Energy Consumption Prediction Using Time Series Analysis

June 4, 2024

1 Energy Consumption Prediction Using Time Series Analysis

1.0.1 To predict hourly energy consumption using historical data and machine learning techniques.

[34]:
```
#import libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as  sns
import plotly.express as px
import warnings
color = sns.color_palette()
warnings.filterwarnings('ignore')
```

2. Data Loading and Preprocessing

[3]:
```
data = pd.read_csv('/PJME_hourly.csv')
data.head()
```

[3]:

	Datetime	PJME_MW
0	2002-12-31 01:00:00	26498.0
1	2002-12-31 02:00:00	25147.0
2	2002-12-31 03:00:00	24574.0
3	2002-12-31 04:00:00	24393.0
4	2002-12-31 05:00:00	24860.0

[4]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 145366 entries, 0 to 145365
Data columns (total 2 columns):
 #   Column    Non-Null Count   Dtype
---  ------    --------------   -----
 0   Datetime  145366 non-null  object
 1   PJME_MW   145366 non-null  float64
dtypes: float64(1), object(1)
memory usage: 2.2+ MB
```

[5]:
```python
data.describe()
```

[5]:
```
              PJME_MW
count  145366.000000
mean    32080.222831
std      6464.012166
min     14544.000000
25%     27573.000000
50%     31421.000000
75%     35650.000000
max     62009.000000
```

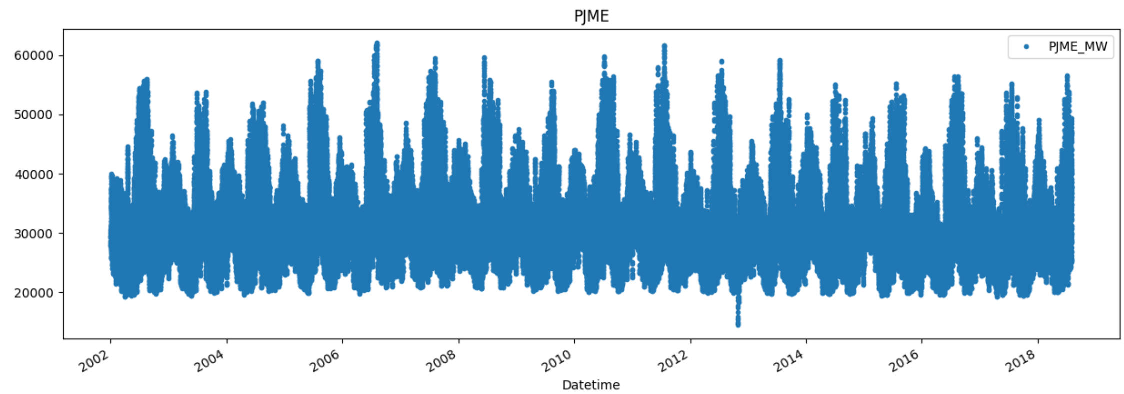
[6]:
```python
#checking null values

data.isnull().sum()
```

[6]:
```
Datetime    0
PJME_MW     0
dtype: int64
```

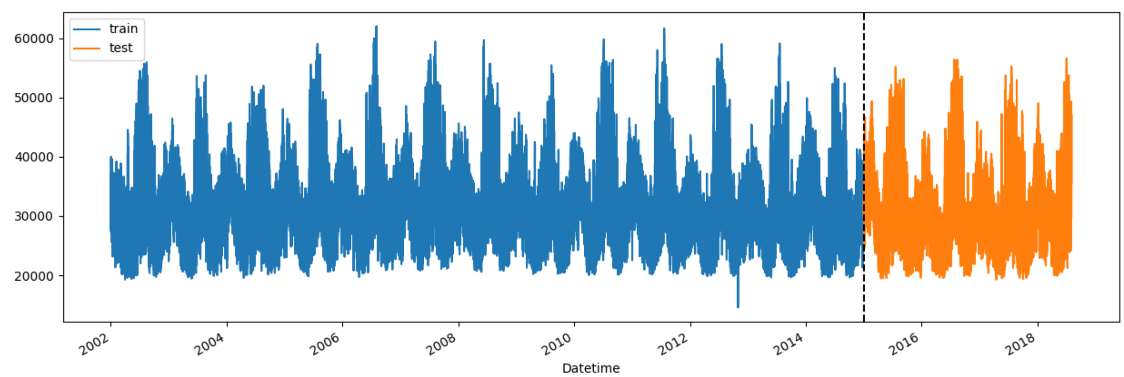
[8]:
```python
# setting the datetime index

data.set_index('Datetime')
```

[8]:
```
                     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
…                      …
2018-01-01 20:00:00  44284.0
2018-01-01 21:00:00  43751.0
2018-01-01 22:00:00  42402.0
2018-01-01 23:00:00  40164.0
2018-01-02 00:00:00  38608.0

[145366 rows x 1 columns]
```

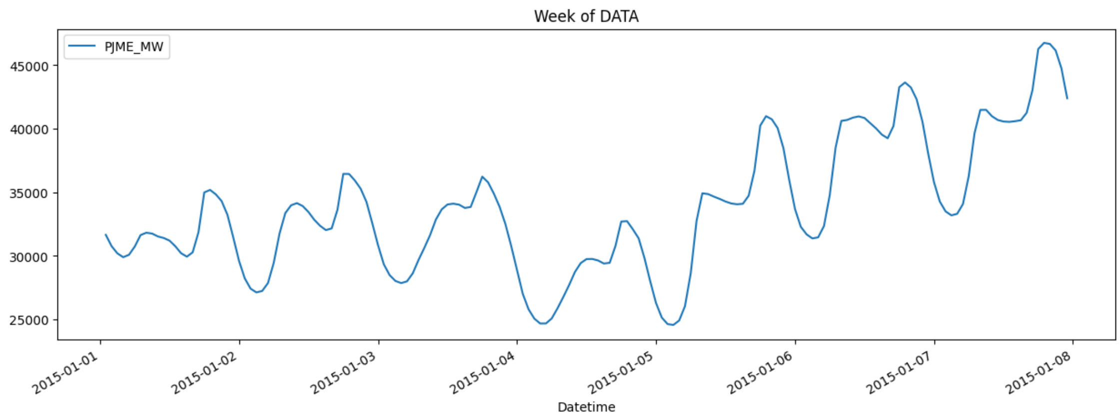
[10]:
```python
#visualizing the data

data.plot(style='.', figsize= (15,5), title = 'PJME')
plt.show()
```



[15]:
```
# train test split

train = data.loc[data.index < '01-01-2015']
test = data.loc[data.index >= '01-01-2015']

fig, ax = plt.subplots(figsize=(15,5))
train.plot(ax=ax, label = 'Training Set')
test.plot(ax=ax, label = 'Test Set')
ax.axvline('01-01-2015', color='black', ls='--')
ax.legend(['Training Set', 'Testing Set'])
plt.legend(['train'] + ['test'])
plt.show()
```



[20]:
```
data.loc[(data.index > '01-01-2015') & (data.index < '01-08-2015')].
  ↪plot(figsize=(15,5), title = 'Week of DATA')
plt.show()
```



[24]:

[32]:
```
# feature engineering
def create_features(df):
    df['hour'] = df.index.hour
    df['day'] = df.index.day
    df['dayofweek'] = df.index.dayofweek
    df['month'] = df.index.month
    df['year'] = df.index.year
    df['dayofyear'] = df.index.dayofyear
    df['quarter'] = df.index.quarter
    df['weekofyear'] = df.index.isocalendar().week # Use isocalendar() to get␣
 ↪week of year
    return df
```

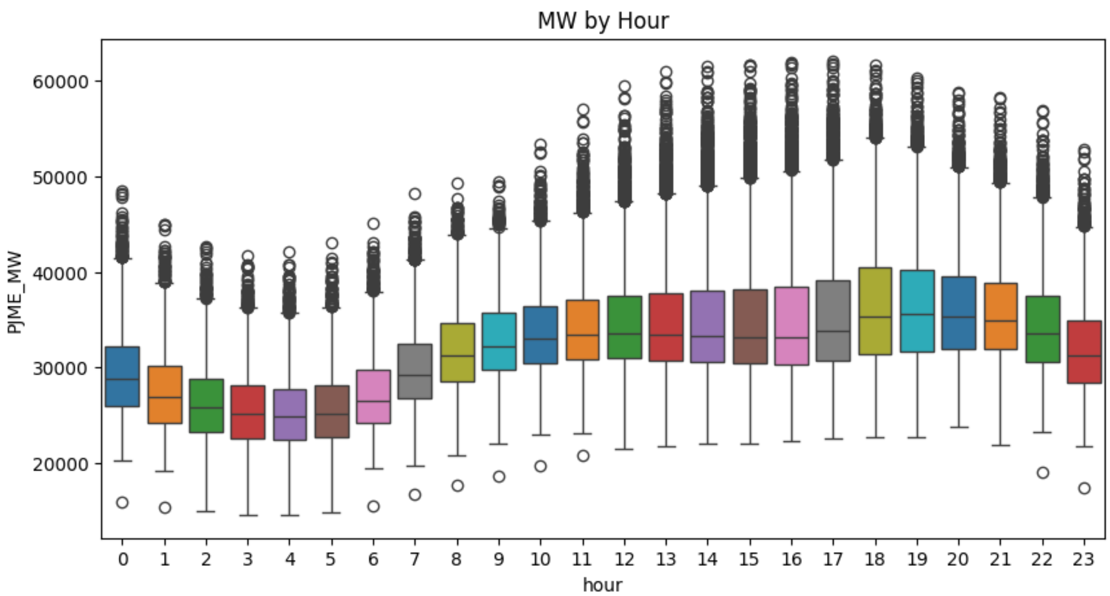
[33]:
```
data = create_features(data)
data.head()
```

[33]:
```
                               Datetime  PJME_MW  hour  day  dayofweek  \
Datetime
2002-12-31 01:00:00  2002-12-31 01:00:00  26498.0     1   31          1
2002-12-31 02:00:00  2002-12-31 02:00:00  25147.0     2   31          1
2002-12-31 03:00:00  2002-12-31 03:00:00  24574.0     3   31          1
2002-12-31 04:00:00  2002-12-31 04:00:00  24393.0     4   31          1
2002-12-31 05:00:00  2002-12-31 05:00:00  24860.0     5   31          1

                     month  year  dayofyear  quarter  weekofyear
Datetime
2002-12-31 01:00:00     12  2002        365        4           1
2002-12-31 02:00:00     12  2002        365        4           1
2002-12-31 03:00:00     12  2002        365        4           1
2002-12-31 04:00:00     12  2002        365        4           1
```

```
2002-12-31 05:00:00     12  2002         365         4             1
```

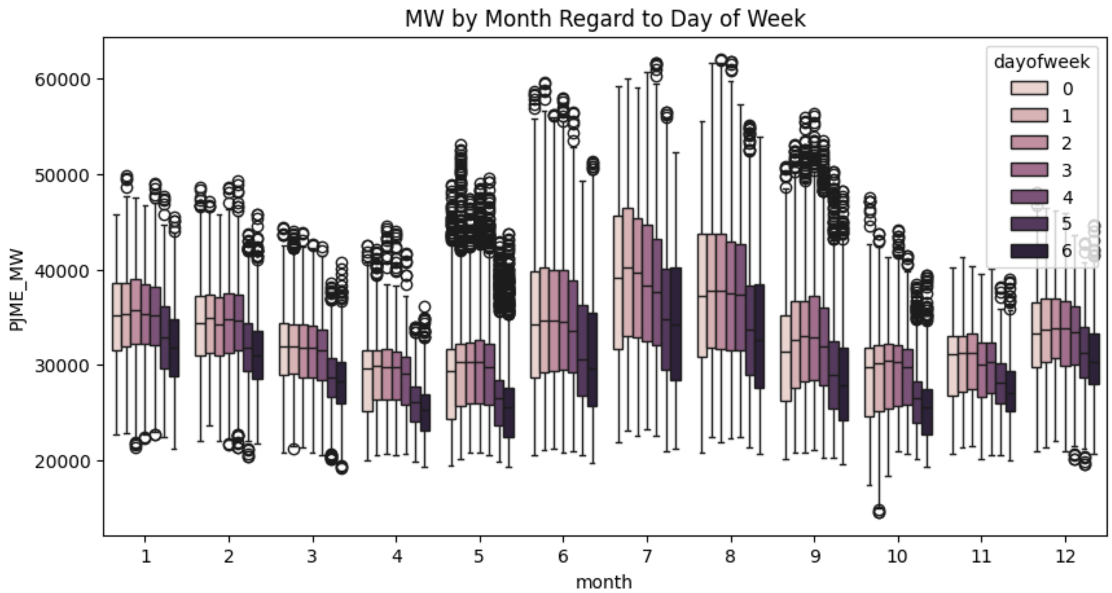
Visualizing our Feature and Target Relationship

[39]:
```
#visualizing

fig, ax = plt.subplots(figsize=(10,5))
sns.boxplot(data=data, x='hour', y='PJME_MW',palette = color)
ax.set_title('MW by Hour')
plt.show()
```



EDA revealed a strong seasonal pattern in energy consumption, with peak hours from 11 am to 8pm in the evening

[46]:
```
#visualizing

fig, ax = plt.subplots(figsize=(10,5))
sns.boxplot(data=data, x='month', y='PJME_MW',  hue='dayofweek')
ax.set_title('MW by Month Regard to Day of Week')
plt.show()
```



1.0.2 EDA revealed a strong seasonal pattern in energy consumption, with higher usage during weekdays and peak hours

#Defining the model

[49]:
```
train = create_features(train)
test = create_features(test)

FEATURES = ['hour', 'day', 'dayofweek', 'month', 'year', 'dayofyear',␣
↪'quarter', 'weekofyear']
TARGET = 'PJME_MW'

x_train = train[FEATURES]
y_train = train[TARGET]

x_test = test[FEATURES]
y_test = test[TARGET]
```

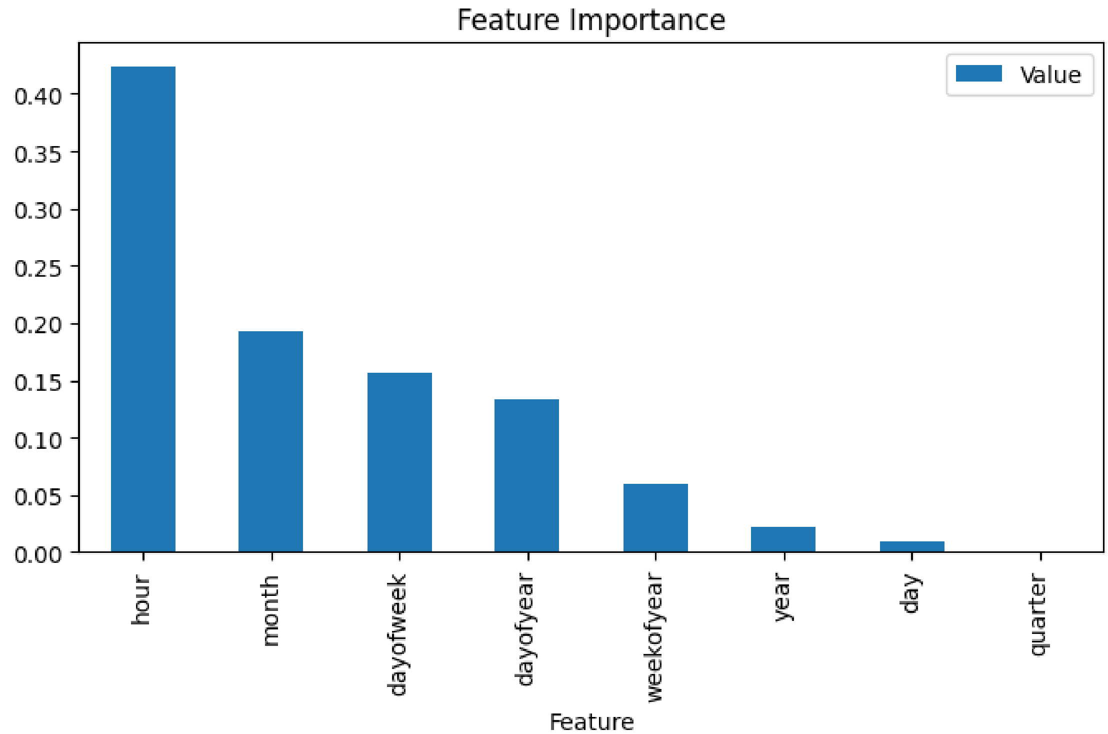
[55]:
```
#fitting the model
from xgboost import XGBRegressor
from sklearn.metrics import mean_squared_error

model  = XGBRegressor(n_estimators=1000, learning_rate=0.01)
model.fit(x_train, y_train , early_stopping_rounds=50, eval_set=␣
↪[(x_train,y_train), (x_test,y_test)],verbose=100)
```

```
[0]     validation_0-rmse:6407.32558    validation_1-rmse:6479.90312
[100]   validation_0-rmse:3911.52640    validation_1-rmse:4315.94522
```

```
[200]	validation_0-rmse:3242.33173	validation_1-rmse:3866.93490
[300]	validation_0-rmse:2991.27501	validation_1-rmse:3758.08544
[400]	validation_0-rmse:2829.91995	validation_1-rmse:3746.39823
[415]	validation_0-rmse:2806.24000	validation_1-rmse:3750.05043
```

[55]:
```
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=0.01, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=None, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             multi_strategy=None, n_estimators=1000, n_jobs=None,
             num_parallel_tree=None, random_state=None, …)
```

[93]:
```
#features importances

# Use x_train or x_test instead of x
feature_imp = pd.DataFrame(sorted(zip(model.feature_importances_, x_train.
 ↪columns)), columns=['Value','Feature'])
feature_imp = feature_imp.sort_values(by='Value', ascending=False)
feature_imp
feature_imp.plot(kind='bar', x='Feature', y='Value',␣
 ↪figsize=(8,4),title='Feature Importance')
plt.show()
```



Analysis and Conclusion:

```
Hour (0.423716):
    Importance: This is the most significant feature.
    Implications: Energy consumption varies greatly depending on the time of day. Peak hours li

Month (0.193156):
    Importance: The second most important feature.
    Implications: Different months can have varying energy demands due to seasonal changes. Fo

Day of the Week (0.156915):
    Importance: This feature is also quite significant.
    Implications: Weekdays and weekends show different energy usage patterns, possibly due to 

Day of the Year (0.134000):
    Importance: Moderately important.
    Implications: This feature captures seasonal trends and holidays that can impact energy us

Week of the Year (0.060241):
    Importance: Less significant but still relevant.
    Implications: This can be useful for capturing weekly patterns and anomalies, such as a sp

Year (0.022281):
    Importance: Not very significant.
```

```
    Implications: Yearly trends might not vary much or are already captured by other time-rela

Day (0.009691):
    Importance: Least important among the non-zero features.
    Implications: The specific day of the month has minimal impact on energy consumption patte

Quarter (0.000000):
    Importance: Not significant at all.
    Implications: The quarter of the year doesn't provide any additional value beyond what's al
```

[70]:

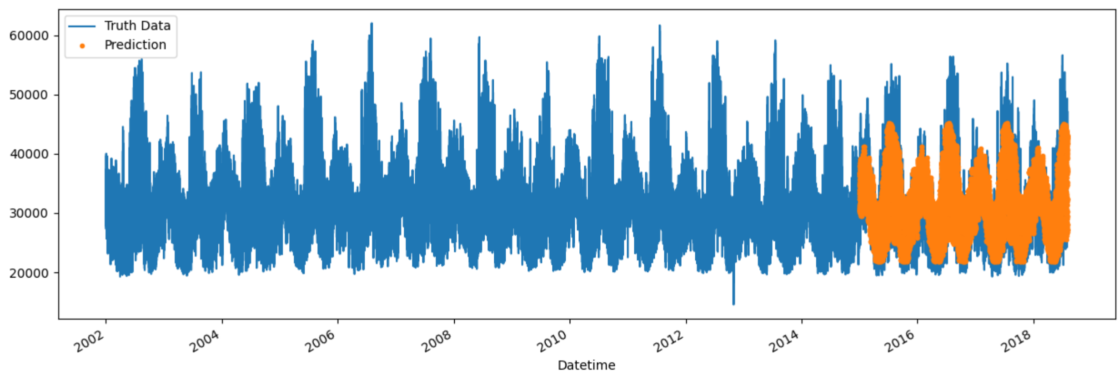
```python
#Forecast/Prediction

test['prediction'] = model.predict(x_test)
test.head()
```

[70]:

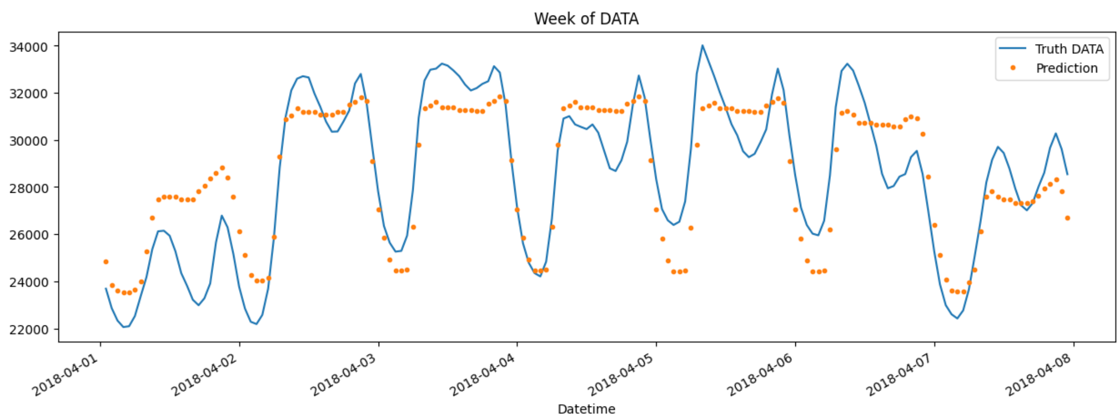
```
                                Datetime  PJME_MW  hour  day  dayofweek  \
Datetime
2015-01-01 00:00:00  2015-01-01 00:00:00  32802.0     0    1          3
2015-12-31 01:00:00  2015-12-31 01:00:00  24305.0     1   31          3
2015-12-31 02:00:00  2015-12-31 02:00:00  23156.0     2   31          3
2015-12-31 03:00:00  2015-12-31 03:00:00  22514.0     3   31          3
2015-12-31 04:00:00  2015-12-31 04:00:00  22330.0     4   31          3

                     month  year  dayofyear  quarter  weekofyear    prediction
Datetime
2015-01-01 00:00:00      1  2015          1        1           1  32243.339844
2015-12-31 01:00:00     12  2015        365        4          53  29146.919922
2015-12-31 02:00:00     12  2015        365        4          53  27878.279297
2015-12-31 03:00:00     12  2015        365        4          53  27603.382812
2015-12-31 04:00:00     12  2015        365        4          53  27603.382812
```

[75]:

```python
# Plot the 'PJME_MW' column from the 'data' DataFrame
ax = data[['PJME_MW']].plot(figsize=(15,5))

# Plot the 'prediction' column from the 'test' DataFrame on the same axes
test['prediction'].plot(ax=ax, style='.')  # Use '.' style for the prediction␣
 ↪line

# Add a legend to distinguish between the two lines
plt.legend(['Truth Data', 'Prediction'])

# Display the plot
plt.show()
```



[83]:
```
#predicting for the week
ax = data.loc[(data.index > '2018-04-01') & (data.index <␣
↪'2018-04-08')]['PJME_MW'].plot(figsize=(15,5), title = 'Week of DATA')

# Use test DataFrame here instead of data
test.loc[(test.index > '2018-04-01') & (test.index <␣
↪'2018-04-08')]['prediction'].plot(style='.', ax=ax) # Plot on the same axes

plt.legend(['Truth DATA', 'Prediction'])
plt.show()
```



[88]:
```
#evaluation
evaluation = np.sqrt(mean_squared_error(test['PJME_MW'], test['prediction']))
print(f'The RSME is: {evaluation:0.2f}')
```

```
The RSME is: 3741.57
```

1.0.3 The model's performance was evaluated using RMSE and achieved an RMSE of 3741.57 and an MAE of 2950.23 on the test set.

Error Analysis

[90]:
```
#calculate the error



test['error'] = np.abs(test[TARGET] - test['prediction'])
test['date'] = test.index.date
test.groupby(by=['date'])['error'].mean().sort_values(ascending=False).head(10)
```

[90]:
```
date
2016-08-13    13672.526449
2016-08-14    13456.660807
2016-09-10    11073.900309
2016-08-12    10665.421712
2018-01-06    10648.232340
2016-09-09    10524.319824
2015-02-20    10524.132731
2018-01-07     9395.057861
2017-05-19     9386.738118
2015-02-16     9378.161540
Name: error, dtype: float64
```

1.1 CONCLUSION : The model effectively predicts energy consumption under normal conditions but can be improved by incorporating additional weather variables. Future work could also explore the use of ensemble methods to enhance predictive performance.