forecasting-with-XGBoost-2017-2019

January 11, 2021

1 Load forecasting of Bangladesh using one time series analysis technique of machine learning (XGboost) (2017-2019)

[65]:
```
# # Hide the code by default from the web page:
# # (from: http://stackoverflow.com/questions/27934885/
 ↪how-to-hide-code-from-cells-in-ipython-notebook-visualized-with-nbviewer#28073228)
from IPython.display import HTML

HTML('''<script>
code_show=true;
function code_toggle() {
 if (code_show){
 $('div.input').hide();
 } else {
 $('div.input').show();
 }
 code_show = !code_show
}
$( document ).ready(code_toggle);
</script>
<form action="javascript:code_toggle()"><input type="submit" value="Click here␣
 ↪to toggle on/off the code."></form>
''')
```

[65]:
```
<IPython.core.display.HTML object>
```

[1]:
```
#Importing necessary files
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import xgboost as xgb
from xgboost import plot_importance, plot_tree
from sklearn.metrics import mean_squared_error, mean_absolute_error
plt.style.use('fivethirtyeight')
```

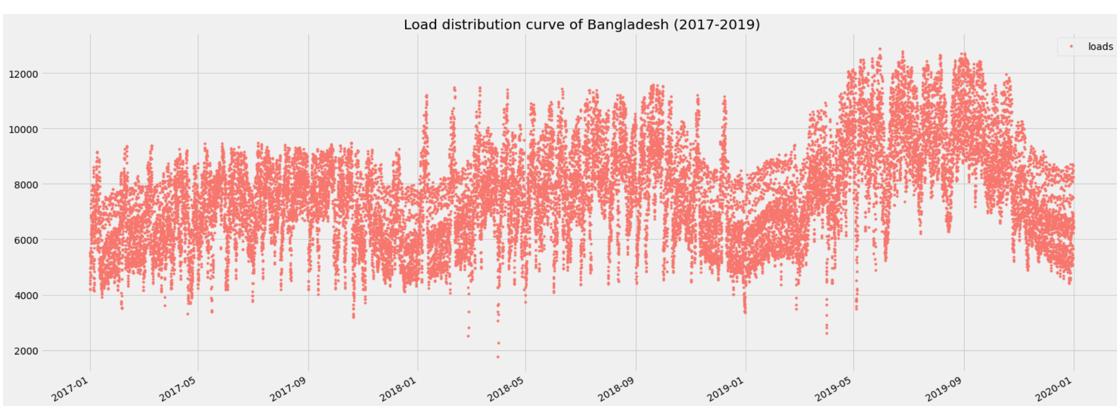
[2]:
```
#Merging the csv files of three years into one csv file
import glob
path = r'C:\Users\Md Samsul Alam\Dropbox\Anaconda_directory\Load␣
↪forecasting\Using ML\with XGBoost' # use your path
three_years_data = glob.glob(path + "/*.csv")

single_year = []

for filename in three_years_data:
    data = pd.read_csv(filename, index_col=[0], parse_dates=[0])
    single_year.append(data)

df = pd.concat(single_year)
```

[3]:
```
df.head(10)
```

[3]:
```
                     loads
date_time
2017-01-01 01:00:00  4807.0
2017-01-01 02:00:00  4525.0
2017-01-01 03:00:00  4395.0
2017-01-01 04:00:00  4211.0
2017-01-01 05:00:00  4197.0
2017-01-01 06:00:00  4415.0
2017-01-01 07:00:00  4620.0
2017-01-01 08:00:00  4957.0
2017-01-01 09:00:00  5515.0
2017-01-01 10:00:00  5518.0
```

[4]:
```
color_pal = ["#F8766D", "#D39200", "#93AA00", "#00BA38", "#00C19F", "#00B9E3",␣
↪"#619CFF", "#DB72FB"]
df.plot(style='.', figsize=(25,10), color=color_pal[0], title='Load␣
↪distribution curve of Bangladesh (2017-2019)')
```

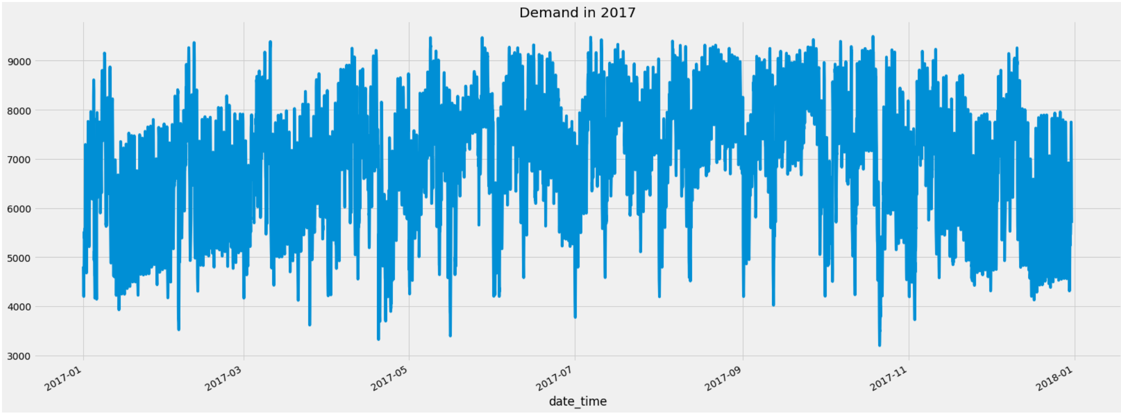
[4]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22b26695d88>
```



2 Yearly demand distribution

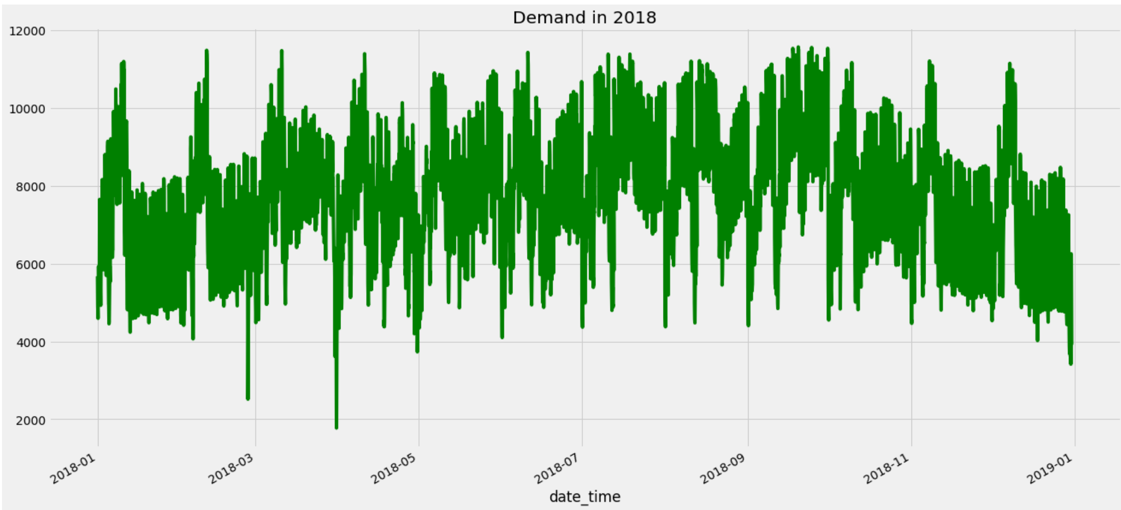
[5]:
```
df['loads'].loc[(df['loads'].index <='2017-12-31')].
↪plot(figsize=(25,10),title='Demand in 2017')
```

[5]: <matplotlib.axes._subplots.AxesSubplot at 0x22b27500888>



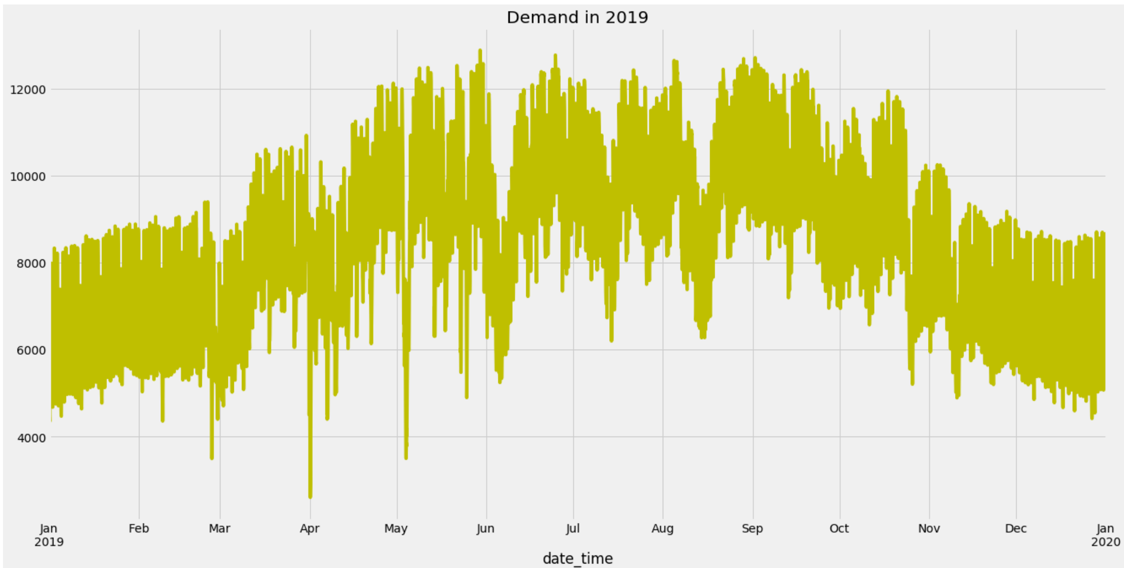
[6]:
```
df['loads'].loc[(df['loads'].index <='2018-12-31') & (df['loads'].index >=␣
↪'2018-01-01')].plot(figsize=(20,10),color='g', title='Demand in 2018')
```

[6]: <matplotlib.axes._subplots.AxesSubplot at 0x22b2705f288>



[7]:
```
df['loads'].loc[(df['loads'].index >='2019-01-01')].
↪plot(figsize=(20,10),color='y',title='Demand in 2019')
```

[7]: <matplotlib.axes._subplots.AxesSubplot at 0x22b27117b48>

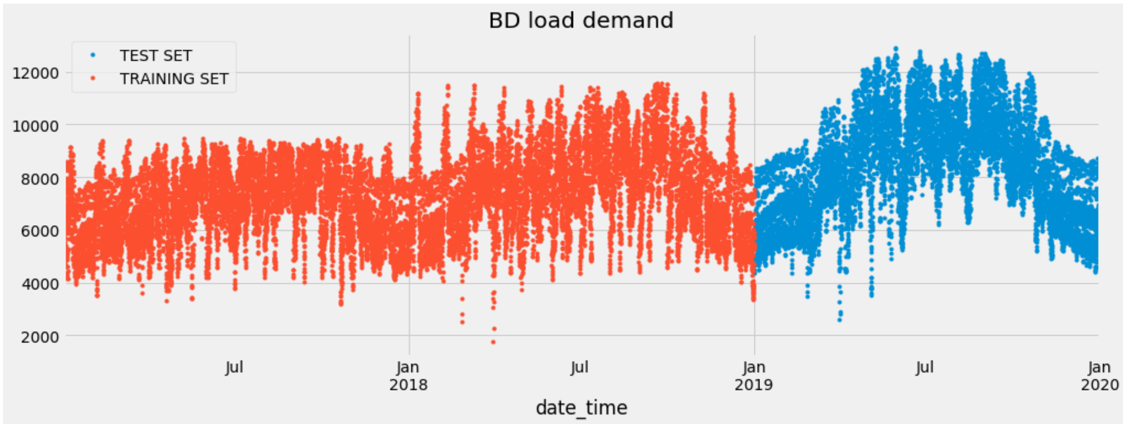


3 Preparing data for training and testing

[8]:
```
split_date = '01-01-2019'
df_train =df.loc[df.index <= split_date].copy()
df_test =df.loc[df.index > split_date].copy()
```

[9]:
```
df_test.rename(columns={'loads': 'TEST SET'}) \
    .join(df_train.rename(columns={'loads': 'TRAINING SET'}), how='outer') \
    .plot(figsize=(15,5), title='BD load demand', style='.')
```

[9]: <matplotlib.axes._subplots.AxesSubplot at 0x22b2724cd48>



4 Create Time Series Features

[10]:
```
def create_features(df, label=None):
    """
    Creates time series features from datetime index
    """
    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
```

[11]:
```
X_train, y_train = create_features(df_train, label='loads')
X_test, y_test = create_features(df_test, label='loads')
```

5 Create XGBoost Model

[12]:
```
reg = xgb.XGBRegressor(n_estimators=1000)
reg.fit(X_train, y_train,
        eval_set=[(X_train, y_train), (X_test, y_test)],
        early_stopping_rounds=50,
       verbose=False) # Change verbose to True if you want to see it train
```

[12]:
```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
             importance_type='gain', interaction_constraints='',
             learning_rate=0.300000012, max_delta_step=0, max_depth=6,
             min_child_weight=1, missing=nan, monotone_constraints='()',
             n_estimators=1000, n_jobs=0, num_parallel_tree=1,
             objective='reg:squarederror', random_state=0, reg_alpha=0,
             reg_lambda=1, scale_pos_weight=1, subsample=1, tree_method='exact',
             validate_parameters=1, verbosity=None)
```

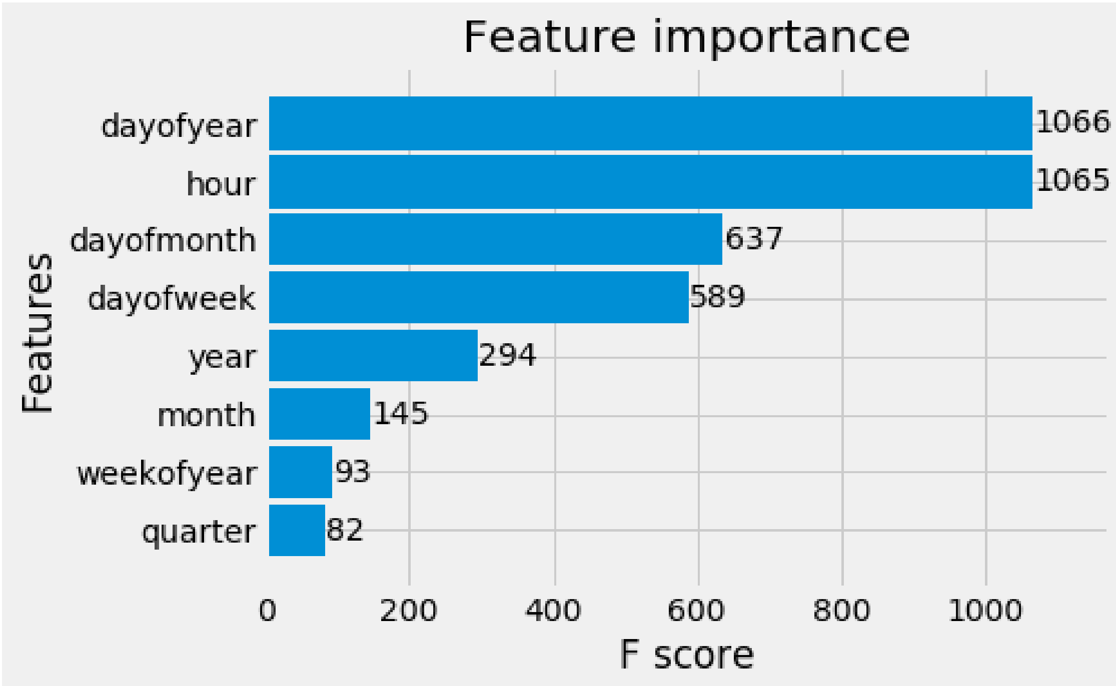
6 Feature Importances

Feature importance is a great way to get a general idea about which features the model is relying on most to make the prediction. This is a metric that simply sums up how many times each feature is split on.

We can see that the day of year was most commonly used to split trees, while hour and year came in next. Quarter has low importance due to the fact that it could be created by different dayofyear splits.

[13]:
```
plot_importance(reg, height=0.9)
```

[13]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x22b27da4548>
```



7 Forecast on Test Set

[14]:
```
df_test['MW_Prediction'] = reg.predict(X_test)
df_all = pd.concat([df_test, df_train], sort=False)
```

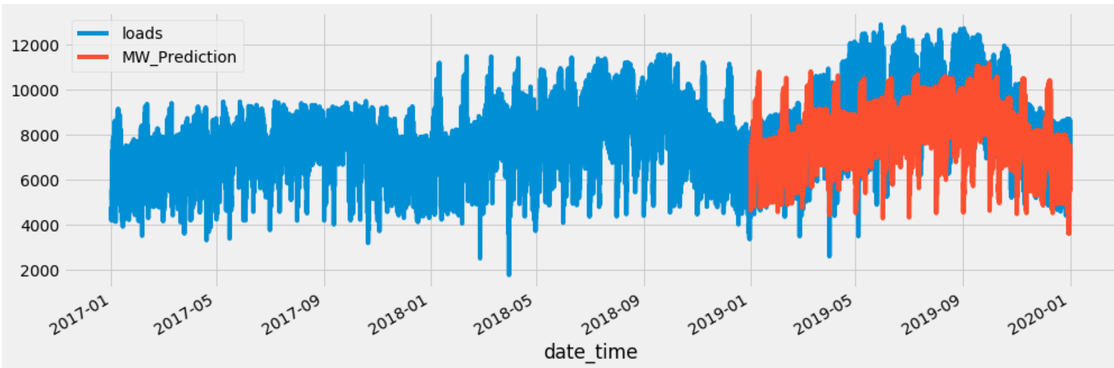
[15]:
```
df_all.head()
```

[15]:
```
                      loads                date  hour  dayofweek  quarter  \
date_time
2019-01-01 01:00:00  4984.0 2019-01-01 01:00:00     1          1        1
2019-01-01 02:00:00  4644.0 2019-01-01 02:00:00     2          1        1
2019-01-01 03:00:00  4487.0 2019-01-01 03:00:00     3          1        1
2019-01-01 04:00:00  4399.0 2019-01-01 04:00:00     4          1        1
2019-01-01 05:00:00  4350.0 2019-01-01 05:00:00     5          1        1

                     month  year  dayofyear  dayofmonth  weekofyear  \
date_time
2019-01-01 01:00:00      1  2019          1           1           1
2019-01-01 02:00:00      1  2019          1           1           1
2019-01-01 03:00:00      1  2019          1           1           1
2019-01-01 04:00:00      1  2019          1           1           1
2019-01-01 05:00:00      1  2019          1           1           1

                     MW_Prediction
```

```
date_time
2019-01-01 01:00:00    5314.390625
2019-01-01 02:00:00    5042.840820
2019-01-01 03:00:00    4879.201660
2019-01-01 04:00:00    4754.636719
2019-01-01 05:00:00    4639.765137
```

[16]:

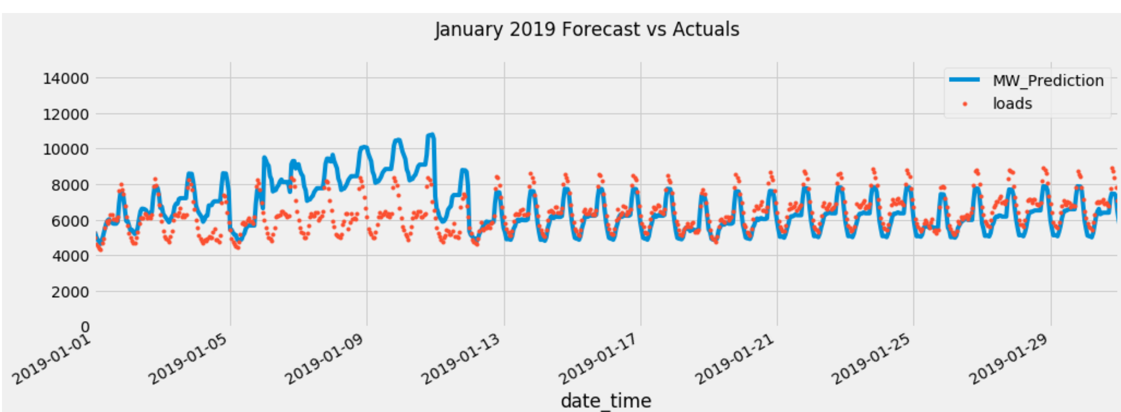
```
_ = df_all[['loads','MW_Prediction']].plot(figsize=(15, 5))
```



8 Look at first month of predictions

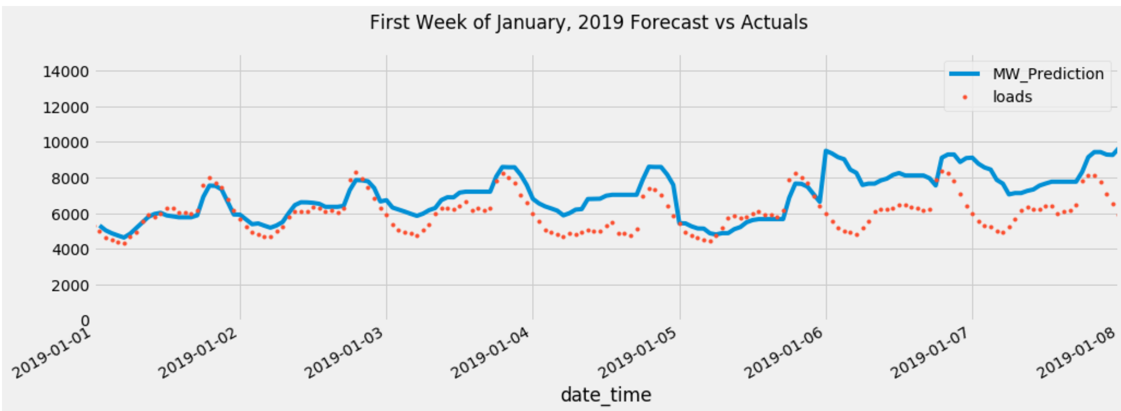
[17]:

```
# Plot the forecast with the actuals
f, ax = plt.subplots(1)
f.set_figheight(5)
f.set_figwidth(15)
_ = df_all[['MW_Prediction','loads']].plot(ax=ax,
                                              style=['-','.'])
ax.set_xbound(lower='2019-01-01', upper='2019-01-31')
ax.set_ylim(0, 15000)
plot = plt.suptitle('January 2019 Forecast vs Actuals')
```



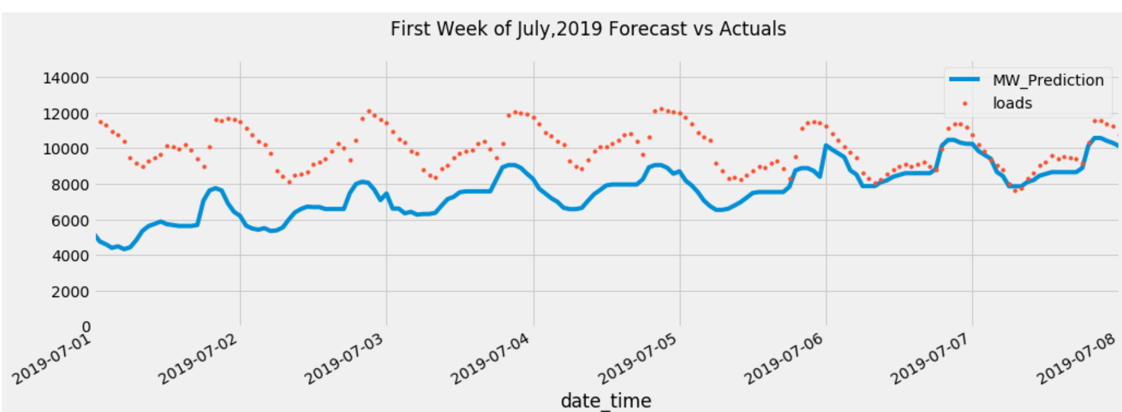
[18]:

```
# Plot the forecast with the actuals
f, ax = plt.subplots(1)
f.set_figheight(5)
f.set_figwidth(15)
_ = df_all[['MW_Prediction','loads']].plot(ax=ax,
                                              style=['-','.'])
ax.set_xbound(lower='2019-01-01', upper='2019-01-08')
ax.set_ylim(0, 15000)
plot = plt.suptitle('First Week of January, 2019 Forecast vs Actuals')
```



[19]:

```
f, ax = plt.subplots(1)
f.set_figheight(5)
f.set_figwidth(15)
_ = df_all[['MW_Prediction','loads']].plot(ax=ax,
                                              style=['-','.'])
ax.set_ylim(0, 15000)
ax.set_xbound(lower='2019-07-01', upper='2019-07-08')
plot = plt.suptitle('First Week of July,2019 Forecast vs Actuals')
```



9 Error Metrics On Test Set

[20]:
```
mean_squared_error(y_true=df_test['loads'],
                   y_pred=df_test['MW_Prediction'])
```

[20]: 2965032.9533133716

[21]:
```
mean_absolute_error(y_true=df_test['loads'],
                   y_pred=df_test['MW_Prediction'])
```

[21]: 1342.1403727369614

I like using mean absolute percent error because it gives an easy to interperate percentage showing how off the predictions are. MAPE isn't included in sklearn so we need to use a custom function.

[22]:
```
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
```

[23]:
```
mean_absolute_percentage_error(y_true=df_test['loads'],
                   y_pred=df_test['MW_Prediction'])
```

[23]: 15.75549170701343

10 Look at Worst and Best Predicted Days

[24]:
```
df_test['error'] = df_test['loads'] - df_test['MW_Prediction']
df_test['abs_error'] = df_test['error'].apply(np.abs)
error_by_day = df_test.groupby(['year','month','dayofmonth']) \
    .mean()[['loads','MW_Prediction','error','abs_error']]
```

11 Over forecasted days

[25]:
```
error_by_day.sort_values('error', ascending=True).head(10)
```

[25]:

year	month	dayofmonth	loads	MW_Prediction	error	abs_error
2019	12	6	5956.880833	8994.115234	-3037.234076	3037.234076
	1	10	6343.908333	9361.252930	-3017.344881	3017.344881
	12	7	6320.187500	9319.593750	-2999.406576	2999.406576
	1	9	6363.221667	9161.496094	-2798.274508	2798.274508
	12	8	6719.351250	9392.729492	-2673.378364	2673.378364

```
1    8          6237.279167    8760.261719 -2522.983020  2522.983020
2    8          6192.895833    8713.820312 -2520.924337  2520.924337
11   10         5761.699583    8265.178711 -2503.478904  2503.478904
4    9          6392.049167    8748.759766 -2356.710884  2356.710884
2    10         6758.243333    9089.299805 -2331.056390  2331.056390
```

12 Under forecasted day

[26]:
```python
error_by_day.sort_values('error', ascending=False).head(10)
```

[26]:
```
                            loads  MW_Prediction        error    abs_error
year month dayofmonth
2019 9     1         11009.269583    5729.312988  5279.956656  5279.956656
     7     1         10337.151250    5714.646484  4622.504928  4622.504928
     8     1         10166.137500    5778.122070  4388.015613  4388.015613
     9     2         10606.080417    6344.965332  4261.114963  4261.114963
     5     2         10157.819167    6190.872559  3966.946608  3966.946608
     6     1          9460.925833    5594.115723  3866.809989  3866.809989
     8     5         11031.496667    7237.166992  3794.329674  3794.329674
     5     12        10497.548333    6782.184082  3715.364394  3715.364394
           1          9198.228750    5561.261719  3636.967235  3636.967235
     9     11        10432.721667    6944.091309  3488.630256  3488.630256
```

13 Worst absolute predicted days

[27]:
```python
error_by_day.sort_values('abs_error', ascending=False).head(10)
```

[27]:
```
                            loads  MW_Prediction        error    abs_error
year month dayofmonth
2019 9     1         11009.269583    5729.312988  5279.956656  5279.956656
     7     1         10337.151250    5714.646484  4622.504928  4622.504928
     8     1         10166.137500    5778.122070  4388.015613  4388.015613
     9     2         10606.080417    6344.965332  4261.114963  4261.114963
     5     2         10157.819167    6190.872559  3966.946608  3966.946608
     6     1          9460.925833    5594.115723  3866.809989  3866.809989
     8     5         11031.496667    7237.166992  3794.329674  3794.329674
     5     12        10497.548333    6782.184082  3715.364394  3715.364394
           1          9198.228750    5561.261719  3636.967235  3636.967235
     9     11        10432.721667    6944.091309  3488.630256  3488.630256
```

14 Best predicted days

[28]:
```python
error_by_day.sort_values('abs_error', ascending=True).head(10)
```

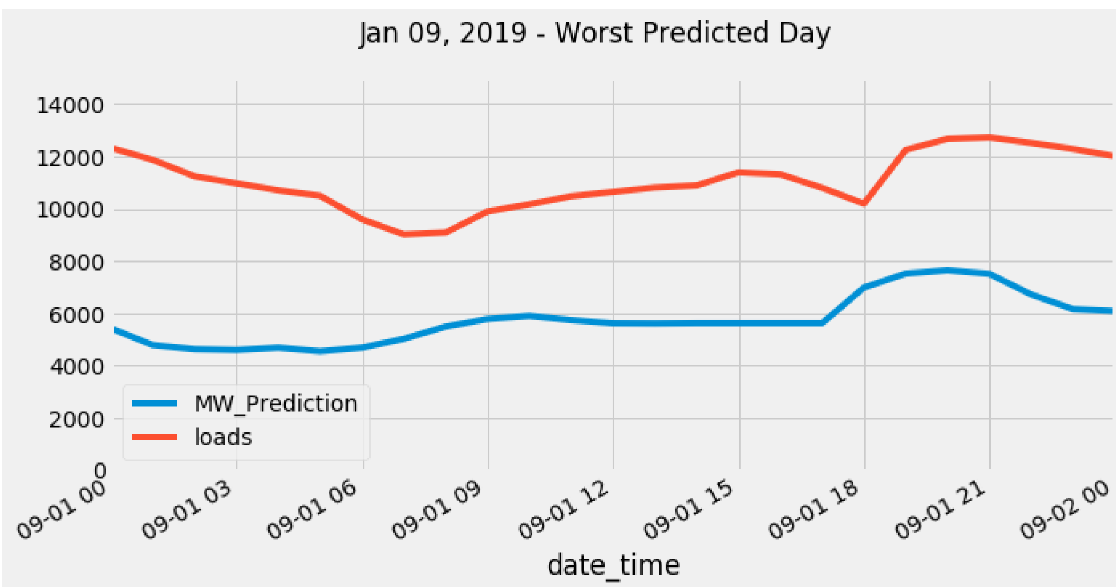
[28]:

```
                               loads  MW_Prediction       error   abs_error
year month dayofmonth
2019 12    13           5860.575833    5924.279297  -63.703687  187.391653
           25           6347.953333    6202.634277  145.318934  206.137241
           2            6650.836667    6722.871582  -72.034915  236.179754
     2     22           6266.400000    6257.895996    8.503780  238.930253
     8     8            9040.593333    9024.657227   15.936453  239.272146
     12    26           6441.729167    6202.634277  239.094767  242.420614
     1     18           5961.616667    5738.749512  222.867358  246.763298
     10    27           7544.520000    7500.739258   43.780681  256.312747
     12    20           5898.452083    5647.488770  250.963497  260.353350
           17           6360.139583    6166.881348  193.258236  262.713232
```

15 Plotting some of the best and worst predicted days

[29]:

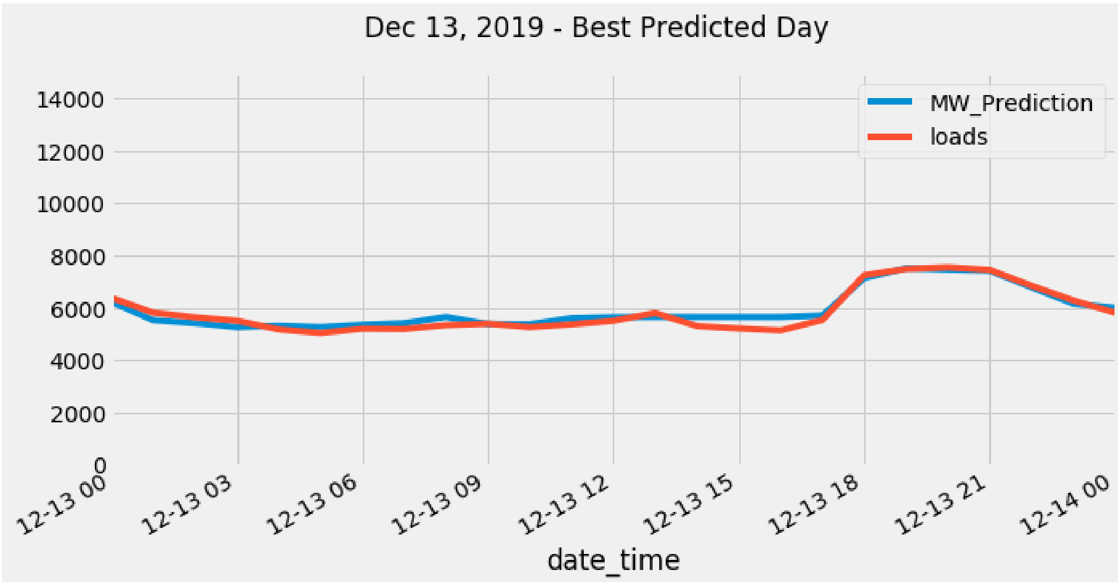
```python
f, ax = plt.subplots(1)
f.set_figheight(5)
f.set_figwidth(10)
_ = df_all[['MW_Prediction','loads']].plot(ax=ax,
                                              style=['-','-'])
ax.set_ylim(0, 15000)
ax.set_xbound(lower='2019-09-01', upper='2019-09-02')
plot = plt.suptitle('Jan 09, 2019 - Worst Predicted Day')
```



[30]:

```python
f, ax = plt.subplots(1)
f.set_figheight(5)
f.set_figwidth(10)
```

```
_ = df_all[['MW_Prediction','loads']].plot(ax=ax,
                                              style=['-','-'])
ax.set_ylim(0, 15000)
ax.set_xbound(lower='2019-12-13', upper='2019-12-14')
plot = plt.suptitle('Dec 13, 2019 - Best Predicted Day')
```

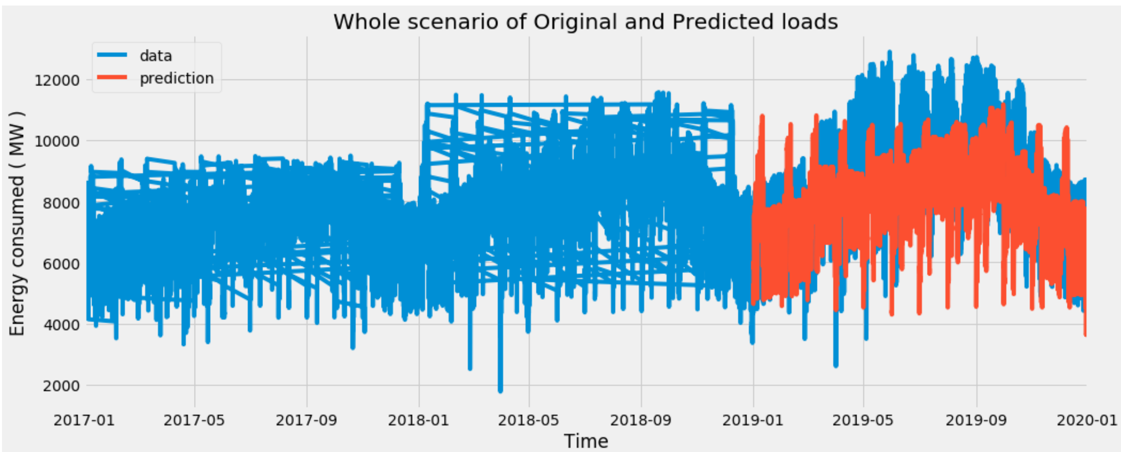


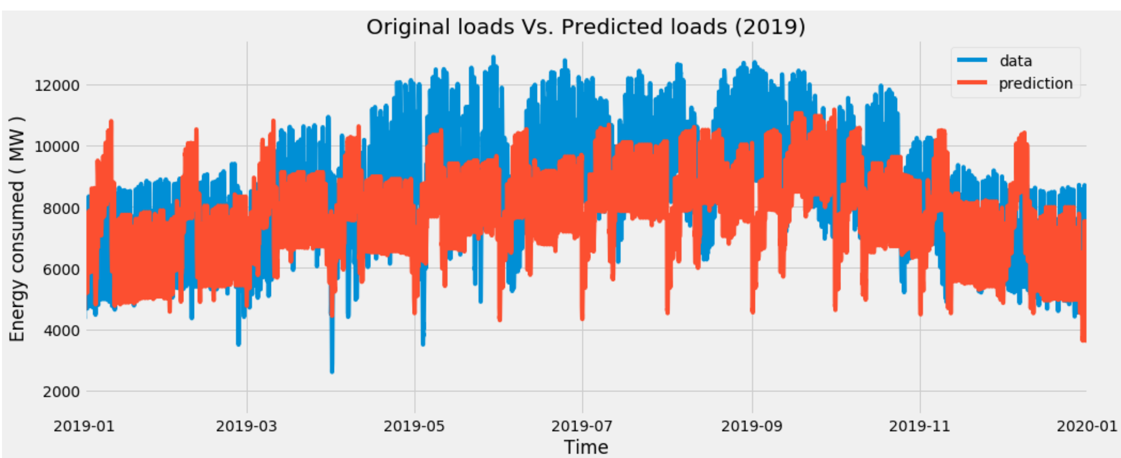
16 Comparison of some other predicted loads with original loads

[31]:
```
data=df
y_true=df_test['loads']
X_test_pred=df_test['MW_Prediction']
```

[32]:
```
def plot_performance(base_data, test_data, test_pred, date_from, date_to,␣
 ↪title=None):
    plt.figure(figsize=(15,6))
    if title == None:
        plt.title('From {0} To {1}'.format(date_from, date_to))
    else:
        plt.title( title )
    plt.xlabel( 'Time' )
    plt.ylabel( 'Energy consumed ( MW )' )
    plt.plot( base_data.index,base_data['loads'], label='data' )
    plt.plot( test_data.index, test_pred, label='prediction' )
    plt.xlim( left=date_from, right=date_to )
    plt.legend()
```

[33]:
```
plot_performance(data, X_test, X_test_pred, data.index[0].date(), data.
↪index[-1].date(),
                 'Whole scenario of Original and Predicted loads')

plot_performance(data, X_test, X_test_pred, y_test.index[0].date(), y_test.
↪index[-1].date(),
                 'Original loads Vs. Predicted loads (2019)')



plt.show()
```





17 Plotting the load distribution of individual month wise original Vs. predicted loads in MW of 2019

[34]:
```
df_for_plot=df_all.drop(['dayofweek','quarter','dayofyear','weekofyear'],axis=1)
df_for_plot['Error'] = df_test['loads'] - df_test['MW_Prediction']
df_for_plot['Abs_error'] = df_test['error'].apply(np.abs)
```

[35]:
```
df_for_plot.rename(columns = {'loads':'Original Load', 'MW_Prediction':
 ↪'Predicted Load'}, inplace = True)
df_for_plot.head()
```

[35]:
```
                     Original Load                date  hour  month  year  \
date_time
2019-01-01 01:00:00         4984.0 2019-01-01 01:00:00     1      1  2019
2019-01-01 02:00:00         4644.0 2019-01-01 02:00:00     2      1  2019
2019-01-01 03:00:00         4487.0 2019-01-01 03:00:00     3      1  2019
2019-01-01 04:00:00         4399.0 2019-01-01 04:00:00     4      1  2019
2019-01-01 05:00:00         4350.0 2019-01-01 05:00:00     5      1  2019

                     dayofmonth  Predicted Load       Error   Abs_error
date_time
2019-01-01 01:00:00           1     5314.390625 -330.390625  330.390625
2019-01-01 02:00:00           1     5042.840820 -398.840820  398.840820
2019-01-01 03:00:00           1     4879.201660 -392.201660  392.201660
2019-01-01 04:00:00           1     4754.636719 -355.636719  355.636719
2019-01-01 05:00:00           1     4639.765137 -289.765137  289.765137
```

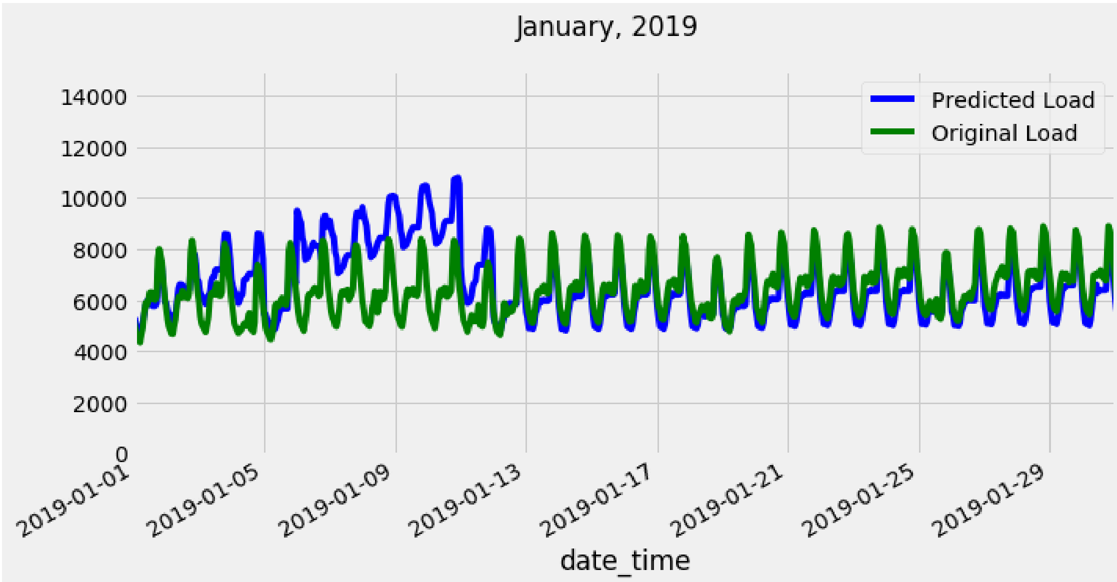
[36]:
```
#Function for showing month wise data and plot.
def month_wise_plot(data_frame, lower_limit, upper_limit,Month_name):
    f, ax = plt.subplots(1)
    f.set_figheight(5)
    f.set_figwidth(10)
    _ = data_frame[['Predicted Load','Original Load']].plot(ax=ax,␣
 ↪style=['-','-'], color=['b','g'])
    ax.set_ylim(0, 15000)
    ax.set_xbound(lower_limit, upper_limit)
    plot = plt.suptitle(Month_name +', 2019')

    #Sorting data monthly based on best and worst error
    #Selecting the defined month
    # Select observations between two datetimes
    month_selection=df_for_plot[(df_for_plot['date'] > lower_limit) &␣
 ↪(df_for_plot['date'] <=upper_limit)]
    error_by_day = month_selection.groupby(['dayofmonth']) \
    .mean()[['Original Load','Predicted Load','Error','Abs_error']]
```

```python
    # Best predicted days
    best=error_by_day.sort_values('Abs_error', ascending=True).head(5)
    print("Top five best predicted day of " + Month_name + '\n\n')
    print(best)
    print('\n\n')

    # worst predicted days
    worst=error_by_day.sort_values('Abs_error', ascending=False).head(5)
    print("Top five worst predicted day of " + Month_name + '\n\n')
    print(worst)
    print('\n\n')
```

18 January 2019

[37]:
```python
month_wise_plot(df_for_plot, lower_limit='2019-01-01',␣
↪upper_limit='2019-01-31', Month_name='January')
```

```
Top five best predicted day of January


            Original Load  Predicted Load       Error   Abs_error
dayofmonth
18            5961.616667     5738.749512  222.867358  246.763298
1             5925.474348     5858.959961   66.514472  274.440352
12            5982.397917     5859.058594  123.339242  309.170168
25            6119.320833     5859.861816  259.459241  319.346545
19            6244.218750     5898.401367  345.817261  352.373576



Top five worst predicted day of January


            Original Load  Predicted Load        Error    Abs_error
dayofmonth
10            6343.908333     9361.252930 -3017.344881  3017.344881
9             6363.221667     9161.496094 -2798.274508  2798.274508
8             6237.279167     8760.261719 -2522.983020  2522.983020
6             6286.012917     8440.374023 -2154.361025  2182.439801
7             6291.183333     8140.192871 -1849.009314  1849.009314
```



19 February 2019

[38]:
```
month_wise_plot(df_for_plot, lower_limit='2019-02-01',␣
↪upper_limit='2019-02-28', Month_name='February')
```

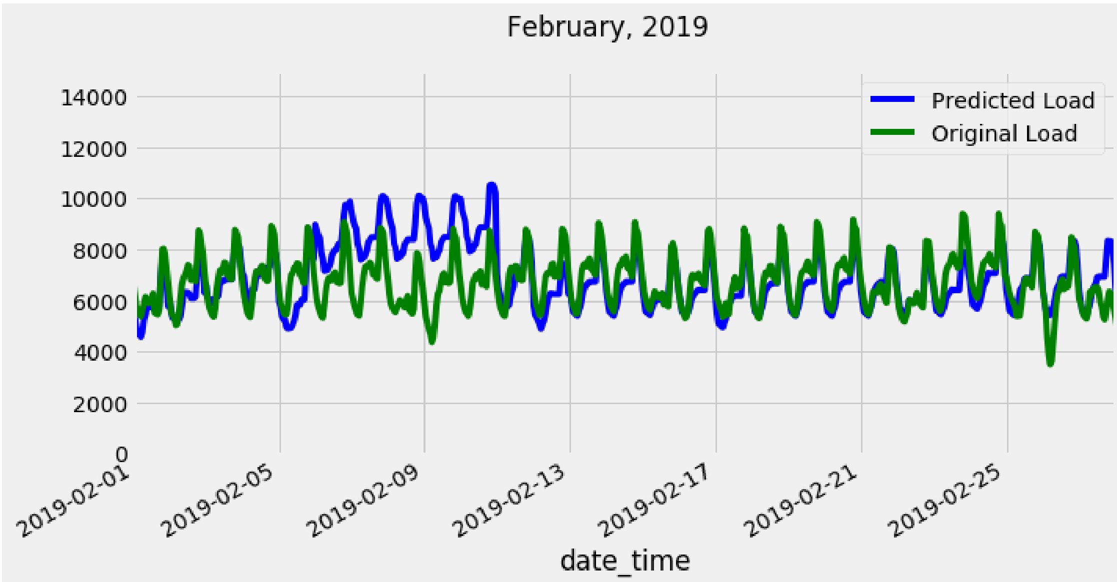
Top five best predicted day of February

dayofmonth	Original Load	Predicted Load	Error	Abs_error
22	6266.400000	6257.895996	8.503780	238.930253
15	6438.321250	6286.580566	151.740602	269.275856
21	6485.888750	6591.068359	-105.179386	286.510660
18	6879.629167	6566.274902	313.354061	333.157365
3	6926.820833	6830.114746	96.706189	347.109713

Top five worst predicted day of February

dayofmonth	Original Load	Predicted Load	Error	Abs_error
8	6192.895833	8713.820312	-2520.924337	2520.924337
10	6758.243333	9089.299805	-2331.056390	2331.056390
9	6426.216667	8748.236328	-2322.019743	2322.019743
7	6992.995833	8718.208984	-1725.213619	1725.213619

```
6             6853.456250     8331.558594 -1478.102710  1478.102710
```



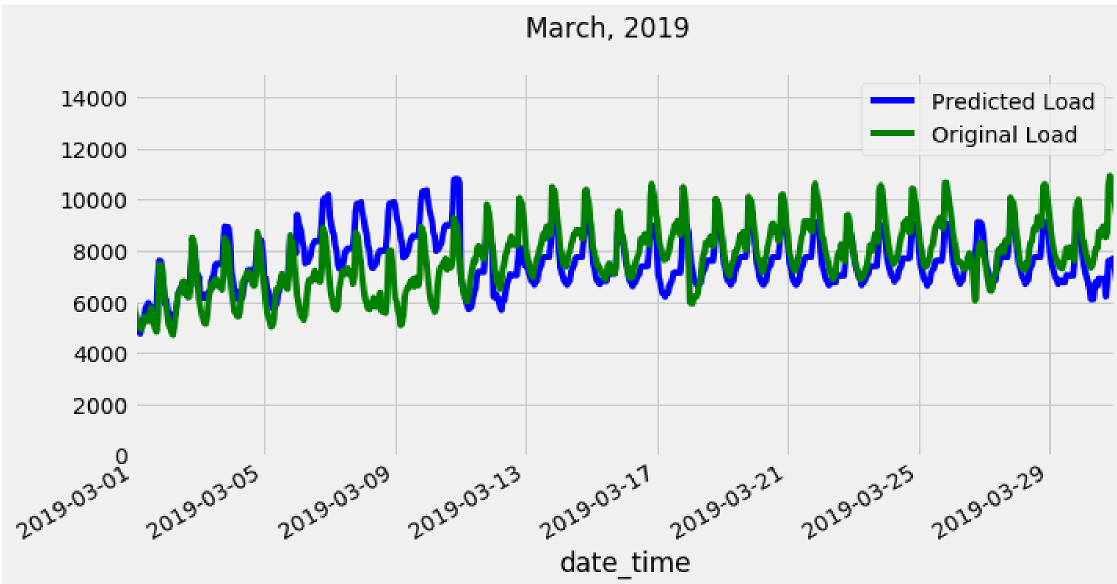
20 March 2019

[39]:

```
month_wise_plot(df_for_plot, lower_limit='2019-03-01',␣
 ↪upper_limit='2019-03-31', Month_name='March')
```

```
Top five best predicted day of March


            Original Load  Predicted Load       Error    Abs_error
dayofmonth
2             6296.000417     6383.906738  -87.906525   289.253354
1             5640.456522     5874.680176 -234.223845   367.365914
15            7765.475000     7418.315430  347.159550   377.133036
27            8011.993333     7763.619141  248.374355   441.248957
5             6547.645833     6870.837402 -323.191650   474.961808



Top five worst predicted day of March


            Original Load  Predicted Load        Error     Abs_error
dayofmonth
```

31	9753.000000	7168.158203	2584.841797	2584.841797
9	6701.942500	8900.352539	-2198.410263	2198.410263
8	6324.370000	8452.825195	-2128.455460	2128.455460
10	7269.612500	9257.068359	-1987.455371	1987.455371
6	6809.566667	8691.629883	-1882.063481	1882.063481



21 April 2019

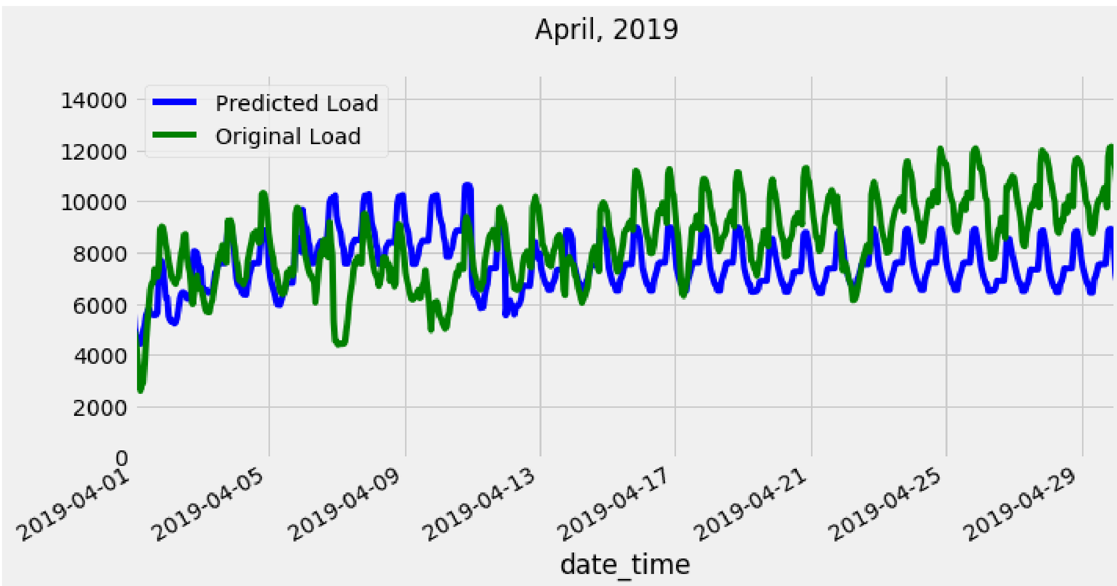
[40]:
```
month_wise_plot(df_for_plot, lower_limit='2019-04-01',␣
↪upper_limit='2019-04-30', Month_name='April')
```

Top five best predicted day of April

dayofmonth	Original Load	Predicted Load	Error	Abs_error
3	7287.521667	7427.816895	-140.295085	418.926222
14	7650.373333	7509.375977	140.997560	484.202716
22	7896.402500	7528.789062	367.613193	575.364276
5	7697.041667	6990.322266	706.719401	730.059173
4	8288.891250	7451.548828	837.342279	837.342279

Top five worst predicted day of April

	Original Load	Predicted Load	Error	Abs_error
dayofmonth				
30	11262.000000	7160.357910	4101.642090	4101.642090
28	10244.366667	7410.598145	2833.768705	2833.768705
29	10315.234167	7504.068848	2811.165197	2811.165197
25	10359.937500	7553.582520	2806.355164	2806.355164
27	10086.745417	7421.382324	2665.363092	2665.363092



22 MAY 2019

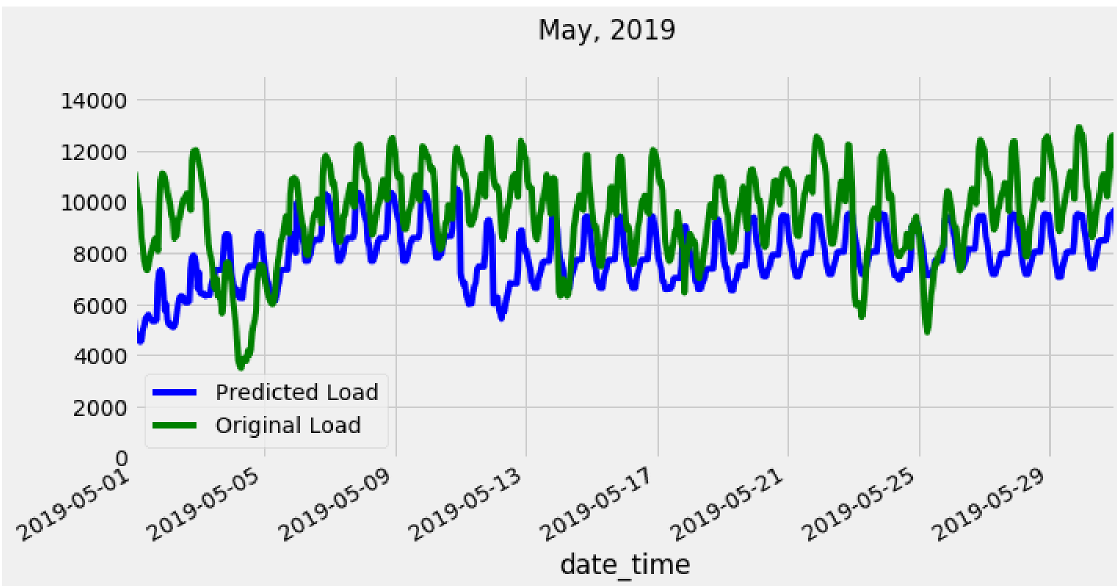
[41]:
```
month_wise_plot(df_for_plot, lower_limit='2019-05-01',␣
↪upper_limit='2019-05-31', Month_name='May')
```

Top five best predicted day of May

	Original Load	Predicted Load	Error	Abs_error
dayofmonth				
25	7695.712500	8048.838867	-353.126184	769.449540
6	9712.941250	8880.041016	832.900682	832.900682
24	8941.805000	7864.389648	1077.415392	1111.665555
10	10109.279167	8983.996094	1125.282849	1125.282849
5	8186.658333	7282.168457	904.489998	1150.913354

Top five worst predicted day of May

	Original Load	Predicted Load	Error	Abs_error
dayofmonth				
2	10157.819167	6190.872559	3966.946608	3966.946608
12	10497.548333	6782.184082	3715.364394	3715.364394
1	9114.847391	5561.602051	3553.245341	3553.245341
11	10655.714583	7341.770508	3313.943974	3313.943974
29	10834.490000	8216.803711	2617.686228	2617.686228



23 June 2019

[42]:
```
month_wise_plot(df_for_plot, lower_limit='2019-06-01',␣
↪upper_limit='2019-06-30', Month_name='June')
```

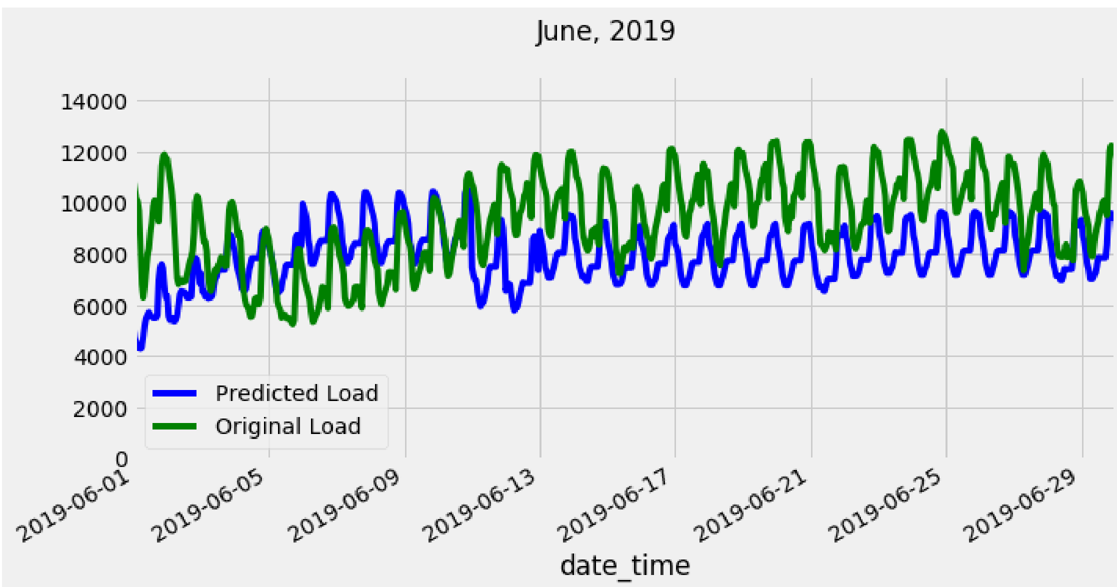
Top five best predicted day of June

	Original Load	Predicted Load	Error	Abs_error
dayofmonth				
10	8996.546667	8972.277344	24.268875	353.482414

9	8209.229583	8891.756836	-682.527334	682.527334
3	8082.697083	7266.474121	816.222759	847.299002
5	6563.944583	7586.475586	-1022.531186	1084.590715
4	7216.300417	7687.170898	-470.870685	1204.721548

Top five worst predicted day of June

dayofmonth	Original Load	Predicted Load	Error	Abs_error
1	9399.270435	5614.981445	3784.288798	3784.288798
12	10368.508333	6927.874512	3440.634045	3440.634045
19	10890.991667	7826.645020	3064.346667	3064.346667
20	10805.680417	7871.243164	2934.437395	2934.437395
25	11112.370000	8295.655273	2816.714727	2816.714727



24 July 2019

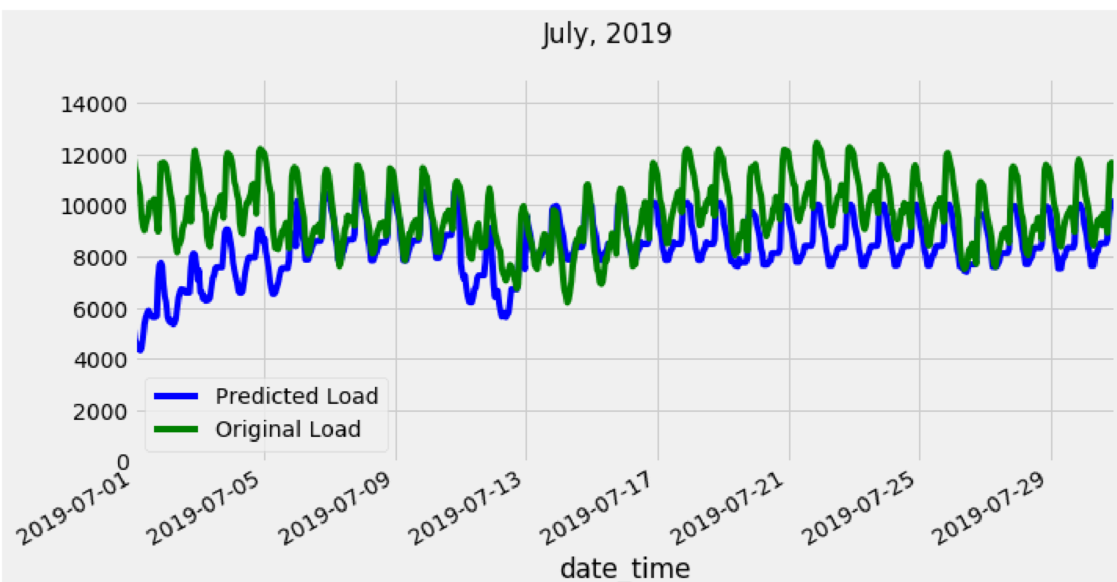
[43]:
```
month_wise_plot(df_for_plot, lower_limit='2019-07-01',␣
↪upper_limit='2019-07-31', Month_name='July')
```

Top five best predicted day of July

dayofmonth	Original Load	Predicted Load	Error	Abs_error
13	8601.066250	8673.873047	-72.806492	312.066082
10	9582.856667	9153.814453	429.042356	464.499543
9	9504.611667	9024.975586	479.636386	480.219543
15	8478.608333	8789.789062	-311.180811	523.676452
7	9551.075833	9055.420898	495.654731	528.261284

Top five worst predicted day of July

dayofmonth	Original Load	Predicted Load	Error	Abs_error
1	10270.114348	5736.083984	4534.030512	4534.030512
2	9991.745833	6518.429199	3473.316675	3473.316675
4	10556.155000	7781.363770	2774.791149	2774.791149
3	10142.347083	7420.746094	2721.600888	2721.600888
5	9818.353333	7645.402832	2172.950359	2172.950359



25 August 2019

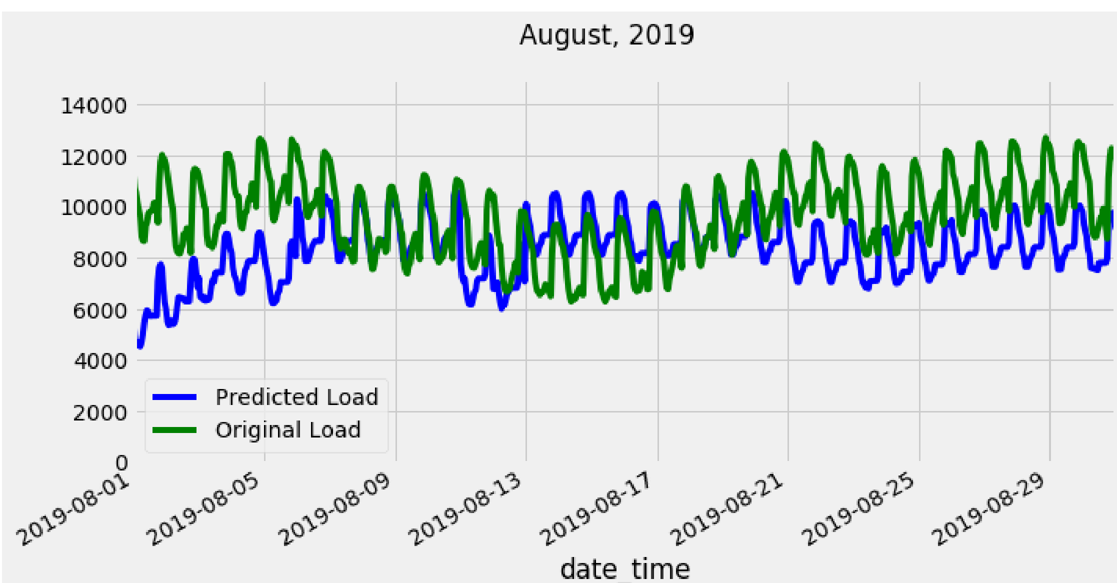
[44]:
```
month_wise_plot(df_for_plot, lower_limit='2019-08-01',␣
↪upper_limit='2019-08-31', Month_name='August')
```

Top five best predicted day of August

dayofmonth	Original Load	Predicted Load	Error	Abs_error
8	9040.593333	9024.657227	15.936453	239.272146
18	9235.520833	9133.299805	102.220581	294.474588
9	9044.594583	8997.736328	46.858560	390.792478
10	9272.768750	9137.162109	135.606376	451.622974
17	8500.280000	8986.620117	-486.340239	598.076685

Top five worst predicted day of August

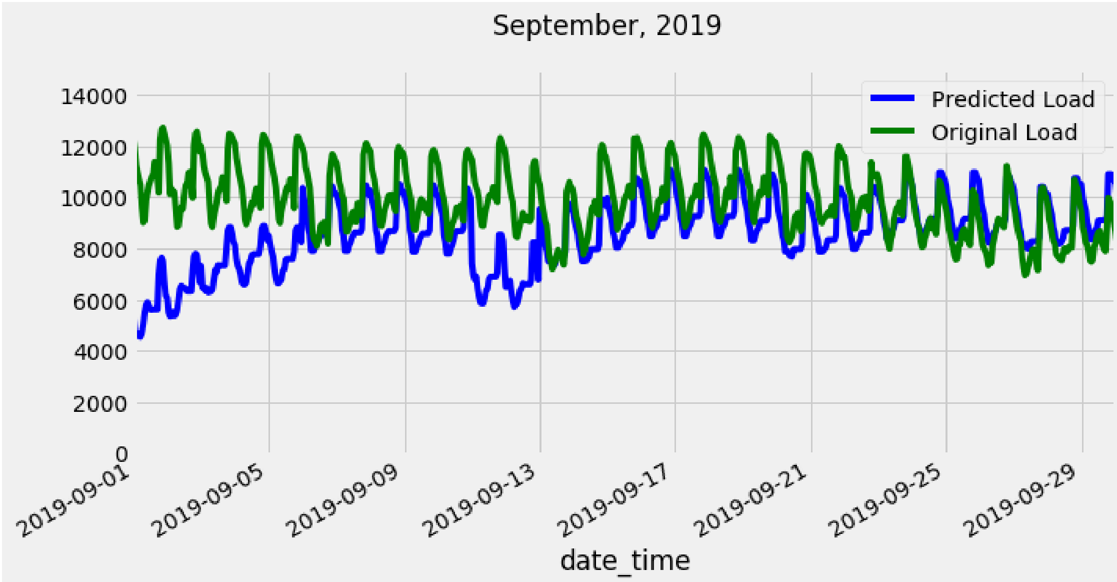
dayofmonth	Original Load	Predicted Load	Error	Abs_error
1	10115.849130	5796.235352	4319.613736	4319.613736
5	11031.496667	7237.166992	3794.329674	3794.329674
2	9653.793750	6363.291016	3290.502938	3290.502938
4	10708.810833	7732.458984	2976.351869	2976.351869
31	12122.270000	9164.111328	2958.158672	2958.158672



26 September 2019

[45]:
```
month_wise_plot(df_for_plot, lower_limit='2019-09-01',␣
 ↪upper_limit='2019-09-30', Month_name='September')
```

```
Top five best predicted day of September


            Original Load  Predicted Load       Error   Abs_error
dayofmonth
24            9207.109583     9478.904297 -271.794876  279.851107
23            9714.711667     9454.111328  260.600339  344.671807
13            8708.723333     8287.946289  420.777431  472.015704
27            8442.962917     8944.430664 -501.467646  501.467646
26            8901.879167     9308.004883 -406.125675  510.727700



Top five worst predicted day of September


            Original Load  Predicted Load        Error    Abs_error
dayofmonth
1            10952.116087     5742.763672  5209.352203  5209.352203
2            10606.080417     6344.965332  4261.114963  4261.114963
11           10432.721667     6944.091309  3488.630256  3488.630256
3            10716.906667     7282.371582  3434.535166  3434.535166
12            9837.114167     6693.325195  3143.789053  3143.789053
```



27 October 2019

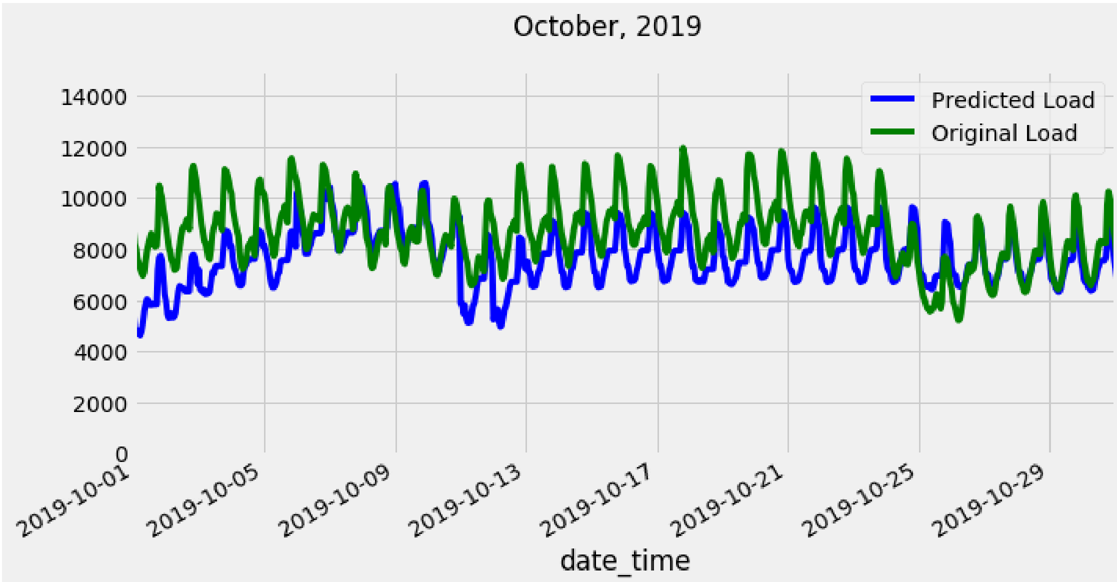
[46]:
```
month_wise_plot(df_for_plot, lower_limit='2019-10-01',
 upper_limit='2019-10-31', Month_name='October')
```

Top five best predicted day of October

dayofmonth	Original Load	Predicted Load	Error	Abs_error
27	7544.520000	7500.739258	43.780681	256.312747
10	8345.825000	8324.266602	21.558297	272.423567
28	7690.441250	7511.120117	179.321296	336.172046
8	8729.710000	9088.077148	-358.366681	438.654965
7	9348.894583	9058.773438	290.121248	502.713993

Top five worst predicted day of October

dayofmonth	Original Load	Predicted Load	Error	Abs_error
2	8839.276250	6328.343262	2510.932927	2510.932927
1	8318.854783	5887.277832	2431.576929	2431.576929
12	8773.742500	6381.913086	2391.829434	2391.829434
3	9215.486250	7229.967773	1985.518314	1985.518314
5	9461.597917	7546.149414	1915.448686	1915.448686

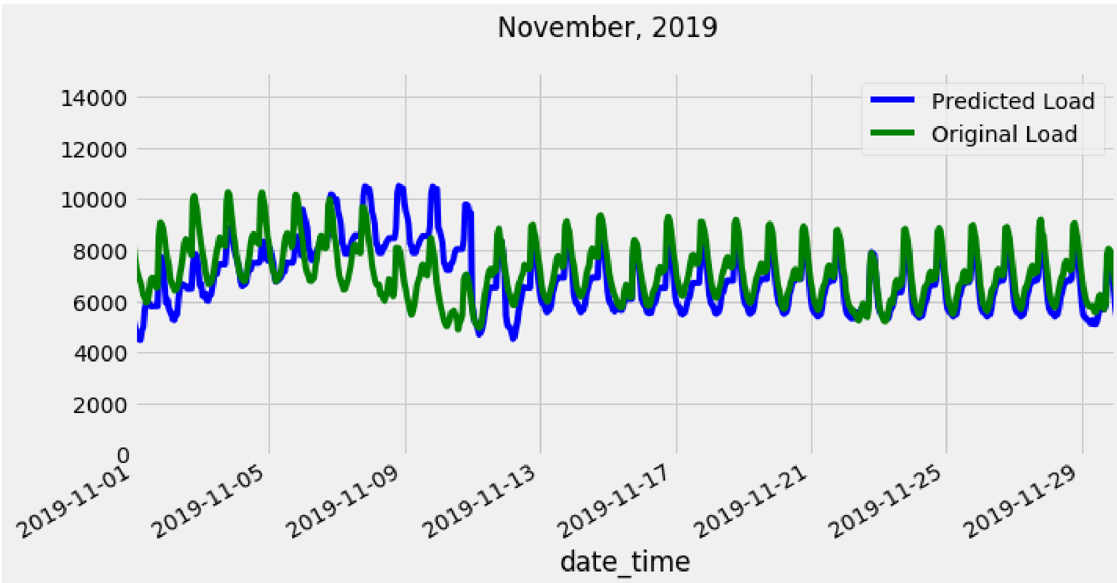


28 November 2019

[47]:
```
month_wise_plot(df_for_plot, lower_limit='2019-11-01',␣
↪upper_limit='2019-11-30', Month_name='November')
```

```
Top five best predicted day of November


            Original Load  Predicted Load       Error   Abs_error
dayofmonth
22            6138.894167     6023.465332  115.428733  265.407249
23            6583.315417     6291.457031  291.858589  321.948066
20            6989.655417     6617.222656  372.432862  372.432862
15            6748.109583     6362.473145  385.636500  392.379594
11            6651.044583     6271.474121  379.570625  399.753226



Top five worst predicted day of November


            Original Load  Predicted Load        Error    Abs_error
dayofmonth
10            5761.699583     8265.178711 -2503.478904  2503.478904
```

9	6851.944167	8937.322266	-2085.378079	2085.378079
8	6905.000833	8916.869141	-2011.868002	2011.868002
2	7902.788750	6421.697266	1481.091464	1481.091464
1	7184.074783	5843.333008	1340.741966	1342.006859



29 December 2019

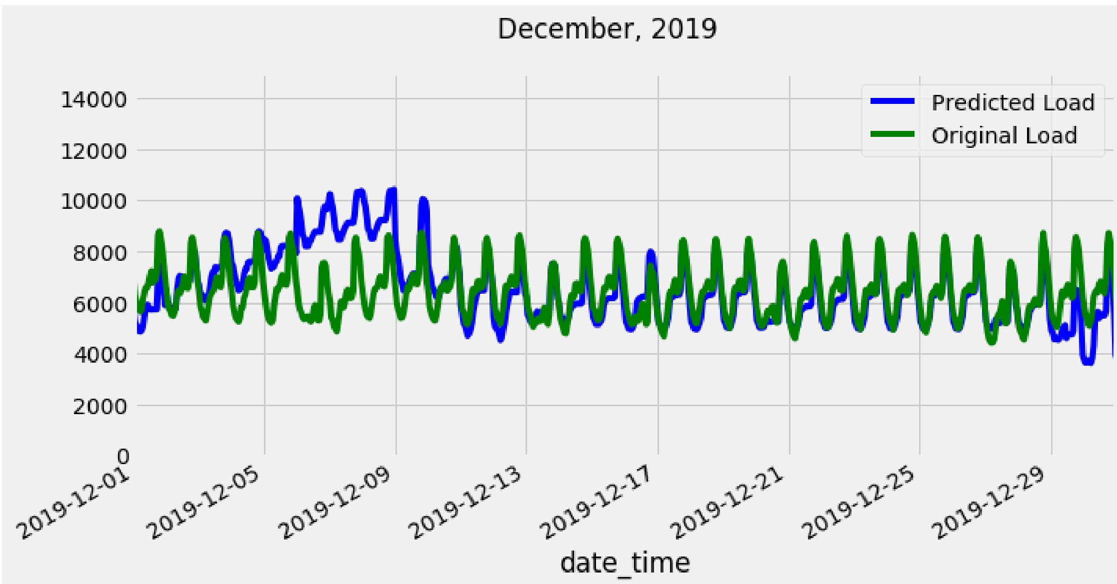
[48]:
```
month_wise_plot(df_for_plot, lower_limit='2019-12-01',␣
↪upper_limit='2019-12-31', Month_name='December')
```

Top five best predicted day of December

	Original Load	Predicted Load	Error	Abs_error
dayofmonth				
13	5860.575833	5924.279297	-63.703687	187.391653
25	6347.953333	6202.634277	145.318934	206.137241
2	6650.836667	6722.871582	-72.034915	236.179754
26	6441.729167	6202.634277	239.094767	242.420614
20	5898.452083	5647.488770	250.963497	260.353350

Top five worst predicted day of December

```
            Original Load  Predicted Load        Error    Abs_error
dayofmonth
6             5956.880833     8994.115234 -3037.234076  3037.234076
7             6320.187500     9319.593750 -2999.406576  2999.406576
8             6719.351250     9392.729492 -2673.378364  2673.378364
31            6226.000000     3939.781738  2286.218262  2286.218262
5             6659.963333     8017.568848 -1357.605738  1390.931780
```



[49]:
```
#df_for_plot=df_for_plot.
 ↪drop(['date','hour','month','year','dayofmonth'],axis=1)
```

[50]:
```
#df_for_plot.to_csv(r'C:\Users\shumo\Dropbox\Anaconda_directory\Load␣
 ↪forecasting\Original_vs_predicted.csv', index = True)
```

30 Load forecasting of 2020

[51]:
```
time = pd.date_range(start='2020-01-01 01:00:00', end='2021-01-01', freq='1H')
```

[52]:
```
time.shape
```

[52]: (8784,)

[53]:
```
data = np.random.randint(1, high=100, size=len(time))
```

[54]:
```
df_new = pd.DataFrame({'date_time': time, 'loads': data})
df_new = df_new.set_index('date_time')
```

[55]:
```
X_new = create_features(df_new)
```

[56]:
```
X_new.head()
```

[56]:
```
                     hour  dayofweek  quarter  month  year  dayofyear  \
date_time
2020-01-01 01:00:00     1          2        1      1  2020          1
2020-01-01 02:00:00     2          2        1      1  2020          1
2020-01-01 03:00:00     3          2        1      1  2020          1
2020-01-01 04:00:00     4          2        1      1  2020          1
2020-01-01 05:00:00     5          2        1      1  2020          1

                     dayofmonth  weekofyear
date_time
2020-01-01 01:00:00           1           1
2020-01-01 02:00:00           1           1
2020-01-01 03:00:00           1           1
2020-01-01 04:00:00           1           1
2020-01-01 05:00:00           1           1
```

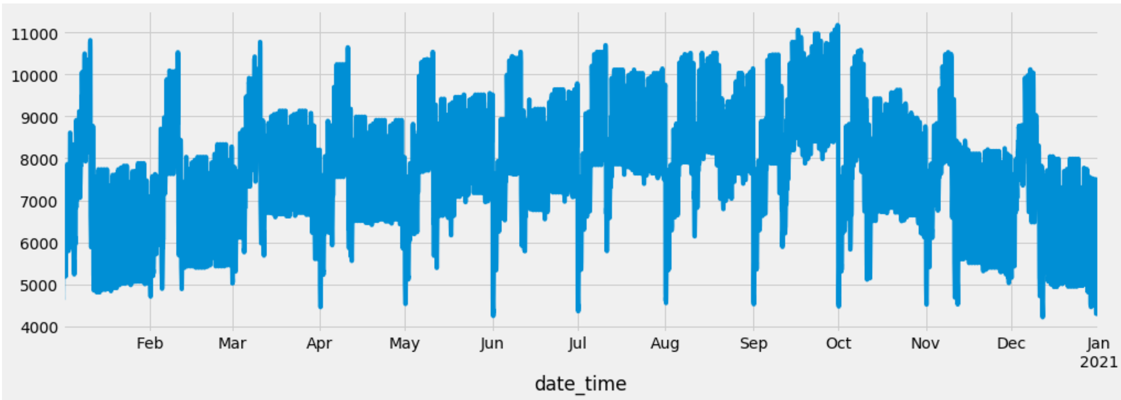
[57]:
```
df_new['MW_Prediction'] = reg.predict(X_new)
```

[58]:
```
df_new.head()
```

[58]:
```
                     loads                date  hour  dayofweek  quarter  \
date_time
2020-01-01 01:00:00     37 2020-01-01 01:00:00     1          2        1
2020-01-01 02:00:00     12 2020-01-01 02:00:00     2          2        1
2020-01-01 03:00:00     55 2020-01-01 03:00:00     3          2        1
2020-01-01 04:00:00     87 2020-01-01 04:00:00     4          2        1
2020-01-01 05:00:00     17 2020-01-01 05:00:00     5          2        1

                     month  year  dayofyear  dayofmonth  weekofyear  \
date_time
2020-01-01 01:00:00      1  2020          1           1           1
2020-01-01 02:00:00      1  2020          1           1           1
2020-01-01 03:00:00      1  2020          1           1           1
2020-01-01 04:00:00      1  2020          1           1           1
2020-01-01 05:00:00      1  2020          1           1           1

                     MW_Prediction
date_time
2020-01-01 01:00:00    5314.390625
2020-01-01 02:00:00    5042.840820
```

```
2020-01-01 03:00:00    4879.201660
2020-01-01 04:00:00    4754.636719
2020-01-01 05:00:00    4639.765137
```

[59]:
```
_ = df_new['MW_Prediction'].plot(figsize=(15, 5))
```



[60]:
```
#df_new.shape
```

30.1 Predict hourwise load

[61]:
```
df_new['MW_Prediction']['2020-01-01 01:00:00']
```

[61]: 5314.3906

[62]:
```
df_2020=df_new['MW_Prediction']
```

[63]:
```
df_2020.shape
```

[63]: (8784,)

[64]:
```
df_2020.to_csv(r'C:\Users\Md Samsul Alam\Dropbox\Anaconda_directory\Load␣
↪forecasting\2020_forecast.csv',index=True)
```

[ ]: