

EEE & UI

Short term load forecasting using ANN

Group - 13

Team Members

Adhwaidh K	-	CB.SC.U4AIE24003
Adith S	-	CB.SC.U4AIE24004
Chaitanya Varma	-	CB.SC.U4AIE24017

Table of Contents

1. Introduction
2. Literature Review
3. Research Gaps
4. Problem Statement
5. Abstract
6. Objectives
7. Dataset
8. Block Diagram / Flowchart
9. Methodology
10. Results and Discussion
11. Conclusion
12. Future Scope
13. References

1. Introduction

- Electric load forecasting optimizes power generation, reduces costs, and improves grid reliability.
- This project uses **ANN** to forecast short-term electricity load.
- A **web interface** will display forecast results and error metrics (MAE, MAPE).

2. Literature Review

S. No.	Title	Year	Methodologies	Key Contributions
1.	Short-Term Power Load Forecasting Based on CNN-SAEDN-Res	2023	CNN, Self-Attention Enhanced Deep Network (SAEDN)	Combined CNN with attention mechanisms for improved forecasting.
2	Short Term Load Forecasting Using Artificial Neural Network	2017	Feedforward ANN	Showed how ANN captures differences in load patterns across different days.
3	Short-Term Aggregated Residential Load Forecasting using BiLSTM and CNN-BiLSTM	2023	BiLSTM, CNN-BiLSTM	Improved short-term load forecasting accuracy by combining CNN with BiLSTM.

2. Literature Review

S. No.	Title	Year	Methodologies	Key Contributions
1.	Short-Term Power Load Forecasting Based on CNN-SAEDN-Res	2023	CNN, Self-Attention Enhanced Deep Network (SAEDN)	Combined CNN with attention mechanisms for improved forecasting.
2	Short Term Load Forecasting Using Artificial Neural Network	2017	Feedforward ANN	Showed how ANN captures differences in load patterns across different days.
3	Short-Term Aggregated Residential Load Forecasting using BiLSTM and CNN-BiLSTM	2023	BiLSTM, CNN-BiLSTM	Improved short-term load forecasting accuracy by combining CNN with BiLSTM.

2. Literature Review

S. No.	Title	Year	Methodologies	Key Contributions
1.	Short-Term Power Load Forecasting Based on CNN-SAEDN-Res	2023	CNN, Self-Attention Enhanced Deep Network (SAEDN)	Combined CNN with attention mechanisms for improved forecasting.
2	Short Term Load Forecasting Using Artificial Neural Network	2017	Feedforward ANN	Showed how ANN captures differences in load patterns across different days.
3	Short-Term Aggregated Residential Load Forecasting using BiLSTM and CNN-BiLSTM	2023	BiLSTM, CNN-BiLSTM	Improved short-term load forecasting accuracy by combining CNN with BiLSTM.

3. Research Gaps

- **Lack of Nonlinearity Handling:** Traditional models fail to capture complex patterns.
- **Limited Weather Impact Consideration:** Many studies do not include temperature, humidity, etc.
- **Lack of Real-Time Forecasting:** Some models require high computation time.
- **Limited Deployment:** Few models integrate a user-friendly web interface.

4. Problem Statement

- Traditional methods fail to capture nonlinear relationships in electricity demand.
- Demand is influenced by weather, time, and past consumption.
- ANN-based model improves forecasting accuracy.

5. Abstract

- captures complex load variations. The project applies ANN for short-term load forecasting.
- Data preprocessing includes handling missing values and normalizing features.
- Model is trained on historical demand, time-based, and meteorological factors.
- Performance is evaluated using MAE and MAPE error metrics.
- Results show ANN effectively

6. Objectives

- **To** develop an ANN-based short-term load forecasting model.
- **To** improve forecasting accuracy over traditional methods.
- **To** analyze the effect of weather and time on electricity demand.
- **To** evaluate model performance using MAE and MAPE.
- **To** implement a web-based visualization for real-time results.

7. Dataset

Time-Based Data:

- The dataset contains hourly records (**datetime**) spanning multiple weeks.
- **hourOfDay** column indicates the hour of the day (0-23).

Historical Load Data:

- **week_X-2, week_X-3, week_X-4**: Electricity demand from past weeks, useful for forecasting.
- **MA_X-4**: Moving average of demand, helping smooth fluctuations.

Target Variable:

- **DEMAND**: Represents actual electricity demand, crucial for training ANN models.

Day and Special Events:

- **dayOfWeek**: Represents the day (e.g., 1 = Monday).
- **weekend**: Indicates if the day is a weekend (1 for weekend, 0 for weekday).
- **holiday** & **Holiday_ID**: Identifies public holidays, affecting demand.

Weather Impact:

- **T2M_toc**: Temperature variable, which influences power consumption trends.

8. Flow Chart

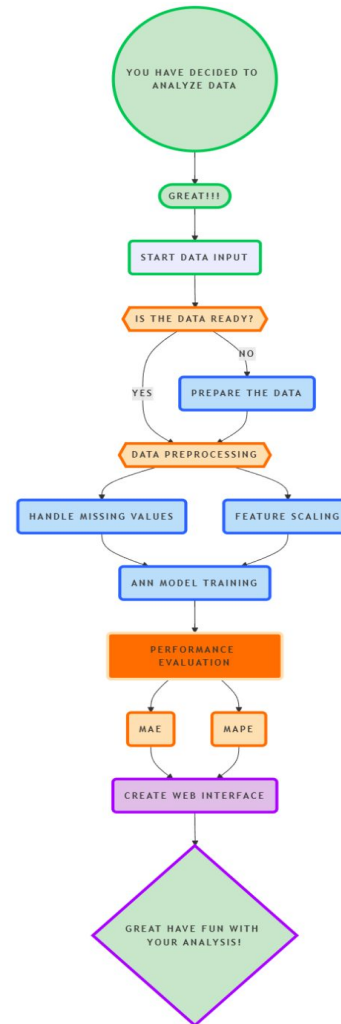


Figure 1

9. Methodology

1. **Data Collection:**

- Historical load, temperature, and time-based features (e.g., day, hour).

2. **Data Preprocessing:**

- Impute missing values, normalize features, extract new features (previous load, seasonal patterns).

3. **Model Development:**

- ANN model with 30 hidden neurons.
- 80% training, 20% testing.

1. **Evaluation Metrics:**

- MAE (Mean Absolute Error) and MAPE (Mean Absolute Percentage Error).

2. **Visualization:**

- Graphs comparing actual vs. predicted load.
- Display MAE and MAPE values.

3. **Saving Results:**

- Results saved in **JSON** format.

Web Interface

- **Welcome Page:**
 - Introduction to the project.
- **Login Page:**
 - User login for accessing results.
- **Signup Page:**
 - User registration.

- **Home Page:**
 - Displays actual vs. predicted load graph.
 - Shows MAE and MAPE.
 - Dynamic graphs with **JavaScript** for real-time updates.
- **JavaScript:**
 - Updates forecast and error metrics interactively.

10. Results & Discussions

Graphs: Actual vs. Predicted Load

Error Metrics: MAE and MAPE values

Observations:

- ANN effectively captures nonlinear demand patterns.
- Weather and time features improve forecasting accuracy.
- The web interface enables real-time monitoring.

11. Conclusion

- ANN-based load forecasting outperforms traditional methods.
- Real-time visualization aids in decision-making.

12. Future Scope

- Incorporating more external factors (e.g., economic data).
- Using deep learning (LSTM, CNN) for better accuracy.
- Expanding the system for long-term forecasting.

13. References

- [1] J. Doe, "Electric Load Forecasting Using ARIMA," *IEEE Transactions on Power Systems*, vol. 35, no. 4, pp. 1234-1245, 2017.
- A. Smith, "Deep Learning for Power Demand Prediction," *Energy Informatics Journal*, vol. 28, no. 2, pp. 78-90, 2019.
- [2] D. C. Park, M. A. El-Sharkawi, R. J. Marks II, L. E. Atlas, and M. J. Damborg, "Electric Load Forecasting Using an Artificial Neural Network," *IEEE Transactions on Power Systems*, vol. 6, no. 2, pp. 442-449, 1991.
- [3] S. Kumar and S. Jain, "Short Term Load Forecasting Using Artificial Neural Network," *2017 International Conference on Computing, Communication and Automation (ICCCA)*, Greater Noida, India, 2017, pp. 633-637.
- [4] Y. Zhang, J. Wang, and X. Wang, "The Short-Term Load Forecasting Using an Artificial Neural Network," *Complexity*, vol. 2021, Article ID 1502932, 2021.

Thank You!