Instituto Superior de Engenharia do Porto

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Time Series Forecasting

A Data Mining Aproach

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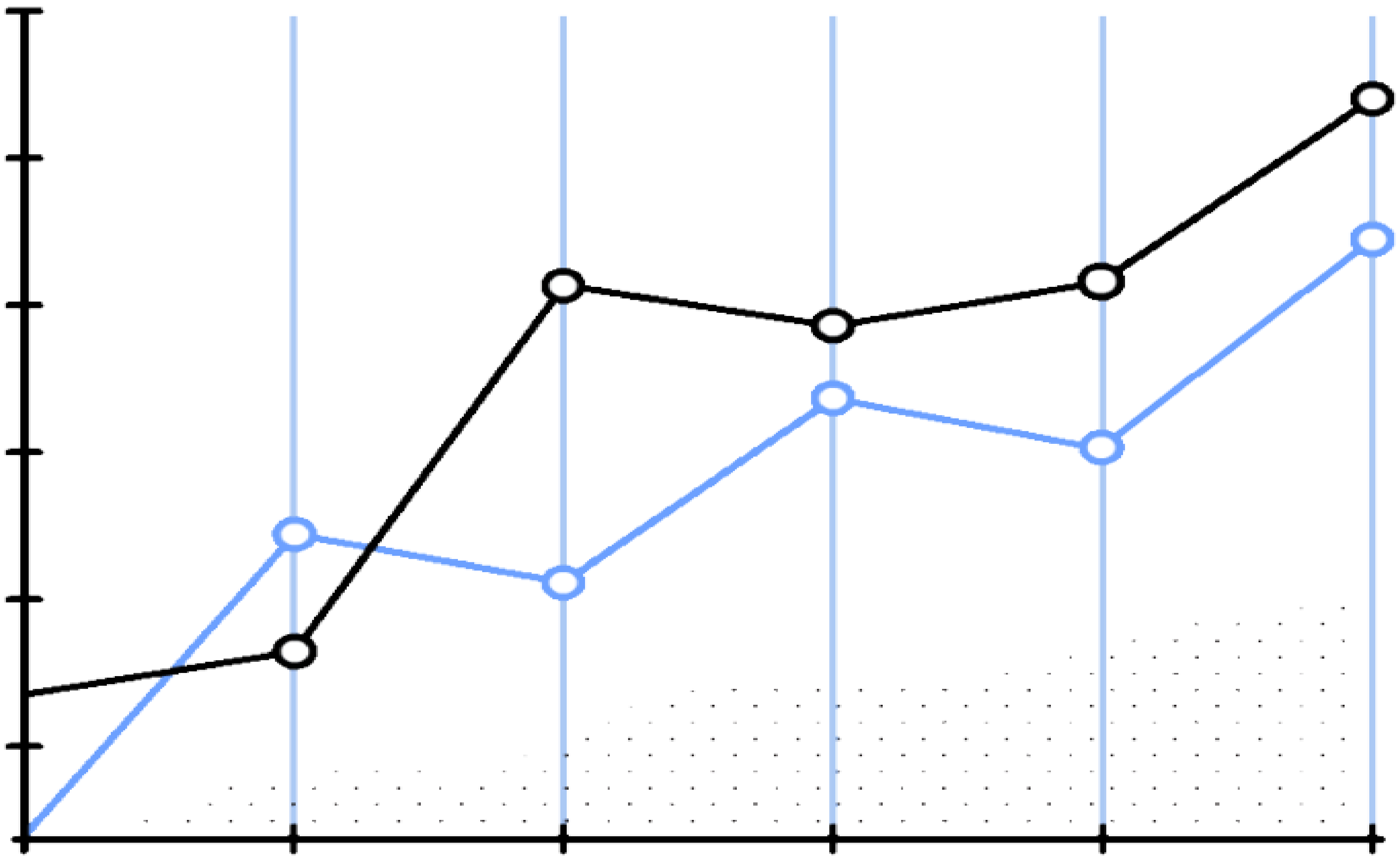

MINDD - P2
2023/2024

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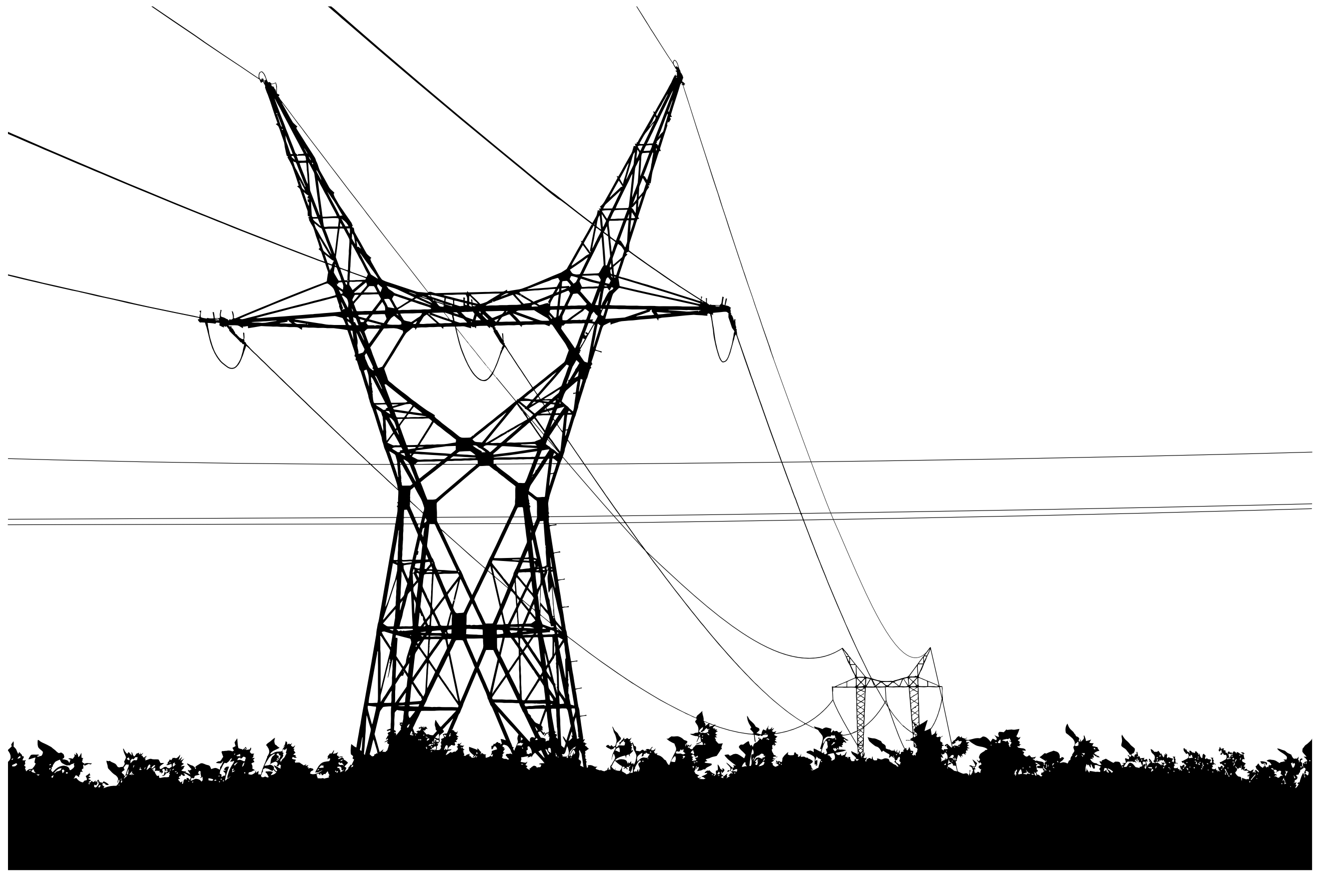
Introduction

Context and motivation

- Household power consumption
  - Track and forecast consumption patterns
- Energy load planing optimization
  - Optimize load distribution for efficiency
- Production Meets Peak Demands
  - Ensure adequate production during peak times
- Prevent Grid Imbalance and Disconnections
  - Mitigate risks of excess electricity and grid issues



Introduction

Goals

- Forecast Energy Consumption
- Utilize single-step and multi-step methods.
- Employ diverse models: baseline, statistical, ML, deep learning.

Data Exploration and Preprocessing

2 Data Exploration and Preprocessing

Initial Overview

Dataset Provided has 4 columns

- Date (yyyy-mm-dd)
- Hour (hh)
- Load (kw/h)
- Temperature (Cº)

Date and hour columns merged

- Datetime (yyyy-mm-dd hh-mm-ss)
- Index

Dataset does not have missing values

- No Missing Values Filling Needed

Low Mathematical Correlation between Load and Temperature

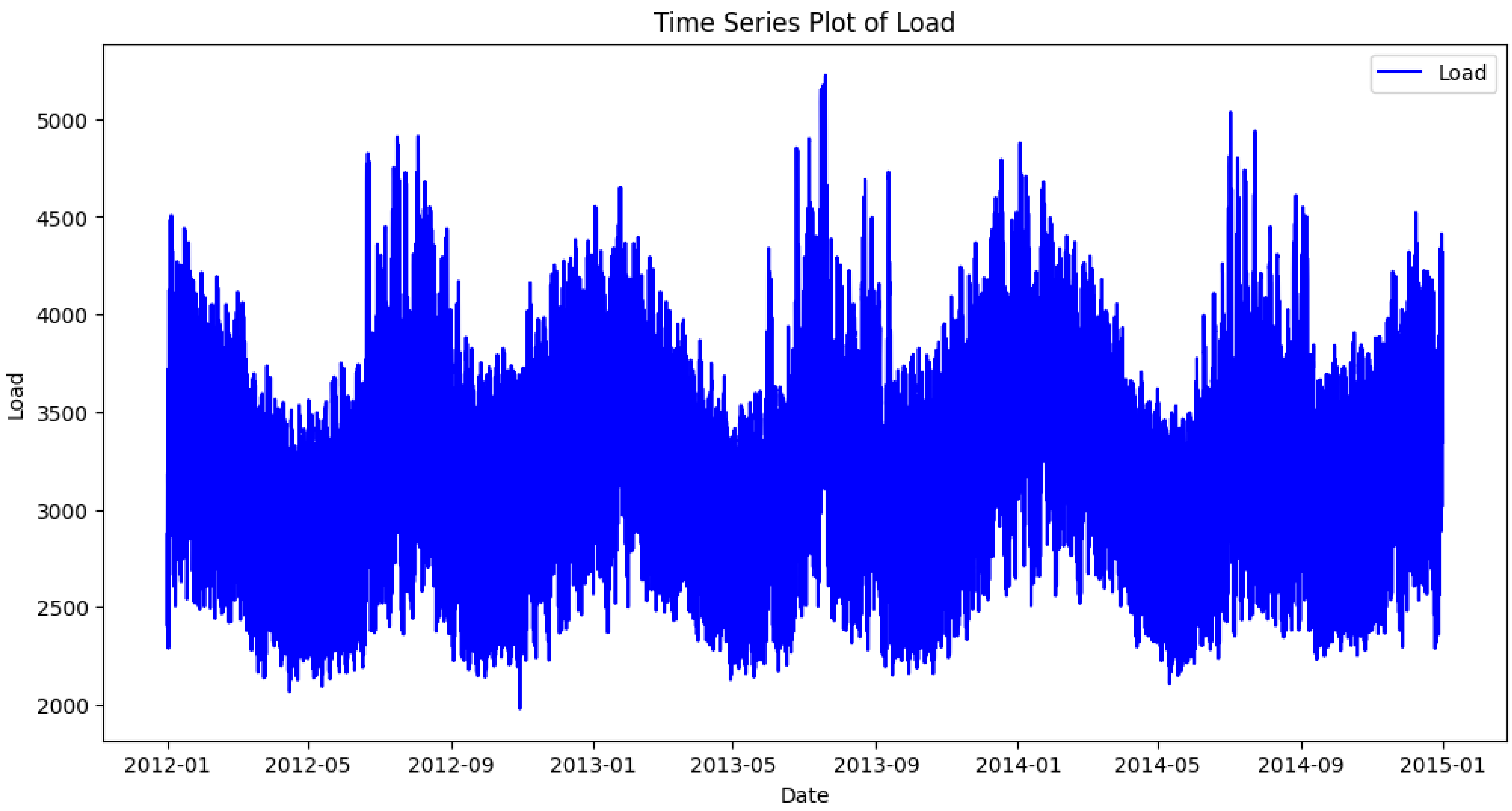
- Despite this, temperature was still experimented with

2 Data Exploration and Preprocessing

Load Time Series plot

Data Recorded: 2012-2014

- Captures a comprehensive three-year period.

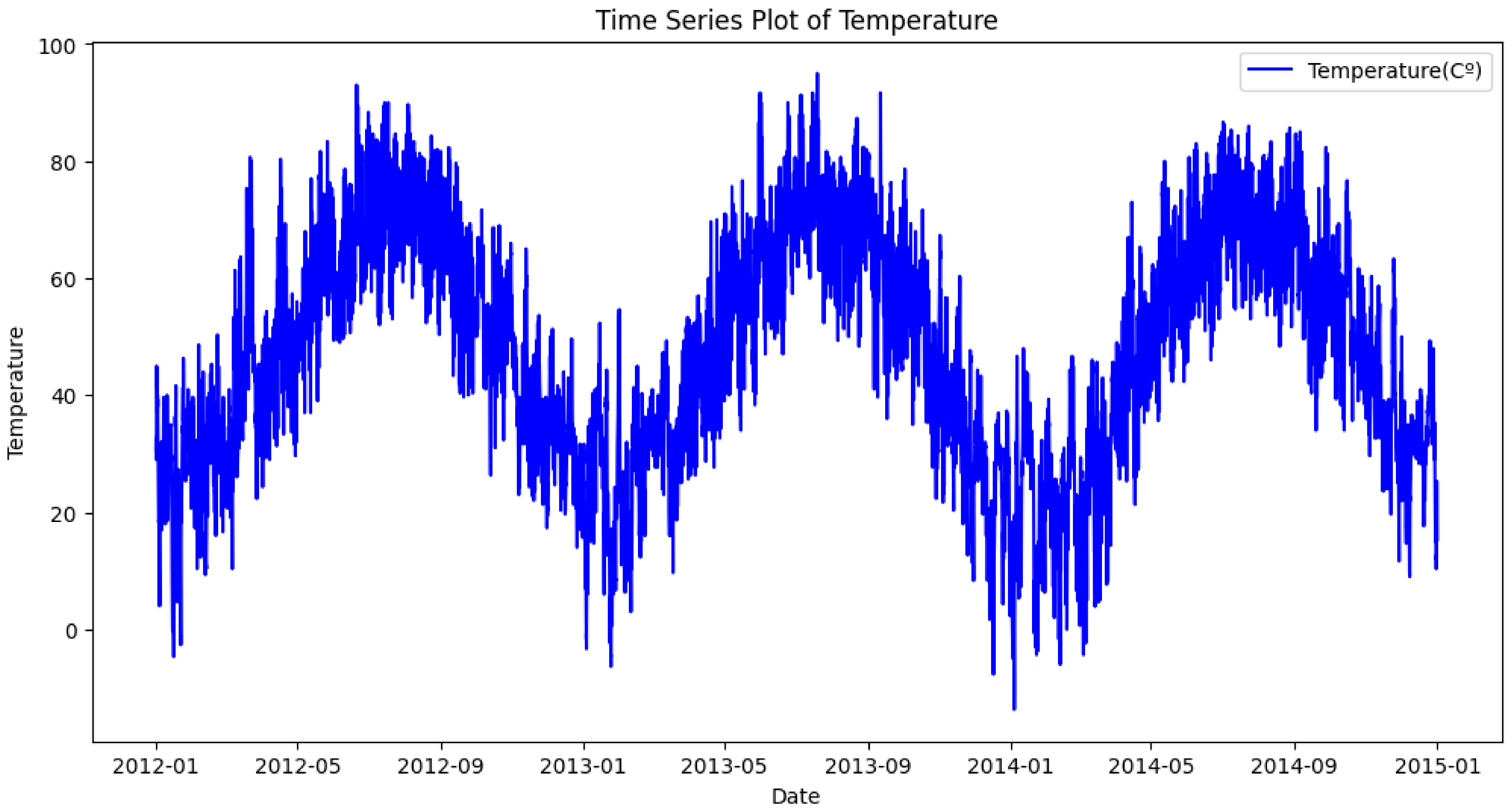


2 Data Exploration and Preprocessing

Temperature plot

Data Recorded: 2012-2014

- Captures a comprehensive three-year period.

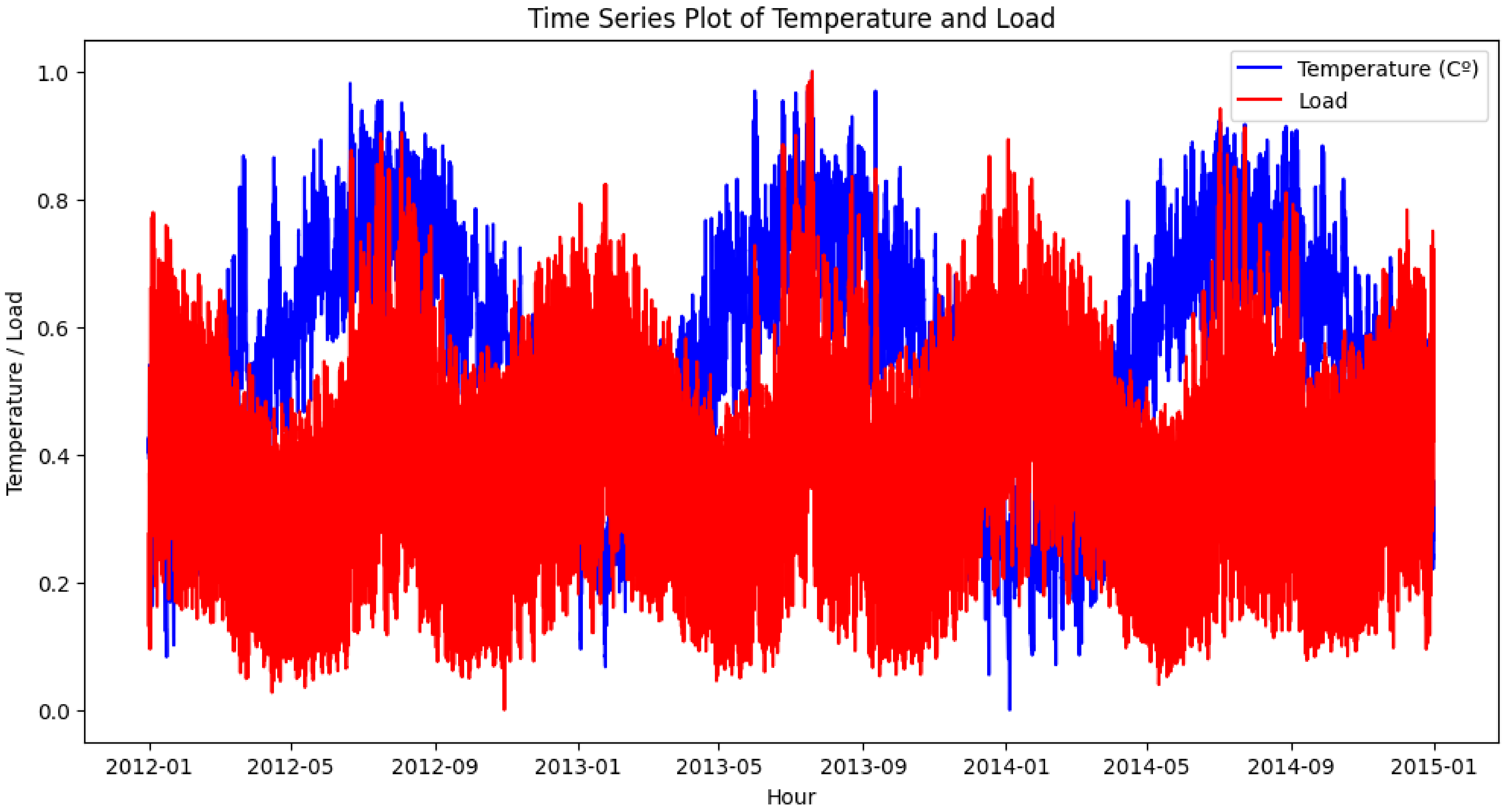


2 Data Exploration and Preprocessing

Load and Temperature plot

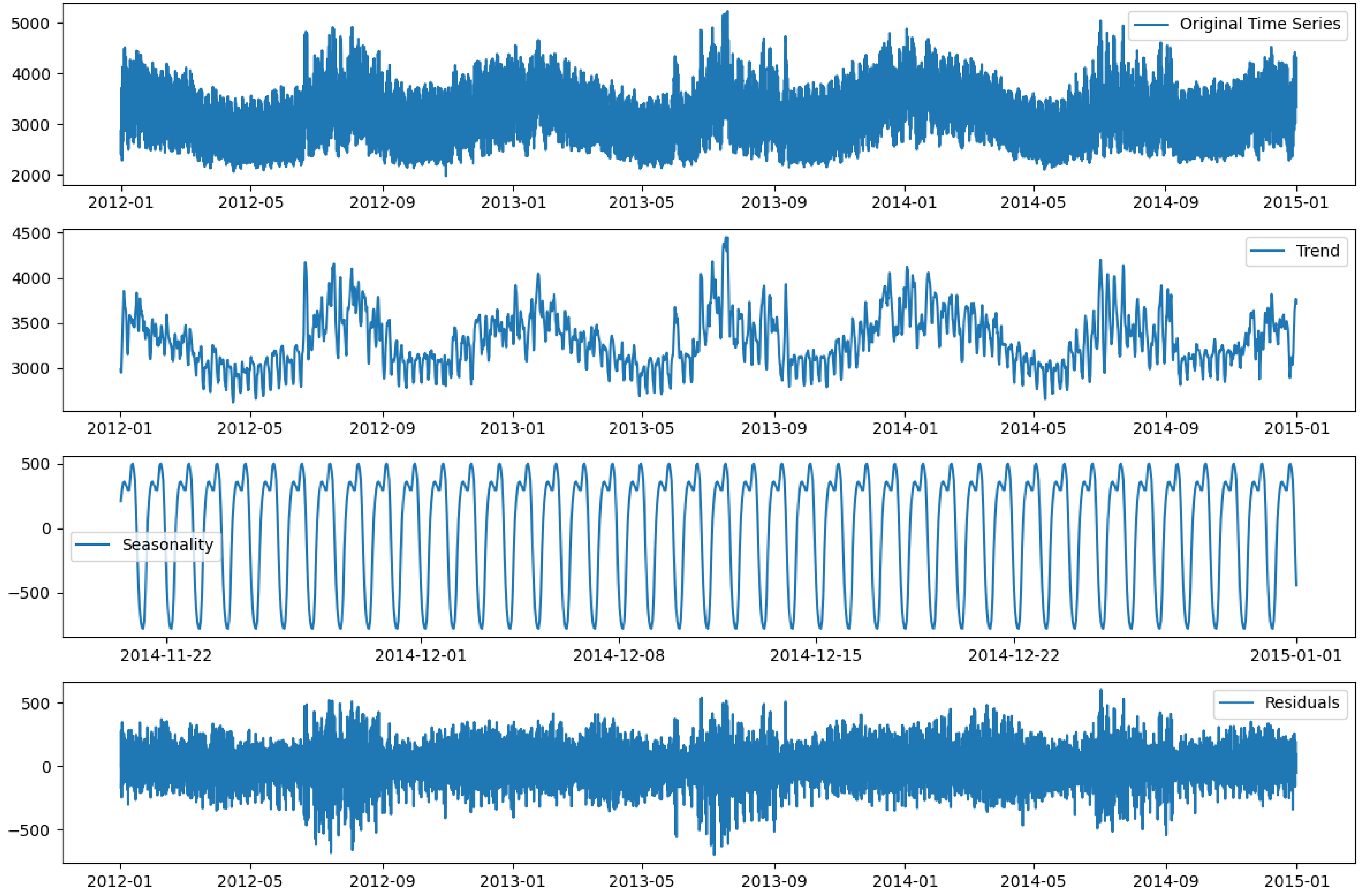
Data Recorded: 2012-2014

- Captures a comprehensive three-year period.



3 Time Series Decomposition

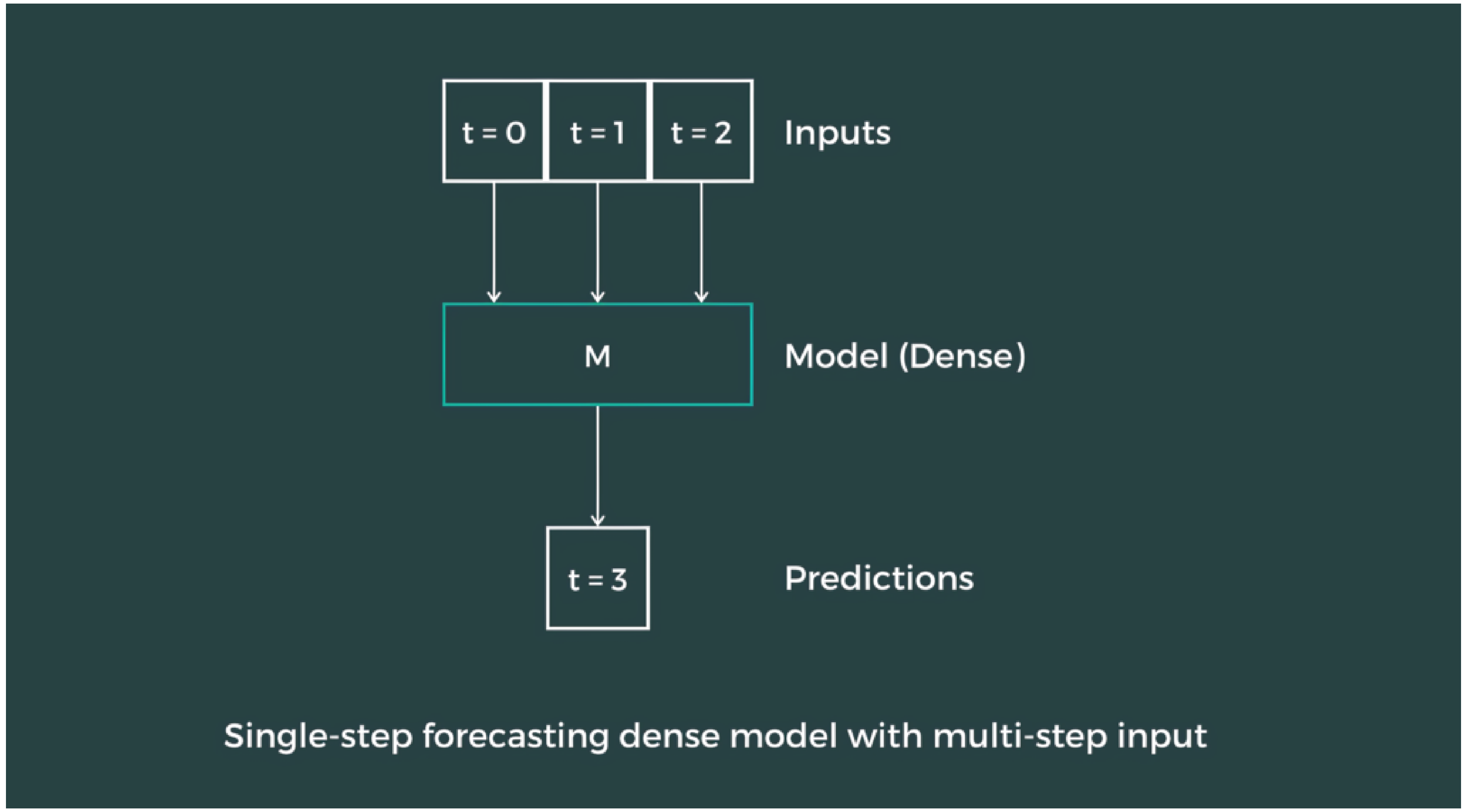
- Three Components
  - Trend
  - Seasonality
  - Residuals



Forecasting Techniques

4 Forecasting Techniques

- Single-step
- Multi-step



Statistical Models

5 Statistical Models

Choosing an appropriate model - SARIMA/SARIMAX

- SARIMA/SARIMAX Model Selected
  - Clear seasonal properties observed.
- Parameters tuning needed: (p, d, q)(P, D, Q).

$$SARIMA\underbrace{(p,d,q)}_{non-seasonal}\underbrace{(P,D,Q)_m}_{seasonal}$$

5 Statistical Models

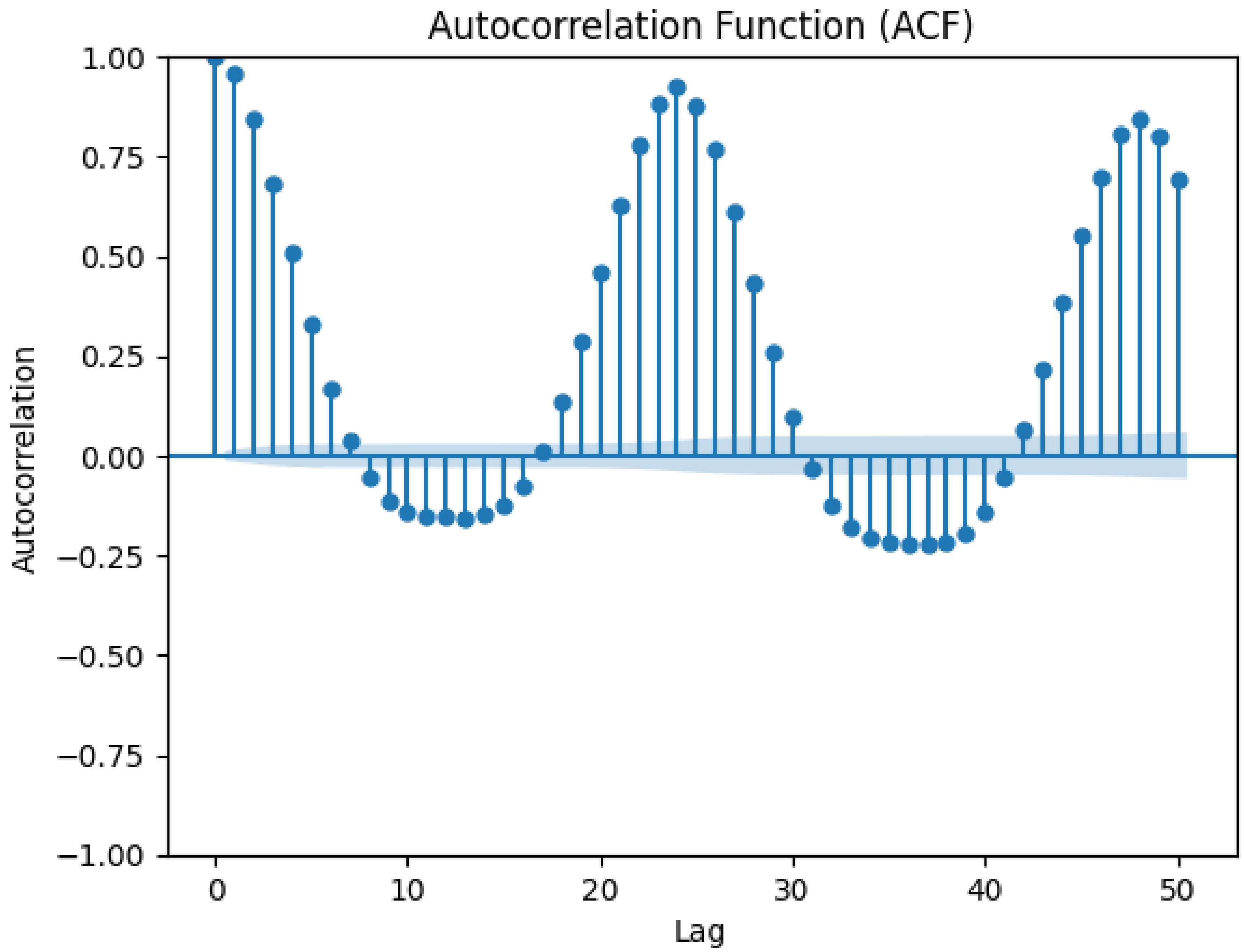
Parameter tuning - Stationarity

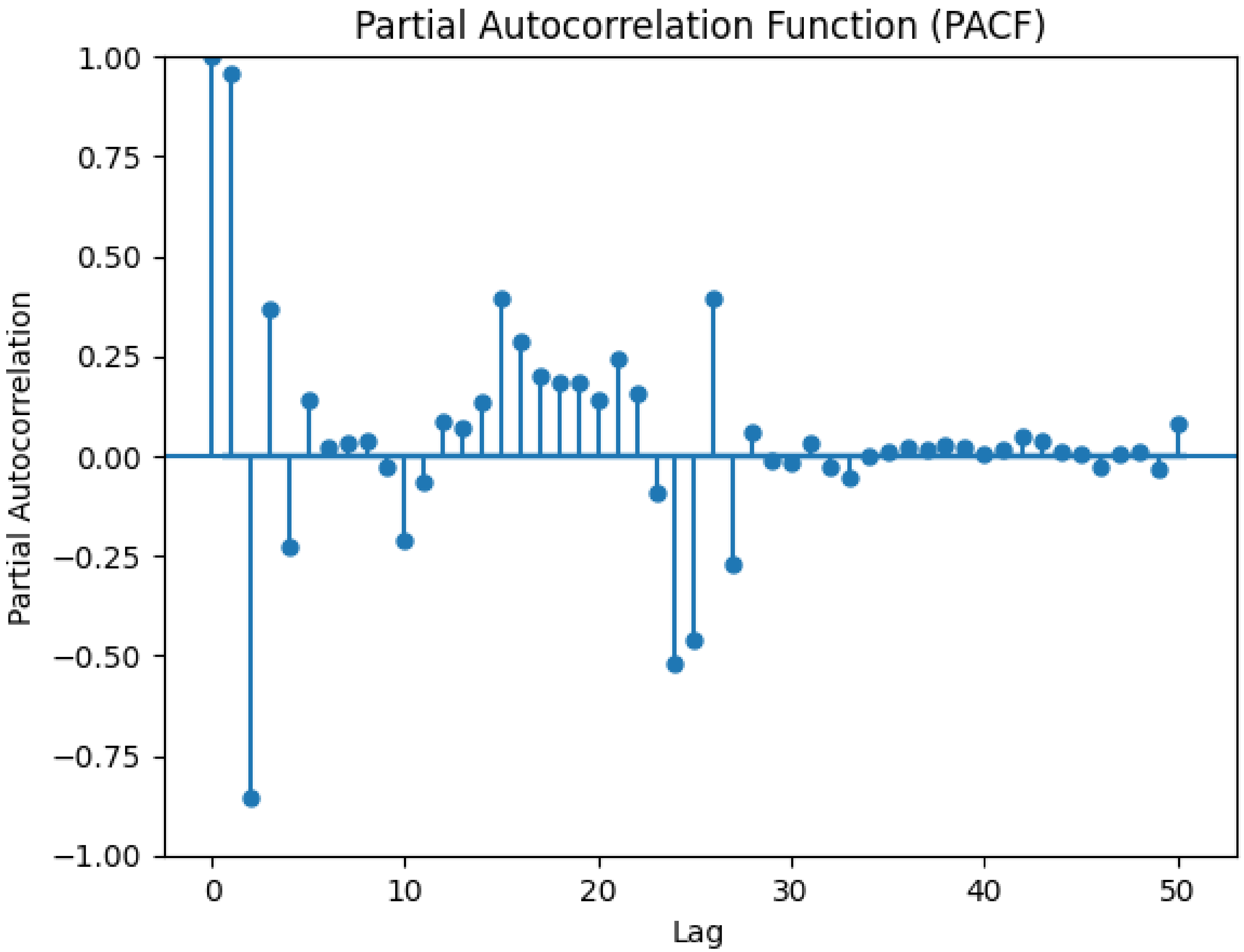
- Augmented Dickey-Fuller (ADF) test was performed
- Time Series was found to already be stationary
  - No transformations required
  - d = D = 0

```
ADF Statistic: -10.406
p-value: 0.0
Time Series is Stationary!
```

5 Statistical Models

Parameter tuning - ACF and PACF plots





5 Statistical Models

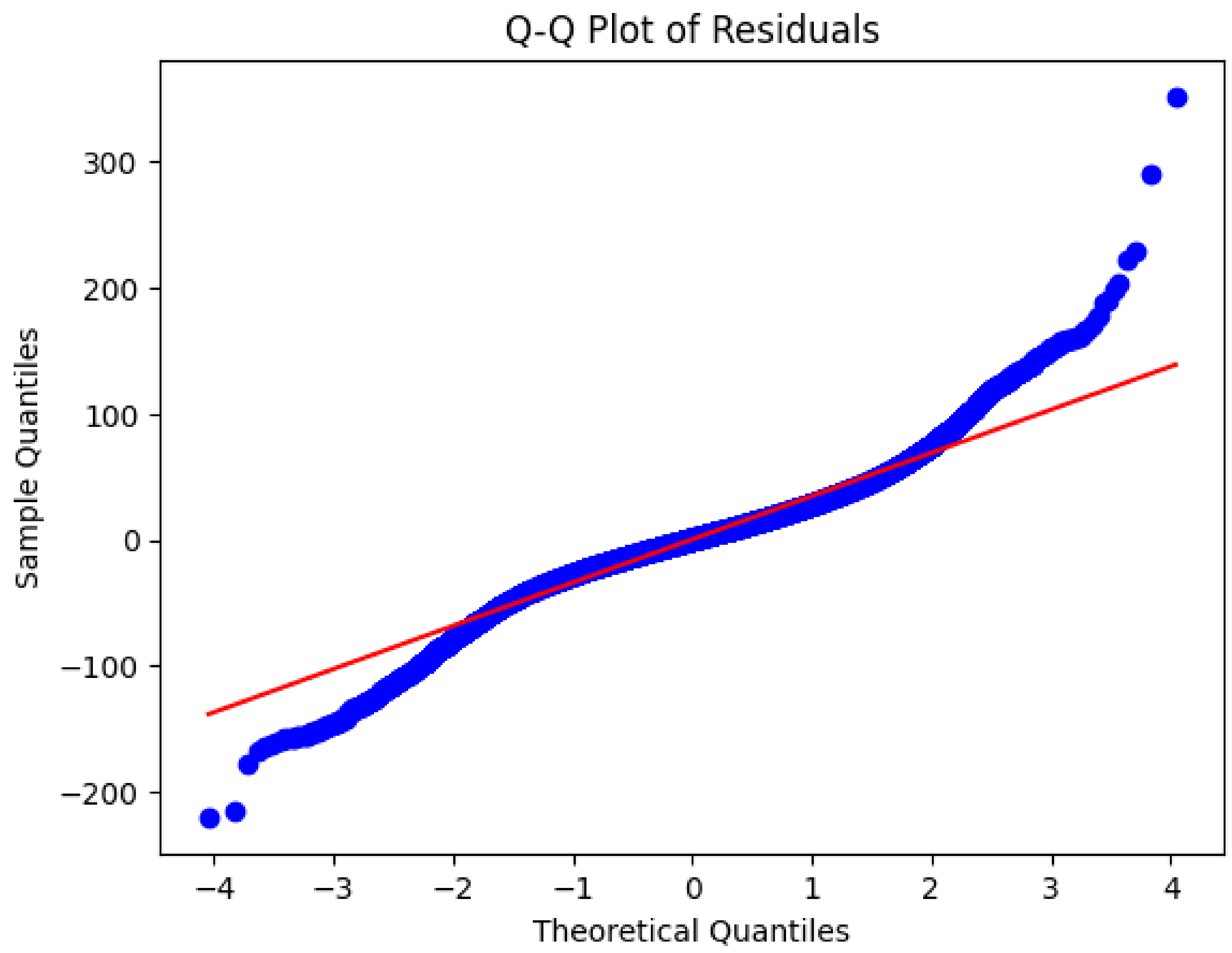
Parameter tuning - Multiple combinations (p, q, P, Q)

- Parameter Tuning:
  - Tested multiple combinations (p, q, P, Q) from 1-3.
  - Optimal values with lowest AIC: p=2, q=3, P=2, Q=2

- Constraint:
  - SARIMA model computationally demanding.
  - Preferably experiment with a larger interval.

5 Statistical Models

Parameter tuning - Residual analysis

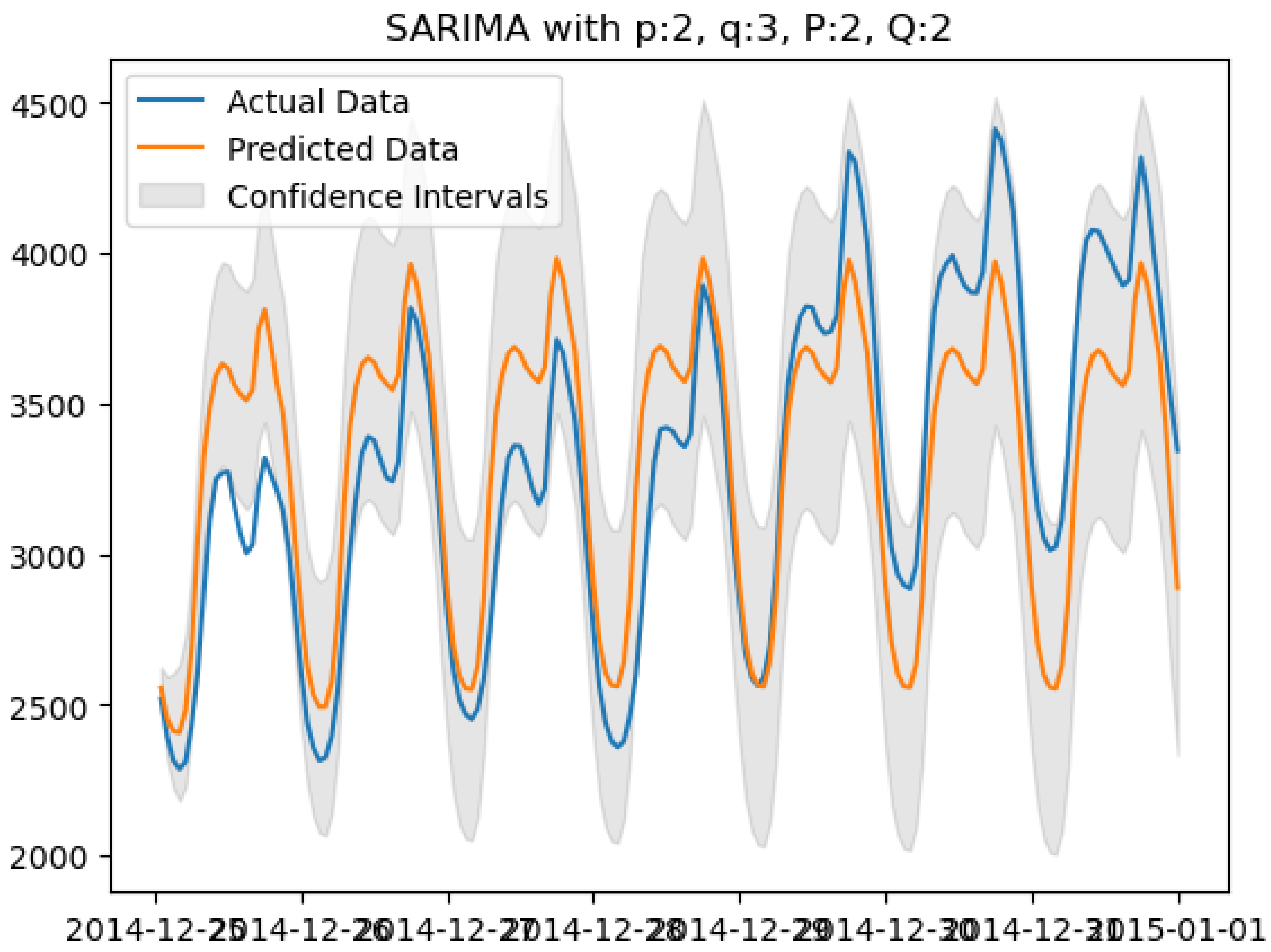


- Ljung-Box Test:
  - Residuals exhibited correlation signs.

Model may not fully capture all the information or patterns in the data

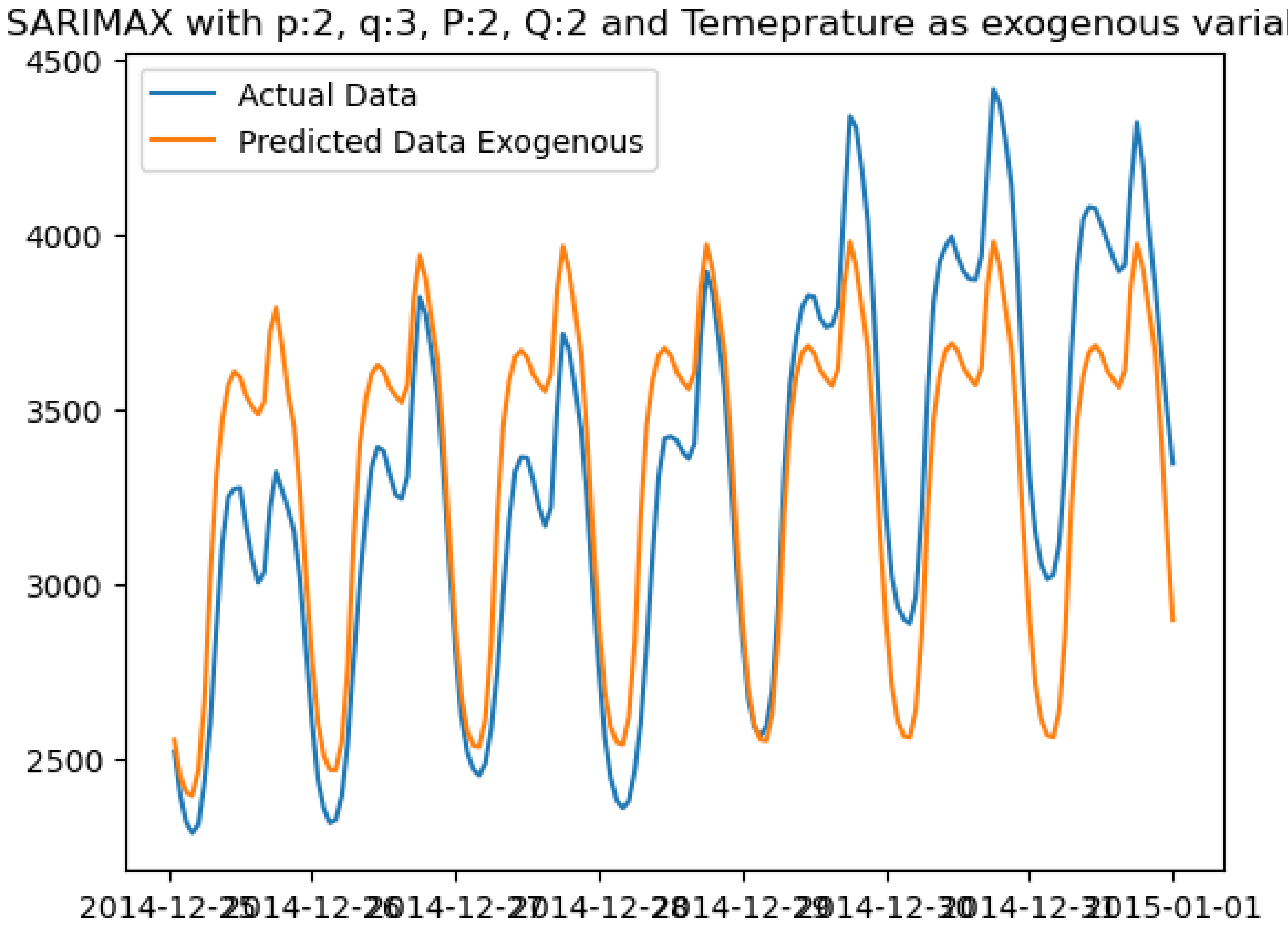
5 Statistical Models

Sarima Forecast (last week comparison)



5 Statistical Models

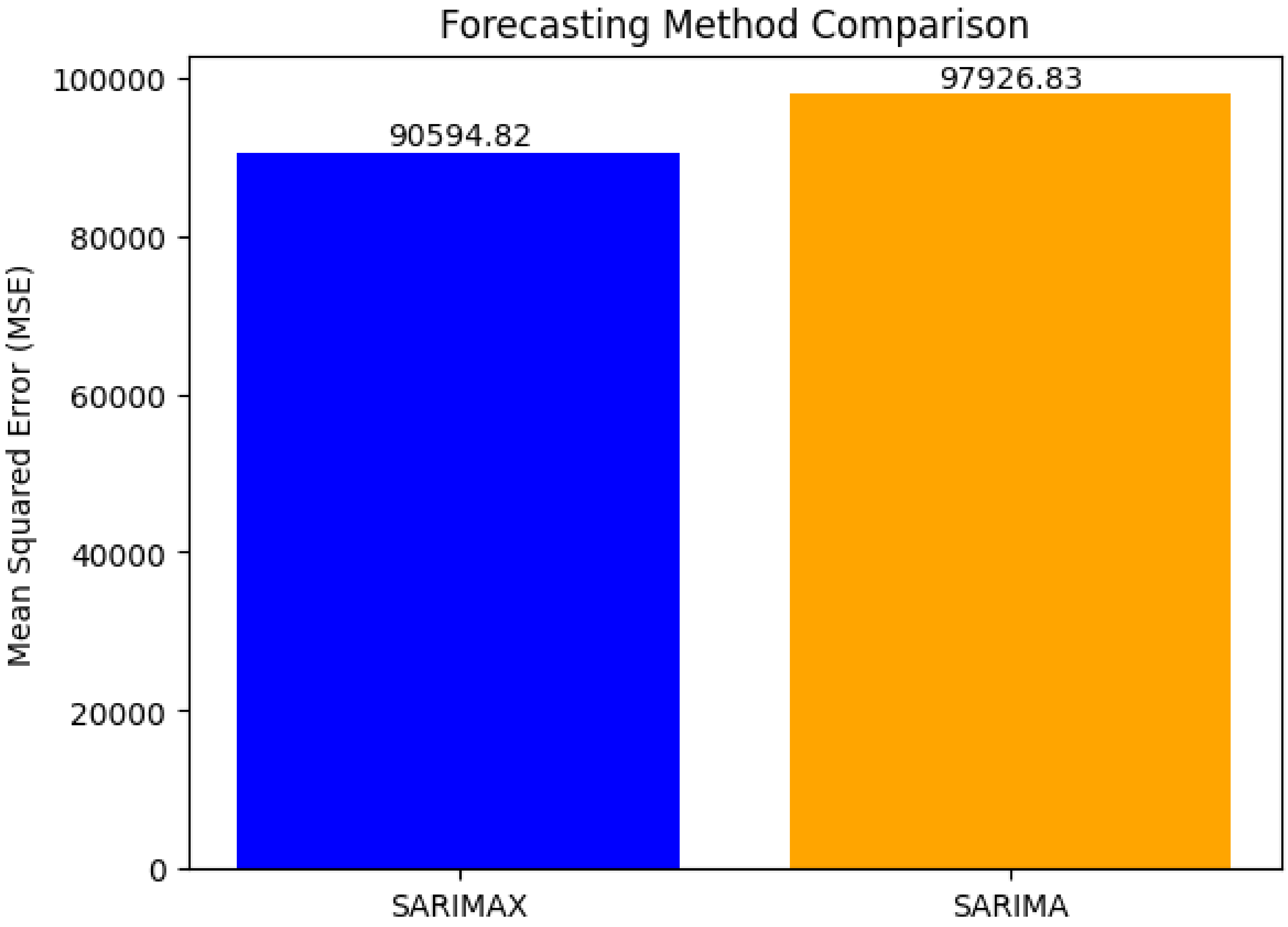
Sarimax Forecast (last week comparison)



- SARIMAX Model implementation:
  - Temperature was included as an exogenous variable

5 Statistical Models

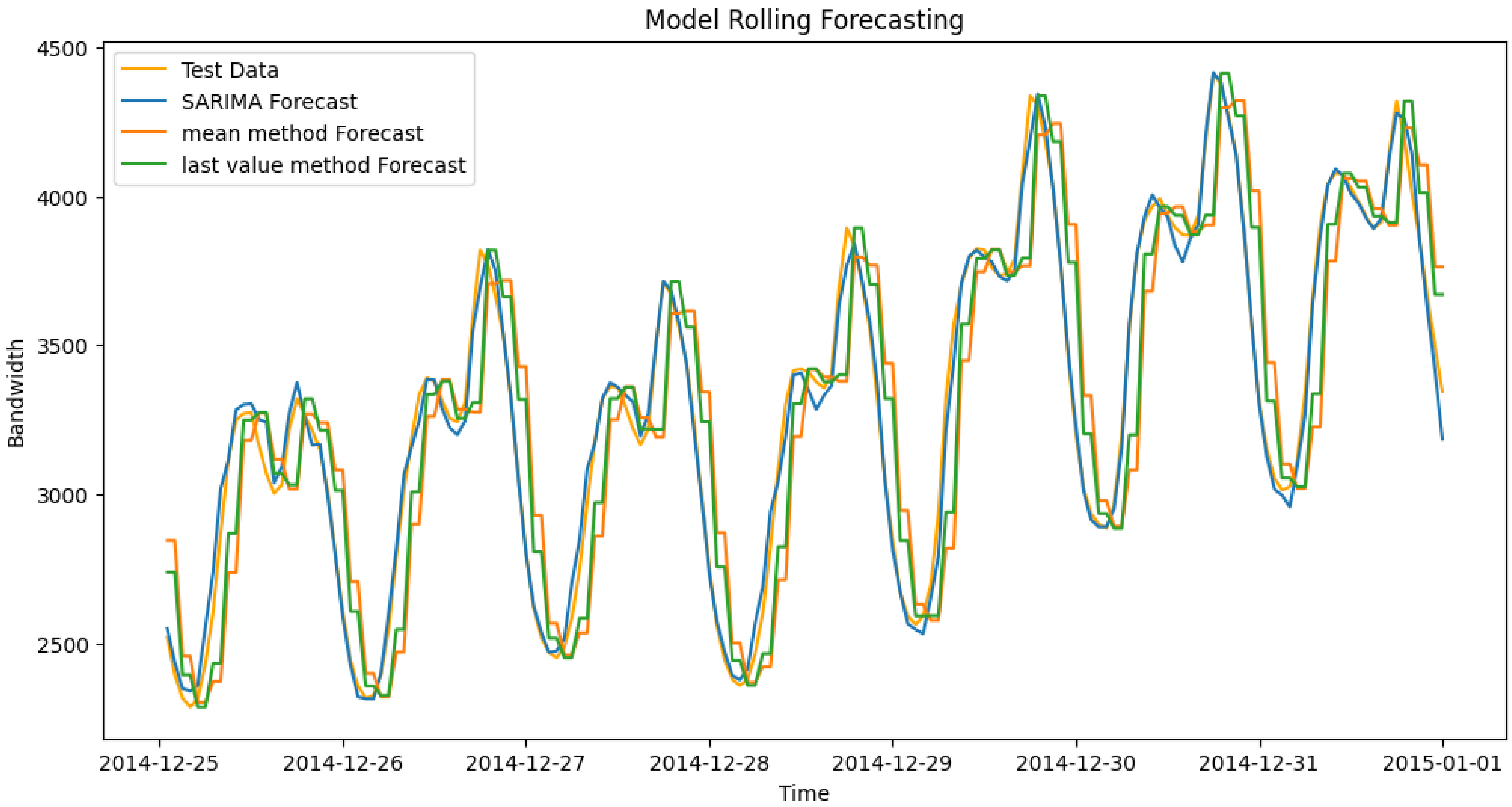
Sarima vs Sarimax (MSE comparison)



5 Statistical Models

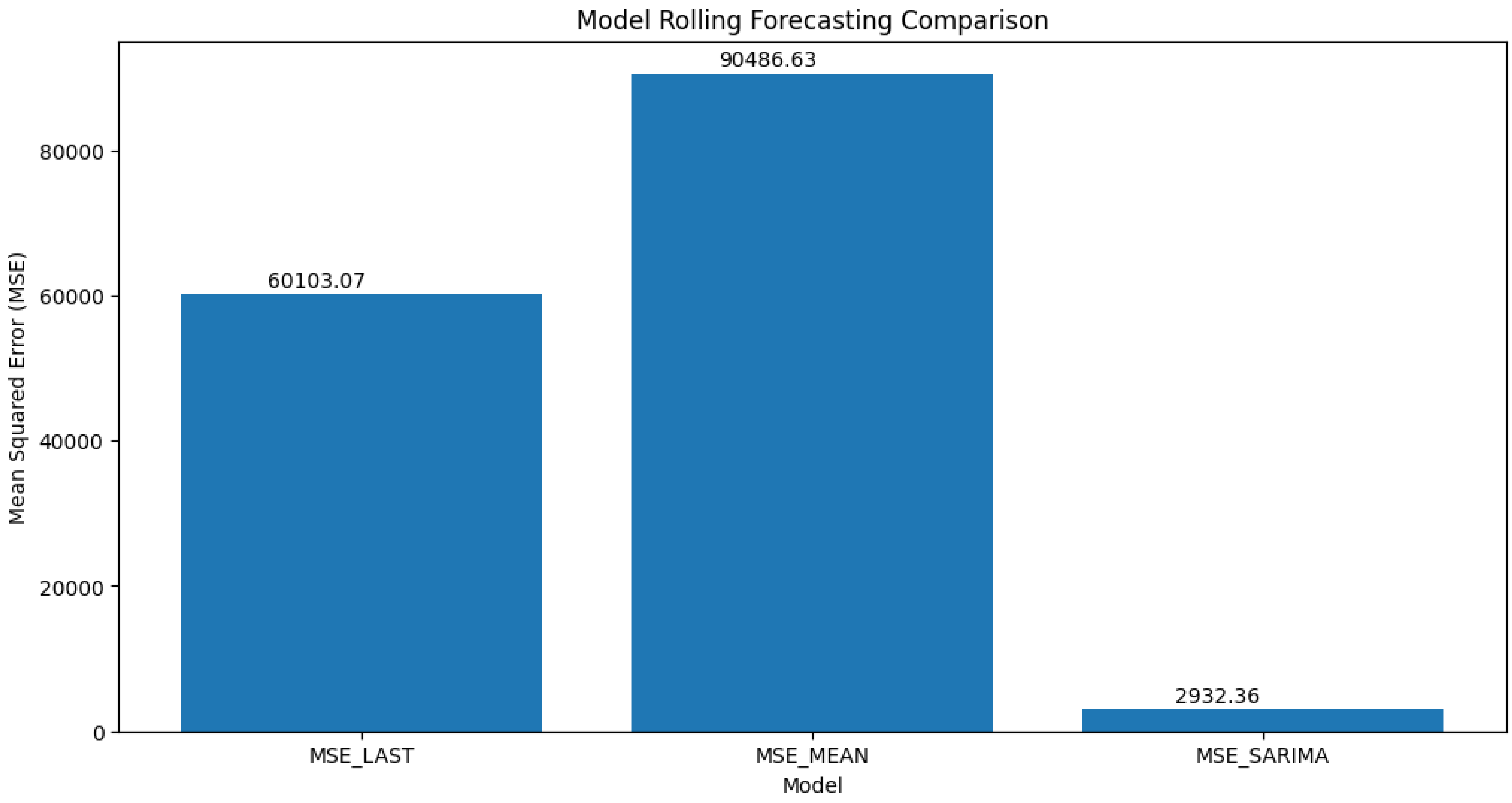
Baseline models and Sarima

- Two baseline models:
  - Historic mean method
  - Last value method
- SARIMA used.
- All models employed rolling forecasts.
- SARIMAX skipped due to high computational demands.
  - Debug time of 20 hours deemed infeasible.



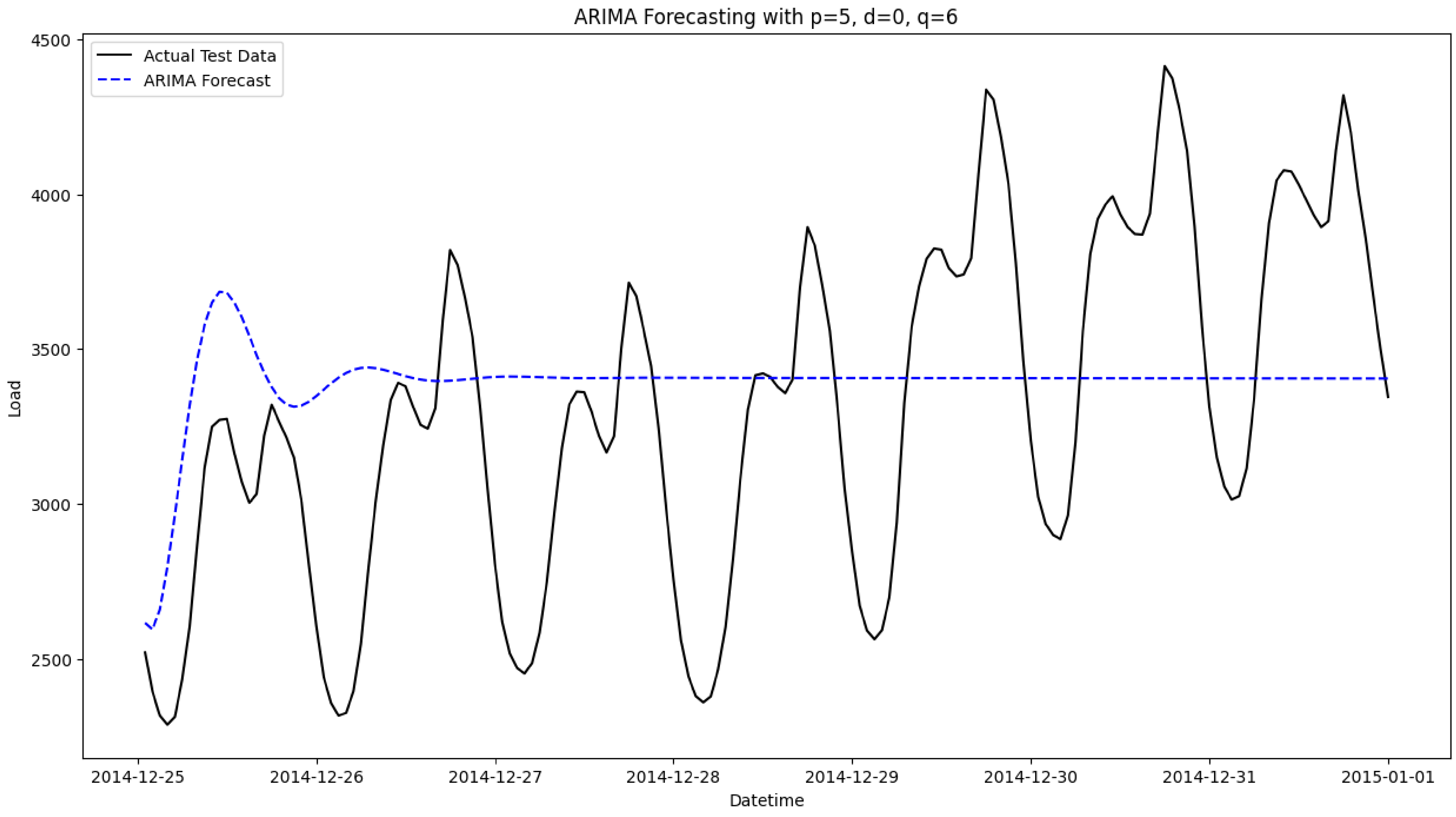
5 Statistical Models

Rolling Forecast MSE comparison



5 Statistical Models

ARIMA Forecast



Machine Learning models

6 Machine Learning Models

Data Preparation - sliding window

- Data Transformation:
  - Converted data to tabular format
  - Applied sliding window technique
  - Window size and horizon could be defined

Window = 6
Horizon = 3

	date	temperature
0	2009-01-01	-6.810629
1	2009-01-02	-3.360486
2	2009-01-03	5.435694
3	2009-01-04	7.283889
4	2009-01-05	12.690069

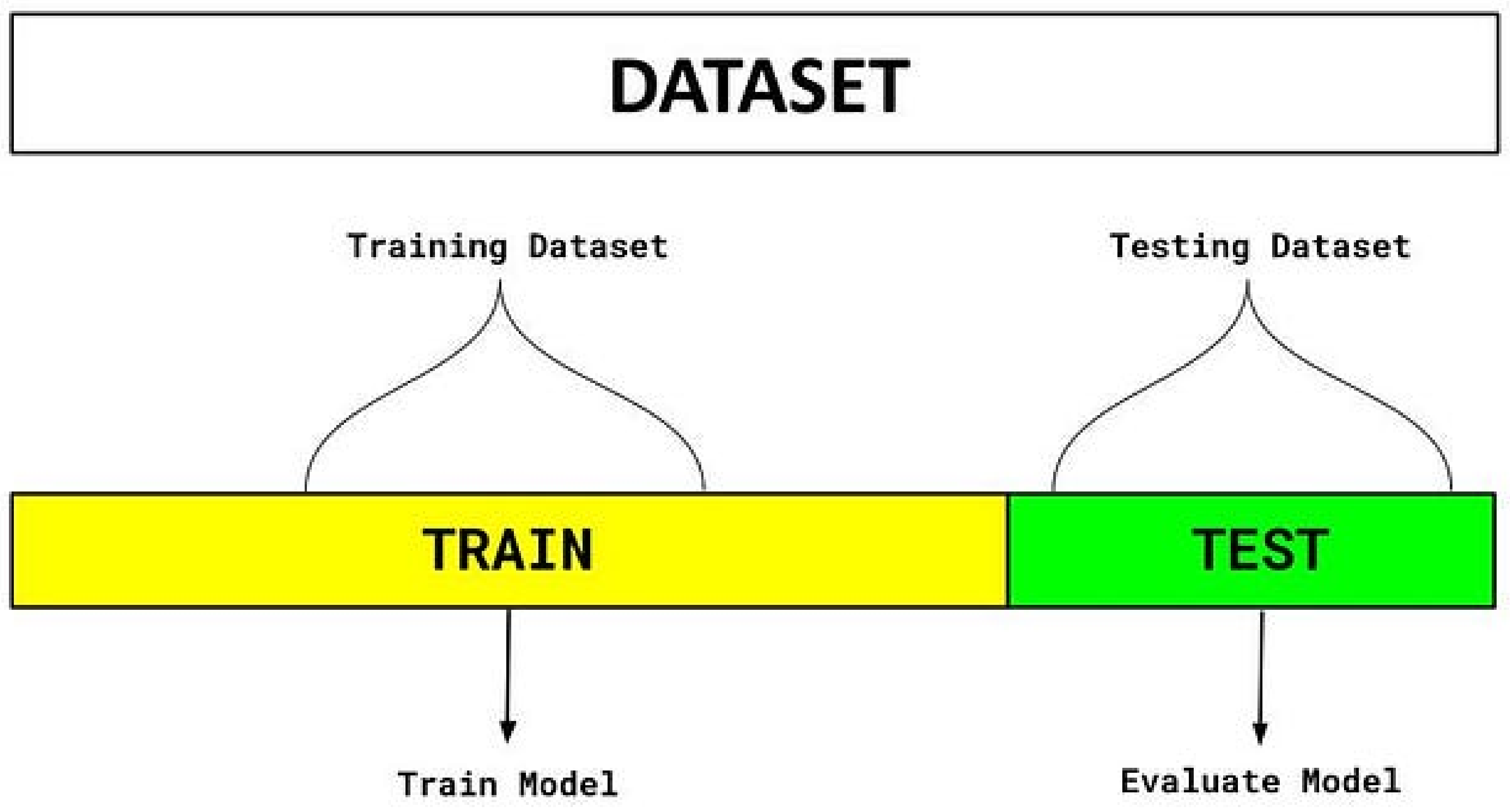
date	x1	x2	x3	x4	x5	x6	y1	y2	y3
2009-01-01	-6.810629	-3.360486	5.435694	7.283889	12.690069	15.201597	20.121875	18.864792	21.289722
2009-01-02	-3.360486	5.435694	7.283889	12.690069	15.201597	20.121875	18.864792	21.289722	11.937847
2009-01-03	5.435694	7.283889	12.690069	15.201597	20.121875	18.864792	21.289722	11.937847	3.210903
2009-01-04	7.283889	12.690069	15.201597	20.121875	18.864792	21.289722	11.937847	3.210903	3.682431
2009-01-05	12.690069	15.201597	20.121875	18.864792	21.289722	11.937847	3.210903	3.682431	-1.678194

6 Machine Learning Models

Data Preparation - Train/test split and scaling

- A train/test split was performed according to the holdout method:
  - Train data -> 0-80 (80%)
  - Test Data -> 80-100 (20%)

- Scaling Applied for Sensitive Models

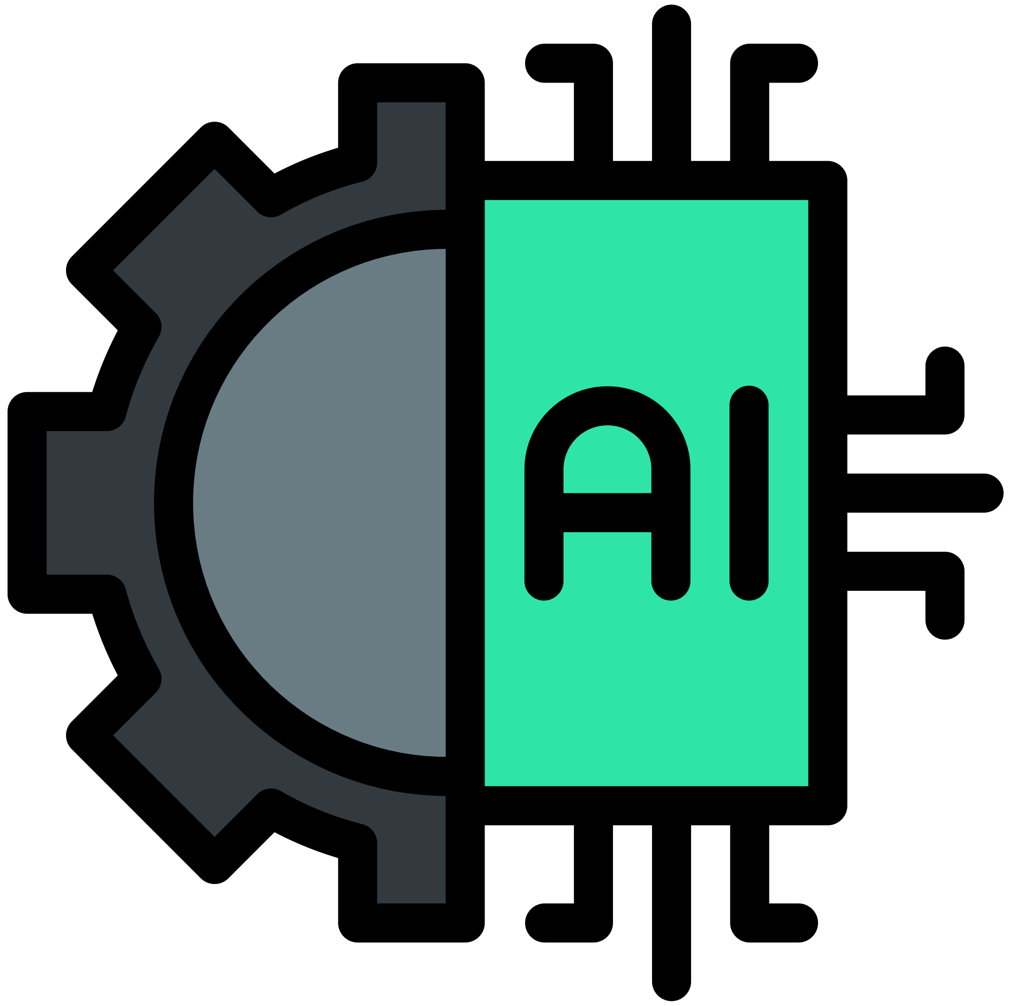


6 Machine Learning Models

Models Used and window/horizon settings

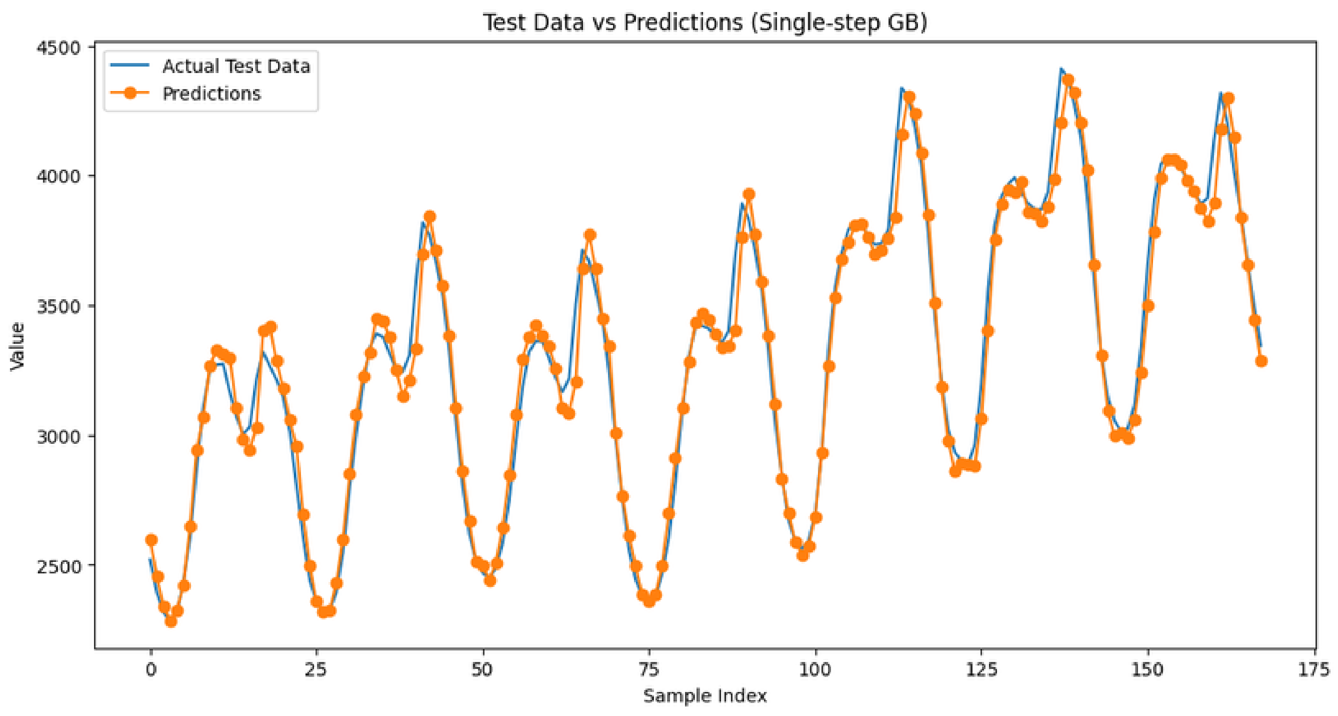
- Models Used (Single-Step and Multi-Step):
  - Linear Regression
  - K-Nearest Neighbors (k=5)
  - Support Vector Regression (SVR)
  - Random Forest
  - Light Gradient Boosting
  - Gradient Boosting
  - XGBoost
  - Neural Networks

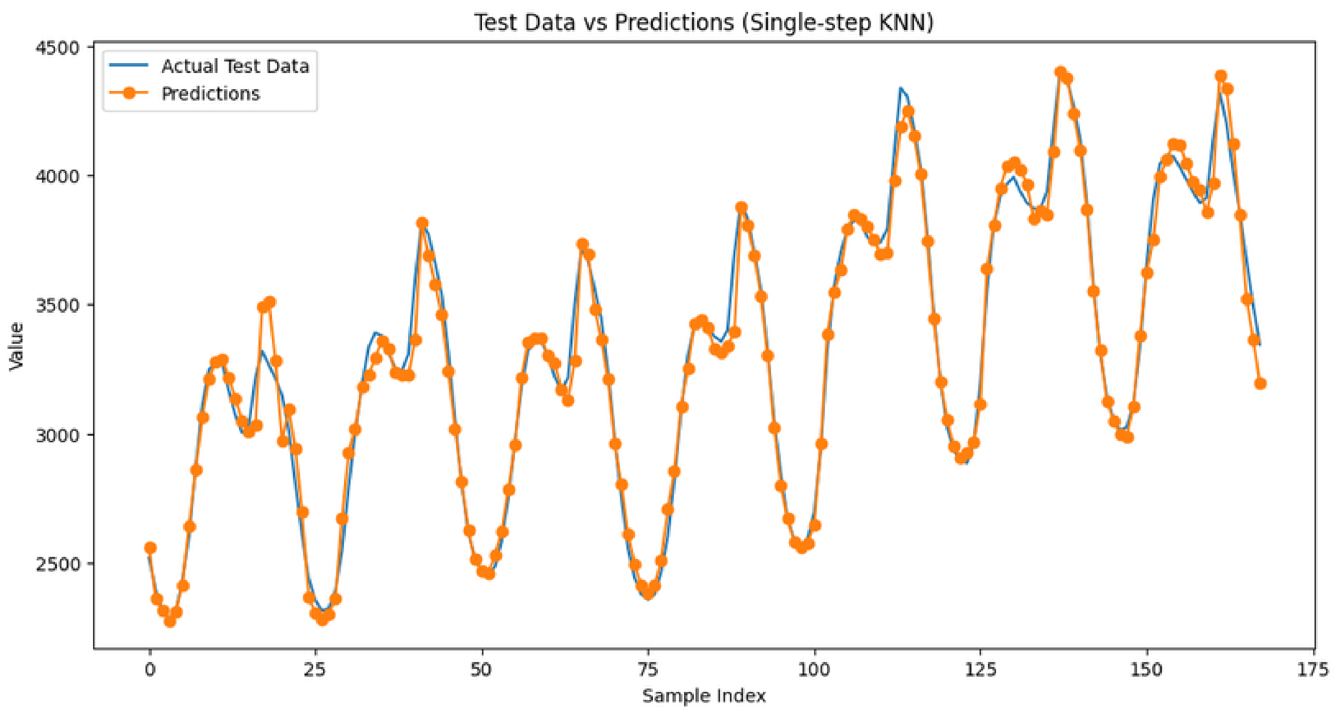
- **Single-step settings:**
  - Window = 6
  - Horizon = 1
- **Multi-Step settings:**
  - Window = 6
  - Horizon = 3

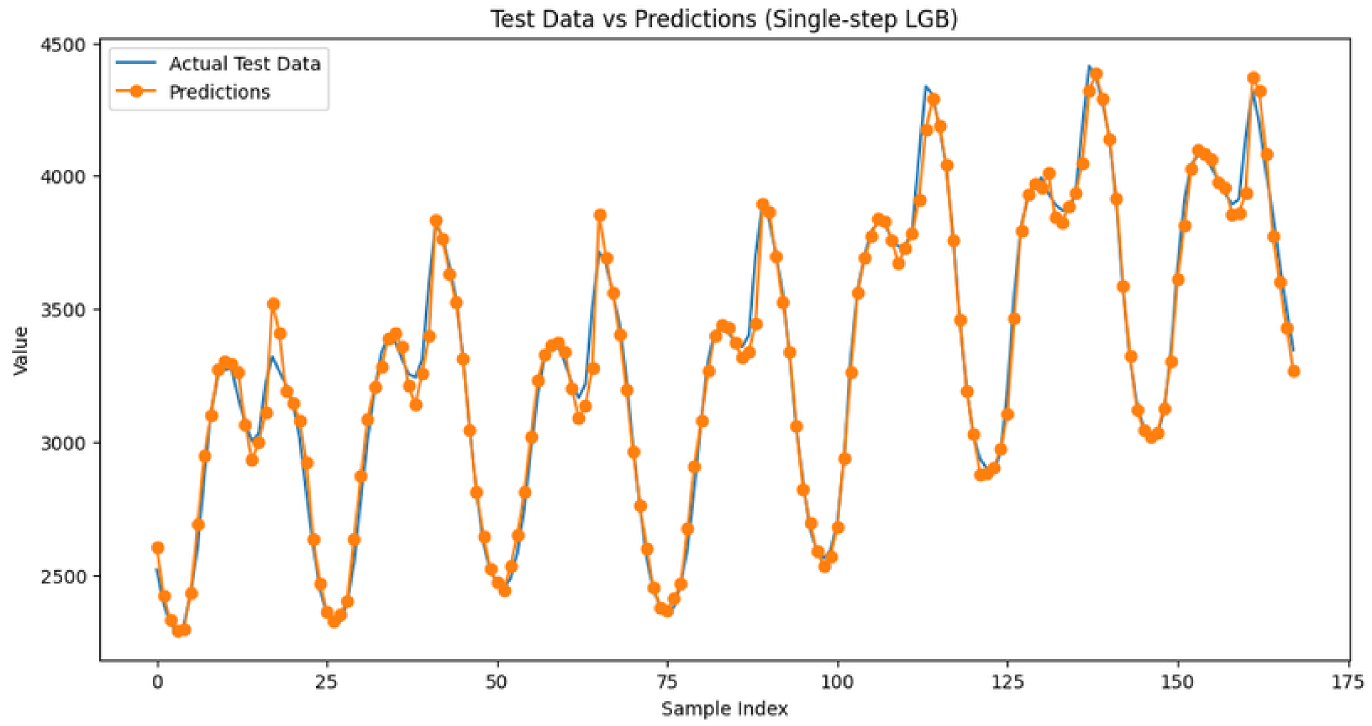


6 Machine Learning Models

Single-step Forecasts

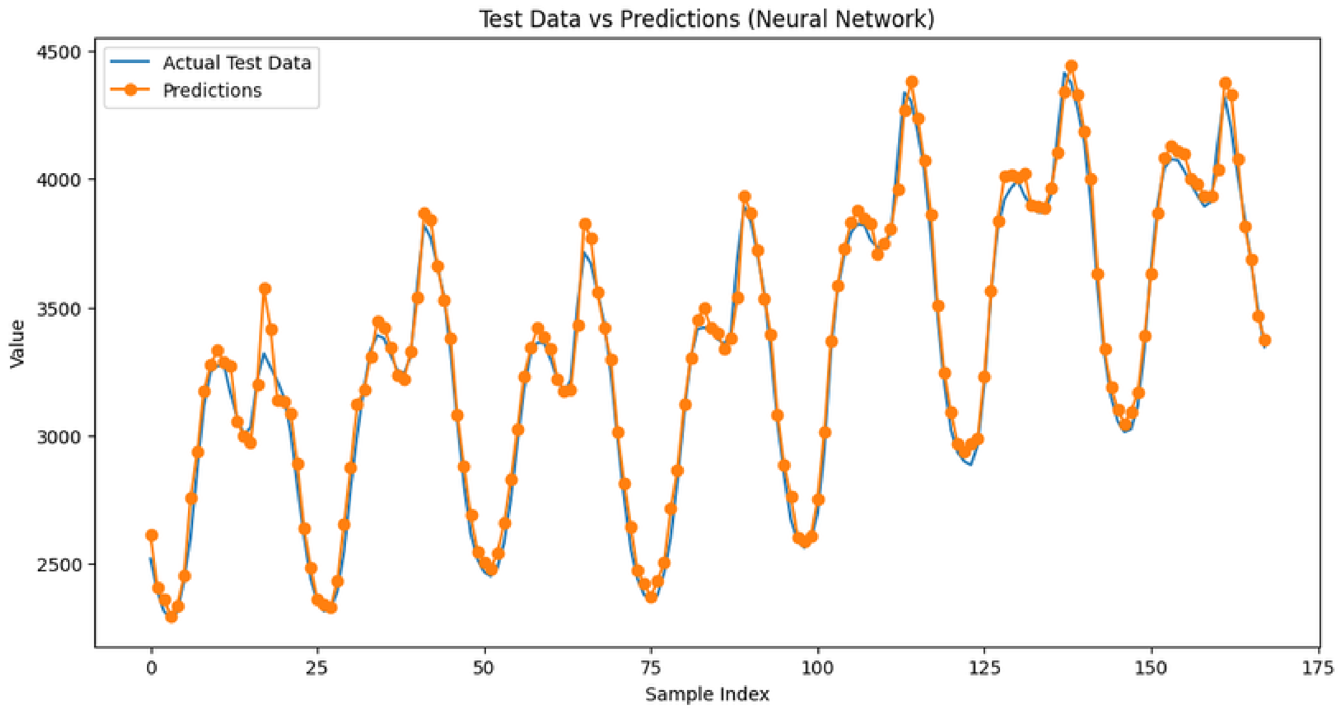


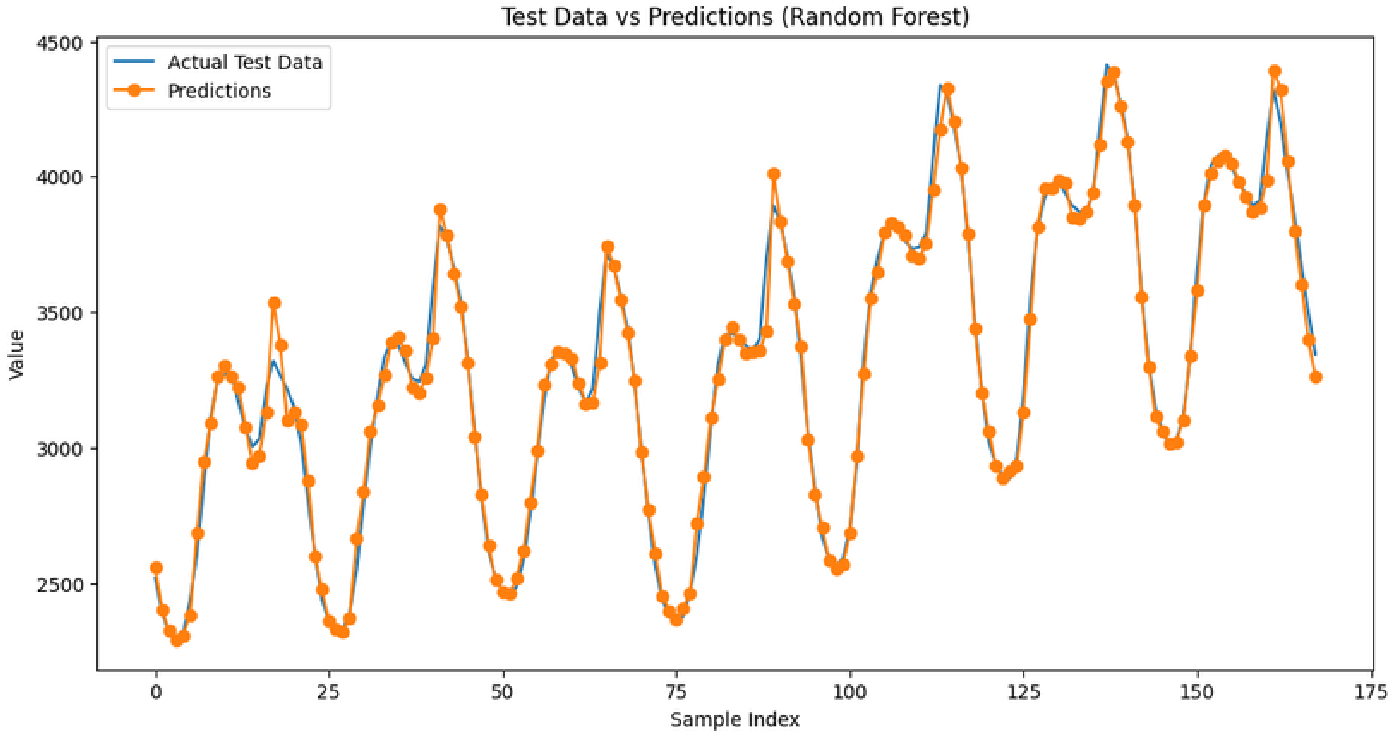


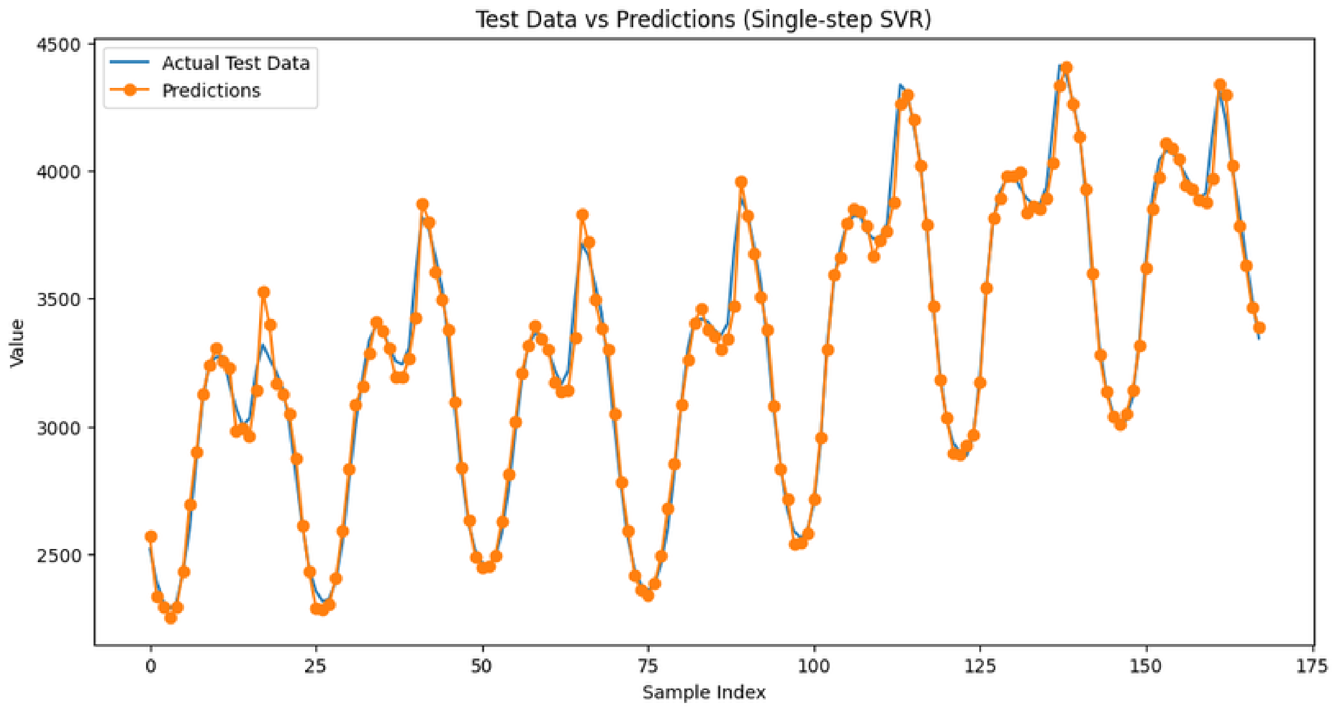


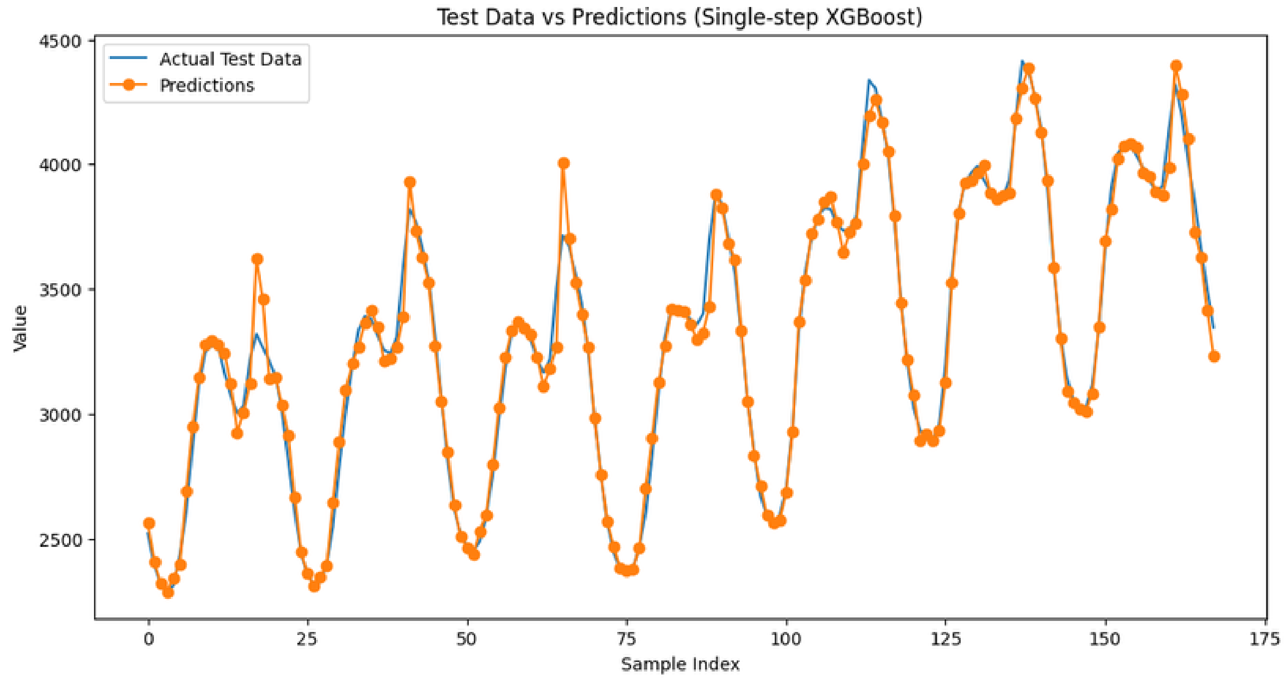
6 Machine Learning Models

Single-step Forecasts





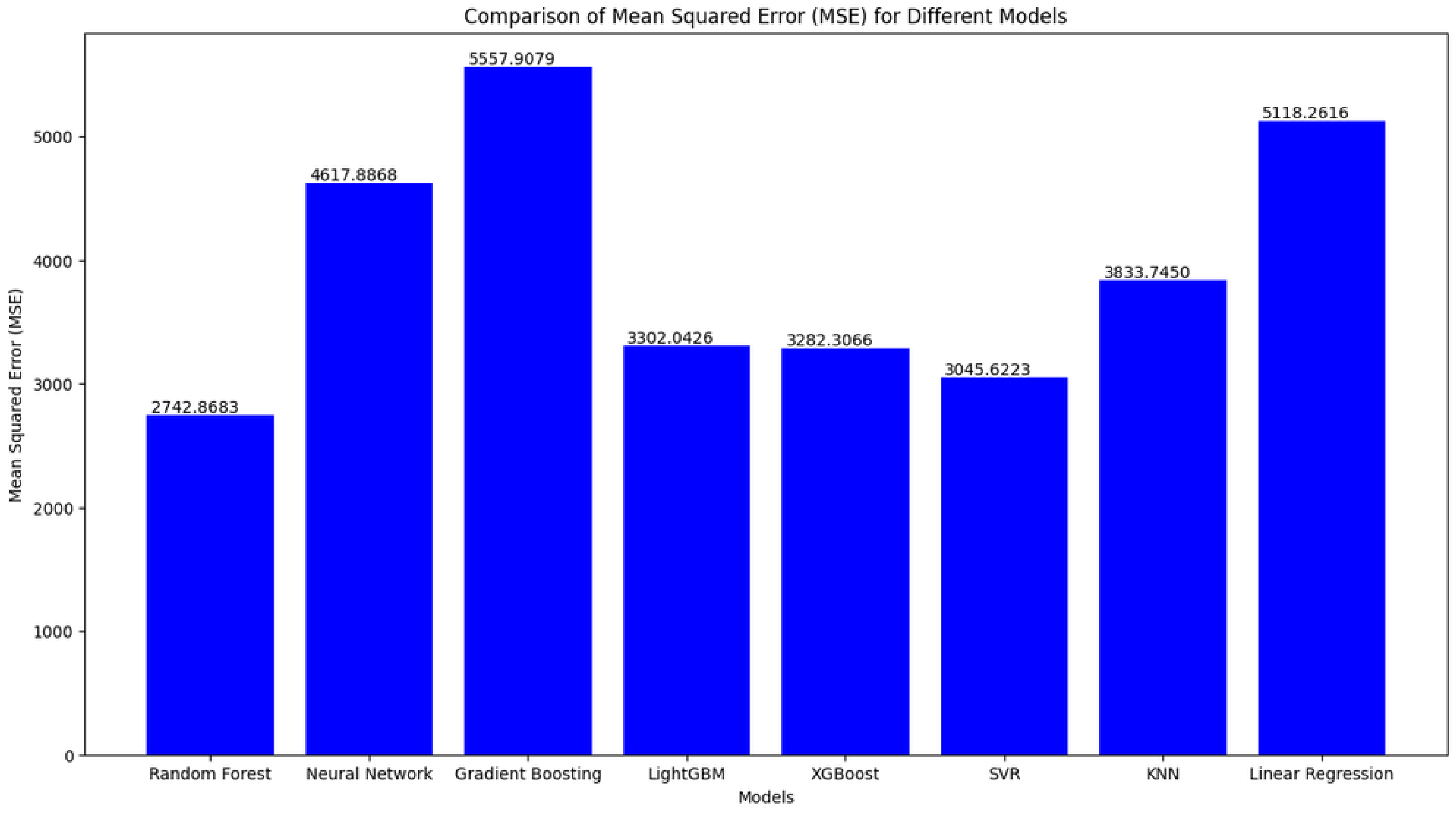


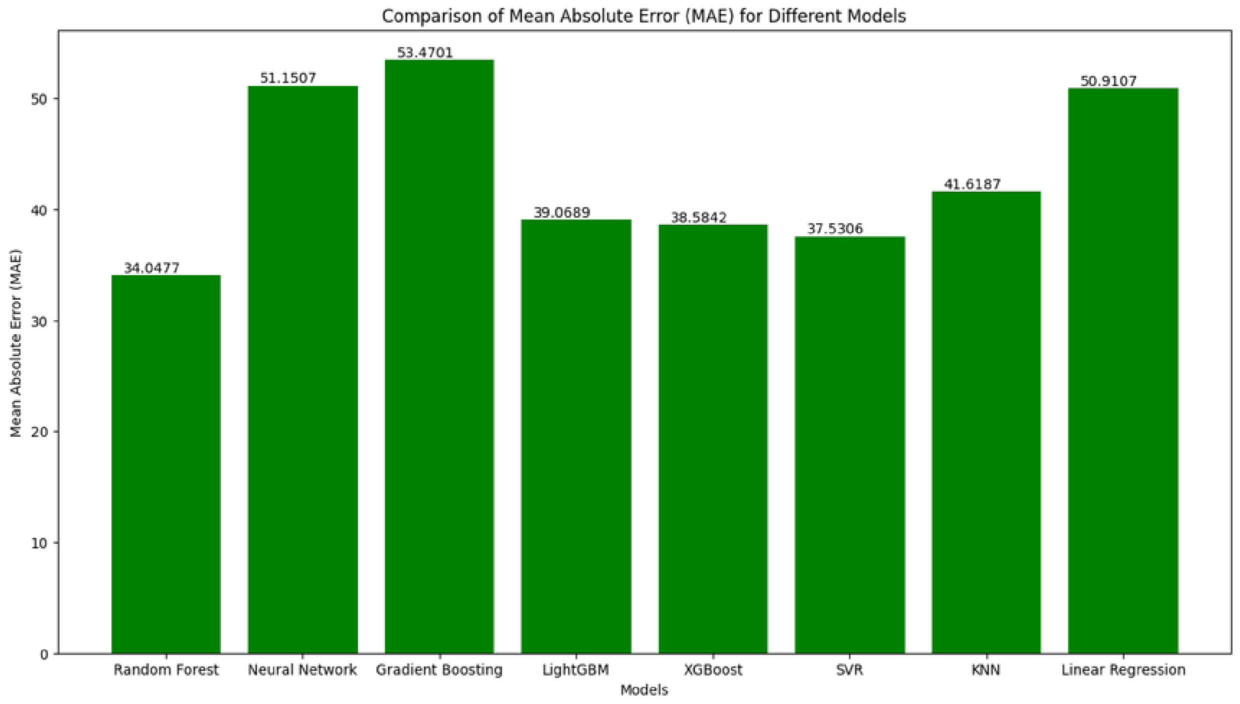


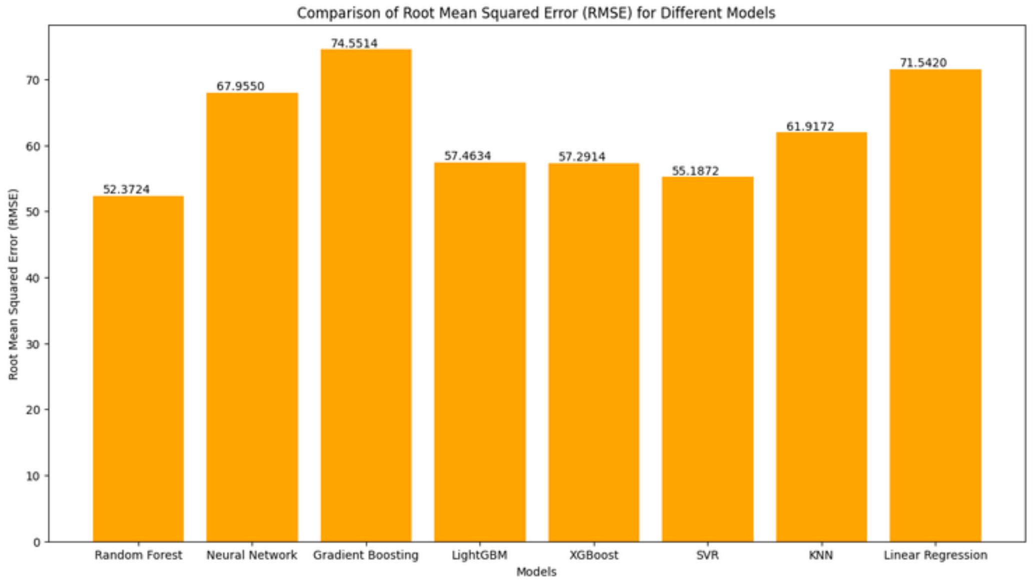
6 Machine Learning Models

Single-step Forecasts assessment

- Metrics Calculated for Model Comparison:
  - Mean Squared Error (MSE)
  - Mean Absolute Error (MAE)
  - Root Mean Squared Error (RMSE)

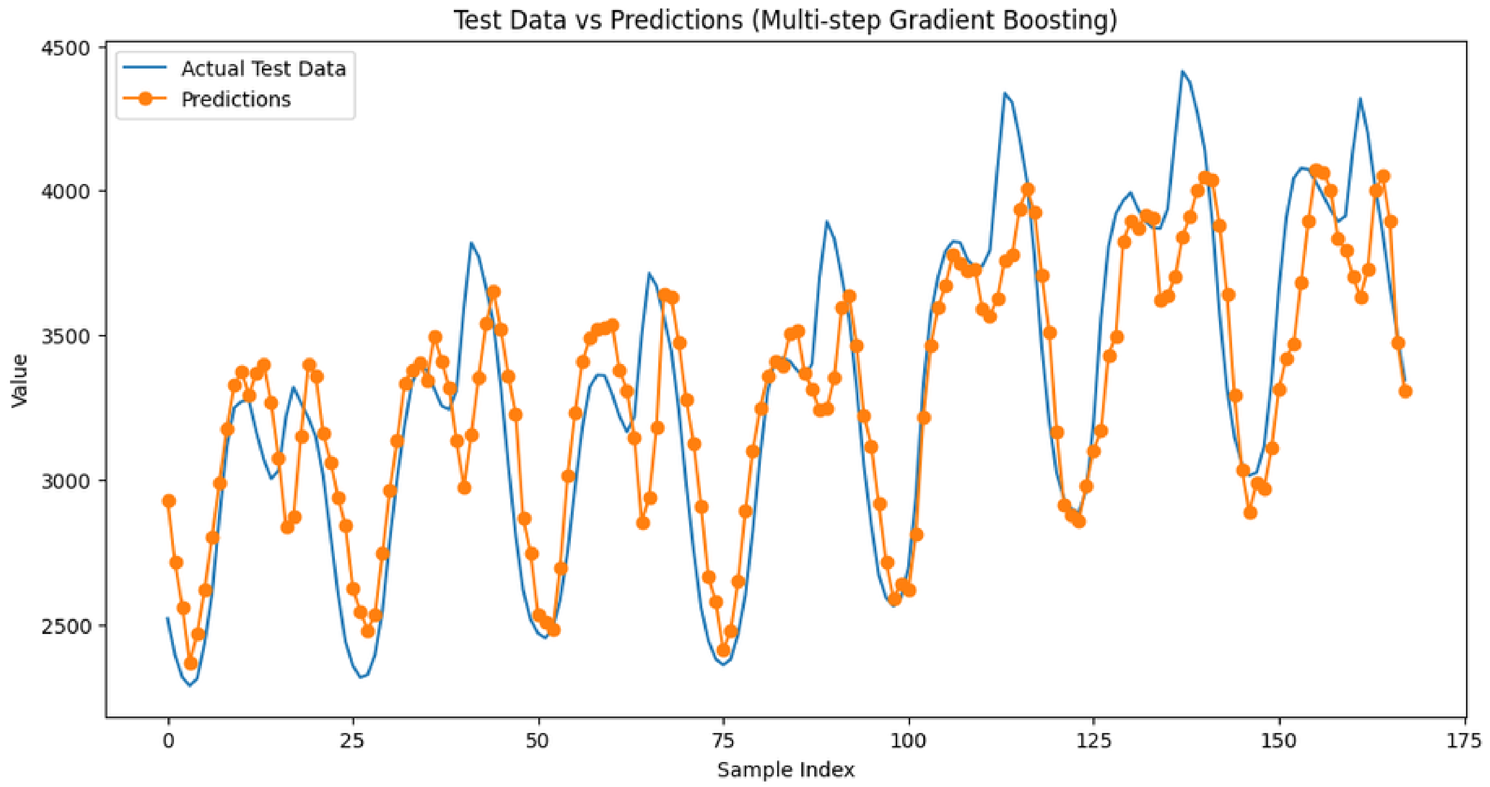


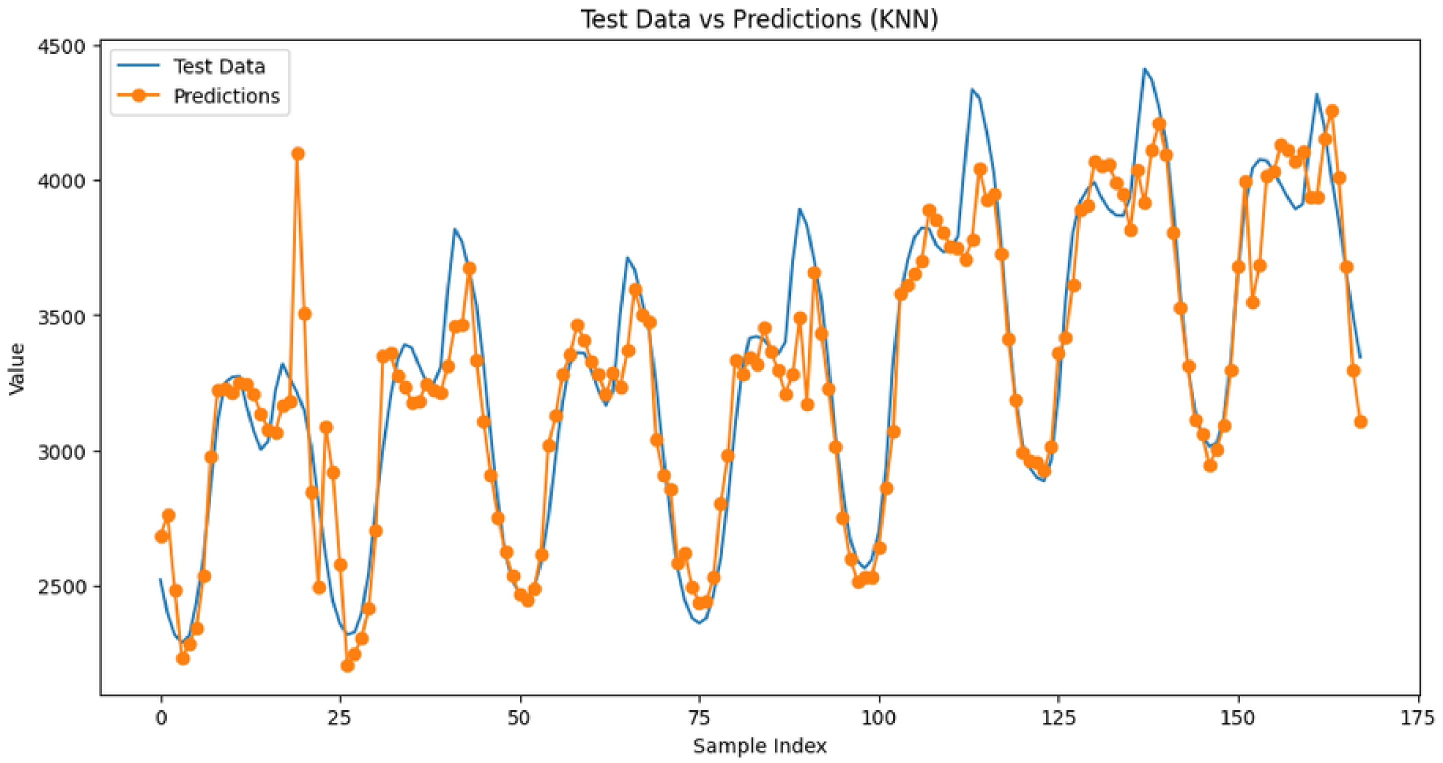


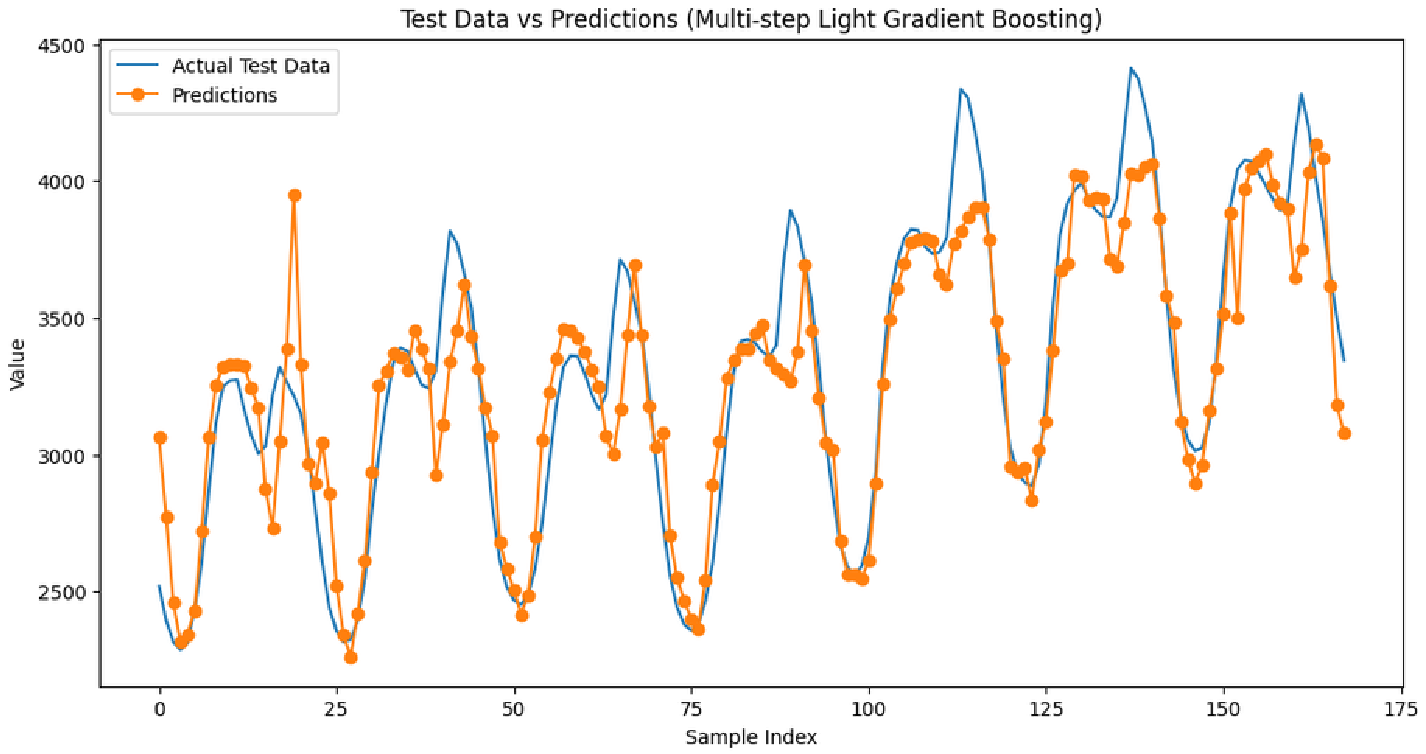


6 Machine Learning Models

Multi-step Forecasts

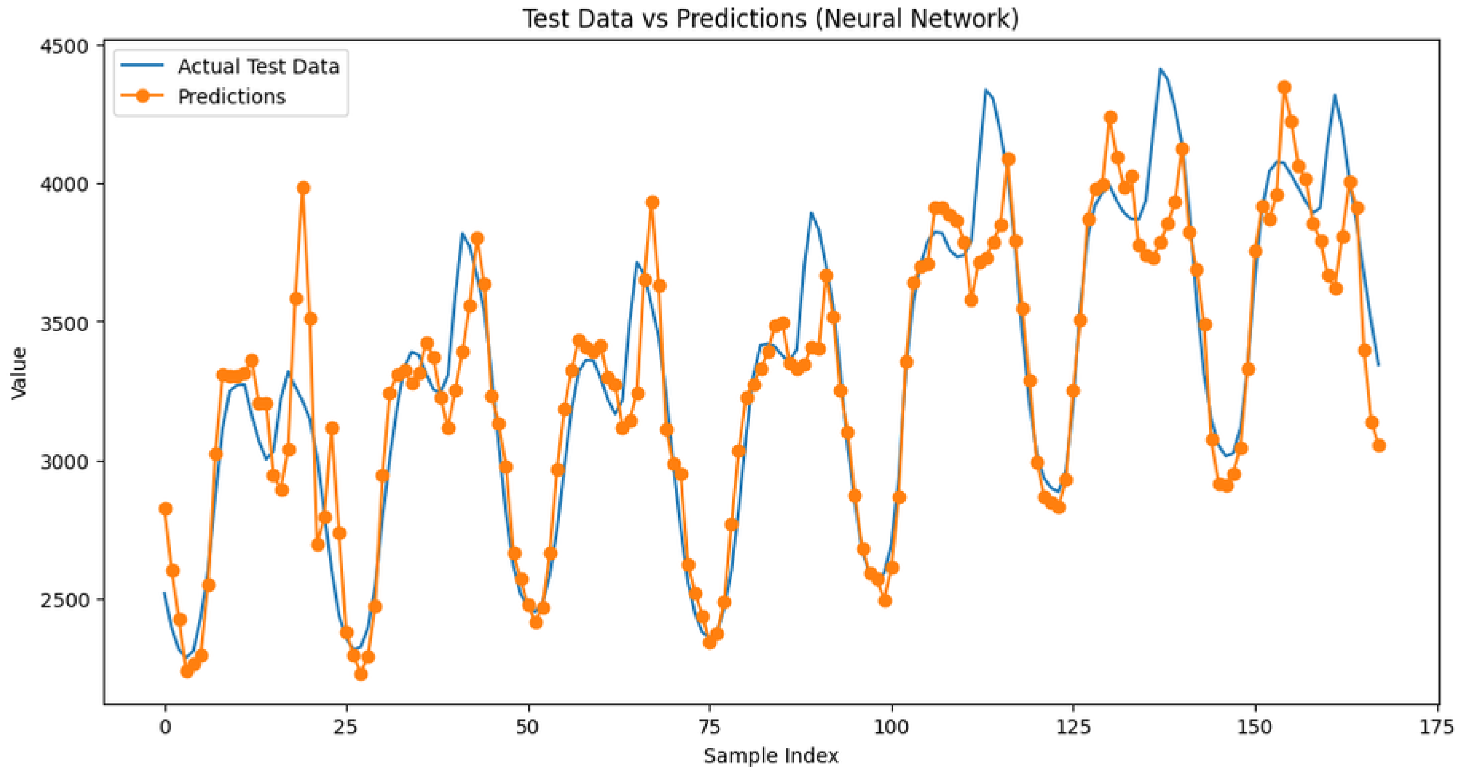


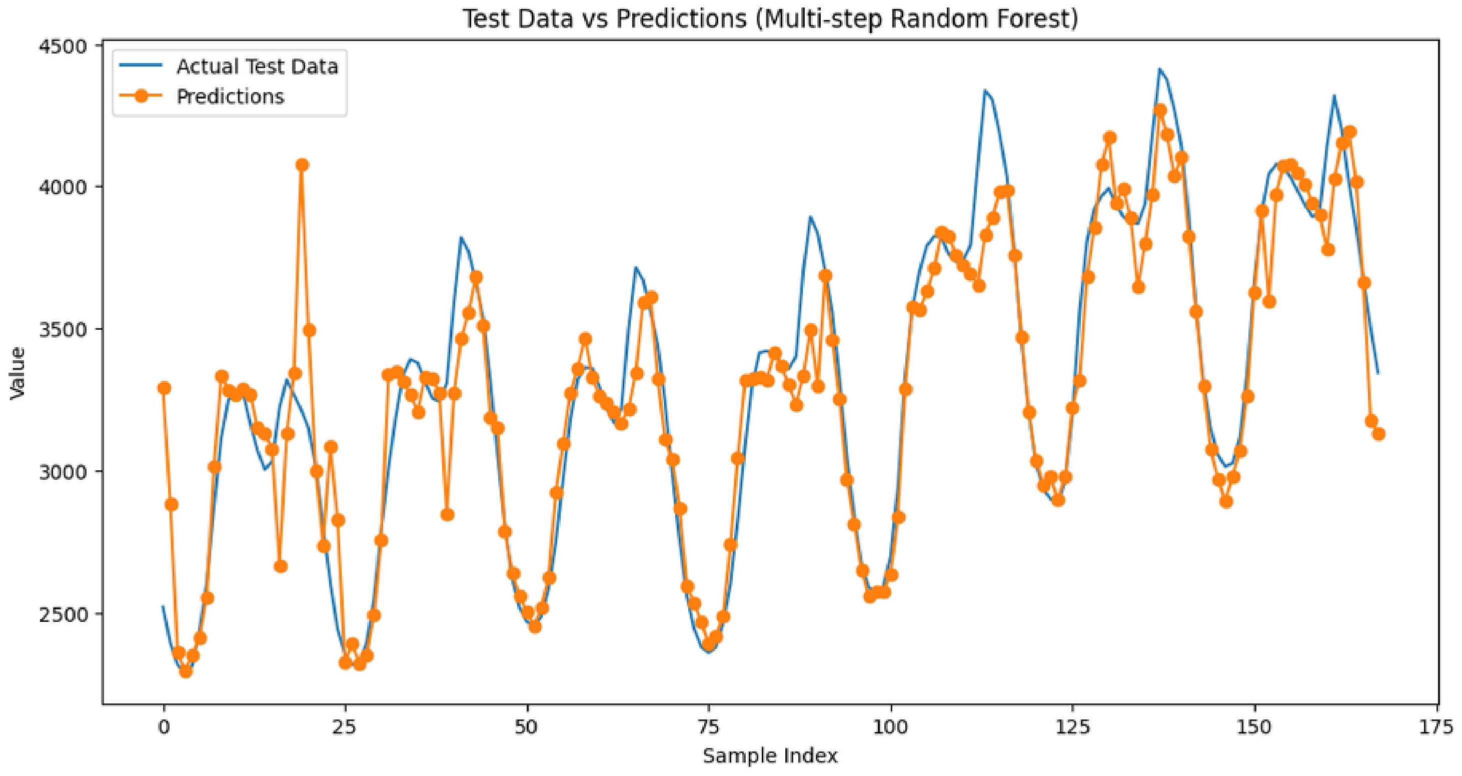


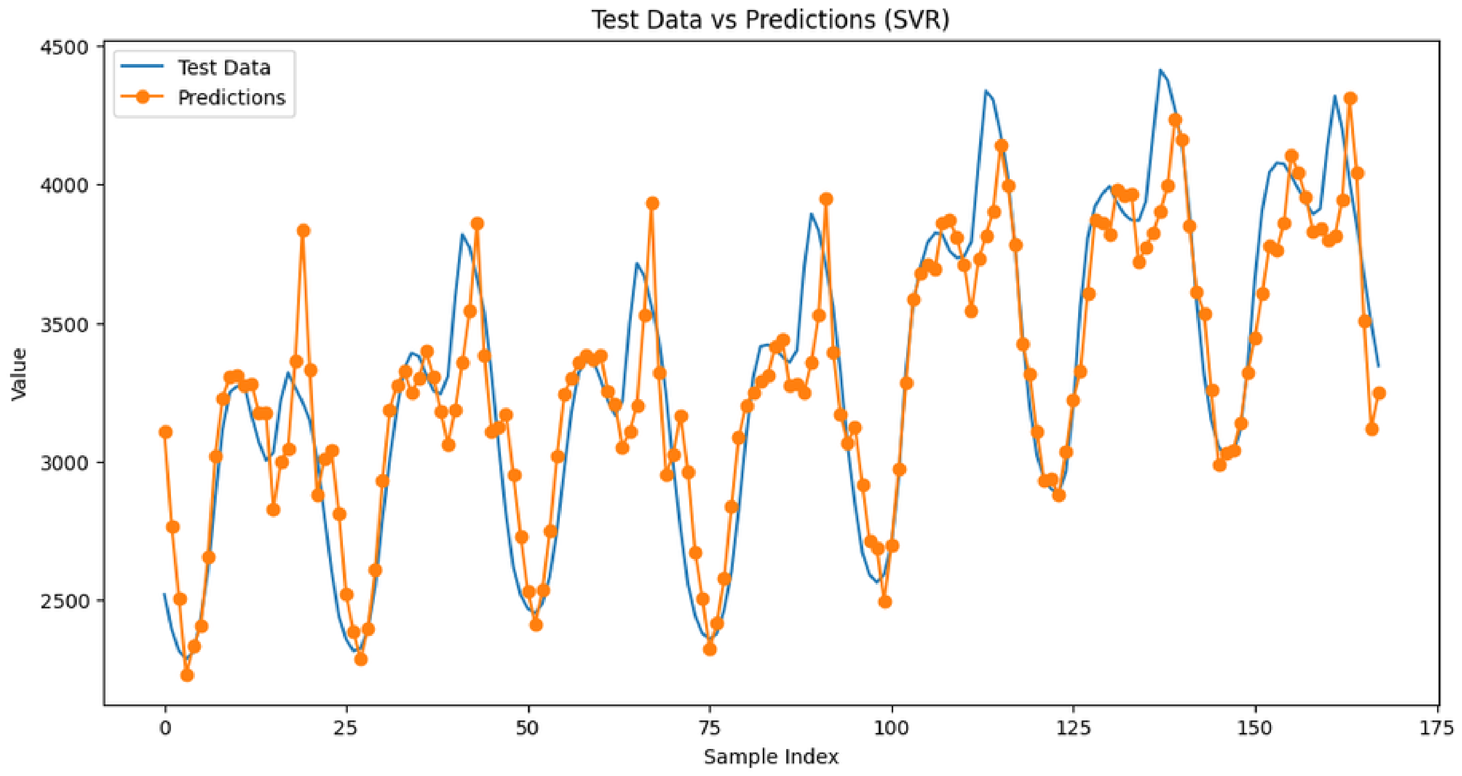


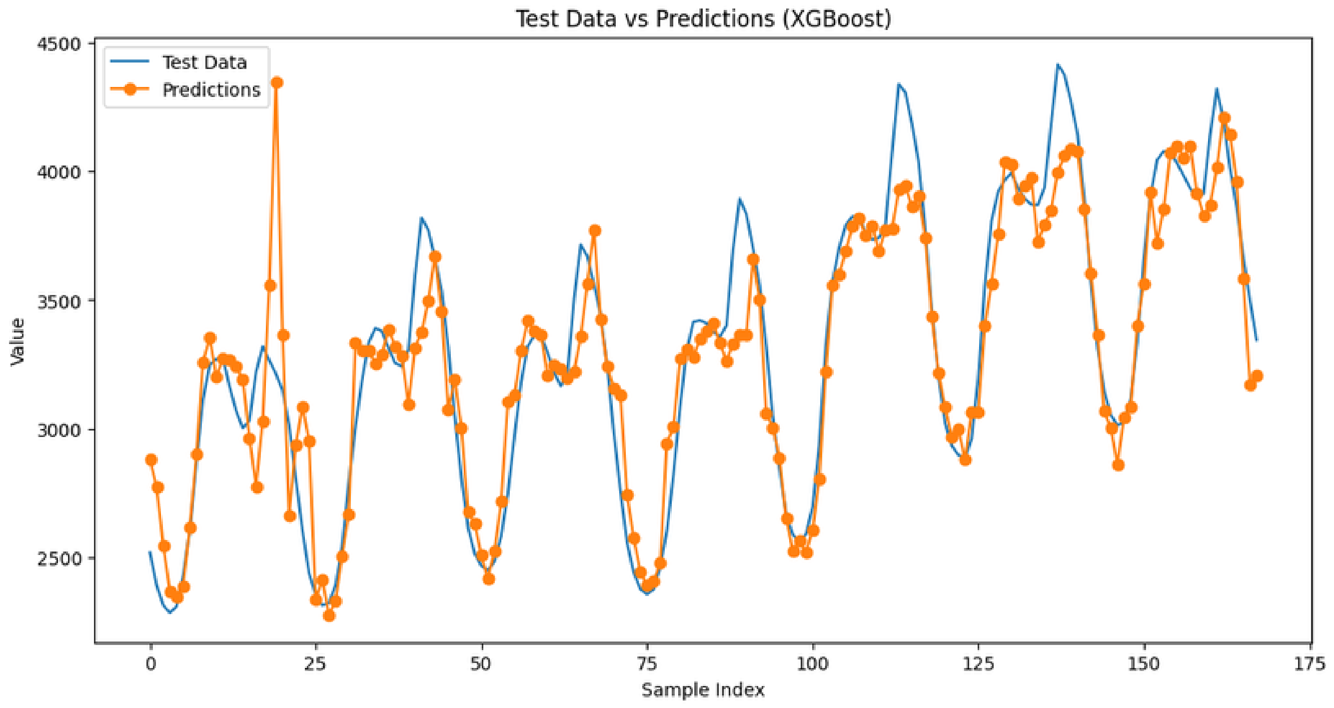
6 Machine Learning Models

Multi-step Forecasts









6 Machine Learning Models

Multi-step Forecasts assessment

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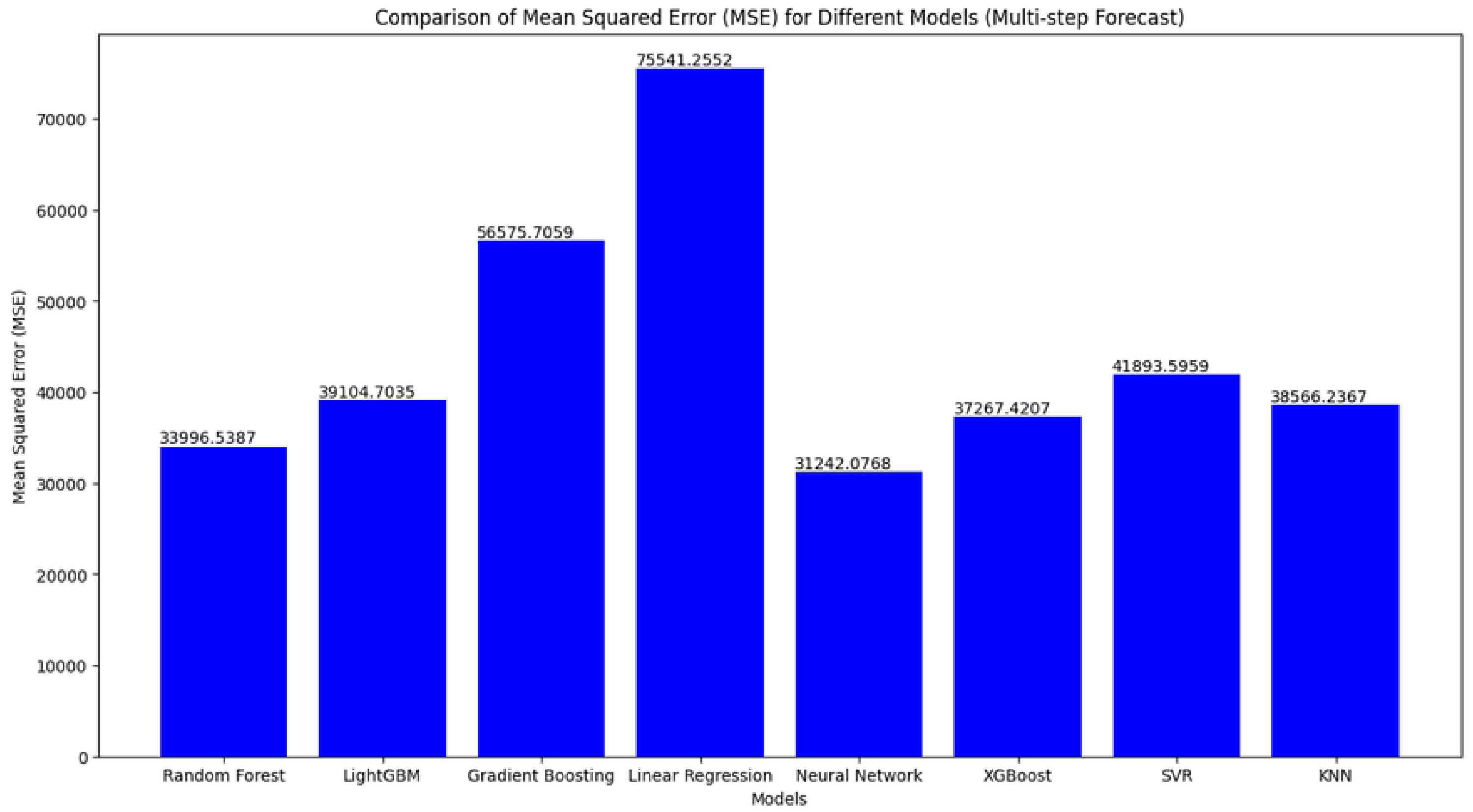
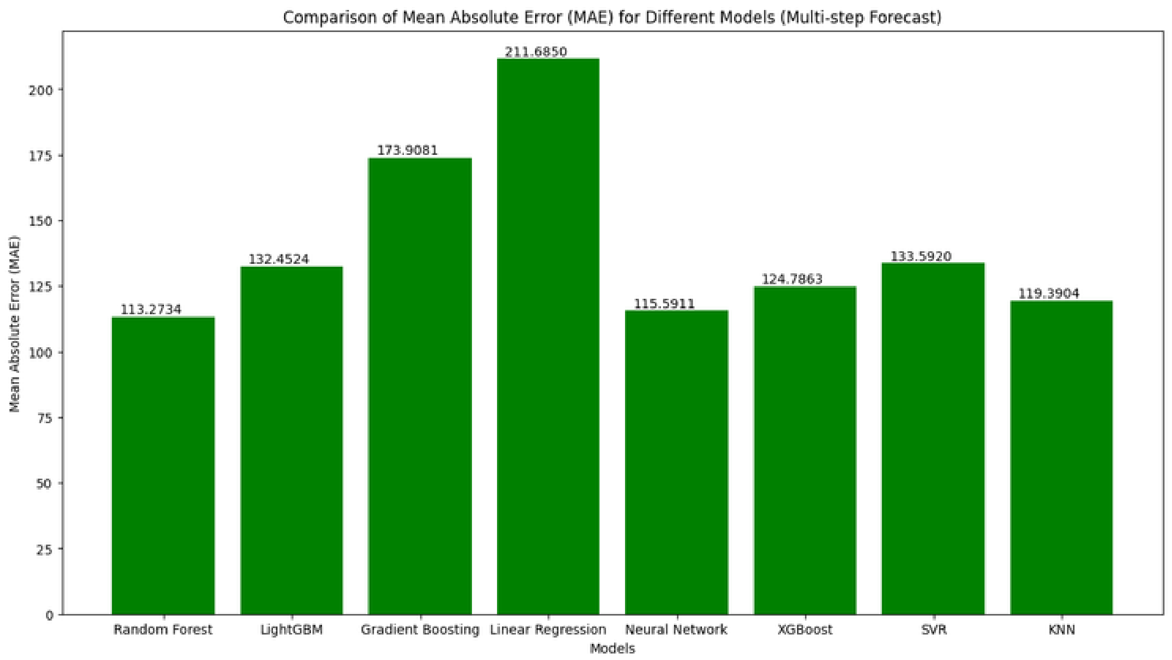
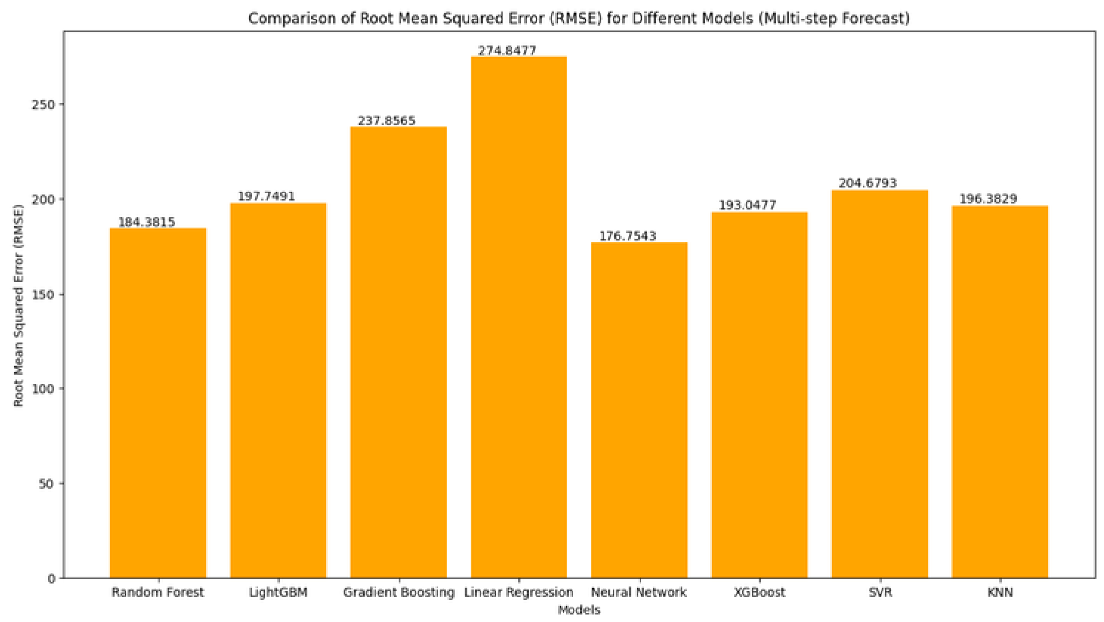
  - (MSE)
  - Mean Absolute Error (MAE)
  - Root Mean Squared Error (RMSE)







6 Machine Learning Models

Conclusion

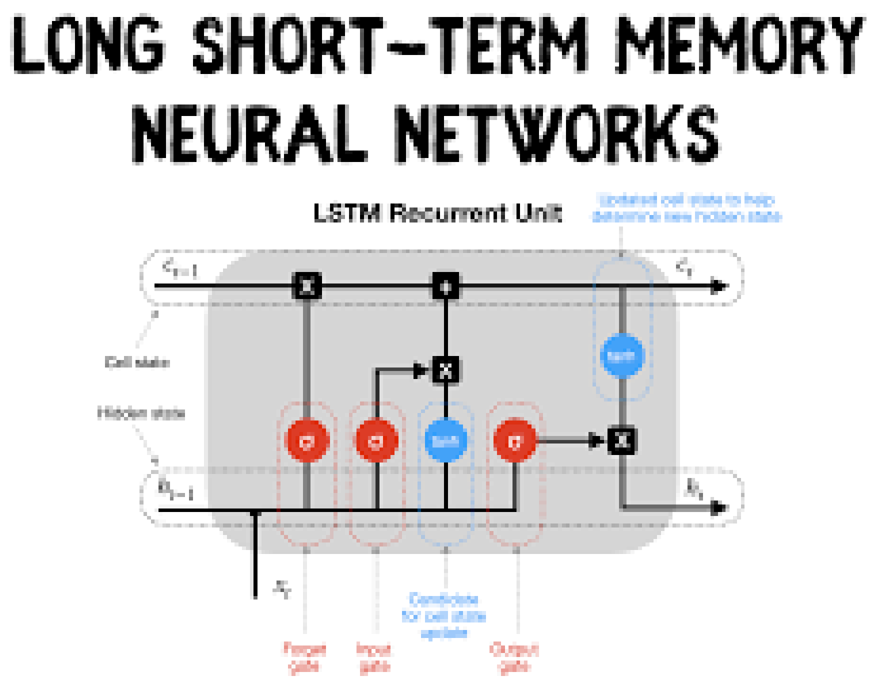
- Single-Step Success:
  - Single-step approach yielded superior results.
- Multi-Step Struggles:
  - Multi-step approach encountered challenges, displaying less favorable outcomes.
-
- This indicates that the model may be more adept at predicting one-step ahead rather than multiple steps, suggesting potential areas for improvement or adjustment in the multi-step forecasting strategy.

Deep Learning

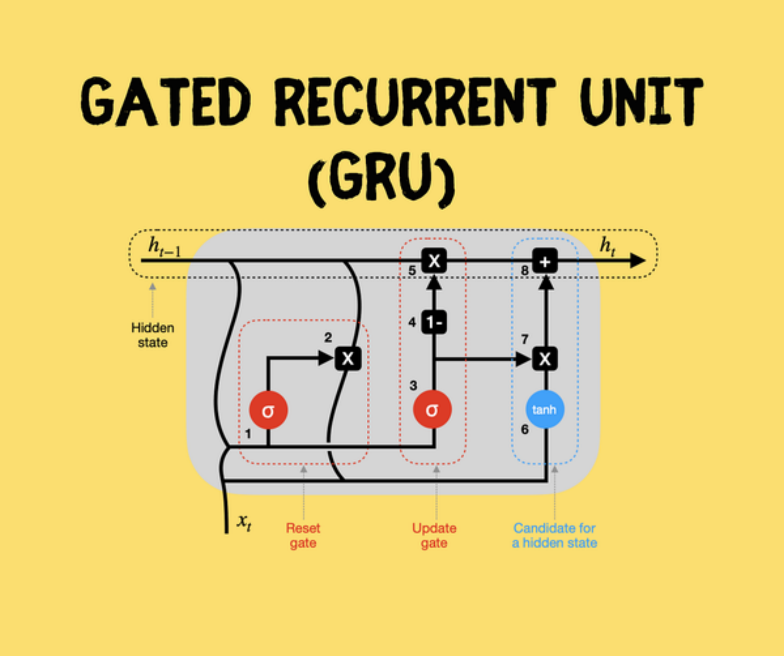
7 Deep Learning Models

Models used

- LSTM - Long Short Term Memory



- GRU - Gated recurrent unit



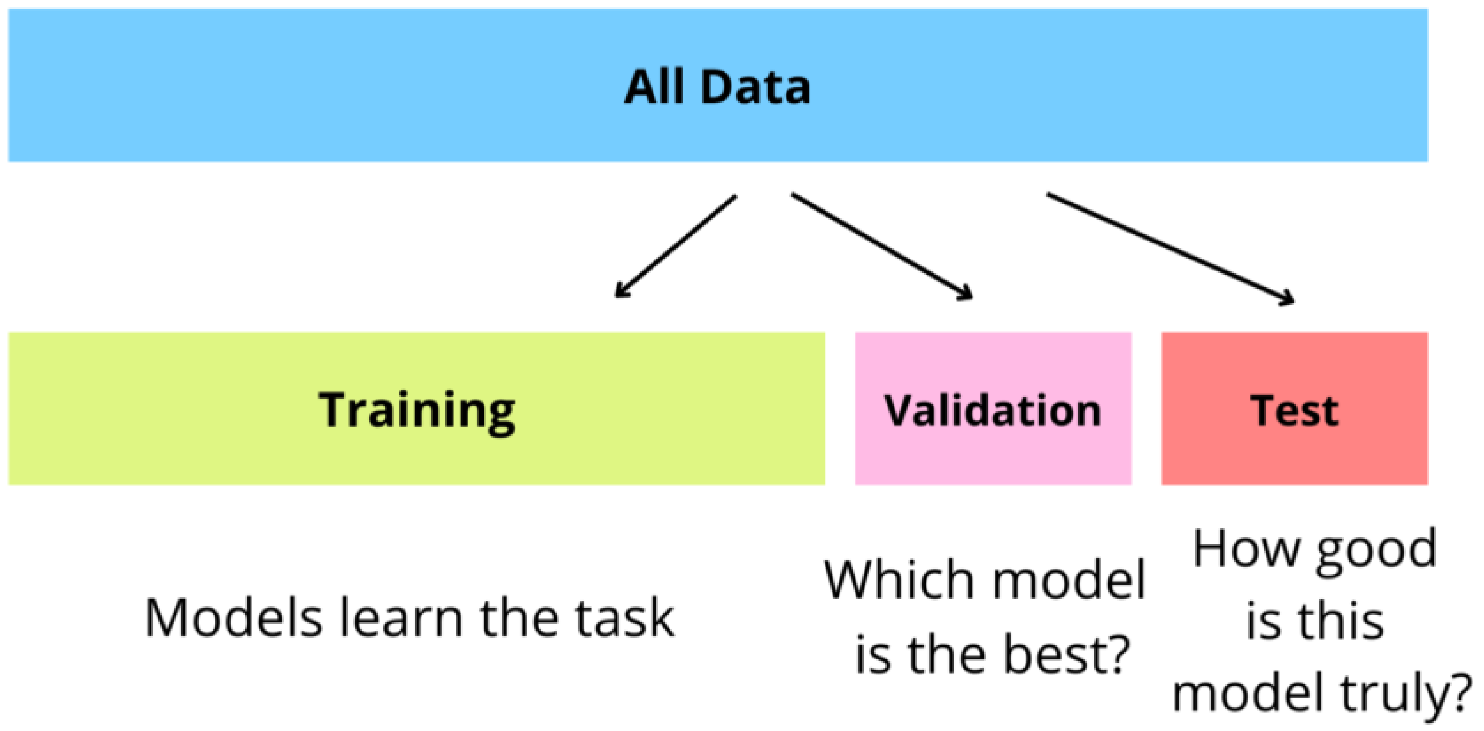
7 Deep Learning Models

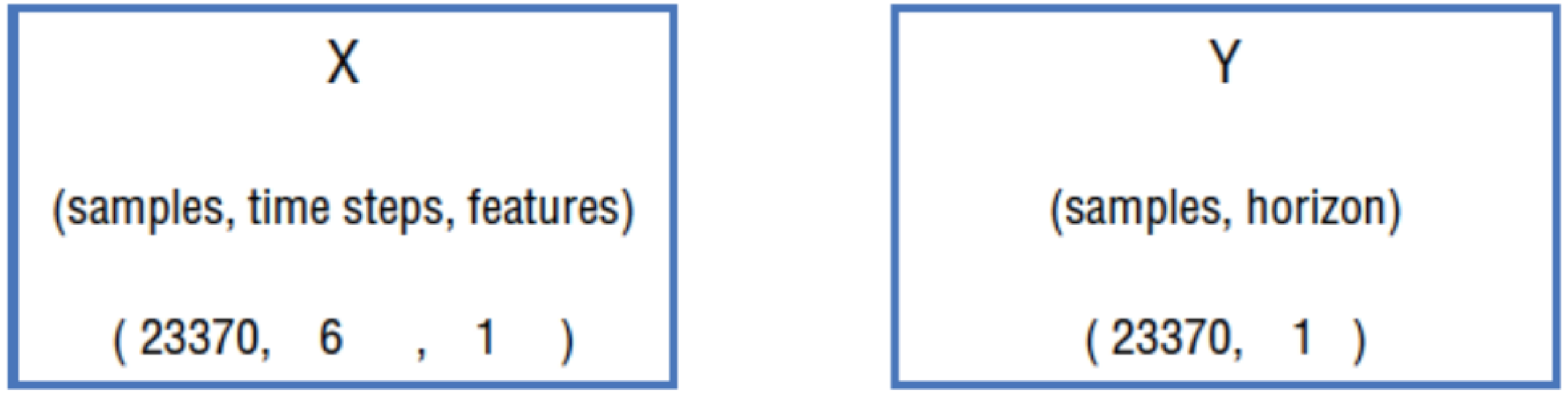
Data Preparation and train/val/test split

- **Data Transformation:**
  - Convert data into tabular format using sliding window.
  - X (Input): 3 dimensions - samples, time steps, features.
  - Y (Target): 2 dimensions - samples.

- Data was scaled via MinMaxScaler

- **Data Split:**
  - Training set: 0-70%
  - Validation set: 70-80%
  - Test set: 80-100%





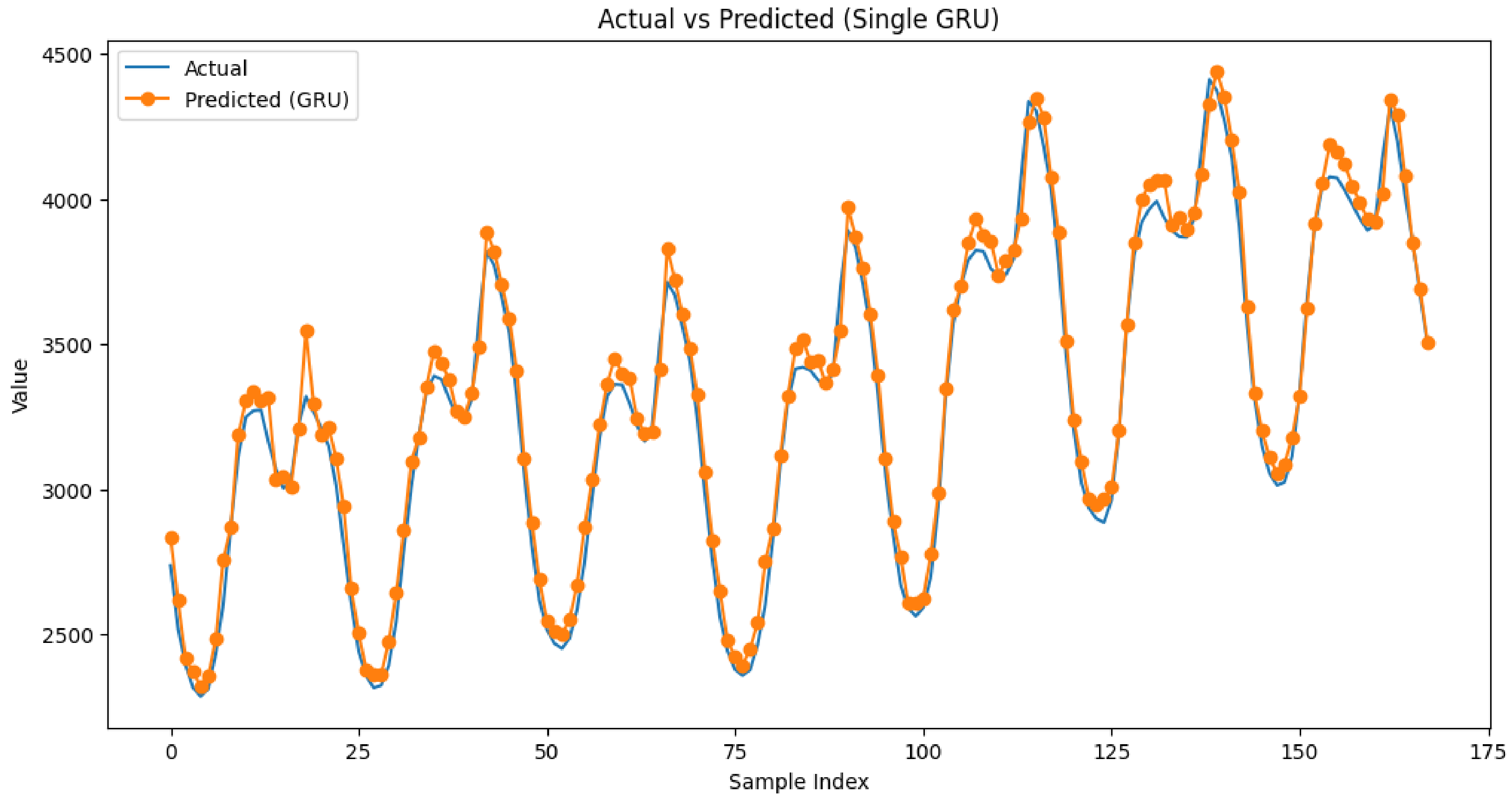
7 Deep Learning Models

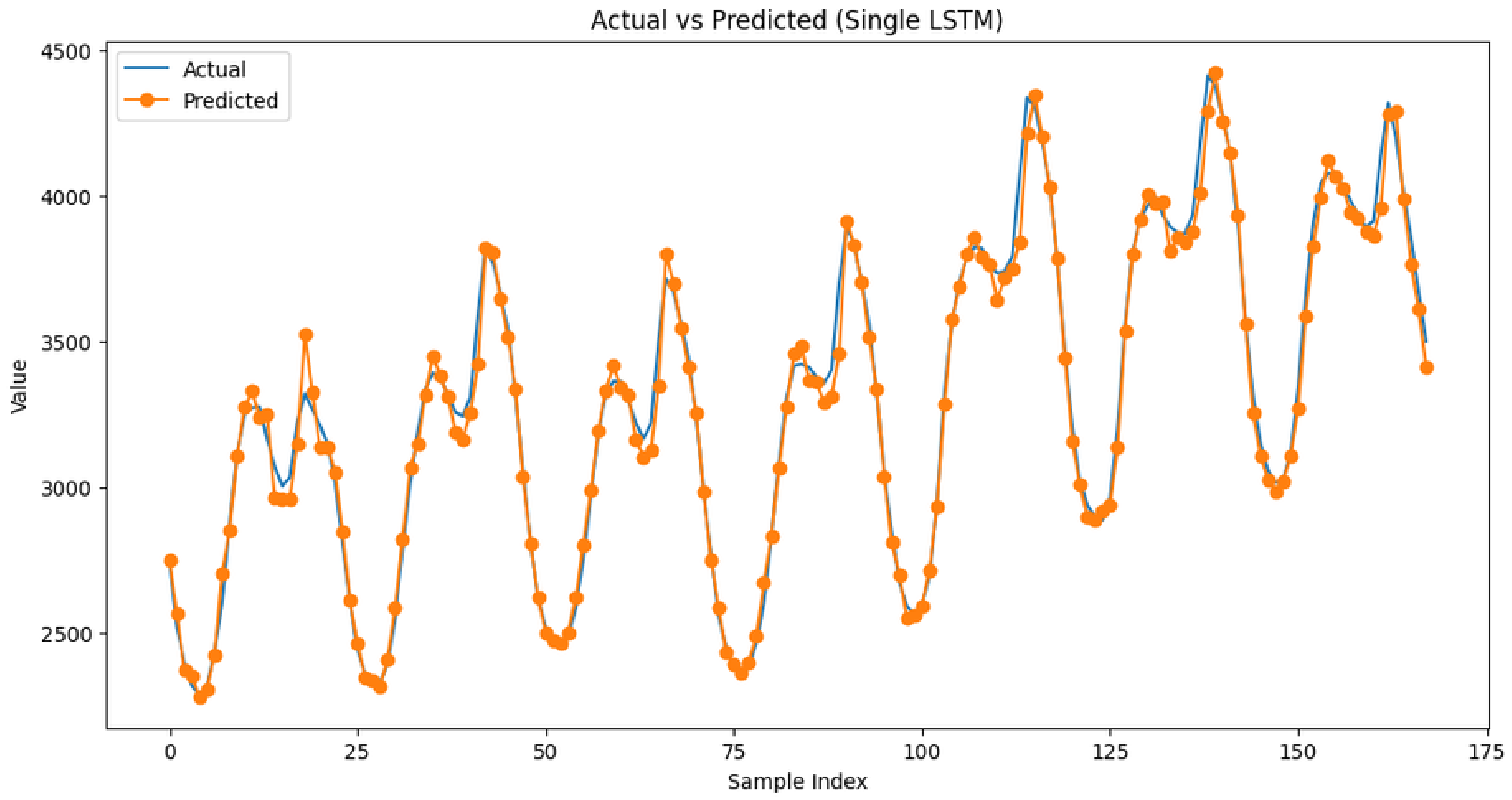
Forecasting Approaches

- Forecasting Approaches:
  - Single-step (window = 6, horizon = 1)
  - Multi-step (window = 8, horizon = 3)
  - Multivariate (temperature as a feature)
  - Applied for both single-step and multi-step scenarios

7 Deep Learning Models

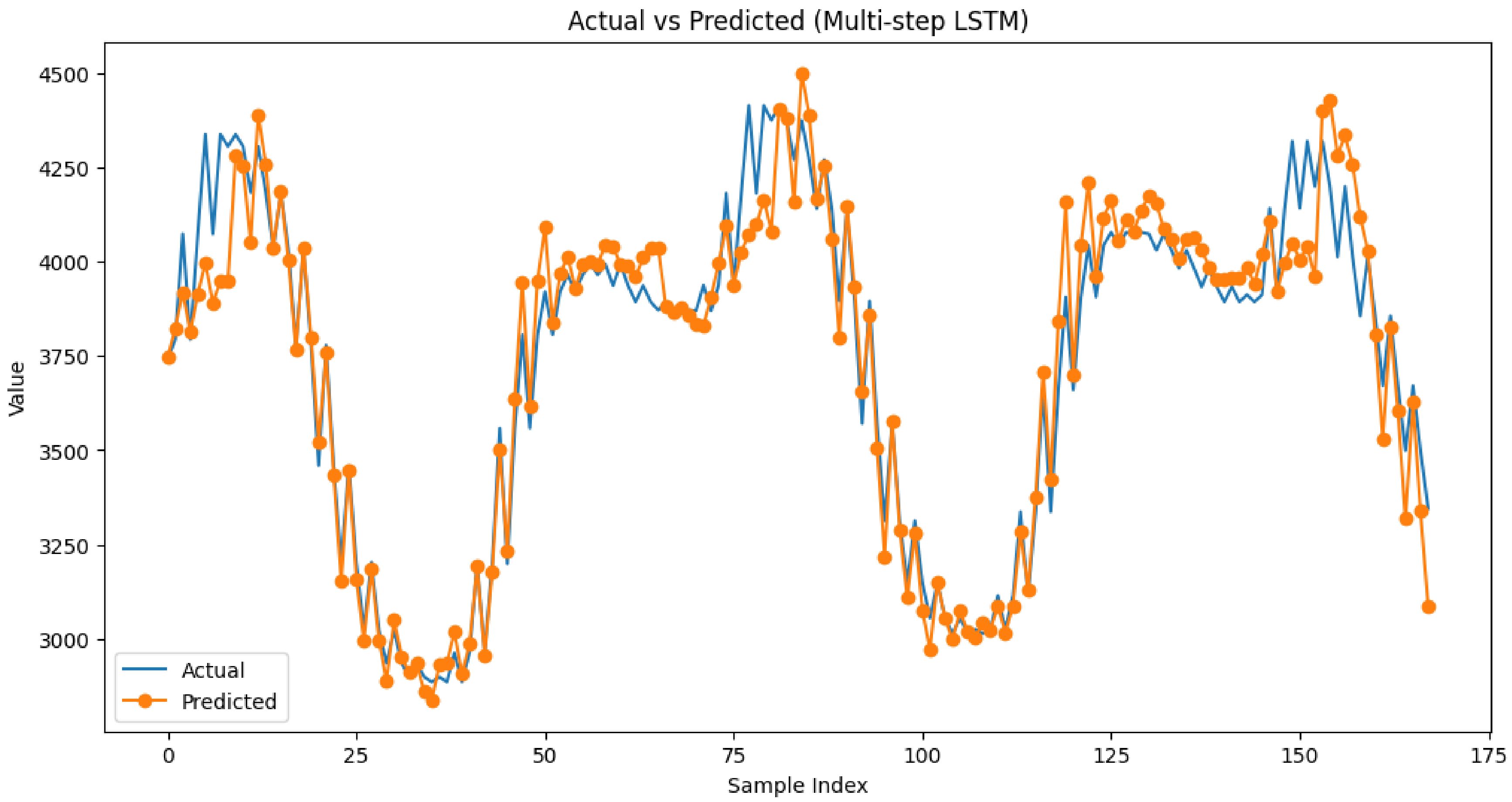
Single-step Forecasts

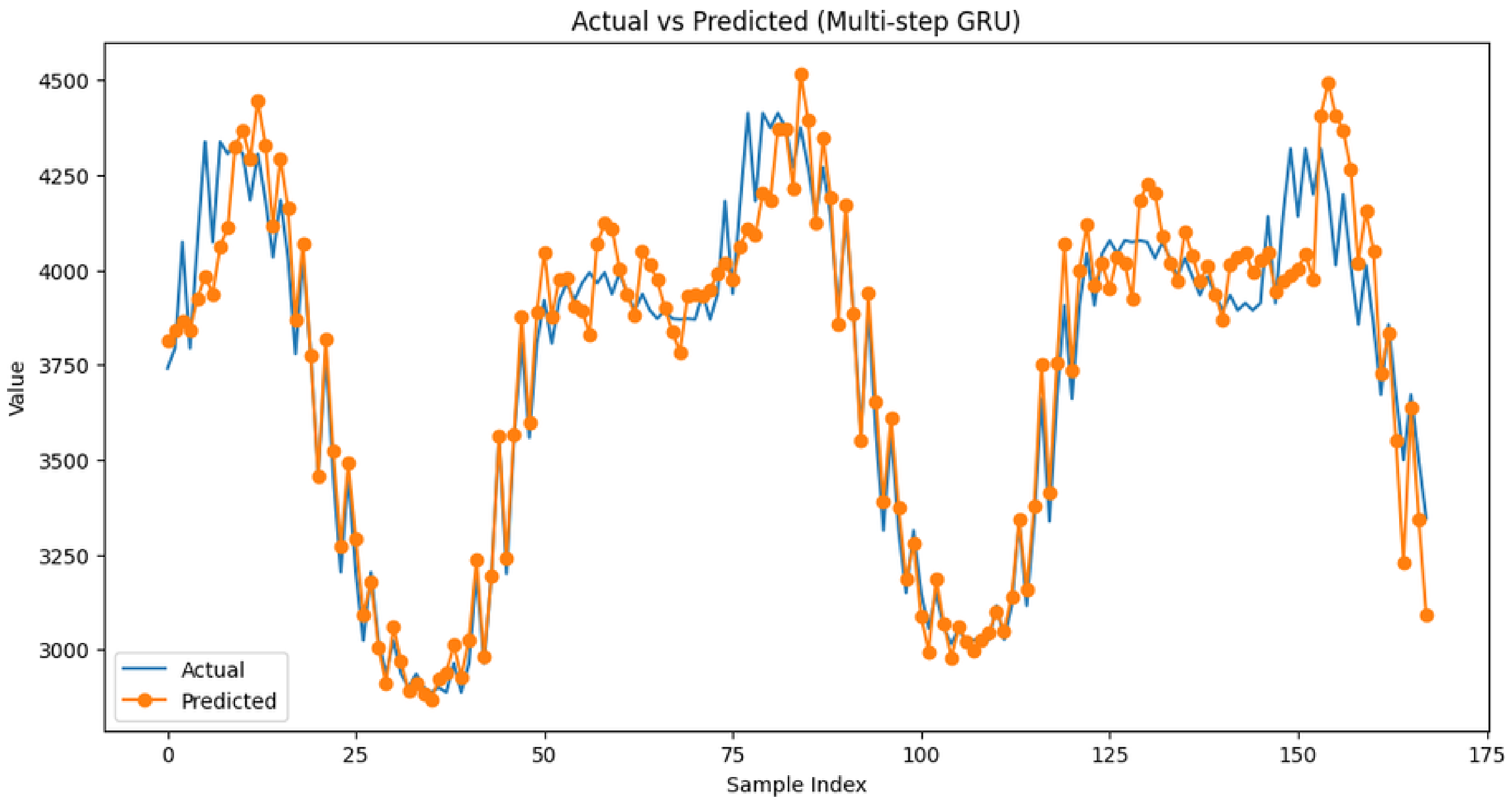




7 Deep Learning Models

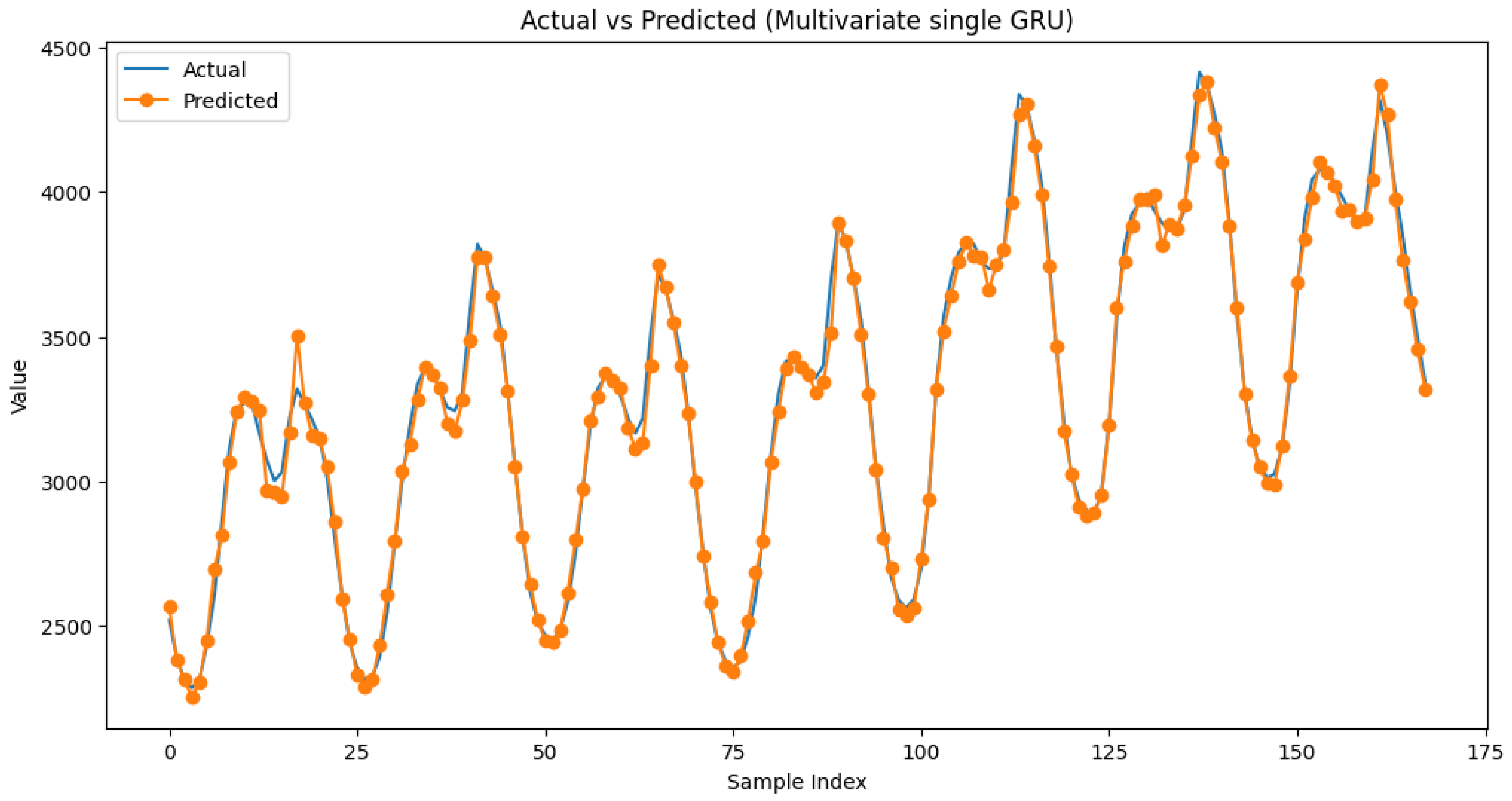
Multi-step Forecasts

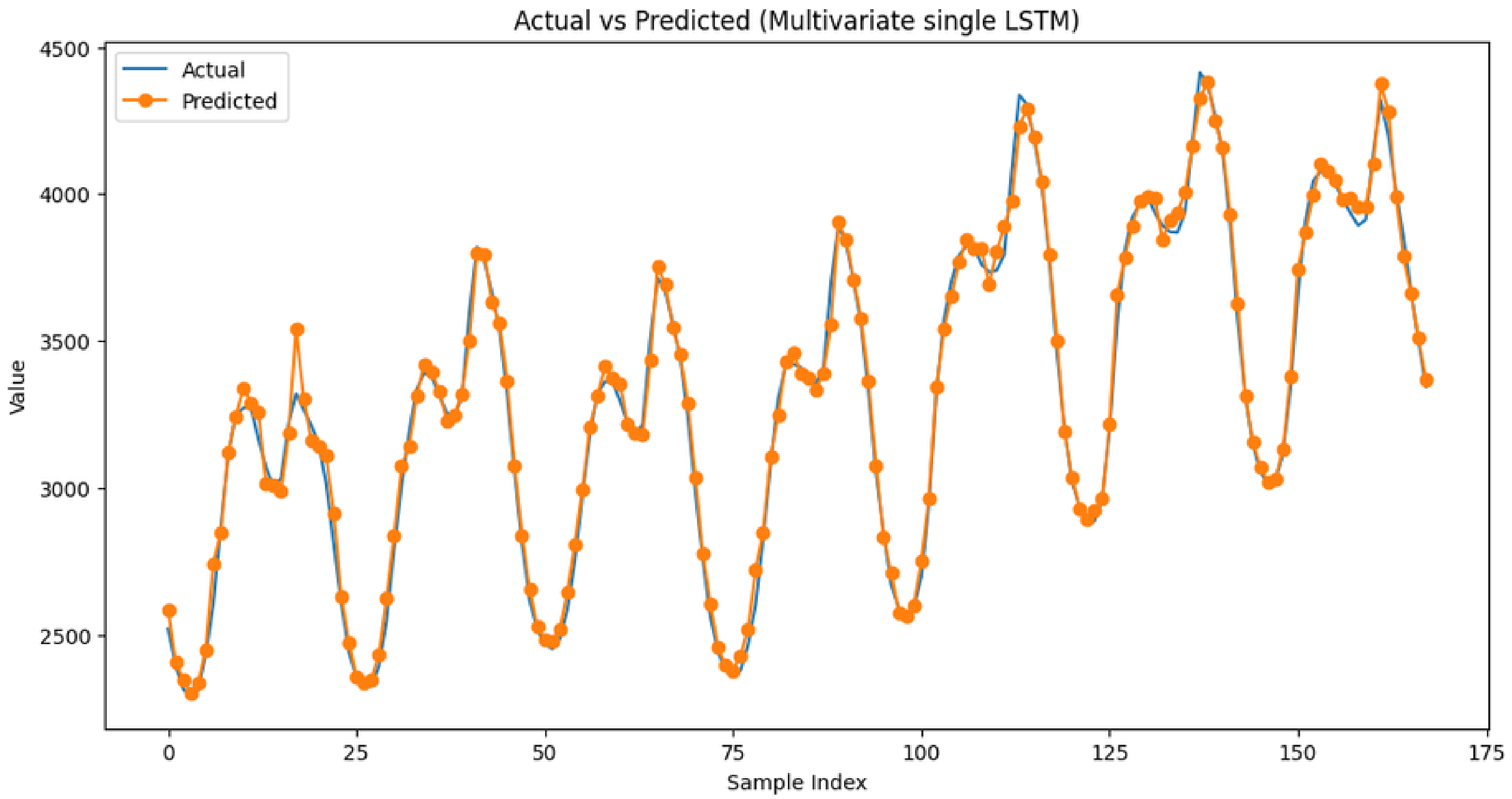




7 Deep Learning Models

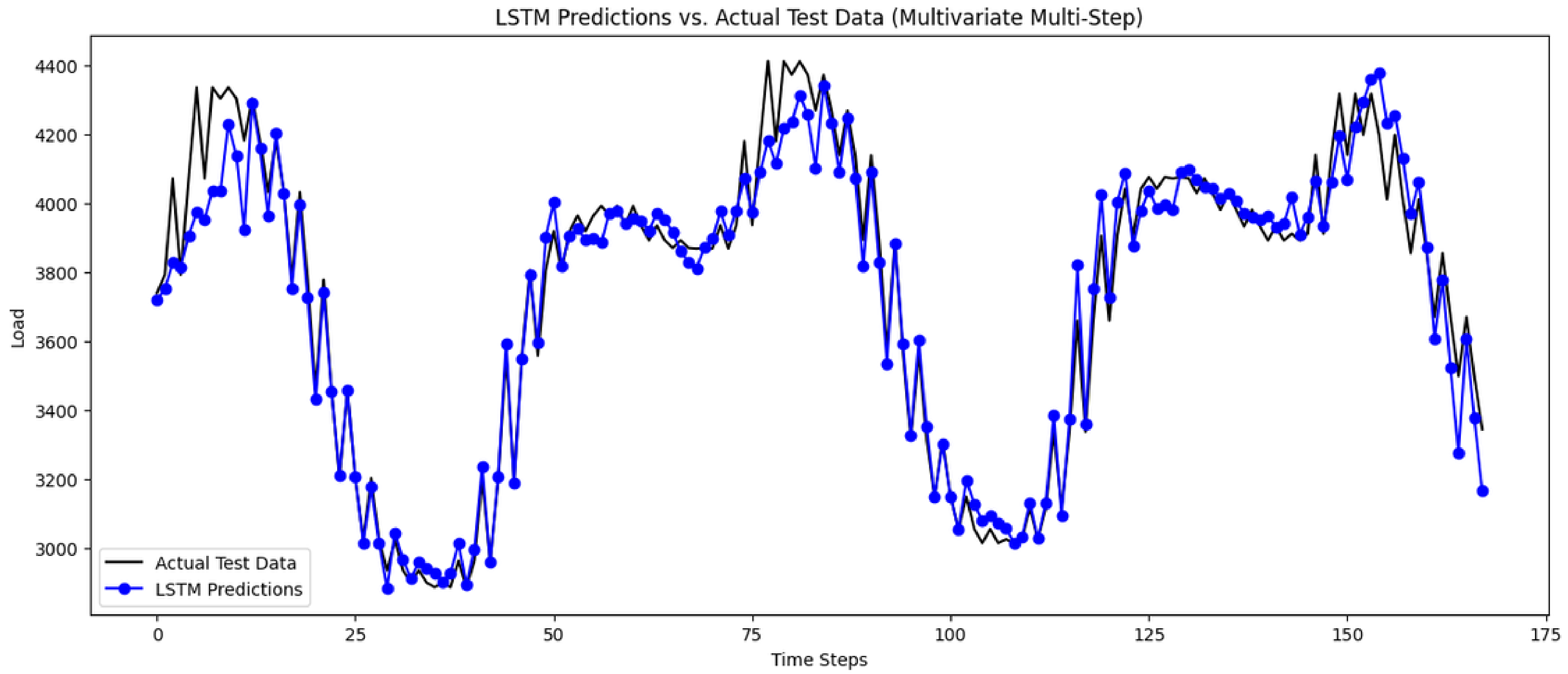
Single-step Multivariate Forecasts

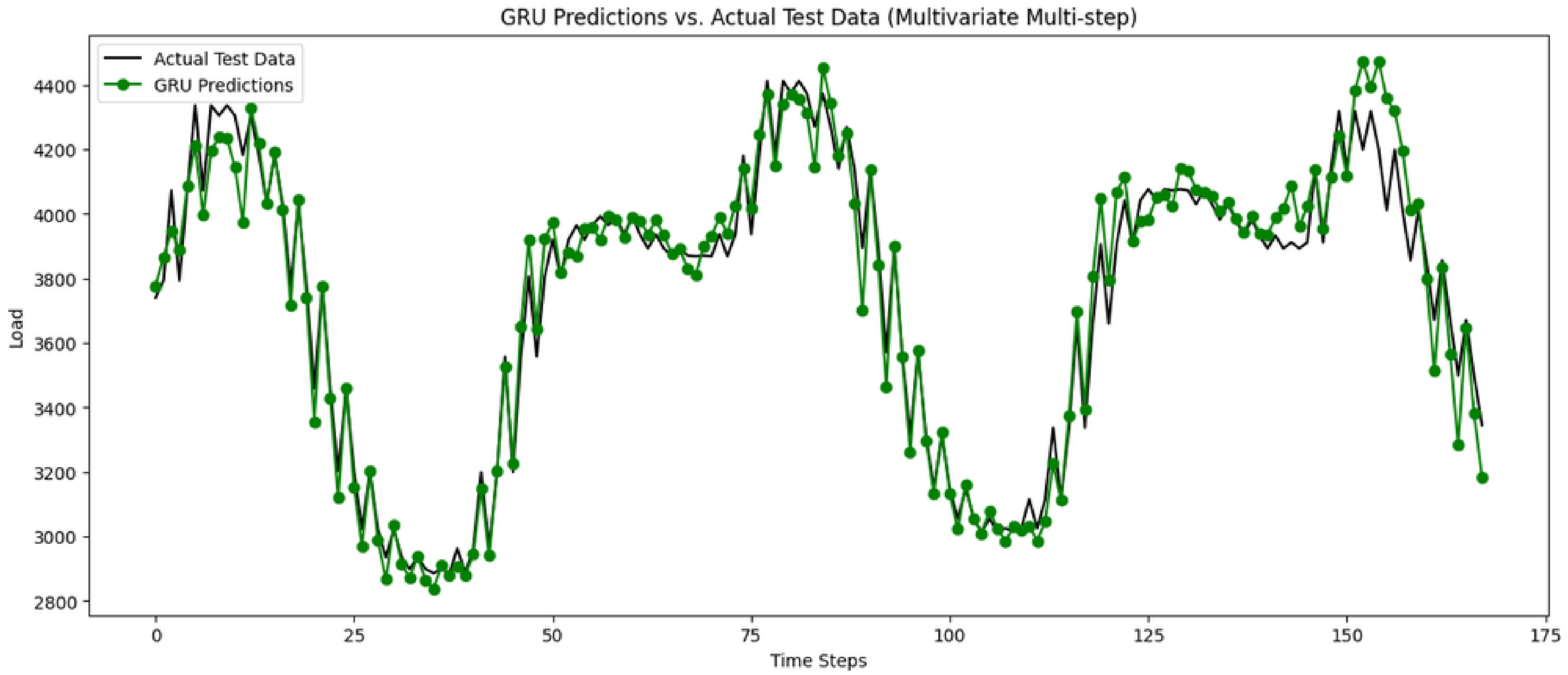




7 Deep Learning Models

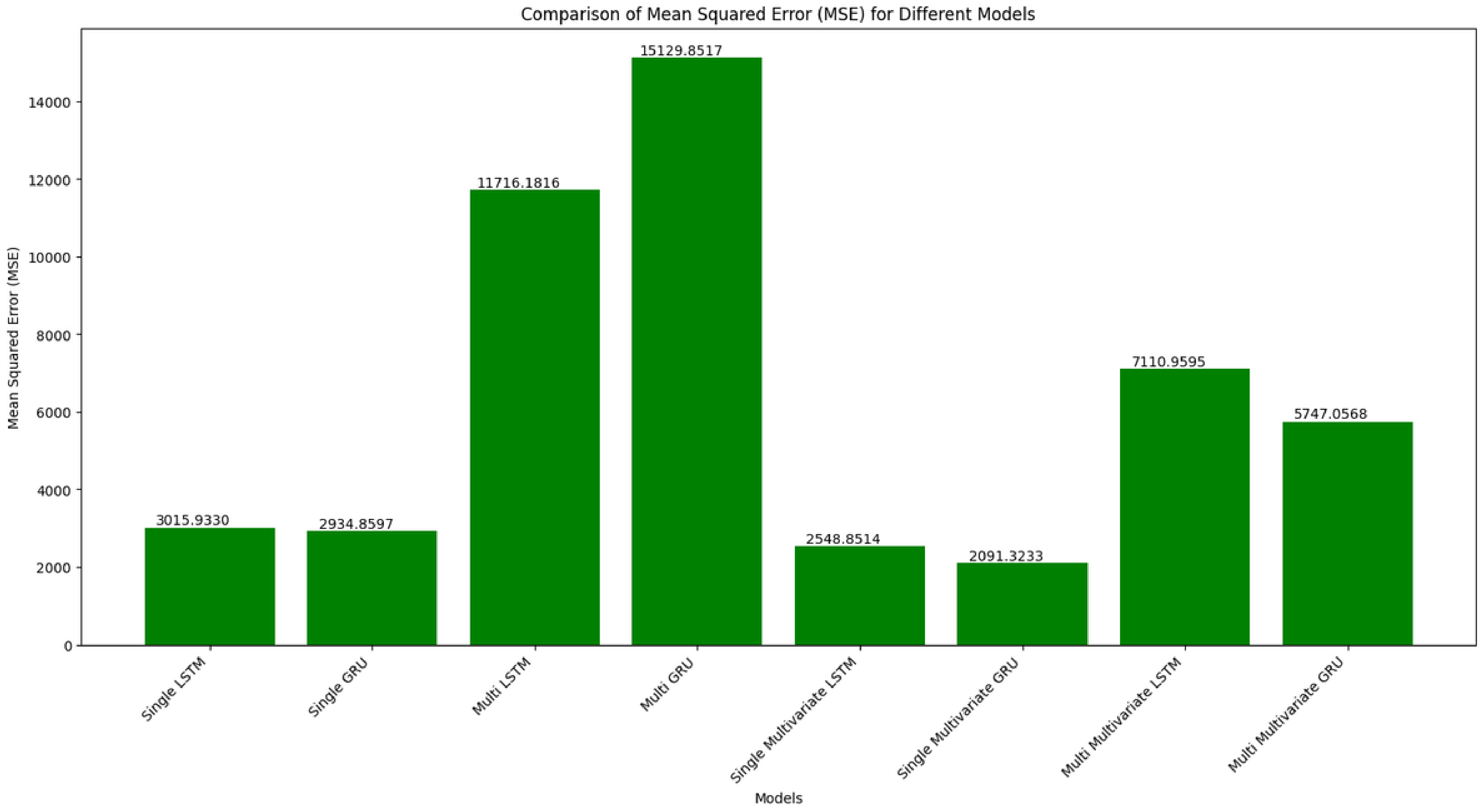
Multi-step Multivariate Forecasts

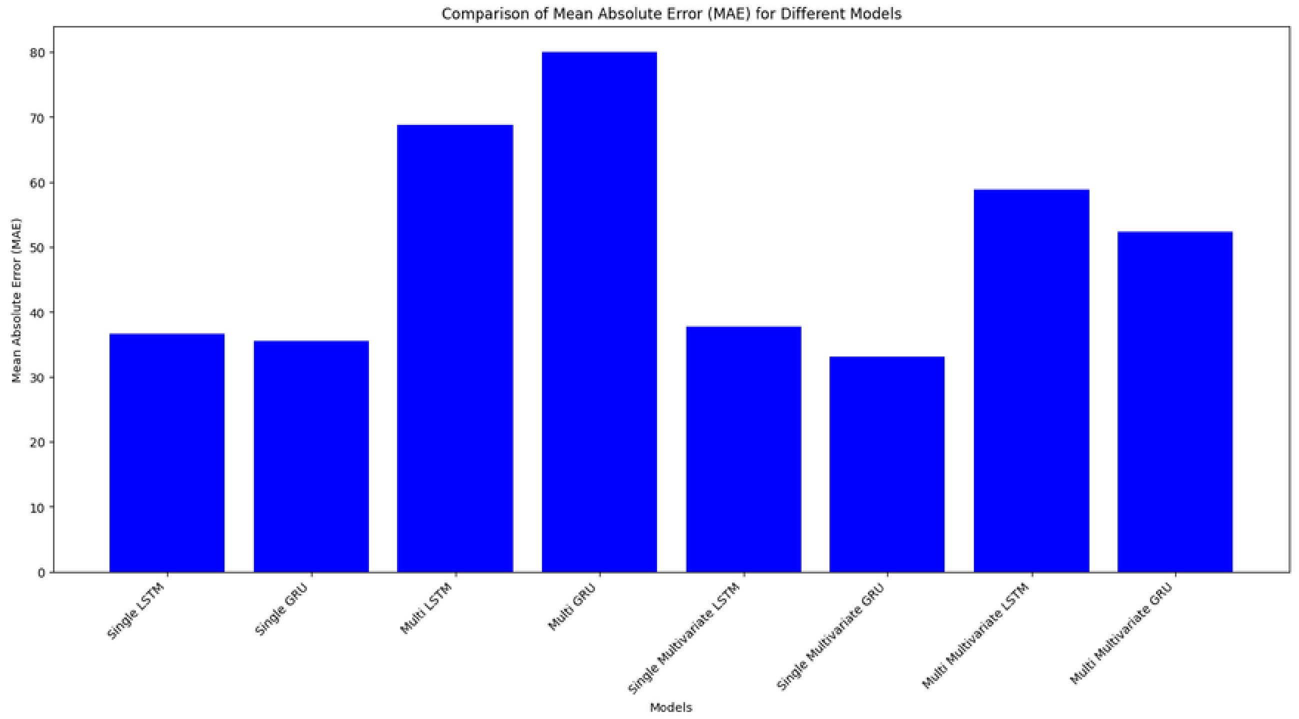


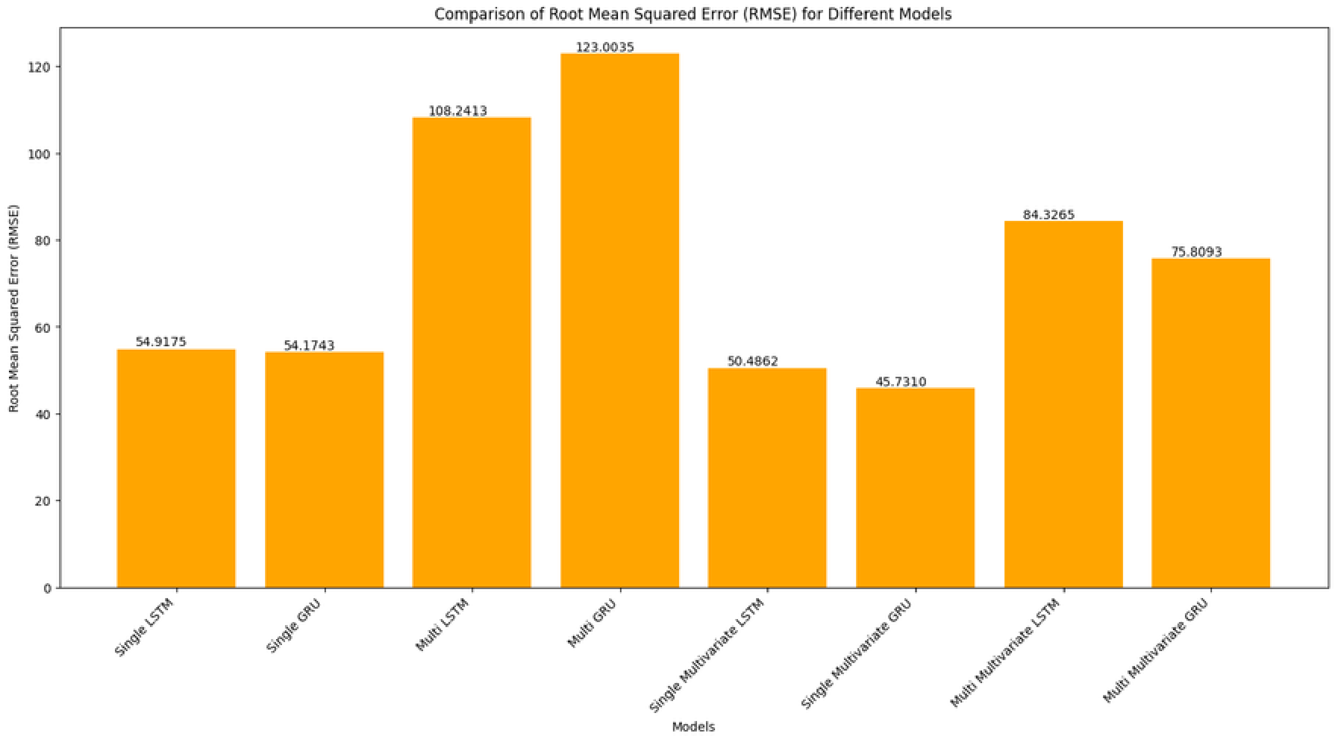


7 Deep Learning Models

Model Assessment







8 Conclusions

Model Performance Overview:

- Deep learning models excelled, highlighting temperature impact on forecasts.
- ML models performed well.
- Statistical models showed lower effectiveness.
- Rolling forecast exhibited improved results, attributed to its nature.

Constraints

- SARIMA(X) Computational Challenges:
  - SARIMA(X) computationally demanding.
  - Ideal scenario involves testing more parameters and applying rolling forecast.
  - Debugging process exceeding 15 hours deemed infeasible.

Future Work

- Feature Engineering:
- Consider more granularity levels for date:
  - Month
  - Weeks
  - Seasons
- Investigate alternative time series forecasting models, such as:
  - Prophet by Facebook
  - Gaussian Processes