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ELECTRICITY DEMAND FORECASTING

A COMPARATIVE ANALYSIS USING PROPHET, LSTM AND BI-LSTM

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INTRODUCTION

- Electricity is the fundamental to an economic growth and daily life across various sectors.
- Accurate demand forecasting ensures grid reliability and cost-efficient energy management.
- Urbanization and smart grids have intensified a need for adaptive forecasting techniques.
- Delhi's dense population and complex infrastructure make the energy planning challenging.
- Seasonal climatic extremes in Delhi causes the sharp and unpredictable demand shifts.

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OBJECTIVES

01

To build a multivariate dataset for Delhi's electricity consumption by integrating diverse external features.

02

To apply Prophet model for interpretable and deployment forecasting.

03

To implement deep learning models, stacked LSTM and stacked BiLSTM LSTM hybrid for load forecasting.

04

To conduct performance evaluation and compare analysis of all models using standard statistical metrics.

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LITERATURE REVIEW

Research Paper Title	Source	Year of Publication	Citation
LSTM vs. Prophet: Achieving Superior Accuracy in Dynamic Electricity Demand Forecasting	MDPI Journal of Energies	2025	Albahli, S. (2025). LSTM vs. Prophet: Achieving Superior Accuracy in Dynamic Electricity Demand Forecasting. Energies, 18(2). https://doi.org/10.3390/en18020278
Future Energy Insights: Time-Series and Deep Learning Models for City Load Forecasting	Journal of Applied Energy (Elsevier)	2024	Maleki, N., Lundström, O., Musaddiq, A., Olsson, T., Ahlgren, F., & Jeansson, J. (2024). Future energy insights: Time-series and deep learning models for city load forecasting. Applied Energy, 374. https://doi.org/10.1016/j.apenergy.2024.124067
Electrical Load Demand Forecast for Gujarat State of India using Machine Learning Models	International Conference on Electrical, Electronics and Computer Science (IEEE)	2024	Chandra, P. K., Bajaj, D., Sharma, H., Bareth, R., & Yadav, A. (2024). Electrical Load Demand Forecast for Gujarat State of India using Machine Learning Models. IEEE International Students Conference on Electrical, Electronics and Computer Science, SCEECS. https://doi.org/10.1109/SCEECS61402.2024.10482140

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DATA EXTRACTION

Electricity Demand Data

- Obtained from website of SLDC State Load Dispatch Centre Delhi.
- Load data retrieved at 15 minute interval resolution for period of years from 2020 to 2024.

Variables included:

- Timestamp
- Load consumption (MW)

Weather Data

- Sourced via WeatherBit API
- Timestamp
- Temperature (°C)
- Apparent Temperature (°C)
- Relative Humidity (rh) (%)
- Wind Speed (m/s)
- Sea Level Pressure (hPa)
- Dew Point (°C)
- Solar Radiation (ghi) (W/m^2)

Public Holiday Data

- Scraped from Timeanddate.com
- Includes official public holiday and the festival dates.

Variables included:

- Date
- Holiday Name
- Holiday Flag

DATA PREPARATION

Timestamp Alignment and Data Merging

- Aligned electricity, weather, and holiday data on the unified 15-minute timestamp index using outer joins across.
- Ensured the temporal consistency by validating duplicates, misalignments, and completeness across all timestamps.

Missing Data Detection and Data Imputation

- Conducted gap analysis post-merging to identify missing entries across variables.
- Applied a 3-stage imputation strategy:

1. Linear interpolation for short gaps.
2. Weekday-based averaging for longer gaps.
3. Forward/ backward fill for completeness.

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DATASET OVERVIEW

	date_time	load_consumption	temperature	apparent_temp	rh	wind_speed	ghi	sea_lvl_pressure	dew_point	holiday_flag
0	2020-01-01 00:00:00	2641.72	5.3	5.4	100	0.8	0	1021	5.3	1
1	2020-01-01 00:15:00	2534.85	5.3	5.4	100	0.8	0	1021	5.3	1
2	2020-01-01 00:30:00	2429.31	5.2	5.3	100	0.8	0	1021	5.2	1
3	2020-01-01 00:45:00	2327.87	5.2	5.3	100	0.8	0	1021	5.2	1
4	2020-01-01 01:00:00	2247.98	5.1	5.2	100	0.8	0	1021	5.1	1
...	...	...	...	...	...	...	...	...	...	...
175387	2024-12-31 22:45:00	3130.67	9.9	9.9	96	1.6	0	1021	9.3	1
175388	2024-12-31 23:00:00	3030.02	9.8	9.8	96	1.6	0	1021	9.2	1
175389	2024-12-31 23:15:00	2907.13	9.6	9.6	96	1.6	0	1021	9.0	1
175390	2024-12-31 23:30:00	2806.63	9.6	9.6	95	1.6	0	1020	9.7	1
175391	2024-12-31 23:45:00	2673.22	9.6	9.6	96	1.6	0	1021	9.7	1

175392 rows × 10 columns

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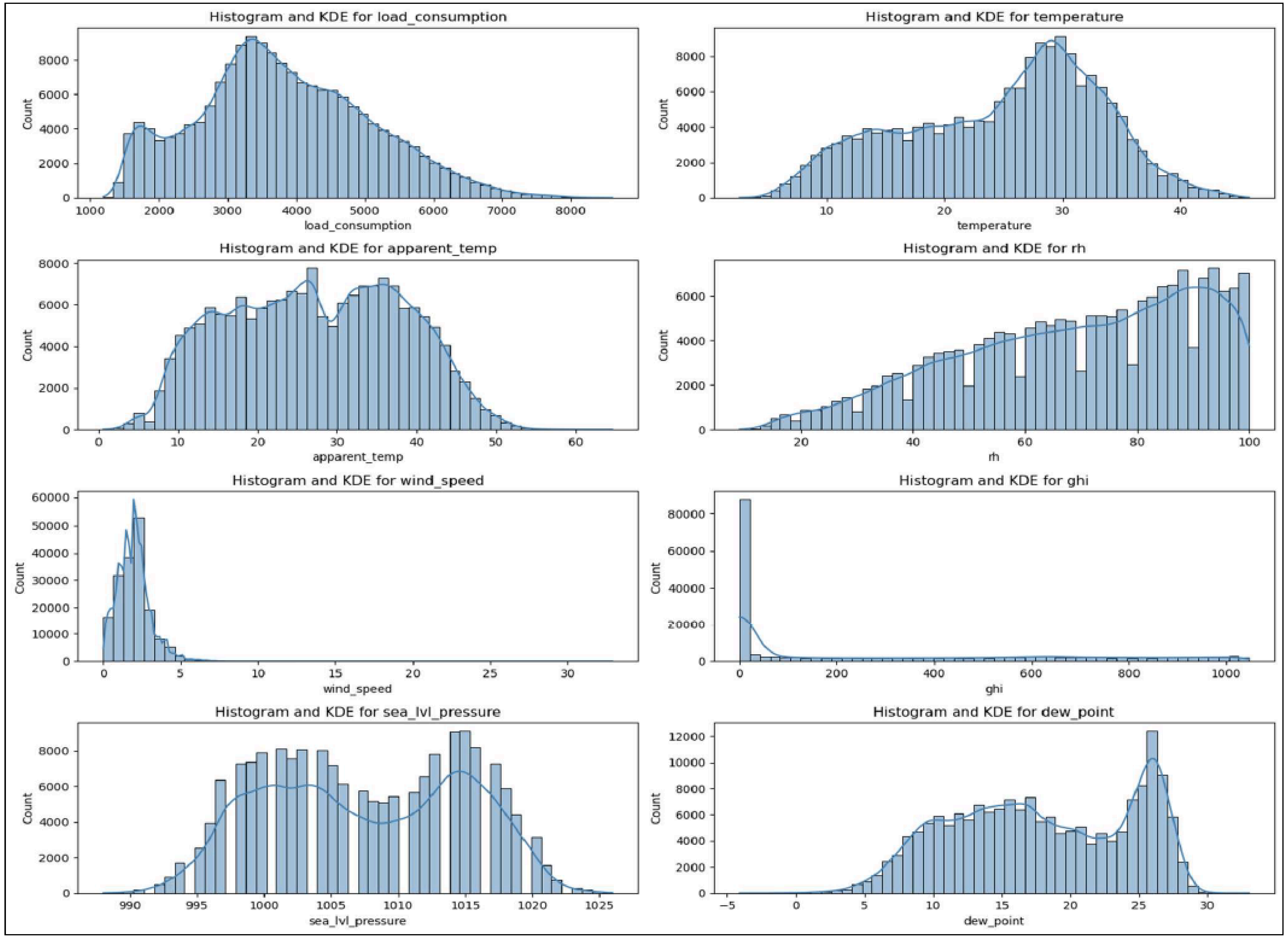
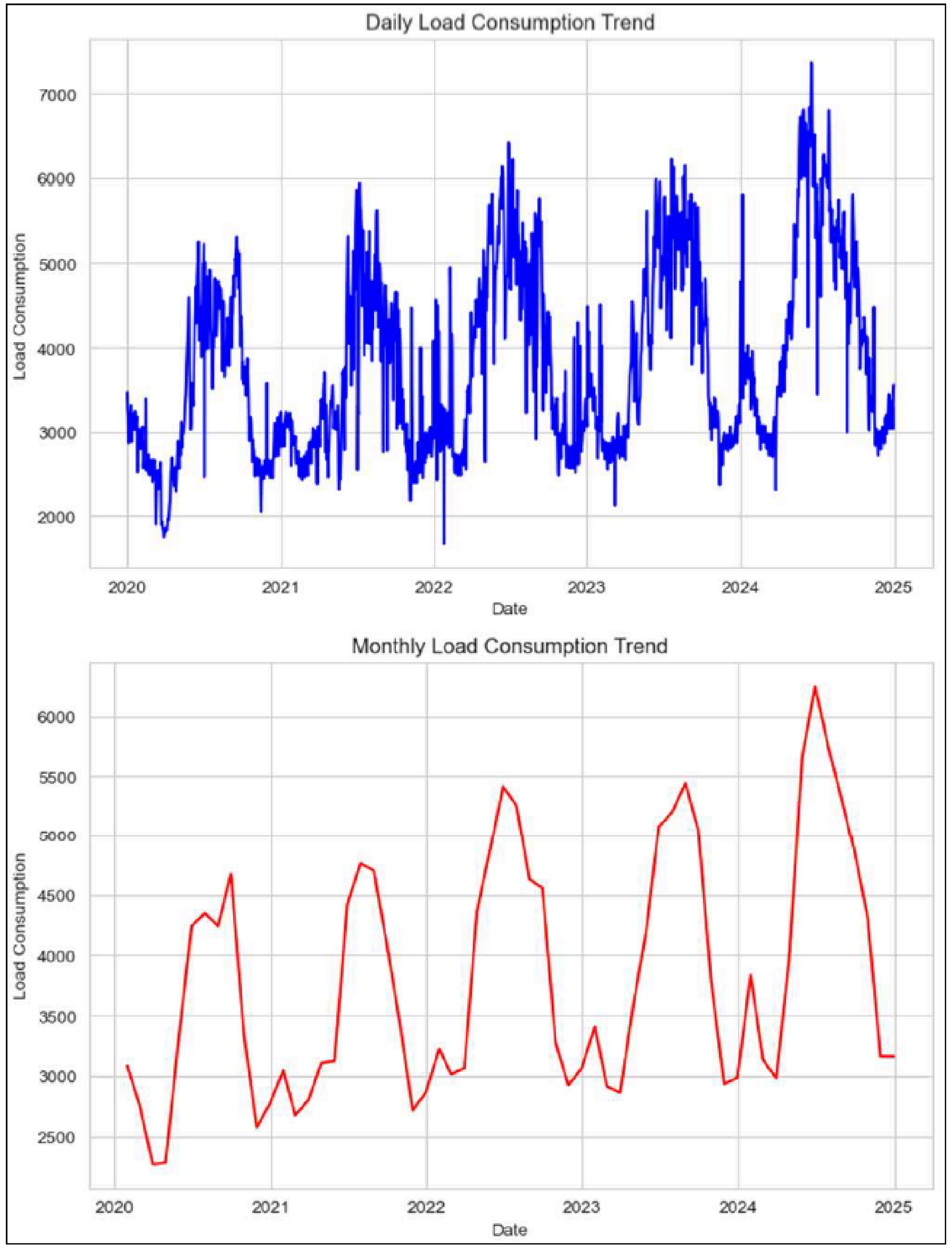
EXPLORATORY DATA ANALYSIS



Histogram and KDE Plots



Trend Plots for Load

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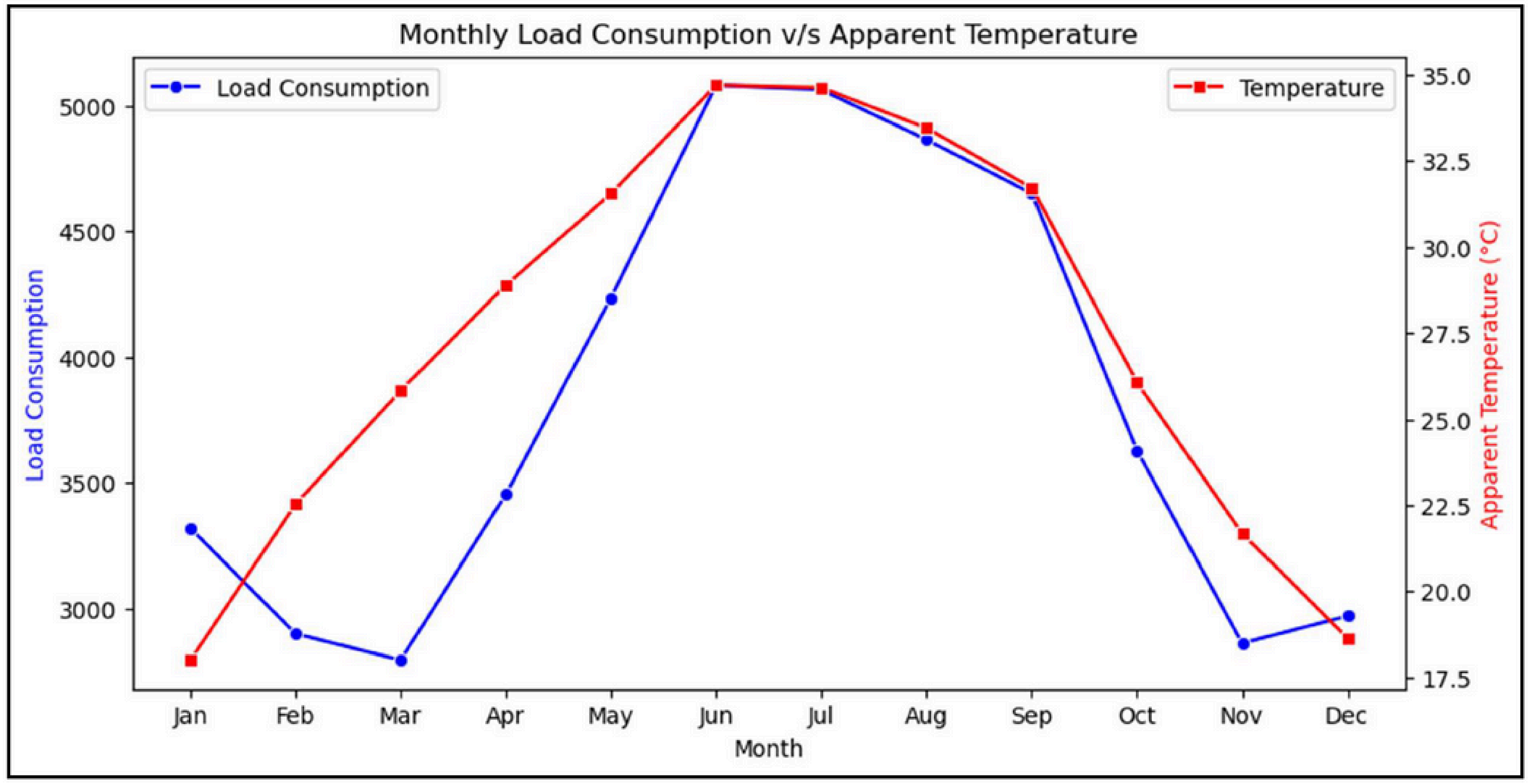
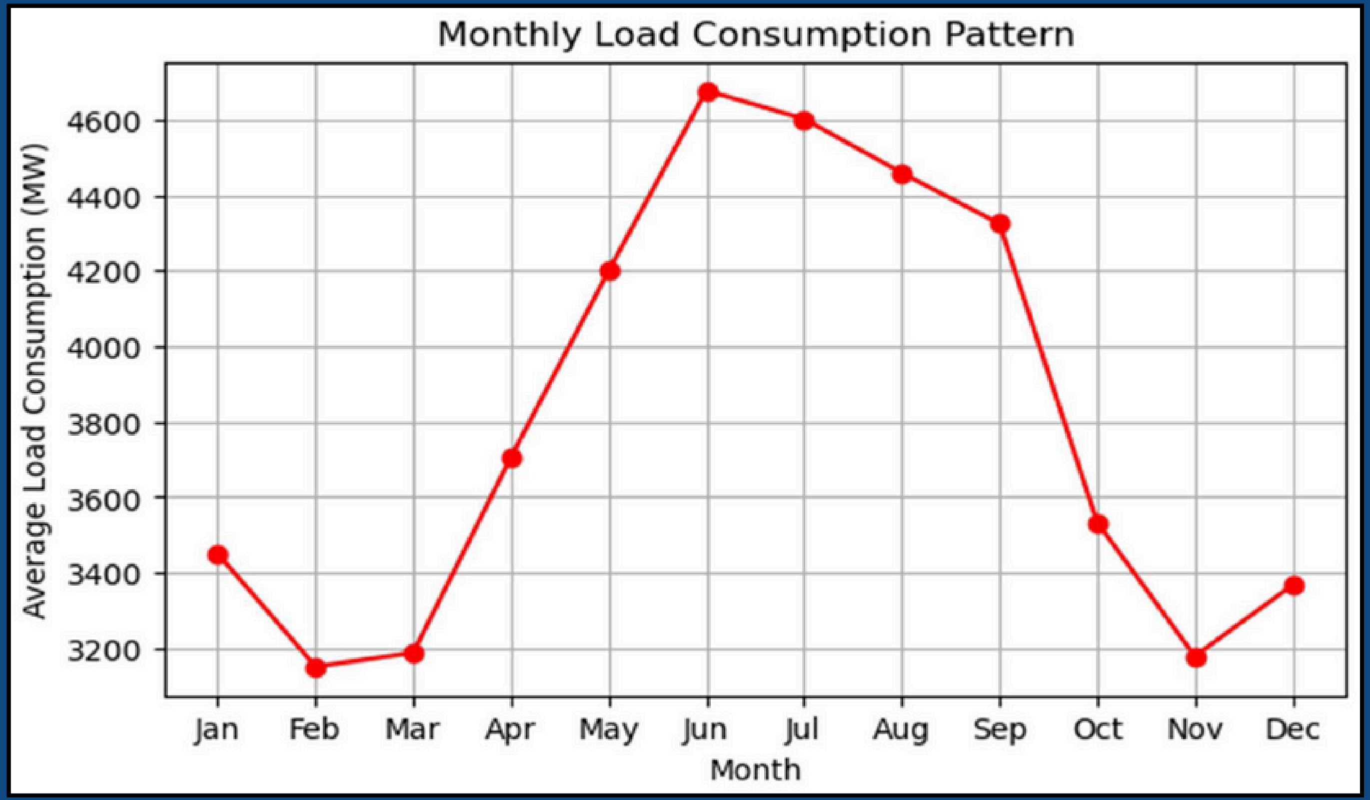


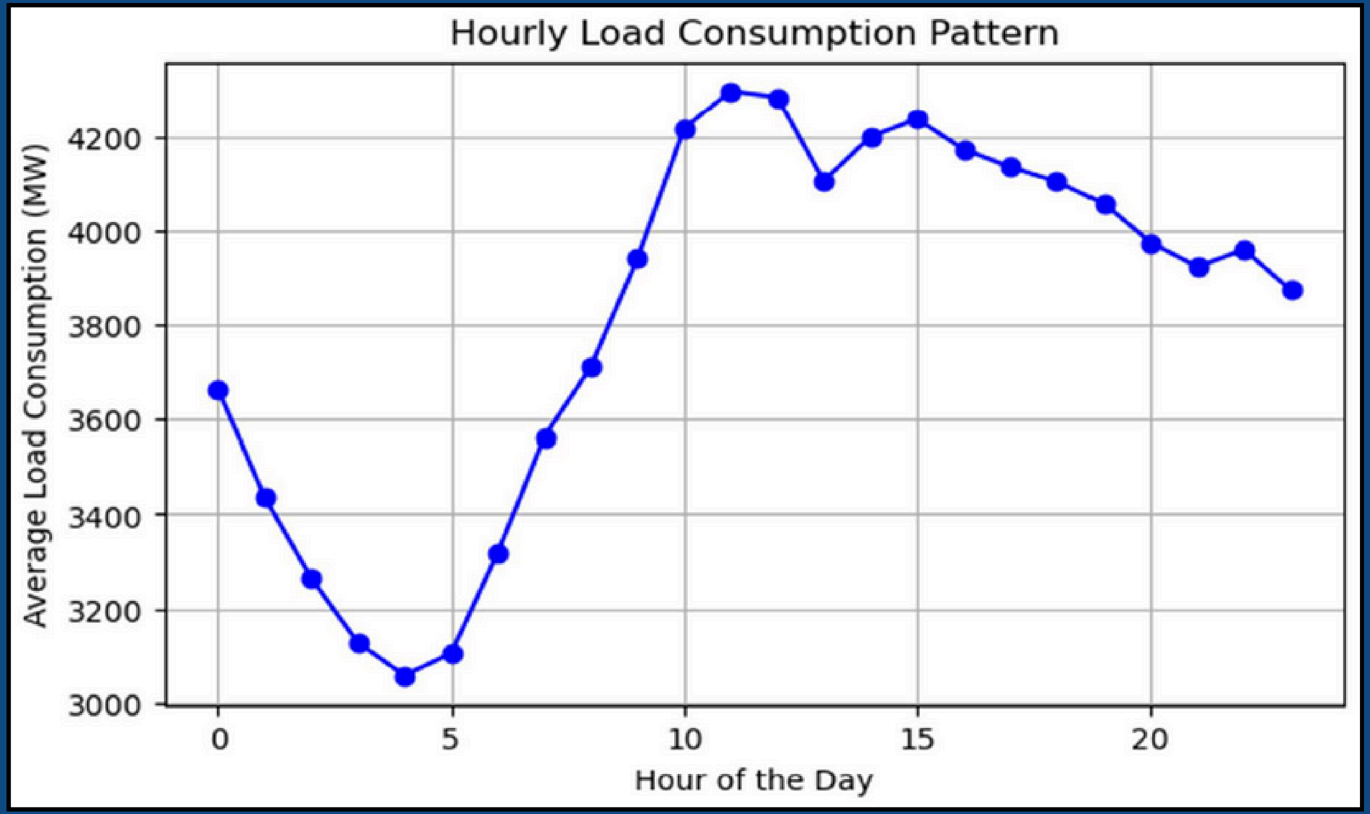
Monthly Load Consumption compared to Apparent Temperature

Apparent temperature exhibits a positively correlated trend with electricity load consumption, confirming as significant exogenous driver.

- Monthly load curves show higher consumption during summer season (May–July) due to the cooling demand.
- Hourly load curves shows peak demand during late morning and evening hours, aligning with residential and commercial activity.



Monthly Electricity Load Consumption



Hourly Electricity Load Consumption

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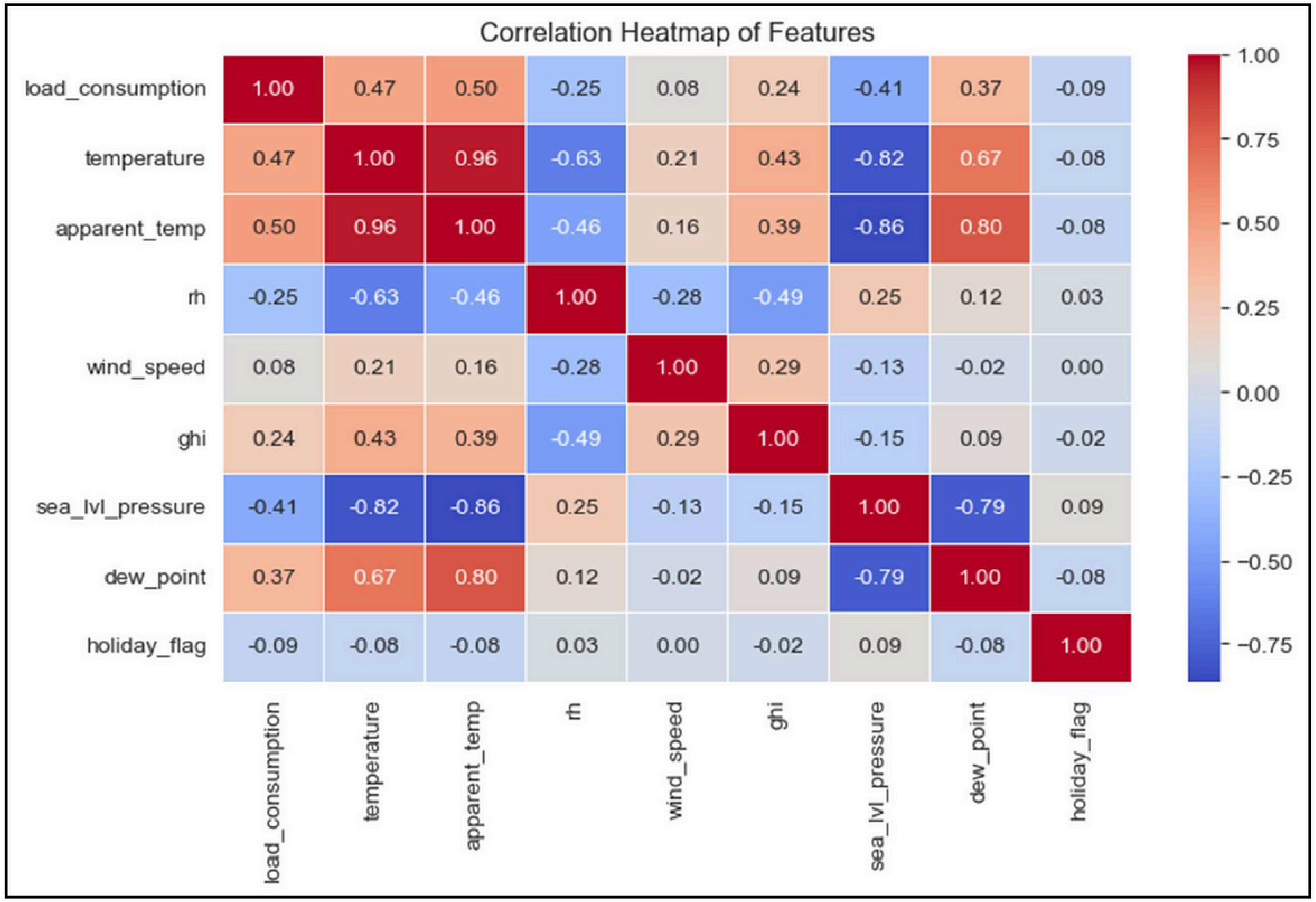
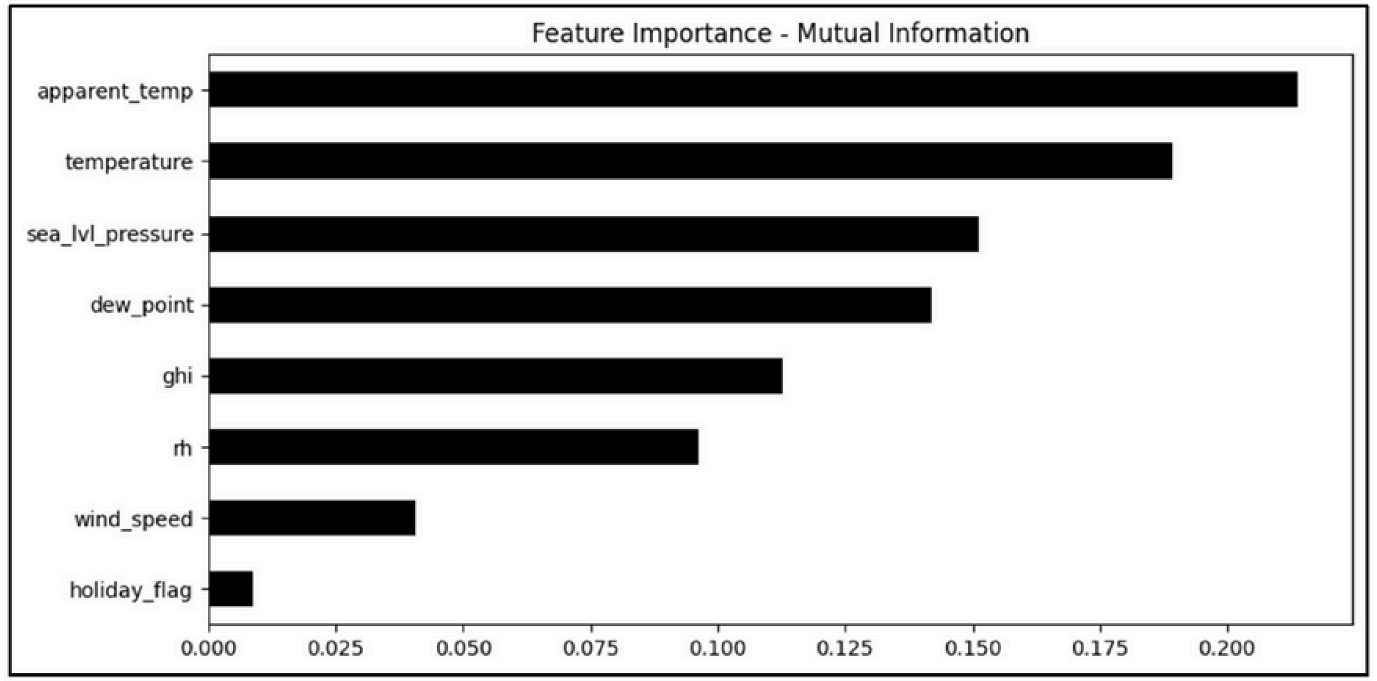
EXPLORATORY DATA ANALYSIS



Pearson Correlation Analysis



Features	MI Scores
Apparent Temperature	0.214
Temperature	0.189
Sea Level Pressure	0.151
Dew Point	0.142
GHI	0.113
Relative Humidity	0.096
Wind Speed	0.041
Holiday Flag	0.009

Mutual Information (MI) Scores

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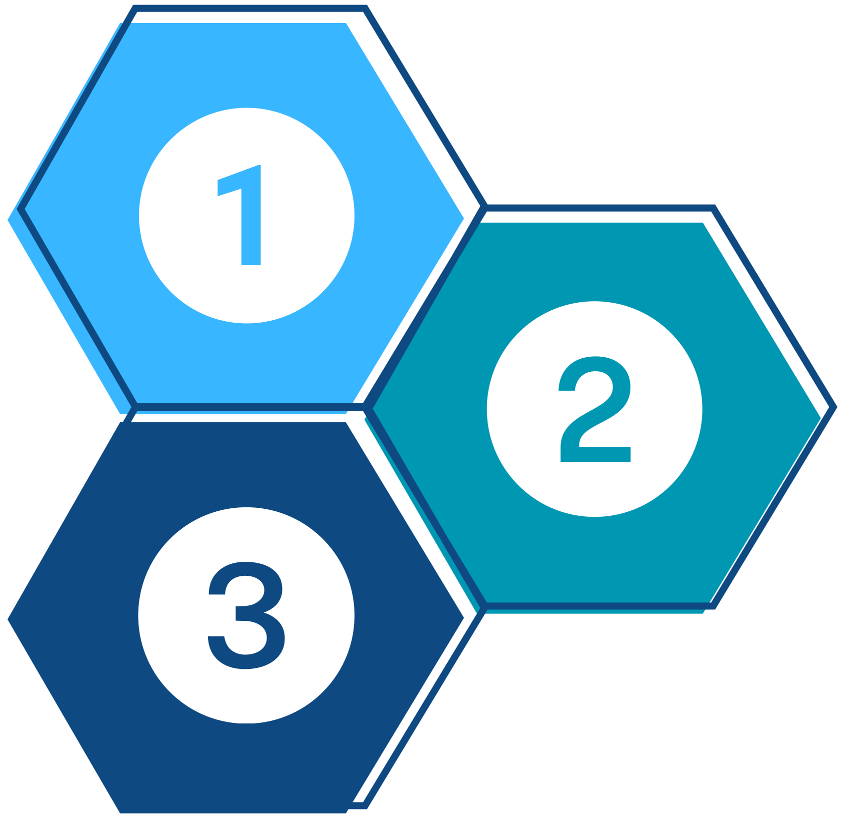
MODELING TECHNIQUES

PROPHET MODEL

- Additive model capturing trend, seasonality and it also supports the external regressors.

- Data Split:

80% train data (140313 records)
20% test data (35079 records)



STACKED LSTM MODEL

- Two-layer LSTM with dropout and batch normalization processes the 12-hour sequences.

- Data Split:

60% train data (105187 records)
20% validation data (35030 records)
20% test data (35031 records)

STACKED BILSTM - LSTM MODEL

- Hybrid architecture combining BiLSTM and LSTM layers to capture both past and future context from the 24-hour sequences.

- Data Split:

60% train data (105139 records)
20% validation data (34982 records)
20% test data (34983 records)

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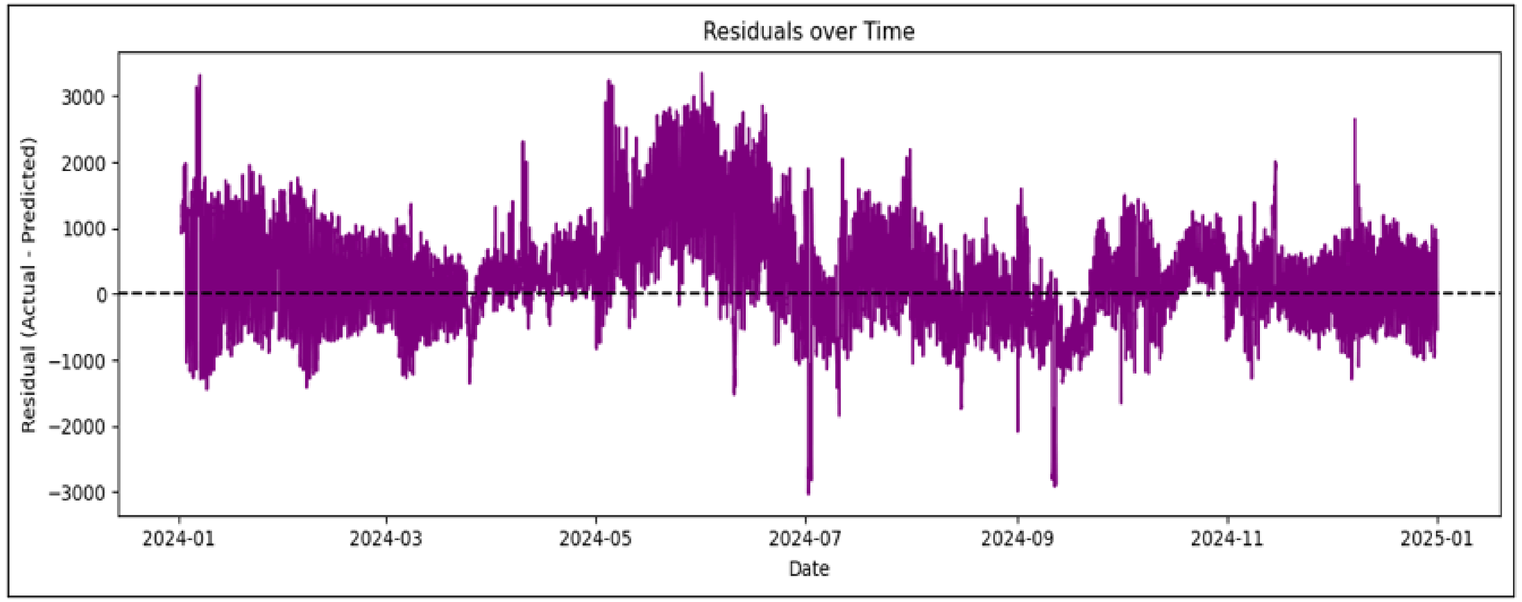
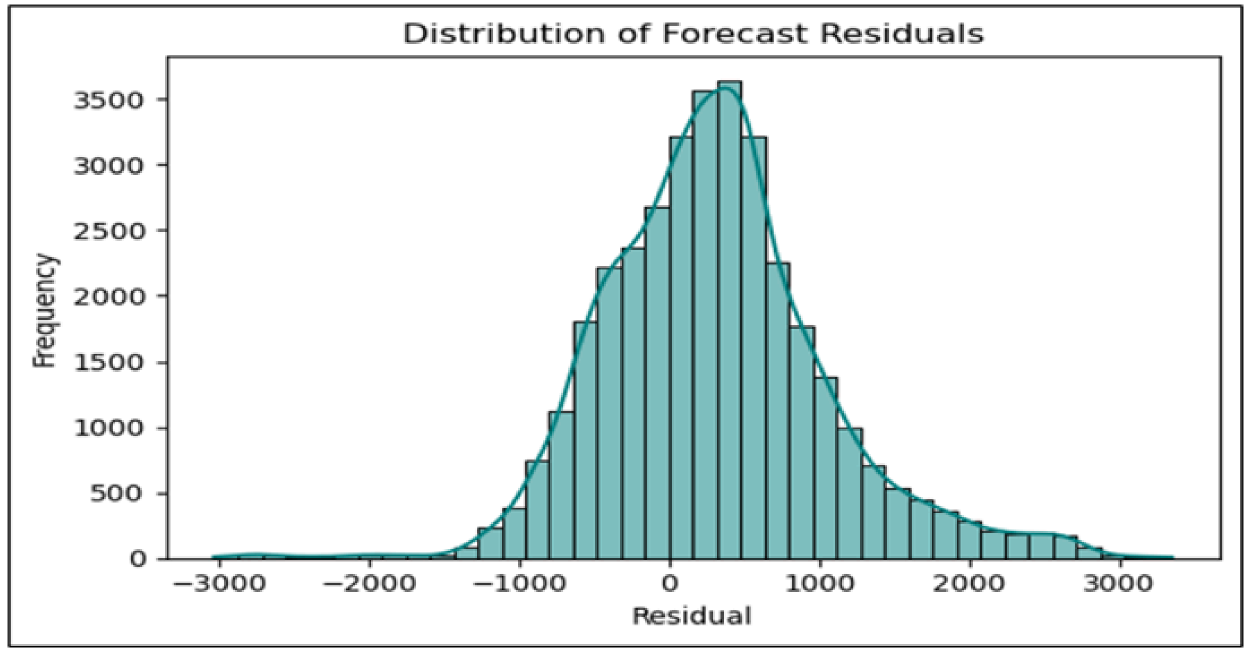
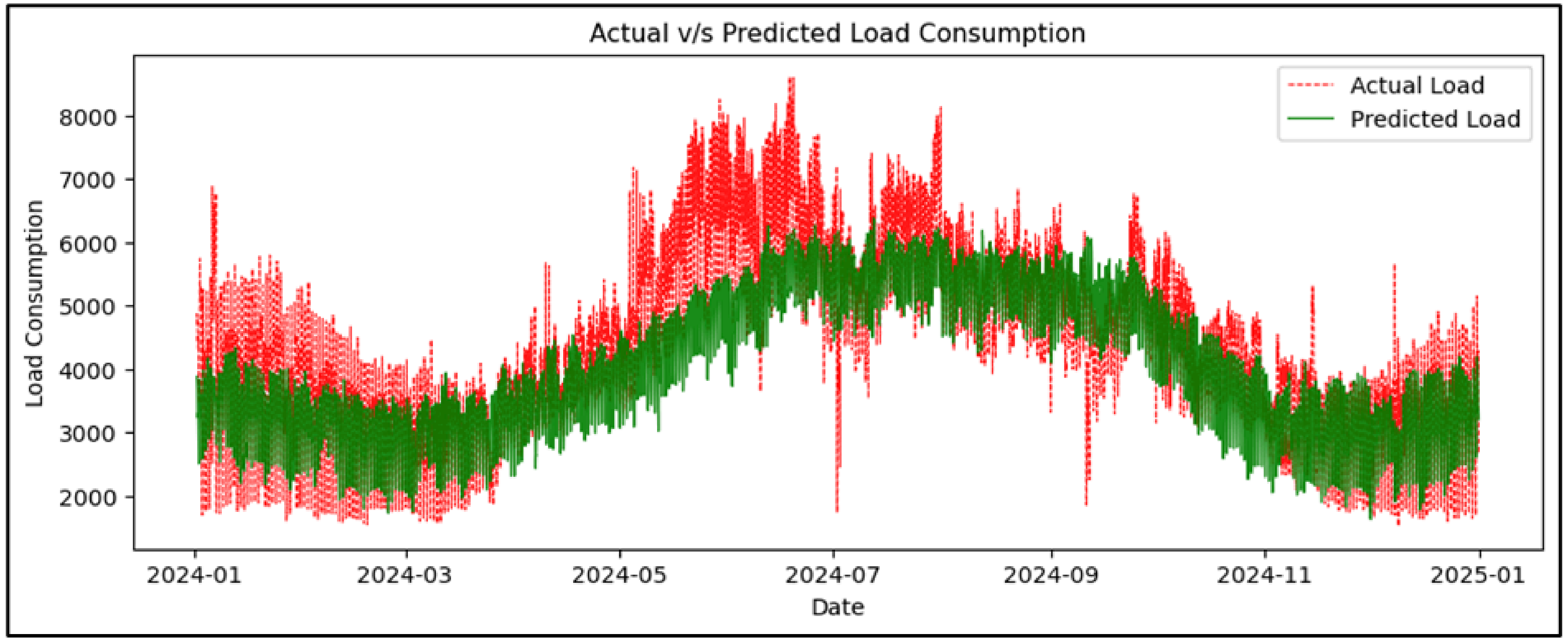
PROPHET MODEL



Model	MAE (Test)	MSE (Test)	RMSE (Test)	MAPE (Test)	R^2 Score (Test)
Prophet	608.24	650382.61	806.46	14.24%	0.6684

Evaluation Metrics for Prophet Model





Residual Analysis

Actual v/s Predicted Plot

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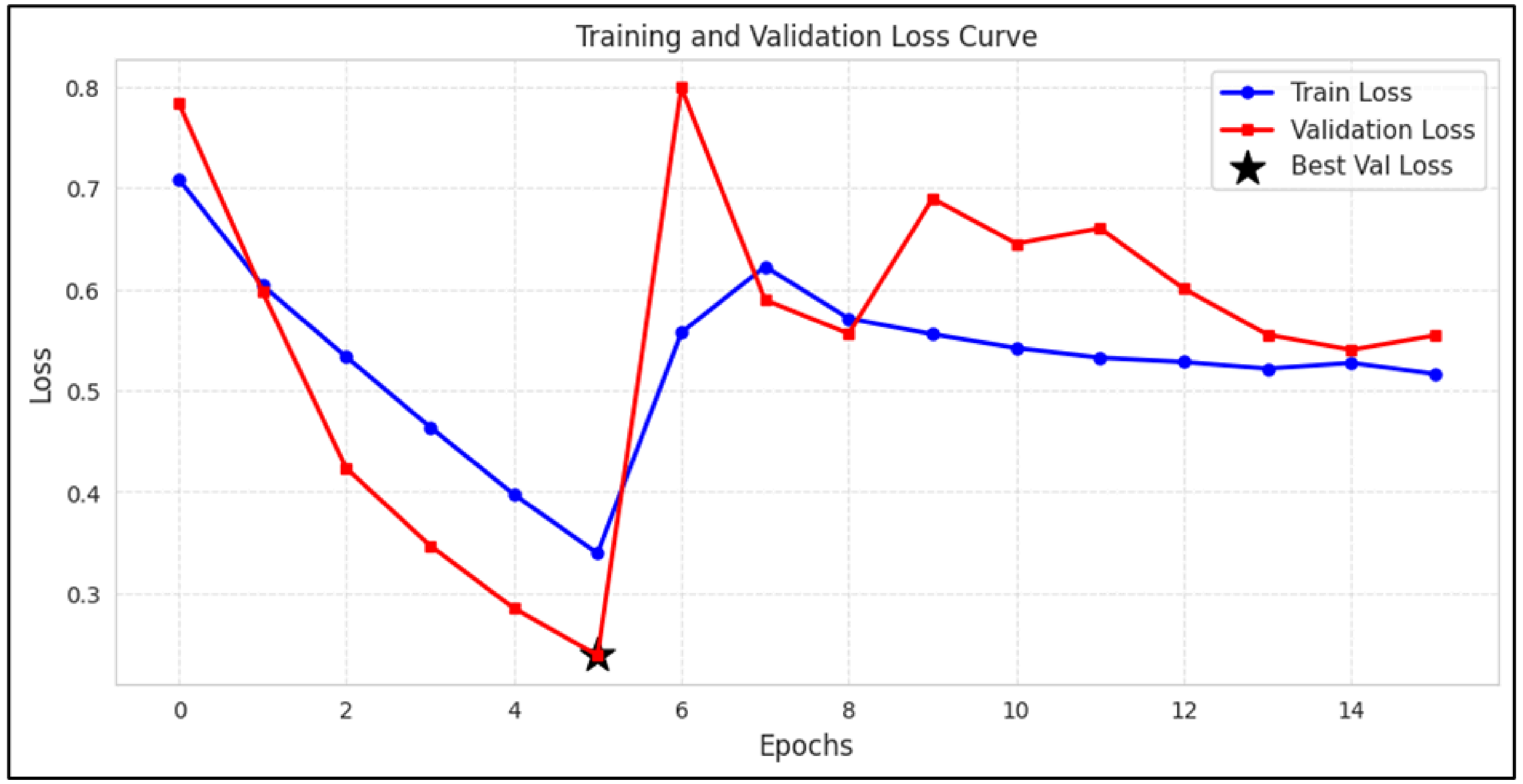
DEEP LEARNING MODELS

STACKED TWO LAYER LSTM MODEL

Dataset	MAE	MSE	RMSE	MAPE	SMAPE
Train	456.91	351378.10	592.77	15.55%	14.11%
Validation	492.80	382324.69	618.32	13.67%	13.26%
Test	605.48	57655.61	759.25	14.45%	14.57%

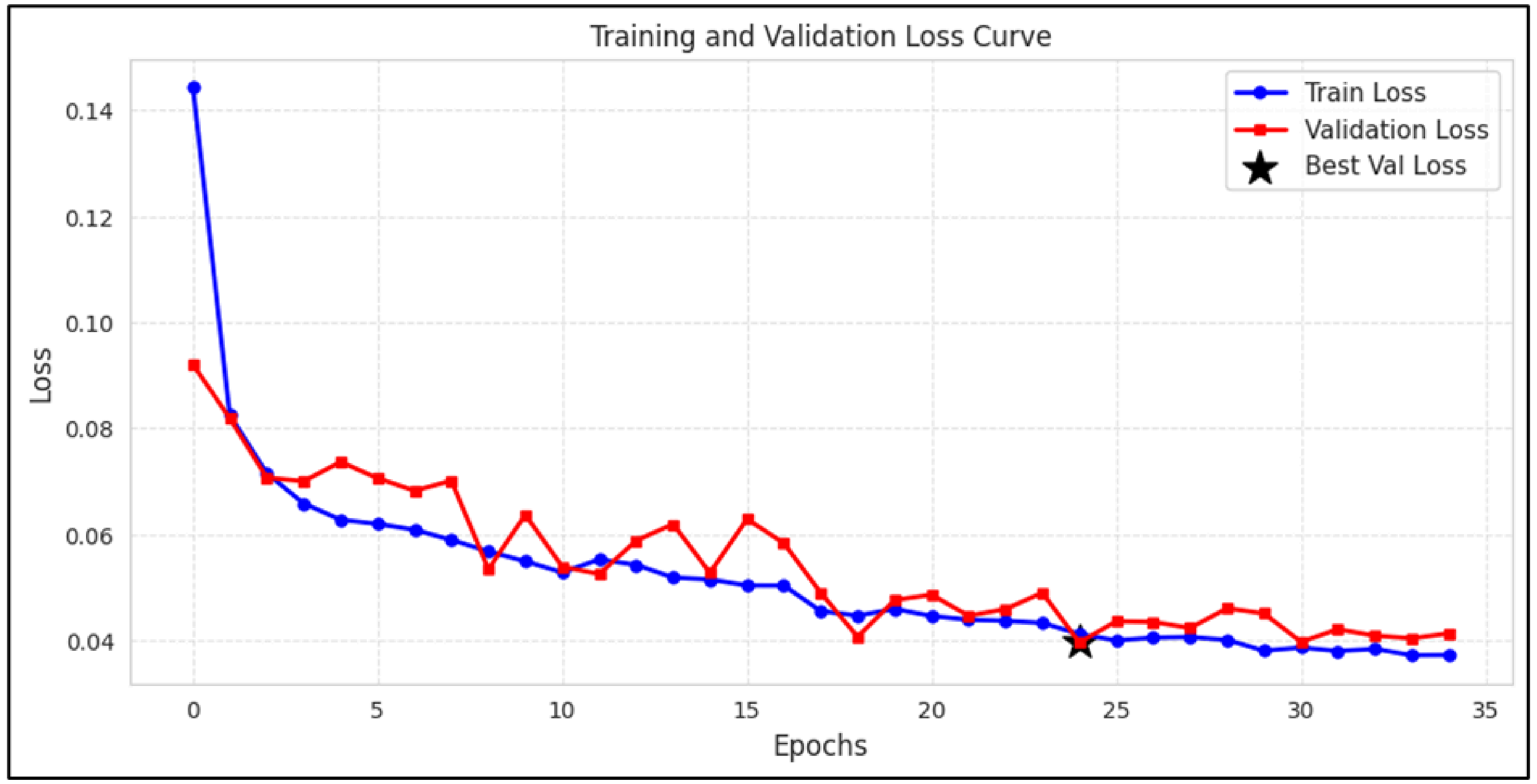
Evaluation Metrics for Stacked Two-Layer LSTM



STACKED BILSTM UNIDIRECTIONAL LSTM MODEL

Dataset	MAE	MSE	RMSE	MAPE	SMAPE
Train	108.90	66638.66	258.14	3.34%	3.19%
Validation	113.69	64121.47	253.22	2.98%	3.01%
Test	154.18	123929.80	352.04	3.45%	3.58%

Evaluation Metrics for Stacked Two-Layer BiLSTM – LSTM



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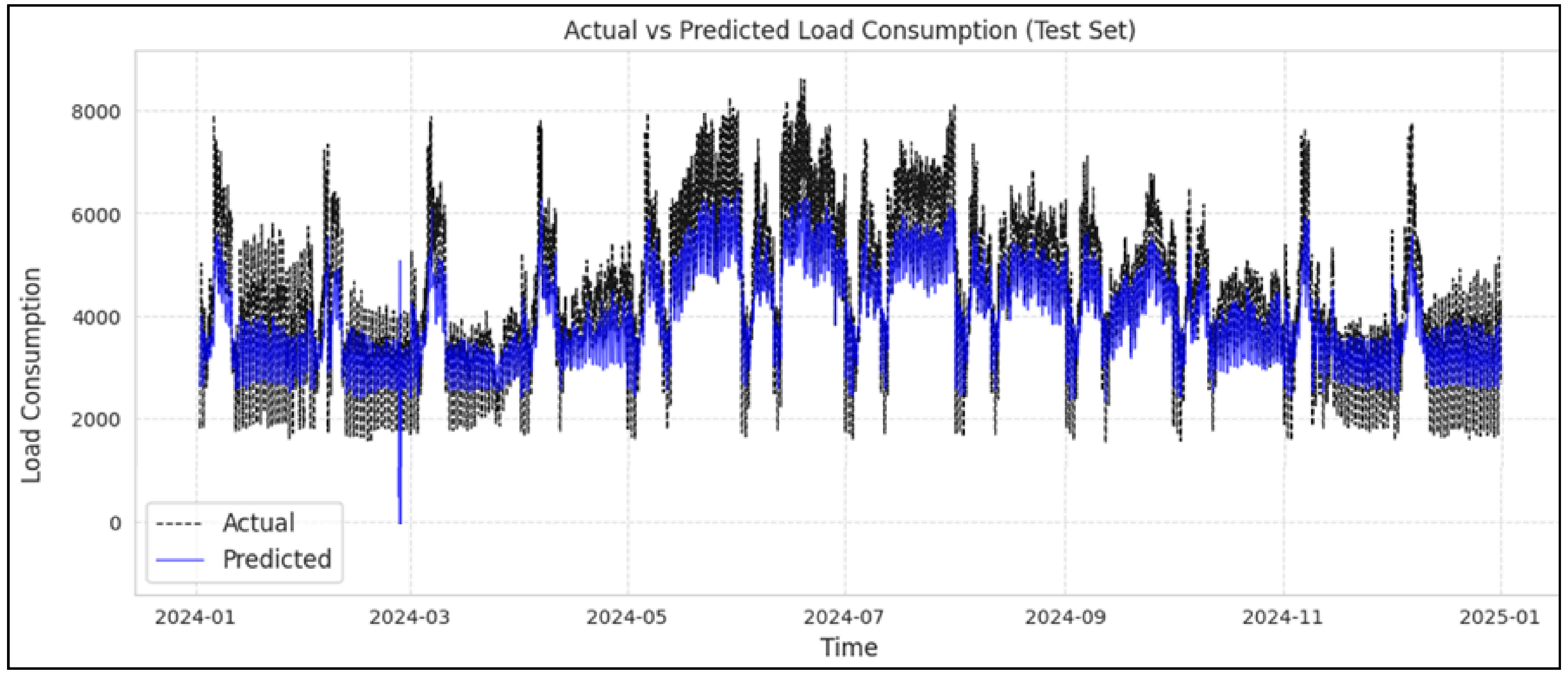
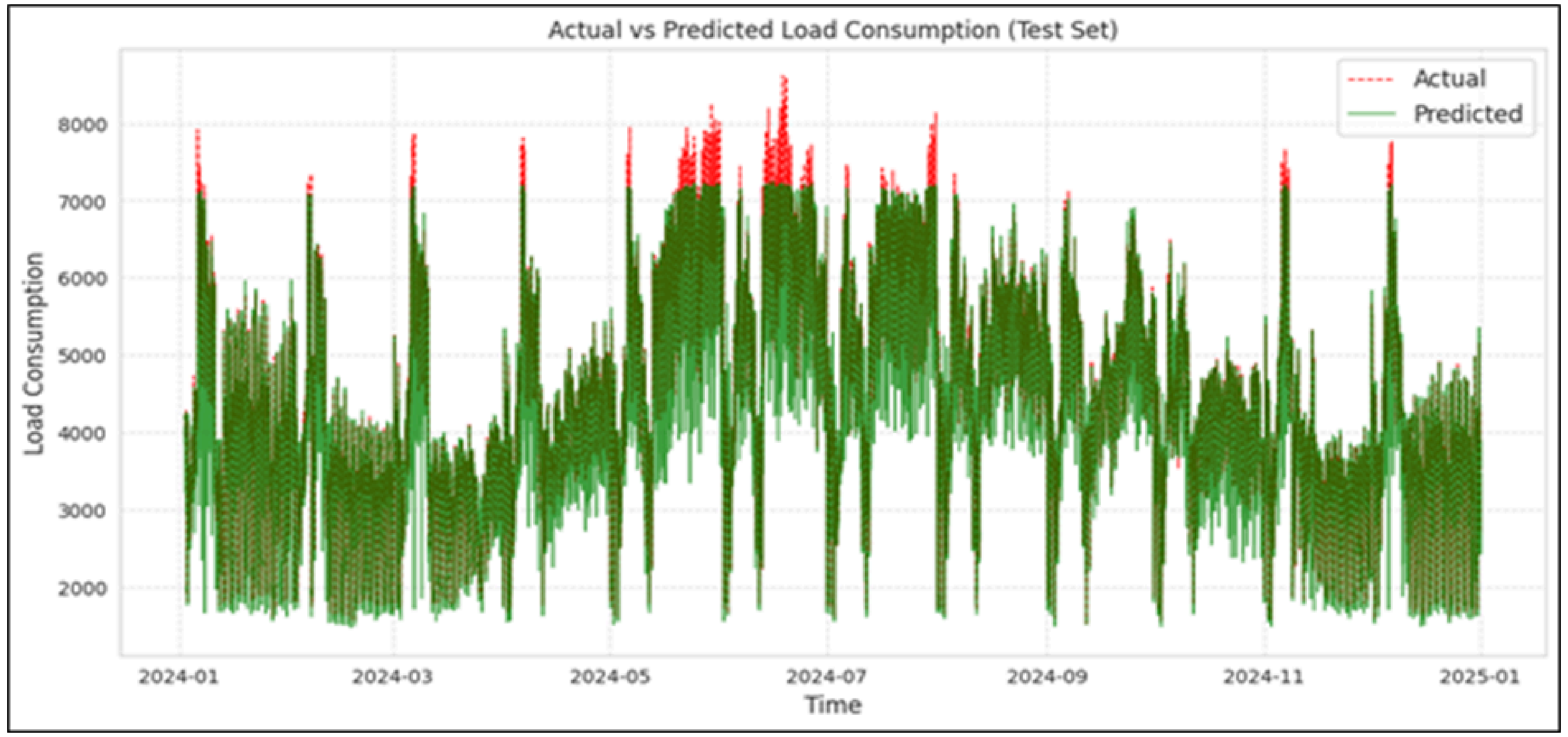
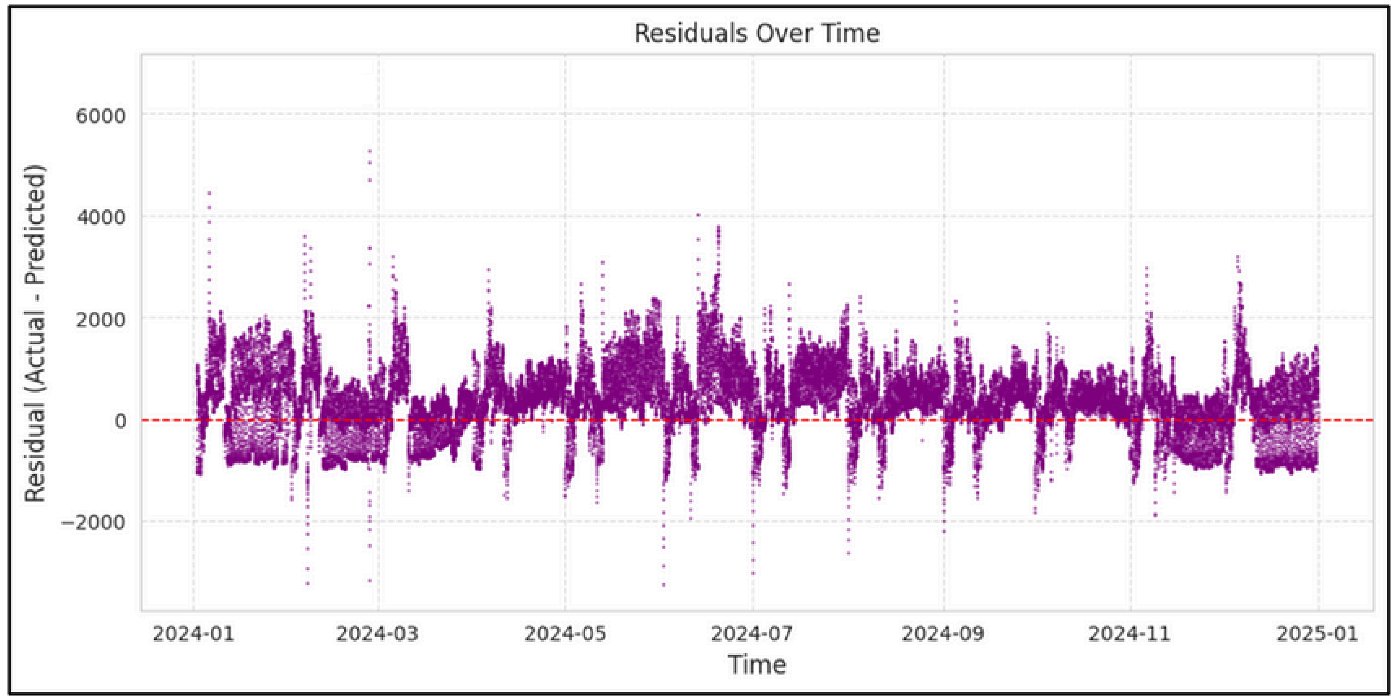
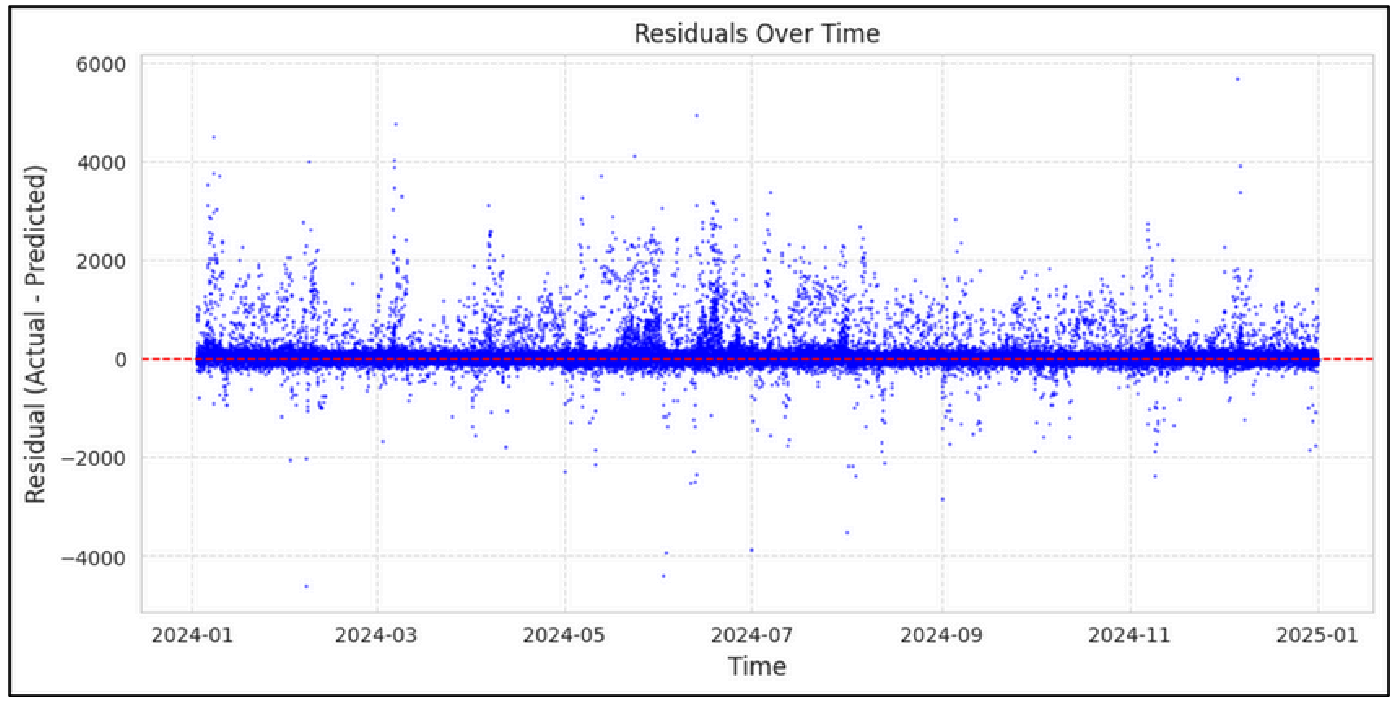
DEEP LEARNING MODELS









STACKED TWO LAYER LSTM MODEL

STACKED BILSTM UNIDIRECTIONAL LSTM MODEL

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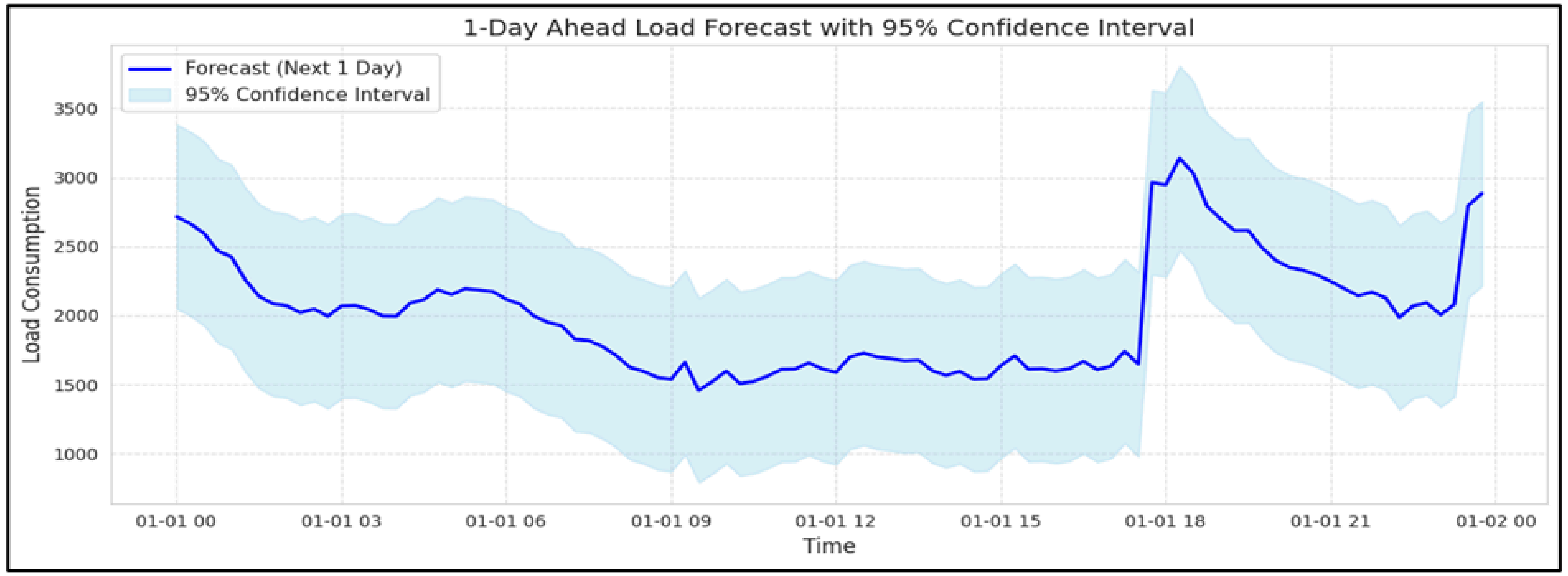
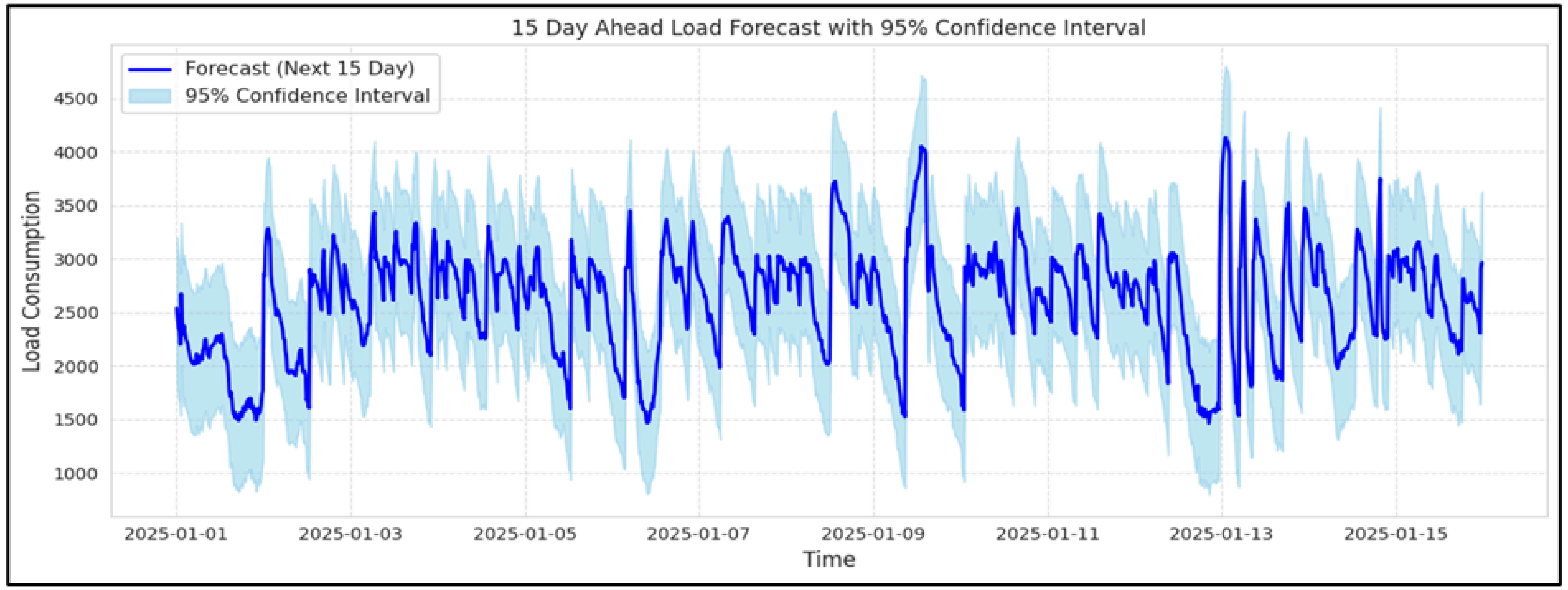
LOAD FORECASTING



Short-Term (1 Day):

- **Date: January 01, 2025**
- **96 time steps forecast(15-min intervals)**



Long Term (15 Days):

- **Period: January 01 to January 15, 2025**
- **1440 time steps with broader coverage**

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LIMITATIONS

- The models were trained using data only from Delhi, limiting their generalizability to other regions.
- The model do not explicitly account for extreme events such as blackout, policy shifts, or disruptions.
- Real-time operational or grid-level data was not incorporated into the modeling process.

FUTURE SCOPE

- Extend models to multi-region or national-scale datasets for broader applicability.
- Integrate anomaly detection to capture rare events and improve out-of-distribution performance.
- Include real-time grid data to enable adaptive, high-frequency forecasting for smart energy systems.

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