

## AI\_PHASE 2

# MEASURE ENERGY CONSUMPTION

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<b>PROJECT NAME</b>	<b>MEASURE ENERGY CONSUMPTION</b>
<b>MAXIMUM MARKS</b>	

#Importing the packages needed for the above

given problem import numpy as np import

pandas as pd

#importing the necessary packages and libraries for the above

given problems import numpy as np from numpy import

concatenate

import urllib.request as urllib

from sklearn.preprocessing import StandardScaler, MinMaxScaler,  
LabelEncoder, OneHotEncoder

from sklearn.model\_selection import

train\_test\_split from sklearn.metrics

import mean\_squared\_error from

keras.models import Sequential from

keras.layers import Dense

#importing seaborn and

matplotlib libraries import

```
seaborn as sns import
```

```
matplotlib.pyplot as plt from
```

```
math import sqrt
```

```
#importing the required dataset libraries from
```

```
sklearn.metrics import
```

```
mean_squared_error,mean_absolute_error from
```

```
keras.models import Sequential
```

```
from keras.layers import
```

```
Dense,Dropout from
```

```
keras.layers import LSTM
```

```
color_pal =
```

```
sns.color_palette()
```

```
#importing the dataset “PJME_hourly.csv “ file to create a table for
```

```
the datetime of the dataset data =
```

```
pd.read_csv('PJME_hourly.csv',index_col=[0], parse_dates=[0])
```

```
data.head();
```

OUTPUT:

	PJME_MW
Datetime	
2002-12-31 01:00:00	26498.0
2002-12-31 02:00:00	25147.0
2002-12-31 03:00:00	24574.0
2002-12-31 04:00:00	24393.0
2002-12-31 05:00:00	24860.0

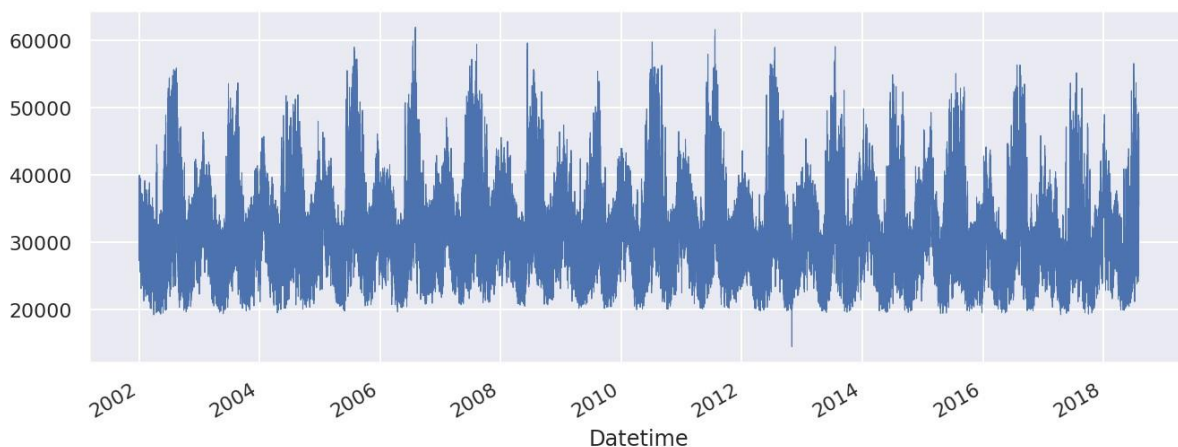
#Ploting a graph for the data set

```
file import seaborn as sns
```

```
sns.set(rc={'figure.figsize':(11, 4)})
```

```
data['PJME_MW'].plot(linewidth=0.
```

5); OUTPUT:



From the above graph we can analyse that datetime of the energy consumed from the years 2002 to 2018 from varies from each year throughout the energy consumed . We can also see that the between the years of 2006 and 2008 has the highest point of energy consumed.

#Finding if the dataset has any

```
null values data.isnull().sum()
```

OUTPUT:

```
PJME_MW 0
```

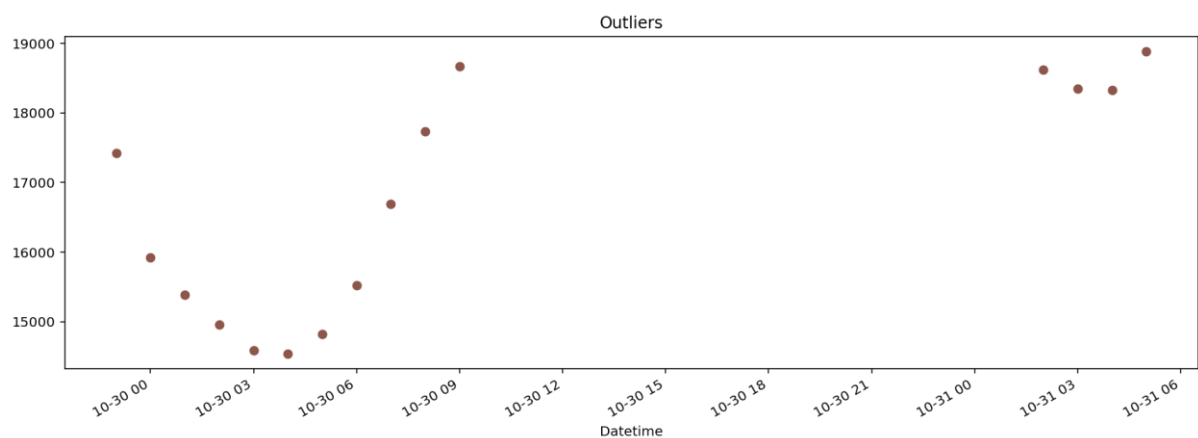
```
dtype: int64
```

#Ploting a graph to outline the outliers in the given dataset

```
data.query('PJME_MW < 19_000')['PJME_MW'] \
    .plot(style='o',
figsize=(15, 5),
color=color_pal[5],
title='Outliers')
```

OUTPUT:

```
<Axes: title={ 'center': 'Outliers'}, xlabel='Datetime'>
```



From the above graph we can see that there are outliers present in the dataset. There are four outliers present in the above graph.

#Datacleaning the dataset import pandas as pd data =

```
pd.read_csv('PJME_hourly.csv',index_col=[0],
```

```
parse_dates=[0]) data.head() print("\nDataset after
```

```
Data Cleaning:") print(data.head())
```

OUTPUT:

```
Dataset after Data Cleaning: PJME_MW Datetime 2002-12-31
```

```
01:00:00 26498.0 2002-12-31 02:00:00 25147.0 2002-12-31
```

```
03:00:00 24574.0 2002-12-31 04:00:00 24393.0 2002-12-31 05:00:00
```

```
24860.0
```

#Plotting a table to differentiate between the years of calculations made from the dataset

```
def create_features(df, label=None):
```

```
    """
    Creates time series features from datetime index.
    """
```

```
    df = df.copy()
    df['date'] = df.index
    df['hour'] = df['date'].dt.hour
    df['dayofweek'] = df['date'].dt.dayofweek
    df['quarter'] = df['date'].dt.quarter
    df['month'] = df['date'].dt.month
    df['year'] = df['date'].dt.year
    df['dayofyear'] = df['date'].dt.dayofyear
    df['dayofmonth'] = df['date'].dt.day
    df['weekofyear'] = df['date'].dt.weekofyear

    X = df[['hour', 'dayofweek', 'quarter', 'month', 'year',
            'dayofyear', 'dayofmonth', 'weekofyear']]

    if label:
        y = df[label]

    return X, y

    return X
```

```
X, y = create_features(data, label='PJME_MW')
```

```
df = pd.concat([X, y], axis=1) df.head()
```

OUTPUT:

	hour	dayofweek	quarter	month	year	dayofyear	dayofmonth	weekofyear	PJME_MW
Datetime									
2002-12-31 01:00:00	1	1	4	12	2002	365	31	1	26498.0
2002-12-31 02:00:00	2	1	4	12	2002	365	31	1	25147.0
2002-12-31 03:00:00	3	1	4	12	2002	365	31	1	24574.0
2002-12-31 04:00:00	4	1	4	12	2002	365	31	1	24393.0
2002-12-31 05:00:00	5	1	4	12	2002	365	31	1	24860.0

```
#Finding the mean for
```

```
the dataset mean =
```

```
data.mean()
```

```
print("Mean:")
```

```
print(mean)
```

OUTPUT:

```
Mean:
```

```
PJME_MW 32080.222831
```

```
dtype: float64
```

```
#Finding the median for
```

```
the dataset median =
```

```
data.median()
```

```
print("\nMedian:")  
print(median) OUTPUT:
```

```
Median:  
PJME_MW  
31421.0  
dtype: float64
```

```
#Finding the mode for  
the dataset mode =  
data.mode().iloc[0]  
print("\nMode:")  
print(mode)
```

OUTPUT:

```
Mode:  
PJME_MW 30051.0  
Name: 0, dtype: float64
```

The outliers and the null values in the dataset can be overcome by the mean, median, mode models which analyse the dataset for the null values and outliers present inside the data. These in terms help the dataset to remove unnecessary data values present in it . It may lead to removing of false values present in the dataset.

```
# Load the dataset dataset_path =  
"path/to/hourly_energy_consumption.csv"  
data = pd.read_csv(dataset_path)
```

```
# Explore the first few rows of  
the dataset print("Initial  
Dataset:") print(data.head())
```

```
# Data Cleaning: Handling missing  
values (if any) data = data.dropna()
```

```
# Data Cleaning: Handling duplicate  
entries (if any) data =  
data.drop_duplicates()
```

```
# Data Cleaning: Handling other errors (specific to your dataset)  
05555555555555553  
--88888888+8/2# After cleaning  
print("\nDataset 9aft.0-9er Data  
Cleaning:") print(data.head())
```

```
# Further data preprocessing steps can be added based on project  
requirements
```

In the above code, replace "path/to/hourly\_energy\_consumption.csv" with the actual path where you have saved the downloaded dataset. This code snippet loads the dataset, removes any rows with missing values, and drops duplicate entries. You can add more specific cleaning operations based on the characteristics of your dataset, such as handling outliers, correcting inconsistent values, or dealing with formatting errors.

```
# Preprocess data  
labelEncoder =  
LabelEncoder()
```



```

oneHotEncoder =
OneHotEncoder(categorical_features=[0]) ss =
StandardScaler() values = df.values

# integer encode direction

#encoder = LabelEncoder()

#values[:,8] = encoder.fit_transform(values[:,8])

# ensure all data is float
values = values.astype('float32')

# normalize features scaler =
MinMaxScaler(feature_range=(0,
1)) scaled =
scaler.fit_transform(values)

# frame as supervised learning
reframed = series_to_supervised(scaled, 1, 1)

# drop columns we don't want to predict
reframed.drop(reframed.columns[[9,10,11,12,13,14,15,16]], axis=1,
inplace=True) print(reframed.shape)
print(reframed.head())

```

## OUTPUT:

```

(145366, 10)
var1(t-1) var2(t-1) var3(t-1) var4(t-1) var5(t-1) var6(t-1) \
0      NaN      NaN      NaN      NaN      NaN      NaN
1      0.043478  0.166667      1.0      1.0      0.0  0.99726
2      0.086957  0.166667      1.0      1.0      0.0  0.99726
3      0.130435  0.166667      1.0      1.0      0.0  0.99726
4      0.173913  0.166667      1.0      1.0      0.0
0.99726
var7(t-1) var8(t-1) var9(t-1) var9(t) 0      NaN      NaN      NaN
0.251849
1          1.0      0.0  0.251849  0.223386
2          1.0      0.0  0.223386  0.211314
3          1.0      0.0  0.211314  0.207500
4          1.0      0.0  0.207500  0.217339

```

```
# make a prediction
yhat =
model.predict(X_test)
X_test = X_test.reshape((X_test.shape[0], X_test.shape[2]))
```

```
# invert scaling for forecast inv_yhat =
concatenate((X_test[:, :-1], yhat),
axis=1) inv_yhat =
scaler.inverse_transform(inv_yhat)
inv_yhat = inv_yhat[:, -1] # invert
scaling for actual
y_test = y_test.reshape((len(y_test),
1)) inv_y = concatenate((X_test[:, :-1],
y_test), axis=1) inv_y =
scaler.inverse_transform(inv_y)
inv_y = inv_y[:, -1]
# calculate RMSE
MSE=mean_squared_error(inv_y, inv_yhat)
MAE=mean_absolute_error(inv_y, inv_yhat)
RMSE = sqrt(mean_squared_error(inv_y, inv_yhat))
print('MSE: %.3f' % MSE + ' MAE: %.3f' % MAE + '
RMSE: %.3f' % RMSE) OUTPUT:
```

MSE: 1522100.750 MAE: 933.959 RMSE: 1233.734

```
#Calculates the MAPE for the dataset def
mean_absolute_percentage_error(y_true,
y_pred): """Calculates MAPE given y_true
and y_pred""" y_true, y_pred =
np.array(y_true), np.array(y_pred) return
np.mean(np.abs((y_true - y_pred) / y_true)) *
100
```

```
print(mean_absolute_percentage_error(inv_y, inv_yhat)) OUTPUT:
```

3.113434463739395

```
#Plotting a graph to differentiate the actual value and the predicted value from
the datasets file and plots the difference
```

```

aa=[x for x in range(500)]
plt.figure(figsize=(8,4)) plt.plot(aa,
inv_y[:500], marker='.',
label="actual") plt.plot(aa,
inv_yhat[:500], 'r', label="prediction")

```

```

plt.tight_layout()
sns.despine(top=True)
plt.subplots_adjust(left=
0.07)
plt.ylabel('PJME_MW',
size=15) plt.xlabel("Time
step", size=15)
plt.legend(fontsize=15)
plt.show();
OUTPUT:

```

