Business Understanding

Objectives:

1. Understand Household Electricity Consumption Patterns: The primary objective of this project is to gain insights into the household's electricity consumption patterns over time. This includes analyzing the trends, seasonality, and any other relevant patterns in the various electricity-related variables.
2. Identify Factors Influencing Electricity Consumption: The project aims to identify the key factors that influence the household's electricity consumption, such as time of day, day of the week, seasons, and the usage of specific appliances (sub-metering data).
3. Develop Predictive Models: Using the time series data, the project may involve developing predictive models to forecast future electricity consumption patterns. This could help the household better manage its energy usage and costs.
4. Optimize Energy Efficiency: The insights gained from the analysis can be used to identify opportunities for improving energy efficiency within the household, such as identifying high-consumption appliances or periods of the day/week with peak demand. Potential Business Applications:
5. Household Energy Management: The analysis can help the household better understand its energy consumption patterns and make informed decisions to optimize energy usage and reduce costs.
6. Utility Company Insights: The project's findings could provide valuable insights to utility companies about residential electricity consumption patterns, which could aid in grid management, demand forecasting, and the development of targeted energy efficiency programs.
7. Energy Policy and Planning: The project's insights could contribute to the development of energy policies and planning initiatives that aim to promote energy efficiency and sustainability at the household and community levels.
8. Research and Development: The dataset and analysis could be used for further research and development in the areas of smart home technologies, energy management systems, and the optimization of household energy consumption. Overall, this time series project on household electricity consumption has the potential to provide valuable insights that can benefit the household, utility companies, policymakers, and researchers in the energy and sustainability domains.

Data Understanding and Loading

```
from google.colab import drive

# Use the 'force_remount=True' argument to remount the drive
drive.mount('/content/drive', force_remount=True)
```

```
Mounted at /content/drive
```

```
#Importing libraries
import sys
import numpy as np # linear algebra
from scipy.stats import randint
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv), data manipulation as in SQL
import matplotlib.pyplot as plt # this is used for the plot the graph
import seaborn as sns # used for plot interactive graph.
from sklearn.model_selection import train_test_split # to split the data into two parts
from sklearn.preprocessing import StandardScaler # for normalization
from sklearn.preprocessing import MinMaxScaler
from sklearn.pipeline import Pipeline # pipeline making
from sklearn.model_selection import cross_val_score
from sklearn.feature_selection import SelectFromModel
from sklearn import metrics # for the check the error and accuracy of the model
from sklearn.metrics import mean_squared_error,r2_score
```

```
#Data Loading
df = pd.read_csv('/content/household_power_consumption[1].txt', sep=';',
                 parse_dates={'dt' : ['Date', 'Time']}, infer_datetime_format=True,
                 low_memory=False, na_values=['nan','?'], index_col='dt')
```

```
<ipython-input-47-2f40051c7c9e>:2: FutureWarning: The argument 'infer_datetime_format' is deprecated and will be removed in a future
  df = pd.read_csv('/content/household_power_consumption[1].txt', sep=';',
<ipython-input-47-2f40051c7c9e>:2: UserWarning: Parsing dates in %d/%m/%Y %H:%M:%S format when dayfirst=False (the default) was spec
  df = pd.read_csv('/content/household_power_consumption[1].txt', sep=';',
```

```
# Ensure 'Datetime' column is present and convert to datetime
if 'Datetime' in df.columns:
    df['Datetime'] = pd.to_datetime(df['Datetime']) # Fixed indentation
    df.set_index('Datetime', inplace=True)
```

```
df.head()
```

	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Sub_metering_3
dt							
2006-12-16 17:24:00	4.216	0.418	234.84	18.4	0.0	1.0	17.0
2006-12-16 17:25:00	5.360	0.436	233.63	23.0	0.0	1.0	16.0
2006-12-16 17:26:00	5.374	0.498	233.29	23.0	0.0	2.0	17.0
2006-12-16	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 2075259 entries, 2006-12-16 17:24:00 to 2010-11-26 21:02:00
Data columns (total 7 columns):
 #   Column                 Dtype
---  ------                 -----
 0   Global_active_power    float64
 1   Global_reactive_power  float64
 2   Voltage                float64
 3   Global_intensity       float64
 4   Sub_metering_1         float64
 5   Sub_metering_2         float64
 6   Sub_metering_3         float64
dtypes: float64(7)
memory usage: 126.7 MB
```

```
df.shape
```

```
(2075259, 7)
```

```
df.describe().T
```

	count	mean	std	min	25%	50%	75%	max
Global_active_power	2049280.0	1.091615	1.057294	0.076	0.308	0.602	1.528	11.122
Global_reactive_power	2049280.0	0.123714	0.112722	0.000	0.048	0.100	0.194	1.390
Voltage	2049280.0	240.839858	3.239987	223.200	238.990	241.010	242.890	254.150
Global_intensity	2049280.0	4.627759	4.444396	0.200	1.400	2.600	6.400	48.400
Sub_metering_1	2049280.0	1.121923	6.153031	0.000	0.000	0.000	0.000	88.000
Sub_metering_2	2049280.0	1.298520	5.822026	0.000	0.000	0.000	1.000	80.000
Sub_metering_3	2049280.0	6.458447	8.437154	0.000	0.000	1.000	17.000	31.000

Double-click (or enter) to edit

Data Cleaning

```
#Checking for missing values
df.isnull().sum()
```

```
Global_active_power      25979
Global_reactive_power    25979
Voltage                  25979
Global_intensity         25979
Sub_metering_1           25979
Sub_metering_2           25979
Sub_metering_3           25979
dtype: int64
```

```
#Checking for duplicates
df.duplicated().sum()
```

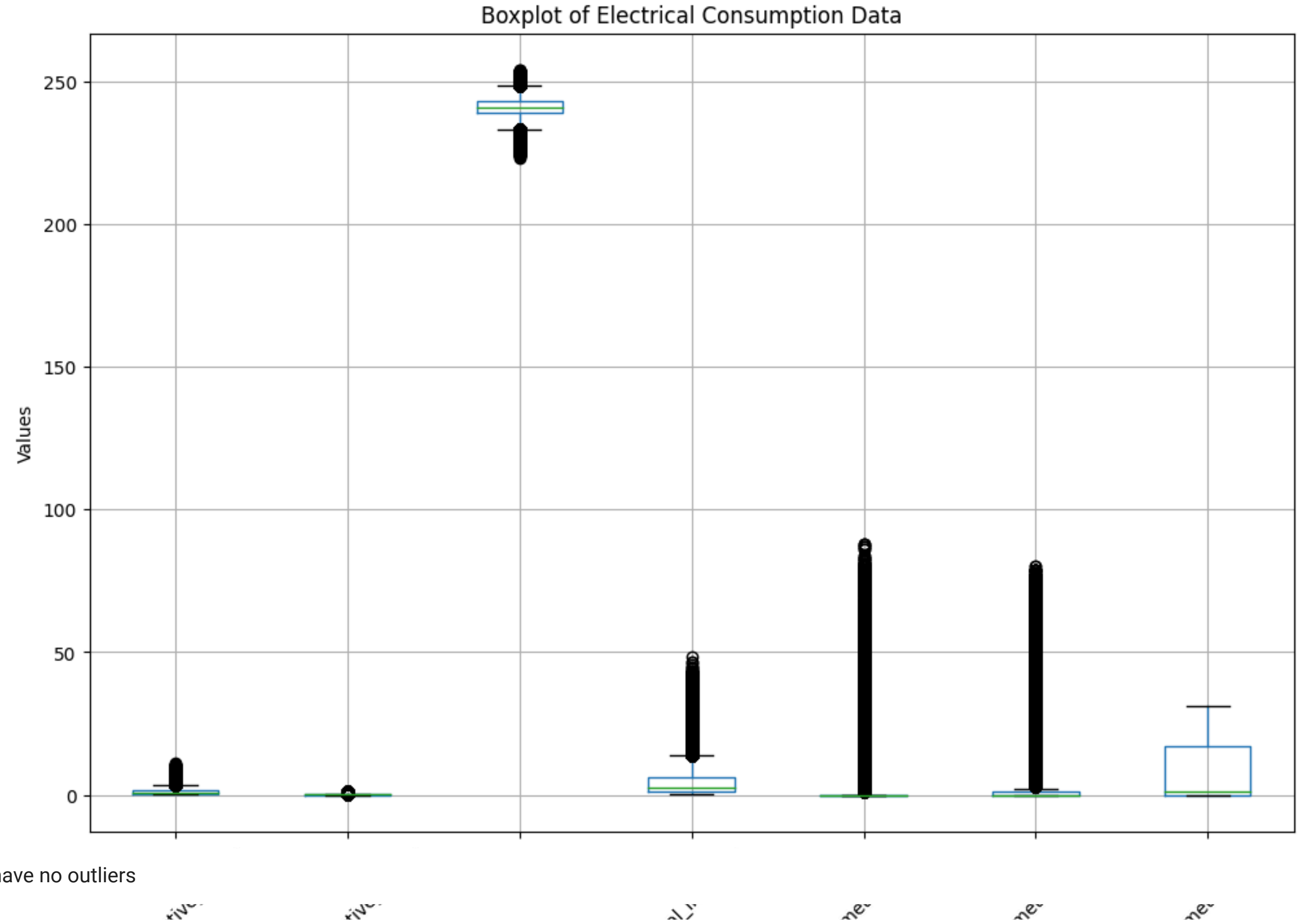
```
168560
```

```
#Checking for missing values
df.isna().sum()
```

```
Global_active_power      25979
Global_reactive_power    25979
Voltage                  25979
Global_intensity         25979
Sub_metering_1           25979
Sub_metering_2           25979
Sub_metering_3           25979
dtype: int64
```

```
#Fill missing values with mean
df['Global_active_power'].fillna(method='ffill', inplace=True)
```

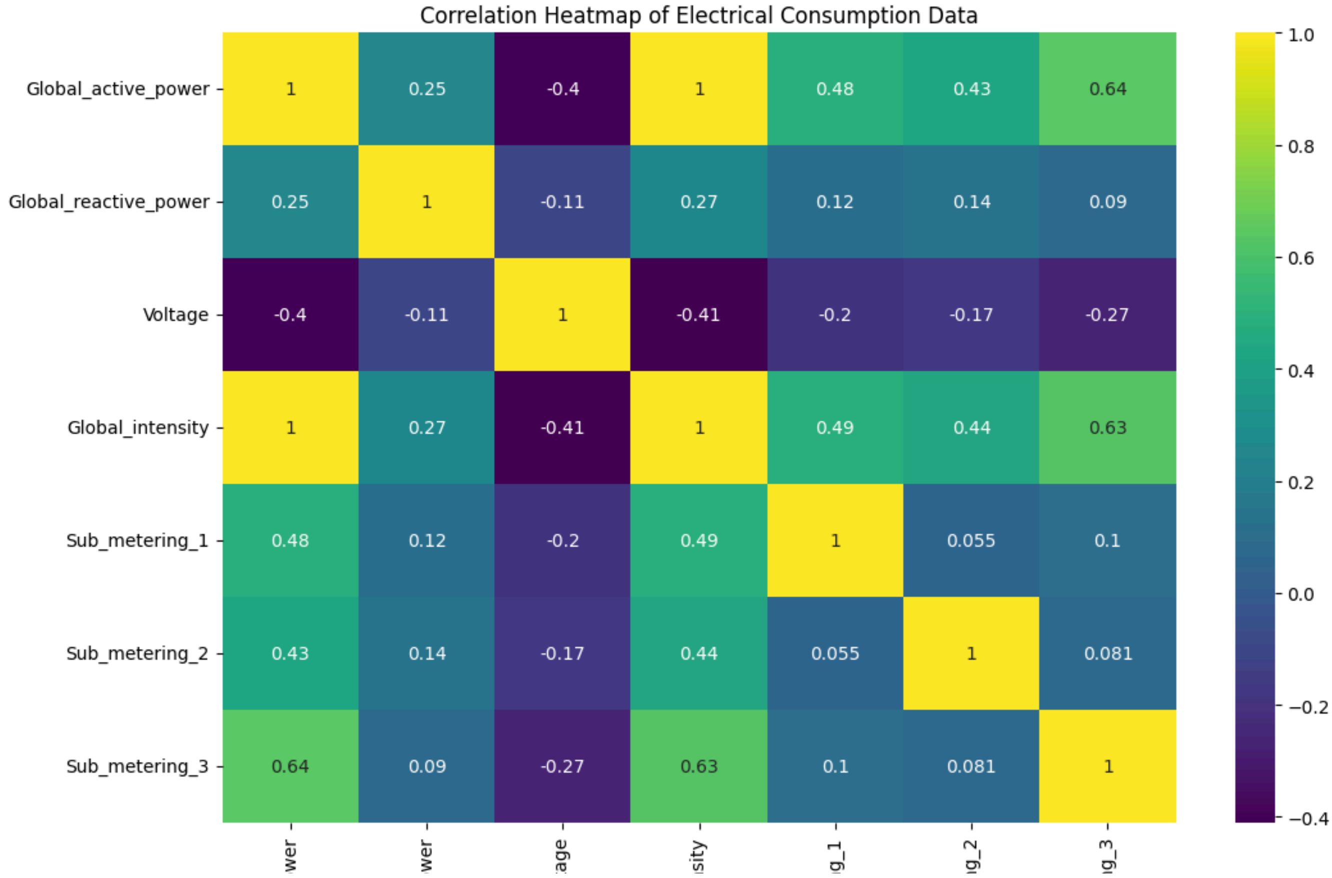
```
#Checking for outliers
plt.figure(figsize=(12, 8))
df.boxplot(column=['Global_active_power', 'Global_reactive_power', 'Voltage', 'Global_intensity', 'Sub_metering_1', 'Sub_metering_2', 'S
plt.title('Boxplot of Electrical Consumption Data')
plt.ylabel('Values')
plt.xticks(rotation=45)
plt.show()
```



We have no outliers

Data Visualiation and EDA

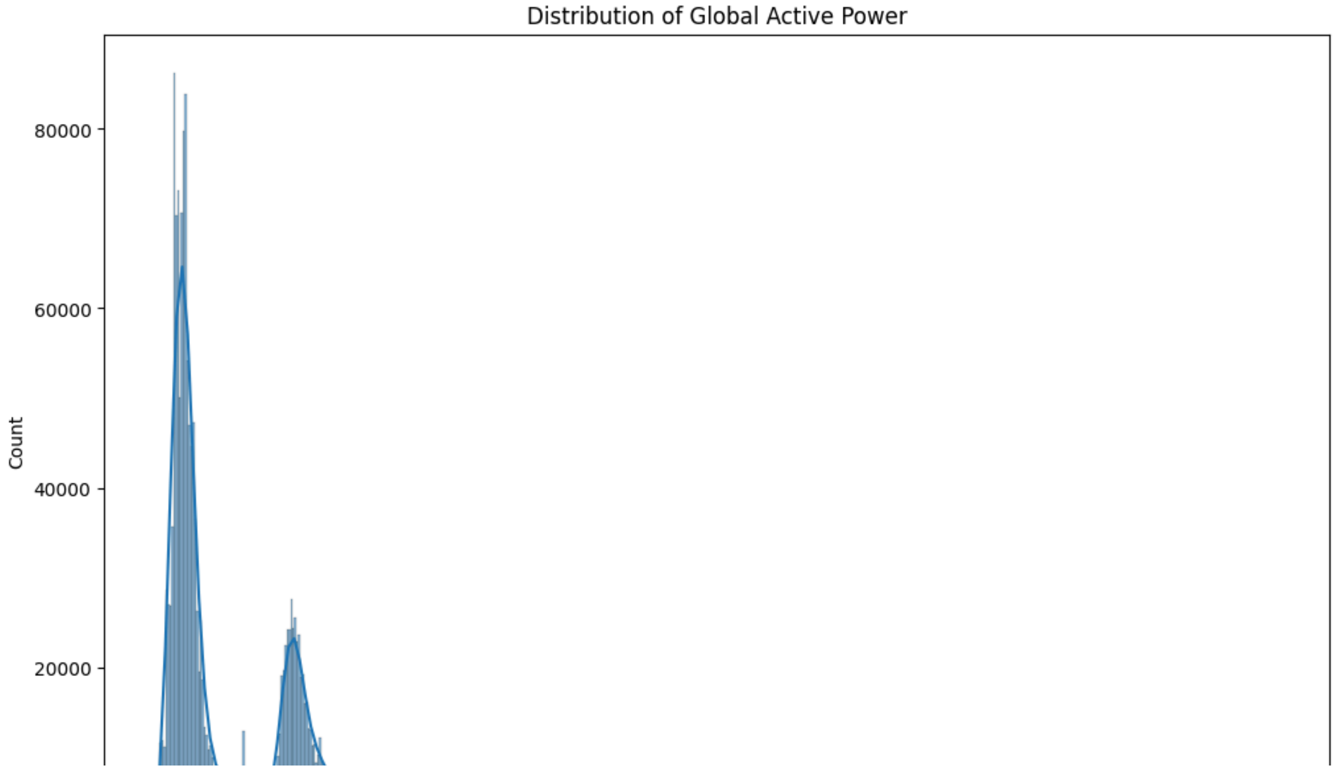
```
#Correlation heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(df.corr(), annot=True, cmap='viridis')
plt.title('Correlation Heatmap of Electrical Consumption Data')
plt.show()
```



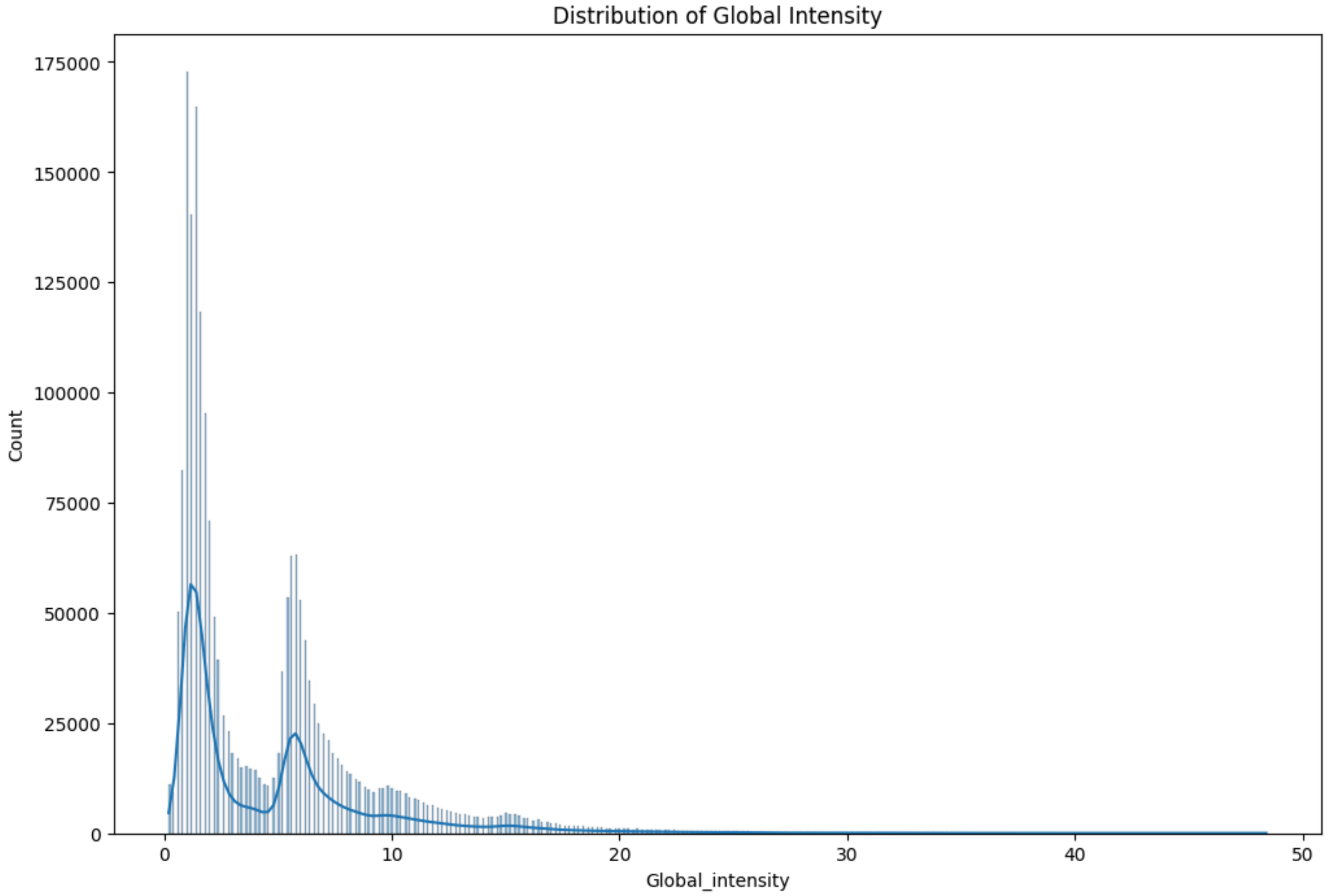

```
#Highly correlated features summary
corr_matrix = df.corr()
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(bool))
to_drop = [column for column in upper.columns if any(abs(upper[column]) > 0.5)]

print(f"The following {len(to_drop)} features are highly correlated (|r| > 0.5):")
print(', '.join(to_drop))
```

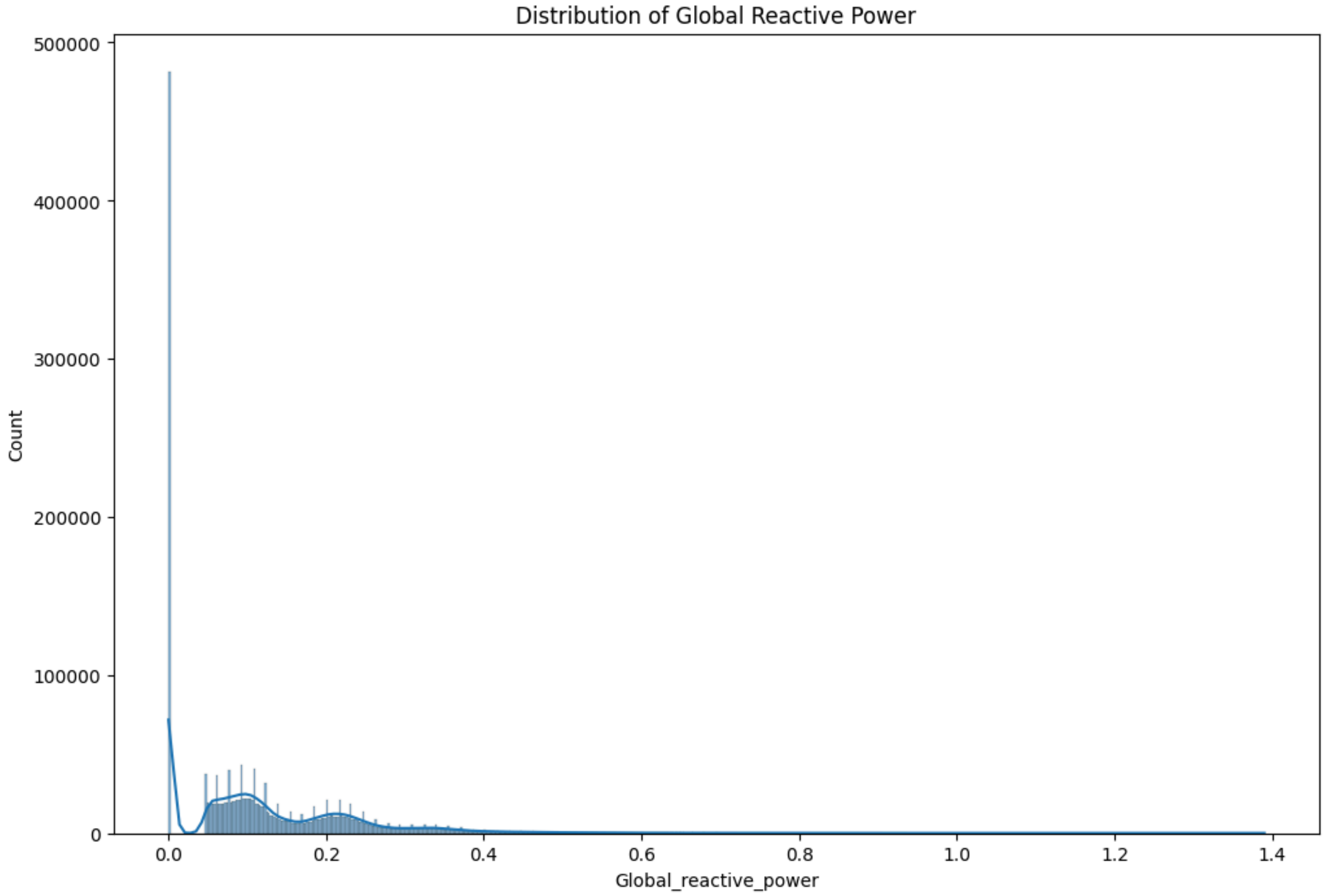
```
The following 2 features are highly correlated (|r| > 0.5):
Global_intensity, Sub_metering_3
```

```
#Univariate analysis on Global active power
plt.figure(figsize=(12, 8))
sns.histplot(data=df, x='Global_active_power', kde=True)
plt.title('Distribution of Global Active Power')
plt.show()
```

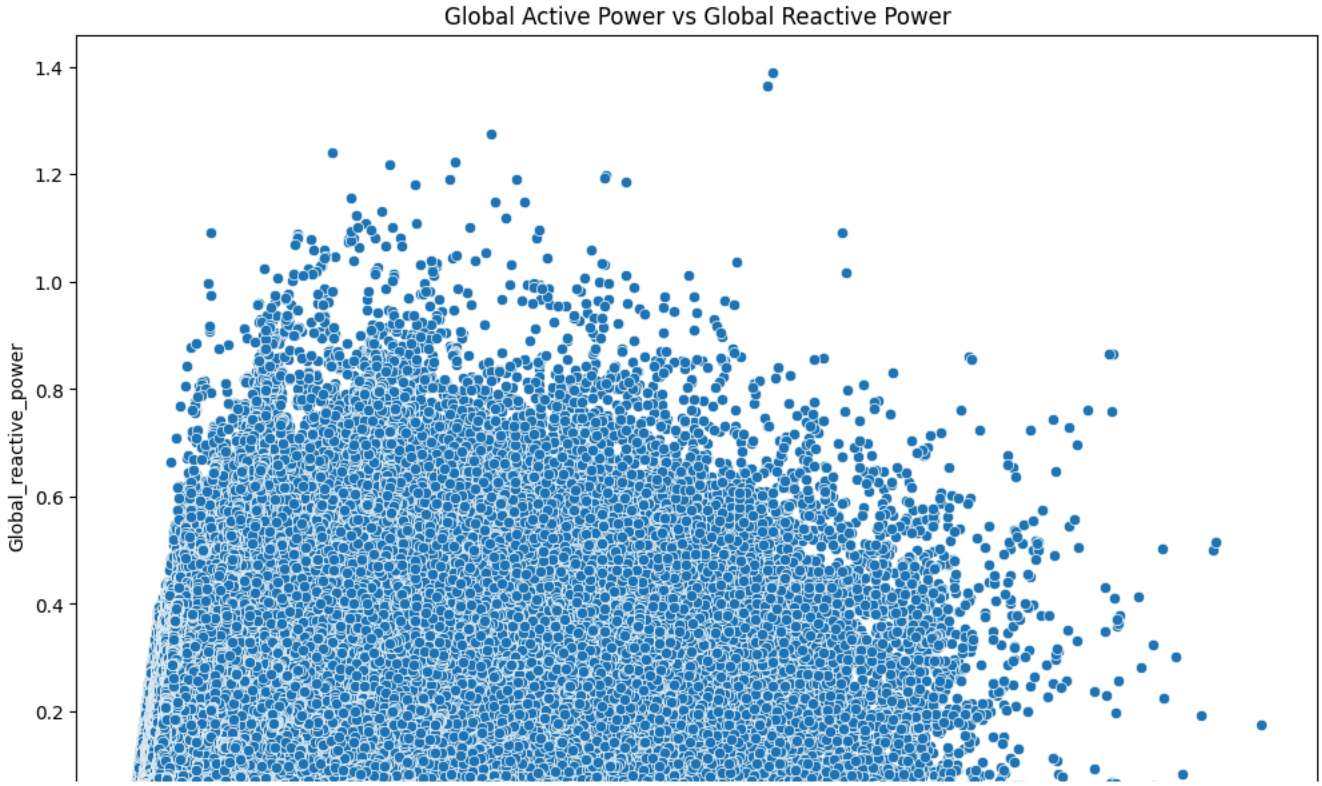



```
##Univariate analysis on Global reactive power and Global intensity
plt.figure(figsize=(12, 8))
sns.histplot(data=df, x='Global_intensity', kde=True)
plt.title('Distribution of Global Intensity')
plt.show()
plt.figure(figsize=(12, 8))
sns.histplot(data=df, x='Global_reactive_power', kde=True)
plt.title('Distribution of Global Reactive Power')
plt.show()
```

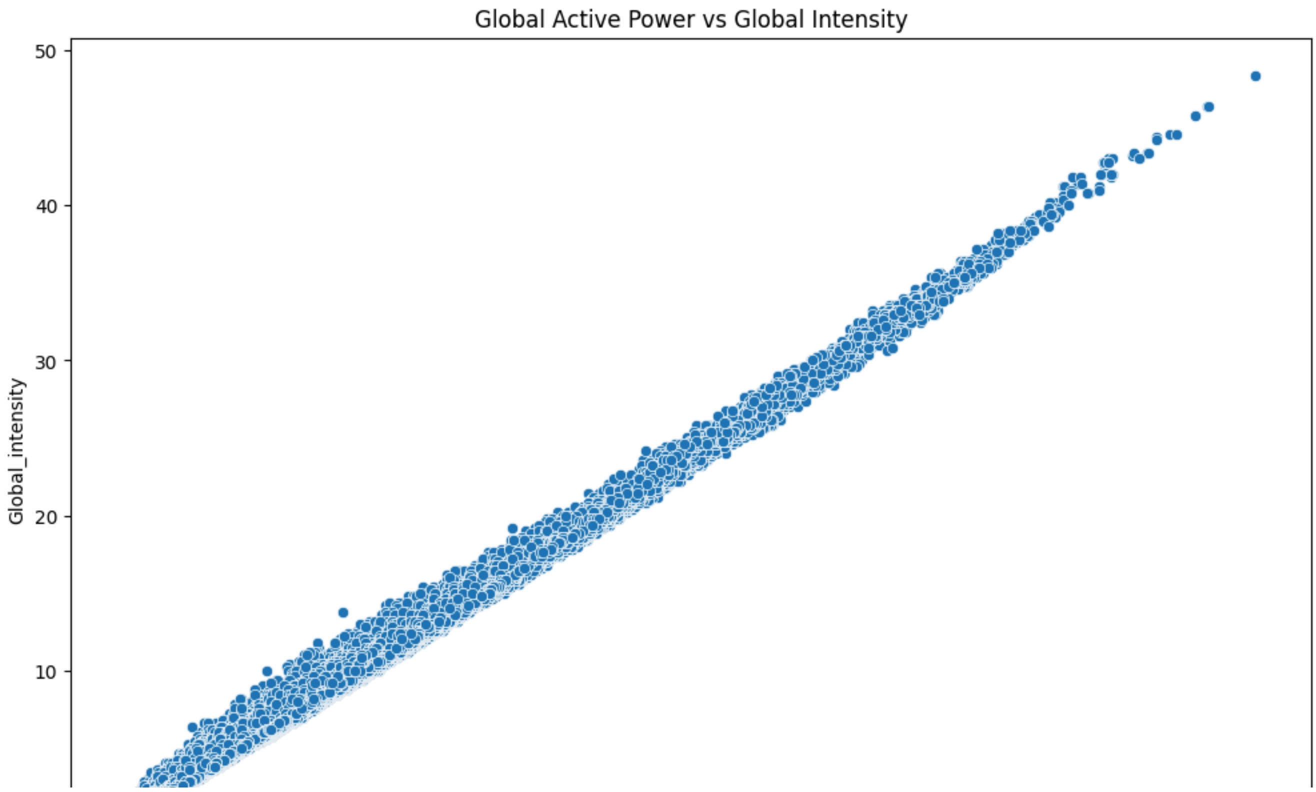




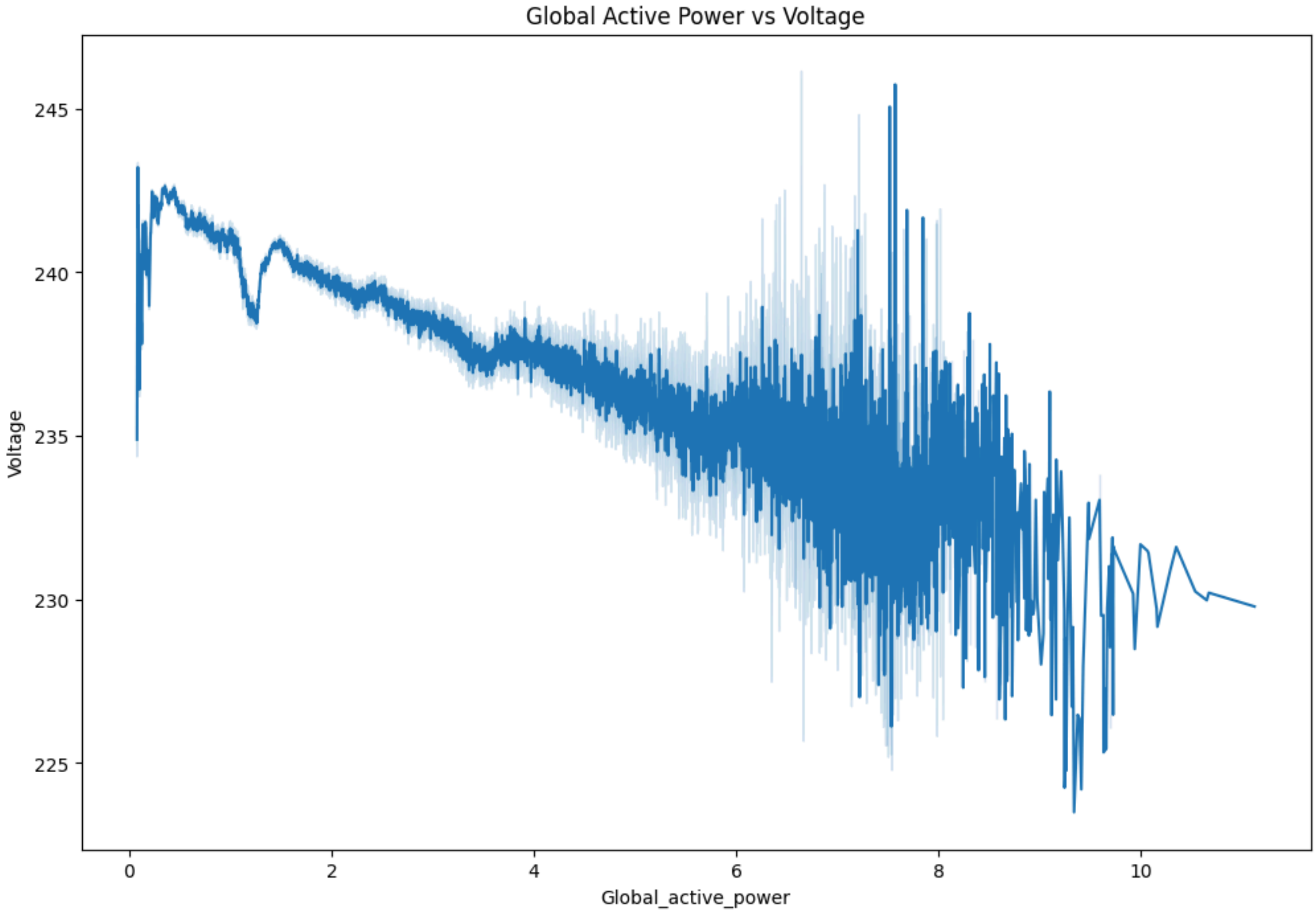

```
#plotting global active power vs global reactive power
plt.figure(figsize=(12, 8))
sns.scatterplot(data=df, x='Global_active_power', y='Global_reactive_power')
plt.title('Global Active Power vs Global Reactive Power')
plt.show()
```




```
#plotting global active power vs global intensity
plt.figure(figsize=(12, 8))
sns.scatterplot(data=df, x='Global_active_power', y='Global_intensity')
plt.title('Global Active Power vs Global Intensity')
plt.show()
```




```
#plotting global active power and voltage line plot
plt.figure(figsize=(12, 8))
sns.lineplot(data=df, x='Global_active_power', y='Voltage')
plt.title('Global Active Power vs Voltage')
plt.show()

#Explain findings
```

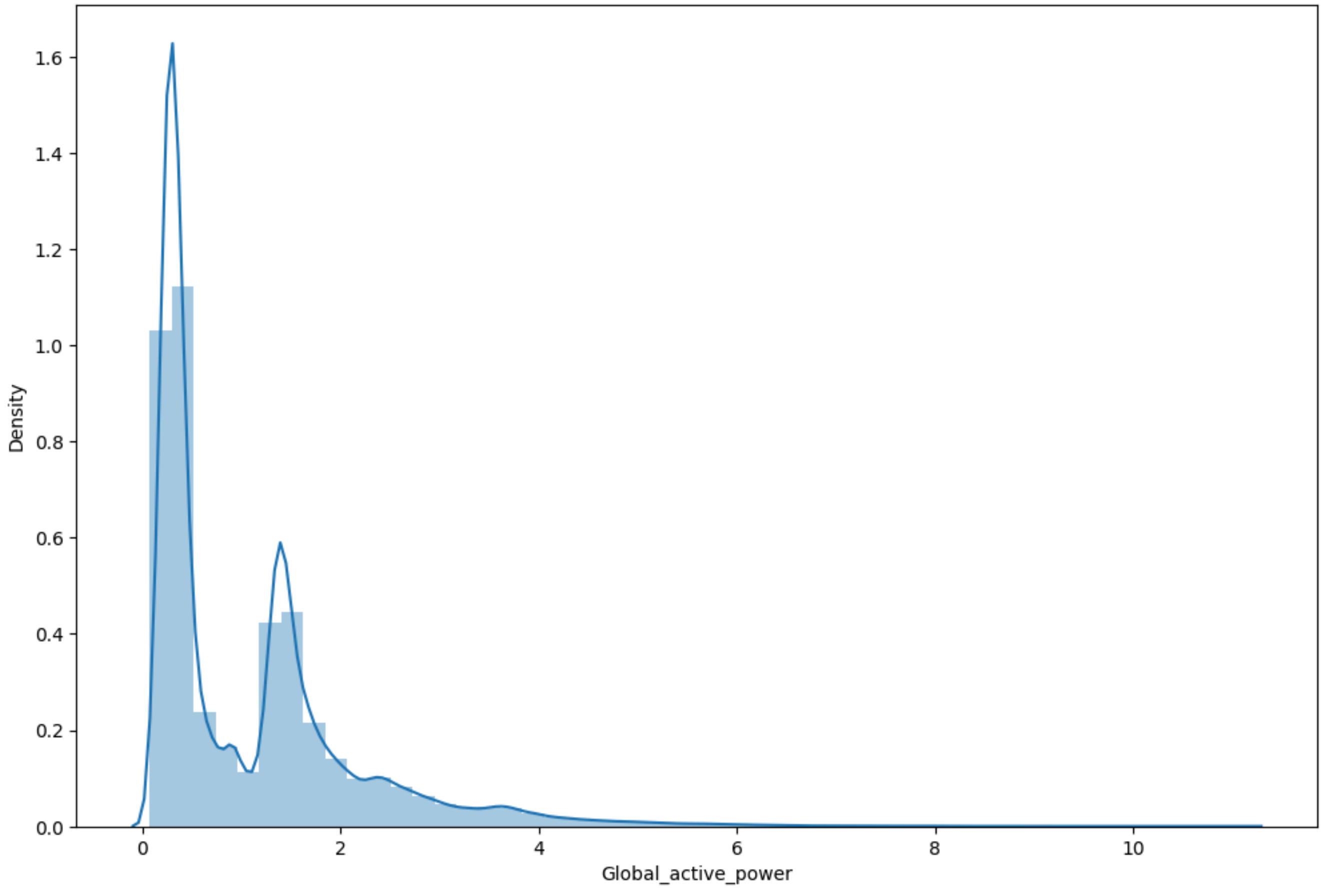



```
#Checking the distribution of out data
df.skew()
```

```
Global_active_power      1.797454
Global_reactive_power    1.261914
Voltage                 -0.326665
Global_intensity         1.849100
Sub_metering_1           5.944541
Sub_metering_2           7.090553
Sub_metering_3           0.724688
dtype: float64
```

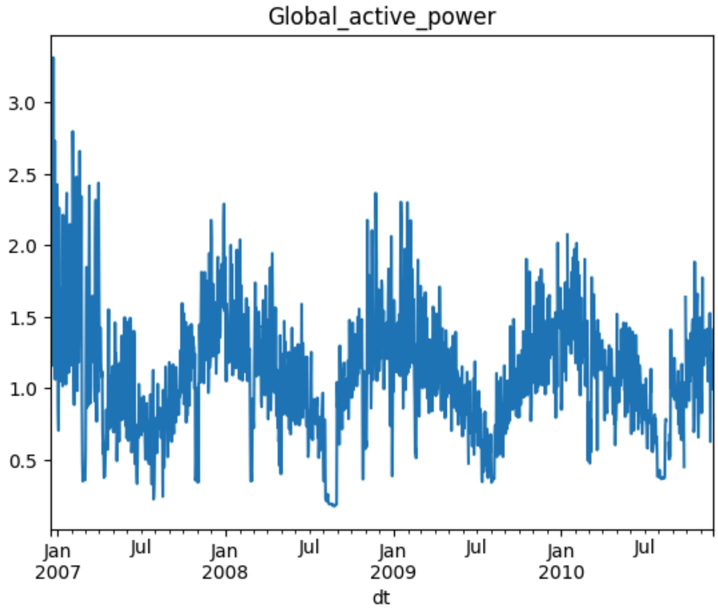
```
#Checking if our data is normally distributed
plt.figure(figsize=(12, 8))
sns.distplot(df['Global_active_power'])
```

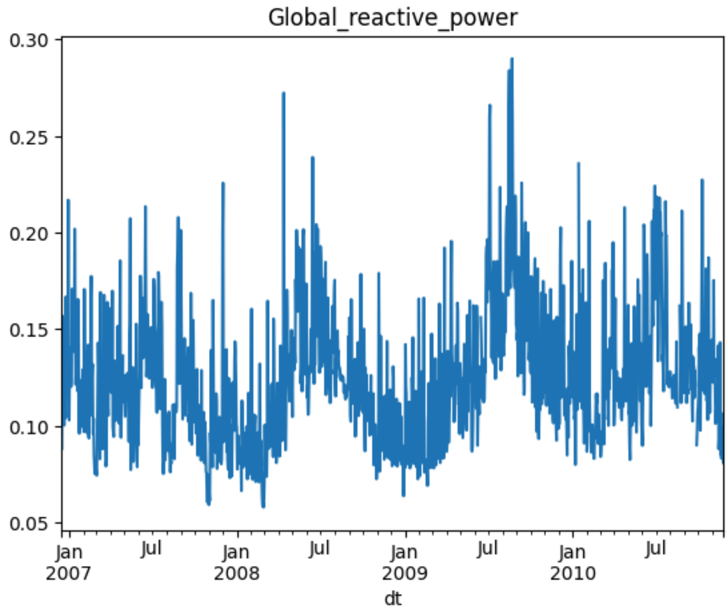
```
<ipython-input-26-a771818689ed>:3: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df['Global_active_power'])
<Axes: xlabel='Global_active_power', ylabel='Density'>
```

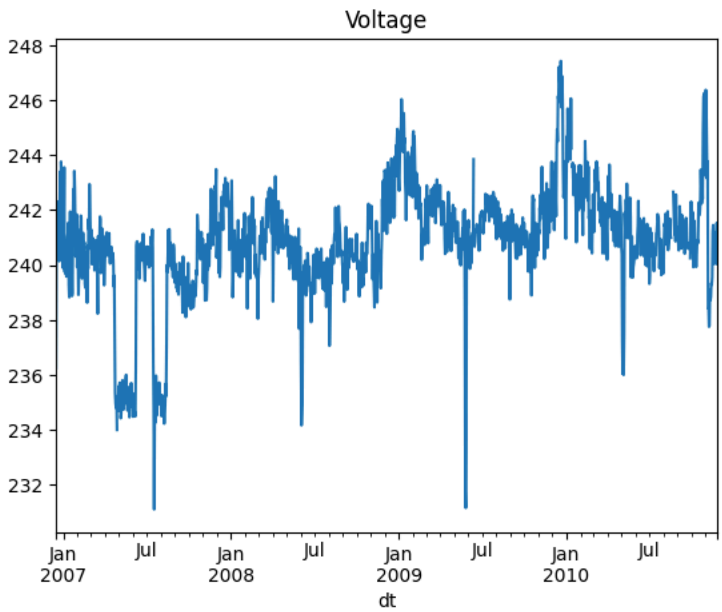


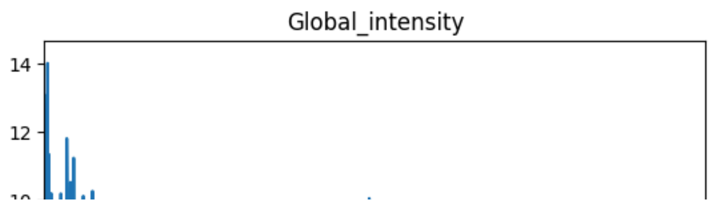

```
def plot_all_columns(df, rule='D'):
    for c in df.select_dtypes(include=['float64']):
        df[c].resample(rule=rule).mean().plot(title=c)
        plt.show()
```

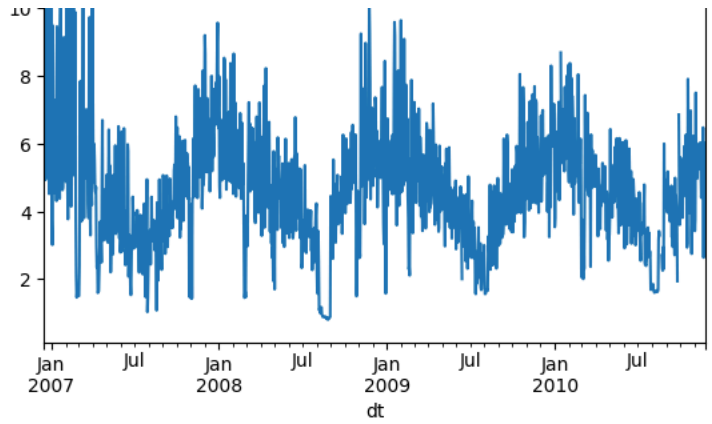
```
plot_all_columns(df)
```

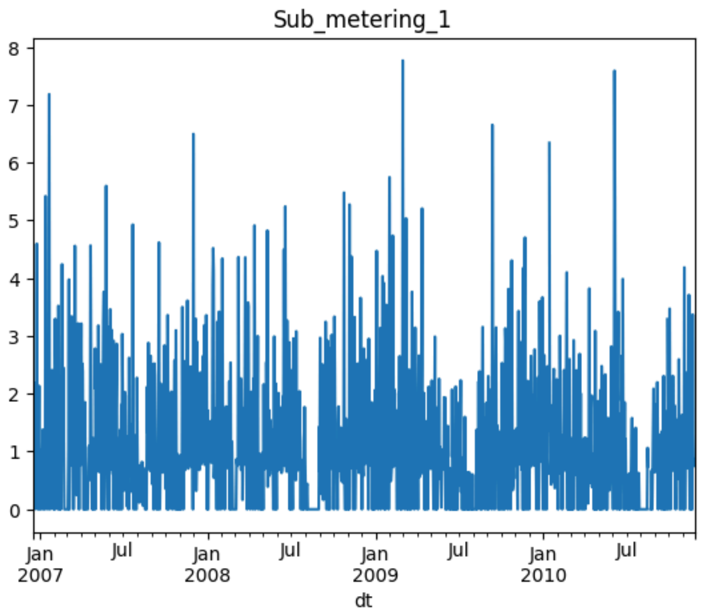

Global_active_power
3.0
2.5
2.0
1.5
1.0
0.5
Jan 2007
Jul
Jan 2008
Jul
Jan 2009
Jul
Jan 2010
Jul
dt

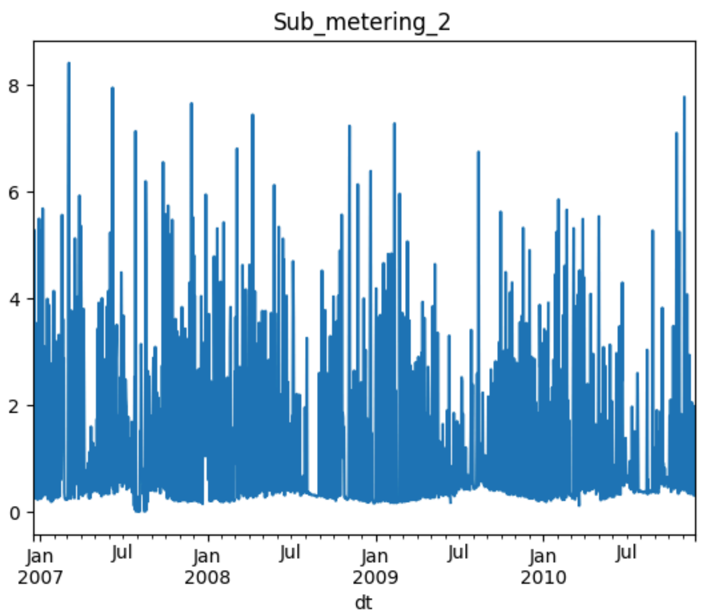

Global_reactive_power
0.30
0.25
0.20
0.15
0.10
0.05
Jan 2007
Jul
Jan 2008
Jul
Jan 2009
Jul
Jan 2010
Jul
dt

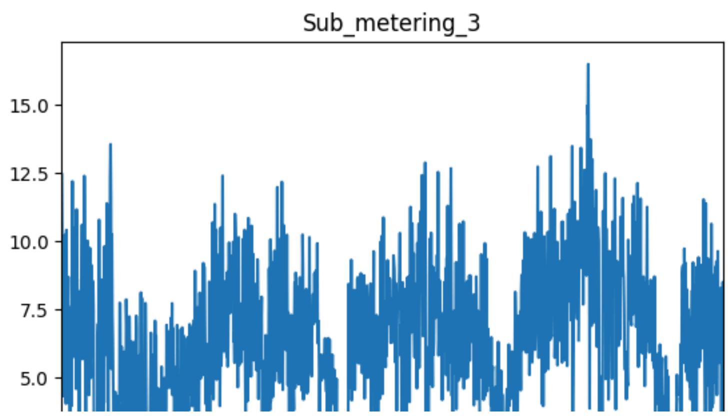

Voltage
248
246
244
242
240
238
236
234
232
Jan 2007
Jul
Jan 2008
Jul
Jan 2009
Jul
Jan 2010
Jul
dt

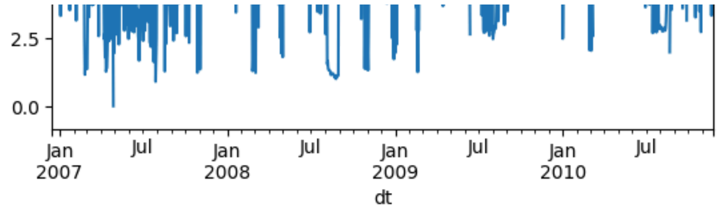

Global_intensity
14
12


10
8
6
4
2
Jan 2007
Jul
Jan 2008
Jul
Jan 2009
Jul
Jan 2010
Jul
dt

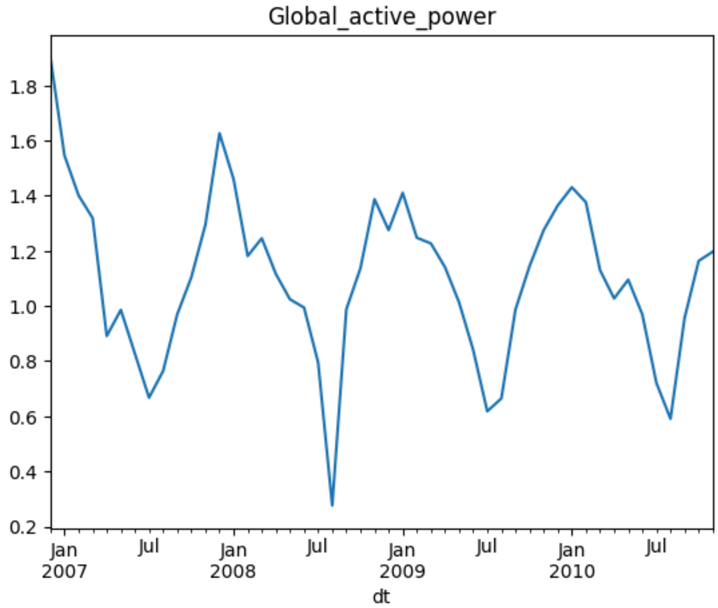

Sub_metering_1
8
7
6
5
4
3
2
1
0
Jan 2007
Jul
Jan 2008
Jul
Jan 2009
Jul
Jan 2010
Jul
dt

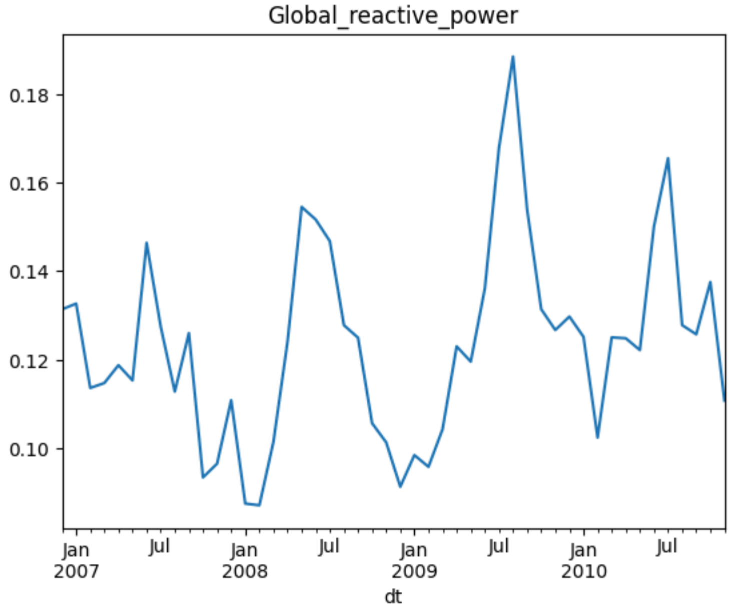

Sub_metering_2
8
6
4
2
0
Jan 2007
Jul
Jan 2008
Jul
Jan 2009
Jul
Jan 2010
Jul
dt

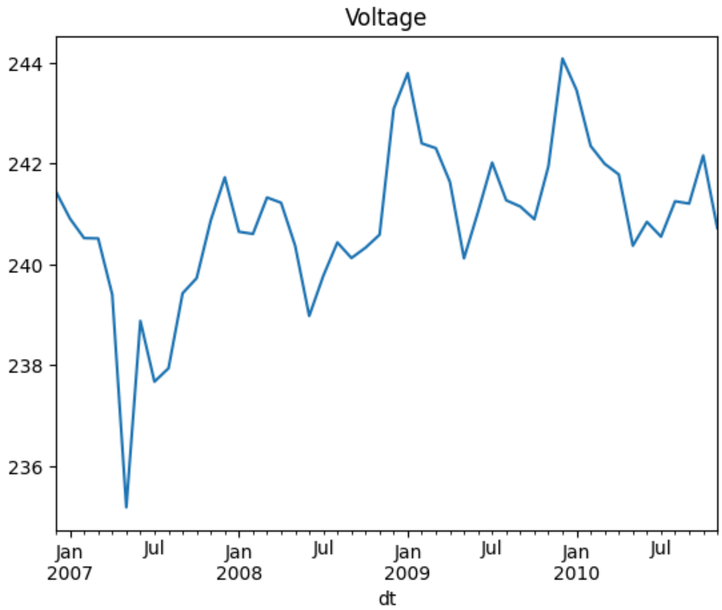

Sub_metering_3
15.0
12.5
10.0
7.5
5.0

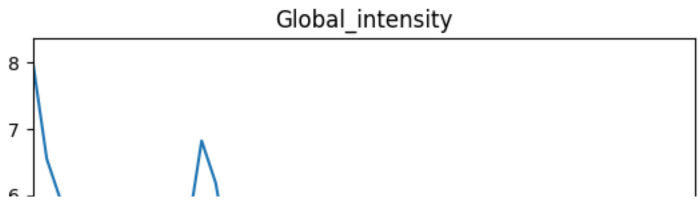


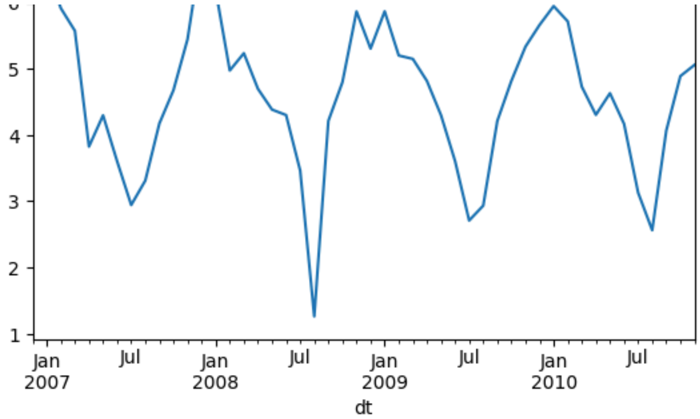

```
plot_all_columns(df, rule='M')
```


Global_active_power
1.8
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
Jan 2007
Jul
Jan 2008
Jul
Jan 2009
Jul
Jan 2010
Jul
dt

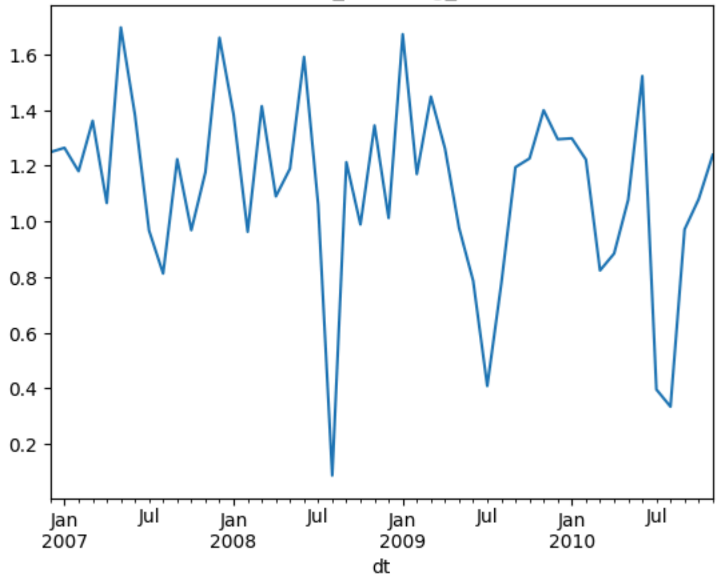

Global_reactive_power
0.18
0.16
0.14
0.12
0.10
Jan 2007
Jul
Jan 2008
Jul
Jan 2009
Jul
Jan 2010
Jul
dt


Voltage
244
242
240
238
236
Jan 2007
Jul
Jan 2008
Jul
Jan 2009
Jul
Jan 2010
Jul
dt

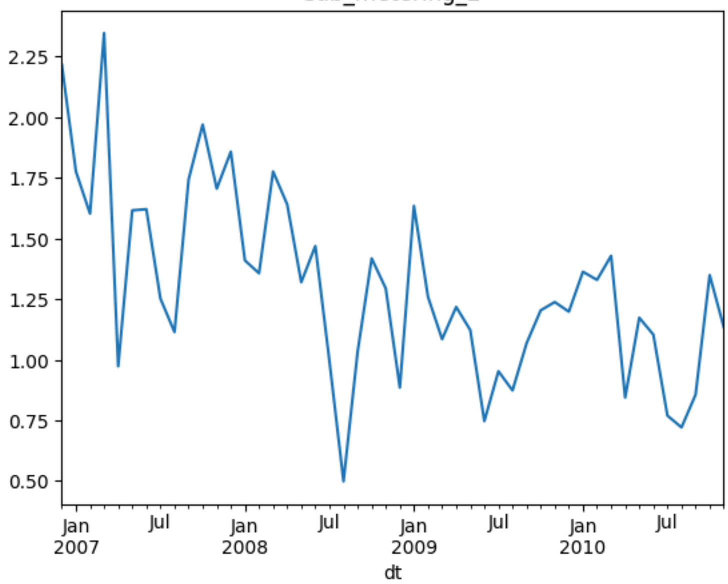

Global_intensity
8
7



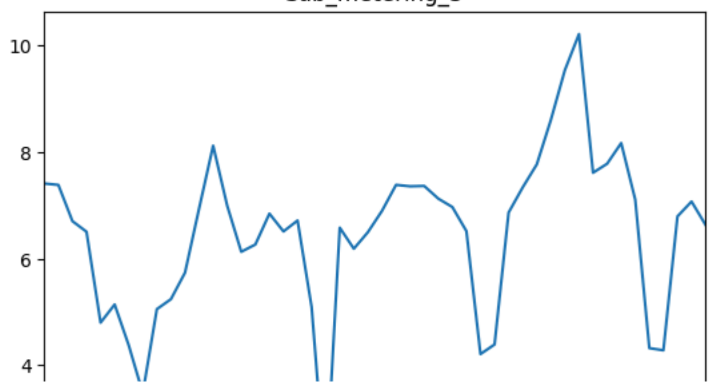
Sub_metering_1

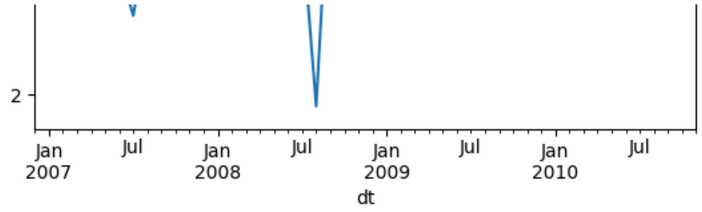


Sub_metering_2

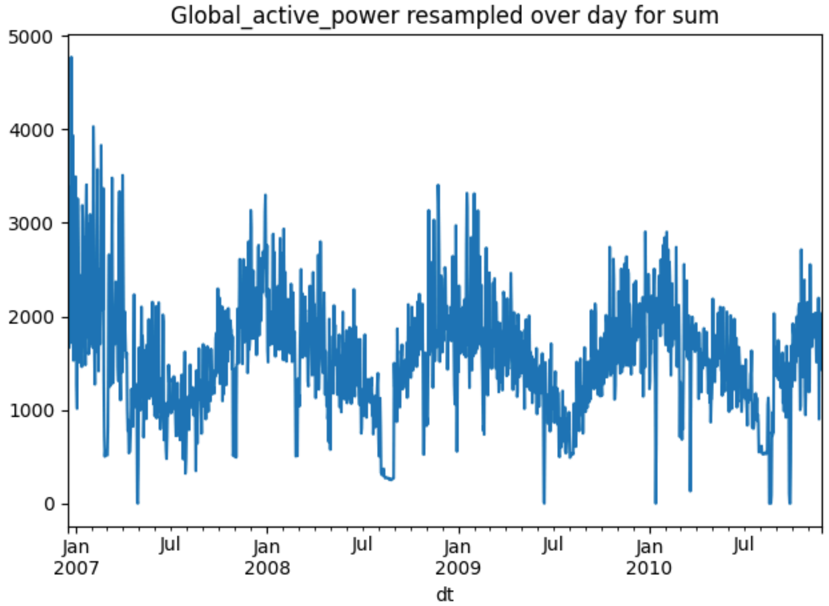


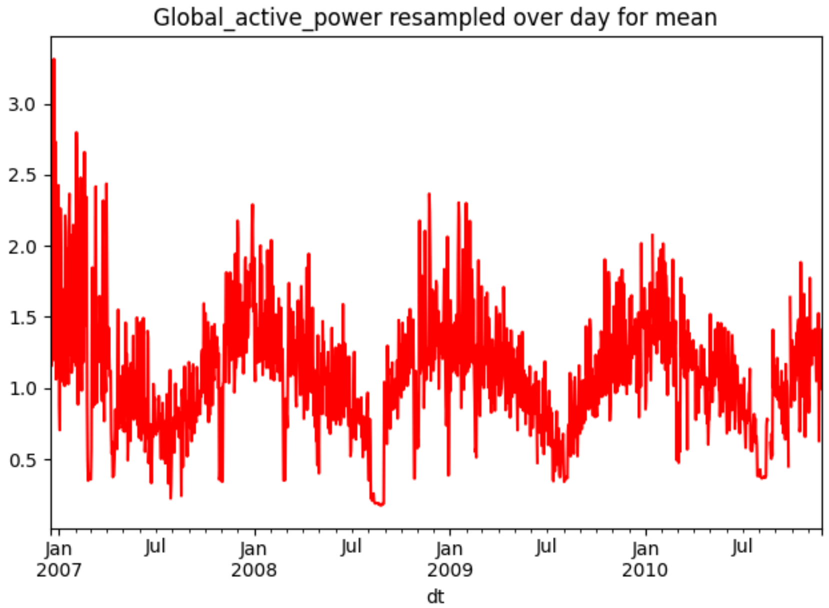
Sub_metering_3






```
#Resampling the data over Day
df.Global_active_power.resample('D').sum().plot(title='Global_active_power resampled over day for sum')
#df.Global_active_power.resample('D').mean().plot(title='Global_active_power resampled over day', color='red')
plt.tight_layout()
plt.show()

df.Global_active_power.resample('D').mean().plot(title='Global_active_power resampled over day for mean', color='red')
plt.tight_layout()
plt.show()
```





The sum plot helps identify total daily consumption patterns. The mean plot helps identify average daily usage, smoothing out multiple entries per day Sum Plot:High consumption on February 23rd and lower on 27th . Mean plot :Highest mean on February 23rd, showing a day with consistently high usage.

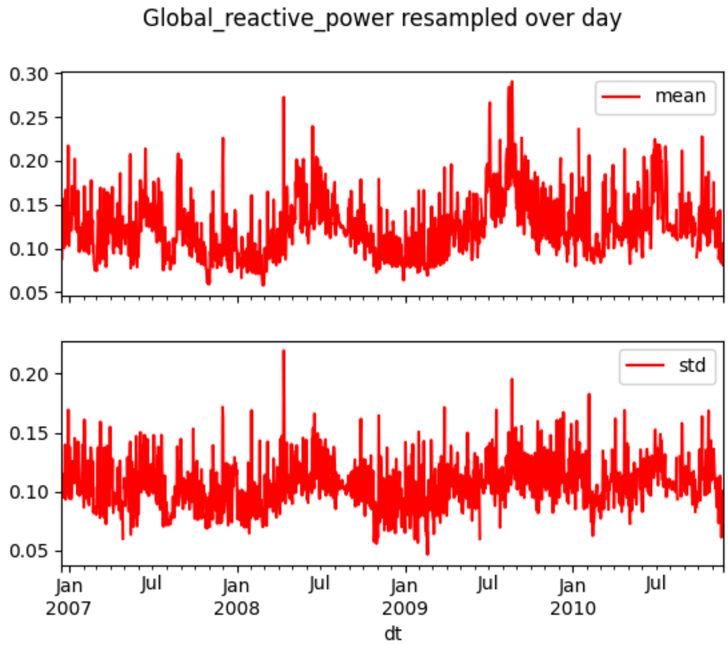
Double-click (or enter) to edit

Below shows the mean and std of 'Global_intensity' resampled over day

```
r = df.Global_intensity.resample('D').agg(['mean', 'std'])
r.plot(subplots = True, title='Global_intensity resampled over day')
plt.show()
```

showing mean and std of 'Global_reactive_power' resampled over day

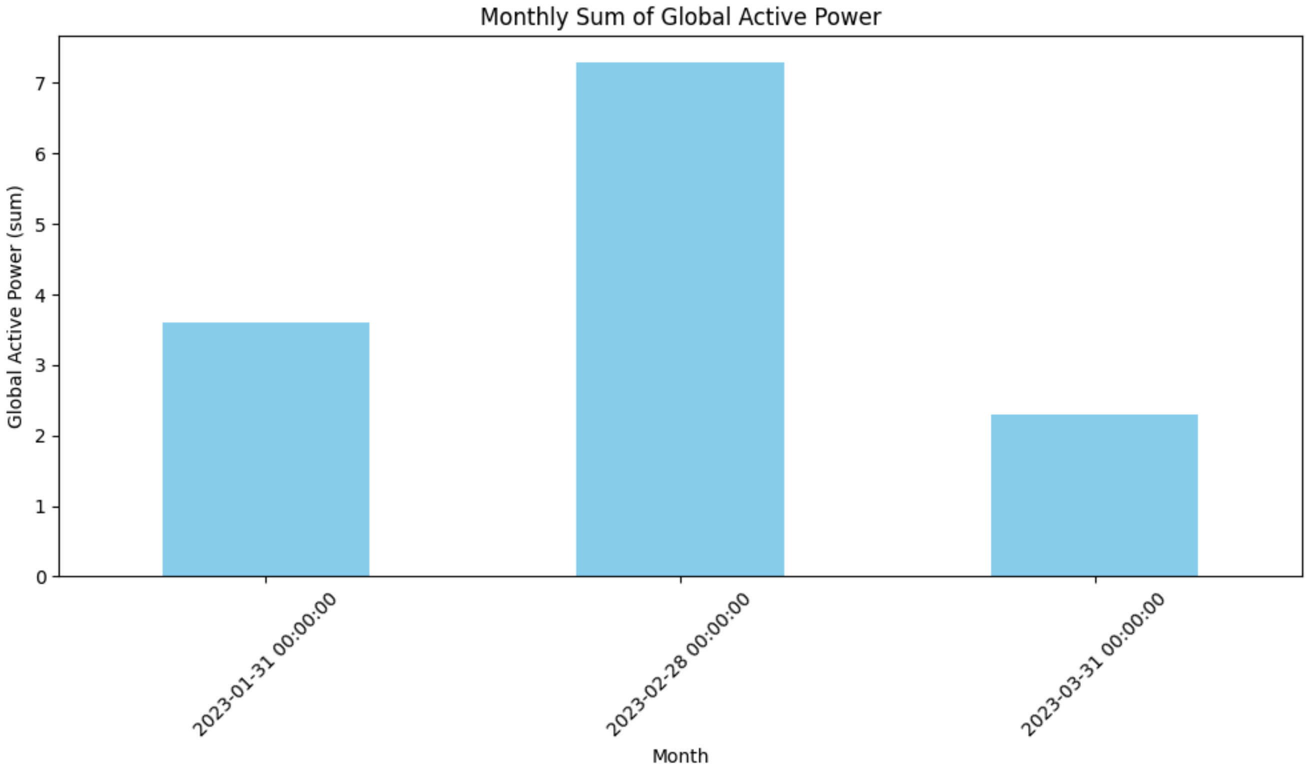
```
r2 = df.Global_reactive_power.resample('D').agg(['mean', 'std'])
r2.plot(subplots = True, title='Global_reactive_power resampled over day', color='red')
plt.show()
```



Sum of 'Global_active_power' resampled over month

```
# Sample data creation
data = pd.DataFrame({
    'Global_active_power': [1.2, 2.4, 3.1, 4.2, 2.3],
    'Datetime': ['2023-01-01', '2023-01-02', '2023-02-01', '2023-02-02', '2023-03-01']
})

# Print the columns to verify
print("Columns in DataFrame:", data.columns)

# Ensure 'Datetime' column is present and convert to datetime
if 'Datetime' in data.columns:
    data['Datetime'] = pd.to_datetime(data['Datetime'])
    data.set_index('Datetime', inplace=True)

    # Resample the data by month and calculate the sum of 'Global_active_power'
    monthly_sum = data['Global_active_power'].resample('M').sum()

    # Display the result
    print("Monthly Sum of Global_active_power:")
    print(monthly_sum)
     # Plot the result
    plt.figure(figsize=(10, 6))
    monthly_sum.plot(kind='bar', color='skyblue')
    plt.title('Monthly Sum of Global Active Power')
    plt.xlabel('Month')
    plt.ylabel('Global Active Power (sum)')
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.show()
else:
    print("The column 'Datetime' does not exist in the DataFrame.")
```

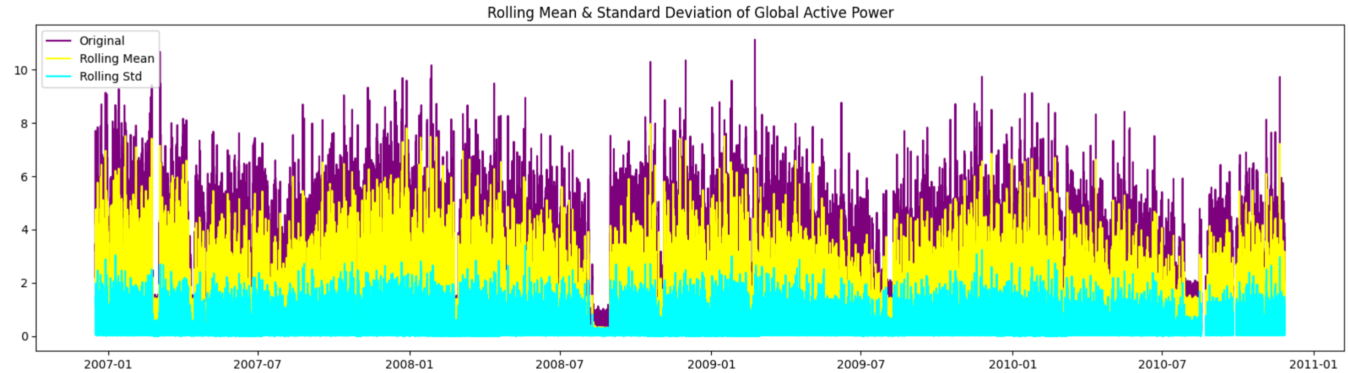
```
Columns in DataFrame: Index(['Global_active_power', 'Datetime'], dtype='object')
Monthly Sum of Global_active_power:
Datetime
2023-01-31    3.6
2023-02-28    7.3
2023-03-31    2.3
Freq: M, Name: Global_active_power, dtype: float64
```



February 2023 has the highest energy consumption (sum of 'Global_active_power'), possibly indicating higher activity or usage during that month. March 2023 has the lowest energy consumption, which could suggest less activity or fewer data points. January 2023 falls in between, showing moderate energy consumption.

Given that the ADF statistic (-25.145043) is much lower than the critical values at all significance levels (1%, 5%, 10%), and the p-value is 0.000000, you can reject the null hypothesis with high confidence.

```
#Dicey-Fuller test to determine stationarity
def test_stationarity(timeseries):
    # Calculate rolling mean and standard deviation
    rolmean = timeseries.rolling(window=30).mean()
    rolstd = timeseries.rolling(window=30).std()

    # Plot timeseries, rolling mean, and rolling standard deviation
    plt.figure(figsize=(20, 5))
    sns.despine(left=True)
    plt.plot(timeseries, color='purple', label='Original')
    plt.plot(rolmean, color='yellow', label='Rolling Mean')
    plt.plot(rolstd, color='cyan', label='Rolling Std')
    plt.legend(loc='best')
    plt.title('Rolling Mean & Standard Deviation of Global Active Power')
    plt.show()

    # Perform and display results of Dickey-Fuller test
    from statsmodels.tsa.stattools import adfuller
    print('<Results of Dickey-Fuller Test>')
    dftest = adfuller(timeseries, autolag='AIC')
    dfoutput = pd.Series(dftest[0:4], index=['Test Statistic', 'p-value', '#Lags Used', 'Number of Observations Used'])
    dfoutput = dfoutput.append(pd.Series(dftest[4], name='Critical Values'))
    print(dfoutput)


test_stationarity(df.Global_active_power)
```




```
<Results of Dickey-Fuller Test>
---------------------------------------------------------------------------
MissingDataError                          Traceback (most recent call last)
<ipython-input-61-23db90dea41d> in <cell line: 1>()
----> 1 test_stationarity(df.Global_active_power)

11 frames

/usr/local/lib/python3.10/dist-packages/statsmodels/base/data.py in _handle_constant(self, hasconst)
    132             exog_max = np.max(self.exog, axis=0)
    133             if not np.isfinite(exog_max).all():
--> 134                 raise MissingDataError('exog contains inf or nans')
    135             exog_min = np.min(self.exog, axis=0)
    136             const_idx = np.where(exog_max == exog_min)[0].squeeze()

MissingDataError: exog contains inf or nans
```

Modelling and Evaluation

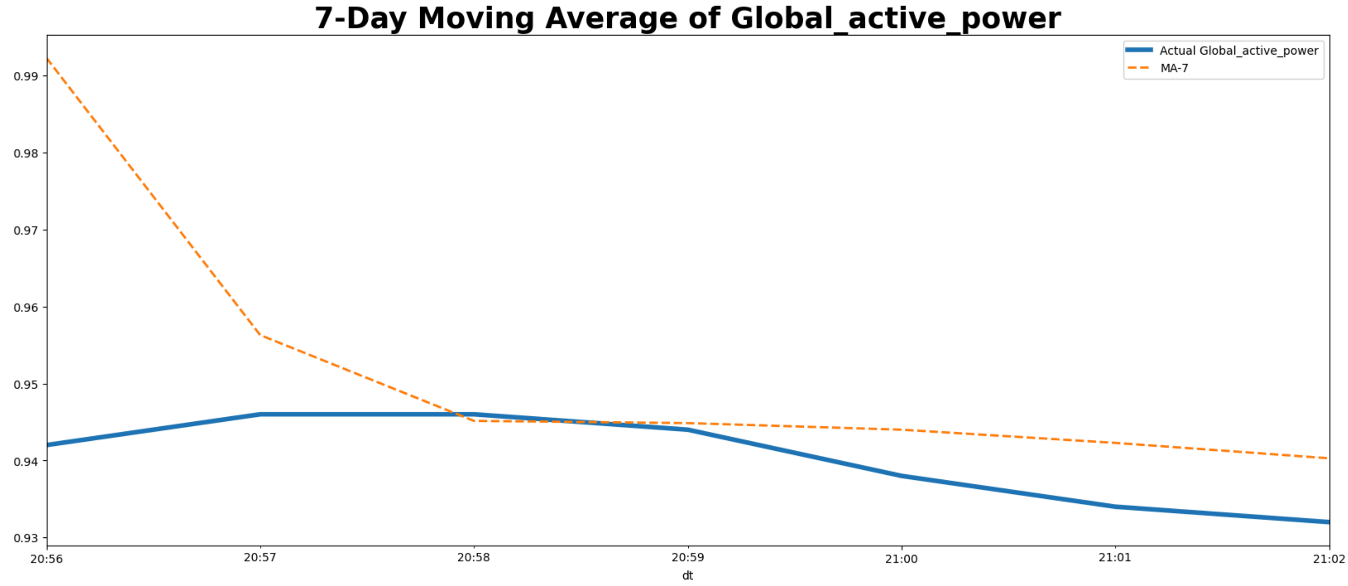
MOVING AVERAGE

```
if 'Datetime' in df.columns:
    df['Datetime'] = pd.to_datetime(df['Datetime'])
    df.set_index('Datetime', inplace=True)
ma = df.resample('D').mean()
ma.head()
```

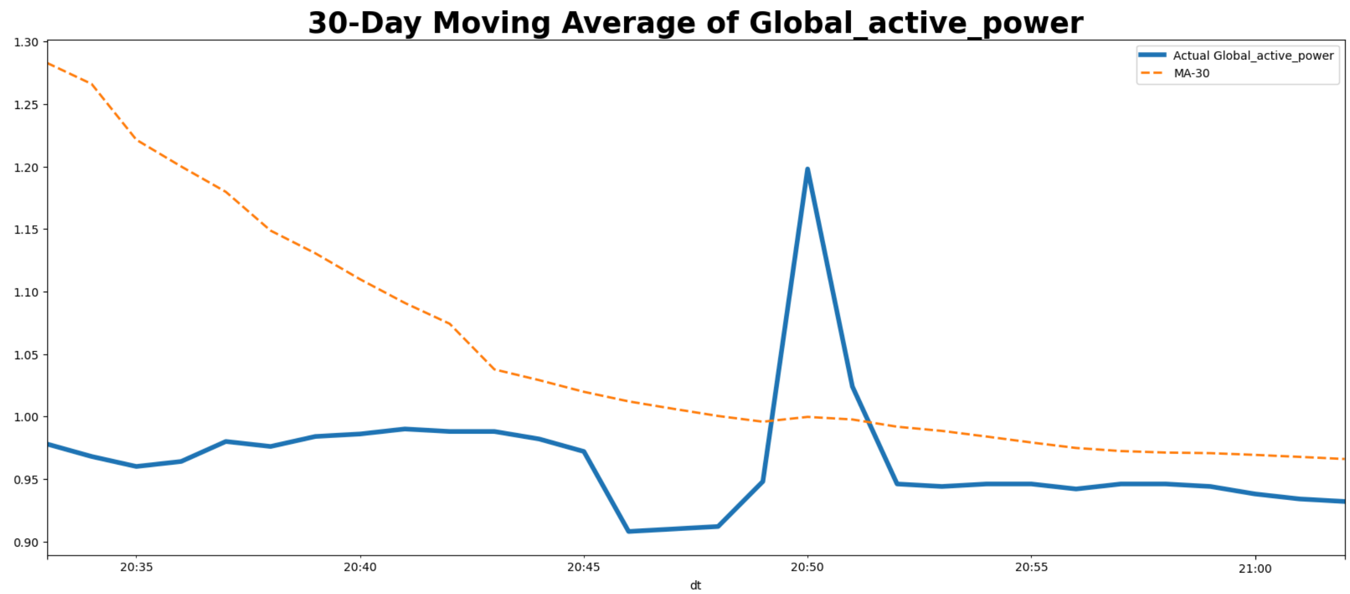
dt	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Sub_metering_3
2006-12-16	3.053475	0.088187	236.243763	13.082828	0.000000	1.378788	12.439394
2006-12-17	2.354486	0.156949	240.087028	9.999028	1.411806	2.907639	9.264583
2006-12-18	1.530435	0.112356	241.231694	6.421667	0.738194	1.820139	9.734722
2006-12-	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

```
import matplotlib.pyplot as plt
```

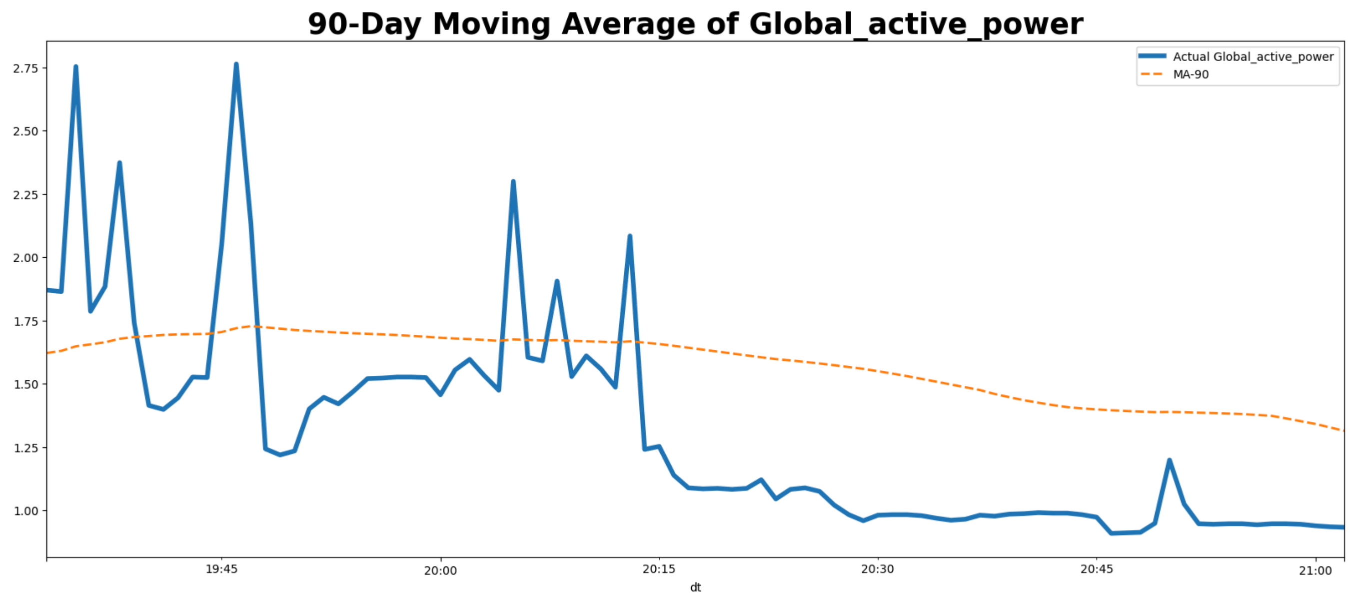
```
def moving_average(df, column_name, window):
    df['Moving Average'] = df[column_name].rolling(window).mean()
    actual = df[column_name][-window:]
    ma = df['Moving Average'][-window:]

    plt.figure(figsize=(20, 8))
    actual.plot(label='Actual {}'.format(column_name), lw=4)
    ma.plot(label='MA-{}'.format(str(window)), ls='--', lw=2)
    plt.title('{}-Day Moving Average of {}'.format(str(window), column_name), weight='bold', fontsize=25)
    plt.legend()

# Example usage:
# Assuming df is your DataFrame with 'Global_active_power' column
moving_average(df, column_name='Global_active_power', window=7)
plt.show()  # Show the plot
```




```
def moving_average(df, column_name, window):
    df['Moving Average'] = df[column_name].rolling(window).mean()
    actual = df[column_name][-window:]
    ma = df['Moving Average'][-window:]

    plt.figure(figsize=(20, 8))
    actual.plot(label='Actual {}'.format(column_name), lw=4)
    ma.plot(label='MA-{}'.format(str(window)), ls='--', lw=2)
    plt.title('{}-Day Moving Average of {}'.format(str(window), column_name), weight='bold', fontsize=25)
    plt.legend()

# Example usage:
# Assuming df is your DataFrame with 'Global_active_power' column
moving_average(df, column_name='Global_active_power', window=30)
plt.show()  # Show the plot
```



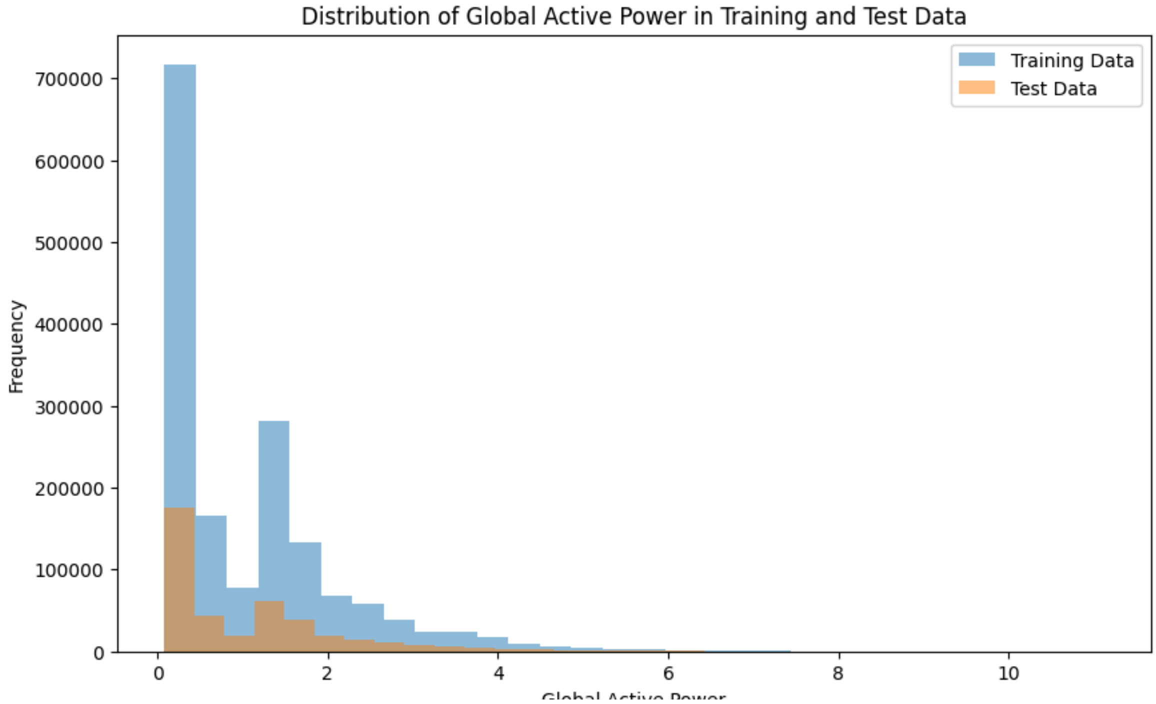
```
def moving_average(df, column_name, window):
    df['Moving Average'] = df[column_name].rolling(window).mean()
    actual = df[column_name][-window:]
    ma = df['Moving Average'][-window:]

    plt.figure(figsize=(20, 8))
    actual.plot(label='Actual {}'.format(column_name), lw=4)
    ma.plot(label='MA-{}'.format(str(window)), ls='--', lw=2)
    plt.title('{}-Day Moving Average of {}'.format(str(window), column_name), weight='bold', fontsize=25)
    plt.legend()

# Example usage:
# Assuming df is your DataFrame with 'Global_active_power' column
moving_average(df, column_name='Global_active_power', window=90)
plt.show()  # Show the plot
```




```
from sklearn.model_selection import train_test_split

#Spliting and training the dataset
X = df.drop('Global_active_power', axis=1)
y = df['Global_active_power']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Create new DataFrames df_train and df_test from the split data
df_train = pd.concat([X_train, y_train], axis=1)
df_test = pd.concat([X_test, y_test], axis=1)
print('Train:\t', len(df_train))
print('Test:\t', len(df_test))
```

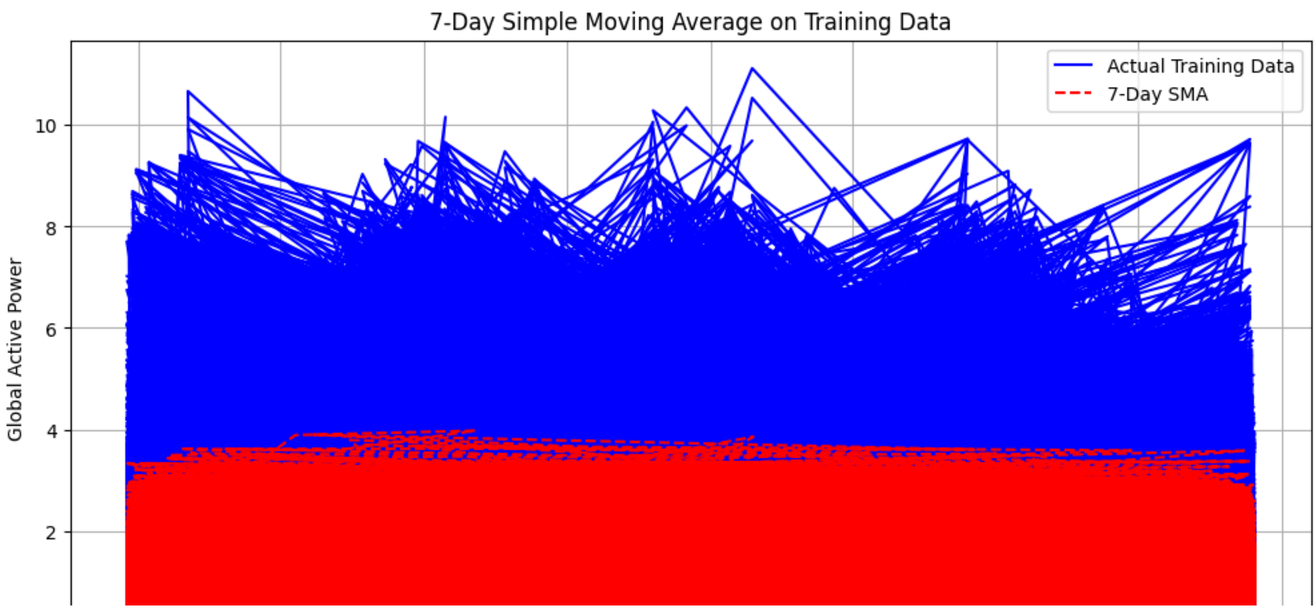
```
Train:   1660207
Test:    415052
```

```
import matplotlib.pyplot as plt

# Example: Visualizing the distribution of 'Global_active_power' in training and test sets
plt.figure(figsize=(10, 6))

plt.hist(df_train['Global_active_power'], bins=30, alpha=0.5, label='Training Data')
plt.hist(df_test['Global_active_power'], bins=30, alpha=0.5, label='Test Data')

plt.xlabel('Global Active Power')
plt.ylabel('Frequency')
plt.title('Distribution of Global Active Power in Training and Test Data')
plt.legend()

plt.show()
```

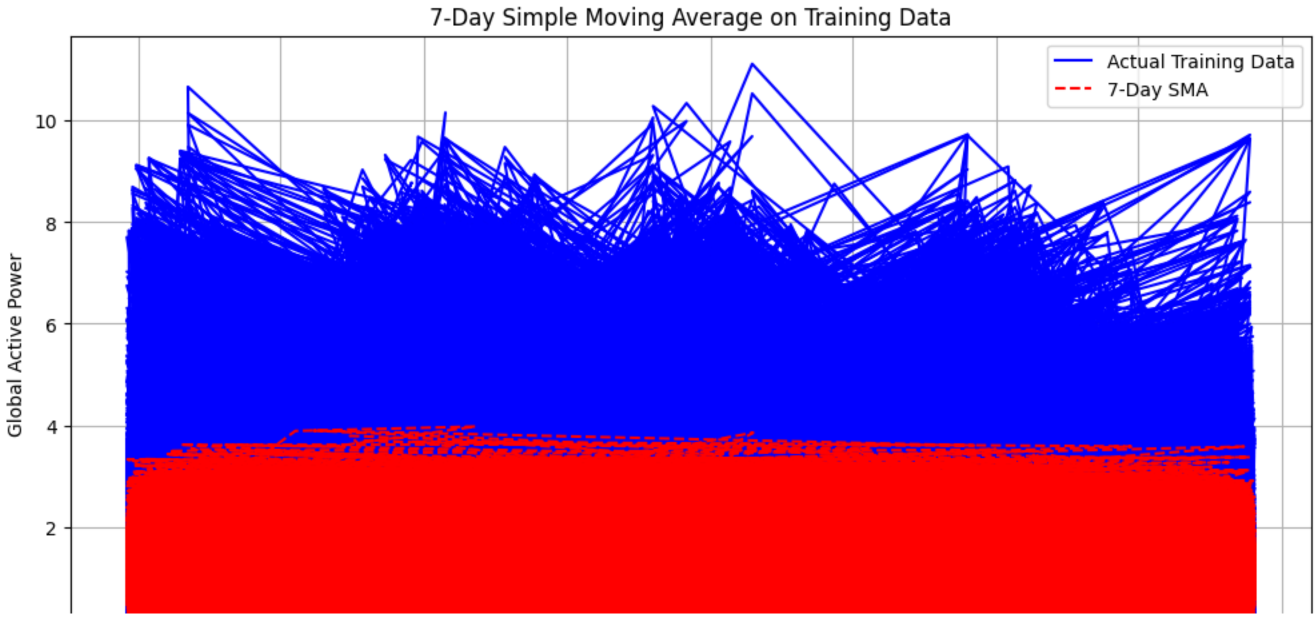


***Building Model with Moving Average**

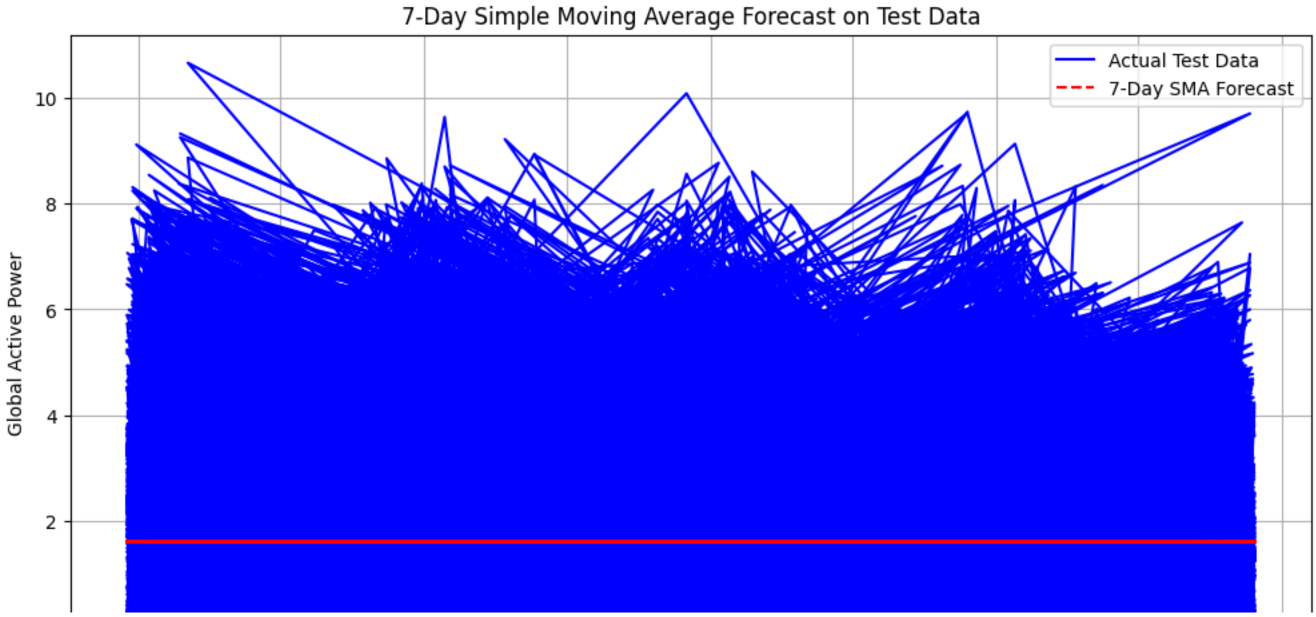
```
#Calculate Simple Moving Average (SMA)
import pandas as pd
import matplotlib.pyplot as plt


# Step 1: Calculate Simple Moving Average (SMA)
window_size = 7  # Example: Using a 7-day moving average
df_train['SMA'] = df_train['Global_active_power'].rolling(window=window_size).mean()

# Step 2: Visualize the Original Data and SMA
plt.figure(figsize=(12, 6))

# Increase the chunksize to handle the complex plot
plt.rcParams['agg.path.chunksize'] = 10000

plt.plot(df_train.index, df_train['Global_active_power'], label='Actual Training Data', color='blue')
plt.plot(df_train.index, df_train['SMA'], label=f'{window_size}-Day SMA', linestyle='--', color='red')
plt.xlabel('Index')
plt.ylabel('Global Active Power')
plt.title(f'{window_size}-Day Simple Moving Average on Training Data')
plt.legend()
plt.grid(True)
plt.show()
```



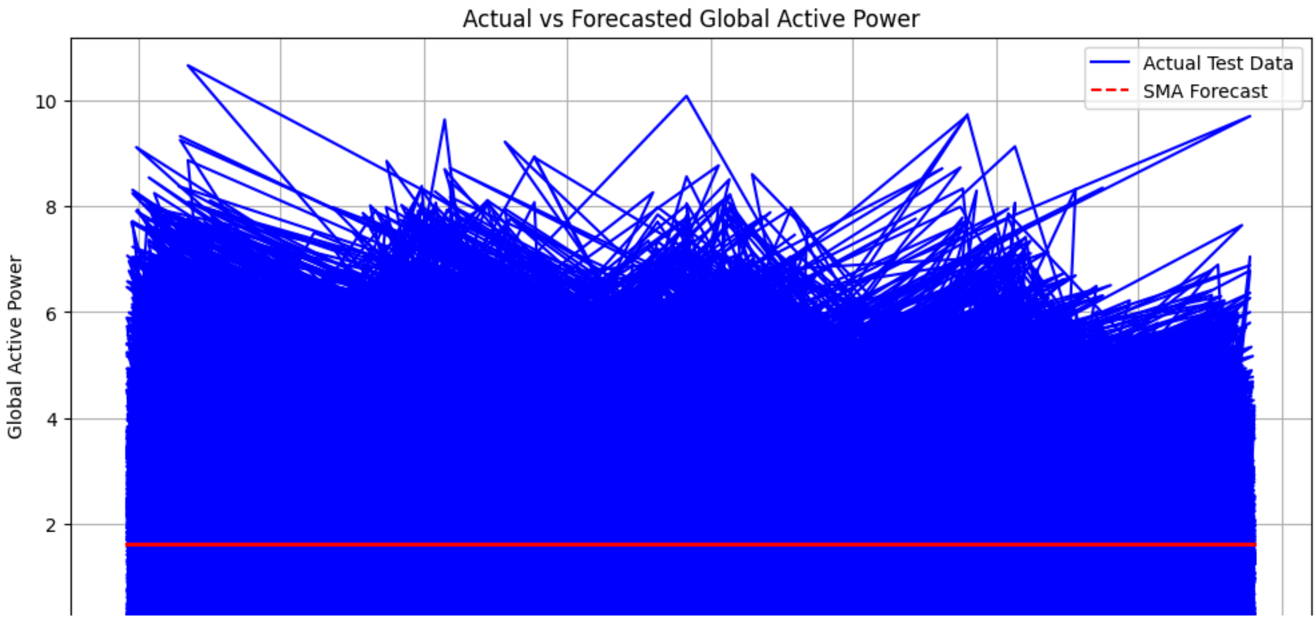
```
#Visualization of Simple Moving Average (SMA)

import matplotlib.pyplot as plt


# Step 1: Calculate Simple Moving Average (SMA)
window_size = 7  # Example: Using a 7-day moving average
df_train['SMA'] = df_train['Global_active_power'].rolling(window=window_size).mean()

# Step 2: Visualize the Original Data and SMA
plt.figure(figsize=(12, 6))
plt.plot(df_train.index, df_train['Global_active_power'], label='Actual Training Data', color='blue')
plt.plot(df_train.index, df_train['SMA'], label=f'{window_size}-Day SMA', linestyle='--', color='red')
plt.xlabel('Index')
plt.ylabel('Global Active Power')
plt.title(f'{window_size}-Day Simple Moving Average on Training Data')
plt.legend()
plt.grid(True)
plt.show()
```




```
#Forecasting Using SMA on Test Data

# Step 3: Forecasting using SMA on Test Data
df_test['SMA_forecast'] = df_train['SMA'].iloc[-1]  # Forecast for test data starts with the last SMA value from training data

# Optionally, visualize SMA on test data
plt.figure(figsize=(12, 6))
plt.plot(df_test.index, df_test['Global_active_power'], label='Actual Test Data', color='blue')
plt.plot(df_test.index, df_test['SMA_forecast'], label=f'{window_size}-Day SMA Forecast', linestyle='--', color='red')
plt.xlabel('Index')
plt.ylabel('Global Active Power')
plt.title(f'{window_size}-Day Simple Moving Average Forecast on Test Data')
plt.legend()
plt.grid(True)
plt.show()
```



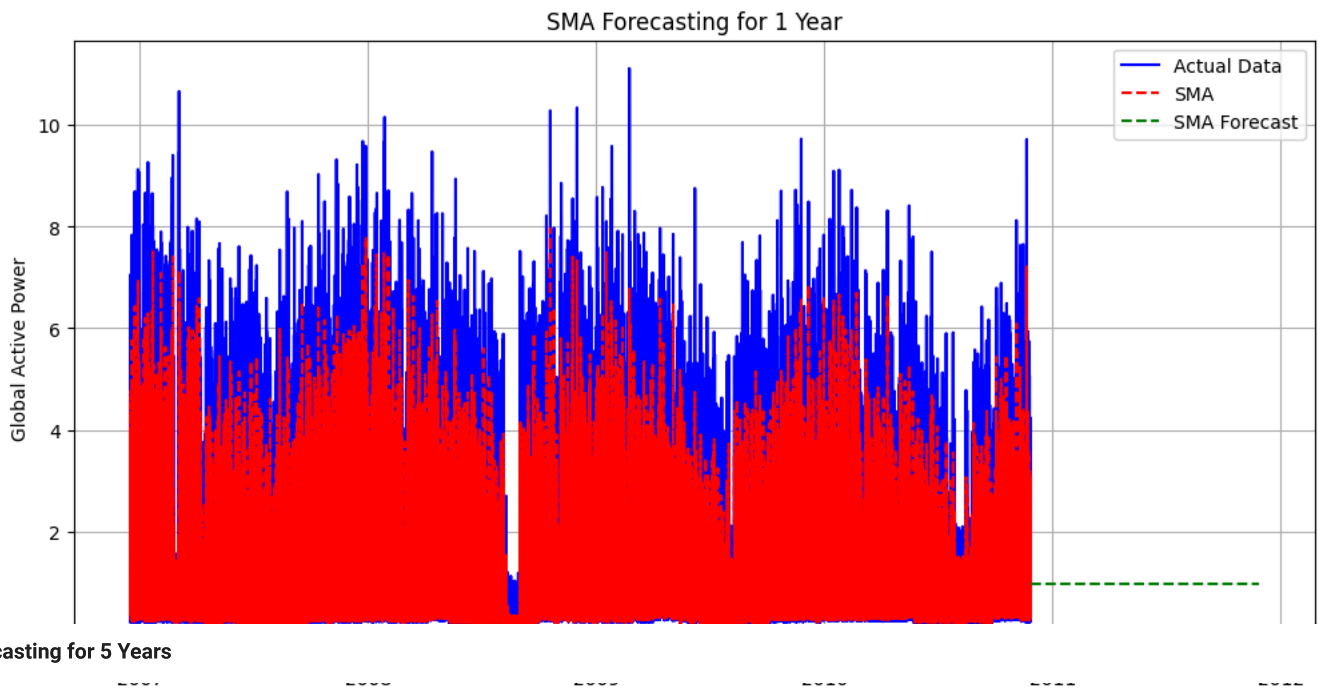

```
#Forecasting Using SMA Model
import matplotlib.pyplot as plt

# Plotting actual vs forecasted values
plt.figure(figsize=(12, 6))
plt.plot(df_test.index, df_test['Global_active_power'], label='Actual Test Data', color='blue')
plt.plot(df_test.index, df_test['SMA_forecast'], label='SMA Forecast', linestyle='--', color='red')
plt.xlabel('Index')
plt.ylabel('Global Active Power')
plt.title('Actual vs Forecasted Global Active Power')
plt.legend()
plt.grid(True)
plt.show()
```




```
# Define window size for SMA (e.g., 30 days)
window_size = 30

# Calculate SMA and store it in a new column 'SMA'
df['SMA'] = df['Global_active_power'].rolling(window=window_size).mean()

# Drop rows with NaN values in 'SMA' column (if any)
df.dropna(subset=['SMA'], inplace=True)
```

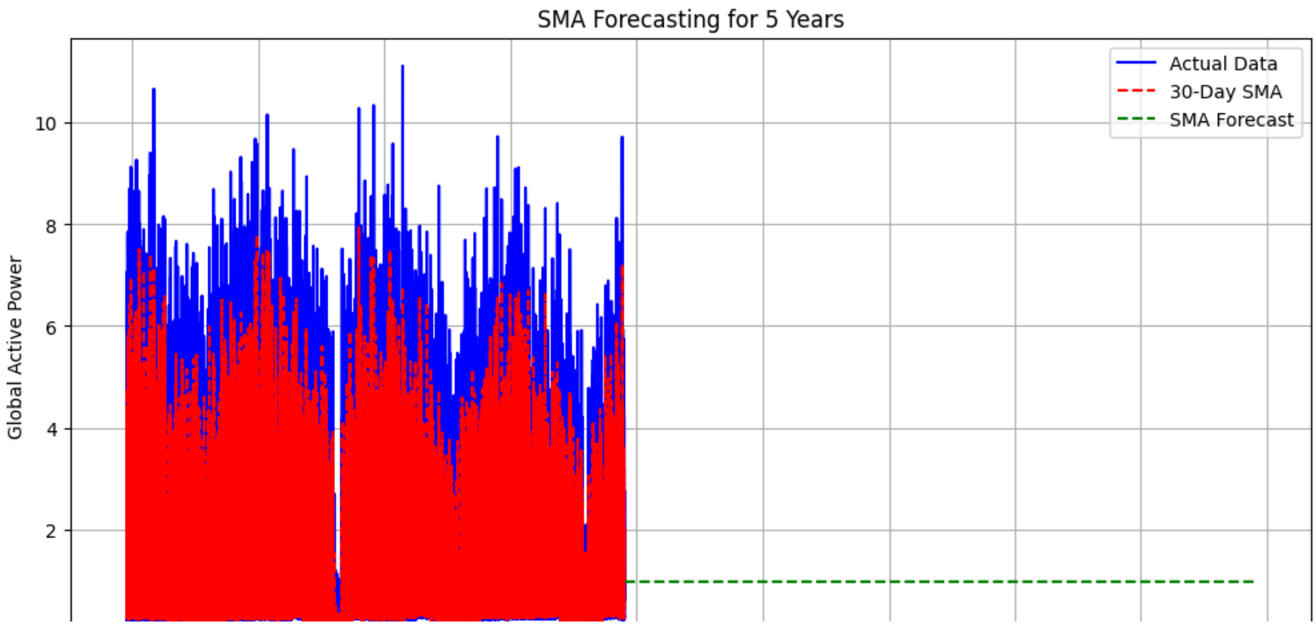
Forecasting for 1 year

```
import matplotlib.pyplot as plt
import pandas as pd  # Import pandas for DateOffset

# Example: Extend index to include future dates for 1 year instead of 5 years
future_dates = pd.date_range(start=df.index[-1] + pd.DateOffset(1), periods=365, freq='D')

# Example: Create a DataFrame for forecasting
forecast = pd.DataFrame(index=future_dates, columns=['SMA_forecast'])

# Example: Assuming 'SMA' was calculated on 'df' and not 'df_train'
if 'SMA' in df.columns:
    # Initialize SMA forecast starting with the last available SMA value
    forecast['SMA_forecast'] = df['SMA'].iloc[-1]
else:
    print("Error: 'SMA' column not found in DataFrame 'df'. Calculate SMA first.")

# Example: Plotting historical data and SMA
plt.figure(figsize=(12, 6))
plt.plot(df.index, df['Global_active_power'], label='Actual Data', color='blue')

# Plot SMA only if it exists
if 'SMA' in df.columns:
    plt.plot(df.index, df['SMA'], label='SMA', linestyle='--', color='red')

plt.plot(forecast.index, forecast['SMA_forecast'], label='SMA Forecast', linestyle='--', color='green')
plt.xlabel('Date')
plt.ylabel('Global Active Power')
plt.title('SMA Forecasting for 1 Year')
plt.legend()
plt.grid(True)
plt.show()
```



Forecasting for 5 Years

```
import matplotlib.pyplot as plt
import pandas as pd  # Import pandas for DateOffset

# Example: Extend index to include future dates for 5 years
future_dates = pd.date_range(start=df.index[-1] + pd.DateOffset(1), periods=5*365, freq='D')

# Example: Create a DataFrame for forecasting
forecast = pd.DataFrame(index=future_dates, columns=['SMA_forecast'])

# Example: Assuming 'SMA' was calculated on 'df' and not 'df_train'
if 'SMA' in df.columns:
    # Initialize SMA forecast starting with the last available SMA value
    forecast['SMA_forecast'] = df['SMA'].iloc[-1]
else:
    print("Error: 'SMA' column not found in DataFrame 'df'. Calculate SMA first.")

# Example: Plotting historical data and SMA
plt.figure(figsize=(12, 6))
plt.plot(df.index, df['Global_active_power'], label='Actual Data', color='blue')

# Plot SMA only if it exists
if 'SMA' in df.columns:
    plt.plot(df.index, df['SMA'], label=f'{window_size}-Day SMA', linestyle='--', color='red')

plt.plot(forecast.index, forecast['SMA_forecast'], label='SMA Forecast', linestyle='--', color='green')
plt.xlabel('Date')
plt.ylabel('Global Active Power')
plt.title(f'SMA Forecasting for 5 Years')
plt.legend()
plt.grid(True)
plt.show()
```




```
#Evaluation of the SMA Model

from sklearn.metrics import mean_absolute_error, mean_squared_error
import numpy as np

# Check for NaN values before dropping and provide feedback
if df_test['Global_active_power'].isnull().all() or df_test['SMA_forecast'].isnull().all():
    print("Error: 'Global_active_power' or 'SMA_forecast' column in 'df_test' contains all NaN values. Cannot calculate metrics.")
else:
    # Handle NaN values before calculating metrics
    df_test_cleaned = df_test.dropna(subset=['Global_active_power', 'SMA_forecast'])

    # Calculate SMA forecast errors using the cleaned DataFrame
    mae = mean_absolute_error(df_test_cleaned['Global_active_power'], df_test_cleaned['SMA_forecast'])
    rmse = np.sqrt(mean_squared_error(df_test_cleaned['Global_active_power'], df_test_cleaned['SMA_forecast']))

    print(f'Mean Absolute Error (MAE): {mae:.2f}')
    print(f'Root Mean Squared Error (RMSE): {rmse:.2f}')
```

```
Mean Absolute Error (MAE): 0.99
Root Mean Squared Error (RMSE): 1.18
```

Interpretation of MAE and RMSE

Mean Absolute Error (MAE):

- MAE measures the average magnitude of the errors in a set of forecasts, without considering their direction (whether the forecast is overestimating or underestimating the actual value).MAE = 0.99 indicates that, on average, your SMA model's predictions are about 0.99 units away from the actual Global_active_power values. Root Mean Squared Error (RMSE):
- RMSE is a measure of the average magnitude of the error, where larger errors are penalized more heavily compared to MAE due to the squaring of the errors. RMSE = 1.18 indicates the square root of the average of squared differences between predicted and actual Global_active_power values.
- The SMA model achieved an MAE of 0.99 and RMSE of 1.18.These metrics indicate that our model generally predicts the Global Active Power within reasonable bounds.

LTSM MODEL

```
# Transform, reshape, scale, and split the data
df = df.Global_active_power.values.astype('float32').reshape(-1, 1)
scaler = MinMaxScaler(feature_range=(0, 1))
df = scaler.fit_transform(df)
train_size = int(len(df) * 0.80)
train, test = df[:train_size], df[train_size:]
print(f'Train:\t{len(train)}')
print(f'Test:\t{len(test)}')
```

```
Train:  1637799
Test:   409450
```

```
# Convert an array of values into a dataset matrix
def create_dataset(data, look_back=1):
    X, Y = [], []
    for i in range(len(data) - look_back):
        X.append(data[i:i + look_back, 0])
        Y.append(data[i + look_back, 0])
    return np.array(X), np.array(Y)
```

```
# reshape into X=t and Y=t+1
look_back = 30
X_train, Y_train = create_dataset(train, look_back)
X_test, Y_test = create_dataset(test, look_back)
# Check shapes before reshaping
print(f'X_train shape before reshaping: {X_train.shape}')
print(f'X_test shape before reshaping: {X_test.shape}')
```

```
X_train shape before reshaping: (1637769, 30)
X_test shape before reshaping: (409420, 30)
```

```
# Reshape input to be [samples, time steps, features]
if len(X_train.shape) == 2:
    X_train = X_train.reshape((X_train.shape[0], 1, X_train.shape[1]))
if len(X_test.shape) == 2:
    X_test = X_test.reshape((X_test.shape[0], 1, X_test.shape[1]))

print(f'X_train shape after reshaping: {X_train.shape}')
print(f'X_test shape after reshaping: {X_test.shape}')
```

```
X_train shape after reshaping: (1637769, 1, 30)
X_test shape after reshaping: (409420, 1, 30)
```

```
X_train.shape
X_test.shape
```

```
(409420, 1, 30)
```

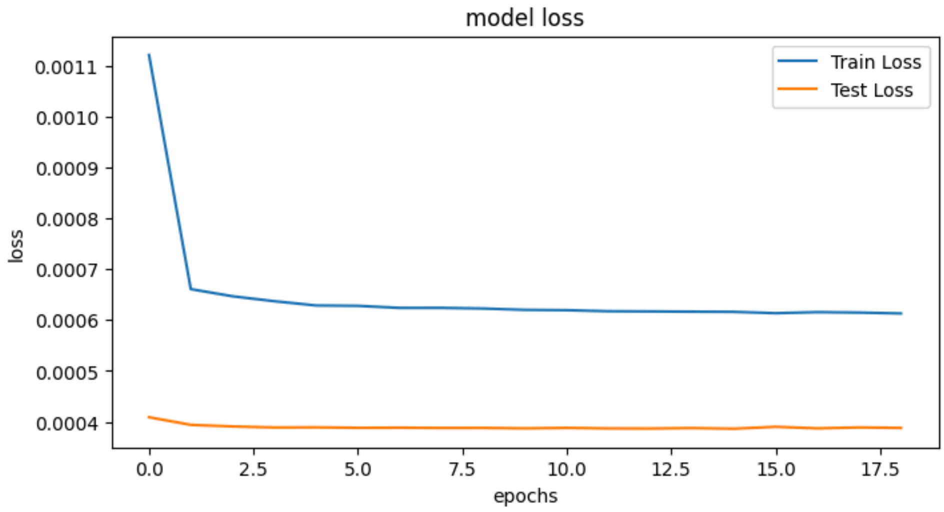
```
#Long Short Term Memory model
#Importing Libraries
from keras.models import Sequential
from keras.layers import LSTM, Dropout, Dense
from keras.callbacks import EarlyStopping
from sklearn.metrics import mean_squared_error, mean_absolute_error
import seaborn as sns
#Modelling
model = Sequential([
    LSTM(100, input_shape=(X_train.shape[1], X_train.shape[2])),
    Dropout(0.2),
    Dense(1)
])
model.compile(loss='mean_squared_error', optimizer='adam')

# Fit the model with early stopping
history = model.fit(X_train, Y_train, epochs=20, batch_size=1240, validation_data=(X_test, Y_test),
                    callbacks=[EarlyStopping(monitor='val_loss', patience=4)], verbose=1, shuffle=False)

# Display model summary
model.summary()
```

```
Epoch 1/20
1321/1321 [==============================] - 37s 25ms/step - loss: 0.0011 - val_loss: 4.0894e-04
Epoch 2/20
1321/1321 [==============================] - 31s 24ms/step - loss: 6.6108e-04 - val_loss: 3.9392e-04
Epoch 3/20
1321/1321 [==============================] - 31s 24ms/step - loss: 6.4699e-04 - val_loss: 3.9079e-04
Epoch 4/20
1321/1321 [==============================] - 32s 24ms/step - loss: 6.3727e-04 - val_loss: 3.8876e-04
Epoch 5/20
1321/1321 [==============================] - 33s 25ms/step - loss: 6.2892e-04 - val_loss: 3.8901e-04
Epoch 6/20
1321/1321 [==============================] - 31s 24ms/step - loss: 6.2819e-04 - val_loss: 3.8809e-04
Epoch 7/20
1321/1321 [==============================] - 32s 24ms/step - loss: 6.2410e-04 - val_loss: 3.8831e-04
Epoch 8/20
1321/1321 [==============================] - 32s 24ms/step - loss: 6.2415e-04 - val_loss: 3.8788e-04
Epoch 9/20
1321/1321 [==============================] - 32s 24ms/step - loss: 6.2288e-04 - val_loss: 3.8796e-04
Epoch 10/20
1321/1321 [==============================] - 32s 24ms/step - loss: 6.2026e-04 - val_loss: 3.8703e-04
Epoch 11/20
1321/1321 [==============================] - 32s 24ms/step - loss: 6.1964e-04 - val_loss: 3.8802e-04
Epoch 12/20
1321/1321 [==============================] - 31s 24ms/step - loss: 6.1752e-04 - val_loss: 3.8692e-04
Epoch 13/20
1321/1321 [==============================] - 30s 23ms/step - loss: 6.1719e-04 - val_loss: 3.8670e-04
Epoch 14/20
1321/1321 [==============================] - 30s 23ms/step - loss: 6.1667e-04 - val_loss: 3.8762e-04
Epoch 15/20
1321/1321 [==============================] - 31s 23ms/step - loss: 6.1630e-04 - val_loss: 3.8637e-04
Epoch 16/20
1321/1321 [==============================] - 32s 24ms/step - loss: 6.1371e-04 - val_loss: 3.9007e-04
Epoch 17/20
1321/1321 [==============================] - 31s 24ms/step - loss: 6.1574e-04 - val_loss: 3.8709e-04
Epoch 18/20
1321/1321 [==============================] - 32s 24ms/step - loss: 6.1489e-04 - val_loss: 3.8884e-04
Epoch 19/20
1321/1321 [==============================] - 31s 24ms/step - loss: 6.1320e-04 - val_loss: 3.8788e-04
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 100)               52400

 dropout (Dropout)           (None, 100)               0

 dense (Dense)               (None, 1)                 101

=================================================================
Total params: 52501 (205.08 KB)
Trainable params: 52501 (205.08 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

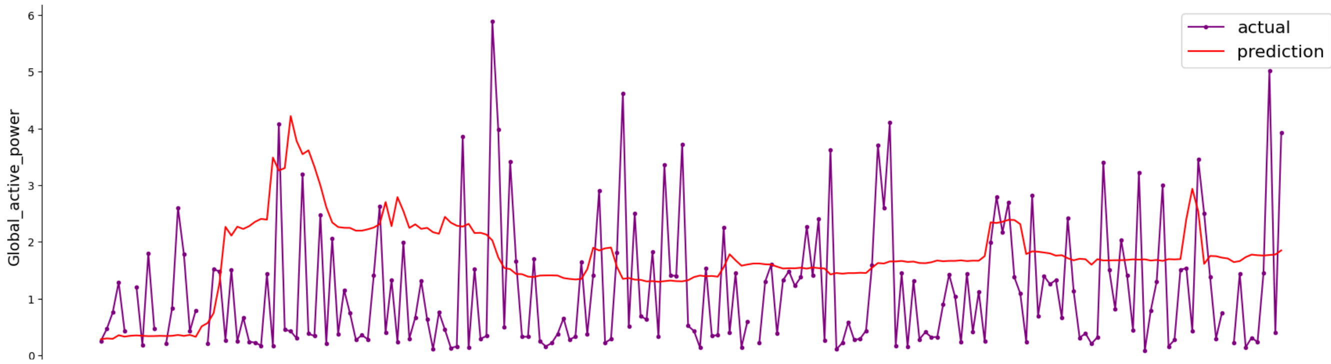
```
#Model Evaluation
# Make predictions and invert them
train_predict = scaler.inverse_transform(model.predict(X_train))
test_predict = scaler.inverse_transform(model.predict(X_test))
Y_train = scaler.inverse_transform([Y_train])[0]
Y_test = scaler.inverse_transform([Y_test])[0]

# Calculate and print errors
print('Train MAE:', mean_absolute_error(Y_train, train_predict[:, 0]))
print('Train RMSE:', np.sqrt(mean_squared_error(Y_train, train_predict[:, 0])))
print('Test MAE:', mean_absolute_error(Y_test, test_predict[:, 0]))
print('Test RMSE:', np.sqrt(mean_squared_error(Y_test, test_predict[:, 0])))
```

```
51181/51181 [==============================] - 124s 2ms/step
12795/12795 [==============================] - 30s 2ms/step
Train MAE: 0.09685471563381381
Train RMSE: 0.26712243853492507
Test MAE: 0.08154983299003572
Test RMSE: 0.21754699641461045
```

```
#AUC -ROC Curve
plt.figure(figsize=(8,4))
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Test Loss')
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epochs')
plt.legend(loc='upper right')
plt.show();
```



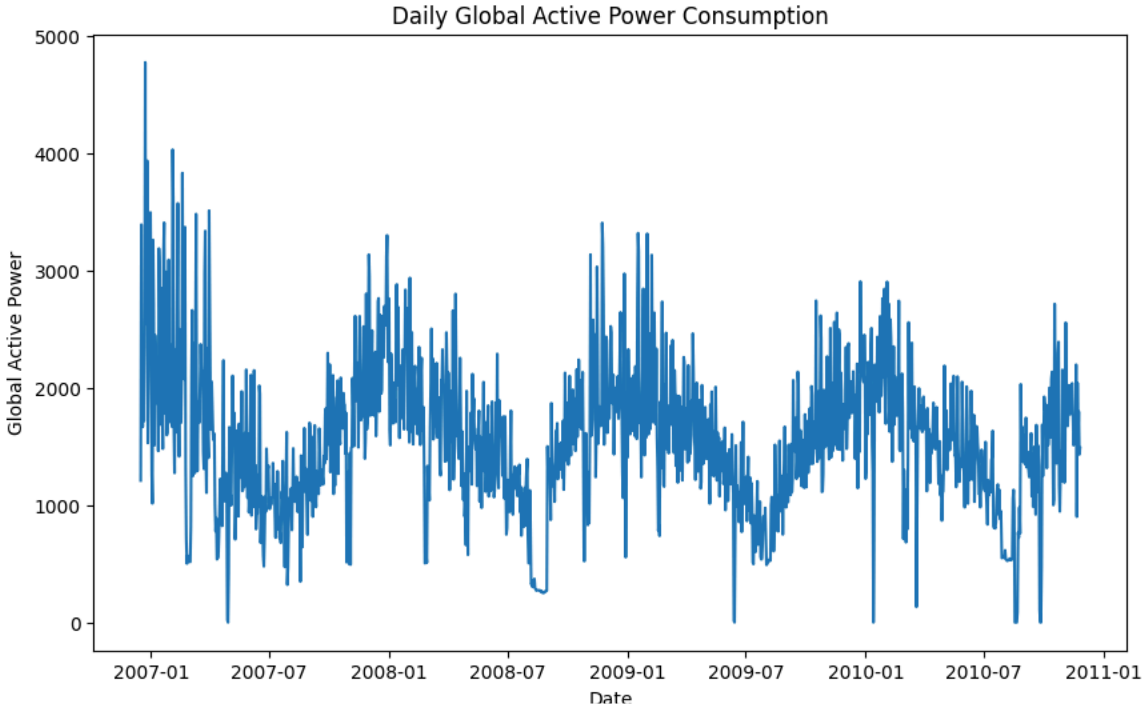

```
# Prepare data for plotting
aa = range(200)

# Create and configure plot
plt.figure(figsize=(20, 6))
# Use .iloc to index into the Pandas Series
plt.plot(aa, y_test.iloc[:200], marker='.', label="actual", color='purple')
plt.plot(aa, test_predict[:, 0][:200], '-', label="prediction", color='red')
sns.despine(top=True)
plt.subplots_adjust(left=0.07)
plt.ylabel('Global_active_power', size=14)
plt.xlabel('Time step', size=14)
plt.legend(fontsize=16)
plt.show()
```



SARIMAX MODEL

```
# Resample data to daily frequency
df_daily = df.resample('D').sum()
```

```
# Plot the data
plt.figure(figsize=(10, 6))
plt.plot(df_daily['Global_active_power'])
plt.xlabel('Date')
plt.ylabel('Global Active Power')
plt.title('Daily Global Active Power Consumption')
plt.show()
```

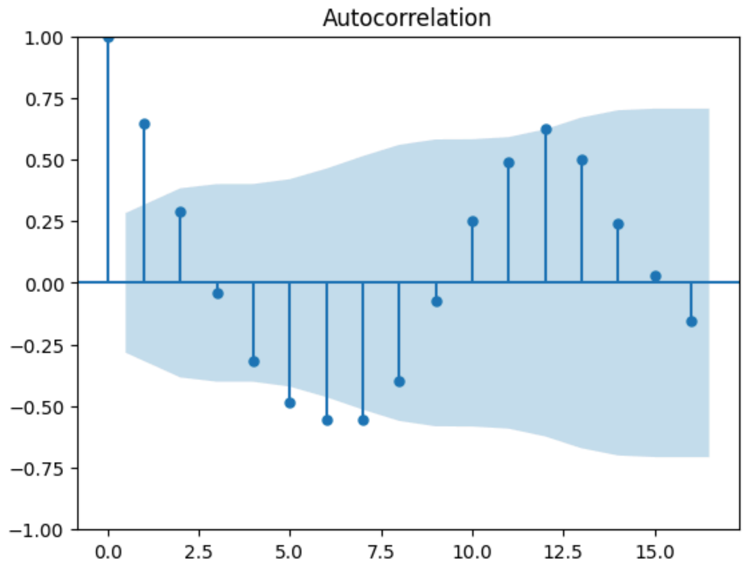


In Jan 2007 shows a higher spike which explains that there is a higher energy demand, which could be useful for managing energy usage and costs.Over the years, shows a decrease in consumption patterns which might indicate improved energy efficiency, possibly from using energy-saving appliances or adopting conservation measures.

```
import statsmodels.api as sm  # Import statsmodels.api for statistical tools
def print_and_plot_acf(df_daily):
    print(sm.tsa.stattools.acf(df_daily, nlags=16))
    sm.graphics.tsa.plot_acf(df_daily, lags=16)
    plt.show()

def print_and_plot_pacf(df_daily):
    print(sm.tsa.stattools.acf(df_daily, nlags=16))
    sm.graphics.tsa.plot_pacf(df_daily, lags=16)
    plt.show()
```

```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

monthly_df = df_daily.resample(rule='M').mean()
print_and_plot_acf(monthly_df['Global_active_power'])
```

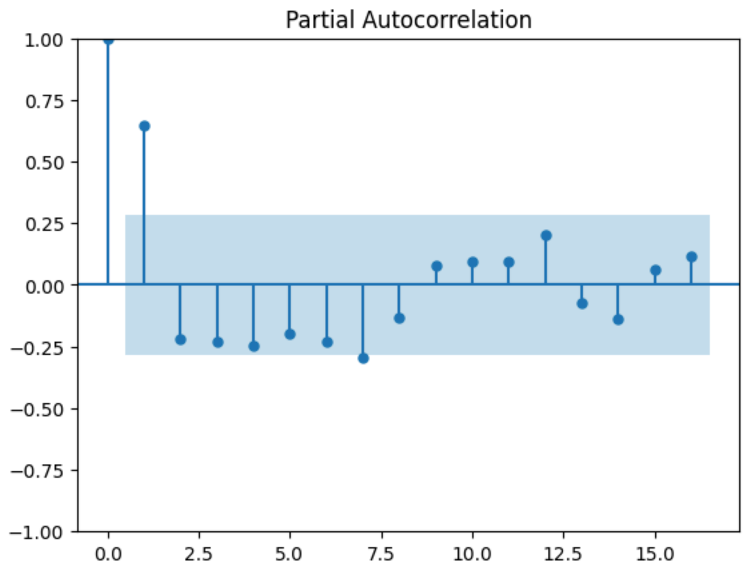
```
[ 1.          0.64642459  0.29004362 -0.03936469 -0.31663492 -0.4845685
 -0.55611073 -0.55513039 -0.3952691  -0.07439165  0.25199873  0.48778023
  0.62333202  0.50124972  0.24087083  0.02845123 -0.15293008]
```



- The high autocorrelation at lag 1 indicates that household energy consumption is likely influenced by daily routines. If one day's consumption is high, it is likely that the following day's consumption will also be high.
- The positive correlations at specific lags could indicate weekly usage patterns, where certain days of the week see similar levels of consumption. Negative correlations might suggest days when household activities differ significantly (e.g., weekends vs. weekdays).
- The reappearance of positive correlations around lag 12 suggests potential monthly or bi-monthly cycles in energy usage. This could be due to billing cycles, specific monthly activities, or seasonal effects.
- The negative correlations at some lags might indicate the impact of energy-saving measures or behaviors that are implemented periodically (e.g., energy-saving weekends or specific off-peak usage strategies).Generally identifying periods of high usage can help in managing peak loads and potentially shifting some energy-intensive activities to off-peak times.

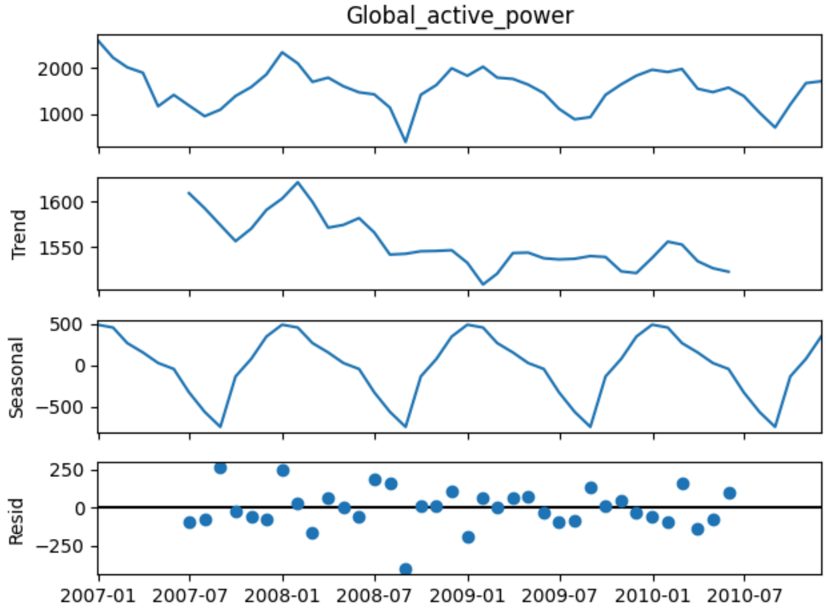
```
monthly_df = df_daily.resample(rule='M').mean()
print_and_plot_pacf(monthly_df['Global_active_power'])
```

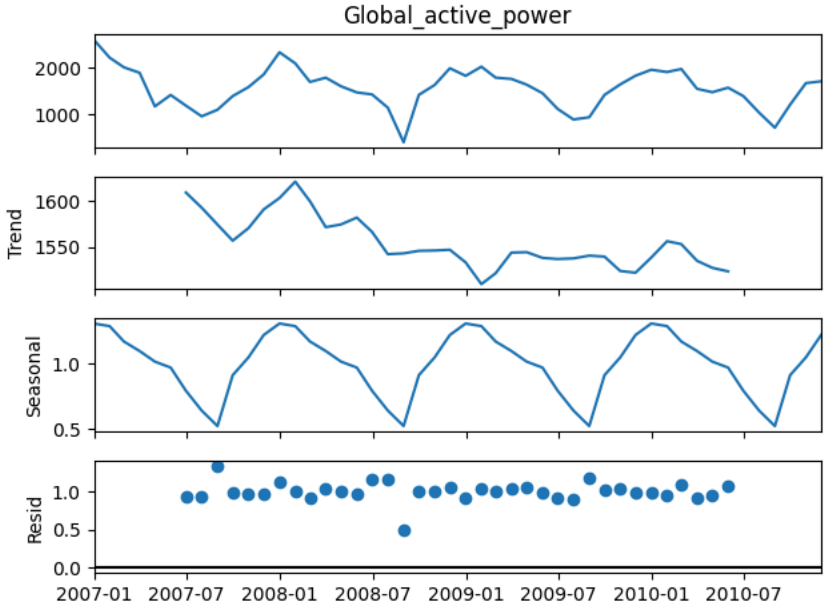
```
[ 1.          0.64642459  0.29004362 -0.03936469 -0.31663492 -0.4845685
 -0.55611073 -0.55513039 -0.3952691  -0.07439165  0.25199873  0.48778023
  0.62333202  0.50124972  0.24087083  0.02845123 -0.15293008]
```



- The strong PACF at lag 1 reinforces the idea that household energy consumption is influenced by daily routines. High energy usage one day is likely to directly influence high usage the next day.
- Negative PACF values at certain lags could suggest weekly patterns where days within the week affect each other negatively. For instance, high usage on weekends might result in lower usage on weekdays.
- Households can plan better for energy usage, adopting measures to smooth out peaks and reduce consumption during high-demand periods.

```
from statsmodels.tsa.seasonal import seasonal_decompose

additive_model = seasonal_decompose(monthly_df['Global_active_power'], model='additive',
                                    period=12)

additive_model.plot()
plt.show()


multiplicative_model = seasonal_decompose(monthly_df['Global_active_power'], model='multiplicative',
                                    period=12)

multiplicative_model.plot()
plt.show()
```





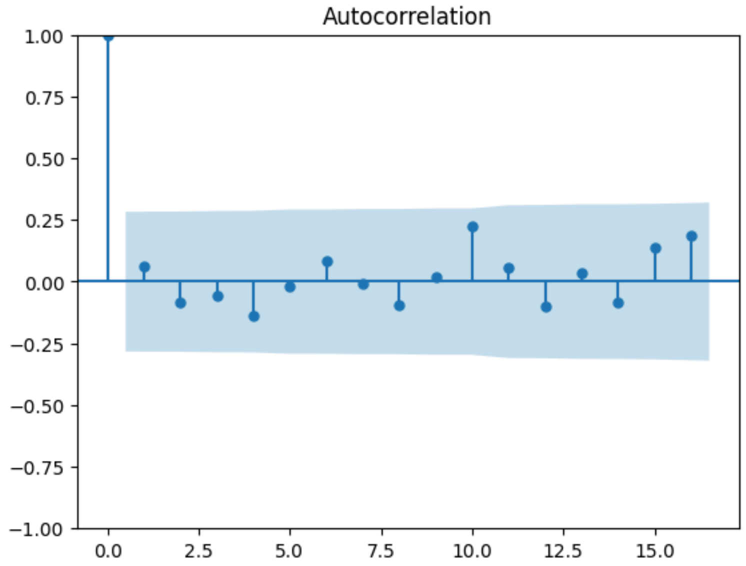
-1) Trend *Additive* The trend is increasing in July it means household energy consumption is generally rising during that period since its known to be a cold season. Then a decreasing trend in January indicating decrease in energy Levels. *Multiplicative* shows the percentage change in the trend.Theres a growth in July and decline in January.

- 2)Seasonal Component:
- Additive* Higher energy usage during winter months(July) due to heating or during summer months due to cooling.
- Multiplicative* Shows the relative seasonal effect in terms of a multiplicative factor
- 3)Residual Component:
- Additive* There is a high variability in July in the residual component indicating that there are other unexplained factors affecting energy consumption.
- Multiplicative* It helps identify periods of unusually high or low energy usage that are not explained by trend and seasonality.

- The residual component can be used to detect anomalies or irregular spikes in energy consumption. This could indicate issues such as faulty appliances, unusual activities, or other external factors affecting energy usage.

```
des = monthly_df['Global_active_power'] - additive_model.seasonal
print_and_plot_acf(des)
```

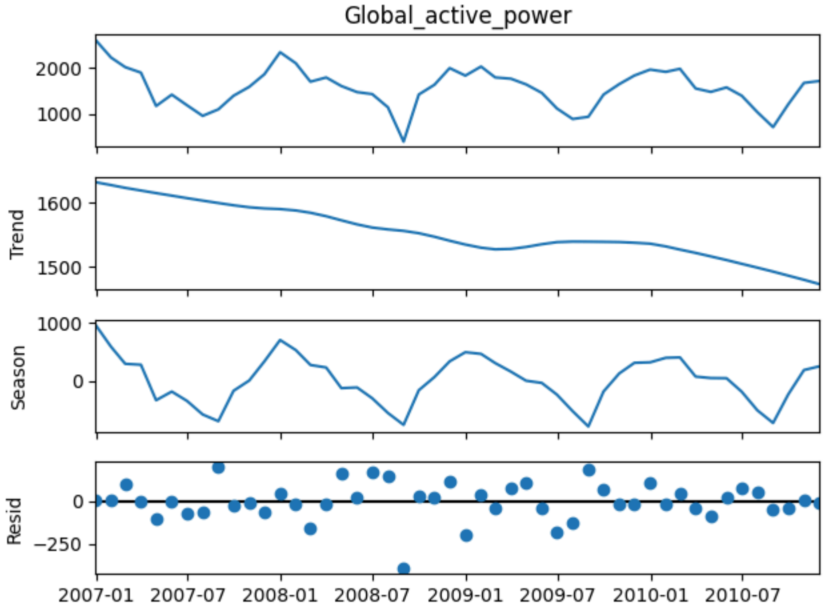
```
[ 1.          0.06349135 -0.08375727 -0.05439698 -0.13628119 -0.01685227
  0.08365774 -0.006746   -0.09535498  0.01820025  0.22216108  0.05776533
 -0.10100642  0.03341776 -0.08182301  0.14055372  0.18483565]
```




```
additive_model.trend
```

```
dt
2006-12-31            NaN
2007-01-31            NaN
2007-02-28            NaN
2007-03-31            NaN
2007-04-30            NaN
2007-05-31            NaN
2007-06-30    1609.104704
2007-07-31    1592.637576
2007-08-31    1574.290087
2007-09-30    1556.709912
2007-10-31    1570.407778
2007-11-30    1590.805356
2007-12-31    1603.192682
2008-01-31    1621.037803
2008-02-29    1599.557975
2008-03-31    1571.422373
2008-04-30    1574.435521
2008-05-31    1581.886072
2008-06-30    1566.231317
2008-07-31    1542.051704
2008-08-31    1542.925950
2008-09-30    1545.665473
2008-10-31    1546.027626
2008-11-30    1546.819319
2008-12-31    1533.072785
2009-01-31    1509.413691
2009-02-28    1521.305559
2009-03-31    1543.743716
2009-04-30    1544.216464
2009-05-31    1538.019920
2009-06-30    1536.768045
2009-07-31    1537.441088
2009-08-31    1540.454159
2009-09-30    1539.390970
2009-10-31    1523.713907
2009-11-30    1521.861653
2009-12-31    1538.399461
2010-01-31    1556.166755
2010-02-28    1552.973580
2010-03-31    1534.824645
2010-04-30    1527.182785
2010-05-31    1523.306447
2010-06-30            NaN
2010-07-31            NaN
2010-08-31            NaN
2010-09-30            NaN
2010-10-31            NaN
2010-11-30            NaN
Freq: M, Name: trend, dtype: float64
```

```
from statsmodels.tsa.seasonal import STL

stl_result = STL(monthly_df['Global_active_power']).fit()
stl_result.plot()
plt.show()
```

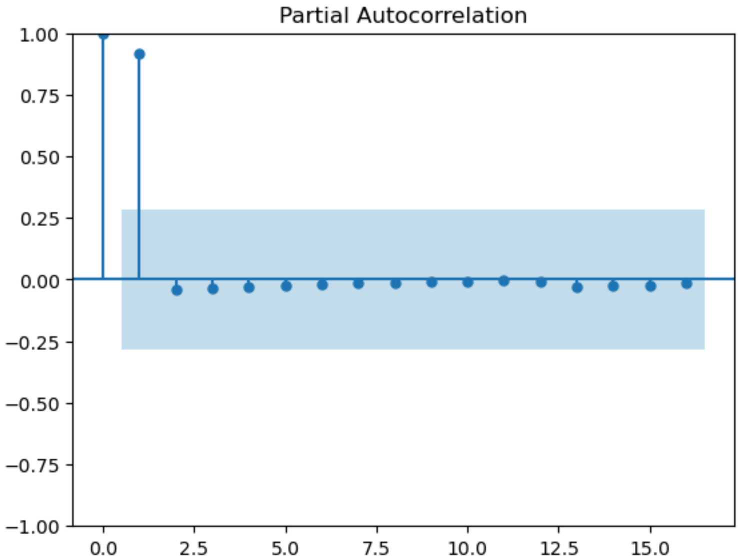


Start coding or generate with AI.

- Observed: The raw data of household energy consumption over time.
- Trend: A smooth curve showing the long-term trend.
- Seasonal: A repeating pattern that highlights periodic variations.
- Residual: Random fluctuations after removing the trend and seasonal components.

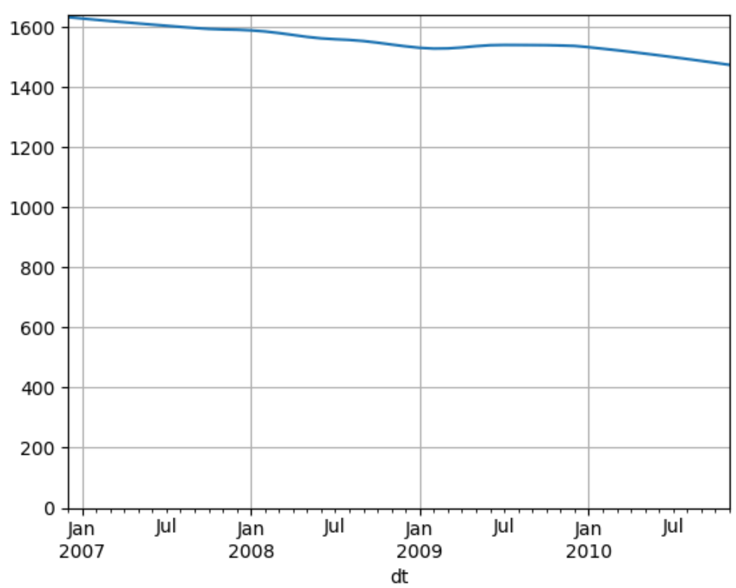
```
print_and_plot_pacf(stl_result.trend)
# AR(1)
```

```
[1.         0.91626883 0.83342435 0.75244521 0.67438421 0.6000977
 0.53014962 0.46485307 0.40444075 0.34916663 0.29931133 0.25505712
 0.21512638 0.17600884 0.1382121  0.10194399 0.06843635]
```



- The high PACF values at the first few lags indicate that the household energy consumption trend is predictable over short to medium terms. This predictability can be leveraged for more accurate forecasting and planning.
- Given the persistence in the trend, households can expect similar consumption patterns over successive periods. This can help in better managing energy resources, scheduling energy-intensive activities, and potentially benefiting from time-of-use pricing by shifting usage to off-peak periods.

```
stl_result.trend.dropna().plot(grid=True)
plt.ylim(ymin=0)
plt.show()
# d = 0
```



- The plotted trend line reveals that energy the energy consumption is increasing, decreasing, or stable over time.
- Households can gain insights into their long-term energy usage patterns and make informed decisions to optimize energy consumption, reduce costs, and contribute to energy sustainability efforts.

```
!pip install pmdarima
```

```
Collecting pmdarima
  Downloading pmdarima-2.0.4-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.manylinux_2_28_x86_64.whl (2.1 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2.1/2.1 MB 20.4 MB/s eta 0:00:00
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.10/dist-packages (from pmdarima) (1.4.2)
Requirement already satisfied: Cython!=0.29.18,!=0.29.31,>=0.29 in /usr/local/lib/python3.10/dist-packages (from pmdarima) (3.0.10)
Requirement already satisfied: numpy>=1.21.2 in /usr/local/lib/python3.10/dist-packages (from pmdarima) (1.25.2)
Requirement already satisfied: pandas>=0.19 in /usr/local/lib/python3.10/dist-packages (from pmdarima) (2.0.3)
Requirement already satisfied: scikit-learn>=0.22 in /usr/local/lib/python3.10/dist-packages (from pmdarima) (1.2.2)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.10/dist-packages (from pmdarima) (1.11.4)
Requirement already satisfied: statsmodels>=0.13.2 in /usr/local/lib/python3.10/dist-packages (from pmdarima) (0.14.2)
Requirement already satisfied: urllib3 in /usr/local/lib/python3.10/dist-packages (from pmdarima) (2.0.7)
Requirement already satisfied: setuptools!=50.0.0,>=38.6.0 in /usr/local/lib/python3.10/dist-packages (from pmdarima) (67.7.2)
Requirement already satisfied: packaging>=17.1 in /usr/local/lib/python3.10/dist-packages (from pmdarima) (24.1)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.19->pmdarima) (2.8
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.19->pmdarima) (2023.4)
Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.19->pmdarima) (2024.1)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.22->pmdarima)
Requirement already satisfied: patsy>=0.5.6 in /usr/local/lib/python3.10/dist-packages (from statsmodels>=0.13.2->pmdarima) (0.5.6)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages (from patsy>=0.5.6->statsmodels>=0.13.2->pmdarima) (1
Installing collected packages: pmdarima
Successfully installed pmdarima-2.0.4
```

```
from pmdarima.arima import auto_arima

data = stl_result.trend

auto_arima_model = auto_arima(data, seasonal=False)

print(auto_arima_model.summary())
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                   48
Model:               SARIMAX(3, 1, 0)   Log Likelihood                 -52.865
Date:                Tue, 02 Jul 2024   AIC                            115.729
Time:                        16:14:33   BIC                            124.980
Sample:                    12-31-2006   HQIC                           119.210
                         - 11-30-2010
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept     -0.3886      0.178     -2.183      0.029      -0.737      -0.040
ar.L1          1.8178      0.122     14.957      0.000       1.580       2.056
ar.L2         -1.2590      0.223     -5.642      0.000      -1.696      -0.822
```

```
ar.L3          0.3340      0.144      2.322      0.020      0.052      0.616
sigma2         0.5139      0.090      5.688      0.000      0.337      0.691
===================================================================================
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):                 6.31
Prob(Q):                              0.93   Prob(JB):                         0.04
Heteroskedasticity (H):               3.37   Skew:                            -0.25
Prob(H) (two-sided):                  0.02   Kurtosis:                         4.72
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

- The AR terms suggest that household energy consumption is heavily influenced by its own past values. The strong AR(1) term (1.8178) indicates a substantial positive autocorrelation, meaning if consumption was high in the previous month, it is likely to be high in the current month.
- The negative AR(2) term (-1.2590) and the positive AR(3) term (0.3340) indicate more complex dynamics, potentially reflecting periodic adjustments in consumption patterns.
- The model appears to fit the data well, with significant AR terms and a reasonable log likelihood.
- The high p-value in the Ljung-Box test suggests no remaining autocorrelation in residuals, indicating a good model fit.
- However, the Jarque-Bera test suggests some deviation from normality in residuals, which could affect the reliability of statistical inferences.
- The heteroskedasticity test indicates potential non-constant variance in residuals, suggesting variability in consumption patterns that may need further investigation.
- By leveraging these model insights, households can optimize their energy consumption, reduce costs, and contribute to sustainability efforts.

```
plt.rcParams.update({'figure.figsize': (16, 12)})

from statsmodels.tsa.arima.model import ARIMA

data = stl_result.trend

q = 0
arima_model = ARIMA(data, order=(2, 0, q))
arima_result = arima_model.fit()

arima_result.plot_diagnostics()

print(arima_result.summary())

from sklearn.metrics import mean_squared_error, r2_score
import math

predictions = arima_result.predict()
rmse = math.sqrt(mean_squared_error(data, predictions))
print(f"RMSE: {rmse:.2f}")
print(f"R2: {r2_score(data, predictions):.2f}")
```