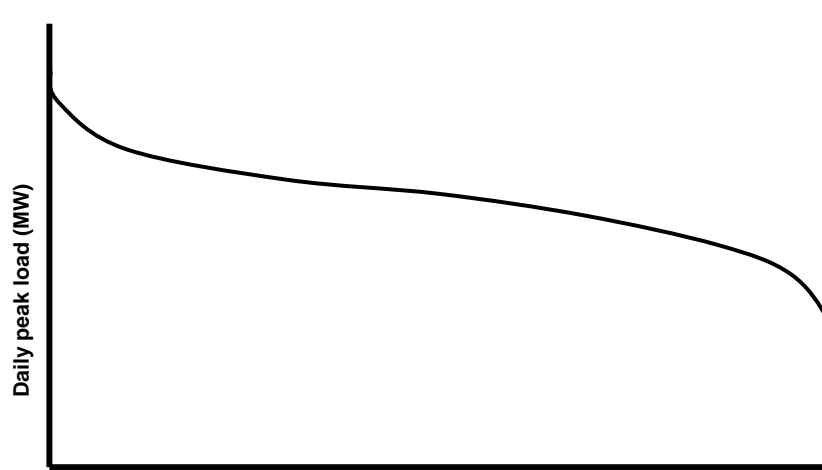


Figure 2.3: Load Duration Curve

Generation system model

A two-state or multi-state model can be used to depict any generating unit in a power system. In two state model, generator can be assumed to be either in up-state (i.e. fully available or operating state) or in down-state (i.e. unavailable or out of service state).

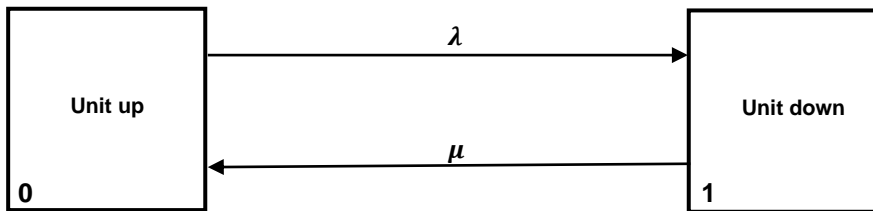


Figure 2.4: Two state model for a generating unit [13]

The unit availability (A) of any generating unit is given by the equation 2.1

$$\begin{aligned}
 \text{Availability} = A &= \frac{\mu}{\lambda + \mu} = \frac{m}{m + r} = \frac{m}{T} = \frac{f}{\lambda} \quad (2.1) \\
 &= \frac{\Sigma[\text{up time}]}{\Sigma[\text{down time}] + \Sigma[\text{up time}]}
 \end{aligned}$$

Similarly, the unavailability of any generating unit is represented by the equation 2.2. It is also known as forced outage rate of this particular unit.

$$\text{Unavailability} = U = \frac{\lambda}{\lambda + \mu} = \frac{r}{m + r} = \frac{r}{T} = \frac{f}{\mu} \quad (2.2)$$

$$= \frac{\Sigma[\text{down time}]}{\Sigma[\text{down time}] + \Sigma[\text{up time}]}$$

Where λ = expected failure rate

μ = expected repair rate

m = mean time to failure = MTF = $\frac{1}{\lambda}$

r = mean time to repair = MTTR = $\frac{1}{\mu}$

$m + r$ = mean time between failures = MTBF = $\frac{1}{f}$

f = cycle frequency = $\frac{1}{T}$

T = cycle time = $\frac{1}{f}$.

Also, four state model of any generating units can be represented shown on figure 2.5.

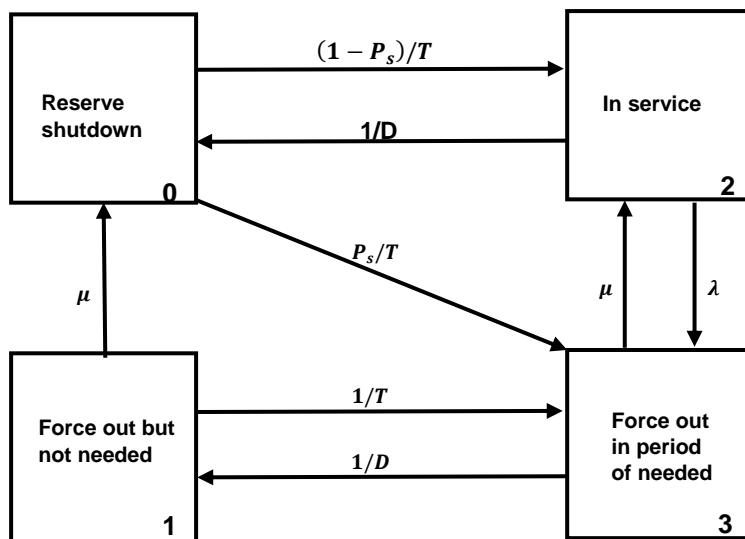


Figure 2.5: Four-state generating unit model [13]

where,

T Average reserve shut-down time between periods of need

D Average in-service time per occasion of demand

P_s Starting failure probability

A group from the IEEE subcommittee on the application of probability methods has proposed this approach [6]. As per this model, there are four different states of generating unit,

State 0: Reverse shutdown state

State 1: Forced out but not needed

State 2: In service

State 3: forced out in period of need

In this model, it is represented that any generating unit can lie on any one of four states at any time. State 2 and state 3 of this four-state model exactly represents the two-state model of any generating unit.

Loss of load indices

A system risk index can be generated by combining a generation model with an appropriate load model. The simplest and most extensively used load model is representation in terms of peak load.

A cumulative load model, also known as a load duration curve, can be created by arranging the separate daily peak loads in descending order. A risk model is obtained by combining the system capacity outage table with the system load characteristics after the generation and load model have been formed. The following are the most used reliability indices used in power system reliability assessments:

LOLP: it is the probability that the available generation capacity will be insufficient to meet the electrical load demands under specific operational conditions and system constraints.

LOLE: It is the expected amount of time within a specified period during which the daily peak load exceeds the available generation capacity. LOLE in hours can be

calculated by multiplying the LOLP by 8,760 hours (the total number of hours in a year).

$$LOLE = \sum_{i=1}^n P_i(C_i - L_i) \text{ days/period} \quad (2.3)$$

Where

C_i = Capacity that is available on day i .

L_i = Peak load that is forecasted on day i .

$P_i(C_i - L_i)$ = Loss of load probability on day i .

It can be obtained from the cumulative capacity outage probability table.

The equation above provides insight into how the LOLE can be evaluated using the COPT table. It can also be evaluated from the daily load duration curve. The figure below illustrates the variation of peak load over a period of 365 days in descending order. Suppose Q_k is the magnitude of an outage that exceeds the magnitude of the reserve, and t_k is the time interval during which an outage of generation Q_k results in a loss of load. Then, the LOLE for this interval is given by

$$LOLE = \sum_{k=1}^n P_k t_k \text{ time units} \quad (2.4)$$

Where, t_k is the individual probability of a capacity outage Q_k .

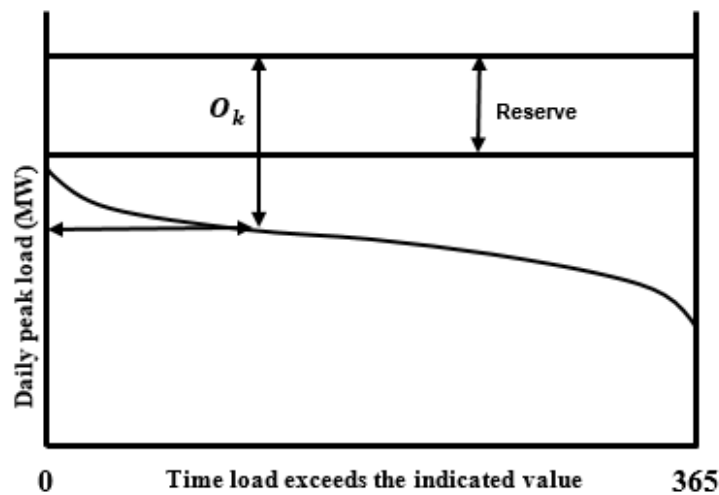


Figure 2.6: Demand, Generation Capacity, and Reserve Overview [13]

Expected Energy Not Supplied (EENS)

It is a most used reliability index used in analytical approach to quantify the amount of energy that is expected to be curtailed or not supplied to consumers due to insufficient generation capacity or failures in the power system. It is typically expressed in megawatt-hours (MWh)

2.3.4. Simulation technique

Monte Carlo simulation is a most used technique for assessing reliability indices through simulation. This technique involves randomly sampling various system states and then computing and analyzing the reliability indices for these sampled states, given a specified tolerance level. By repeatedly simulating these potentially risky states, the expected value is determined by averaging the results obtained from multiple simulations.

Monte Carlo simulation encompasses two main approaches: sequential and non-sequential. Non-sequential simulation, or random sampling, determines system states based on probability distributions without considering the sequence of events, which complicates the calculation of frequency indices. In contrast, sequential simulation relies on the duration of component states and generates event sequences using random numbers and probability distributions. This approach is particularly useful for power generation studies, while the random sampling method is more applicable to transmission system reliability evaluations.

2.4. Comparison among deterministic and probabilistic approach

Deterministic approaches in assessing generation adequacy of a power system offer several advantages, such as simplicity, ease of implementation, and reduced computational effort. They provide clear and fixed outcomes based on predetermined conditions, making the analysis straightforward and easy to understand. However, their limitations include a lack of consideration for variability or uncertainty in power demand and generation, which can lead to unrealistic results in dynamic or complex power systems. Additionally, deterministic methods may oversimplify real-world scenarios and fail to capture the full range of potential system behaviors and stresses.

Probabilistic approaches provide a more comprehensive view of generation adequacy by incorporating randomness and uncertainty. They account for variability in power

demand, generation, and other factors, offering a range of possible outcomes that better reflect real-world conditions. This approach allows for a more detailed and realistic assessment of system reliability under different scenarios. However, probabilistic methods can be more complex and computationally intensive, require extensive data for accurate modelling, and often involve sophisticated statistical tools for result interpretation.

When comparing analytical techniques with Monte Carlo simulations for assessing generation adequacy using probabilistic approach, analytical methods offer several strong advantages. First, they typically provide more direct and efficient solutions, requiring less computational time and resources compared to the iterative nature of Monte Carlo simulations. Second, analytical techniques often yield clear, closed-form solutions that are easier to interpret and apply, whereas Monte Carlo simulations can generate large volumes of data that require extensive analysis. Lastly, analytical methods can be less susceptible to numerical errors and convergence issues that may arise in Monte Carlo simulations, leading to more stable and reliable results.

2.5. Load forecast

For power system planning, load forecasting is crucial. It is often divided into two categories: long-term load forecasting and short-term load forecasting. Real-time load data as well as historical load and weather data are necessary for short-term load forecasting. In long term load forecasting, historical variables and forecasted exogenous variables required for accurate result. It can be done either by statistical technique or by using machine learning approach.

2.5.1. Load forecast using statistical technique

The most popular statistical methods for predicting load are ARIMA, SARIMA, multiple linear regression and exponential smoothing. ARIMA model is mostly used for time series forecasting. If there is seasonality in time series data then SARIMA model can work effectively than ARIMA model. Also, in multiple linear regression load is modelled as a linear combination of different exogenous variables.

2.5.2. Load forecast using machine learning

Load forecasting can be done by using different machine learning models like LSTM,

ANN, XGBOOST, random forest and support vector regression. In machine learning models, first it is trained by using historical data and other exogenous factors. After that, the model is tested by using different statistical parameters like MAE, RMSE and MAPE. Those statistical data shows how accurately the model is working.

CHAPTER 3. METHODOLOGY

In this chapter, the methodology employed to evaluate the generation adequacy of the existing Integrated Nepal Power System (INPS) and future projection up to 2034 AD is outlined. The steps undertaken for this assessment include:

Generation Adequacy Assessment of INPS for Existing System:

1. Data collection of existing generating stations in Nepal.
2. Collection of daily peak load data of INPS for 2023/24AD.
3. Formation of individual COPT tables for each province (Province 1 to Province 7) considering wet, dry and normal seasons.
4. Combination of seven individual COPT tables to form a comprehensive COPT table for existing INPS.
5. Evaluation of reliability indices of generation system (LOLP, LOLE, and EENS) using the combined COPT table and existing load duration curve.

Future Projection:

6. Peak load forecast up to 2034AD using machine learning algorithms (LSTM and MLP) and selection of the best model.
7. Formation of individual COPT tables for each province (Province 1 to 7) considering under-construction projects.
8. Combination of seven individual COPT tables to form a comprehensive COPT table for INPS with under-construction projects.
9. Merging existing COPT of INPS with under-construction COPT to form a combined COPT for 2034AD.
10. Forecasting generation reliability indices (LOLP, LOLE, and EENS) for 2034AD using the combined COPT table and load duration curve based on peak load forecasting.

3.1. Flow Chart

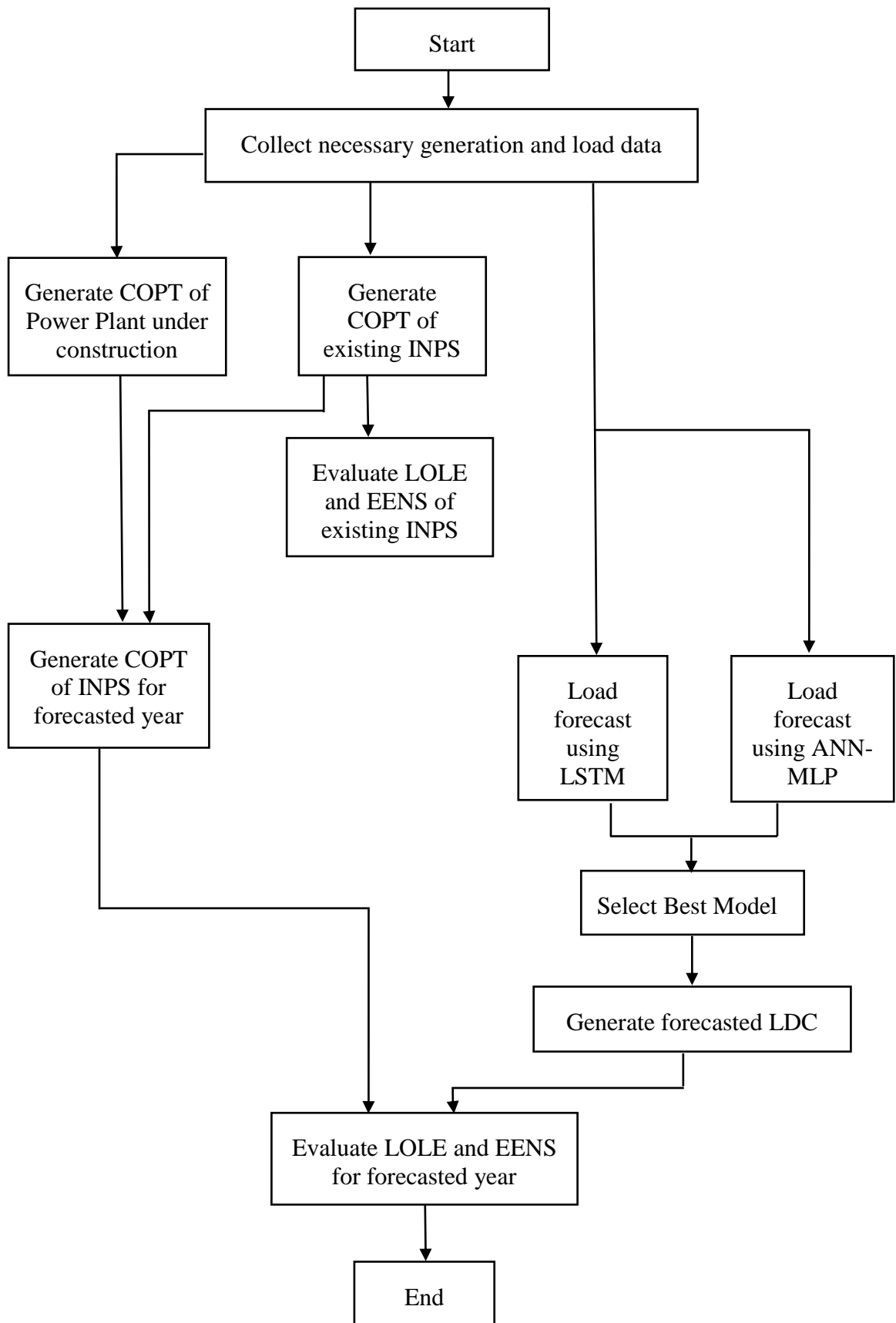


Figure 3.1: Detailed Methodology Flowchart

3.2. Collection of data

All the information regarding existing generation and generation under construction has been collected from the Annual Report of the Nepal Electricity Authority, published for the fiscal year 2023/24 and Department of Electricity Development (DoED). Additionally, daily peak load data for FY 2023/24 has been obtained from daily operational reports of NEA. For the forced outage rates of some large generating plants, the research paper "Adequacy Assessment of Integrated Nepal Power System" [11] by Bharat Chetry and Nava Raj Karki has been used as a reference. For other generating units with unknown forced outage rates, a rate of 0.02 has been assumed, considering the less developed power system network in Nepal. Also, to evaluate the seasonal variations in electricity generation, a detailed analysis was carried out focusing on the generation data of most of the hydropower projects under the Dordi Corridor. The seasonal average generation—categorized into wet, normal, and dry seasons—is calculated based on this analysis. These seasonal averages were subsequently used in the assessment of generation adequacy for the Integrated Nepal Power System (INPS), both for the existing and for future projections.

3.3. Tools and Software

In this research, MATLAB software is used to evaluate the COPT table for all seven provinces and the entire Integrated Nepal Power System (INPS). For peak load forecasting using machine learning algorithms (Long Short-Term Memory (LSTM) and ANN-MLP, python programming language is used, which provides the necessary libraries for accurate forecasting.

3.4. Single Line Diagram of INPS under study

SLD in the figure 3.2 shows the information about existing as well as under construction Power plants, Transmission lines as well as Substations of Integrated Nepal Power System.

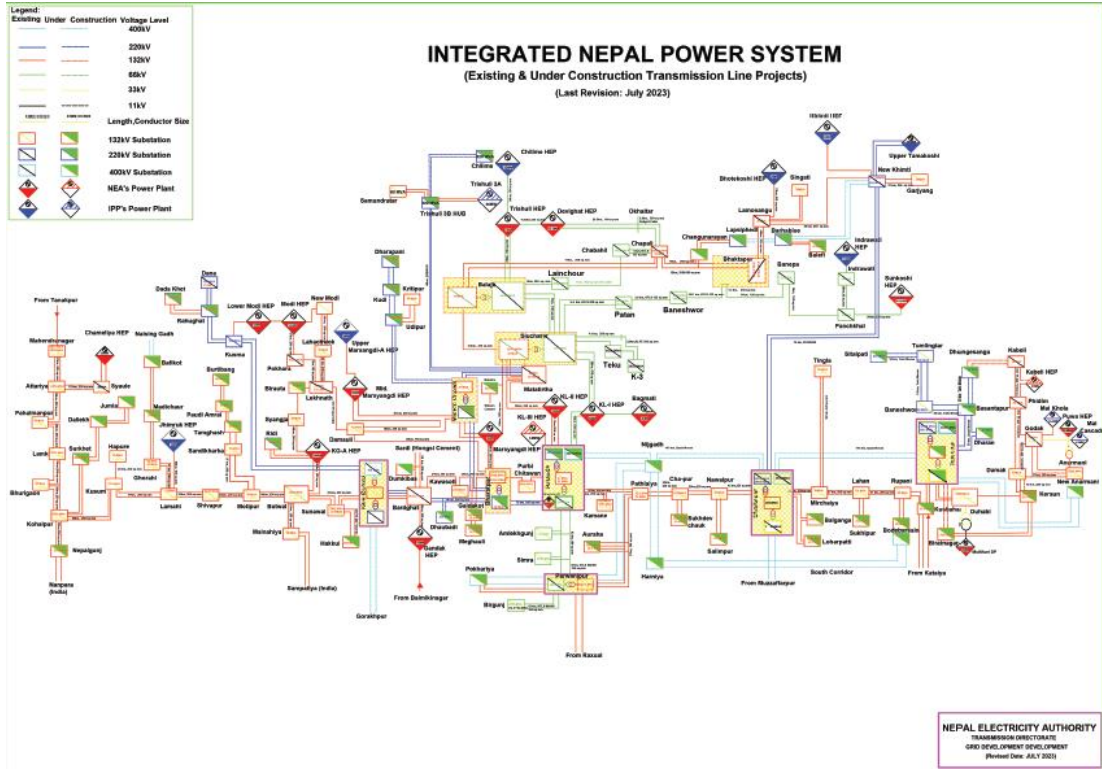


Figure 3.2: Single Line Diagram of INPS [10]

3.5. Capacity Outage Probability Table (COPT):

The Capacity Outage Probability Table (COPT) is utilized to represent the probability of outages in power systems. Due to the randomness associated with outages, there are numerous possible combinations of outages that can occur, making their evaluation complex and computationally intensive. To simplify the evaluation process, the COPT can be approximated by rounding the capacity out or capacity in to increments of 5 MW, 10 MW, 15 MW, or more.

This rounding process can be applied using the following expressions:

$$P(C_q) = \frac{C_r - C_p}{C_r - C_q} P(C_p) \quad (3.1)$$

$$P(C_r) = \frac{C_p - C_q}{C_r - C_q} P(C_p) \quad (3.2)$$

For all states p falling between the required rounding states q and r.

3.6. Long Short Term Memory (LSTM)

Each memory block that is composed of the LSTM architecture has a collection of subnets that are connected recurrently. Memory cells, input gates, forget gates, and output gates make up these memory blocks. The LSTM architecture is composed of memory blocks, each containing a set of recurrently connected subnets. These memory blocks consist of memory cells, input gates, forget gates, and output gates. Unlike traditional recurrent units that overwrite their content at every time step, LSTM units can retain or discard information through their gates. This feature allows LSTMs to manage long-term dependencies more effectively, enabling them to remember information for extended periods.

A series of repeating modules is a defining feature of all recurrent neural networks (RNNs). These modules usually have a straightforward structure, like a single tanh layer, in conventional RNNs. The recurring module structure of LSTMs is more intricate, though. LSTMs use meticulously regulated gates to govern the addition or deletion of information from the cell state. These gates selectively let information through because they are made up of a sigmoid neural net layer and a pointwise multiplication operation. The numbers that the sigmoid layer generates range from zero to one, signifying how much of each element should be kept (one) or thrown away (zero).

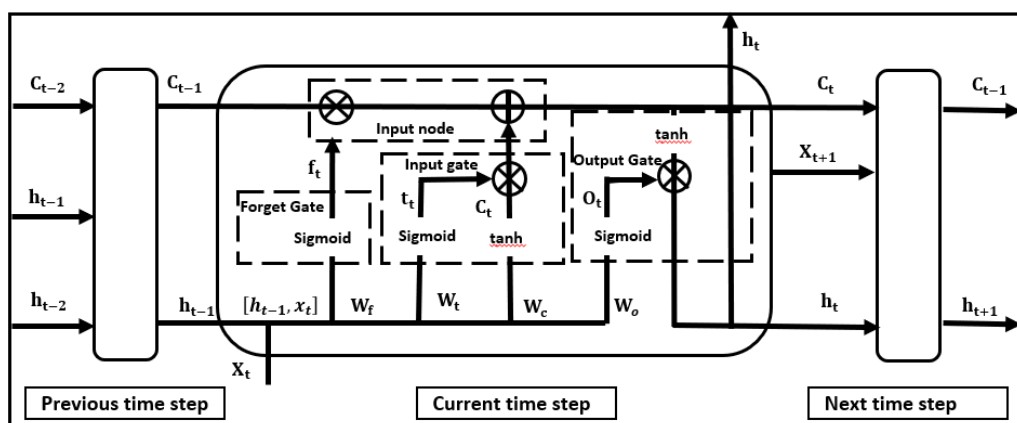


Figure 3.3: Block Diagram of LSTM architecture

An LSTM contains three types of gates that govern and protect the cell state:

Which data should be removed from the cell state is determined by the forget gate. It

outputs a value between 0 and 1 for each element in the cell state after evaluating the current input and the previous hidden state using a sigmoid layer. Which new data should be stored in the cell state is decided by the input gate. It is composed of a tanh layer that creates a vector of new candidate values to add to the state and a sigmoid layer that determines which values to update. The cell state is updated by adding the new candidate values (scaled by the input gate's output) and multiplying the previous state by the forget gate's output (to forget specific information). Also, the output gate determines the next hidden state based on the cell state. It uses a sigmoid layer to filter the cell state, followed by passing the cell state through a tanh layer and multiplying it by the output of the sigmoid gate to produce the final output.

This architecture allows LSTMs to selectively retain or discard information at each time step, making them highly effective for tasks that involve sequences and long-term dependencies, such as time series prediction, language modelling, and speech recognition.

Mathematical formulation of LSTM is shown below,

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t]) + b_f$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t]) + b_i$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t]) + b_o$$

$$C_t = \tanh(W_c \cdot [h_{t-1}, x_t]) + b_c$$

$$C_t = f_t \odot C_{t-1} + i_t \odot C_t$$

$$C_t = o_t * \tanh(C_t)$$

Where W and b are weight and bias of LSTM cell.

3.7. ANN MLP

Artificial Neural Networks (ANNs) are computational systems inspired by the human brain. They are made up of layers of nodes, or "neurons," which process information. There are three main layers in an ANN: the input layer, hidden layers, and the output layer. The input layer receives data, while the hidden layers process it, and the output

layer generates the result. Neurons in these layers are connected with weights that help the network learn. The network uses activation functions, like ReLU or Sigmoid, to introduce non-linearity and help the model capture complex patterns in data.

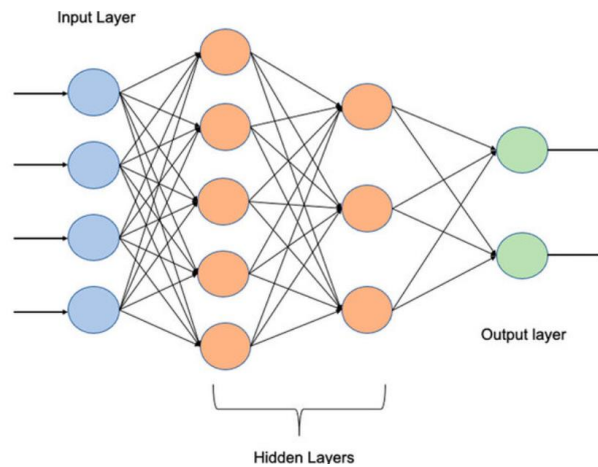


Figure 3.4: MLP with two hidden layers

A specific type of ANN is the Multilayer Perceptron (MLP), which consists of multiple hidden layers and is especially effective for tasks that require learning non-linear relationships, such as prediction or classification. MLPs learn by adjusting the weights of these connections to minimize errors in predictions, using techniques like backpropagation and gradient descent. This makes MLPs versatile for tasks like time series forecasting, image recognition, and more.

3.8. Random Forest Algorithm

Random Forests (RFs) are a popular machine learning method used for both classification and regression problems. The idea behind RFs is to build a large number of decision trees, each trained on different random parts of the data and features. Unlike traditional decision trees, which use the entire dataset and all features, RFs introduce randomness by selecting a subset of data points and a subset of features at each split.

Each tree in a Random Forest is grown using a method called bootstrap sampling, where a random sample of the training data is used to build the tree. At each decision point (node) in the tree, a random subset of features is selected, and the best feature from this subset is used to split the data. The trees are grown fully without any pruning, meaning they can become quite complex.

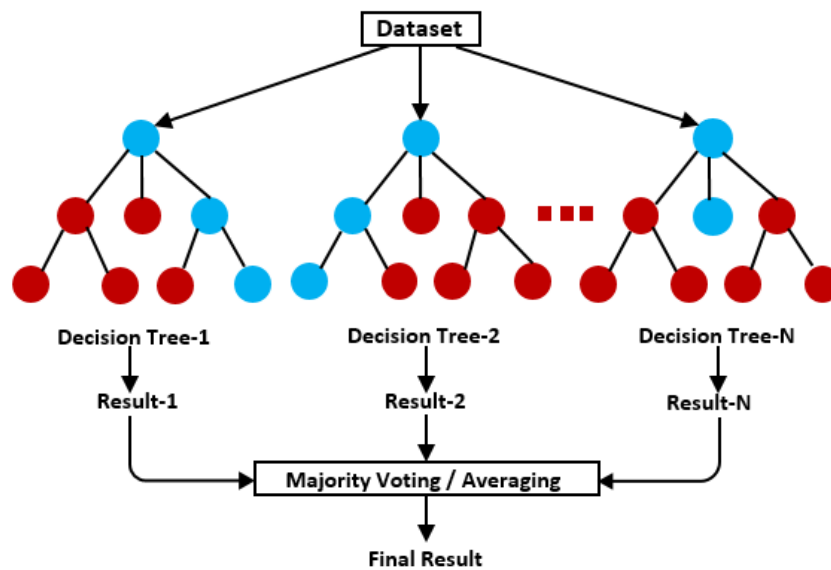


Figure 3.3: Random Forest Algorithm

After all the trees are built, the RF model makes predictions by combining the results of all the trees. For regression tasks, it averages the predictions from each tree. For classification tasks, it takes a vote, and the class with the most votes is the final prediction. This combination of many trees, known as bagging, helps the model become more accurate and less likely to overfit to the training data.

One of the strengths of RFs is that adding more trees doesn't cause the model to overfit. Instead, the model's performance stabilizes as more trees are added. The accuracy of the model is often measured using the out-of-bag (OOB) error, which is calculated using the data points not included in the bootstrap samples. This OOB error is similar to what you would get from cross-validation and provides a way to evaluate the model as it's being trained.

Random forest algorithm for regression is shown below:

1. For $k = 1$ to K :
 - 1.1. Draw a bootstrap sample L of size N from the training data.
 - 1.2. Grow a random-forest tree T_k to the bootstrapped data, by recursively repeating the following steps for each node of the tree, until the minimum node size m is reached.
 - 1.2.1. Select F variables at random from the n variables.

1.2.2. Pick the best variables/split-point among the F.

2. Output the ensemble of trees $\{T_k\}_{k=1,2,\dots,K}$.

To make a prediction at a new point x :

$$f(x) = \frac{1}{K} \sum_{k=1}^K T_k(x) \quad (3.3)$$

Two important parameters in RFs are the number of trees and the number of features considered at each split. These are usually set through experimentation to find the best model performance.

3.9. Performance Evaluation Parameters

3.9.1. Root Mean Squared Error (RMSE)

RMSE is used to evaluate the performance of trained machine learning model. It can be mathematically formulated as:

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (p_i - q_i)^2} \quad (3.4)$$

Where,

N : total number of complete training data

p_i : estimated value

q_i : actual value

Value of RMSE can be ranged from 0 to infinity. Also, lower value of RMSE indicates better performance of system

3.9.2. Mean absolute error (MAE)

MAE is also most used statistical parameter for performance evaluation of machine learning model. Mathematical formulation of MAE is shown below:

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N |p_i - q_i| \quad (3.5)$$

Where,

N : total number of complete training data

p_i : estimated value

q_i : actual value

Value of MAE can be ranged from 0 to infinity. Also, lower value of MAE indicates better performance of system.

3.9.3. Mean Absolute Percentage Error (MAPE)

It shows the average magnitude of model error as well as reflects how accurate the prediction on average is. MAPE value of 10% indicates that average absolute percentage difference between actual and predicted value is 10%. Mathematical formulation of MAPE is shown below:

$$\text{MAPE} = \sqrt{\frac{1}{N} \sum_{i=1}^N \left[\frac{p_i - q_i}{p_i} \right]} \times 100 \quad (3.6)$$

Where,

N: total number of complete training data

p_i : estimated value

q_i : actual value

Value of MAPE can be ranged from 0 to infinity. Also, higher value of RMSE indicates poor performance of system.

CHAPTER 4. RESULT AND DISCUSSION

This section presents the capacity tables for evaluation of Loss of Load Probability (LOLP) and Loss of Load Expectation (LOLE) for all seven provinces of Nepal, as well as for the entire Integrated Nepal Power System (INPS) under the existing conditions. Additionally, the Expected Energy Not Supplied (EENS) for the whole INPS is analysed for the current load scenario.

Moreover, two machine learning algorithms—Long Short-Term Memory (LSTM) and Artificial Neural Network-Multilayer Perceptron (ANN-MLP) were employed for peak load forecasting. The performance of these models was compared using metrics such as R^2 , RMSE, and MAE. The best-performing model was then utilized to assess the generation adequacy of the INPS over the next 10 years. The results of this assessment are also presented in this chapter.

4.1. Load Duration Curve of existing system

For the year 2023/24, the daily peak load data over 365 days has been analysed to construct the annual load curve of the Integrated Nepal Power System (INPS). The highest recorded daily peak load during this period was 2212 MW, while the lowest was 1107 MW.

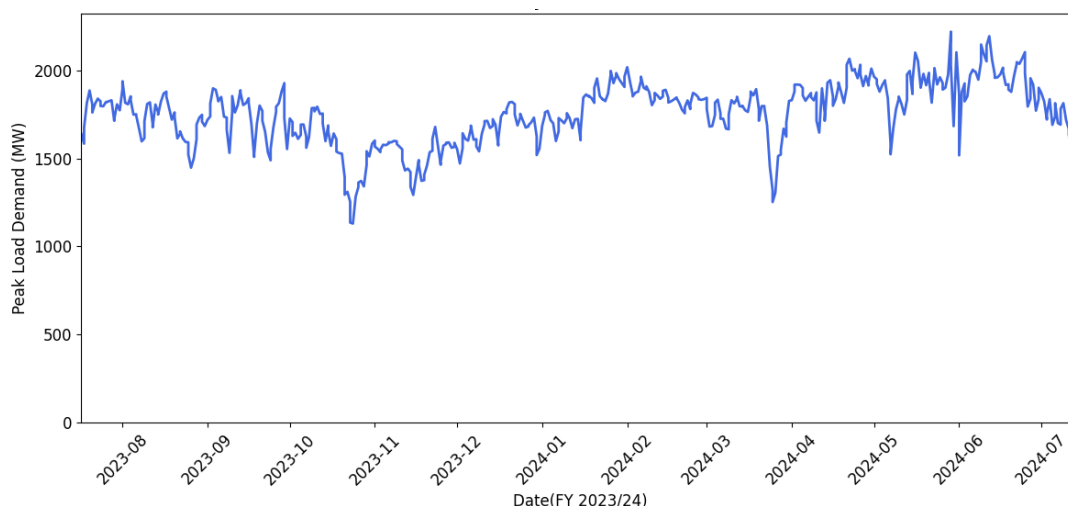


Figure 4.1: Daily Load Curve of INPS for FY 2023/24AD

To develop the Load Duration Curve (LDC), these daily peak load values were

systematically arranged in descending order. This curve provides a clear representation of load variations throughout the year.

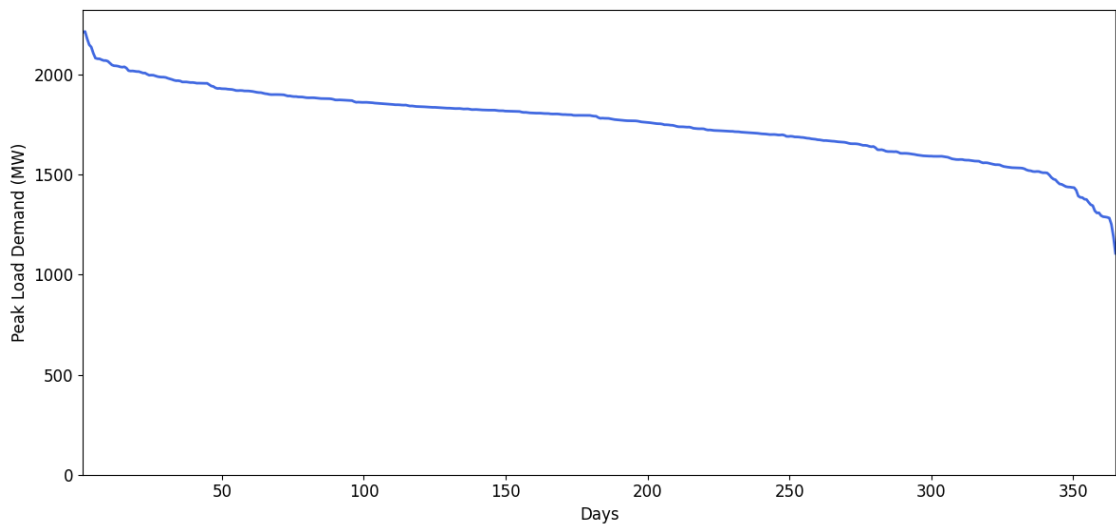


Figure 4.2: LDC of INPS for FY 2023/24AD

The yearly load duration curve of following FY is divided into three Load duration curves for three different seasons.

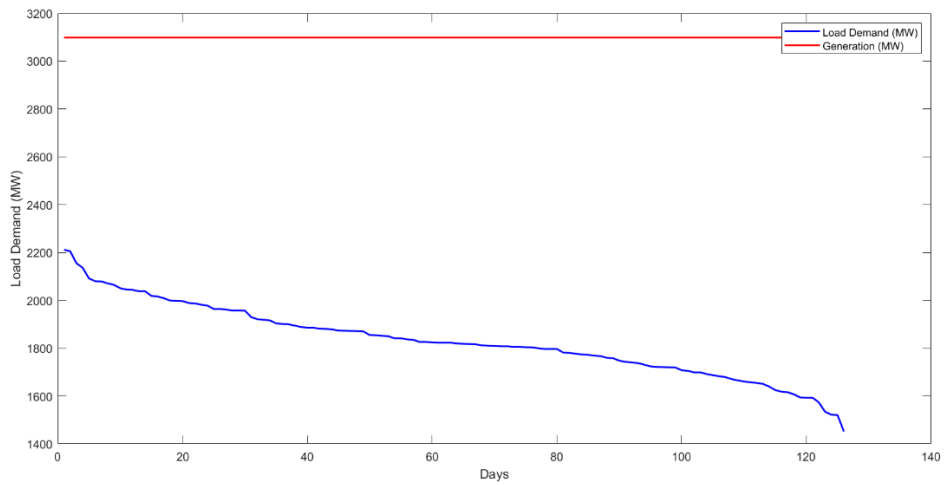


Figure 4.3: Daily Load Curve of INPS for Wet Season

In figure 4.3 blue curve represents the daily load duration curve and red line represents the available generation for wet season for fiscal year 2023/24 where peak load demand is approximately 2212 MW where available generation is found to be approximately 3100 MW. From this graph, it is found that there is approximately 900 MW of reserve

margin. So, there is no loss of load and energy curtailment if there is capacity out of 900MW or below.

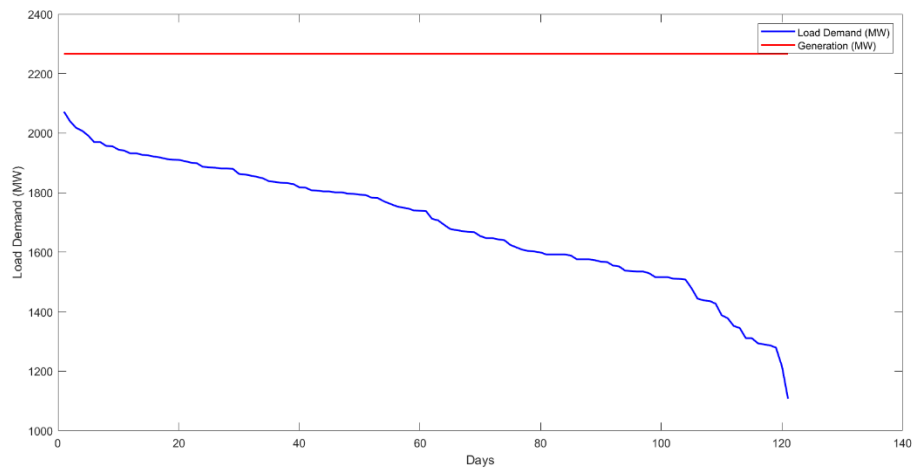


Figure 4.4: Daily Load Curve of INPS for Normal Season

Similarly, figure 4.4 shows the load duration curve and available generation for normal season for fiscal year 2023/24 where peak load demand is approximately 2100MW where available generation is found to be approximately 2267MW. From this graph, it is found that there is approximately 167MW of reserve margin. So, there is no loss of load and energy curtailment if there is capacity out of 167MW or below. Also, it can be concluded that there will be loss of load with minimum capacity out in comparison to wet season due to low reserve margin in this season.

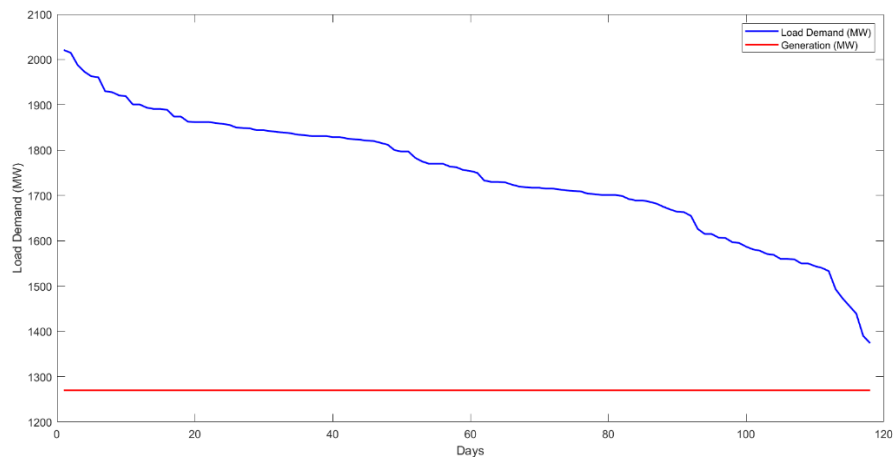


Figure 4.5: Daily Load Curve of INPS for Dry Season

Figure 4.5 shows the load duration curve and available generation for the dry season for fiscal year 2023/24 where peak load demand is approximately 2000MW where available generation is found to be approximately 1270MW. From this graph, it is found that there is negative reserve margin of approximately 730MW. So, there will be loss of load and energy curtailment even if there is no capacity out in this season. From all the load duration curve of different seasons, it can be concluded that there is more chance loss of load and energy not served in dry season in comparison to normal season and minimum loss of load is in normal season.

4.2. Study of Dordi Corridor:

There are total of 7 power plants which are connected to Dordi corridor, they are Dordi-27, Upper Dordi, Super Dordi, Dordi-12, Chepe, Chepe-A, and Super Chepe with total installed capacity of 142.9 MW. The Hydropower of Nepal needs to sign Power Purchase Agreement (PPA) with the NEA. The PPA contains the contract energy that the projects needs to produce and sell to NEA. To evaluate the average generation for the different seasons of a year, the installed capacity and PPA contract energy of 4 major projects for fiscal year 2023/24 of Dordi corridor given in Table 4.1 is taken as reference.

Table 4.1: Dordi Corridor Generation (GWh)

	Upper Dordi (25MW)	Super Dordi (54MW)	Dordi-1 (12MW)	Dordi (27MW)
Shrawan	17.253	32.744	8.485	19.003
Bhadra	17.254	32.744	8.485	19.003
Ashoj	17.254	30.744	8.485	19.003
Kartik	15.243	26.744	6.899	12.151
Mangsir	9.236	21.258	4.214	8.221
Poush	6.672	13.258	3.044	6.314
Magh	5.405	13.258	2.461	5.026
Falgun	5.072	13.258	2.307	4.943
Chaitra	5.016	16.372	2.272	5.083
Baishakh	7.890	21.372	3.585	7.501
Jestha	13.172	44.116	6.260	16.454
Ashad	17.253	49.116	8.759	19.616

The available average capacity for a season is then evaluated as given by equation 4.1 to develop Table 4.2.

$$Average\ Production = \frac{\Sigma Energy}{Days * Installed\ Capacity} \quad (4.1)$$

Table 4.2: Average energy production of projects of Dordi corridor

Projects	Capacity(MW)	Wet	Normal	Dry
Upper Dordi	25	85.89%	62.54%	37.27%
Super Dordi	54	97.20%	60.73%	39.91%
Dordi-1	12	88.15%	60.95%	35.39%
Dordi	27	90.73%	73.49%	32.05%

From table 4.2, the average generation on wet, normal and dry seasons are found to be 90%, 65%, and 35% of total installation capacity. Hence, by taking it as a reference, assessment of generation adequacy of INPS is conducted for existing as well as for future.

4.3. COPT of Existing INPS System:

To evaluate the reliability of the Integrated Nepal Power System (INPS) using the Capacity Outage Probability Table (COPT) method, the year is divided into three seasons: wet (Jestha, Ashad, Shrawan, and Bhadra), dry (Mangsir, Poush, Magh, and Falgun), and normal (Ashwin, Kartik, Chaitra, and Baishakh), based on hydropower generation. These seasonal changes are important for assessment of generation adequacy in INPS.

There are 54 power plants in province 1 with installed capacity of 642.53 MW. The largest power plant of province 1 is Solu Khola (Dudhkoshi) with installed capacity of 86MW. As of now, there are five number of power stations located on different area of province -2 and all of them are solar power stations. The largest plant is Mithila solar PV electric project with installed capacity of 10MW and total installed capacity of Province 2 is 19MW. In Province 3, there are total of 63 numbers of electric power stations. The largest power plant installed in this province is Upper Tamakoshi with installed capacity of 456MW and total installed capacity of this province is

approximately 1500MW. The largest power plant installed in province 4 is Kaligandaki 'A' with installed capacity of 144 MW. Total installed capacity of this province is approximately 1000 MW. There are 62 Generating stations located in this province. As of now, total installed capacity of province 5 is 78MW. There are total of 13 generating stations including 6 solar PV projects. Largest power plant installed in this province is Gandak Power station with installed capacity of 15 MW. In province-6, there are 2 power stations named Padam Khola and Dwari Khola with installed capacity of 4.8 MW and 3.75 MW respectively. Therefore, total installed capacity of this province is 8.55MW. In province-7, there are 10 number of power stations with installed capacity of 177 MW. The largest power installed in this province is Upper Chameliya with installed capacity of 40 MW. So, total installed capacity of INPS system is approximately 3,431 MW. COPT tables for all seven provinces of INPS have been generated for different seasons.

Capacity Outage probability tables of all seven provinces are combined to get a COPT table of Integrated Nepal Power System. In COPT, individual loss of load probability of capacity outage is not included if the probability is less than 10^{-20} . Combined COPT table of INPS for existing case is shown in the tables (refer to Annex A).

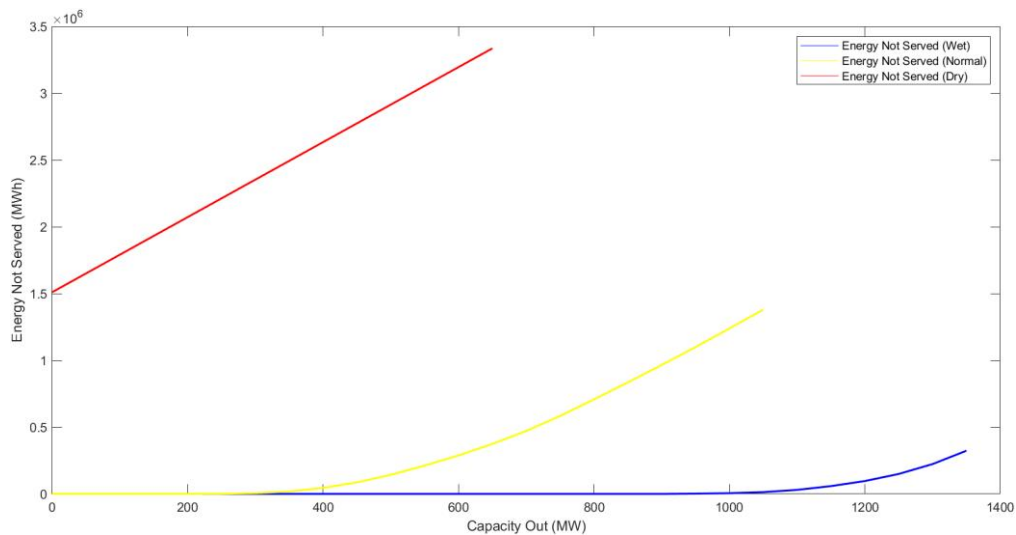


Figure 4.6: Capacity Out vs Energy Not Served for Existing INPS

Figure 4.6 shows the relation between capacities out vs energy not served for three different seasons of a year for existing INPS where red, yellow, and blue curve represents relationship between them for dry, normal and wet seasons respectively.

From adequacy assessment of existing INPS, it is concluded that there is loss of load in dry season even if there is no capacity outage. Also, in normal season there is loss of load if capacity out is more than 150MW and in wet season, there is very low loss of load even with high capacity outage due to high reserve margin in this season.

4.4. Reliability Indices of Existing INPS

Reliability indices of existing INPS system is evaluated using COPT method. Based on the evaluation of reliability indices for the existing INPS system over three different seasons considering generation to 90%, 65%, and 35% of installed capacity during wet, normal and dry seasons, LOLP, LOLE and EENS of INPS for fiscal year 2023/24 are found to be 3.12E-01, 110.70 days/year and 1.48E+06 MWh. In wet and normal seasons, there are very low LOLE and EENS due to sufficient generation and positive reserve margin, whereas the dry season has higher LOLE and EENS because the available generation is insufficient to meet the load demand due to negative reserve margin.

Table 4.3: Reliability indices of existing INPS

Existing System FY 2023/24	Reliability		
	LOLP	LOLE	EENS
Wet Season	6.05E-08	1.28698E-07	2.98E-05
Normal Season	2.88E-02	0.294392374	3.67E+02
Dry Season	9.36E-01	110.4082945	1.48E+06
Reliability/Year	3.12E-01	110.702687	1.48E+06

4.5. COPT table of INPS for Generations under Construction

All information regarding generation projects under construction with a capacity of more than 1 MW has been collected from the Department of Electricity Development (DoED). As per the data, there are 255 hydropower projects with a total installed capacity of approximately 10,080 MW, and 10 solar projects with a combined capacity of 82 MW that have already received construction licenses and are currently under construction. Therefore, it is assumed that around 10,162 MW of additional generation capacity will be connected to the national grid within the next 10 years.

Similar as existing scenario, all the generating units which are under construction and their force outage rates are used to generate capacity outage probability table for all

seven provinces. Individual loss of load probability of capacity outage is not included if the probability is less than 10^{-20} . All COPT of seven provinces are combined to get a COPT table of INPS for under Construction scenario.

4.6. Load forecast up to 2034 AD

4.6.1. Datasets

Different parameters which can affect peak load demand is collected from year 1987AD to 2024AD. These parameters are number of total consumers, domestic consumers, non-commercial consumers, commercial consumers, industrial consumers, water supply, irrigation, streetlight, temporary supply, transport, temple, bulk supply to India, Energy sales in GWH, Energy Availability (GWH), Average minimum temperature and Average Maximum Temperature. Some of these parameters have yearly data. These data are converted to monthly data by using interpolation so that there will be enough data for training the model.

4.6.2. Correlation between parameters.

Figure 4.7 shows the correlation between different performing parameters. From this, dependency of one parameter with another can be evaluated. As per this heat map, darker the red box higher the positive correlation between these two parameters. Similarly, darker the blue box, higher the negative correlation between these two parameters. Also, white box indicates that there is no correlation between associative parameters.

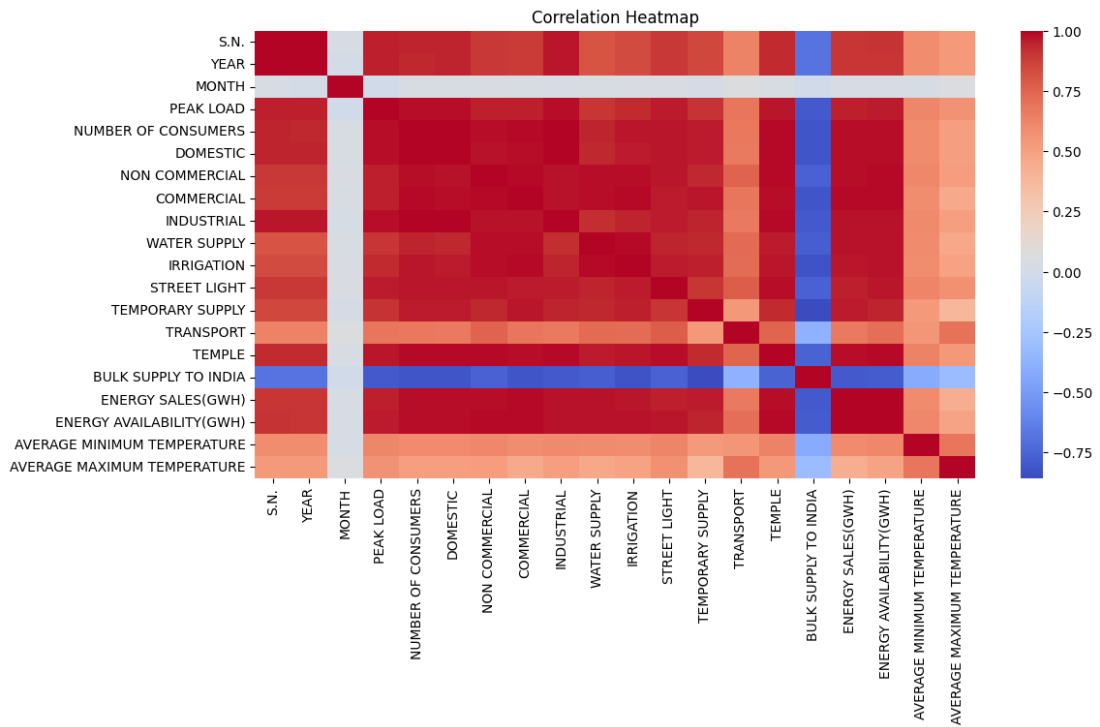


Figure 4.7: Correlation Heat map

4.6.3. Load forecast using LSTM

LSTM (Long Short-Term Memory) model is employed to forecast peak load demand by analysing historical data from 1987 to 2024 where all these parameters which can affect peak load demand is used to train, test and validate the model. After validation, forecast of peak demand extends up to 2034 AD.

Firstly, the model is trained using historical data. Figure 4.8 indicates that loss is decreasing with increased value of epochs where number of epochs indicates how many times the model is trained with the same data. A decreasing trend in loss indicates effective training and a refinement of the model’s predictions over time.

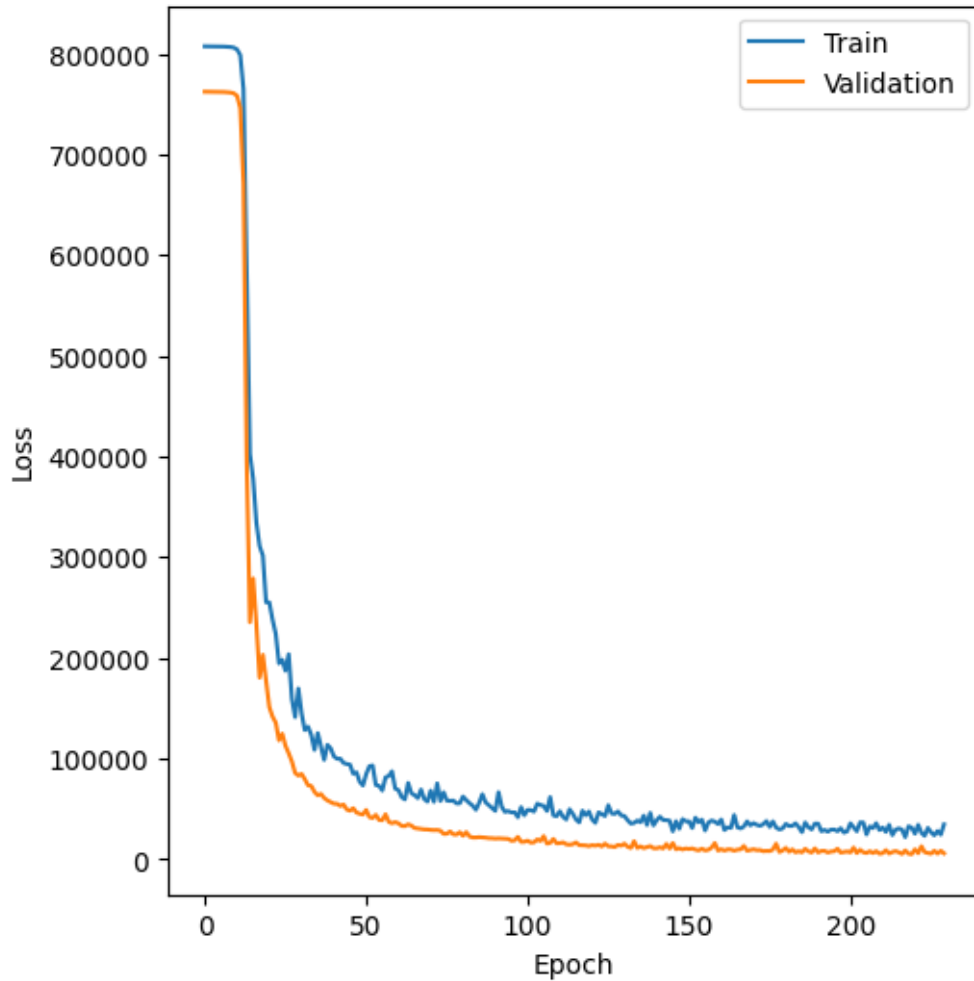


Figure 4.8: LSTM-Model Loss Graph (Loss vs Epoch)

Secondly, the performance of model is validated by comparing actual and predicted peak load for the historical data which is shown on scatter plot of figure 4.5 where a close alignment between actual and predicted values demonstrates the model's effectiveness in capturing demand patterns.

After that, peak load is forecasted up to 2034AD using this model. Figure 4.9 represents actual peak load demand from 1987AD to 2024AD as well as projected peak load for next 10 years i.e. from 2024AD to end of 2034AD. After forecasting the peak load using LSTM model, forecasted peak load is found to be approximately 5430MW

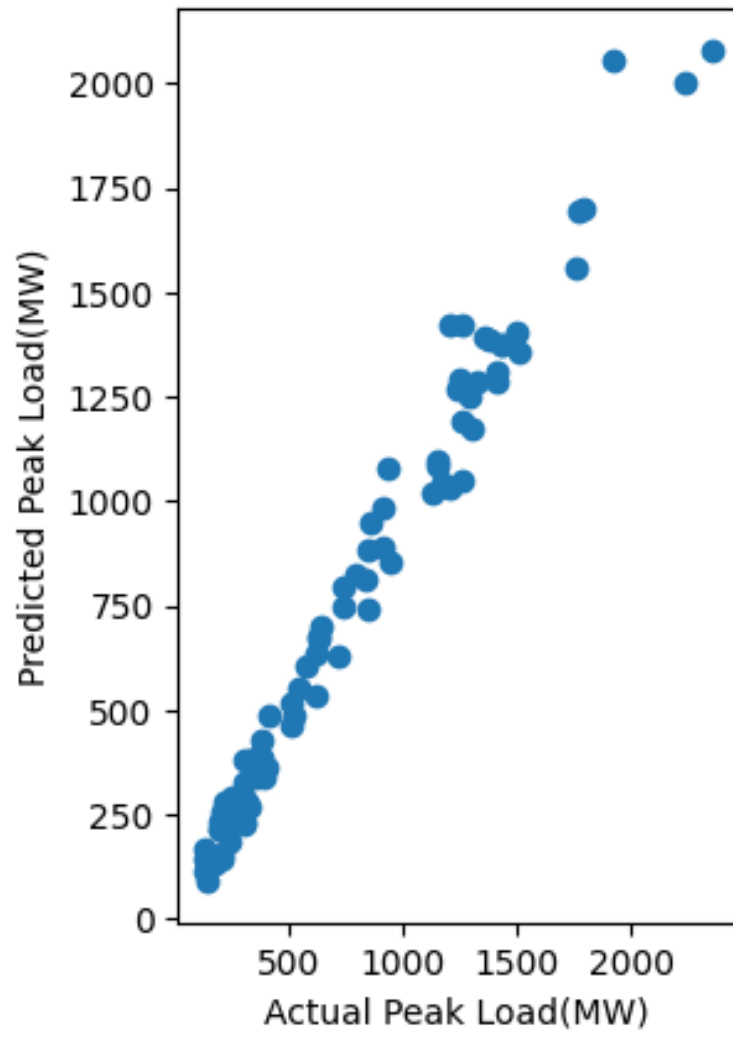


Figure 4.9: LSTM-Prediction vs Actual Peak load

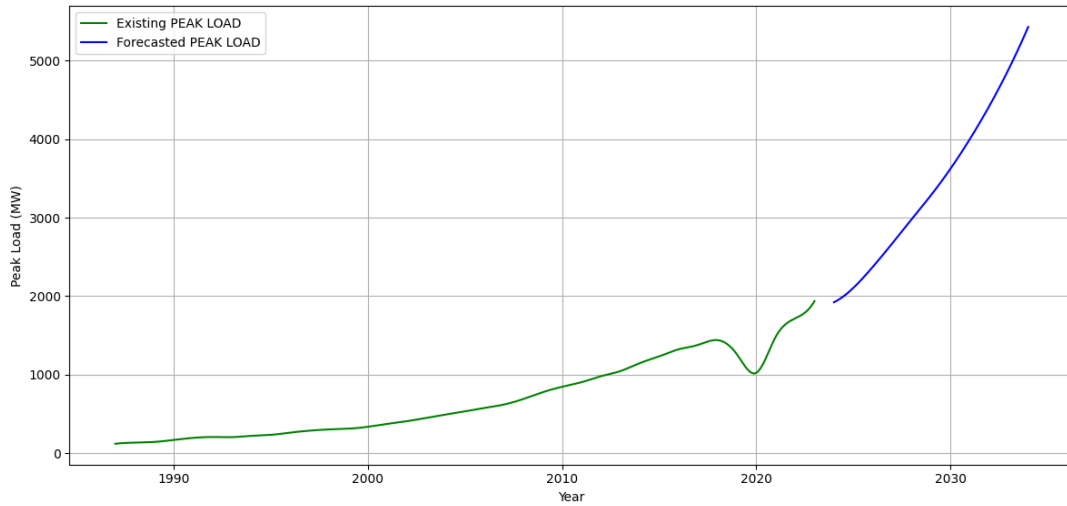


Figure 4.10: LSTM-Existing and Forecasted peak load

4.6.4. Load forecast using ANN MLP

An Artificial Neural Network (ANN) model with a Multi-Layer Perceptron (MLP) architecture is employed to forecast peak load demand using historical data from 1987 to 2024. This model is trained, tested, and validated with various parameters impacting peak load demand, and peak load is forecasted up to 2034.

The model is trained by feeding the historical data into it. Figure 4.11 illustrates how the loss decreases as the number of epochs increases. This decreasing trend in loss signifies the model's progressive accuracy improvement.

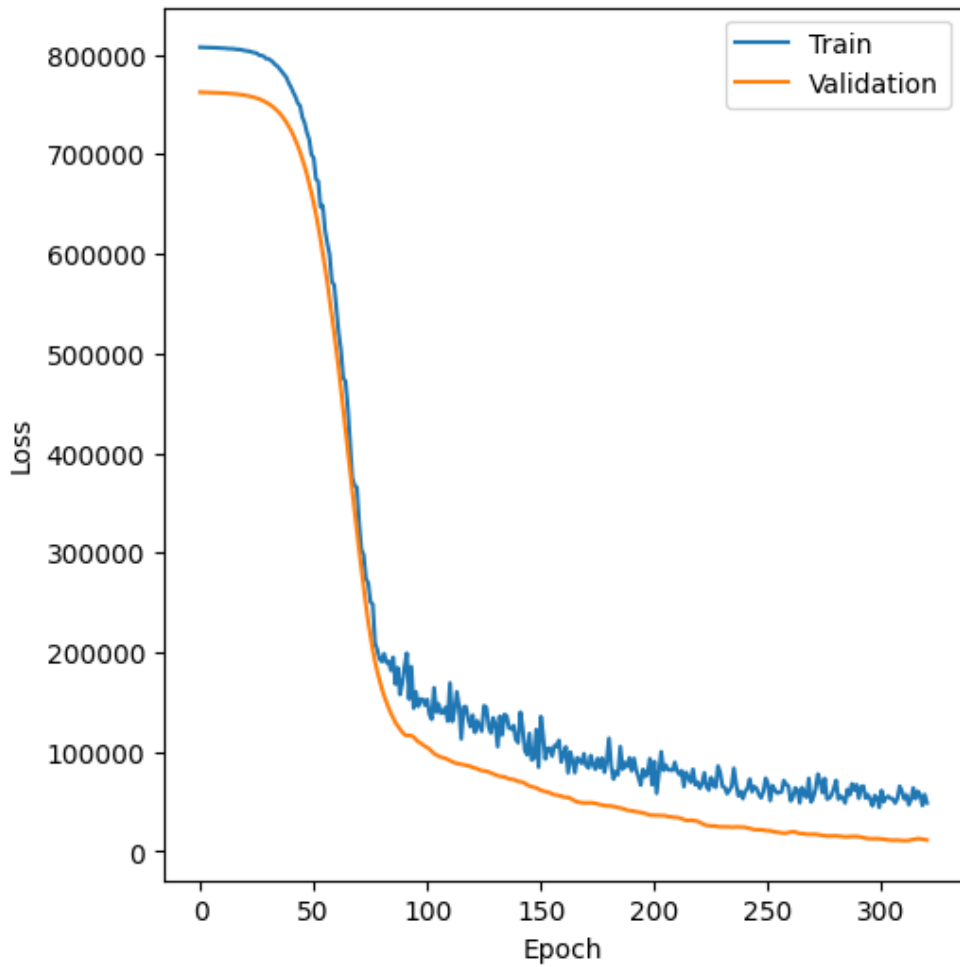


Figure 4.11: ANN MLP- Model Loss Graph (Loss vs Epoch)

Also the model performance is validated by comparing the actual peak load values with those predicted by the MLP model for past period. In figure 4.12 shown below, close alignment between actual and predicted values demonstrates the model's effectiveness in capturing demand patterns.

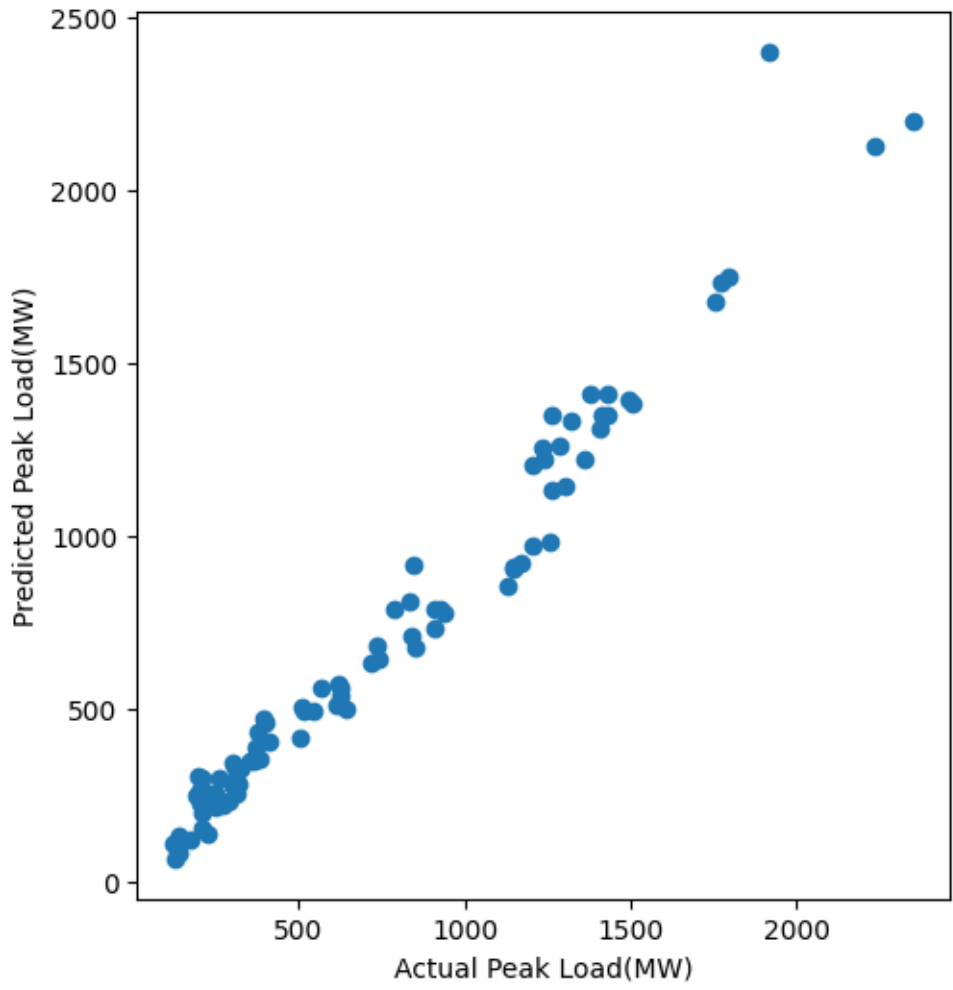


Figure 4.12: ANN MLP- Prediction vs Actual Peak load

Lastly, the MLP model is utilized to forecast peak load demand until 2034. The graph below shows historical peak load demand from 1987 to 2024, along with projected values up to 2034. By the end of the forecast period, the peak load demand projected by ANN MLP model is approximately 5285MW.

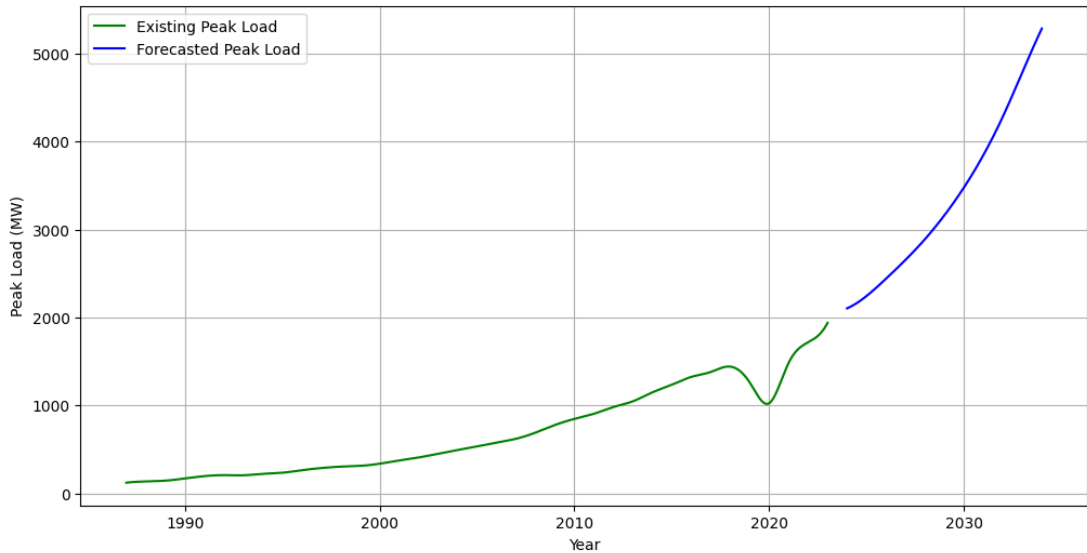


Figure 4.13: ANN MLP- Existing and Forecasted peak load

4.6.5. Selection of best model of Machine Learning

For the selection of best model between LSTM and ANN MLP, model performance is compared for the test set using R-Squared(R^2) value, Root Mean Squared Error(RMSE), Mean Absolute Error(MAE) and Mean Absolute Percentage Error(MAPE).

Table 4.4: Performance Parameters of ML models

	R^2 Value	RMSE	MAE	MAPE
LSTM	0.9760526	84.3768503	63.4892880	10.59%
ANN MLP	0.9587729	110.709716	77.7299002	13.22%

As per the above table, it is found that test set of Long Short Term Memory (LSTM) has less value of R^2 , RMSE, MAE and MAPE than that of ANN MLP machine learning model but MAE and RMSE values are quiet high for both the cases so linear regression can be done to validate the same result for better accuracy. In conclusion, model performance of LSTM is better as compare to ANN MLP.

4.7. Forecasted Load Duration Curve

Over the next decade, forecasts for the Integrated Nepal Power System's load demand

have been developed under two distinct scenarios. The base case assumes that growth will continue along its current trajectory without significant external factors triggering a rapid increase, while the optimistic scenario considers the potential for accelerated demand driven by factors such as increased power exports, the rising adoption of electric vehicles, and a surge in the use of electrical appliances.

4.7.1. Forecasted Load Duration Curve for 2034 AD-Base Case

In the fiscal year 2023/24, the Integrated Nepal Power System (INPS) recorded a peak load demand of 2,212 MW. Projections using a Long Short-Term Memory (LSTM) machine learning model indicate that by the fiscal year 2033/34, the peak load demand is expected to reach 5,430 MW. This suggests an approximate increase of 2.455 times, or 245.5%, over the next decade.

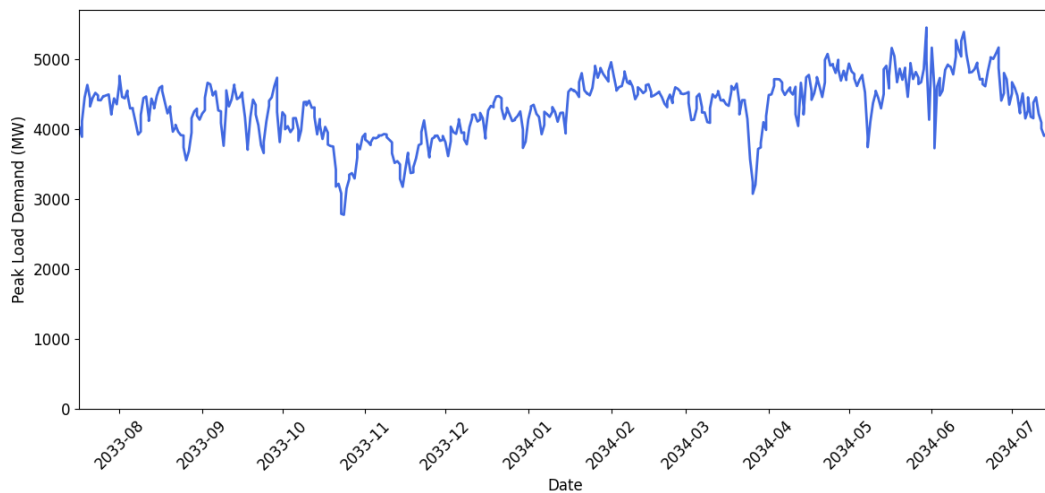


Figure 4.14: Forecasted daily load curve for base case

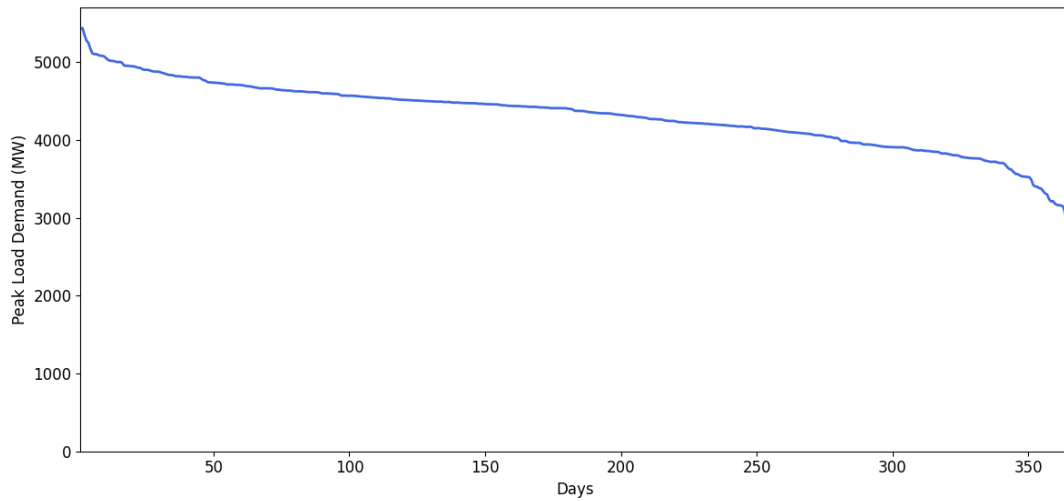


Figure 4.15: Forecasted load duration curve for base case

4.7.2. Forecasted Load Duration Curve for 2034 AD-Worst Case

In optimistic scenario, generation adequacy of Integrated Nepal Power System is evaluated by increasing the maximum load demand by four times of existing load demand as there is possibility of increase in load due to export, increase in electric vehicles and other electrical appliances and many more.

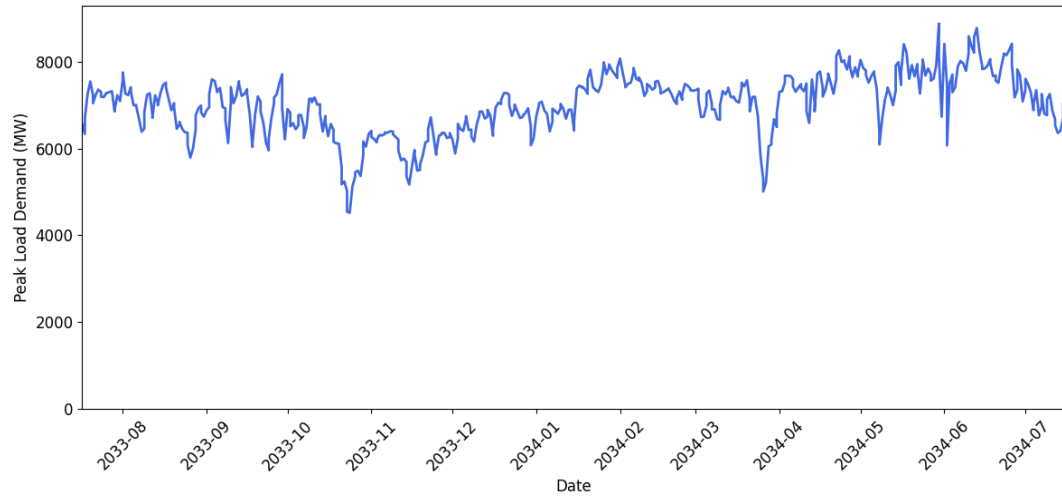


Figure 4.16: Forecasted daily load curve for optimistic case

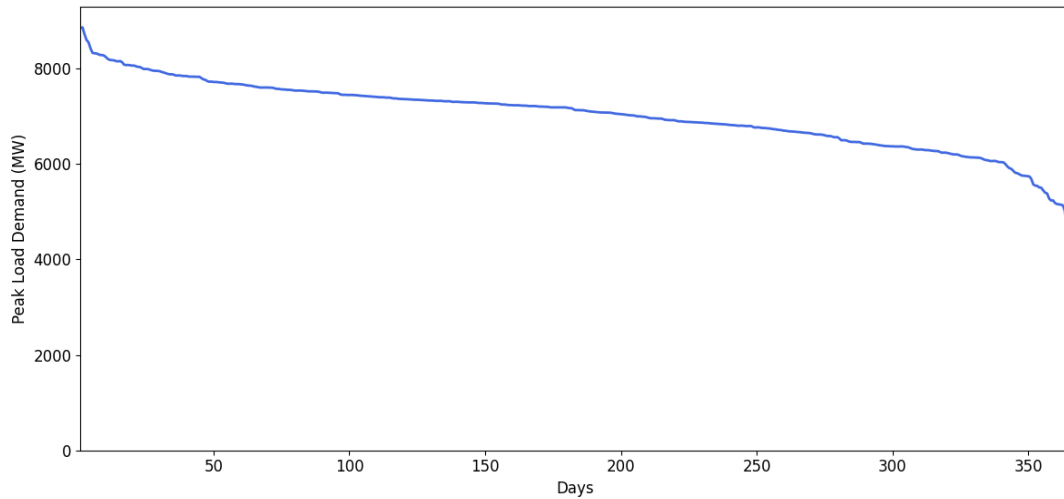


Figure 4.17: Forecasted load duration curve for optimistic case

4.8. COPT of INPS -2034 AD

The reliability of INPS for the next 10 years has been estimated by combining the COPT of the existing power plants with the COPT of the power plants under construction. This analysis has been done separately for three seasons: dry, normal, and wet. The reliability indices from these three seasons are then combined to calculate the overall reliability for respective year.

Also, load is forecasted considering two different cases. In base case scenario, actual forecasted load for next decade is considered where it is found that load will be increased by 2.455 times of existing load in normal scenario. Also, in optimistic scenario, load is increased by four times by considering the possibility of increase in export, use of electric vehicles and other electrical appliances (refer to Annex B).

4.9. Reliability indices of INPS for next decade (Base Case)

If all the expected generation will be connected to national grid and peak load will be increased to 2.455 times of existing peak load, there will be no loss of load probability and expected energy not served in wet and normal seasons because there will be sufficient generation to supply in the period of peak load demand. But, in dry season,

there will be LOLE and EENS with values of approximately 5.67 days/year and 1.31E+04MWh. The main reason for energy curtailment in dry season is due to insufficient generation due to reduction on water discharge which will make negative reserve margin for this season.

Table 4.5: Forecasted Reliability indices of INPS-Base Case

FY 2033/34 (Base Case)	Reliability		
	LOLP	LOLE	EENS
Wet Season	0.00E+00	0	0.00E+00
Normal Season	0.00E+00	0	0.00E+00
Dry Season	8.79E-01	5.669506147	1.31E+04
Reliability/Year	2.84E-01	5.669506147	1.31E+04

4.10. Reliability indices of INPS for next decade (Worst Case)

Also, if all the expected generation will be connected to national grid and peak load will be increased to four times of existing peak load, there will be very low loss of load probability and expected energy not served in wet and normal seasons because there will be sufficient generation to supply in the period of peak load demand. But, in dry season, there will be LOLE and EENS with values of approximately 104 days/year and 5.42E+06MWh. So, in comparison to base case scenario, LOLE and EENS will be very high resulting in reducing the reliability of the system. The main reason for high energy curtailment in dry season is due to insufficient generation to meet the expected increment in load resulting in low reserve margin.

Table 4.6: Forecasted Reliability indices of INPS-Worst Case

FY 2033/34 (Worst Case)	Reliability		
	LOLP	LOLE	EENS
Wet Season	5.90E-18	1.18E-17	5.13E-15
Normal Season	1.88E-02	0.038822263	8.11E+01
Dry Season	8.79E-01	103.683879	5.42E+06
Reliability/Year	2.90E-01	103.7227012	5.42E+06

CHAPTER 5. CONCLUSIONS

In this dissertation, the generation adequacy assessment of the existing Integrated Nepal Power System is conducted to verify whether the system is adequate to supply load demand or not. For this, energy import from the external grid during the dry season is not considered and, analysis is done by considering the case where the generation is assumed to be 90%, 65%, and 35% of its installation capacity in wet, normal, and dry seasons.

By doing the adequacy assessment of existing system, LOLE of the system is found to be approximately 111 Days/Year and the EENS of the system is found to be 1.48E+06 MWh. Also, it is found that LOLE and EENS are negligible in the wet and normal seasons compared to the dry season. The main reason for the higher EENS in dry season is due to inadequate generation to maintain the peak load demand due to negative reserve margin in the system.

Moreover, the system adequacy is also forecasted for the next 10 years. Firstly, peak load forecasting is done for this period using LSTM and MLP. Various external parameters that could have affect the peak load demand were considered to train and test the model, and it was found that LSTM has better performance than MLP. Therefore, the forecasted result of LSTM was considered for peak load forecasting, and it was found that the peak load demand will increase to approximately 2.455 times that of existing peak load of 2212 MW, which is considered as the base case scenario. The scenario where the peak load demand is increased up to 4 times the existing peak load was also considered.

For both the case, generation adequacy assessment was done. In the base case scenario, it is found that there will be sufficient generation to meet the load demand in wet and normal seasons if all the generating units which are under construction are connected to the national grid within the 10-year timeframe. But, in dry season, due to low reserve margin in the system, there will be expected loss of load and energy not served with values of approximately 5.67 days/year and 1.31E+04 MWh.

Similarly, in worst case scenario, if the forecasted peak load increases to four times the existing peak load, the INPS will lose system reliability due to the negative/low reserve

margin between generation and load. In this case, the forecasted LOLE and EENS are found to be approximately 104 days/year and 5.42E+06 MWh which is very high as compare to base case scenario. It is also found that the generation expected to be connected to the grid over the next 10 years will not be sufficient to meet the load demand if load growth rate rises above expectation. Therefore, to improve system adequacy, either additional generation must be connected to the system, or electricity imports from external grids must be prioritized during the dry season. Furthermore, research findings indicate that the primary reason for the system's poor reliability is the inadequate generation capacity during the dry season to meet the required load demand.

In conclusion, while the reliability of the INPS system remains strong during the wet and normal seasons, enhancing its reliability in the dry season requires increasing the reserve margin. This can be achieved either by increasing the generation of the system or by importing electrical energy from external grid during the dry season. Also, in future if the load growth rate will be higher than historical growth rate, generation of INPS will not be sufficient to supply the load demand without/with minimum interruption in dry season so more generation needs to be connected to the grid or energy needs to be imported to maintain the adequacy of the system.

CHAPTER 6. FUTURE RECOMMENDATION

Future work could focus on finding how much new generation (in MW) needs to be added to the Integrated Nepal Power System (INPS) so that the reliability stays within an acceptable range, with very LOLE and EENS even in dry season. Also, doing a composite reliability analysis of both generation and transmission (HL-II system) can give a clearer idea of the overall system reliability and help in better planning for the future.

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APPENDICES

APPENDIX A: COPT – EXISTING SYSTEM

Capacity Outage Probability Table for Wet Season

COPT_ Wet Season					
Capacity Out (MW)	Individual Probability	Time of Curtailment	LOLE	Energy Curtailed(MWh)	EENS(MWh)
<=850	9.99E-01	0	0.00E+00	0.00E+00	0.00E+00
900	5.38E-08	2	1.08E-07	2.31E+02	1.24E-05
950	6.13E-09	3	1.84E-08	2.18E+03	1.34E-05
1000	5.75E-10	4	2.30E-09	5.70E+03	3.27E-06
1050	4.37E-11	10	4.37E-10	1.38E+04	6.03E-07
1100	2.68E-12	18	4.83E-11	3.04E+04	8.16E-08
1150	1.32E-13	30	3.95E-12	5.87E+04	7.72E-09
1200	5.10E-15	37	1.89E-13	9.65E+04	4.92E-10
1250	1.54E-16	53	8.16E-15	1.50E+05	2.30E-11
1300	3.55E-18	77	2.73E-16	2.24E+05	7.94E-13
1350	6.00E-20	89	5.34E-18	3.24E+05	1.94E-14
LOLE=			1.28698E-07	EENS=	0.00003

Capacity Outage Probability Table for Normal Season

COPT-Normal Season					
Capacity Out (MW)	Individual Probability	Time of Curtailment	LOLE	Energy Curtailed(MWh)	EENS(MWh)
0	4.15E-01	0	0	0.00E+00	0.00E+00
50	3.43E-01	0	0	0.00E+00	0.00E+00
100	1.44E-01	0	0	0.00E+00	0.00E+00
150	4.06E-02	0	0	0.00E+00	0.00E+00
200	8.51E-03	1	8.51E-03	1.03E+02	8.74E-01
250	1.68E-03	3	5.03E-03	1.19E+03	1.99E+00
300	8.81E-03	7	6.17E-02	5.82E+03	5.13E+01
350	6.48E-03	17	1.10E-01	1.79E+04	1.16E+02
400	2.53E-03	29	7.34E-02	4.54E+04	1.15E+02
450	6.76E-04	40	2.70E-02	8.63E+04	5.83E+01
500	1.34E-04	54	7.22E-03	1.43E+05	1.92E+01
550	2.03E-05	61	1.24E-03	2.12E+05	4.32E+00

COPT-Normal Season						
Capacity Out (MW)	Individual Probability	Time of Curtailment	LOLE	Energy Curtailed(MWh)	EENS(MWh)	
600	2.42E-06	68	1.65E-04	2.88E+05	6.98E-01	
650	2.25E-07	75	1.69E-05	3.74E+05	8.42E-02	
700	1.63E-08	90	1.46E-06	4.72E+05	7.67E-03	
750	8.98E-10	98	8.80E-08	5.84E+05	5.24E-04	
800	3.70E-11	105	3.89E-09	7.08E+05	2.62E-05	
850	1.11E-12	109	1.21E-10	8.35E+05	9.23E-07	
900	2.31E-14	111	2.57E-12	9.66E+05	2.24E-08	
950	3.26E-16	113	3.69E-14	1.10E+06	3.59E-10	
1000	2.94E-18	119	3.50E-16	1.24E+06	3.64E-12	
1050	2.00E-20	119	2.38E-18	1.38E+06	2.76E-14	
			LOLE=	2.94E-01	EENS=	3.67E+02

Capacity Outage Probability Table for Dry Season

COPT-Dry Season						
Capacity Out (MW)	Individual Probability	Time of Curtailment	LOLE	Energy Curtailed(MWh)	EENS(MWh)	
0	5.69E-01	118	6.71E+01	1.51E+06	8.59E+05	
50	2.86E-01	118	3.38E+01	1.65E+06	4.72E+05	
100	5.75E-02	118	6.78E+00	1.79E+06	1.03E+05	
150	1.43E-02	118	1.69E+00	1.93E+06	2.77E+04	
200	6.80E-03	118	8.02E-01	2.07E+06	1.41E+04	
250	1.67E-03	118	1.97E-01	2.21E+06	3.69E+03	
300	1.99E-04	118	2.34E-02	2.35E+06	4.67E+02	
350	1.25E-05	118	1.48E-03	2.49E+06	3.12E+01	
400	4.40E-07	118	5.19E-05	2.63E+06	1.16E+00	
450	8.69E-09	118	1.03E-06	2.77E+06	2.41E-02	
500	9.27E-11	118	1.09E-08	2.91E+06	2.70E-04	
550	4.70E-13	118	5.55E-11	3.05E+06	1.44E-06	
600	8.23E-16	118	9.71E-14	3.20E+06	2.63E-09	
650	5.50E-19	118	6.49E-17	3.34E+06	1.83E-12	
			LOLE=	1.10E+02	EENS=	1.48E+06

APPENDIX B: COPT – NEXT 10 YEARS

Capacity Outage Probability Table for Wet Season-Base Case

COPT-Wet Season(Base Case)					
Capacity Out (MW)	Individual Probability	Time of Curtailment	LOLE	Energy Curtailed(MWh)	EENS
>=0	1	0	0	0	0

Capacity Outage Probability Table for Wet Season-Worst Case

COPT-Wet Season(Worst Case)					
Capacity Out (MW)	Individual Probability	Time of Curtailment	LOLE	Energy Curtailed(MWh)	EENS
<=3400	9.99E-01	0	0	0	0
3450	5.28E-18	2	1.06E-17	7.34E+02	3.87E-15
3500	5.70E-19	2	1.14E-18	1.93E+03	1.10E-15
3550	5.00E-20	2	1.00E-19	3.13E+03	1.57E-16
LOLE=			1.18E-17	EENS= 5.13E-15	

Capacity Outage Probability Table for Normal Season-Base case

COPT-Normal Season(Base Case)					
Capacity Out (MW)	Individual Probability	Time of Curtailment	LOLE	Energy Curtailed(MWh)	EENS
>=0	1	0	0	0	0

Capacity Outage Probability Table for Normal Season-Worst Case

COPT-Normal Season(Worst Case)					
Capacity Out (MW)	Individual Probability	Time of Curtailment	LOLE	Energy Curtailed(MWh)	EENS
<=600	1.07E-01	0	0	0	0
650	4.92E-03	1	4.92E-03	8.61E+02	4.24E+00
700	4.53E-03	1	4.53E-03	2.06E+03	9.33E+00

COPT-Normal Season(Worst Case)					
Capacity Out (MW)	Individual Probability	Time of Curtailment	LOLE	Energy Curtailed(MWh)	EENS
750	3.39E-03	2	6.78E-03	1.72E+03	5.85E+00
800	2.21E-03	2	4.41E-03	2.92E+03	6.45E+00
850	1.36E-03	3	4.07E-03	5.66E+03	7.67E+00
900	8.71E-04	4	3.49E-03	9.25E+03	8.07E+00
950	5.96E-04	5	2.98E-03	1.40E+04	8.34E+00
1000	3.99E-04	5	2.00E-03	1.88E+04	7.51E+00
1050	2.48E-04	7	1.74E-03	2.60E+04	6.45E+00
1100	1.44E-04	9	1.29E-03	3.50E+04	5.03E+00
1150	8.02E-05	11	8.82E-04	4.63E+04	3.71E+00
1200	4.47E-05	14	6.25E-04	6.03E+04	2.69E+00
1250	2.49E-05	17	4.24E-04	7.88E+04	1.96E+00
1300	1.37E-05	22	3.01E-04	1.02E+05	1.40E+00
1350	7.25E-06	23	1.67E-04	1.29E+05	9.34E-01
1400	3.71E-06	29	1.07E-04	1.60E+05	5.95E-01
1450	1.85E-06	29	5.37E-05	1.94E+05	3.59E-01
1500	9.11E-07	33	3.01E-05	2.32E+05	2.11E-01
1550	4.40E-07	34	1.50E-05	2.72E+05	1.20E-01
1600	2.08E-07	39	8.11E-06	3.16E+05	6.57E-02
1650	9.57E-08	41	3.92E-06	3.63E+05	3.47E-02
1700	4.30E-08	47	2.02E-06	4.14E+05	1.78E-02
1750	1.89E-08	51	9.62E-07	4.72E+05	8.90E-03
1800	8.09E-09	53	4.29E-07	5.34E+05	4.32E-03
1850	3.38E-09	54	1.83E-07	5.97E+05	2.02E-03
1900	1.36E-09	56	7.62E-08	6.63E+05	9.03E-04
1950	5.29E-10	60	3.17E-08	7.33E+05	3.87E-04
2000	2.00E-10	61	1.22E-08	8.05E+05	1.61E-04
2050	7.39E-11	61	4.51E-09	8.77E+05	6.48E-05
2100	2.67E-11	63	1.68E-09	9.52E+05	2.54E-05
2150	9.33E-12	64	5.97E-10	1.03E+06	9.59E-06
2200	2.87E-12	65	1.86E-10	1.10E+06	3.16E-06
2250	7.26E-13	69	5.01E-11	1.18E+06	8.59E-07
2300	1.49E-13	70	1.04E-11	1.27E+06	1.89E-07
2350	2.48E-14	74	1.84E-12	1.35E+06	3.35E-08
2400	3.33E-15	74	2.47E-13	1.44E+06	4.80E-09
2450	3.61E-16	76	2.74E-14	1.53E+06	5.52E-10
2500	3.12E-17	79	2.46E-15	1.62E+06	5.06E-11
2550	2.13E-18	85	1.81E-16	1.72E+06	3.66E-12
2600	1.10E-19	88	9.68E-18	1.82E+06	2.00E-13
		LOLE=	0.038822263	EENS=	8.11E+01

Capacity Outage Probability Table for Dry Season-Base Case

COPT-Dry Season(Base Case)					
Capacity Out (MW)	Individual Probability	Time of Curtailment	LOLE	Energy Curtailed(MWh)	EENS
0	1.62E-01	2	3.23E-01	1.77E+03	2.86E+02
50	2.67E-01	4	1.07E+00	5.72E+03	1.52E+03
100	2.11E-01	6	1.27E+00	1.14E+04	2.41E+03
150	1.19E-01	8	9.55E-01	1.86E+04	2.22E+03
200	5.91E-02	10	5.91E-01	2.89E+04	1.71E+03
250	2.68E-02	16	4.29E-01	4.35E+04	1.17E+03
300	1.30E-02	18	2.33E-01	6.29E+04	8.16E+02
350	8.78E-03	28	2.46E-01	9.09E+04	7.98E+02
400	5.98E-03	42	2.51E-01	1.32E+05	7.91E+02
450	3.27E-03	48	1.57E-01	1.87E+05	6.10E+02
500	1.56E-03	51	7.95E-02	2.46E+05	3.84E+02
550	7.02E-04	57	4.00E-02	3.10E+05	2.18E+02
600	2.90E-04	61	1.77E-02	3.80E+05	1.10E+02
650	1.08E-04	66	7.16E-03	4.55E+05	4.94E+01
700	3.75E-05	78	2.93E-03	5.40E+05	2.03E+01
750	1.21E-05	86	1.04E-03	6.39E+05	7.75E+00
800	3.65E-06	91	3.32E-04	7.44E+05	2.71E+00
850	1.02E-06	92	9.39E-05	8.53E+05	8.71E-01
900	2.67E-07	93	2.48E-05	9.64E+05	2.57E-01
950	6.49E-08	97	6.30E-06	1.08E+06	6.99E-02
1000	1.47E-08	101	1.49E-06	1.20E+06	1.76E-02
1050	3.09E-09	104	3.22E-07	1.32E+06	4.08E-03
1100	5.96E-10	111	6.62E-08	1.45E+06	8.63E-04
1150	1.05E-10	112	1.17E-08	1.58E+06	1.65E-04
		LOLE=	5.6695	EENS=	1.31E+04

Capacity Outage Probability Table for Dry Season-Worst Case

COPT-Dry Season(Worst Case)					
Capacity Out (MW)	Individual Probability	Time of Curtailment	LOLE	Energy Curtailed(MWh)	EENS
0	1.62E-01	118	1.91E+01	5.90E+06	9.54E+05

COPT-Dry Season(Worst Case)					
Capacity Out (MW)	Individual Probability	Time of Curtailment	LOLE	Energy Curtailed(MWh)	EENS
50	2.67E-01	118	3.15E+01	6.04E+06	1.61E+06
100	2.11E-01	118	2.49E+01	6.18E+06	1.31E+06
150	1.19E-01	118	1.41E+01	6.32E+06	7.55E+05
200	5.91E-02	118	6.98E+00	6.46E+06	3.82E+05
250	2.68E-02	118	3.16E+00	6.60E+06	1.77E+05
300	1.30E-02	118	1.53E+00	6.74E+06	8.74E+04
350	8.78E-03	118	1.04E+00	6.88E+06	6.04E+04
400	5.98E-03	118	7.06E-01	7.02E+06	4.20E+04
450	3.27E-03	118	3.85E-01	7.16E+06	2.34E+04
500	1.56E-03	118	1.84E-01	7.30E+06	1.14E+04
550	7.02E-04	118	8.29E-02	7.44E+06	5.23E+03
600	2.90E-04	118	3.43E-02	7.58E+06	2.20E+03
650	1.08E-04	118	1.28E-02	7.72E+06	8.38E+02
700	3.75E-05	118	4.43E-03	7.86E+06	2.95E+02
750	1.21E-05	118	1.43E-03	8.00E+06	9.71E+01
800	3.65E-06	118	4.30E-04	8.14E+06	2.97E+01
850	1.02E-06	118	1.20E-04	8.28E+06	8.45E+00
900	2.67E-07	118	3.15E-05	8.43E+06	2.25E+00
950	6.49E-08	118	7.66E-06	8.57E+06	5.56E-01
1000	1.47E-08	118	1.74E-06	8.71E+06	1.28E-01
1050	3.09E-09	118	3.65E-07	8.85E+06	2.74E-02
1100	5.96E-10	118	7.03E-08	8.99E+06	5.36E-03
1150	1.05E-10	118	1.23E-08	9.13E+06	9.54E-04
		LOLE=	103.683879	EENS=	5415887.347

APPENDIX C: PEAK LOAD DATA FOR FY 2023/24

Date	Peak Load (MW)	Date	Peak Load (MW)	Date	Peak Load (MW)
7/17/2023	1640	11/16/2023	1427	3/17/2024	1884
7/18/2023	1607	11/17/2023	1493	3/18/2024	1857
7/19/2023	1780	11/18/2023	1374	3/19/2024	1885
7/20/2023	1885	11/19/2023	1390	3/20/2024	1712
7/21/2023	1767	11/20/2023	1439	3/21/2024	1797
7/22/2023	1804	11/21/2023	1540	3/22/2024	1792
7/23/2023	1841	11/22/2023	1560	3/23/2024	1738
7/24/2023	1808	11/23/2023	1682	3/24/2024	1436
7/25/2023	1797	11/24/2023	1544	3/25/2024	1287
7/26/2023	1826	11/25/2023	1456	3/26/2024	1279
7/27/2023	1818	11/26/2023	1571	3/27/2024	1538
7/28/2023	1826	11/27/2023	1581	3/28/2024	1508
7/29/2023	1687	11/28/2023	1597	3/29/2024	1668
7/30/2023	1806	11/29/2023	1560	3/30/2024	1624
7/31/2023	1782	11/30/2023	1578	3/31/2024	1807
8/1/2023	1957	12/1/2023	1569	4/1/2024	1833
8/2/2023	1823	12/2/2023	1473	4/2/2024	1906
8/3/2023	1823	12/3/2023	1626	4/3/2024	1921
8/4/2023	1852	12/4/2023	1615	4/4/2024	1918
8/5/2023	1748	12/5/2023	1615	4/5/2024	1881
8/6/2023	1758	12/6/2023	1701	4/6/2024	1829
8/7/2023	1692	12/7/2023	1606	4/7/2024	1861
8/8/2023	1593	12/8/2023	1607	4/8/2024	1863
8/9/2023	1661	12/9/2023	1533	4/9/2024	1832
8/10/2023	1803	12/10/2023	1655	4/10/2024	1848
8/11/2023	1797	12/11/2023	1703	4/11/2024	1616
8/12/2023	1651	12/12/2023	1717	4/12/2024	1910
8/13/2023	1808	12/13/2023	1669	4/13/2024	1674
8/14/2023	1740	12/14/2023	1713	4/14/2024	1913
8/15/2023	1806	12/15/2023	1692	4/15/2024	1925
8/16/2023	1873	12/16/2023	1559	4/16/2024	1808
8/17/2023	1872	12/17/2023	1715	4/17/2024	1838
8/18/2023	1797	12/18/2023	1764	4/18/2024	1927
8/19/2023	1721	12/19/2023	1762	4/19/2024	1899
8/20/2023	1772	12/20/2023	1816	4/20/2024	1818
8/21/2023	1616	12/21/2023	1820	4/21/2024	1970
8/22/2023	1657	12/22/2023	1783	4/22/2024	2072
8/23/2023	1625	12/23/2023	1689	4/23/2024	1992
8/24/2023	1594	12/24/2023	1750	4/24/2024	2018
8/25/2023	1573	12/25/2023	1729	4/25/2024	1956

Date	Peak Load (MW)	Date	Peak Load (MW)	Date	Peak Load (MW)
8/26/2023	1452	12/26/2023	1675	4/26/2024	2040
8/27/2023	1522	12/27/2023	1689	4/27/2024	1911
8/28/2023	1665	12/28/2023	1699	4/28/2024	1970
8/29/2023	1731	12/29/2023	1724	4/29/2024	1901
8/30/2023	1743	12/30/2023	1550	4/30/2024	2008
8/31/2023	1683	12/31/2023	1550	5/1/2024	1957
9/1/2023	1722	1/1/2024	1718	5/2/2024	1945
9/2/2023	1760	1/2/2024	1756	5/3/2024	1881
9/3/2023	1889	1/3/2024	1770	5/4/2024	1932
9/4/2023	1881	1/4/2024	1710	5/5/2024	1941
9/5/2023	1812	1/5/2024	1717	5/6/2024	1836
9/6/2023	1855	1/6/2024	1595	5/7/2024	1516
9/7/2023	1719	1/7/2024	1709	5/8/2024	1640
9/8/2023	1720	1/8/2024	1720	5/9/2024	1793
9/9/2023	1534	1/9/2024	1704	5/10/2024	1853
9/10/2023	1850	1/10/2024	1754	5/11/2024	1817
9/11/2023	1774	1/11/2024	1730	5/12/2024	1755
9/12/2023	1816	1/12/2024	1663	5/13/2024	1932
9/13/2023	1901	1/13/2024	1711	5/14/2024	1998
9/14/2023	1809	1/14/2024	1715	5/15/2024	1854
9/15/2023	1824	1/15/2024	1587	5/16/2024	2079
9/16/2023	1837	1/16/2024	1831	5/17/2024	2038
9/17/2023	1699	1/17/2024	1858	5/18/2024	1871
9/18/2023	1479	1/18/2024	1856	5/19/2024	1982
9/19/2023	1654	1/19/2024	1844	5/20/2024	1916
9/20/2023	1804	1/20/2024	1831	5/21/2024	2009
9/21/2023	1739	1/21/2024	1963	5/22/2024	1817
9/22/2023	1667	1/22/2024	1848	5/23/2024	2044
9/23/2023	1516	1/23/2024	1844	5/24/2024	1930
9/24/2023	1516	1/24/2024	1826	5/25/2024	1964
9/25/2023	1671	1/25/2024	1889	5/26/2024	1904
9/26/2023	1782	1/26/2024	2015	5/27/2024	1900
9/27/2023	1804	1/27/2024	1930	5/28/2024	2019
9/28/2023	1887	1/28/2024	1988	5/29/2024	2212
9/29/2023	1880	1/29/2024	1961	5/30/2024	1679
9/30/2023	1552	1/30/2024	1928	5/31/2024	2155
10/1/2023	1750	1/31/2024	1919	6/1/2024	1520
10/2/2023	1643	2/1/2024	2021	6/2/2024	1894
10/3/2023	1647	2/2/2024	1921	6/3/2024	1874
10/4/2023	1608	2/3/2024	1850	6/4/2024	1835
10/5/2023	1678	2/4/2024	1874	6/5/2024	1989
10/6/2023	1692	2/5/2024	1891	6/6/2024	1999

Date	Peak Load (MW)	Date	Peak Load (MW)	Date	Peak Load (MW)
10/7/2023	1592	2/6/2024	1973	6/7/2024	1997
10/8/2023	1592	2/7/2024	1901	6/8/2024	1958
10/9/2023	1801	2/8/2024	1901	6/9/2024	2136
10/10/2023	1763	2/9/2024	1894	6/10/2024	2092
10/11/2023	1796	2/10/2024	1800	6/11/2024	2071
10/12/2023	1747	2/11/2024	1862	6/12/2024	2205
10/13/2023	1740	2/12/2024	1862	6/13/2024	2045
10/14/2023	1599	2/13/2024	1839	6/14/2024	1964
10/15/2023	1707	2/14/2024	1874	6/15/2024	1961
10/16/2023	1573	2/15/2024	1891	6/16/2024	1987
10/17/2023	1647	2/16/2024	1829	6/17/2024	2016
10/18/2023	1568	2/17/2024	1823	6/18/2024	1919
10/19/2023	1529	2/18/2024	1837	6/19/2024	1921
10/20/2023	1510	2/19/2024	1849	6/20/2024	1870
10/21/2023	1311	2/20/2024	1821	6/21/2024	1978
10/22/2023	1311	2/21/2024	1770	6/22/2024	2051
10/23/2023	1216	2/22/2024	1770	6/23/2024	2038
10/24/2023	1107	2/23/2024	1831	6/24/2024	2080
10/25/2023	1294	2/24/2024	1775	6/25/2024	2065
10/26/2023	1345	2/25/2024	1863	6/26/2024	1800
10/27/2023	1378	2/26/2024	1862	6/27/2024	1882
10/28/2023	1352	2/27/2024	1842	6/28/2024	1958
10/29/2023	1535	2/28/2024	1834	6/29/2024	1769
10/30/2023	1511	2/29/2024	1840	6/30/2024	1885
10/31/2023	1604	3/1/2024	1824	7/1/2024	1878
11/1/2023	1576	3/2/2024	1686	7/2/2024	1810
11/2/2023	1555	3/3/2024	1701	7/3/2024	1708
11/3/2023	1536	3/4/2024	1797	7/4/2024	1841
11/4/2023	1576	3/5/2024	1833	7/5/2024	1671
11/5/2023	1576	3/6/2024	1730	7/6/2024	1820
11/6/2023	1592	3/7/2024	1733	7/7/2024	1699
11/7/2023	1592	3/8/2024	1664	7/8/2024	1724
11/8/2023	1602	3/9/2024	1701	7/9/2024	1823
11/9/2023	1589	3/10/2024	1829	7/10/2024	1705
11/10/2023	1567	3/11/2024	1812	7/11/2024	1655
11/11/2023	1535	3/12/2024	1860	7/12/2024	1593
11/12/2023	1438	3/13/2024	1797	7/13/2024	1618
11/13/2023	1444	3/14/2024	1801	7/14/2024	1738
11/14/2023	1388	3/15/2024	1783	7/15/2024	1777
11/15/2023	1290	3/16/2024	1771		

APPENDIX D: FORECASTED PEAK LOAD DATA UP TO 2034 AD

Year	Forecasted Peak Load		Year	Forecasted Peak Load	
	LSTM	ANN-MLP		LSTM	ANN-MLP
2024-03	1957.45	2130.23	2029-04	3395.87	3261.86
2024-04	1970.88	2140.60	2029-05	3423.46	3287.58
2024-05	1985.18	2151.59	2029-06	3451.33	3313.62
2024-06	2000.30	2163.17	2029-07	3479.48	3340.00
2024-07	2016.22	2175.31	2029-08	3507.91	3366.71
2024-08	2032.90	2187.98	2029-09	3536.63	3393.77
2024-09	2050.30	2201.15	2029-10	3565.63	3421.18
2024-10	2068.39	2214.81	2029-11	3594.94	3448.96
2024-11	2087.13	2228.90	2029-12	3624.54	3477.11
2024-12	2106.49	2243.42	2030-01	3654.45	3505.63
2025-01	2126.43	2258.33	2030-02	3684.65	3534.54
2025-02	2146.91	2273.60	2030-03	3715.16	3563.85
2025-03	2167.90	2289.20	2030-04	3745.97	3593.55
2025-04	2189.37	2305.11	2030-05	3777.07	3623.67
2025-05	2211.27	2321.30	2030-06	3808.47	3654.19
2025-06	2233.57	2337.74	2030-07	3840.16	3685.15
2025-07	2256.24	2354.40	2030-08	3872.14	3716.53
2025-08	2279.24	2371.25	2030-09	3904.41	3748.35
2025-09	2302.53	2388.27	2030-10	3936.98	3780.62
2025-10	2326.08	2405.42	2030-11	3969.82	3813.34
2025-11	2349.85	2422.69	2030-12	4002.96	3846.52
2025-12	2373.81	2440.03	2031-01	4036.38	3880.17
2026-01	2397.93	2457.43	2031-02	4070.09	3914.30
2026-02	2422.19	2474.88	2031-03	4104.09	3948.92
2026-03	2446.59	2492.41	2031-04	4138.39	3984.03
2026-04	2471.14	2510.01	2031-05	4172.99	4019.66
2026-05	2495.82	2527.68	2031-06	4207.89	4055.80

Year	Forecasted Peak Load		Year	Forecasted Peak Load	
	LSTM	ANN-MLP		LSTM	ANN-MLP
2026-06	2520.63	2545.45	2031-07	4243.11	4092.48
2026-07	2545.56	2563.31	2031-08	4278.64	4129.69
2026-08	2570.62	2581.27	2031-09	4314.48	4167.46
2026-09	2595.80	2599.34	2031-10	4350.66	4205.78
2026-10	2621.09	2617.53	2031-11	4387.15	4244.67
2026-11	2646.49	2635.84	2031-12	4423.98	4284.15
2026-12	2672.00	2654.28	2032-01	4461.15	4324.21
2027-01	2697.61	2672.86	2032-02	4498.66	4364.80
2027-02	2723.30	2691.59	2032-03	4536.52	4405.88
2027-03	2749.06	2710.48	2032-04	4574.75	4447.39
2027-04	2774.87	2729.54	2032-05	4613.36	4489.27
2027-05	2800.72	2748.79	2032-06	4652.35	4531.48
2027-06	2826.57	2768.23	2032-07	4691.73	4573.96
2027-07	2852.43	2787.89	2032-08	4731.51	4616.65
2027-08	2878.26	2807.76	2032-09	4771.71	4659.51
2027-09	2904.05	2827.87	2032-10	4812.33	4702.47
2027-10	2929.79	2848.22	2032-11	4853.38	4745.48
2027-11	2955.45	2868.83	2032-12	4894.88	4788.50
2027-12	2981.03	2889.70	2033-01	4936.82	4831.46
2028-01	3006.50	2910.85	2033-02	4979.22	4874.32
2028-02	3031.89	2932.29	2033-03	5022.10	4917.02
2028-03	3057.24	2954.00	2033-04	5065.46	4959.50
2028-04	3082.56	2975.99	2033-05	5109.30	5001.71
2028-05	3107.90	2998.26	2033-06	5153.64	5043.61
2028-06	3133.28	3020.81	2033-07	5198.50	5085.12
2028-07	3158.74	3043.65	2033-08	5243.87	5126.21
2028-08	3184.30	3066.76	2033-09	5289.77	5166.82
2028-09	3209.99	3090.15	2033-10	5336.20	5206.89
2028-10	3235.85	3113.83	2033-11	5383.19	5246.36

Year	Forecasted Peak Load		Year	Forecasted Peak Load	
	LSTM	ANN-MLP		LSTM	ANN-MLP
2028-11	3261.90	3137.78	2033-12	5430.73	5285.20
2028-12	3288.18	3162.02			
2029-01	3314.71	3186.53			
2029-02	3341.50	3211.34			
2029-03	3368.55	3236.45			

APPENDIX E: PUBLICATION



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Submission of Paper

IEEE Power & Energy Society Nepal Chapter <ieeepesnp@gmail.com>

Wed, Apr 16, 2025 at 10:29 PM

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Dear Authors

RESSD-2025 technical committee is pleased to inform you that your paper **has been Accepted** to be presented in the conference, congratulations!

Additional details will be sent in the upcoming days.

Regards,
RESSD2025 Technical Committee

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Assessment of Generation Adequacy of Integrated Nepal Power System for Next 10 Years

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Abstract—The paper evaluates the generation adequacy of the current Integrated Nepal Power System (INPS) and its reliability over the next decade by analyzing system performance under various seasonal conditions using a probabilistic approach. Capacity Outage Probability Tables (COPT) are developed for wet, normal, and dry seasons highlighting that the dry season experiences negative reserve margin due to significantly lower generation. Key reliability indices such as Loss of Load Expectation (LOLE) and Expected Energy Not Supplied (EENS) are evaluated and assessed based on HL-1 criteria. To examine the worst-case scenario, the study excludes energy imports from the external grid, highlighting the challenges of maintaining a reliable power supply through domestic generation alone. Additionally, load forecasting for the next 10 years is conducted using two machine learning models—Long Short-Term Memory (LSTM) and an Artificial Neural Network-based Multi-Layer Perceptron (ANN-MLP)—with LSTM demonstrating superior accuracy. The results suggest that if energy demand continues to grow at historical rates, system reliability may remain under acceptable range; however, any sharp increase in demand could significantly compromise adequacy, underscoring the need for proactive planning and capacity expansion to meet future energy needs

Index Terms—EENS, Generation Adequacy, Integrated Nepal Power System, INPS, Load Forecast, LOLE, NEA, Nepal Electricity Authority, Power System Reliability, Power System Security

I. INTRODUCTION

A power system is responsible for generating, transmitting, and distributing electricity efficiently. Its primary goal is to ensure a reliable and cost-effective power supply, as disruptions can have significant negative impacts on industries, businesses, and households [1]. These disruptions can lead to industrial production losses, interrupted commercial operations, and household inconveniences, all underscoring the importance of a stable power system.

Reliability and economic limitations are key challenges in managing power systems. Achieving high reliability requires substantial investments in infrastructure and maintenance. However, financial constraints may prevent necessary system upgrades, impacting overall performance. Finding a balance between reliability and cost is essential for efficient system operation.

Power system reliability is assessed through two main aspects: adequacy and security [2]. Adequacy determines whether the system has enough resources to meet demand

while accounting for outages and operational limits, whereas security refers to the system's ability to handle disturbances without cascading failures.

Assessment of generation adequacy can be done by using Analytical [3] or Simulation [4] Techniques. The reliability indices of different load centers of INPS is evaluated using Monte-Carlo Simulation in [5]. Analytical approach was used by [6] to evaluate the reliability of the then existing INPS in 2015. This paper uses Analytical approach, which involves the evaluation of reliability indices such as Loss of Load Probability (LOLP), Loss of Load Expectation (LOLE), and Expected Energy Not Served (EENS) of the existing system as well as forecasts for the next 10 years. LOLP represents the likelihood that the available generation will not be sufficient to meet the load demand. LOLE indicates the expected average number of hours or days per year when the existing generating capacity is unable to meet demand. EENS refers to the estimated amount of energy that will not be supplied to consumers due to system capacity shortages or unexpected major power outages during the specified period usually a year.

In this paper, the objective is to conduct the Generation Adequacy Assessment of the Integrated Nepal Power System (INPS) to determine if the existing generation is adequate to meet the present load demand with a high degree of reliability. Furthermore, it aims to assess whether the planned generation expansion will be sufficient to meet the increased load demand in the next 10 years.

The paper is organized as follows. Section II provides an overview of the INPS. Section III covers the fundamentals of generation system adequacy, including basic assessment models, various approaches for evaluating adequacy, and adequacy indices. Section IV outlines the methodologies used in this study. The results are presented in Section V. Finally, Section VI concludes the paper.

II. INTEGRATED NEPAL POWER SYSTEM - OVERVIEW

The electricity supply system of Nepal is vertical one. There is only one organization which is under government. The power system structure of Nepal is called Integrated Nepal Power System (INPS).

There are 54 power plants in Koshi Province with an installed capacity of 642.53 MW. The largest power plant in this

province is Solu Khola (Dudhkoshi) with an installed capacity of 86 MW. In Madesh Province, there are five power stations located in different areas all of which are solar power stations. The largest plant is the Mithila Solar PV Electric Project, with an installed capacity of 10 MW, and the total installed capacity of Province 2 is 19 MW. In Bagmati Province, there are a total of 63 electric power stations. The largest power plant in this province is Upper Tamakoshi, with an installed capacity of 456 MW, and the total installed capacity of the province is approximately 1,500 MW. In Gandaki Province, there are 62 generating station. The largest power plant in this is Kaligandaki 'A' with an installed capacity of 144 MW. The total installed capacity of this province is 1000 MW. In Lumbini Province, there are 13 generating stations including 6 PV projects. As of now, the total installed capacity of this province is 78 MW. The largest power plant in this province is the Gandak Power Station, with an installed capacity of 15 MW. In Karnali Province, there are 2 power stations named Padam Khola and Dwari Khola, with installed capacities of 4.8 MW and 3.75 MW, respectively. In Sudurpaschim (Far West) Province, there are 11 power stations with a total installed capacity of 177 MW. The largest power plant in this province is Upper Chameliya, with an installed capacity of 40 MW.

Thus, the total installed capacity of the Integrated Nepal Power System (INPS) is approximately 3,431 MW. Also, there are 255 hydropower plants more than 1 MW and 10 solar projects which are under construction with total installed capacity of 10080 MW and 82 MW respectively.

In the FY 2023/24, NEA's total power generation amounted to 2,911 GWh, representing a slight decrease from the 2,930 GWh generated in FY 2022/23. This reduction was primarily due to diminished rainfall and lower river discharge compared to the previous year. Also, total domestic consumption increased to 10,243 GWh in FY 2023/24, reflecting a 9.46% rise from 9,358 GWh in FY 2022/23.

III. GENERATION ADEQUACY ASSESSMENT

The purpose of generating adequacy assessment is to measure the ability of the installed generating capacity to meet the requirements of a specified load demand. In adequacy evaluation, generating unit model and load model are two main components of a generating system [7]. Both the generating unit and the load models are then combined to form the risk model. In a generation model, a generating unit is represented by a two-state model. In the up state, the generating unit is in operating condition. On the other hand, in down-state, the generating unit is not in operating condition. In this paper, assumption is made that each generating unit is in either up-state or down-state at their full capacities rather than different percentages of their full capacity. Forced outages are unlike scheduled outages where entire electrical systems are deliberately taken out of service due to maintenance or other emergencies. The forced outage rate (FOR) of the generating unit is defined as the probability that the unit will not be in service when required. It is generally estimated based on the

TABLE I
MONTHS IN SEASON

Season	Month (Nepali)	Month (English)
Wet	Jestha to Bhadra	16 May to 15 September
Normal	Chaitra - Baisakh	16 March to 15 May
	Asoj - karthik	16 September to 15 November
Dry	Mangsir to Falgun	16 November to 15 March

historical operating data of the unit. FOR can also be expressed as follows:

$$FOR = \frac{\lambda}{\lambda + \mu} \quad (1)$$

where λ and μ represent the failure rate and repair rate, respectively. FOR of the generators is obtained from [6] and if not available is assumed to be 0.02.

Accurate generation and load modeling is crucial for assessing generation adequacy as it helps predict how power consumption changes under different conditions and ensures reliable power delivery. The generation model can be represented in the form of an array of capacity levels and their associated probabilities, called Capacity Outage Probability Table (COPT) while the load model can be represented by a Load Duration Curve (LDC). COPT and LDC can be studied together to develop a risk model.

IV. METHODOLOGY

Most of the generating stations in Nepal are Run-of-River (RoR) and Peaking Run-of-River (PRoR) hydropower plants, with generation subject to seasonal fluctuations. In this research, the year is divided into three seasons: wet, normal, and dry. The months in a season is given in Table I. The months are divided based upon the available water discharge in the rivers of Nepal.

To assess the available generation across the INPS, the Dordi Corridor of the INPS is studied, assuming that the same seasonal percentage capacity applies across the entire INPS. The Average energy produced by Dordi Corridor Hydropower Project is taken as basis for the energy and power availability of the entire INPS.

The day to day peak load demand of the INPS is obtained from the annual reports of Nepal Electricity Authority (NEA) to develop the LDC. Also, required information of power plants—specifically hydropower projects with installation capacity more than 1 MW and solar power plants that are either operational or under construction—is obtained from the Department of Electricity Development (DoED).

First, the Capacity Outage Probability Tables (COPT) is generated for all seven provinces of Nepal, considering the existing power plants. Additionally, load duration curves for three different seasons is developed using daily peak load. By integrating the COPT with the seasonal load duration curves, the overall adequacy of the INPS for the fiscal year 2023/24 is obtained.

Various machine learning model can be used for load forecasting [10], [11]. Peak load forecasting over a ten-year period is conducted in Python using two machine learning

models: an LSTM and an MLP. Historical consumers data of 30 years are used to train the model, while a one-year period is reserved for model validation. Model performance of these two models are compared by using different statistical performance parameters, and the one with high accuracy is selected for long-term peak load forecasting.

Also, COPT is generated for power plants projects- which are assumed to be completed and connected to the grid in ten years- under construction. This COPT is combined with Existing COPT of INPS to obtain the COPT for the fiscal year 2033/34. By using forecasted outage table and LDC, reliability indices are obtained for the following year.

The events with a probability 1E-20 or lower are ignored while preparing the COPT and it is rounded in the capacity out increment of 50 MW. The rounding process can be applied using the following expressions [7]:

$$P(C_j) = \frac{C_k - C_i}{C_k - C_j} P(C_i) \quad (2)$$

$$P(C_k) = \frac{C_i - C_j}{C_k - C_j} P(C_i)$$

For all states i falling between the required rounding states j and k .

V. RESULT AND ANALYSIS

A. Study of Dordi corridor

The Hydropower of Nepal needs to sign Power Purchase Agreement (PPA) with the NEA. The PPA contains the contract energy that the projects needs to produce and sell to NEA. To evaluate the available energy and power, the installed capacity and PPA contract energy of the Dordi corridor given in Table II is taken as reference.

TABLE II
DORDI CORRIDOR GENERATION (GWH)

Months	Upper Dordi	Super Dordi	Dordi-12	Dordi-27
Shrawan	17.253051	32.74375	8.485	19.0030
Bhadra	17.253951	32.74375	8.485	19.0030
Ashoj	17.253951	30.74375	8.485	19.0030
Kartik	15.242901	26.74375	6.899	12.1507
Mangsir	9.23619	21.2575	4.214	8.2206
Poush	6.671708	13.2575	3.044	6.3144
Magh	5.404667	13.2575	2.4608	5.0258
Falgun	5.071619	13.2575	2.3069	4.9434
Chaitra	5.015893	16.371875	2.2717	5.0832
Baishakh	7.890122	21.371875	3.5848	7.5009
Jestha	13.172469	44.115625	6.2598	16.4542
Ashad	17.253051	49.115625	8.7588	19.6160

The available average capacity for a season is then evaluated as given by (3) to develop Table III.

$$AverageProduction = \frac{\sum Energy}{Days * InstalledCapacity} \quad (3)$$

Hence, by taking the average of energy production of different power plants of Dordi corridor, average energy production is assumed to be 90% for wet season, 65% for normal season, and 35% for dry season for the entire INPS.

TABLE III
CAPACITY AND AVERAGE ENERGY PRODUCTION OF PROJECTS IN DORDI CORRIDOR

Projects	Capacity (MW)	Average Energy Production		
		Wet	Normal	Dry
Upper Dordi	25	85.89 %	62.54 %	37.27 %
Super Dordi	54	97.20 %	60.73 %	39.91 %
Dordi-12	12	88.15 %	60.95 %	35.39 %
Dordi-27	27	90.73%	73.49%	32.05%

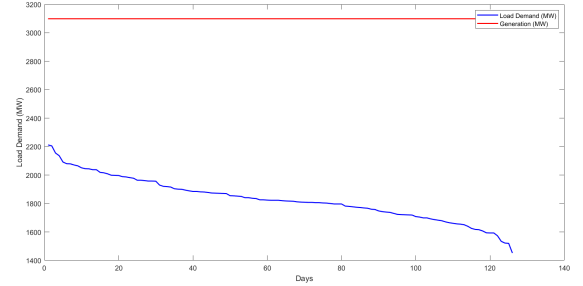


Fig. 1. LDC of INPS for Wet Season of FY 2023/24

B. Adequacy Assessment of existing INPS

The day to day peak demand of INPS is obtained from annual reports of NEA for Fiscal Year 23/24 available on [12] to develop the Fig. 1, Fig. 2, and Fig. 3. The Generation is plotted based upon the INPS installed capacity of 3431 MW and available seasonal generation. From, Fig. 1, Fig. 2, and Fig. 3, it is clear that the INPS has a positive margin for wet and normal season while it has a negative margin for dry season.

The COPT for wet, normal, and dry season was developed on MATLAB and tabulated in Table IV, Table V, and Table VI. The reliability indices are then evaluated and shown in Table VII. The LOLP for the wet season is found to be 6.05E-08 followed by normal and dry seasons with values 2.88E-02, and 9.36E-01, which is shown on Table VII. So, the overall LOLP of existing INPS is found to be 3.12E-01. Also, LOLE and EENS for wet and normal seasons are found to be very low but increased to 110 days and 1.48E+06 MWh in the dry season. The main reason for higher LOLE and EENS during the dry season is due to a negative reserve margin of approximate 900 MW.

The Capacity Out and Expected Energy Not Served for the Fiscal Year 23/24 is plotted in Fig. 4. From this, it is clear that the loss of some generation units during wet and normal season does not means the loss of energy demand and as such has high reliability but in dry season even without the loss of units, there is loss of energy demand and as such has low reliability as given in Table VII.

C. Load Forecast upto 2034

Various models for load forecasting exists such as LSTM, ANN MLP, RNN, CNN, Random forest, and k-nearest neighbour among others. As shown by [8] and [9], LSTM and ANN

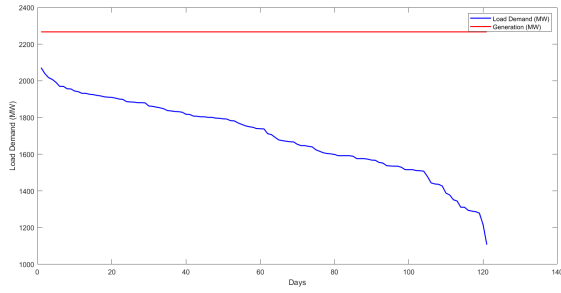


Fig. 2. LDC of INPS for Normal Season of FY 2023/24

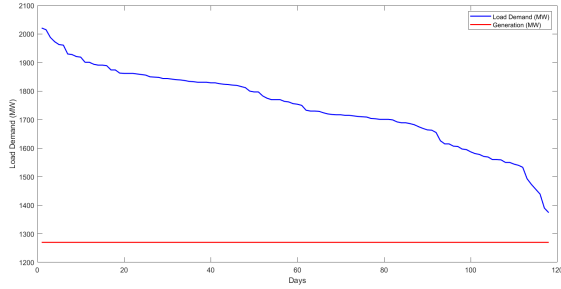


Fig. 3. LDC of INPS for Dry Season of FY 2023/24

TABLE IV
COPT FOR WET SEASON OF FY 2023/24

Capacity Out (MW)	Individual Probability	LOLE (days)	Energy Curtailed (MWh)	EENS (MWh)
≤ 850	0.970688	0.00E+00	0.00E+00	0.00E+00
900	5.38E-08	1.08E-07	2.31E+02	1.24E-05
950	6.13E-09	1.84E-08	2.18E+03	1.34E-05
1000	5.75E-10	2.30E-09	5.70E+03	3.27E-06
1050	4.37E-11	4.37E-10	1.38E+04	6.03E-07
1100	2.68E-12	4.83E-11	3.04E+04	8.16E-08
1150	1.32E-13	3.95E-12	5.87E+04	7.72E-09
1200	5.10E-15	1.89E-13	9.65E+04	4.92E-10
1250	1.54E-16	8.16E-15	1.50E+05	2.30E-11
1300	3.55E-18	2.73E-16	2.24E+05	7.94E-13
1350	6.00E-20	5.34E-18	3.24E+05	1.94E-14

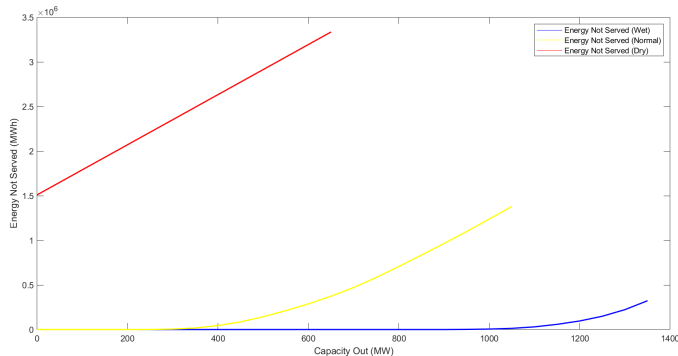


Fig. 4. Capacity Out vs Energy Not Served for FY 2023/24

TABLE V
COPT FOR NORMAL SEASON OF FY 2023/24

Capacity Out (MW)	Individual Probability	LOLE (days)	Energy Curtailed (MWh)	EENS (MWh)
≤ 150	9.42E-01	0.00E+00	0.00E+00	0.00E+00
200	8.51E-03	8.51E-03	1.03E+02	8.74E-01
250	1.68E-03	5.03E-03	1.19E+03	1.99E+00
300	8.81E-03	6.17E-02	5.82E+03	5.13E+01
350	6.48E-03	1.10E-01	1.79E+04	1.16E+02
400	2.53E-03	7.34E-02	4.54E+04	1.15E+02
450	6.76E-04	2.70E-02	8.63E+04	5.83E+01
500	1.34E-04	7.22E-03	1.43E+05	1.92E+01
550	2.03E-05	1.24E-03	2.12E+05	4.32E+00
600	2.42E-06	1.65E-04	2.88E+05	6.98E-01
650	2.25E-07	1.69E-05	3.74E+05	8.42E-02
700	1.63E-08	1.46E-06	4.72E+05	7.67E-03
750	8.98E-10	8.80E-08	5.84E+05	5.24E-04
800	3.70E-11	3.89E-09	7.08E+05	2.62E-05
850	1.11E-12	1.21E-10	8.35E+05	9.23E-07
900	2.31E-14	2.57E-12	9.66E+05	2.24E-08
950	3.26E-16	3.69E-14	1.10E+06	3.59E-10
1000	2.94E-18	3.50E-16	1.24E+06	3.64E-12
1050	2.00E-20	2.38E-18	1.38E+06	2.76E-14

TABLE VI
COPT FOR DRY SEASON OF FY 2023/24

Capacity Out (MW)	Individual Probability	LOLE (days)	Energy Curtailed (MWh)	EENS (MWh)
0	5.69E-01	6.71E+01	1.51E+06	8.59E+05
50	2.86E-01	3.38E+01	1.65E+06	4.72E+05
100	5.75E-02	6.78E+00	1.79E+06	1.03E+05
150	1.43E-02	1.69E+00	1.93E+06	2.77E+04
200	6.80E-03	8.02E-01	2.07E+06	1.41E+04
250	1.67E-03	1.97E-01	2.21E+06	3.69E+03
300	1.99E-04	2.34E-02	2.35E+06	4.67E+02
350	1.25E-05	1.48E-03	2.49E+06	3.12E+01
400	4.40E-07	5.19E-05	2.63E+06	1.16E+00
450	8.69E-09	1.03E-06	2.77E+06	2.41E-02
500	9.27E-11	1.09E-08	2.91E+06	2.70E-04
550	4.70E-13	5.55E-11	3.05E+06	1.44E-06
600	8.23E-16	9.71E-14	3.20E+06	2.63E-09
650	5.50E-19	6.49E-17	3.34E+06	1.83E-12

MLP outperform the other models for load forecasting and as such these two models are used for load forecasting in this paper. For the selection of the best model between LSTM and ANN MLP, model performance is compared for the test set using R-Squared (R^2) value, Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) as shown in Table VIII.

From Table VIII, it is found that test set of Long Short Term

TABLE VII
RELIABILITY INDICES FOR FY 2023/24

FY 2023/24	LOLP	LOLE (days/ year)	EENS (MWh)
Wet Season	6.05E-08	1.29E-07	2.98E-05
Normal Season	2.88E-02	2.94E-01	3.67E+02
Dry Season	9.36E-01	1.10E+02	1.48E+06
Year	3.12E-01	1.11E+02	1.48E+06

TABLE VIII
PERFORMANCE PARAMETERS OF ML MODELS

	R ² Value	RMSE	MAE	MAPE
LSTM	0.9760526	84.3768503	63.4892880	10.59%
ANN MLP	0.9587729	110.709716	77.7299002	13.22%

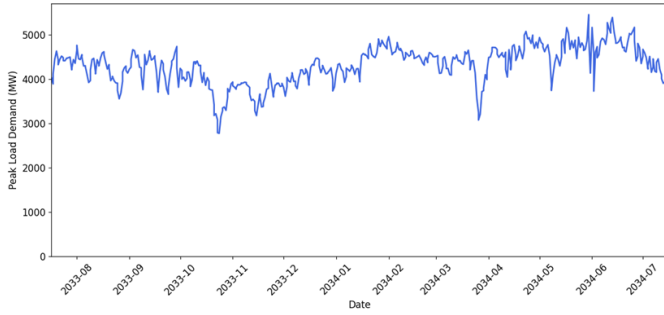


Fig. 5. Forecasted Load Curve for FY 2033/34

Memory (LSTM) has less value of R², RMSE, MAE, and MAPE than that of MLP and hence is chosen to forecast the load for Fiscal Year 2033/34. The forecasted load curve and load duration curve is given in Fig. 5 and Fig. 6. Additionally, it is found that if the load growth follows historical trends, the peak load is expected to increase 2.455 times over the next 10 years.

D. Adequacy Assessment of INPS for FY 2033/34-Base Case

The forecasted load duration curve, the existing generation, and the expected generation to be connected to INPS by Fiscal Year 2033/34 are then used to obtain the COPT, and the reliability indices were calculated which is tabulated in Table IX. The expected generation to be connected to INPS by Fiscal Year 2033/34 is taken as the projects of capacity greater than 1 MW and has obtained the construction license form DoED available on [13]. In this case, it is found that there is no energy curtailment during the wet and normal seasons. LOLE and EENS for this year are found to be 5.67 days/year and 1.31E+04 MWh, which is due to negative reserve margin during the dry season but is very low as compared to existing and forecasted worse-case scenario.

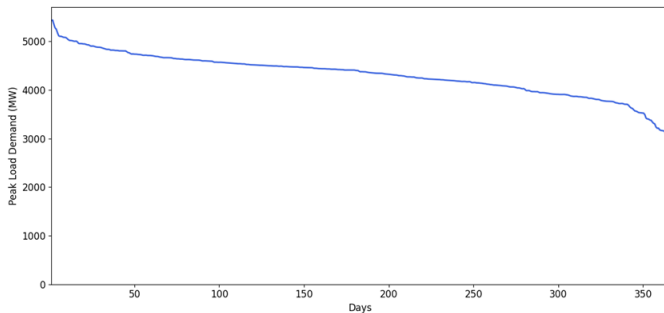


Fig. 6. Forecasted load duration curve for FY 2033/34

TABLE IX
RELIABILITY INDICES FOR FY 2033/34 - BASE CASE

FY 2033/34 (Base Case)	LOLP	LOLE (days/ year)	EENS (MWh)
Wet Season	0	0	0
Normal Season	0	0	0
Dry Season	8.79E-01	5.67E+00	1.31E+04
Year	2.84E-01	5.67E+00	1.31E+04

E. Adequacy Assessment of INPS for FY 2033/34-Worse Case

Adequacy assessment is also done for the worst-case scenario, where the peak load is assumed to increase four times the existing peak load due to the possibility of higher-than-expected electricity consumption, driven by the increasing use of electric vehicles, growth in commercial and industrial consumers, and other factors. The result is then tabulated in Table X. It is found that if the load demand increases beyond expectations, there will be a significant loss of load and energy curtailment. There will be the highest energy curtailment during the dry season, with LOLE of 104 days and EENS of 5.42E+06 MWh. Also, during the wet season, energy curtailment is minimal, with LOLE of 1.18E-17 days and EENS of 5.13E-15 MWh.

TABLE X
RELIABILITY INDICES FOR FY 2033/34-WORST CASE

FY 2033/34 (Worse Case)	LOLP	LOLE (days/ year)	EENS (MWh)
Wet Season	5.90E-18	1.18E-17	5.13E-15
Normal Season	1.88E-02	3.88E-02	8.11E+01
Dry Season	8.79E-01	1.04E+02	5.42E+06
Year	2.90E-01	1.04E+02	5.42E+06

VI. CONCLUSIONS

In this research, adequacy assessment is carried out considering existing generation as well as the generation expected to be connected to the national grid in the next 10 years in INPS using a probabilistic approach. The result shows that the existing generation system can meet load demand during the wet and normal seasons even without energy import from the external grid. However, in the dry season, it faces challenges due to a low reserve margin. To ensure system reliability, importing electricity from the external grid during the dry season is necessary. Also, if the load growth follows historical trends over the next 10 years, the planned generation additions will be sufficient to maintain reliability, even in the dry season, with minimal energy curtailment. However, if demand grows beyond expectations, energy curtailment will be significant, with a high LOLE. To sustain system reliability under such conditions, either additional large generations must be added to the grid, or energy imports must be prioritized during the dry season.

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APPENDIX F: PLAGIARISM TEST REPORT

Sandesh Neupane

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