Energy Demand Forecasting

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Problem Formulation

27555

HOURLY DEMAND

	datetime	Demand (MW)
0	2020-01-01 00:00:00	445.8
1	2020-01-01 01:00:00	424.5
2	2020-01-01 02:00:00	423.5
3	2020-01-01 03:00:00	418.8
4	2020-01-01 04:00:00	414.8

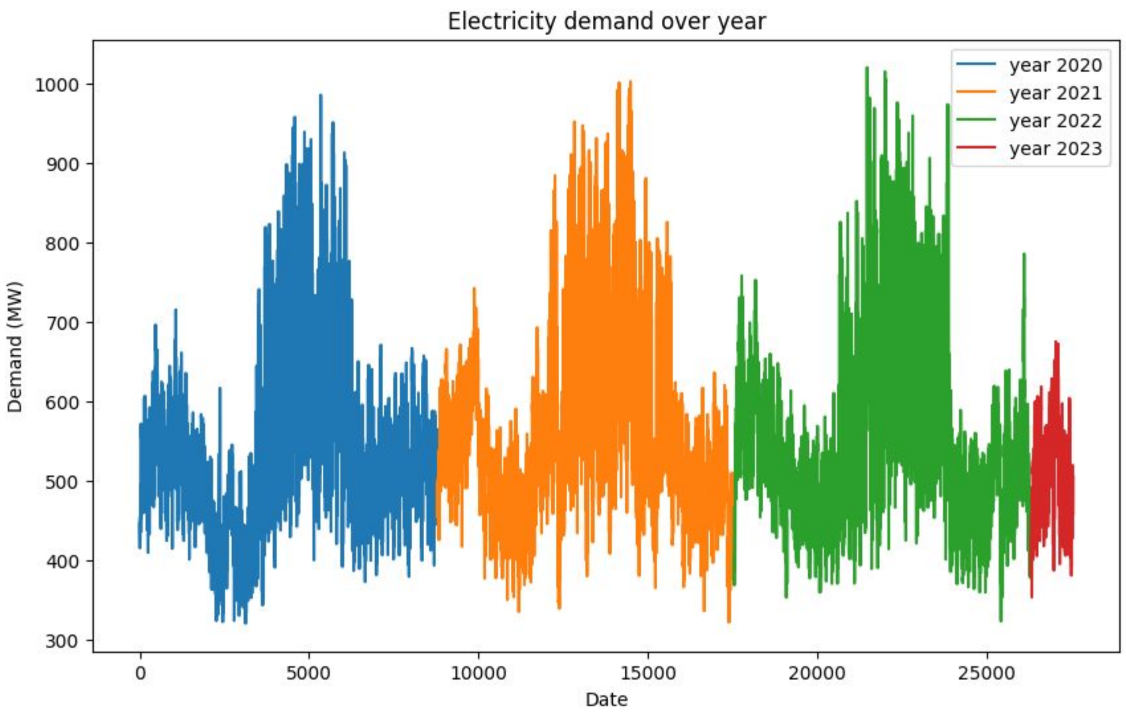
→ MODEL →

Prediction:

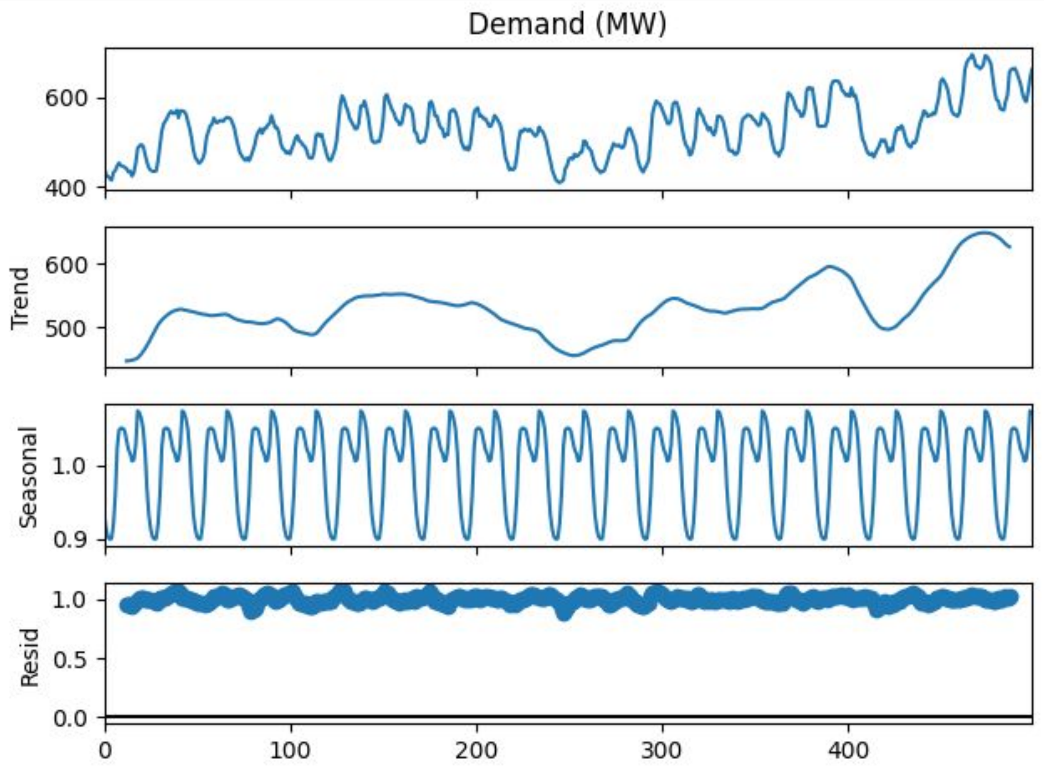
Next Week Hourly Forecast

7*24=168 Hour

Energy Demand Time Series Plot

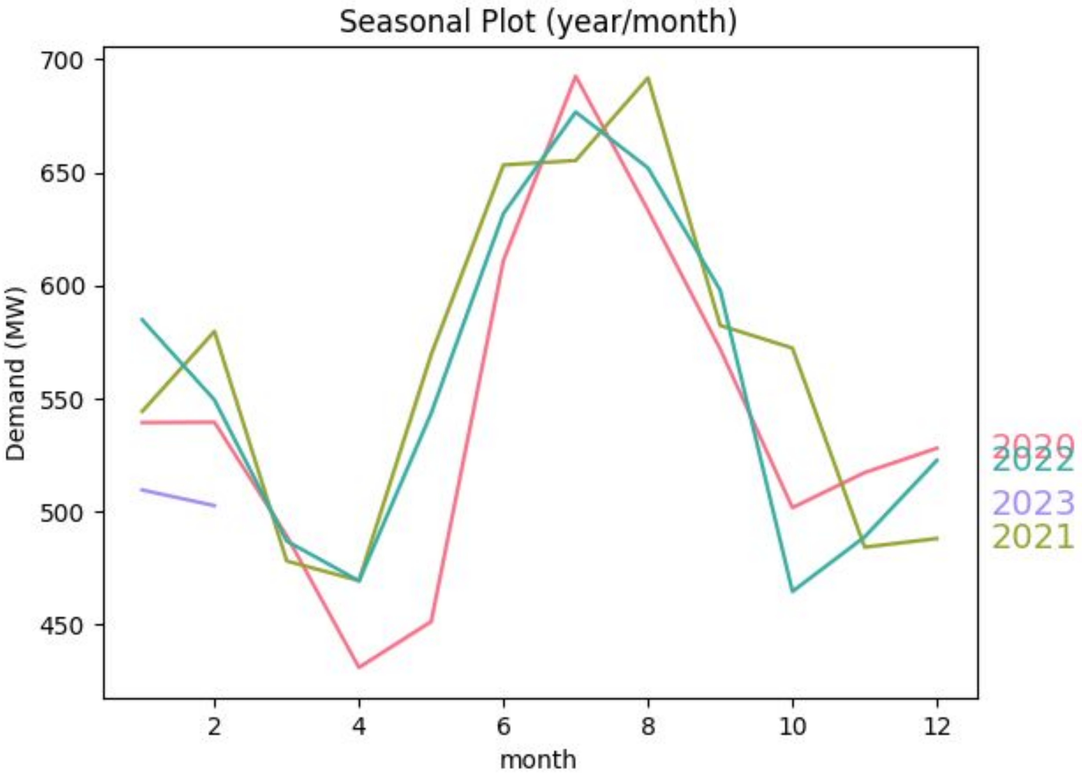


Energy Demand Decomposition



Multiplicative seasonal decomposition of First 500 Data Points

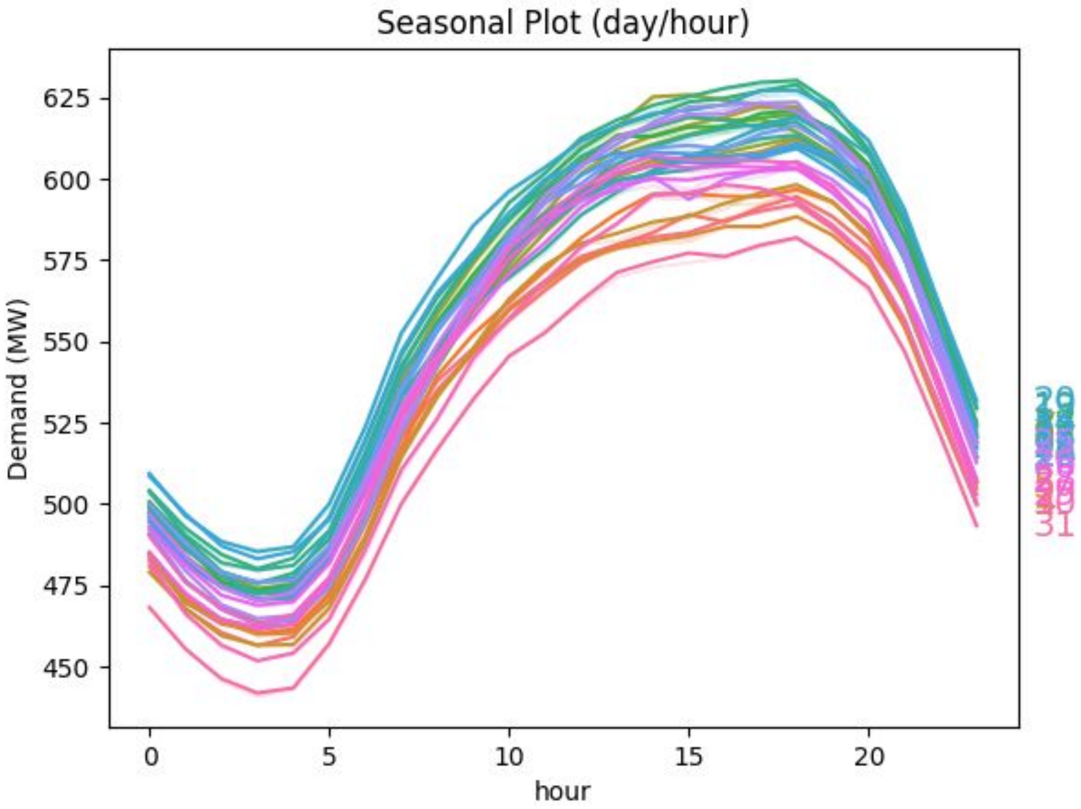
Seasonality in a Year



July (7)
Highest Energy Demand

April (4) and October(10)
Relatively Lower Energy Demand

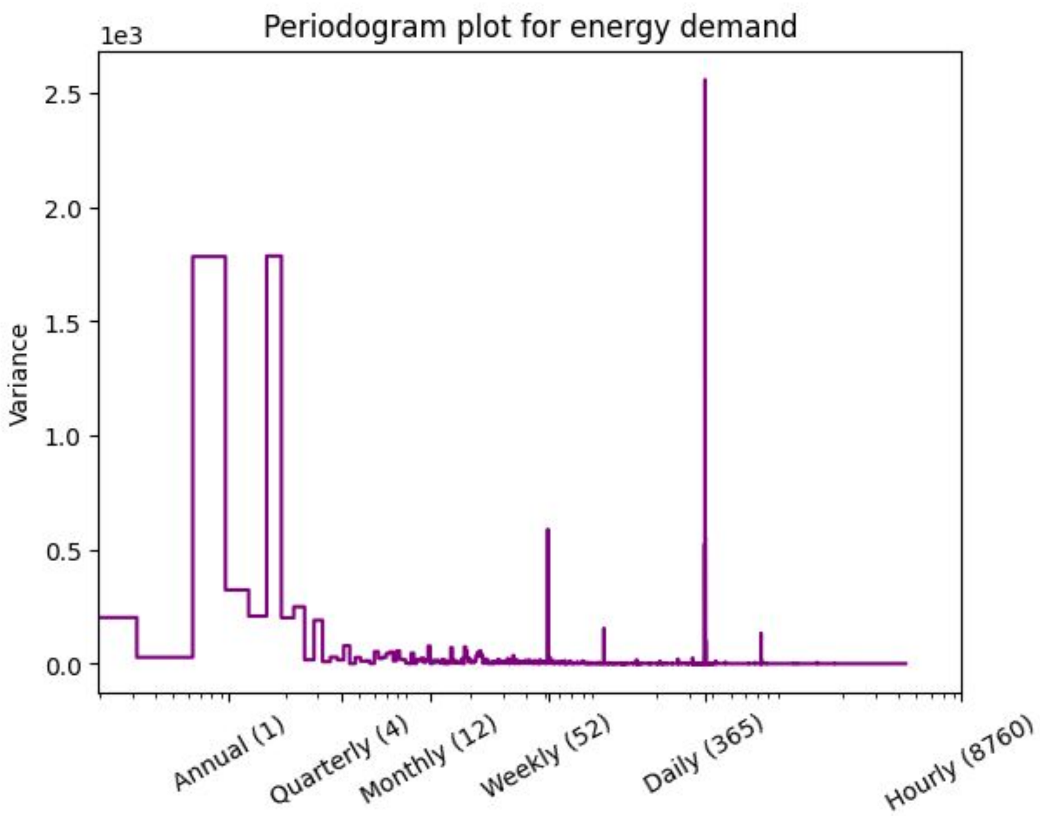
Seasonality in a Day



3pm - 8pm
Highest Energy Demand

1am - 5am
Relatively Lower Energy Demand

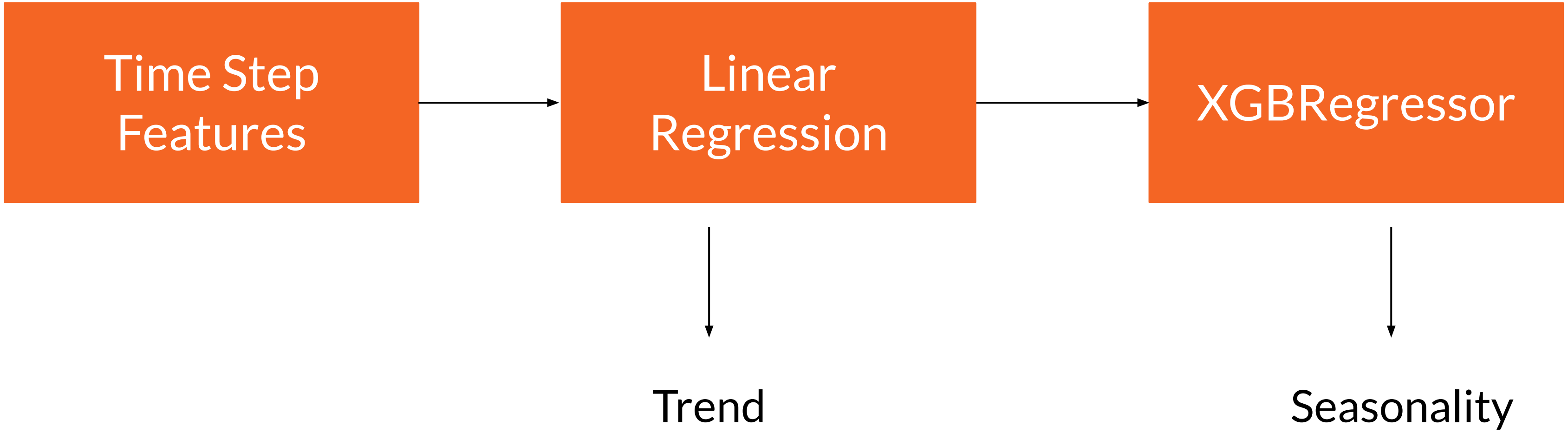
Periodogram



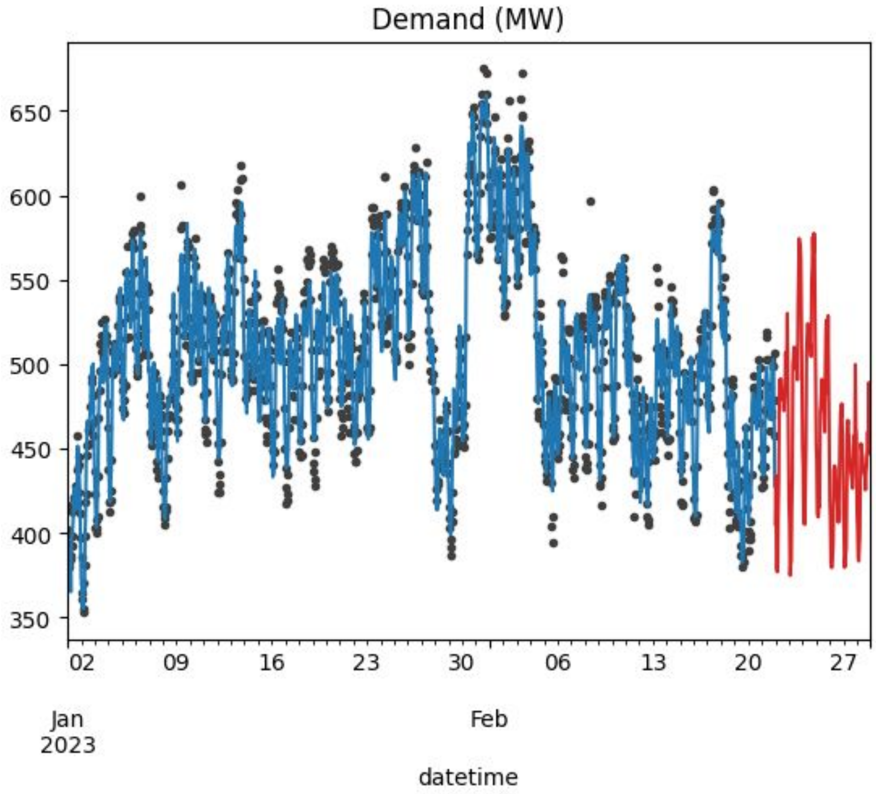
High Variance observed

Daily and
Annual Period

Hybrid Model



1 Week Forecast



Actual Demand
Predicted Demand
1 week forecast

mae	374.23
rmse	19.345

Forecasting Using Lag Features

ADF Test for Stationarity

H0: The time series is non-stationary. In other words, it has some time-dependent structure and doesn't have constant variance over time.

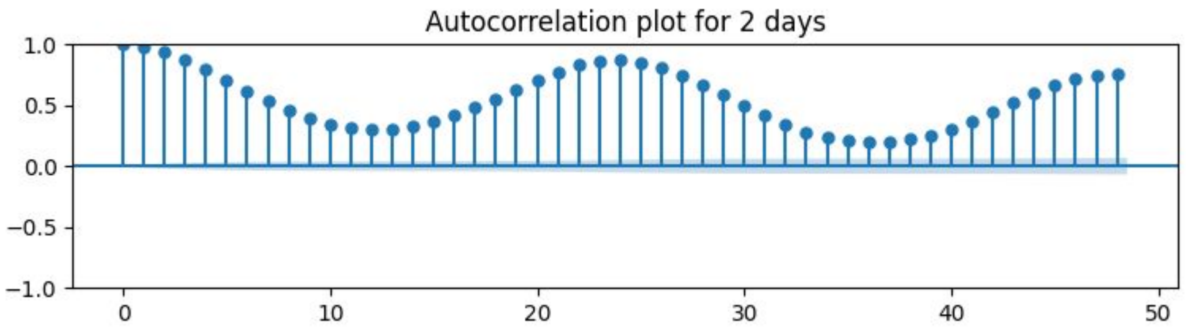
H1: The time series is stationary

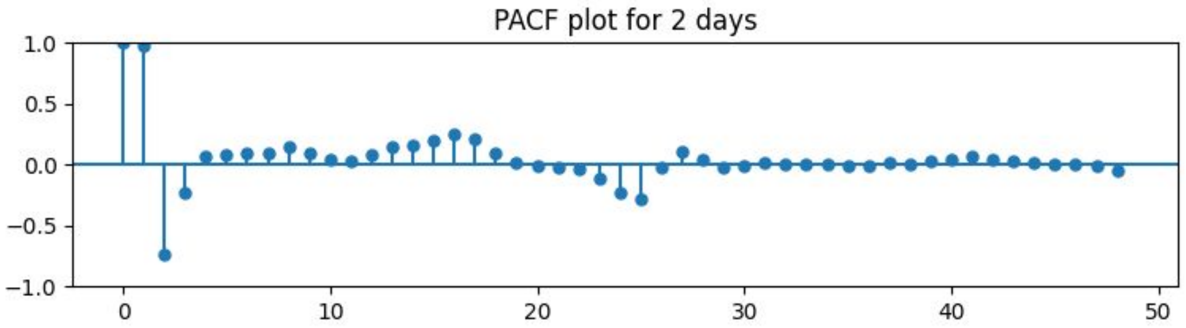
ADF Test for Stationarity

-10.35	2.45 * 10^(-18)
test statistics	p-value

Conclusion: From the above ADF test, we can observe p-value < 0.05, hence Null Hypothesis is rejected.

ACF and PACF

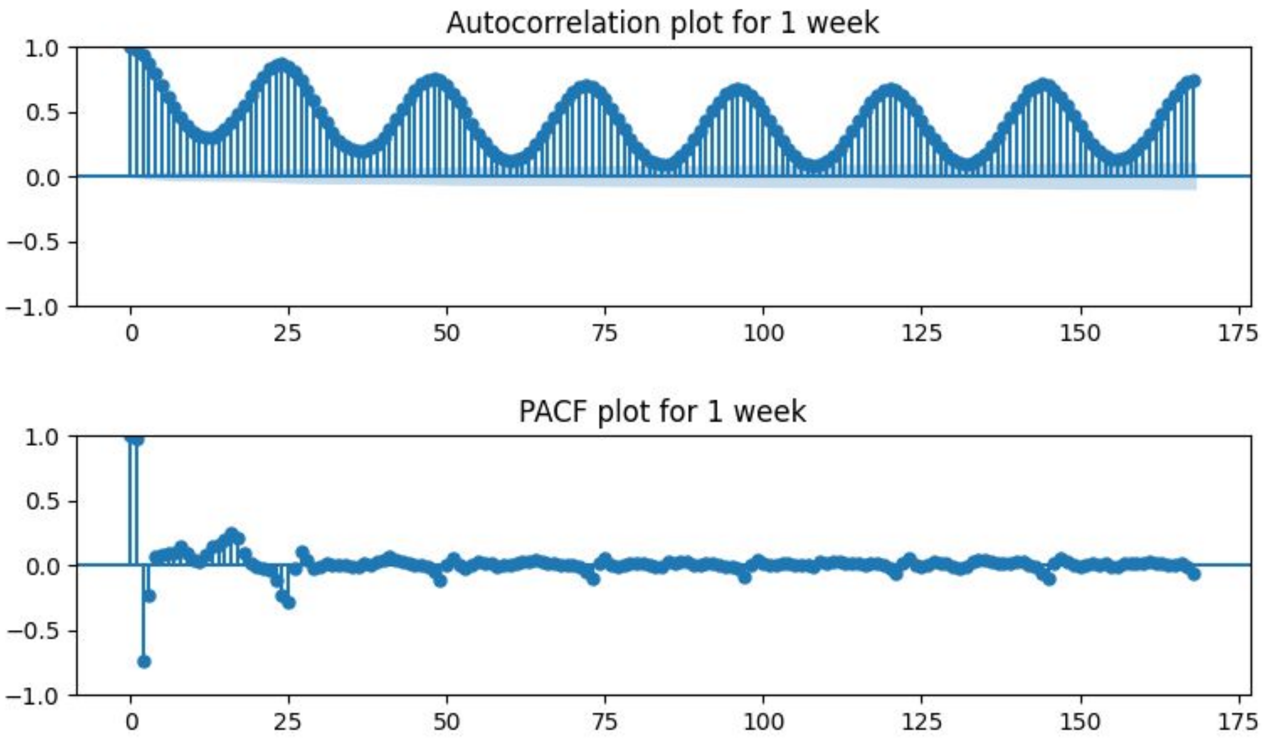




Highly correlated with lag 24

Almost all lags are significant as they are outside the confidence interval

ACF and PACF



Highly correlated with lag 24

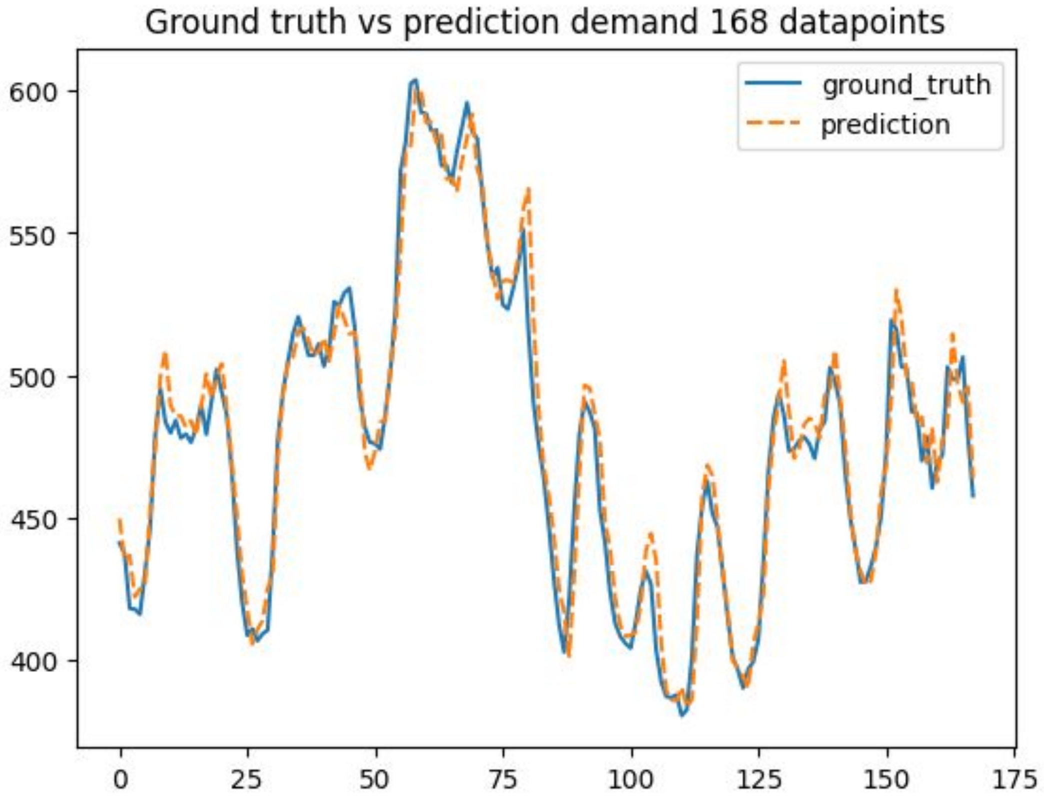
Almost all lags are significant as they are outside the confidence interval

Random Forest Regressor

Train Test Split

160 Week Training	1 Week Validation	1 Week Prediction

Validation



train mae	18.53
val_mae	124.63

1 Week Forecast