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A THESIS PROPOSAL ON

**SHORT-TERM ELECTRICAL LOAD FORECASTING FOR LEKHNATH
FEEDER USING MACHINE AND DEEP LEARNING MODELS**

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SUBMITTED TO:

THE DEPARTMENT OF ELECTRICAL ENGINEERING
MASTERS OF SCIENCE IN
POWER SYSTEM ENGINEERING

August 2025

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LIST OF ABBREVIATIONS

DL Deep Learning. 1

ML Machine Learning. 1

RNN Recurrent Neural Network. 4

STLF Short-Term Load Forecasting. 1

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CHAPTER 1 INTRODUCTION

1.1 Background

Electrical load forecasting plays a vital role in the planning, operation, and control of modern power systems. It enables utilities to anticipate future demand, schedule generation resources efficiently, minimize operational costs, and maintain a stable and reliable supply of electricity. Among the different types of load forecasting, Short-Term Load Forecasting (STLF)—with a prediction horizon ranging from a few minutes to a few days ahead—is particularly important for economic dispatch, generation scheduling, load flow analysis, and system security assessment.

Traditional load forecasting approaches, such as multiple linear regression, exponential smoothing, and autoregressive integrated moving average (ARIMA) models, have been widely used in power systems. While effective for certain patterns, these methods often fail to capture the nonlinear and dynamic nature of electrical load, especially under rapidly changing demand influenced by multiple factors such as weather conditions, socio-economic activities, and holidays.

In recent years, Machine Learning (ML) and Deep Learning (DL) techniques have emerged as powerful alternatives for load forecasting. ML methods such as Support Vector Regression (SVR), Random Forest (RF), and Extreme Gradient Boosting (XG-Boost) can model complex relationships between input variables and load demand. DL models, particularly recurrent neural networks (RNNs) and their variants such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, are capable of learning temporal dependencies in time-series data, making them highly suitable for forecasting applications.

The Lekhnath Feeder, located in Lekhnath Municipality, Kaski, is an important distribution feeder that supplies electricity to residential, commercial, and small industrial consumers. The load profile of this feeder exhibits daily, weekly, and seasonal variations influenced by local climate, socio-economic activities, and population growth. Accurate load forecasting for this feeder is essential for efficient power system operation, reduction of operational costs, and minimization of technical losses. However, the current forecasting approaches used for Lekhnath Feeder may not fully leverage modern data-driven techniques.

The increasing complexity of load patterns, coupled with the availability of historical load and weather data, presents an opportunity to develop and apply advanced ML and DL models tailored to the Lekhnath Feeder's characteristics for improved forecasting accuracy.

1.2 Problem Statement

The existing load forecasting methods for Lekhnath Feeder are either based on manual estimation or traditional statistical techniques. These approaches have limitations in accurately capturing the nonlinear and dynamic patterns of load demand, particularly when multiple influencing factors are involved. Moreover, the growing demand, seasonal variability, and stochastic nature of load in the Lekhnath area increase the difficulty of accurate prediction.

Inaccurate load forecasts can result in inefficient generation scheduling, increased operational costs, higher technical losses, and potential reliability issues. There is a lack of research that systematically applies and compares advanced ML and DL techniques for short-term load forecasting specific to the Lekhnath Feeder.

Therefore, there is a pressing need to design, implement, and evaluate robust data-driven forecasting models that can provide high-accuracy short-term load predictions and support decision-making in power system operation.

1.3 Objectives

1.3.1 Main Objective

To develop and evaluate machine learning and deep learning models for short-term electrical load forecasting of the Lekhnath Feeder to improve prediction accuracy and operational efficiency.

1.3.2 Specific Objectives

1. To collect and preprocess historical load data and relevant influencing factors such as weather variables and calendar effects for the Lekhnath Feeder.
2. To analyze consumption patterns and influencing factors (e.g., time, weather, festivals).
3. To implement various machine learning models, including Support Vector Regression (SVR), Random Forest (RF), and XGBoost, for load forecasting.
4. To design and train deep learning models such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks to capture temporal dependencies in load data.
5. To evaluate and compare the performance of ML and DL models using standard error metrics (e.g., RMSE, MAPE, MAE, MSE, R-squared).
6. To compare and select the most effective forecasting model.
7. To recommend the most suitable forecasting model for operational use in the Lekhnath Feeder.

1.4 Scope

- Geographical Scope: This study is limited to the Lekhnath Feeder under the Nepal Electricity Authority.
- Temporal Scope: The focus is on short-term load forecasting, with a prediction horizon of up to 24 hours ahead, based on historical hourly load data.
- Data Scope: The dataset includes historical load data from the Lekhnath Feeder, weather data (temperature, humidity, rainfall, etc.), and calendar data (weekdays, weekends, holidays).
- Technical Scope:
 - Machine Learning models: SVR, Random Forest, XGBoost.
 - Deep Learning models: LSTM, GRU
 - Performance evaluation using RMSE, MAPE, MAE, MSE, R-squared.
- Limitations:
 - The accuracy of forecasts depends on the quality and completeness of the historical data.
 - The study does not consider medium-term or long-term forecasting.
 - Renewable generation forecasting is excluded from this work.

CHAPTER 2 LITERATURE REVIEW

2.1 Review of Literature

There are many previous work done for electrical load forecasting from short-term electrical load forecasting, to medium-term and long-term. Most of the studies have done short-term load forecasting.

(Singla et al., 2019) uses Artificial Neural Network for short term load forecasting for 24 hours duration. The input features taken are dew point, dry bulb temperature, and humidity, and forecast for load. On the another hand (Desai et al., 2021) employed Prophet model from Meta to perform short-term load forecast using features such as time, temperature, humidity, and weather forecast. (Chapagain et al., 2021) also explores time series and regression along with machine learning and deep learning models for electricity demand forecast of Kathmandu valley. They found LSTM having outstanding performance in terms of MAPE, and RMSE. Deterministic variables taken are type of days, and temperature. (Acharya et al., n.d.) has performed short-term electrical load forecasting of Gothatar feeder with 6 input features, and found Recurrent Neural Network (RNN) outperforming the base line methods: Single Exponential Smoothing, Double Exponential Smoothing, and Holt-Winter's method. Different from other studies (Matrenin et al., 2022) performs medium-term load forecasting using ensemble machine learning models such as XGBoost, AdaBoost and compared with SVR, decision tree, and random forest. (Aguilar Madrid & Antonio, 2021) tested five machine learning models and found XGBoost to be most accurate for predictions, they have used input features like historical load data, weather, and holiday data.

(Guo et al., 2021) analyzes three popular ML methods for load forecasting: SVM, RF, and LSTM, and showed that a fusion forecasting approach combining all the output of these models helped to improve prediction accuracy. Conv-1D model is explored in study (Cordeiro-Costas et al., 2023) in-addition to other AI techniques such as RF, SVR, XGBoost, MLP, and LSTM. They found out LSTM model to be outperforming other models with lowest errors. (Saglam et al., 2024) performs comparison between optimization methods (PSO, DO, GRO) and machine learning model (SVR, ANN) for instantaneous peak electrical load forecasting, and found ANN and GRO outperforming other models. They also found strong positive correlation between GDP and peak load.

CHAPTER 3 METHODOLOGY

The methodology outlines the systematic approach for developing, training, and evaluating machine learning and deep learning models for short-term load forecasting of the Lekhnath Feeder. The process involves data acquisition, preprocessing, model development, training and validation, performance evaluation, and result interpretation. The overall diagram of the methodology is shown in Figure 3.1.

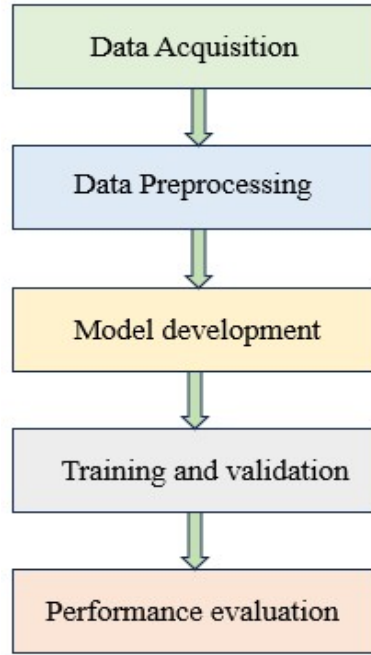


Figure 3.1: Proposed methodology for the thesis

3.1 Data Acquisition

The first step of our methodology is data acquisition. Hourly historical load data from Lekhnath Feeder will be collected. Weather Data such as temperature, humidity, and rainfall data will be collected from the Department of Hydrology and Meteorology, Nepal. And finally, the information on weekdays, weekends are obtained from official government calendars.

3.2 Data Preprocessing

The data is first cleaned, with missing values handled using imputation techniques like linear interpolation or a forward-fill method. We then perform feature engineering to create a more effective set of features, such as time-based data (day of the week, month) and calendar flags to distinguish between weekdays and weekends. After that, the data is normalized using z-score normalization before being fed into the machine learning

model. Finally, the dataset is split chronologically into a training set (80%), a validation set (10%), and a testing set (10%).

3.3 Model Development

Two model categories will be developed:

1. Machine learning models: Support Vector Regression, Random Forest, Extreme Gradient Boosting, Decision Tree will be implemented as a base line model.
2. Deep learning models: Recurrent Neural Network variants such as Long Short-Term Memory and Gated Recurrent Unit will be implemented. Our hypothesis is that the deep learning models should outperform the machine learning model, as it has does in previous studies.

3.4 Model training and validation

After the model is developed, these models are training in our local PC with GPU computing. Since, we are taking input features: historical load data, temperature, humidity, rainfall, wind speed, weedend, weekday, month of year, total of 8 features set to forecast the load demand in hourly resolution. The simplified block diagram of the training process is depicted in figure 3.2, which shows the training the deep learning models, same applies for the machine learning model except the ML models instead of neural networks. Since in the input, we have 8 features and output has single feature to be forecasted, the problem we are dealing is multivariate regression task. In this thesis work we are going to forecast the load demand for next 24 hours. The models hyperparameters will be searched using grid-search technique to find the optimal best hyperparameters in both machine and deep learning techniques. These models are validated with walk-forward validation to mimic real-world forecasting.

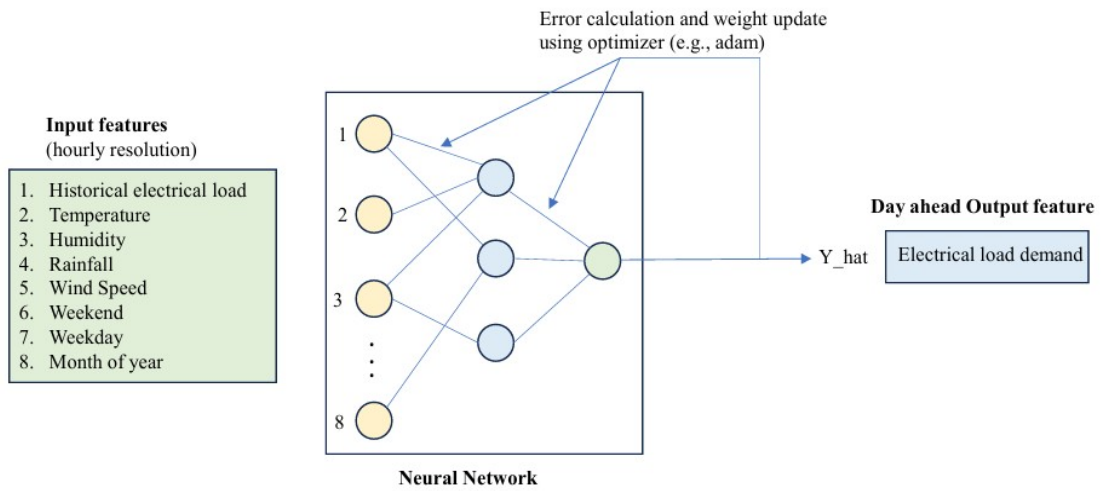


Figure 3.2: Training of the Machine and Deep Learning models

3.5 Performance evaluation

The performance of models are measured using: RMSE, MAE, MSE, MAPE, and R-squared.

CHAPTER 4 EXPECTED OUTCOMES

The proposed thesis work is expected to yield the following outcomes:

1. Development of machine learning (SVR, Random Forest, DT, XGBoost) and deep learning (LSTM, GRU) models tailored to the load characteristics of the Lekhnath feeder.
2. A systematic comparison between ML and DL approaches in terms of prediction accuracy, computational requirements.
3. Identification of load consumption patterns (hourly/daily/weekly trends).
4. Analysis of the correlations between load demand and different influencing features such as temperature, humidity, rainfall, wind, and so on.
5. Insights for NEA or local grid operators to improve load planning.
6. Contribution to the academic literature on feeder-level short-term load forecasting by applying and evaluating advanced ML/DL techniques in a developing country's power system context.
7. Publication-ready results suitable for journal submission in the power systems and AI/ML domains.

CHAPTER 5 WORK PLAN AND TIMELINE

The proposed time schedule of the thesis is shown in the Figure 5.1.

	Month					
	Sharawn, Bhadra, and Ashoj					
Week	1	2	3	4	5	6
Planning and Literature Review						
Data Collection and Preprocessing						
Model Development and Implementation						
Analysis and Evaluation						
Documentation						
Report Preparation						

Figure 5.1: Proposed time schedule for the thesis

CHAPTER 6 RESOURCES AND REQUIREMENTS

6.1 System Under Consideration

The system under consideration is the Lekhnath Feeder, a distribution feeder operated under the NEA, supplying electricity to a mixed load comprising residential, commercial, and small industrial consumers in the Lekhnath, and Pokhara area of Kaski district of Nepal.

The feeder is metered at the substation level, and historical load data are logged at hourly intervals. Additional exogenous variables such as temperature, humidity, and rainfall will be collected from the nearest meteorological station.

6.2 Tools

The following tools will be used in the research:

- Programming Environment:
 - Python (primary language for data analysis and model development)
 - Jupyter Notebook for interactive experimentation.
- Machine Learning and Deep Learning Frameworks:
 - Scikit-learn (SVR, Random Forest, DT, XGBoost)
 - PyTorch (LSTM, GRU models)
 - XGBoost library for gradient boosting
- Data Handling and Visualization:
 - Pandas, NumPy for data preprocessing and numerical computation.
 - Matplotlib, Seaborn for data visualization
- Version Control:
 - Git and GitHub for code and experiment tracking
- Documentaion and Reporting:
 - LaTeX for report and thesis writing

6.3 Resources

- Hardware Resources:Laptop/PC with GPU
- Data Resources:
 - Historical load data from Lekhnath Feeder (hourly resolution).
 - Weather data from Department of Hydrology and Meteorology, Nepal (hourly resolution) or other sources (Nepal Open Data).
 - Calendar data for holidays, weekdays/weekends.

6.4 Requirements

The most important requirement for the thesis work is the data access requirements. We need permission from Lekhnath Feeder for the availability of historical load data, as well as access to meteorological datasets for the study period.

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