Energy Load Time Series Prediction

Tim Prause, Kadisatou Fane, Cosima Birkmaier

Contents

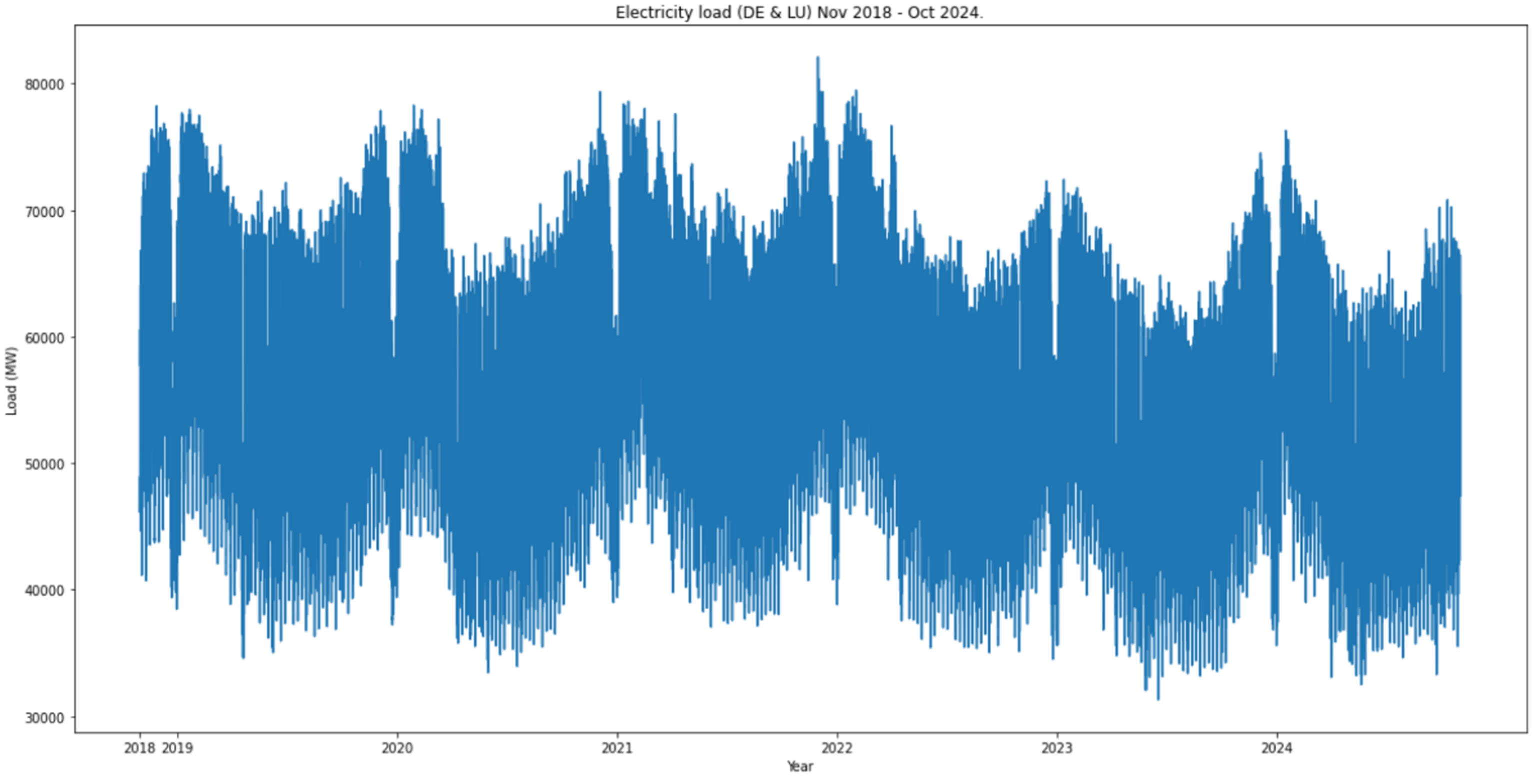
Motivation

- more renewable energy sources
- new challenges for power grids
- electricity generation must be flexibly adapted to power consumption
- one solution: **batteries:**
    - Battery Energy Storage Systems (BESS)
    - charge, when more energy is generated than needed
    - discharge to the grid, when demand is higher than (renewable) generation
    - financially: buy energy, when prices are low, sell it, when prices are high
        - supply and demand
- goal of our project: predict energy load

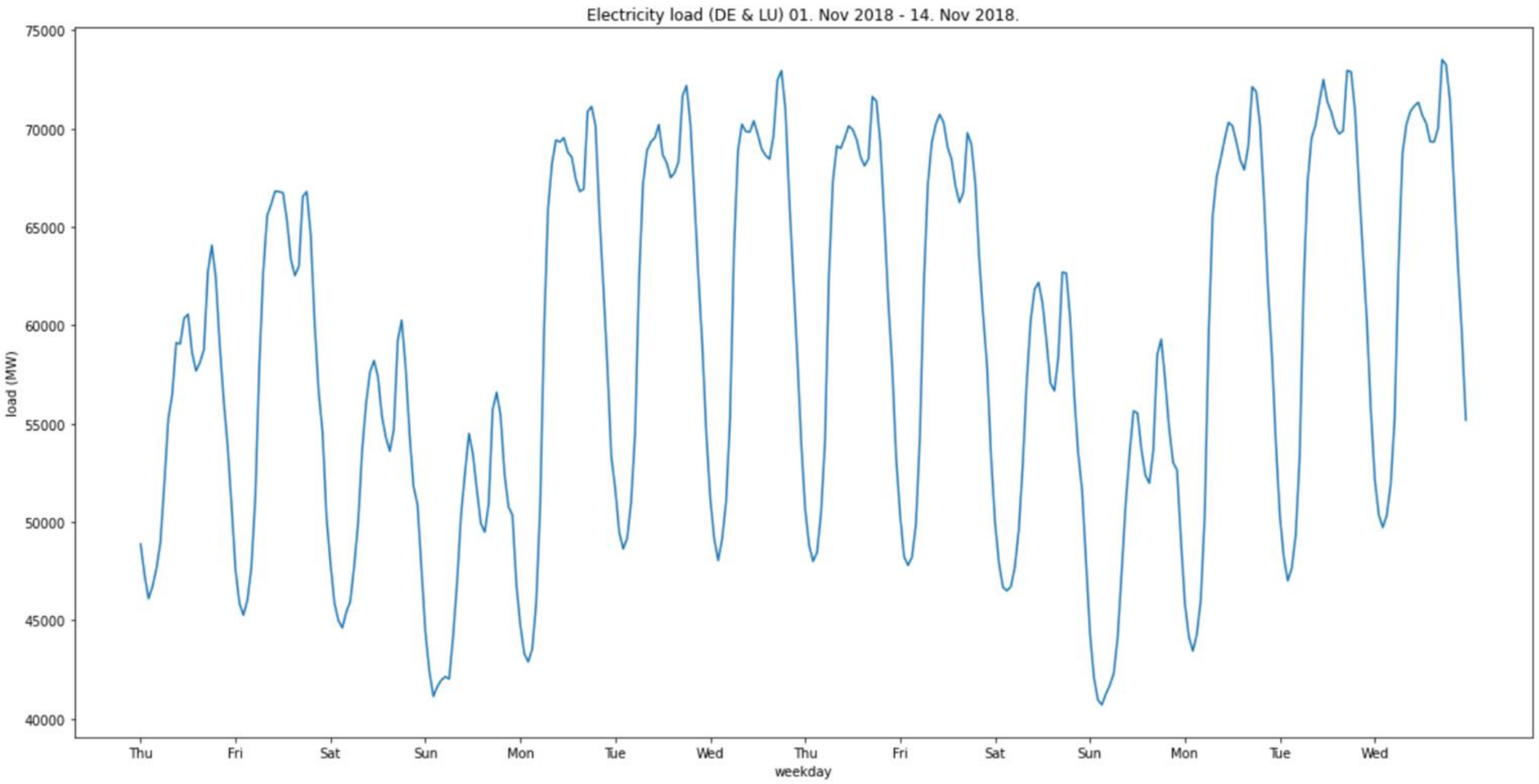
Dataset

- Dataset obtained from Bundesnetzagentur (Federal Agency for Grids)
- Total energy load from Germany and Luxembourg
- From 01.11.2018 to 31.10.2024
- Energy production per production type (e.g. wind, solar...)
- Hourly data
- Added features:
  - Time Features (hour, weekday, holidays...)
  - Energy Prices in Europe
- Final dataset:
  - 52,620 samples
  - 35 features

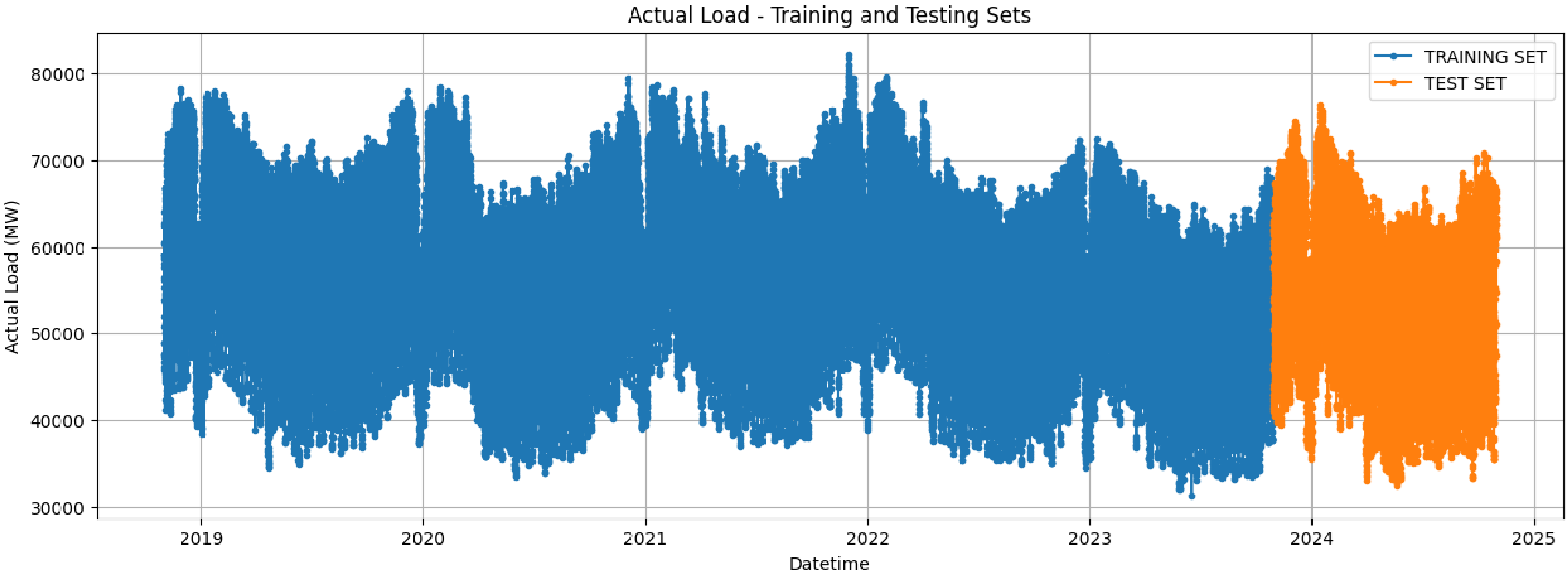
Data Visualization & Preparation



Data Visualization & Preparation



Train-Test split for all models:



Feature Engineering:

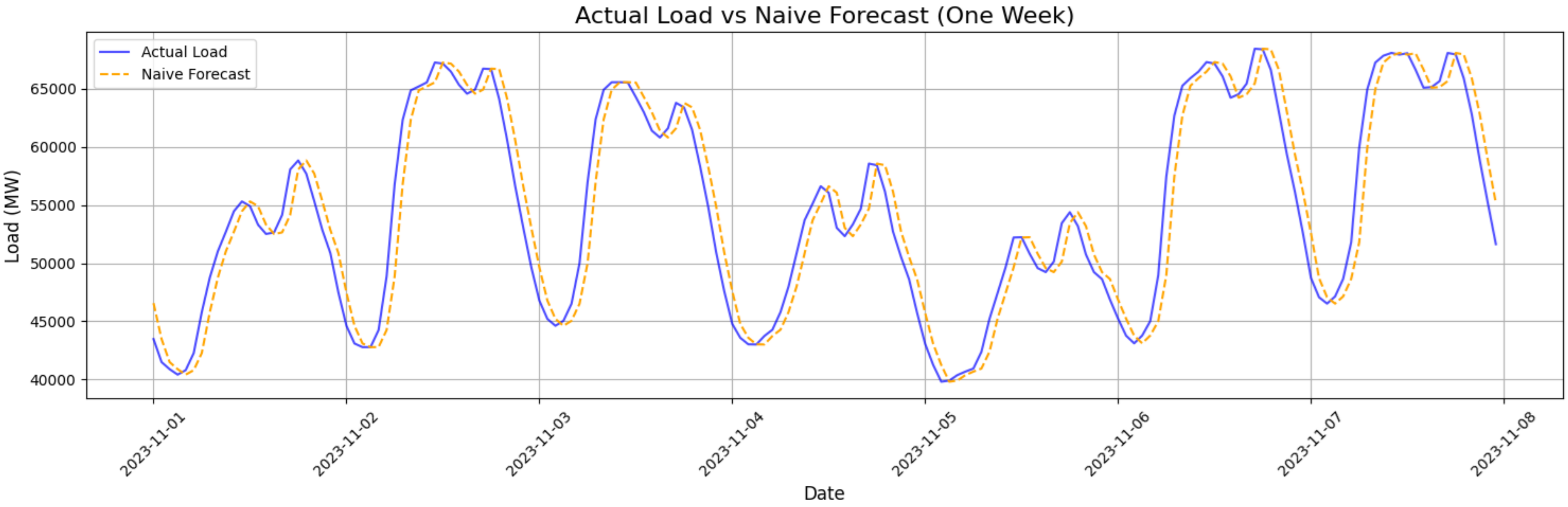
Added features:

- Time Features
  - hour of day in cos and sin
  - weekday cos and sin
  - day of year cos and sin
  - holiday
  - workday True or False
- Energy Prices in Germany
- Energy Production in Germany
  - Wind, solar, coal, gas...

Feature selection:

- Random forest Regressor for feature selection: Feature and importance
  - hour: 0.40
  - day of week: 0.086
  - nuclear energy: 0.028
  - holiday: 0.023
  - coal energy: 0.024
  - ...
- Threshold = 0.1 resulted in 13 remaining features

Baseline Models: Naive Forecast

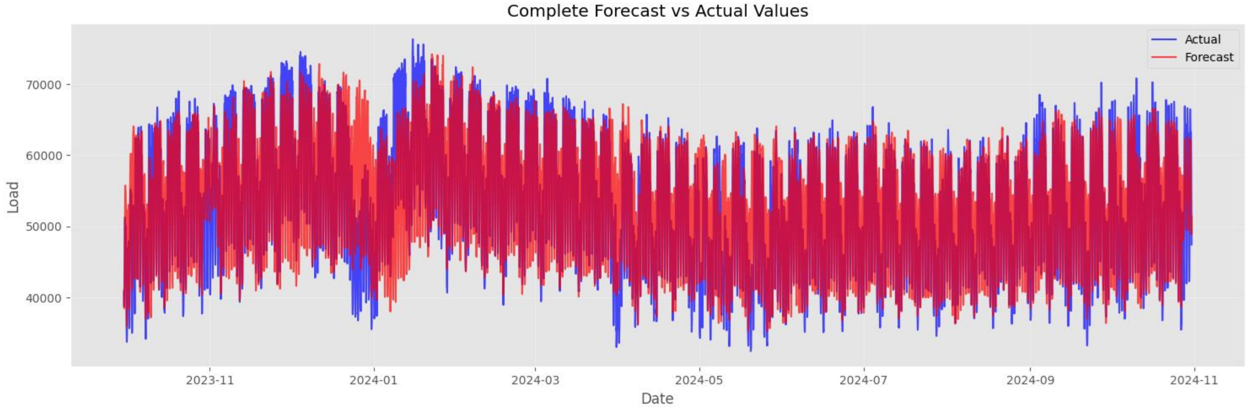


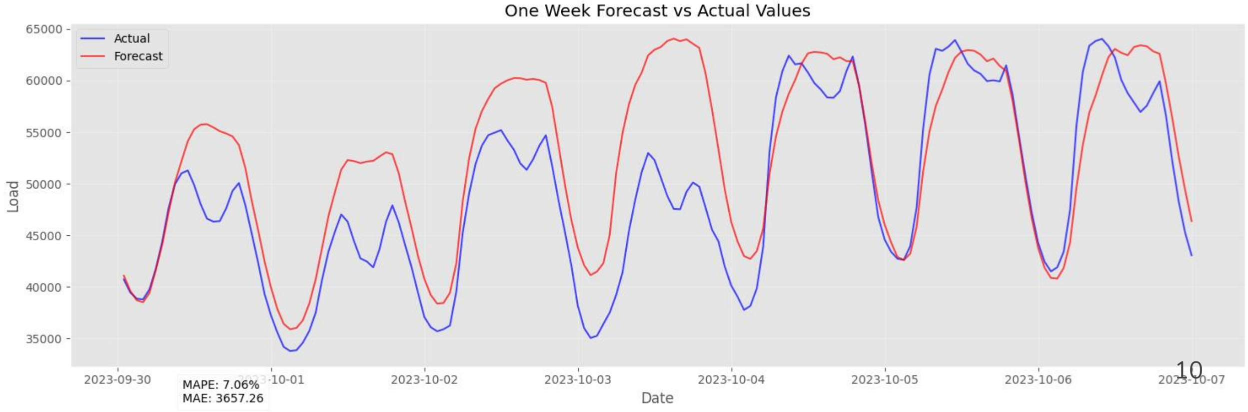
Mean Absolute Percentage Error (MAPE): 3.4592% Mean Absolute Error (MAE): 1807.92

Baseline Models: Sarimax 1

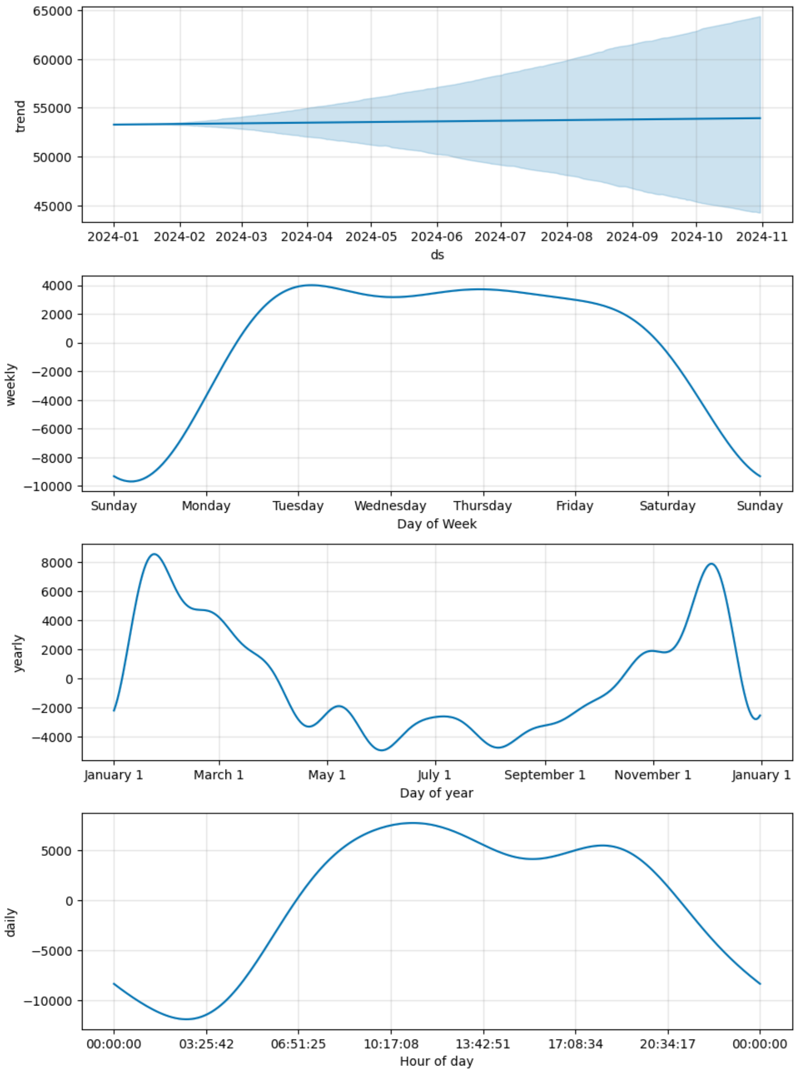
Mean Absolute Percentage Error (MAPE): 7.06%

Mean Absolute Error (MAE): 3657.26

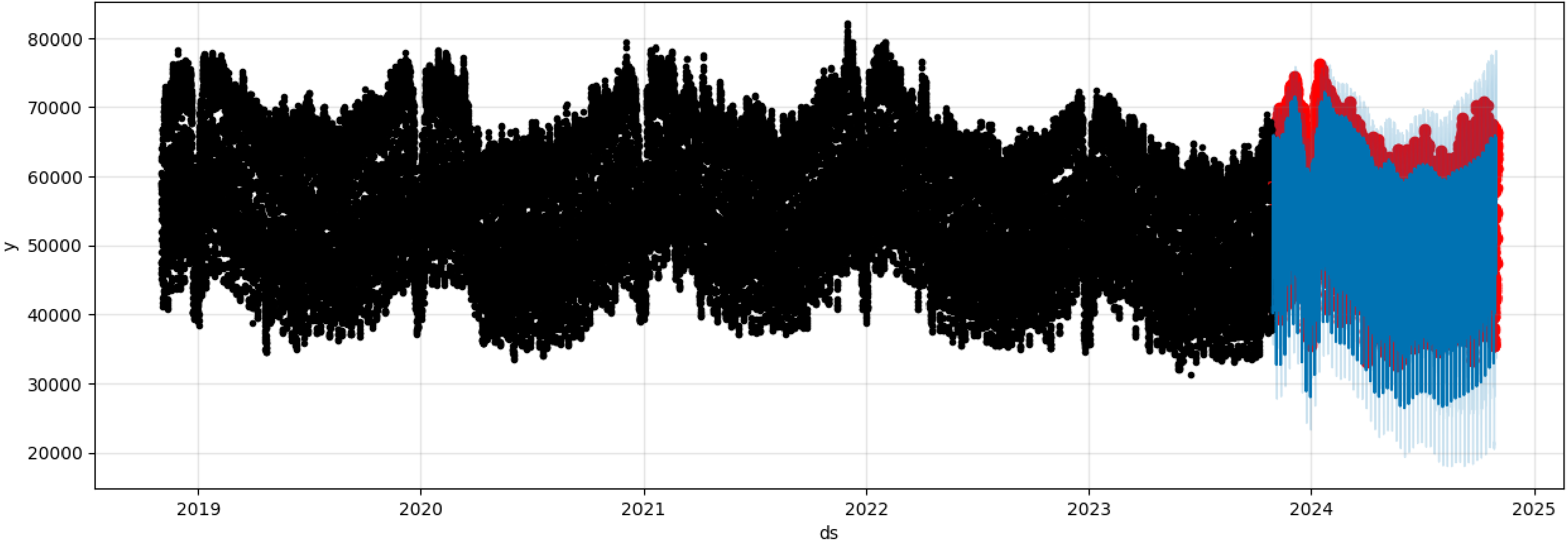




FB Prophet:

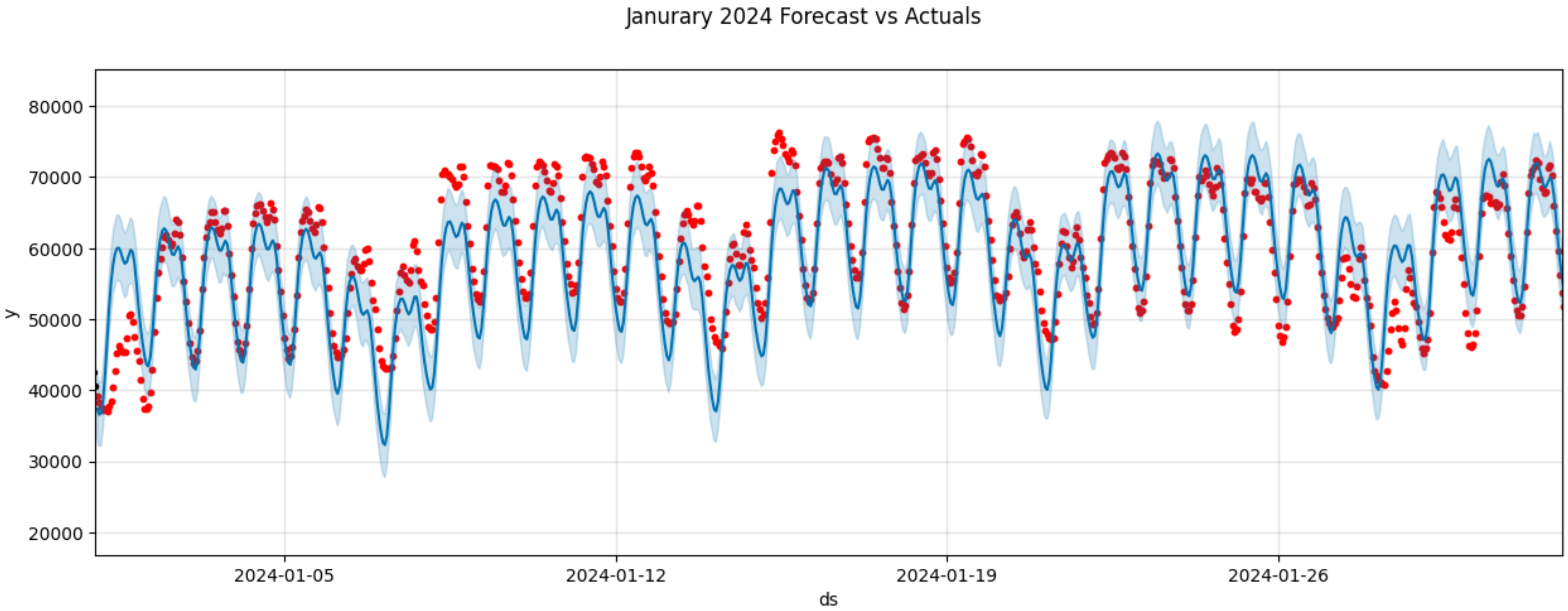

65000
60000
55000
50000
45000
trend
2024-01
2024-02
2024-03
2024-04
2024-05
2024-06
2024-07
2024-08
2024-09
2024-10
2024-11
ds
4000
2000
0
−2000
−4000
−6000
−8000
−10000
weekly
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Sunday
Day of Week
8000
6000
4000
2000
0
−2000
−4000
yearly
January 1
March 1
May 1
July 1
September 1
November 1
January 1
Day of year
5000
0
−5000
−10000
daily
00:00:00
03:25:42
06:51:25
10:17:08
13:42:51
17:08:34
20:34:17
00:00:00
Hour of day

FB Prophet:



80000
70000
60000
50000
40000
30000
20000
y
2019
2020
2021
2022
2023
2024
2025
ds

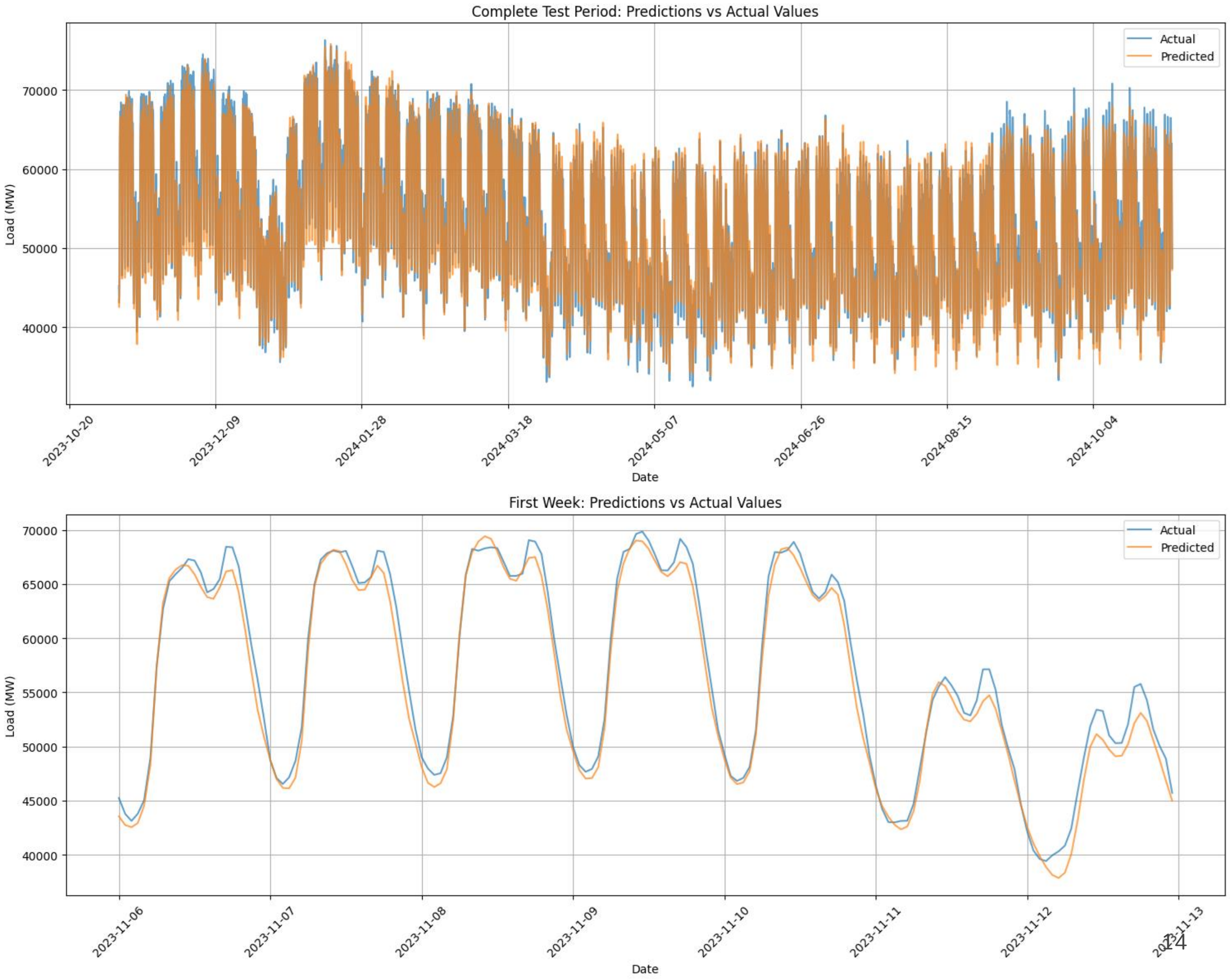
FB Prophet:



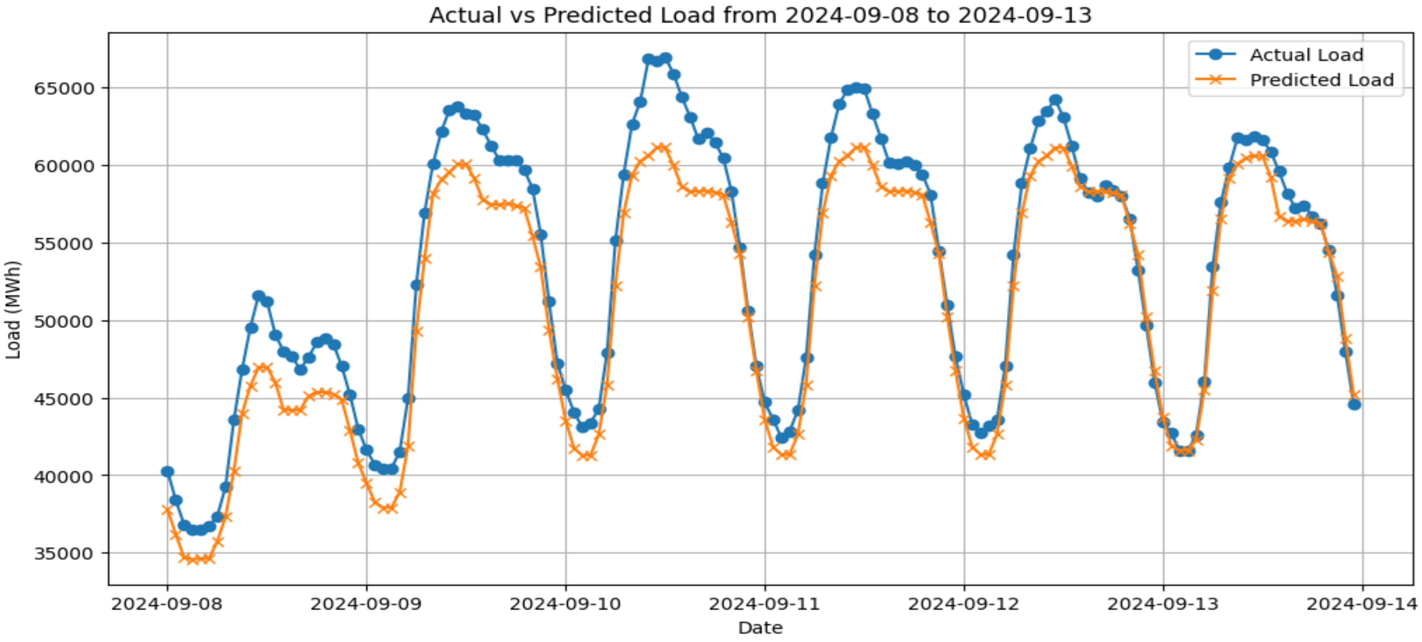
Mean Absolute Percentage Error (MAPE): 5.3319% Mean Absolute Error (MAE): XXX

LSTM:

- Architecture:
  - 3 layers
  - 128 neurons
  - 0.2 dropout layer
  - 48 window size
- Test Set MAPE: 1.85%
- Test Set MAE: 957.33



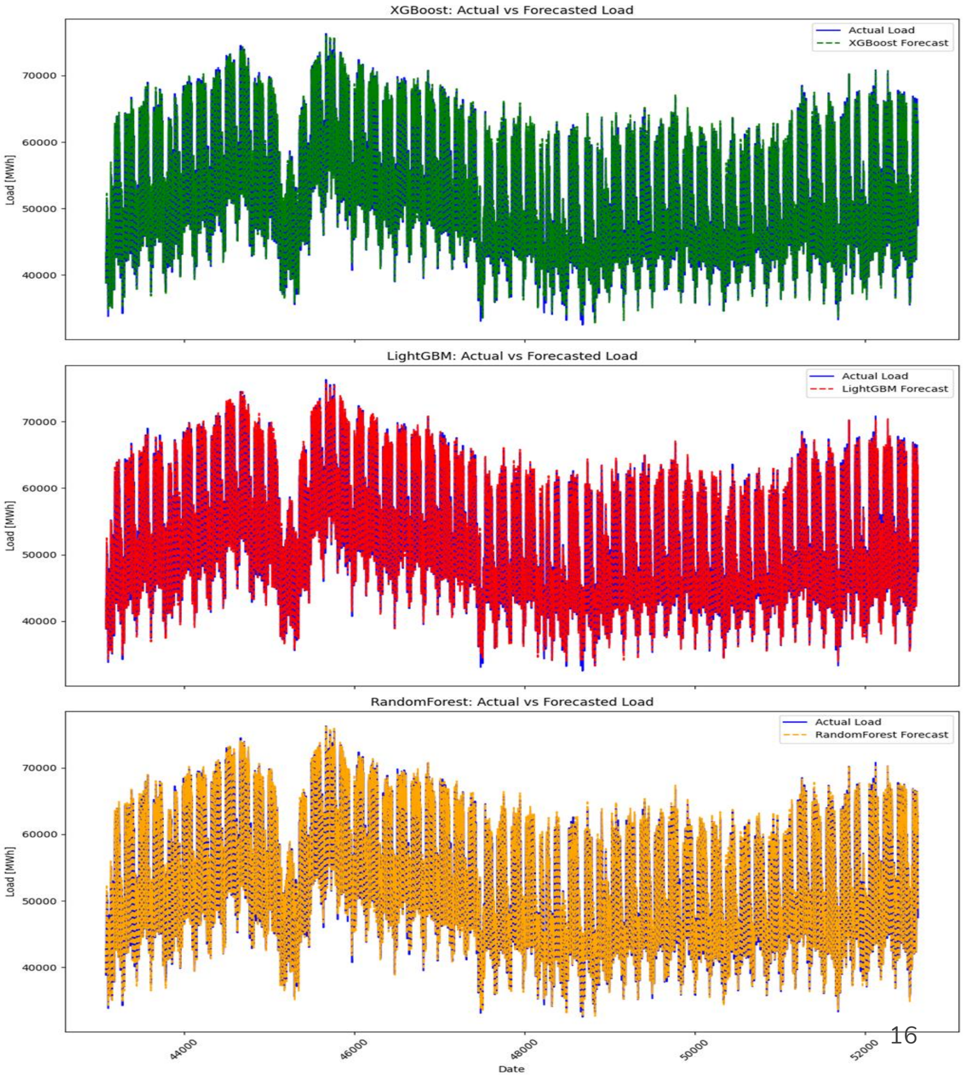
Univariate XGBoost:



Mean Absolute Percentage Error (MAPE): 3.8462% Mean Absolute Error (MAE): 1988.07

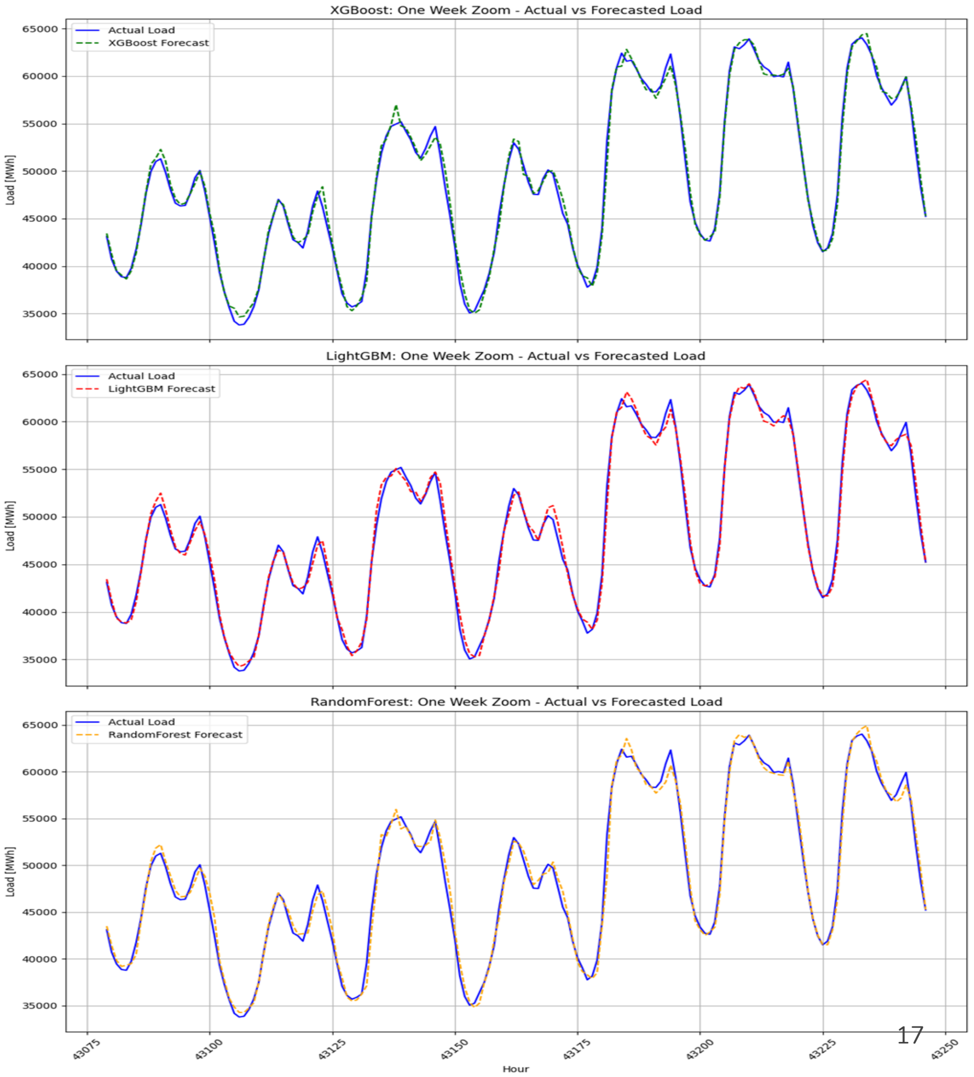
Multivariate Tree Models:

- XGBoost
    - 1000 estimators
    - 30 max depth
    - learning rate 0.01
- LightGBoost:
    - 3000 estimators
    - 35 max depth
    - learning rate 0.05
- RandomForest;
    - 30 estimators
    - 25 max depth



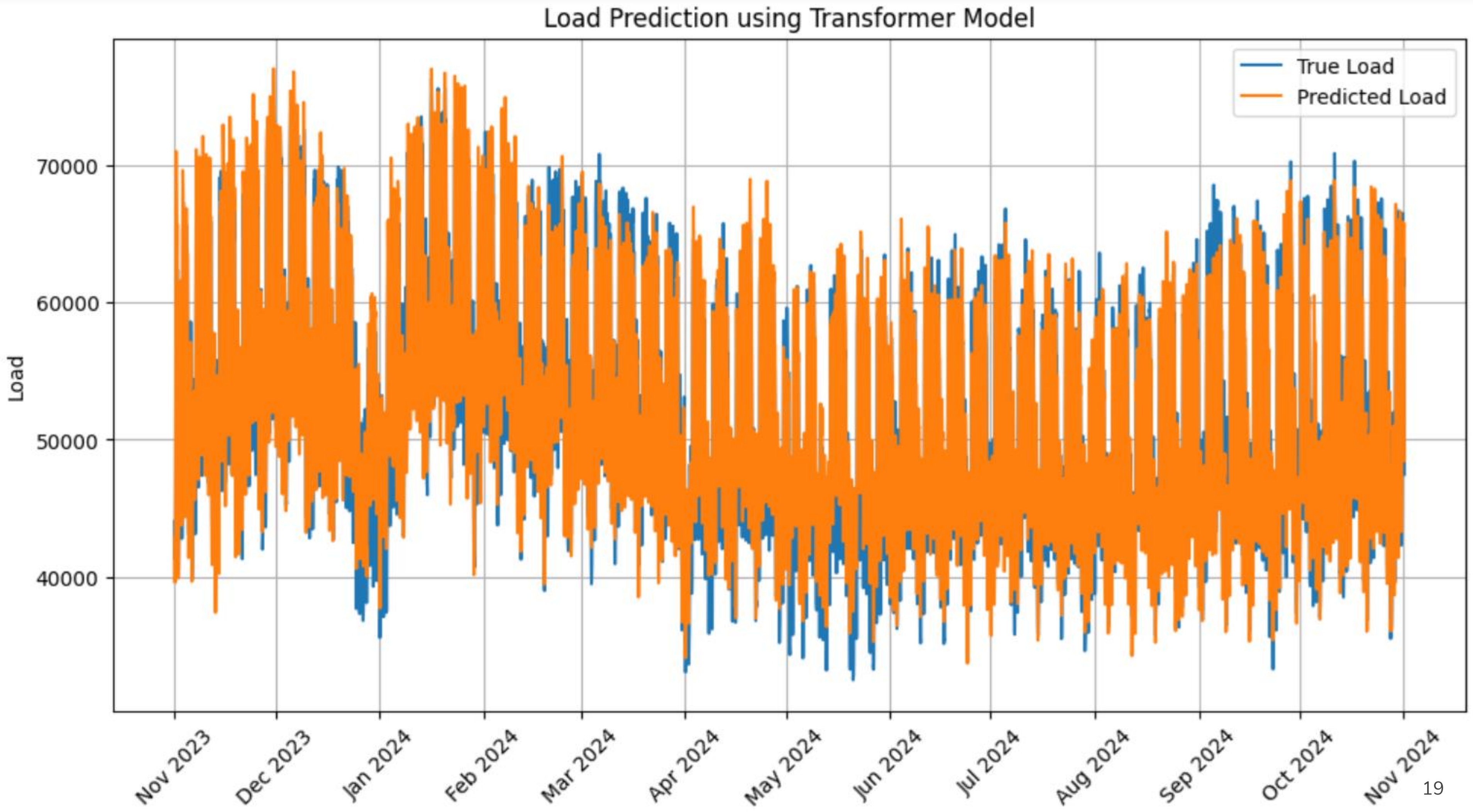
Multivariate Tree Models:

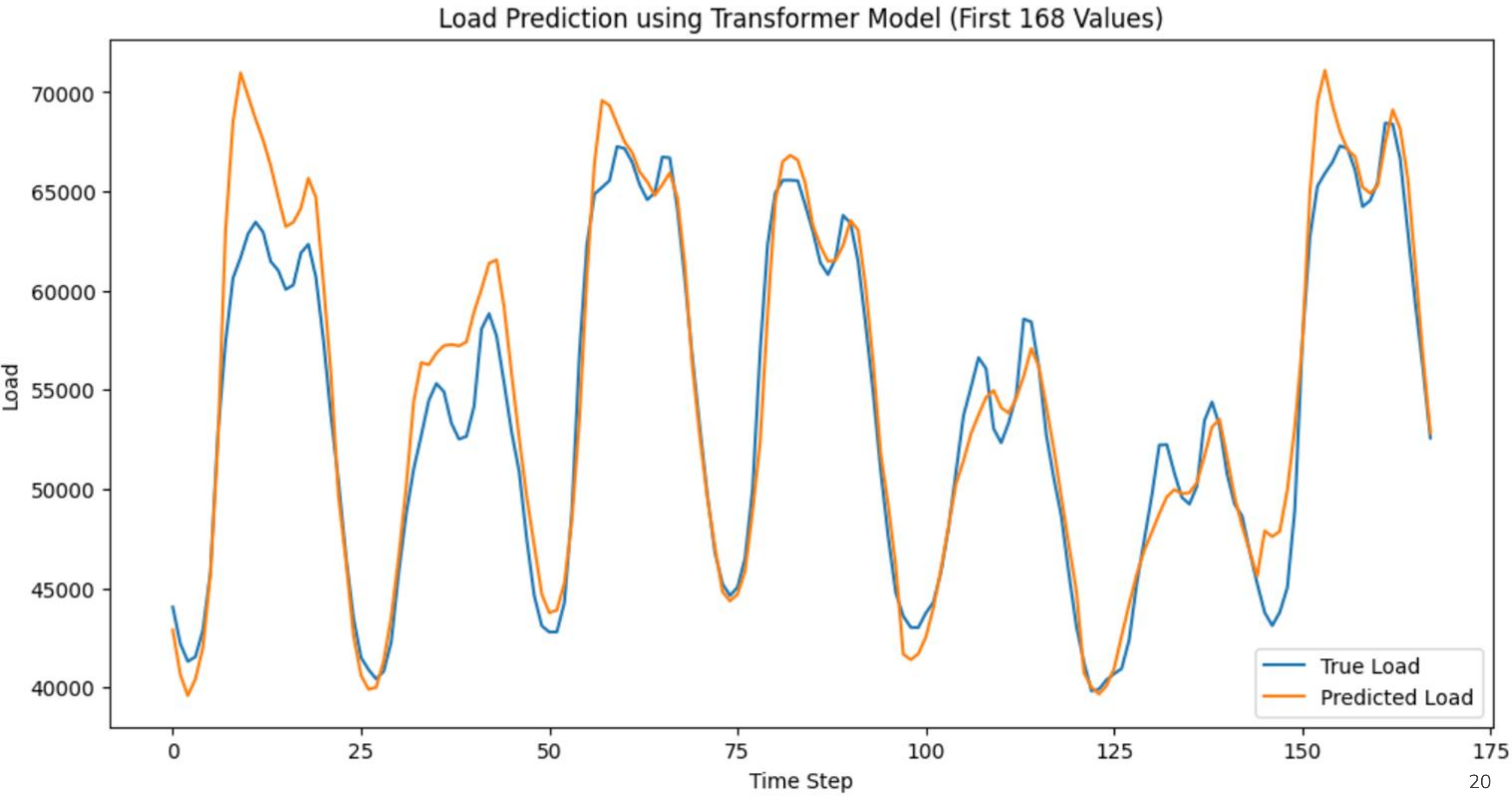
- XGBoost
  - mape: 0.86%
  - mae: 489.51
- LightGBoost:
  - mape: 1.09%
  - mae: 450.10
- RandomForest;
  - mape: 0.89%
  - mae: 515.27



Transformer Model

- TensorFlow
- 34,718 parameters (all trainable)
- 4 attention heads
- batch size = 1
- 50 epochs
- training time: 1:04 h
- MAPE: 3.69 %
- MAE: 1,898.06

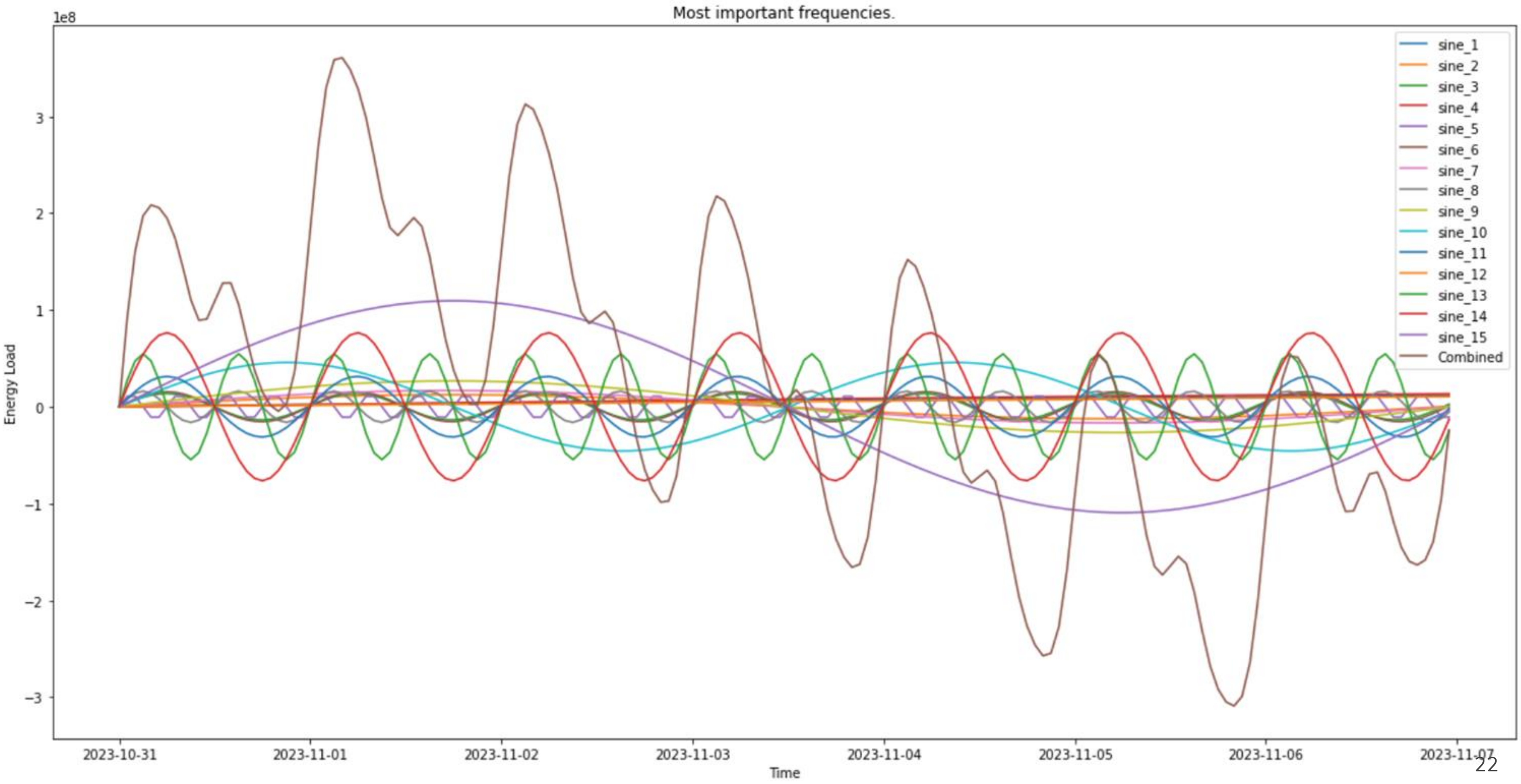

Load Prediction using Transformer Model
True Load
Predicted Load
Load
70000
60000
50000
40000
Nov 2023
Dec 2023
Jan 2024
Feb 2024
Mar 2024
Apr 2024
May 2024
Jun 2024
Jul 2024
Aug 2024
Sep 2024
Oct 2024
Nov 2024



Load Prediction using Transformer Model (First 168 Values)
70000
65000
60000
55000
50000
45000
40000
Load
0
25
50
75
100
125
150
175
Time Step
True Load
Predicted Load

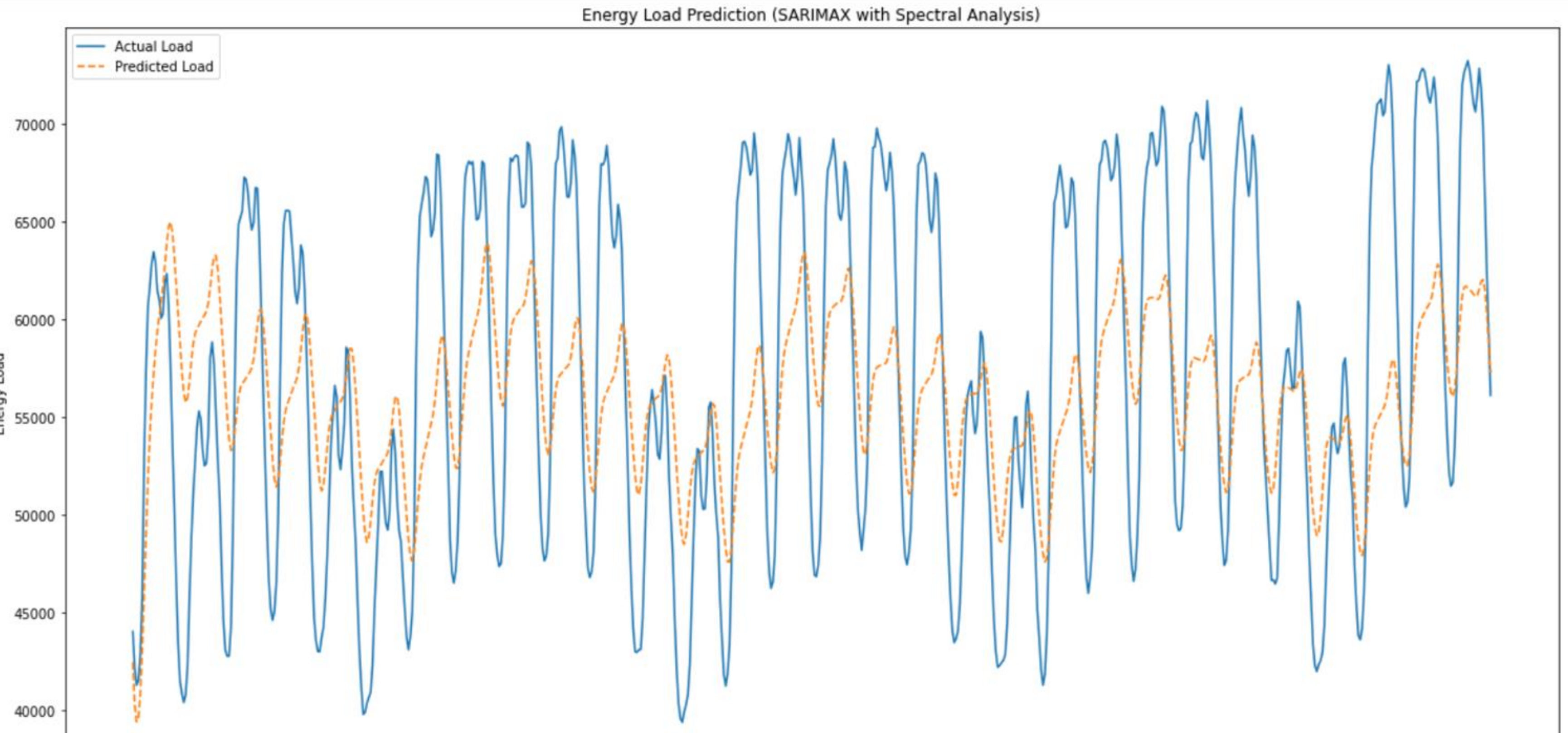
FFT and Spectral Analysis

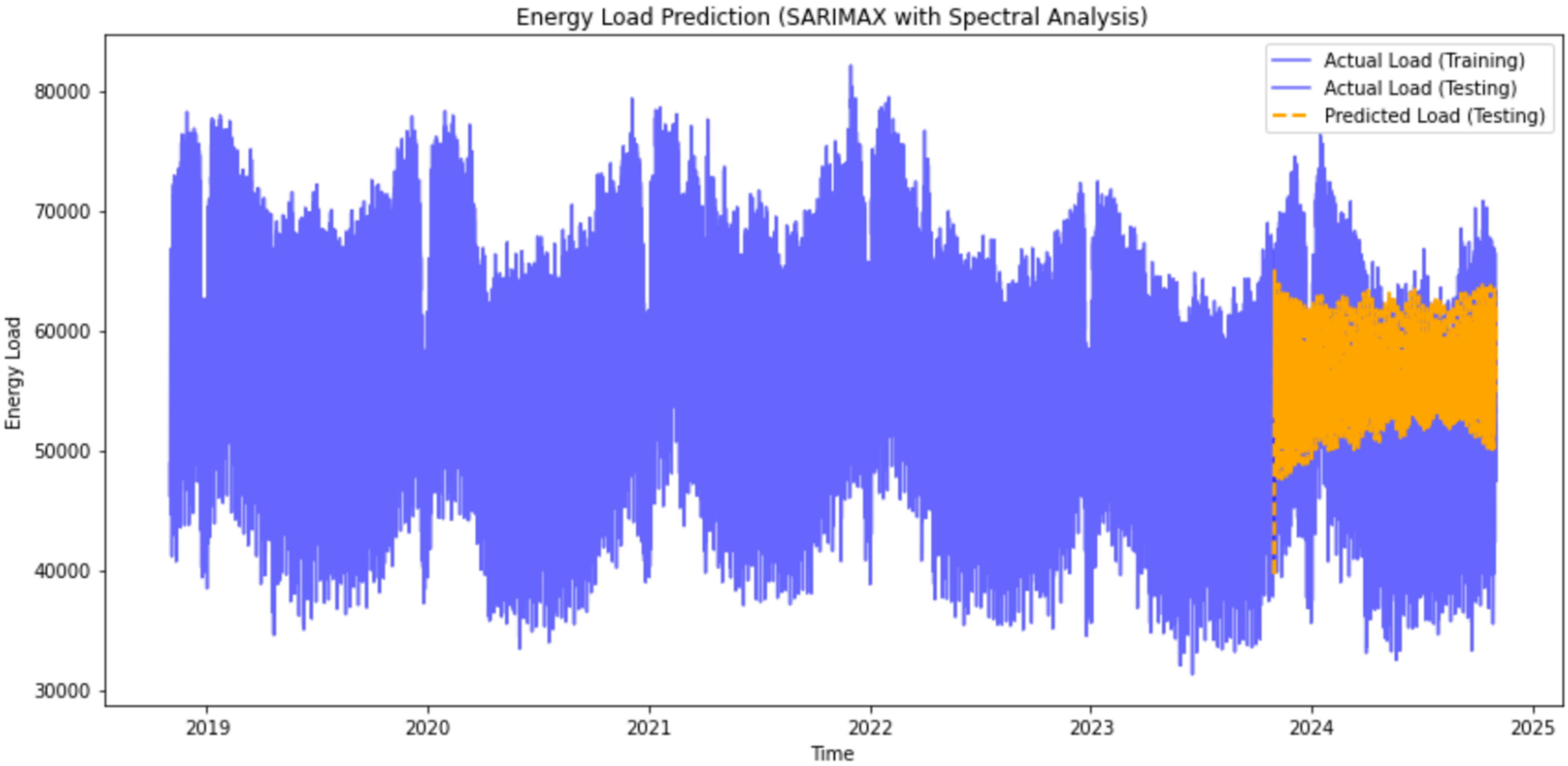
- Perform FFT
- Filter results to obtain most relevant frequencies
- Represent those frequencies with their amplitudes (and phases) as sine waves
- Add the sine waves as new columns to the dataset
- Perform SARIMAX with those columns as exogenous factors
- MAPE: 15.78 %
- MAE: 7,634.24
- Quick computation time (a few minutes for FFT, spectral analysis and SARIMAX)



Most important frequencies.
1e8
3
2
1
0
−1
−2
−3
Energy Load
2023-10-31
2023-11-01
2023-11-02
2023-11-03
2023-11-04
2023-11-05
2023-11-06
2023-11-07
Time
sine_1
sine_2
sine_3
sine_4
sine_5
sine_6
sine_7
sine_8
sine_9
sine_10
sine_11
sine_12
sine_13
sine_14
sine_15
Combined

SARIMAX with FFT





Energy Load Prediction (SARIMAX with Spectral Analysis)
Actual Load (Training)
Actual Load (Testing)
Predicted Load (Testing)
Energy Load
80000
70000
60000
50000
40000
30000
2019
2020
2021
2022
2023
2024
2025
Time

Recall the main 3 types of Features

📌Lag-Based Features (e.g., load_lag_1, load_lag_2, ..., load_lag_7):

❖ Historical Load Features (Lag Variables)
❖ External Market and Weather Features
❖ Basic Temporal (Time-Based) Features

📌Time-Based and Categorical Features:

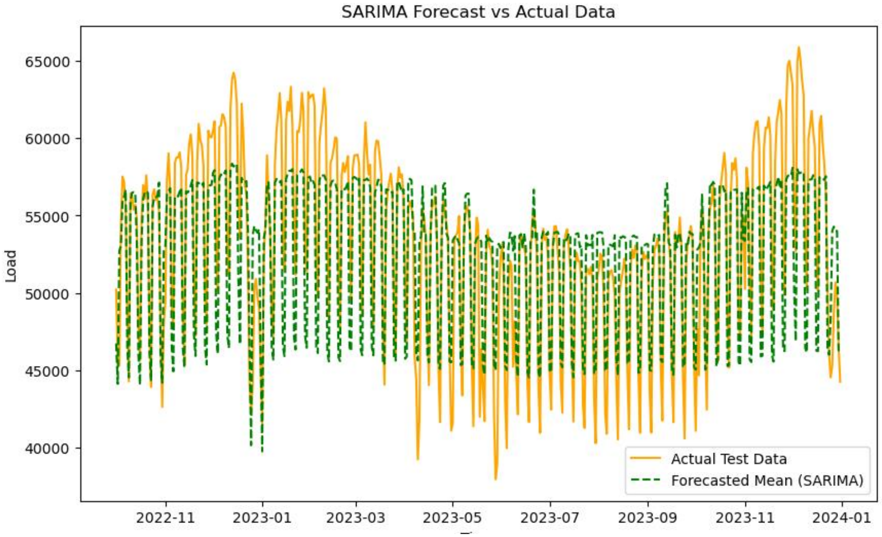
❖ Holiday and Workday Features e.g., is_workday
❖ Expanded Calendar Features (Time Representation) e.g., date, hour, dayofweek
❖ Cyclical Features (Fourier Transformed Time Variables) e.g., hour_sin

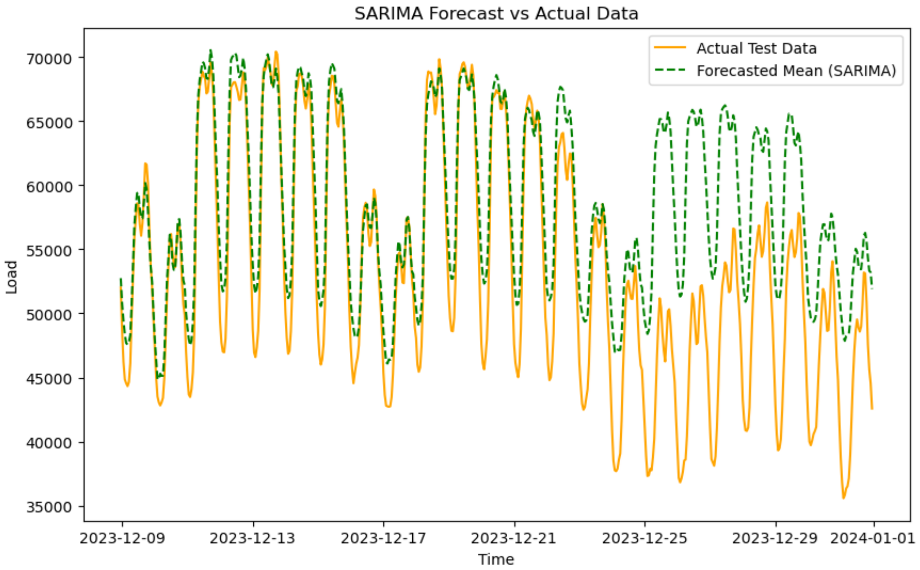
📌 Energy Source-Based Features(e.g.,,):

❖ Electricity Market Features e..g, Gesamt (Netzlast) [MWh]
❖ Energy Generation-Based Features e.g., Biomasse [MWh]
❖ Renewable Energy Sources e.g. Biomasse [MWh]
❖ Conventional Energy Sources e.g. Kernenergie [MWh]
❖ Grid Demand (Net Load) Features

SARIMAX 2:
weekly load forecast with hourly and daily data

- *Does model accuracy improve with higher frequency data ?*
- Regressors: hour, is_weekend, is_holiday,is_low, price, temperature, is_high_load, load_time_temp
- Hyper parameters: ARIMA components: AR(p), MA(q), d
- Hyper parameters: Seasonal Components: P, Q, D





Frequency = weekly using average hourly load
Interval: 2019-01-01:2023-12-31 | Data points: 1826
Split: 75%
Model : SARIMAX(4, 1, 0)x(1, 0, [1], 7)
Heteroskedasticity (H): 0.55
AIC:833.944
MAPE :0.048
Runtime: 94.254 seconds

Frequency = 24x7
Interval: 2023-10-01:2023-12-31 | Data points: 2160
Split: 75%
Model : SARIMAX(0, 0, 3)x(1, 0, [1], 168)
Heteroskedasticity (H): 0.31
AIC:-2532.929
MAPE:0.1061
Runtime: 12m59s

Kalman Filter with expansion window: Hourly load Forecast

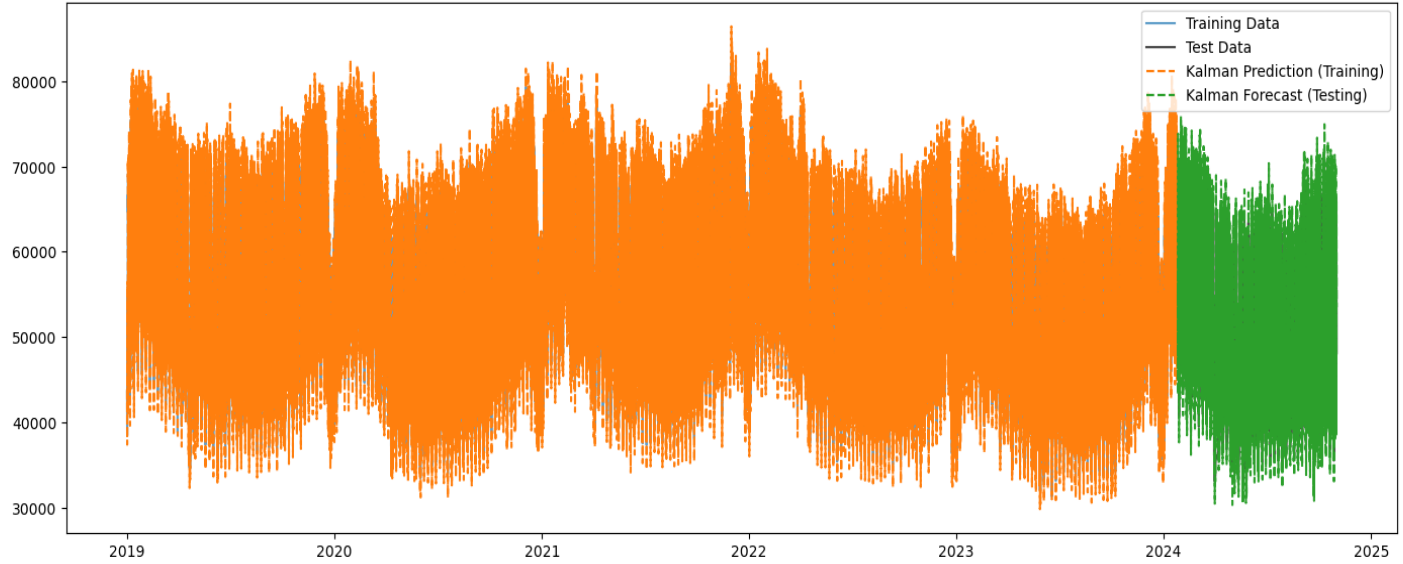
- Regressors: hour, is_weekend, is_holiday
- State variables: short-term trend & seasonality, long-term trend & seasonality
- Hyperparameters: state transition matrix (A), Observation matrix (H), Process noise covariance (Q), Observation noise covariance (R), Initial state vector, Initial state covariance

```
for t in range(forecast_steps):
    # Predict step
    state_pred = A @ state_prev  # Predict the next state
    P_pred = A @ P_prev @ A.T + Q  # Predict the state covariance

    # Predict energy load (observation)
    energy_load_pred = H @ state_pred
    forecasted_energy_load.append(energy_load_pred[0])

    # Optional: Expanding or Rolling window correction
    if t < len(test_data):
        # Use expanding window: update with test data as it becomes
available
        observation_residual = test_data[t] - energy_load_pred  #
Residual
        S = H @ P_pred @ H.T + R  # Innovation covariance
        K = P_pred @ H.T @ np.linalg.inv(S)  # Kalman Gain

        # Update states based on test observation
        state_updated = state_pred + K @ observation_residual
        P_updated = (np.eye(n_states) - K @ H) @ P_pred
    else:
        # For rolling window: Use the rolling window states
        state_updated = state_pred
        P_updated = P_pred
```



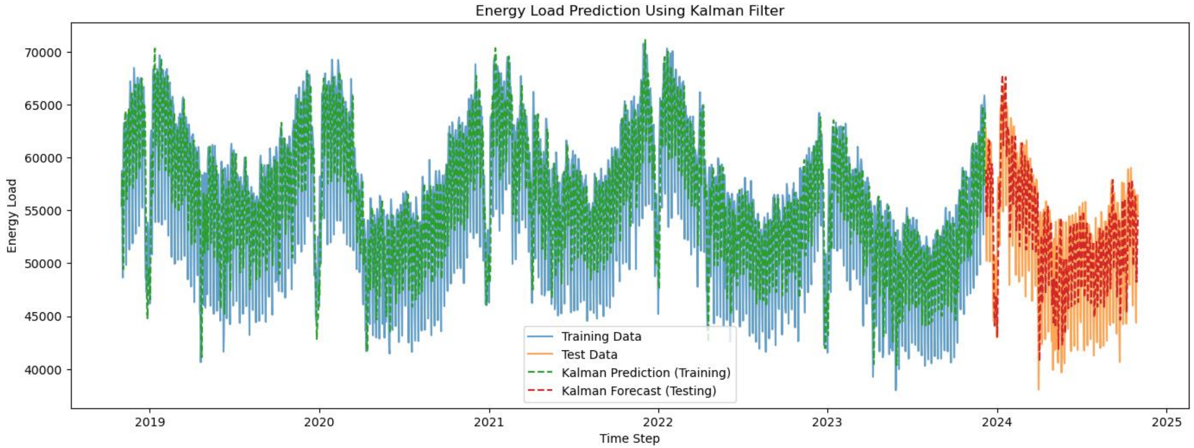
Frequency = hourly

Interval: 2022-10-01: 2023-12-31|
Data points: 10969

split: 80%

MAPE: 0.0817

Runtime: 4 seconds



Frequency = daily

Interval: 2018-11-01: 2024-10-31|
Data points: 2192

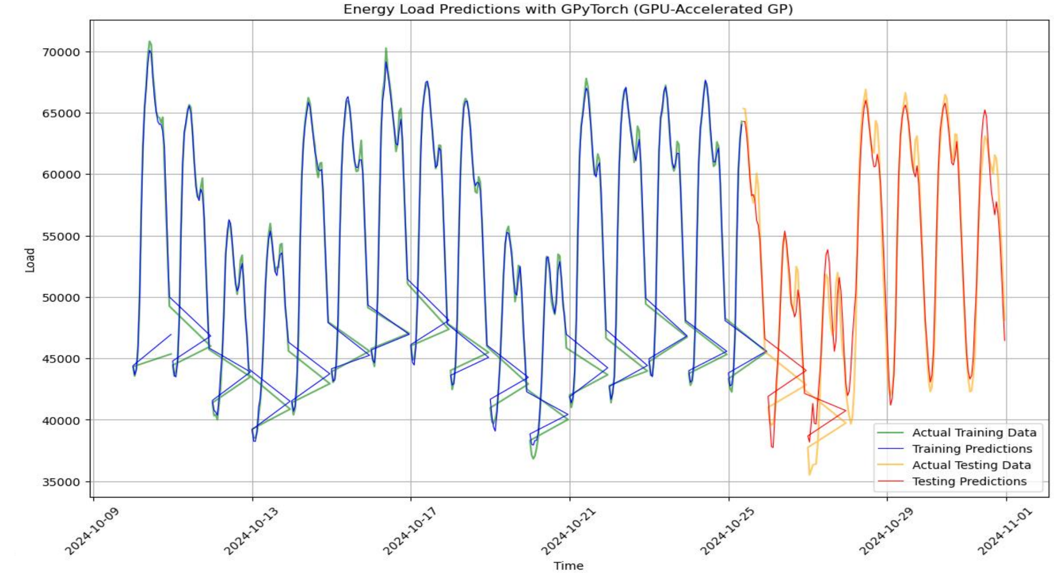
split: 80%

MAPE: 0.1004

Runtime: 4 seconds

GP model: another advanced architecture

- Features: load_lag_1, load_lag_2, load_lag_3, load_lag_4, load_lag_5, load_lag_6, load_lag_7, price, temperature, day_of_week, month
- Hyperparameters:
  - Out layer: **M**ean function, **R**BF kernel, **P**eriodic Kernel, **M**atern Kernel, **G**aussian Likelihood noise variance, Learning rate, Number of iterations
  - In layer: length scale, periodic length,ν, output scale
  - RBF Kernel models smooth trends over multiple features.
  - Periodic Kernels captures yearly and weekly seasonality (based on time-related features).
  - Matern Kernel adds flexibility for irregular variations.



Frequency = hourly

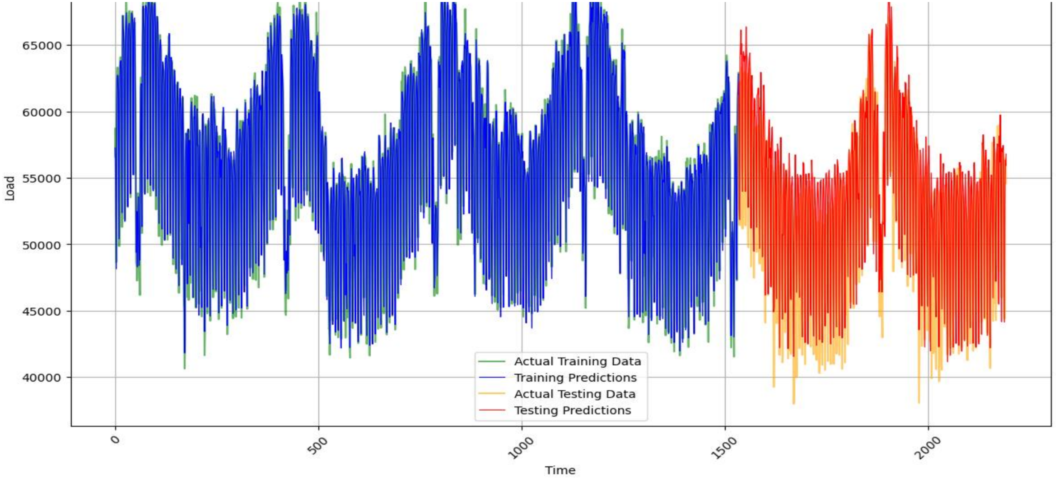
Interval: 2023-10-10: 2024-10-31| Data points: 640

split: 70%

MAPE: [0.0068, 0.02795]

Runtime: < 1m

Loss: [1.562, 0.445]



Frequency = daily

Interval: 2019-01-01: 2024-10-31| Data points: 20100

split: 70%

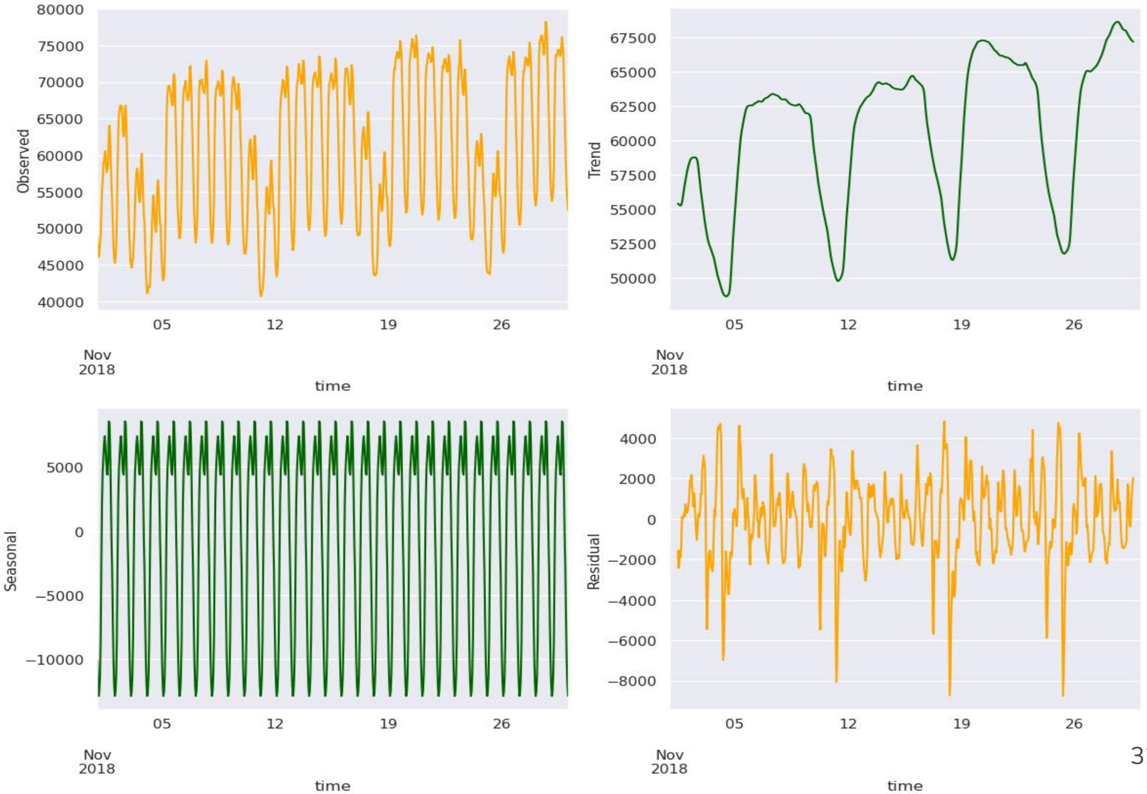
MAPE: [0.0103, 0.0349]

Runtime: < 1m

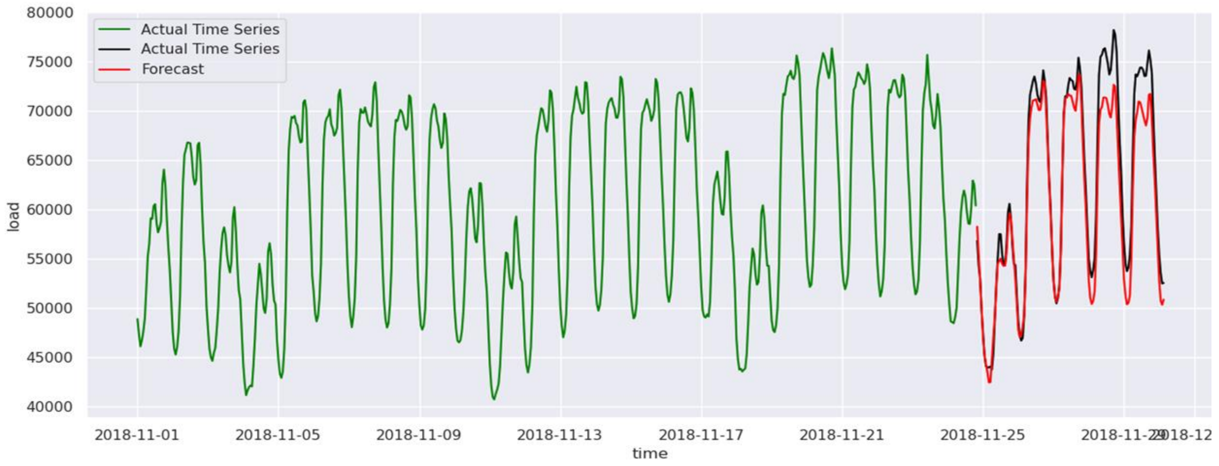
Loss: [1.552, 0.490]

Times FM at the edge

Hourly load decomposition into state components



- ❖ Features: no external features during forecast
- ❖ Hyperparameters: context_len, horizon_len, imput_patch_len, output_patch_len, num_layers, model_dims, backend



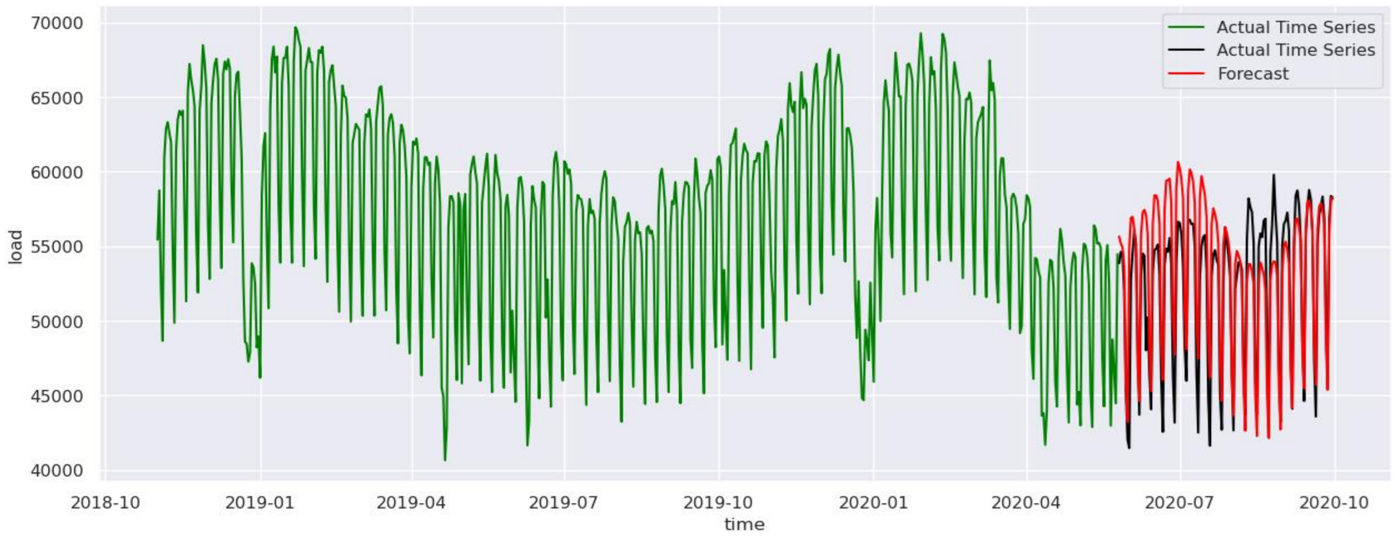
Frequency : hourly

Interval: 2018-11-1: 2028-11-29| Data points: 8640

split: 82%

MAPE: 0.0332

Runtime: < 1m



Frequency : daily

Interval: 2018-11-1: 2028-11-29| Data points: 8640

split: 82%

MAPE: 0.0458

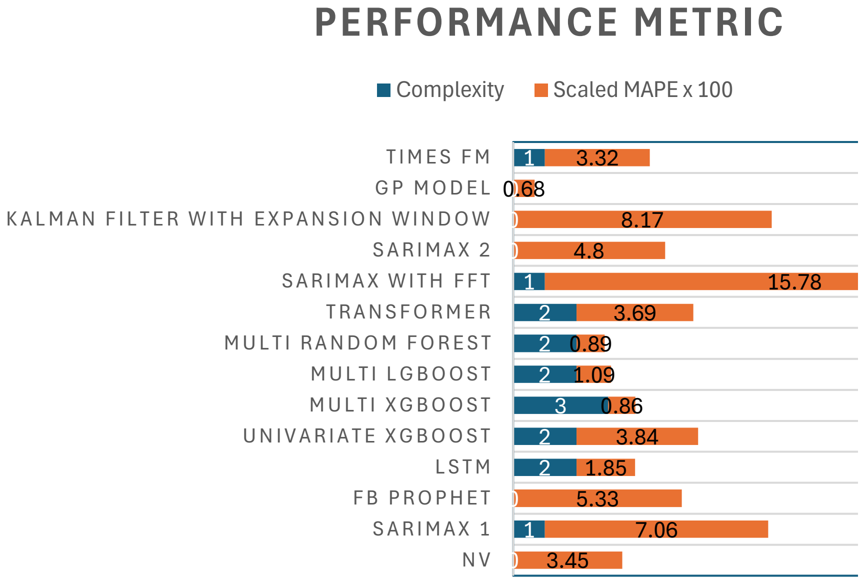
Runtime: < 1m

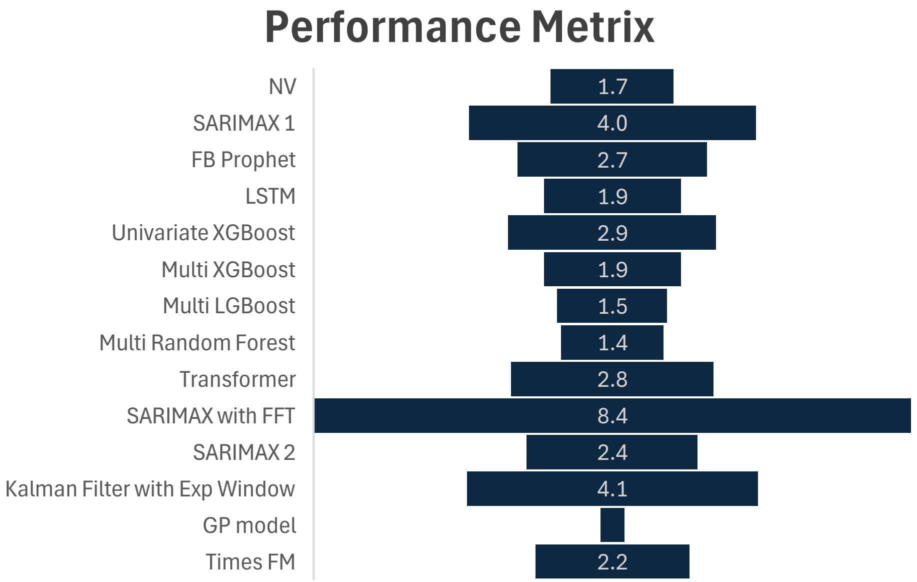
Model Comparison

Model	MAPE	MAE	training time (estimated)
Naive Forecast	0.034592	1807.92	—
Sarimax 1	0.0706	3657.26	10 min
FBProphet	0.053319	---	4 min
LSTM	0.0185	957.33	20 min
Univariat XGBoost	0.038462	1988.07	4 min
Multi XGBoost	0.0086	489.51	10 min
Multi LGBoost	0.0109	450.10	3 min
Multi Random Forest	0.0089	515.27	7 min
Transformer	0.0369	1898.06	1 hour
Sarimax with FFT & Sine Waves	0.1578	7634.2403	2 min
Sarimax 2 Daily load forecast	0.048	—	1m34s
Kalman Filter with expansion window	0.0817	—	4s
Gaussian Process	[0.0068, 0.02795]	—	<1 min
Times FM	0.0332	__	< 1 min

Best Performing Models at a glance

- 3 basic criterions: Runtime, Number of hyperparameters, Number of features.
- Runtime criterion: takes {0,1} based on wether model runtime is larger or smaller than the weighted average of runtime of the model
- complexity: the sum of the 3 criterion for each model can take {0,1,2,3}
- Performance: avg(MAPE x 100, and complexity)





Summary:

- Energy load data is mainly composed of short-term seasonality, long-term seasonality, and long-term trend.
- There is no volatility clustering observed therefore avoid models that assume this.
- (Classical time series models s.a., SARIMAX can provide good forecasting results when estimated with the right features, using the appropriate parameter value.)
- The most general external features to predict energy load are price and weather time series
- The averaged hourly data for energy load forecast can help the model produce smoother predictions and improve fitness.

Outlook:

- Add more Features
- More fine tuning for each model
- Use models optimized for rolling forecasts
- Forecast Energy price as well
- Forecast different regions
- Consider official and unofficial regional holidays (carnival) and the regions affected
- Consider long “bridge” weekends
- Reproduce the models with alternative set of features

References

- Energy load data from https://www.smard.de/home/downloadcenter/download-marktdaten/?downloadAttributes=%7B%22selectedCategory%22:1,%22selectedSubCategory%22:false,%22selectedRegion%22:false,%22selectedFileType%22:false%7D
- International Energy Agency (2024): Batteries and Secure Energy Transitions. https://iea.blob.core.windows.net/assets/cb39c1bf-d2b3-446d-8c35-aae6b1f3a4a0/BatteriesandSecureEnergyTransitions.pdf
- Lewinson, E. (2022): Three Approaches to Encoding Time Information as Features for ML Models. https://developer.nvidia.com/blog/three-approaches-to-encoding-time-information-as-features-for-ml-models/
- “EEX-Hourly Spot Price E/Mwh” Data from Refinitiv Eikon
- Temperature data from https://open-meteo.com/en/docs/historical-weather-api#latitude=51.5&longitude=10.5&start_date=2018-01-01&end_date=2025-01-01&hourly=temperature_2m&daily=&models=

Photo credit

Slide 3, top center:

https://unsplash.com/de/fotos/luftaufnahme-des-rasenplatzes-mit-blauen-sonnenkollektoren-Ilpf2eUPpUE

Slide 3, right:

https://pixabay.com/de/photos/windrad-energie-windkraft-5267130/

Slide 4, top center:

https://www.bundesnetzagentur.de/SharedDocs/Bilder/_init_bild_stromleitung.png?__blob=normal&v=3

Slide 4, right:

https://unsplash.com/de/fotos/weisse-windmuhle-auf-gelbblattrigem-blumenfeld-tagsuber-E56cTF65xFw