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AI_Phase4

Topic: Measure Energy Consumption

The provided code appears to be a Python script for time series analysis and forecasting of energy consumption data. I'll describe what each section of the code does:

1. Imports Libraries:

The code starts by importing necessary libraries, including NumPy, Pandas, Matplotlib, Seaborn, and various modules from Statsmodels for time series analysis and forecasting.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
matplotlib inline import
seaborn as sns import
warnings
warnings.filterwarnings("ignore")
from pandas.plotting import lag_plot
from pylab import rcParams
from statsmodels.tsa.seasonal import
seasonal_decompose from pandas import DataFrame from
pandas import concat
```

2. Data Loading and Preprocessing:

- It loads a CSV file containing energy consumption data and parses it into a Pandas DataFrame.
- The DataFrame is sorted by the 'Datetime' column, which is assumed to represent timestamps.
- Basic information about the data frame is displayed using `df. shape`, `df.info()`, and `df. describe()`.
- The 'Datetime' column is converted to a datetime data type.
- Additional columns like 'Month,' 'Year,' 'Date,' 'Hour,' 'Week,' and 'Day' are extracted from the datetime index.

```
df=pd.read_csv("../input/Energy_Consumption_Dataset.csv",index_
col='Datetime', parse_dates=True)
df.head()
```

	AEP_MW
Datetime	
2004-12-31 01:00:00	13478.0
2004-12-31 02:00:00	12865.0
2004-12-31 03:00:00	12577.0
2004-12-31 04:00:00	12517.0
2004-12-31 05:00:00	12670.0

3. Data Visualization:

- The code generates a line plot to visualize the energy consumption data.

```
df.sort_values(by='Datetime', inplace=True)
print(df)
```

```
                      AEP_MW
Datetime
2004-10-01 01:00:00  12379.0
2004-10-01 02:00:00  11935.0
2004-10-01 03:00:00  11692.0
2004-10-01 04:00:00  11597.0
2004-10-01 05:00:00  11681.0
...                      ...
2018-08-02 20:00:00  17673.0
2018-08-02 21:00:00  17303.0
2018-08-02 22:00:00  17001.0
2018-08-02 23:00:00  15964.0
2018-08-03 00:00:00  14809.0

[121273 rows x 1 columns]
```

4. Autocorrelation Plot:

- An autocorrelation plot is created to understand the autocorrelation of the energy consumption data.

```
# Extract all Data Like Year MOnth Day Time etc
df["Month"] = df.index.month df["Year"] =
df.index.year df["Date"] = df.index.date
df["Hour"] = df.index.hour df["Week"] =
df.index.week df["Day"] = df.index.day_name()
df.head()
 df.shape
```

```
(121273, 1)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 121273 entries, 2004-10-01 01:00:00 to 2018-08-03 00:00:00
Data columns (total 1 columns):
 #   Column   Non-Null Count   Dtype
---  ------   --------------   -----
 0   AEP_MW   121273 non-null  float64
dtypes: float64(1)
memory usage: 1.9 MB
```

```
df.describe()
```

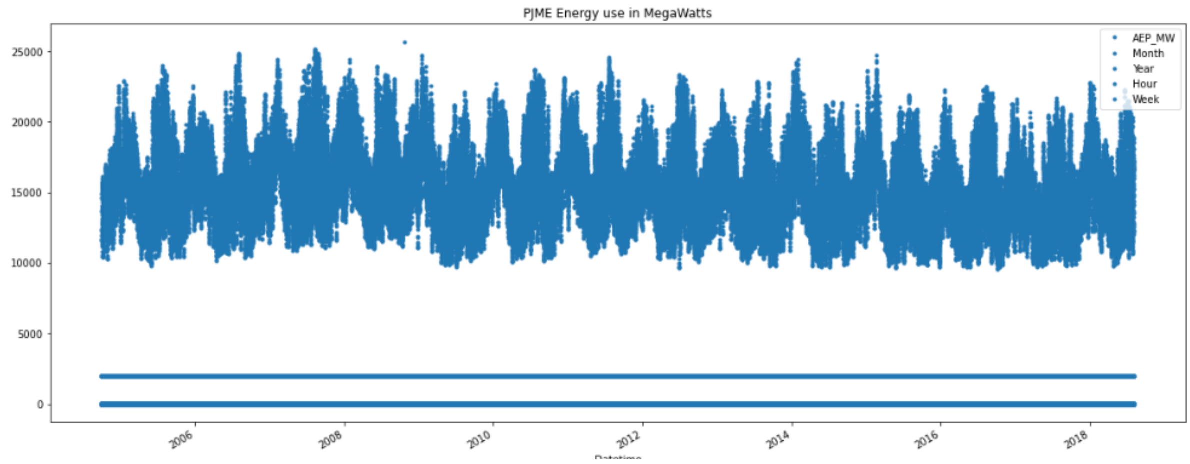
	AEP_MW
count	121273.000000
mean	15499.513717
std	2591.399065
min	9581.000000
25%	13630.000000
50%	15310.000000
75%	17200.000000
max	25695.000000

```
df.index = pd.to_datetime(df.index)


# Extract all Data Like Year MOnth Day Time etc
df["Month"] = df.index.month
df["Year"] = df.index.year
df["Date"] = df.index.date
df["Hour"] = df.index.hour
df["Week"] = df.index.week
df["Day"] = df.index.day_name()
```

```
df.head()
```

	AEP_MW	Month	Year	Date	Hour	Week	Day
Datetime							
2004-10-01 01:00:00	12379.0	10	2004	2004-10-01	1	40	Friday
2004-10-01 02:00:00	11935.0	10	2004	2004-10-01	2	40	Friday
2004-10-01 03:00:00	11692.0	10	2004	2004-10-01	3	40	Friday
2004-10-01 04:00:00	11597.0	10	2004	2004-10-01	4	40	Friday
2004-10-01 05:00:00	11681.0	10	2004	2004-10-01	5	40	Friday

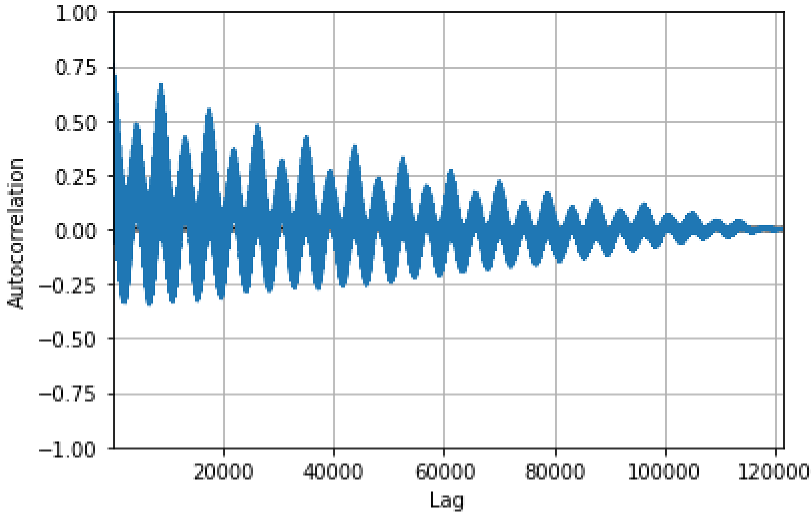
```
df.plot(title="PJME Energy use in MegaWatts",
        figsize=(20, 8),
        style=".",
        color=sns.color_palette()[0])

plt.show()
```




```
df.tail()
```

	AEP_MW	Month	Year	Date	Hour	Week	Day
Datetime							
2018-08-02 20:00:00	17673.0	8	2018	2018-08-02	20	31	Thursday
2018-08-02 21:00:00	17303.0	8	2018	2018-08-02	21	31	Thursday
2018-08-02 22:00:00	17001.0	8	2018	2018-08-02	22	31	Thursday
2018-08-02 23:00:00	15964.0	8	2018	2018-08-02	23	31	Thursday
2018-08-03 00:00:00	14809.0	8	2018	2018-08-03	0	31	Friday

```
from pandas.plotting import autocorrelation_plot
autocorrelation_plot(df['AEP_MW'])
plt.show()
```



5. Modeling Imports:

- The code imports various time series modeling libraries such as AR, ARMA, ARIMA, and parts of Keras for neural network-based models.

```
from sklearn.metrics import mean_squared_error, mean_absolute_error
from math import sqrt
from sklearn.preprocessing import MinMaxScaler

# Analysis imports
from pandas.plotting import lag_plot from
pylab import rcParams
from statsmodels.tsa.seasonal import
seasonal_decompose from pandas import DataFrame from
pandas import concat

# Modelling imports
from statsmodels.tsa.ar_model import AR from
statsmodels.tsa.arima_model import ARMA from
statsmodels.tsa.arima_model import ARIMA
from keras.models import Sequential from
keras.layers import Dense from keras.layers
import LSTM, GRU, RNN from keras.layers
import Dropout
```

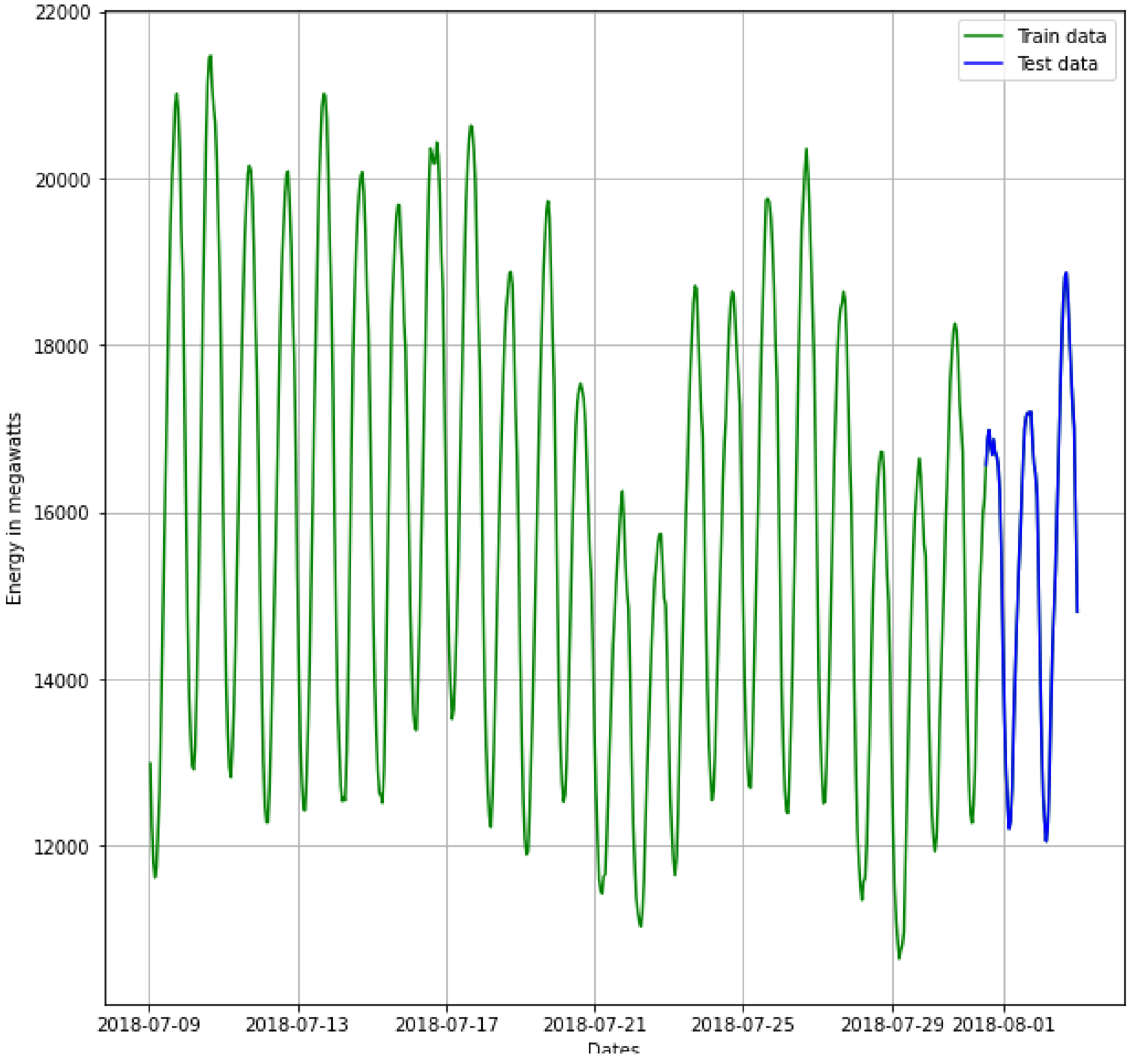
6. Feature Engineering:

- The code creates a lag plot by shifting the 'AEP_MW' values by different time intervals (1, 5, 10, and 30) and combines them into a new data frame. This can be used for lag-based feature engineering.

```
values = DataFrame(df['AEP_MW'].values)
dataframe =
concat([values.shift(1),values.shift(5),values.shift(10),values
.sh ift(30), values], axis=1)
dataframe.columns = ['t', 't+1', 't+5', 't+10', 't+30']
result = dataframe.corr() print(result)
```

	t	t+1	t+5	t+10	t+30
t	1.000000	0.731161	0.345667	0.501972	0.976223
t+1	0.731161	1.000000	0.630009	0.847210	0.630007
t+5	0.345667	0.630009	1.000000	0.644479	0.317277
t+10	0.501972	0.847210	0.644479	1.000000	0.408315
t+30	0.976223	0.630007	0.317277	0.408315	1.000000

```
train_data, test_data = df[0:-60], df[-60:]
plt.figure(figsize=(10,10))
plt.grid(True)
plt.xlabel('Dates')
plt.ylabel('Energy in megawatts')
plt.plot(df['AEP_MW'].tail(600), 'green', label='Train data')
plt.plot(test_data['AEP_MW'], 'blue', label='Test data')
plt.legend()
```

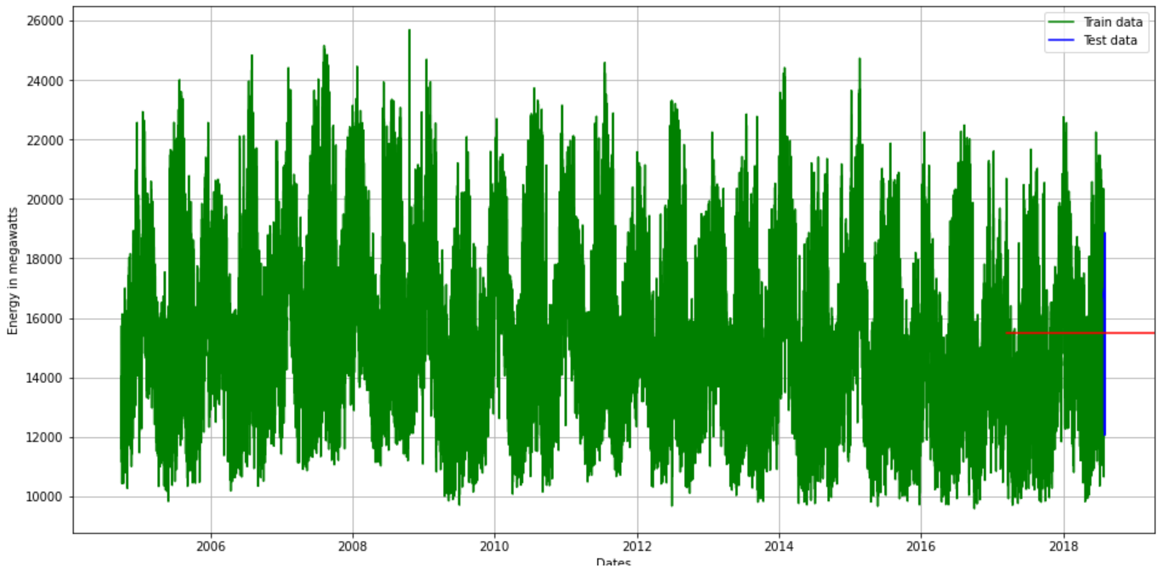


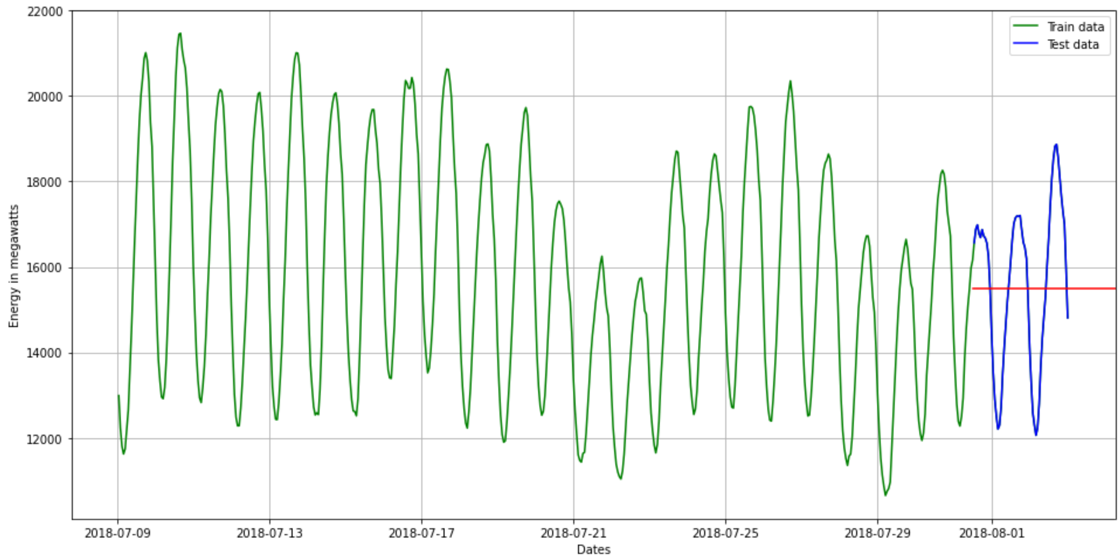
7. Correlation Analysis:

- The code calculates the correlation between lagged features and the original 'AEP_MW' data and prints the correlation matrix.

```
mean_value = df['AEP_MW'].mean() # calculation of mean price

plt.figure(figsize=(16,8))
plt.grid(True)
plt.xlabel('Dates')
plt.ylabel('Energy in megawatts')
plt.plot(df['AEP_MW'], 'green', label='Train data')
plt.plot(test_data['AEP_MW'], 'blue', label='Test data')
plt.axhline(y=mean_value, xmin=0.864, xmax=1, color='red')
plt.legend()

plt.figure(figsize=(16,8))
plt.grid(True)
plt.xlabel('Dates')
plt.ylabel('Energy in megawatts')
plt.plot(df['AEP_MW'].tail(600), 'green', label='Train data')
plt.plot(test_data['AEP_MW'], 'blue', label='Test data')
plt.axhline(y=mean_value, xmin=0.864, xmax=1, color='red')
plt.legend()

print('MSE: '+str(mean_squared_error(test_data['AEP_MW'],
np.full(len(test_dat a), mean_value))))
print('MAE: '+str(mean_absolute_error(test_data['AEP_MW'],
np.full(len(test_da ta), mean_value))))
print('RMSE: '+str(sqrt(mean_squared_error(test_data['AEP_MW'],
np.full(len(te st_data), mean_value)))))
```

```
MSE: 3700885.0406027567
MAE: 1667.1805899362046
RMSE: 1923.768447761517
```






```
from statsmodels.tsa.stattools import adfuller


def adf_test(dataset):
     dftest = adfuller(dataset, autolag = 'AIC')
     print("1. ADF : ",dftest[0])
     print("2. P-Value : ", dftest[1])
     print("3. Num Of Lags : ", dftest[2])
     print("4. Num Of Observations Used For ADF Regression:",      dftes
t[3])
     print("5. Critical Values :")
     for key, val in dftest[4].items():
          print("\t",key, ": ", val)
```

```
adf_test(df['AEP_MW'])
```

```
1. ADF :  -18.285883882257217
2. P-Value :  2.3029539101747796e-30
3. Num Of Lags :  71
4. Num Of Observations Used For ADF Regression: 121201
5. Critical Values :
	1% :  -3.430403955318047
	5% :  -2.8615638474512295
	10% :  -2.566782693155802
```

8. Train-Test Split:

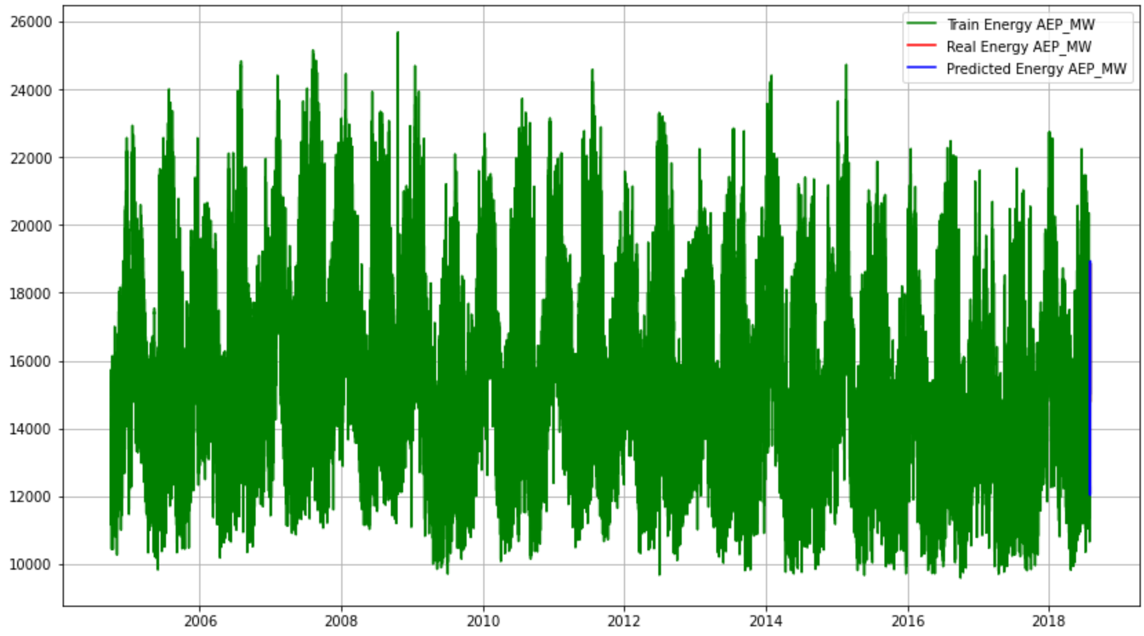
- The data is split into training and test sets. The last 60 data points are used for testing.

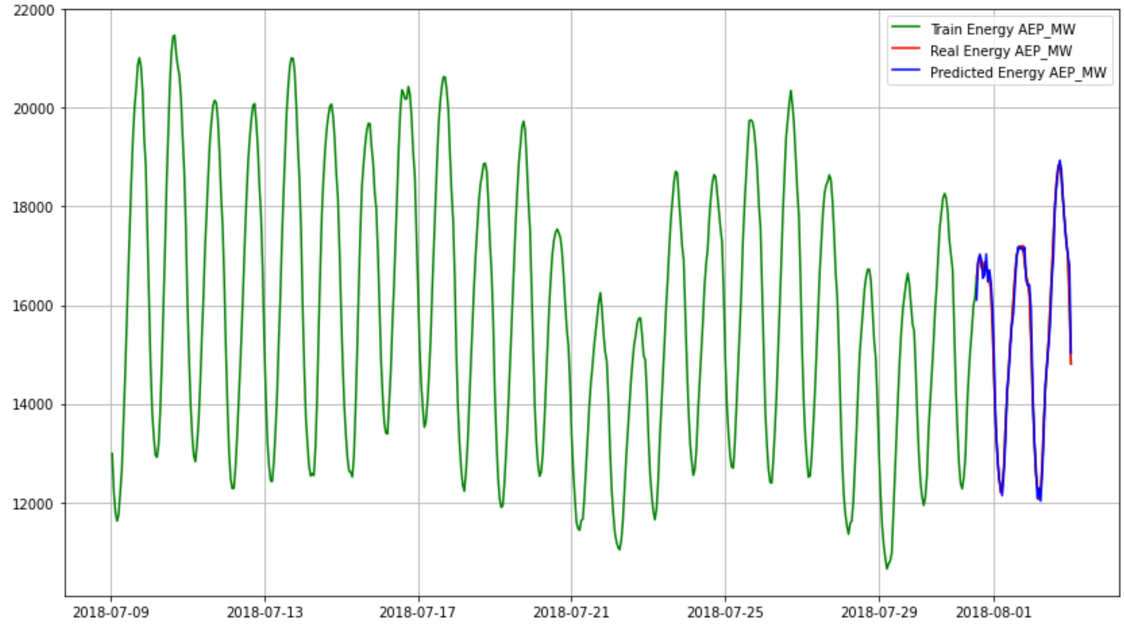
```
#Train Arima Model
train_arima = train_data['AEP_MW']
test_arima = test_data['AEP_MW']

history = [x for x in train_arima]
y = test_arima
# make first prediction
predictions = list()
model = sm.tsa.arima.ARIMA(history,
order=(5,1,0)) model_fit = model.fit() yhat =
model_fit.forecast()[0] predictions.append(yhat)
history.append(y[0]) # rolling forecasts for i in
range(1, len(y)):


    # predict
    model = sm.tsa.arima.ARIMA(history,
order=(5,1,0))     model_fit = model.fit()     yhat =
model_fit.forecast()[0]     # invert transformed
prediction     predictions.append(yhat)
    # observation
obs = y[i]
history.append(obs)
```

9. Visualization of Training and Test Data:

- The code generates line plots to visualize the training and test data, along with a red line indicating the mean value of 'AEP_MW' for reference.

```
plt.figure(figsize=(14,8)) plt.plot(df.index, df['AEP_MW'], color='green',
label = 'Train Energy AEP_MW') plt.plot(test_data.index, y, color = 'red',
label = 'Real Energy AEP_MW') plt.plot(test_data.index, predictions, color =
'blue', label = 'Predicted Ener gy AEP_MW') plt.legend() plt.grid(True)
plt.show()

plt.figure(figsize=(14,8))
plt.plot(df.index[-600:], df['AEP_MW'].tail(600), color='green', label =
'Trai n Energy AEP_MW')
plt.plot(test_data.index, y, color = 'red', label = 'Real Energy AEP_MW')
plt.plot(test_data.index, predictions, color = 'blue', label = 'Predicted
Ener gy AEP_MW') plt.legend() plt.grid(True) plt.show()
print('MSE: '+str(mean_squared_error(y, predictions)))
print('MAE: '+str(mean_absolute_error(y, predictions)))
print('RMSE: '+str(sqrt(mean_squared_error(y,
predictions))))
```





10. Model Evaluation Metrics:

- The code calculates Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) for a baseline model that predicts the mean value.

11. Augmented Dickey-Fuller Test:

- The Augmented Dickey-Fuller (ADF) test is performed to check for stationarity in the time series data.

12. ARIMA Model Training and Forecasting:

  - An ARIMA model is trained using the training data with order (5,1,0) and is used to make forecasts for the test data.

13. Visualization of ARIMA Model Predictions:

  - The code generates line plots to visualize the actual, predicted, and training data.

14. Model Evaluation Metrics for ARIMA:

  - The code calculates MSE, MAE, and RMSE for the ARIMA model's predictions.

```
MSE: 57710.45153428949
MAE: 177.320844006739
RMSE: 240.2299971574938
```

CONCLUSION:

In conclusion, the provided Python script showcases a comprehensive approach to time series analysis and forecasting of energy consumption data. It begins by importing necessary libraries and proceeds through data loading, preprocessing, visualization, feature engineering, modeling, and evaluation.

The code examines key aspects of time series analysis, including autocorrelation, mean value, and stationarity. It employs ARIMA modeling to make predictions and evaluates the model's performance using metrics like Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE).

The script offers a systematic framework for understanding and modeling energy consumption data, enabling data-driven insights and forecasting. By following these steps, organizations can make informed decisions and optimize energy management, contributing to more efficient resource utilization and sustainability.