AIM:

To perform Energy demand forecasting using different models and compare the results

DATASET:

For this analysis, I have considered only a single building energy data for 1 year:

Period: 16/7/2023 to 17/7/2024

Rows: 53936

Features: 4 – Timestamp, R[kWh], Y[kWh], B[kWh]

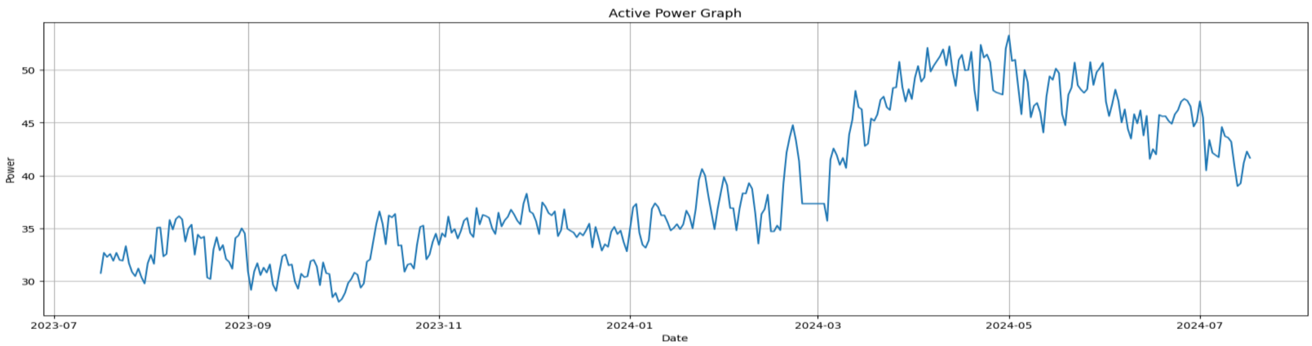
In a three-phase system, active power is measured separately for each of the three phases (**R**, **Y**, and **B**), and the total active power is the sum of the power consumed in all three phases.

The top 5 entries of the dataset are:

	TIME [UTC Seconds]	R[kW]	Y[kW]	B[kW]
0	1.709577e+12	13.48	13.11	13.61
1	1.709578e+12	13.40	12.29	15.80
2	1.709578e+12	13.16	12.28	10.16
3	1.709579e+12	13.10	12.00	11.64
4	1.709579e+12	13.10	12.26	11.70

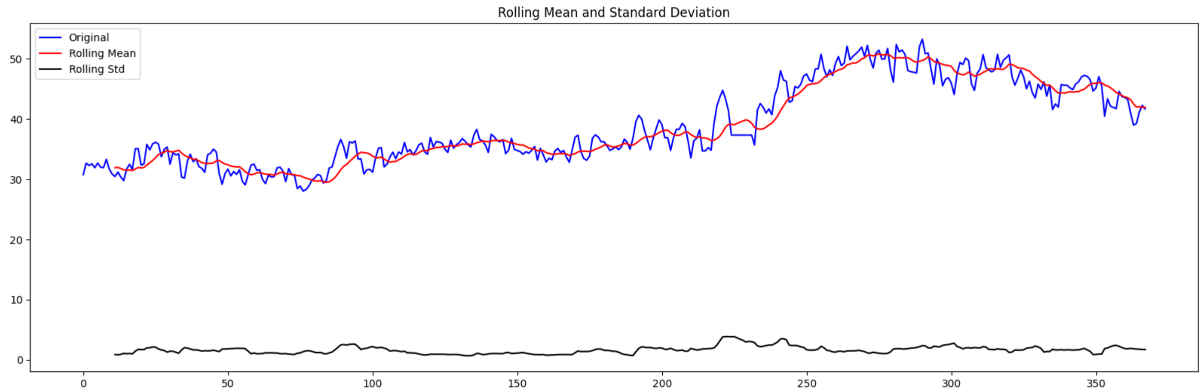
METHODOLOGY:

1. Data Cleaning and Pre-Processing
    - Converting the Time Column to Datetime format
    - Create a new column – 'Total Active Power' which is the sum of three columns – R+Y+B
    - Resample the data to daily intervals and calculate the mean for each day
    - Remove null values my forward fill method
    - Plot a line plot with Date on X axis and Power on Y axis



2. <u>ARIMA MODEL</u>

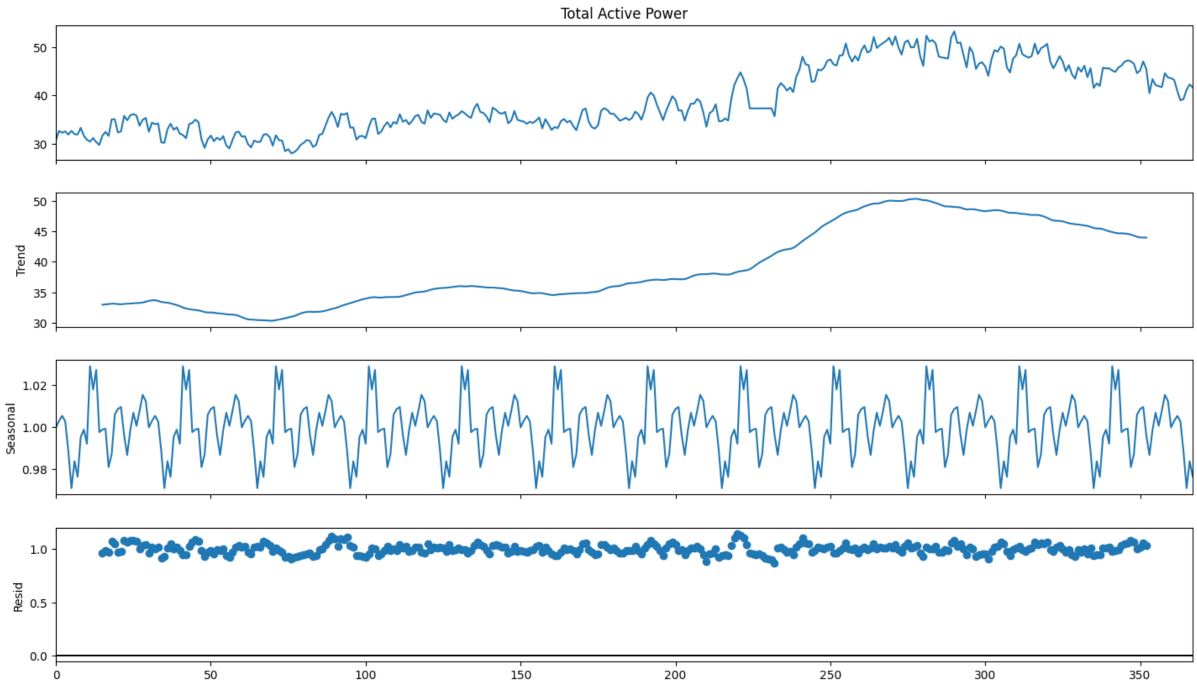
- Test for Stationary



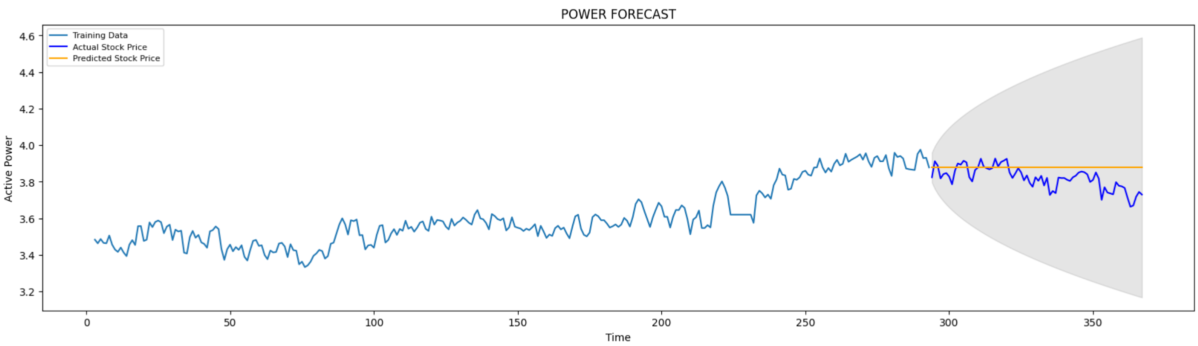
Results of dickey fuller test

Test Statistics	-1.308778
p-value	0.625147
No. of lags used	14.000000
Number of observations used	353.000000
critical value (1%)	-3.449011
critical value (5%)	-2.869763
critical value (10%)	-2.571151

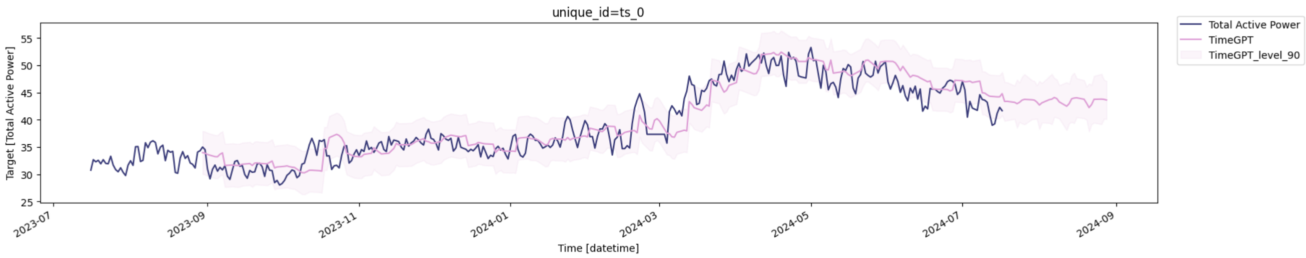
- Decomposing the time series



- Split into training and test set
  80% train data and 20% test data
- Use Auto Arima model to get the best parameters
  Best Model – (0,1,0)
- Fit the model and perform forecasting



3. TIMEGPT MODEL
    - Consider a forecast horizon of 30 days
    - Parameters:
      Confidence level: 90%
      Fine Tuning steps: 200
      Fine Tuning Loss: MAPE



RESULTS:

METRICS	TIMEGPT	ARIMA
MSE	1.84216	0.007068
MAE	5.74742	0.067003
RMSE	2.39737	0.084076
MAPE	4.64%	1.77%

Still work is going on to enhance the forecasting models.