Decision Tree Regression implementation of household electricity consumption dataset

Activities

- Data cleaning
- EDA and FE
- Model Building
- Accuracy check

Dataset: https://archive.ics.uci.edu/ml/datasets/individual+household+electric+power+consumption

In [44]:
```
import pandas as pd
import numpy as np
### Visualisation libraries
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
### For Q-Q Plot
import scipy.stats as stats
### To ignore warnings
import warnings
warnings.filterwarnings('ignore')
```

In [18]:
```
df=pd.read_csv('household_power_consumption.txt',sep=';')
df.head()
```

```
C:\Users\subho\AppData\Local\Temp\ipykernel_8260\4214271158.py:1: DtypeWarning: Columns
(2,3,4,5,6,7) have mixed types. Specify dtype option on import or set low_memory=False.
  df=pd.read_csv('household_power_consumption.txt',sep=';')
```

Out[18]:

	Date	Time	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1
0	16/12/2006	17:24:00	4.216	0.418	234.840	18.400	0.000
1	16/12/2006	17:25:00	5.360	0.436	233.630	23.000	0.000
2	16/12/2006	17:26:00	5.374	0.498	233.290	23.000	0.000
3	16/12/2006	17:27:00	5.388	0.502	233.740	23.000	0.000
4	16/12/2006	17:28:00	3.666	0.528	235.680	15.800	0.000

Basic Analysis

In [19]:
```
df.shape
```

Out[19]:
```
(2075259, 9)
```

In [20]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2075259 entries, 0 to 2075258
Data columns (total 9 columns):
 #   Column                 Dtype  
---  ------                 -----  
 0   Date                   object 
 1   Time                   object 
 2   Global_active_power    object 
 3   Global_reactive_power  object 
 4   Voltage                object 
 5   Global_intensity       object 
 6   Sub_metering_1         object 
 7   Sub_metering_2         object 
 8   Sub_metering_3         float64
dtypes: float64(1), object(8)
memory usage: 142.5+ MB
```

In [21]:

```
#### Taking 50000 samples from this huge dataset
data=df.sample(n=50000,replace=False)
data.reset_index(inplace=True)
data.head()
```

Out[21]:

	index	Date	Time	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_m
0	1565696	8/12/2009	00:20:00	0.272	0.000	244.340	1.200	
1	1941687	26/8/2010	02:51:00	0.342	0.208	239.760	1.600	
2	1579267	17/12/2009	10:31:00	1.440	0.106	243.860	5.800	
3	1652380	6/2/2010	05:04:00	0.250	0.000	244.300	1.000	
4	38696	12/1/2007	14:20:00	0.288	0.156	243.650	1.400	

In [23]:

```
data.drop('index',axis=1,inplace=True)
data.shape
```

Out[23]:

```
(50000, 9)
```

In [24]:

```
#### All the features are of object type except 'Sub_metering_3'. Need to convert all of
data['Date']=pd.to_datetime(data['Date'], format="%d/%m/%Y")
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50000 entries, 0 to 49999
Data columns (total 9 columns):
 #   Column                 Non-Null Count  Dtype         
---  ------                 --------------  -----         
 0   Date                   50000 non-null  datetime64[ns]
 1   Time                   50000 non-null  object        
 2   Global_active_power    50000 non-null  object        
 3   Global_reactive_power  50000 non-null  object        
 4   Voltage                50000 non-null  object        
 5   Global_intensity       50000 non-null  object        
 6   Sub_metering_1         50000 non-null  object        
 7   Sub_metering_2         50000 non-null  object        
 8   Sub_metering_3         49362 non-null  float64       
dtypes: datetime64[ns](1), float64(1), object(7)
memory usage: 3.4+ MB
```

In [25]:

```
#### Creating day, month column to reduce dependancy on the 'Date' column
data['day']=data['Date'].dt.day
data['month']=data['Date'].dt.month
data.head()
```

Out[25]:

	Date	Time	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub
0	2009-12-08	00:20:00	0.272	0.000	244.340	1.200	0.000	
1	2010-08-26	02:51:00	0.342	0.208	239.760	1.600	0.000	
2	2009-12-17	10:31:00	1.440	0.106	243.860	5.800	0.000	
3	2010-02-06	05:04:00	0.250	0.000	244.300	1.000	0.000	
4	2007-01-12	14:20:00	0.288	0.156	243.650	1.400	0.000	

In [26]:

```
data['year']=data['Date'].dt.year
data.head()
```

Out[26]:

	Date	Time	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub
0	2009-12-08	00:20:00	0.272	0.000	244.340	1.200	0.000	
1	2010-08-26	02:51:00	0.342	0.208	239.760	1.600	0.000	
2	2009-12-17	10:31:00	1.440	0.106	243.860	5.800	0.000	
3	2010-02-06	05:04:00	0.250	0.000	244.300	1.000	0.000	
4	2007-01-12	14:20:00	0.288	0.156	243.650	1.400	0.000	

In [27]:

```
#### dropping the date and time column
data.drop(['Date','Time'],axis=1,inplace=True)
data.head()
```

Out[27]:

	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Sul
0	0.272	0.000	244.340	1.200	0.000	0.000	
1	0.342	0.208	239.760	1.600	0.000	1.000	
2	1.440	0.106	243.860	5.800	0.000	0.000	
3	0.250	0.000	244.300	1.000	0.000	0.000	
4	0.288	0.156	243.650	1.400	0.000	2.000	

In [31]:

```
#### Checking null values in terms of '?'
for features in data.columns:
    c=0
    for values in data[features]:
        if values=='?':
            c+=1
    print(f'{features} has {c} null values')
```

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```
Global_active_power has 638 null values
Global_reactive_power has 638 null values
Voltage has 638 null values
Global_intensity has 638 null values
Sub_metering_1 has 638 null values
Sub_metering_2 has 638 null values
Sub_metering_3 has 0 null values
day has 0 null values
month has 0 null values
year has 0 null values
```

In [37]:

```
#### handling null values
data.replace('?',np.nan,inplace=True)
data.isnull().sum()
```

Out[37]:

```
Global_active_power      638
Global_reactive_power    638
Voltage                  638
Global_intensity         638
Sub_metering_1           638
Sub_metering_2           638
Sub_metering_3           638
day                        0
month                      0
year                       0
dtype: int64
```

In [38]:

```
data.dropna(inplace=True)
data.isnull().sum()
```

Out[38]:

```
Global_active_power      0
Global_reactive_power    0
Voltage                  0
Global_intensity         0
Sub_metering_1           0
Sub_metering_2           0
Sub_metering_3           0
day                      0
month                    0
year                     0
dtype: int64
```

In [39]:

```
data.shape
```

Out[39]:

```
(49362, 10)
```

In [40]:

```
data.reset_index(inplace=True)
data.head()
```

Out[40]:

	index	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering
0	0	0.272	0.000	244.340	1.200	0.000	0.0
1	1	0.342	0.208	239.760	1.600	0.000	1.0
2	2	1.440	0.106	243.860	5.800	0.000	0.0
3	3	0.250	0.000	244.300	1.000	0.000	0.0
4	4	0.288	0.156	243.650	1.400	0.000	2.0

In [41]:

```
data.drop('index',axis=1,inplace=True)
data.head()
```

Out[41]:

	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Sul
0	0.272	0.000	244.340	1.200	0.000	0.000	
1	0.342	0.208	239.760	1.600	0.000	1.000	
2	1.440	0.106	243.860	5.800	0.000	0.000	
3	0.250	0.000	244.300	1.000	0.000	0.000	
4	0.288	0.156	243.650	1.400	0.000	2.000	

In [42]:

```
#### we can now safely convert the features into numerical
for features in data.columns:
    data[features]=data[features].astype(float)
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 49362 entries, 0 to 49361
Data columns (total 10 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   Global_active_power    49362 non-null  float64
 1   Global_reactive_power  49362 non-null  float64
 2   Voltage                49362 non-null  float64
 3   Global_intensity       49362 non-null  float64
 4   Sub_metering_1         49362 non-null  float64
 5   Sub_metering_2         49362 non-null  float64
 6   Sub_metering_3         49362 non-null  float64
 7   day                    49362 non-null  float64
 8   month                  49362 non-null  float64
 9   year                   49362 non-null  float64
dtypes: float64(10)
memory usage: 3.8 MB
```

In [43]:

```
data.describe().T
```

Out[43]:

	count	mean	std	min	25%	50%	75%	max
Global_active_power	49362.0	1.090352	1.062314	0.078	0.308	0.594	1.526	8.892
Global_reactive_power	49362.0	0.123314	0.112505	0.000	0.048	0.100	0.192	1.148
Voltage	49362.0	240.817051	3.268253	225.110	238.950	240.990	242.900	253.090
Global_intensity	49362.0	4.624898	4.468123	0.200	1.400	2.600	6.400	38.800
Sub_metering_1	49362.0	1.131255	6.179609	0.000	0.000	0.000	0.000	77.000
Sub_metering_2	49362.0	1.300089	5.813686	0.000	0.000	0.000	1.000	75.000
Sub_metering_3	49362.0	6.403245	8.419046	0.000	0.000	1.000	17.000	31.000
day	49362.0	15.711357	8.829163	1.000	8.000	16.000	23.000	31.000
month	49362.0	6.458024	3.423900	1.000	3.000	6.000	9.000	12.000
year	49362.0	2008.418318	1.123438	2006.000	2007.000	2008.000	2009.000	2010.000

Basic Graphical analysis

In [51]:

```
#### Checking the distribution of the dataset
for i in data:
    plt.figure(figsize=(15,6))
    plt.subplot(1,2,2)
    sns.histplot(data=data, x=i, kde=True, bins=30)
    plt.title("{}'s distribution".format(i),fontweight="bold")
```

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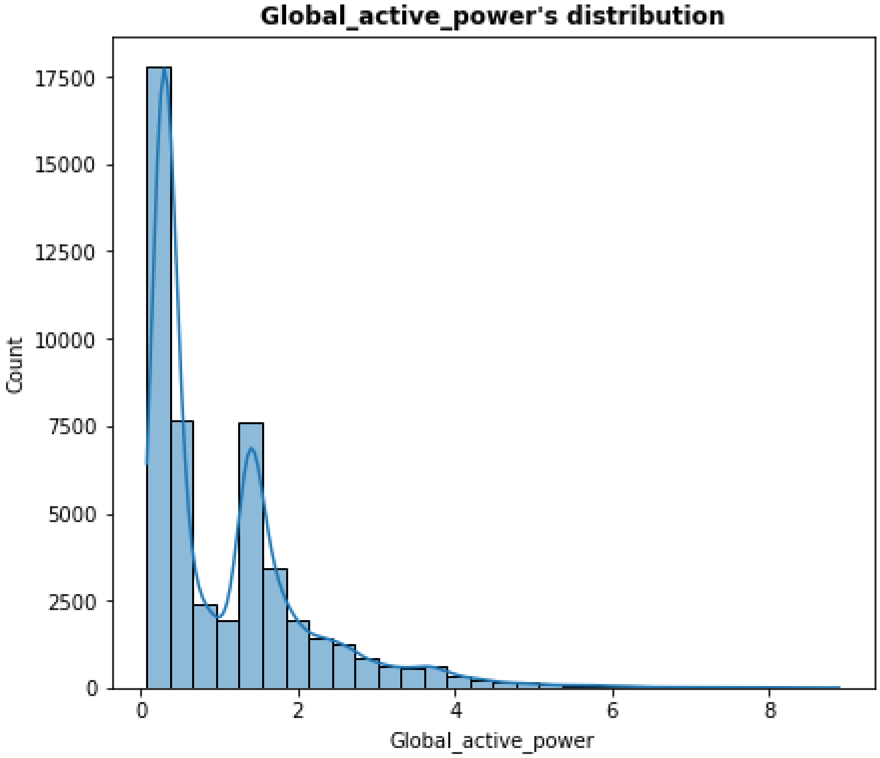
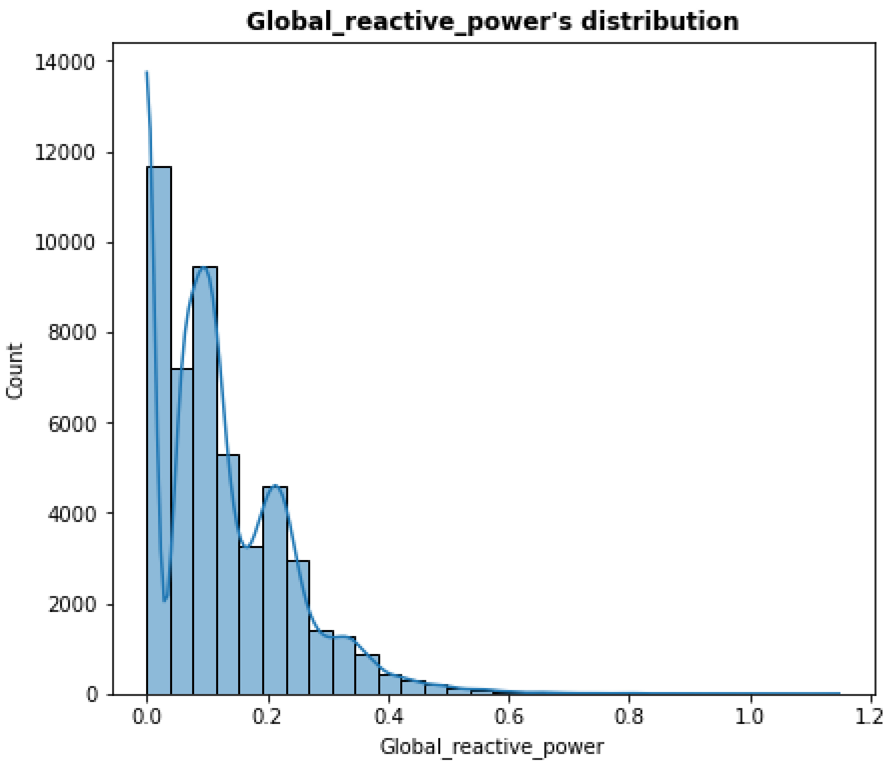
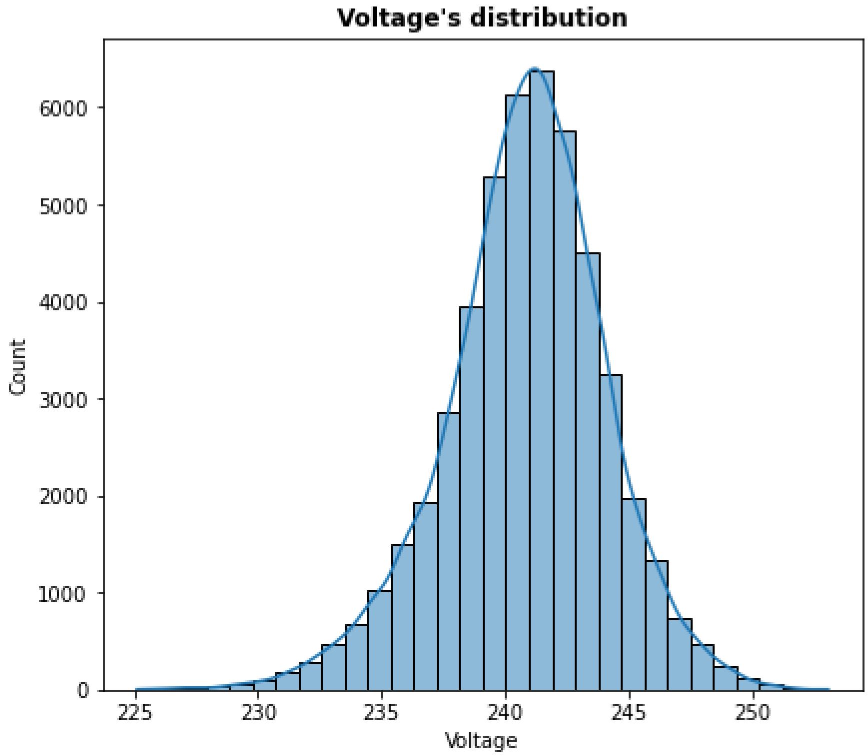
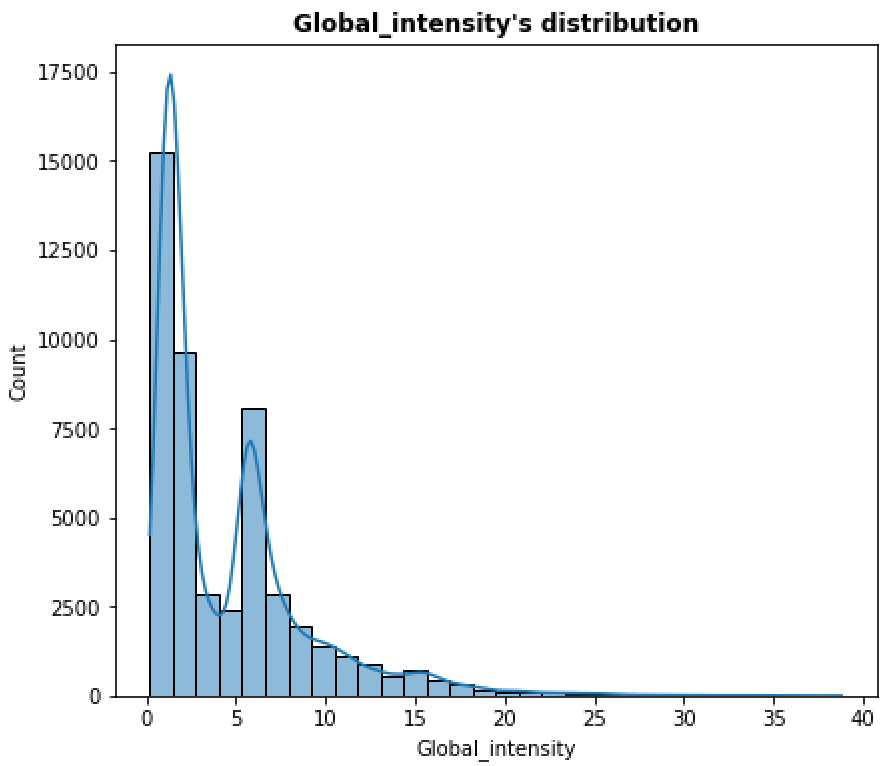

Global_active_power's distribution
Count
0
2500
5000
7500
10000
12500
15000
17500
0
2
4
6
8
Global_active_power


Global_reactive_power's distribution
Count
0
2000
4000
6000
8000
10000
12000
14000
0.0
0.2
0.4
0.6
0.8
1.0
1.2
Global_reactive_power





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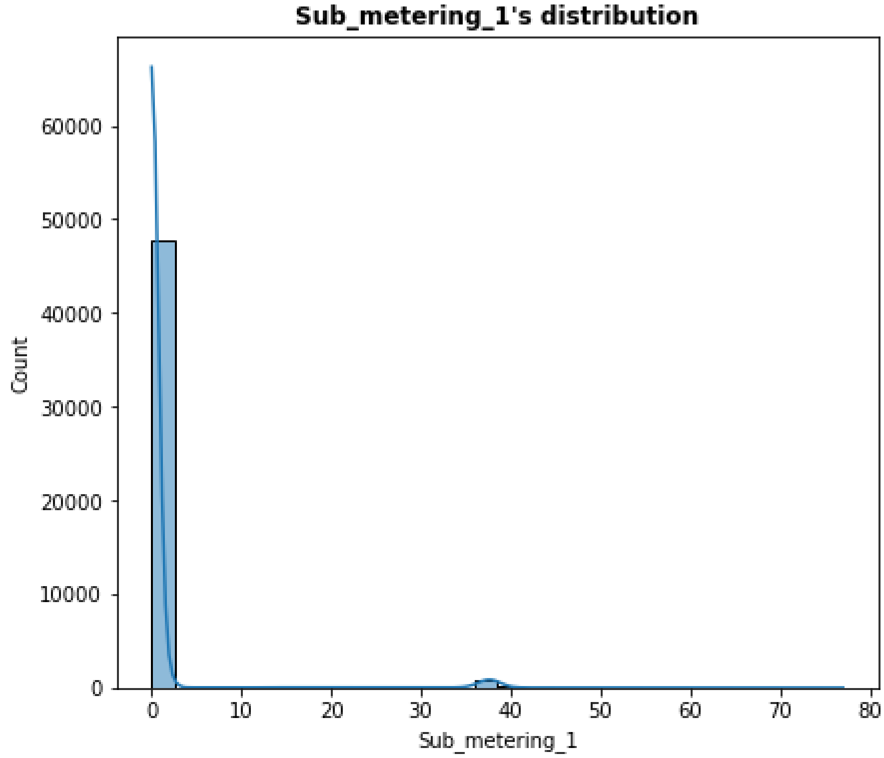
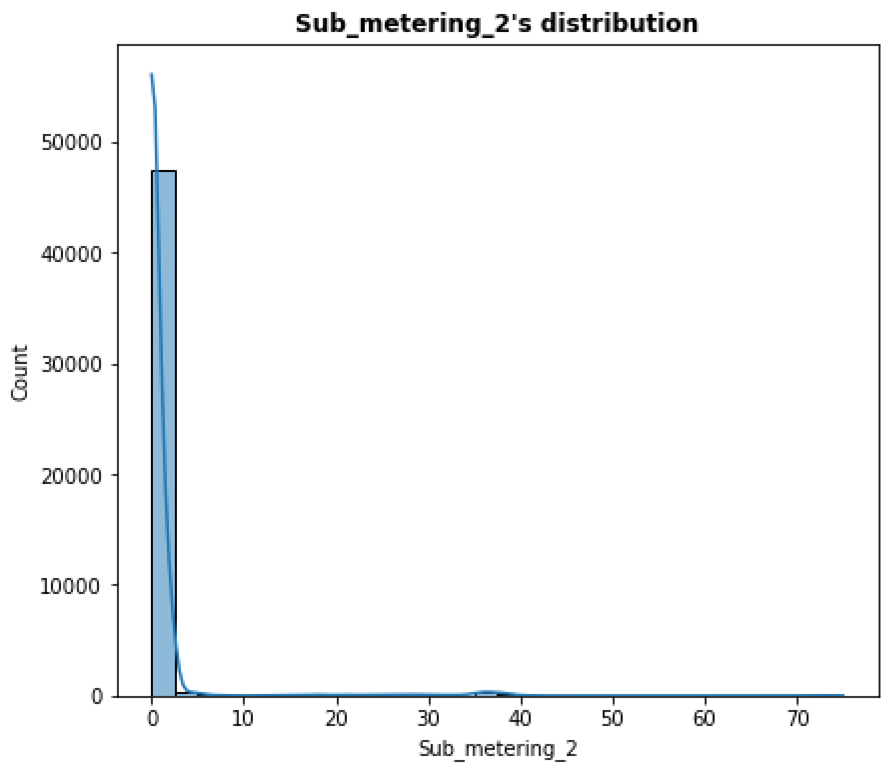
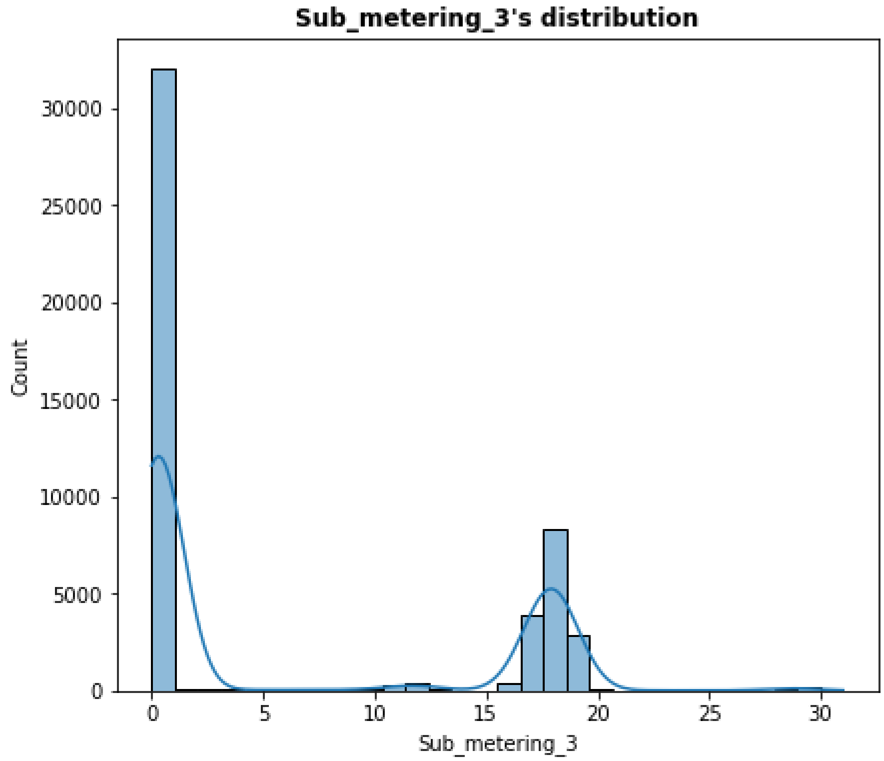
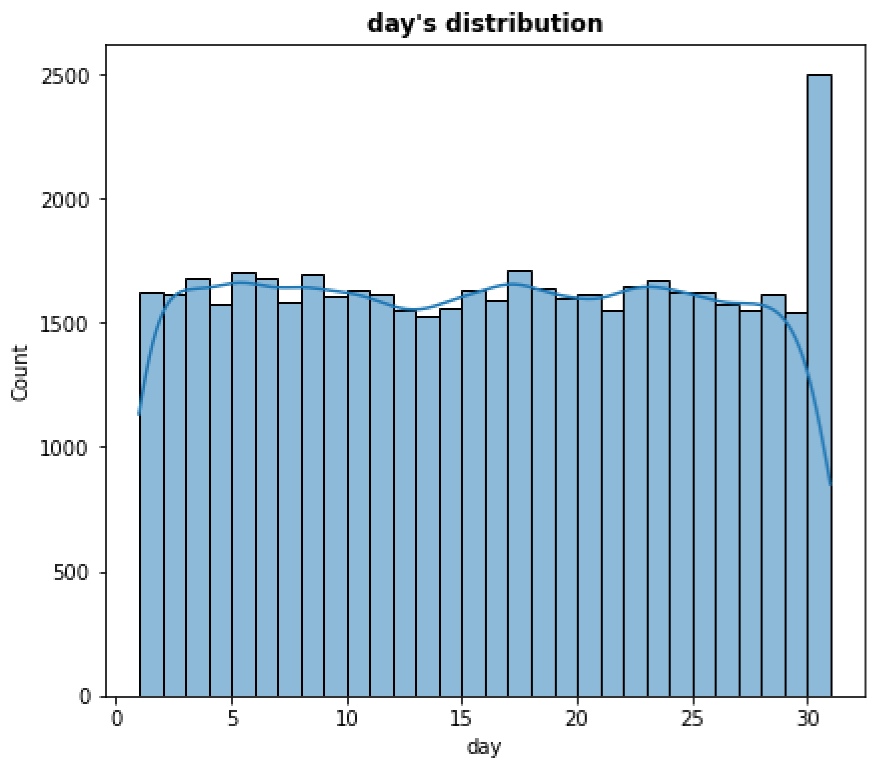
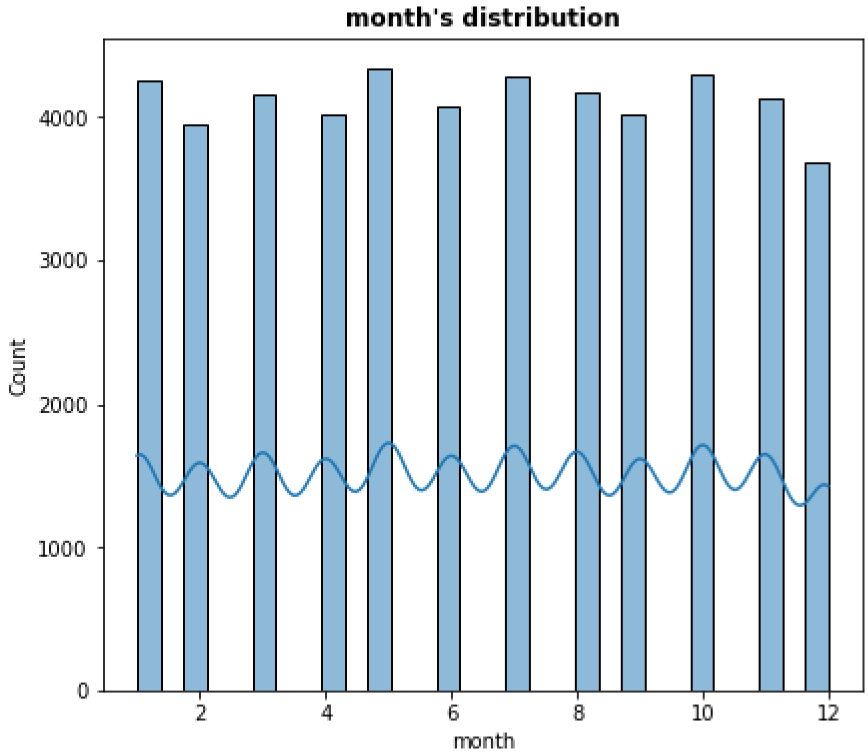


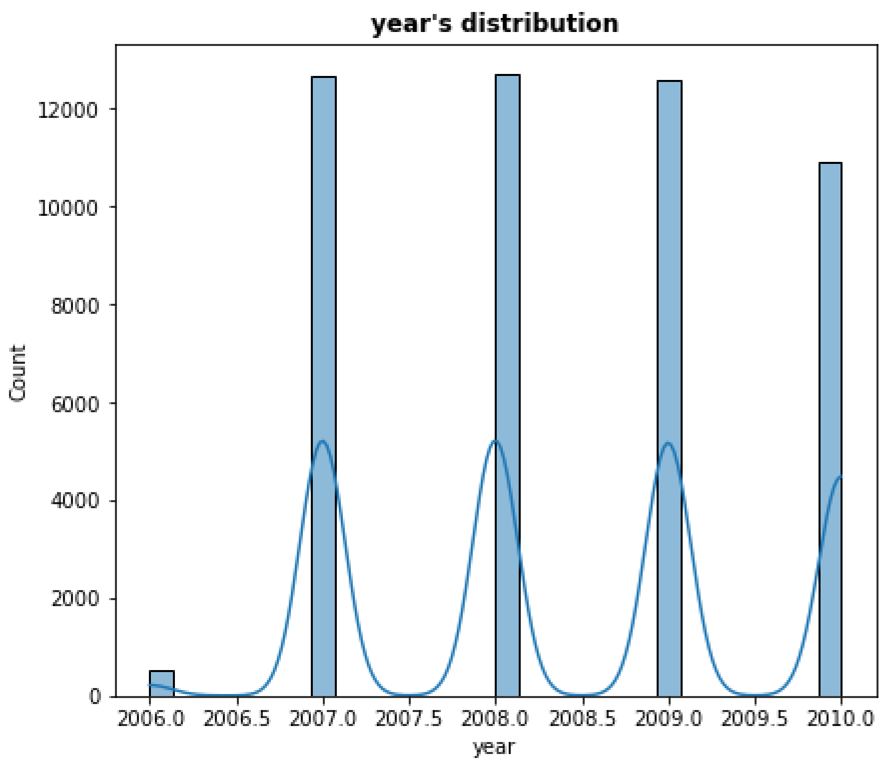


Loading [MathJax]/extensions/Safe.js


Sub_metering_3's distribution
Count
Sub_metering_3
0
5000
10000
15000
20000
25000
30000
0
5
10
15
20
25
30


day's distribution
Count
day
0
500
1000
1500
2000
2500
0
5
10
15
20
25
30





In [52]:
```
#### Crating a dependant feature 'Total_Power_Usage'
data['Total_Power_Usage']=data['Sub_metering_1']+data['Sub_metering_2']+data['Sub_meteri
data.head()
```

Out[52]:

	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Sul
0	0.272	0.000	244.34	1.2	0.0	0.0	
1	0.342	0.208	239.76	1.6	0.0	1.0	
2	1.440	0.106	243.86	5.8	0.0	0.0	
3	0.250	0.000	244.30	1.0	0.0	0.0	
4	0.288	0.156	243.65	1.4	0.0	2.0	

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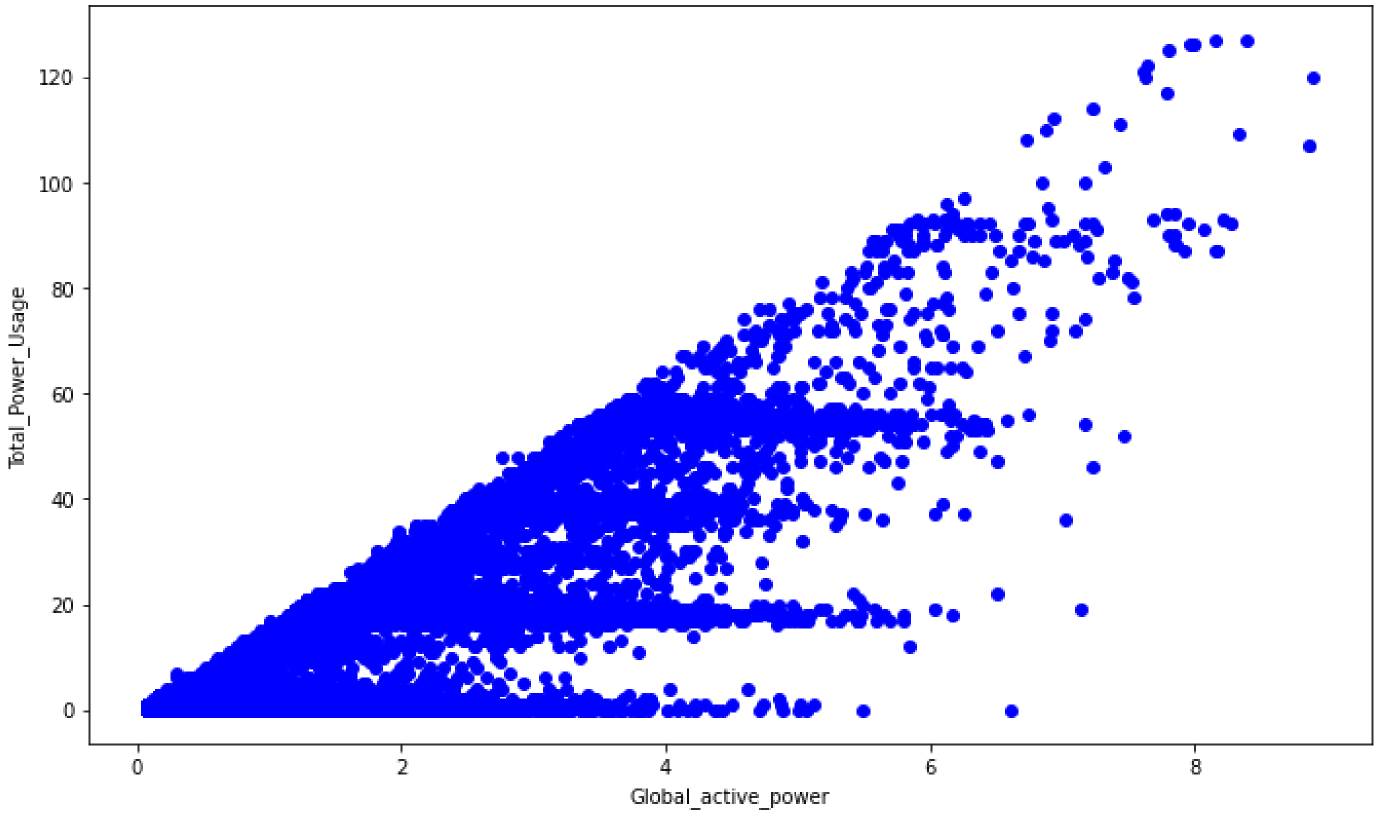
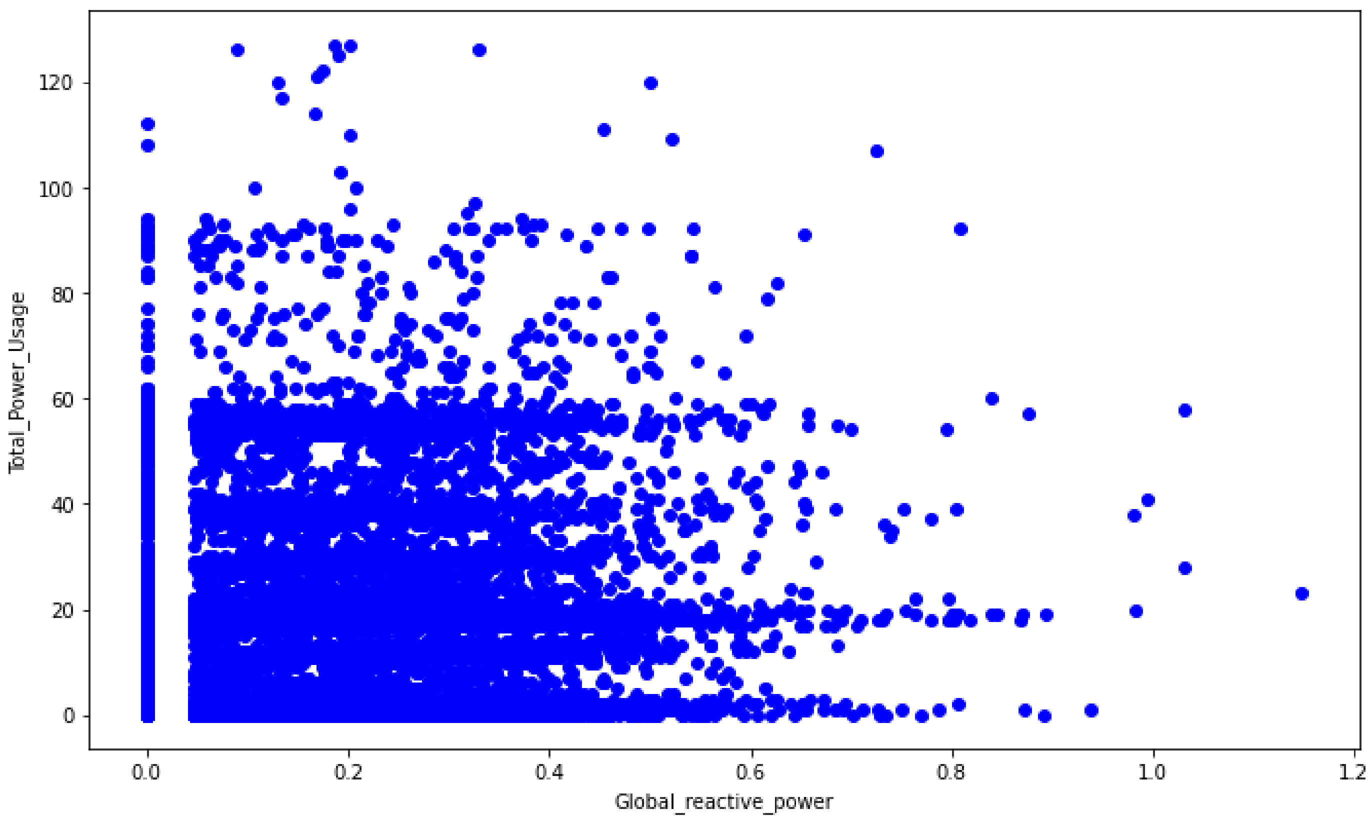
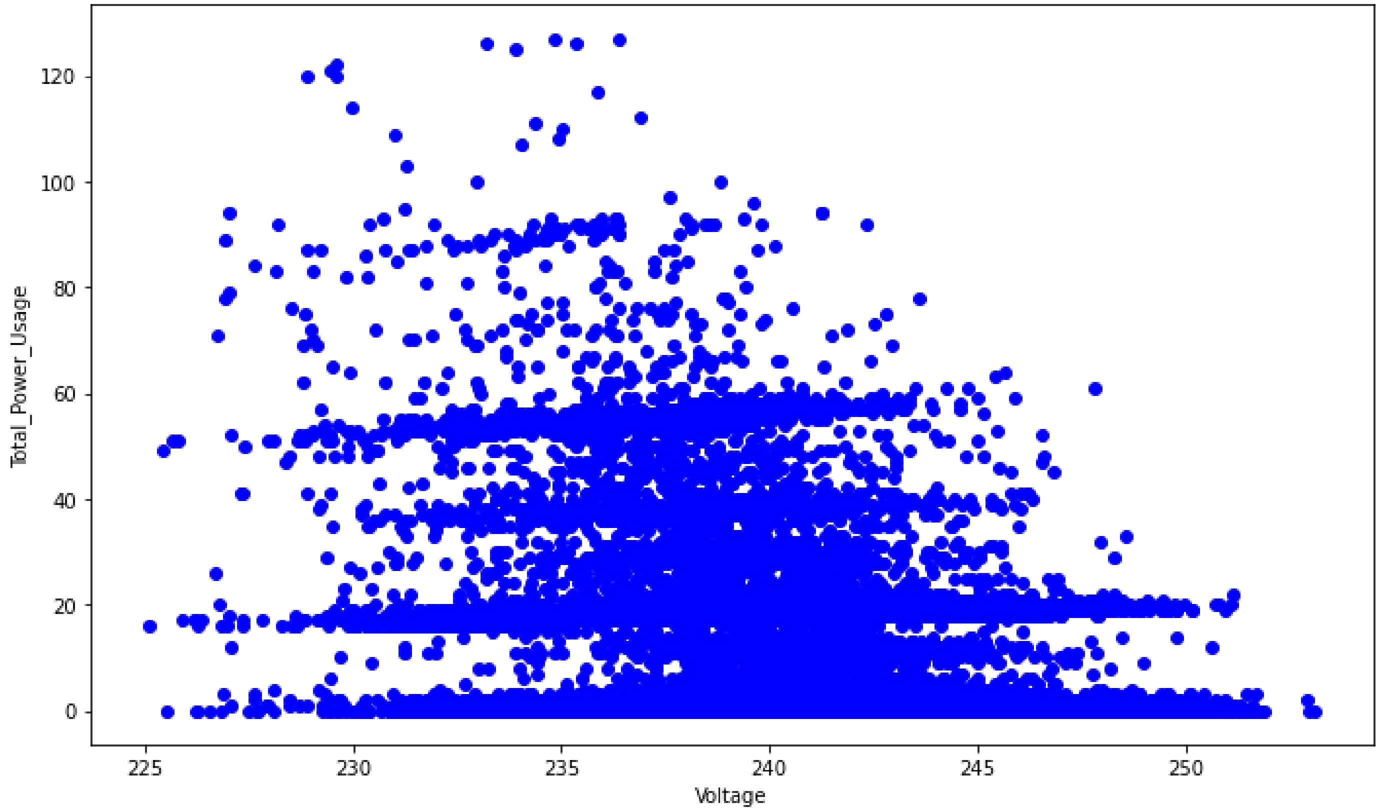
In [64]:

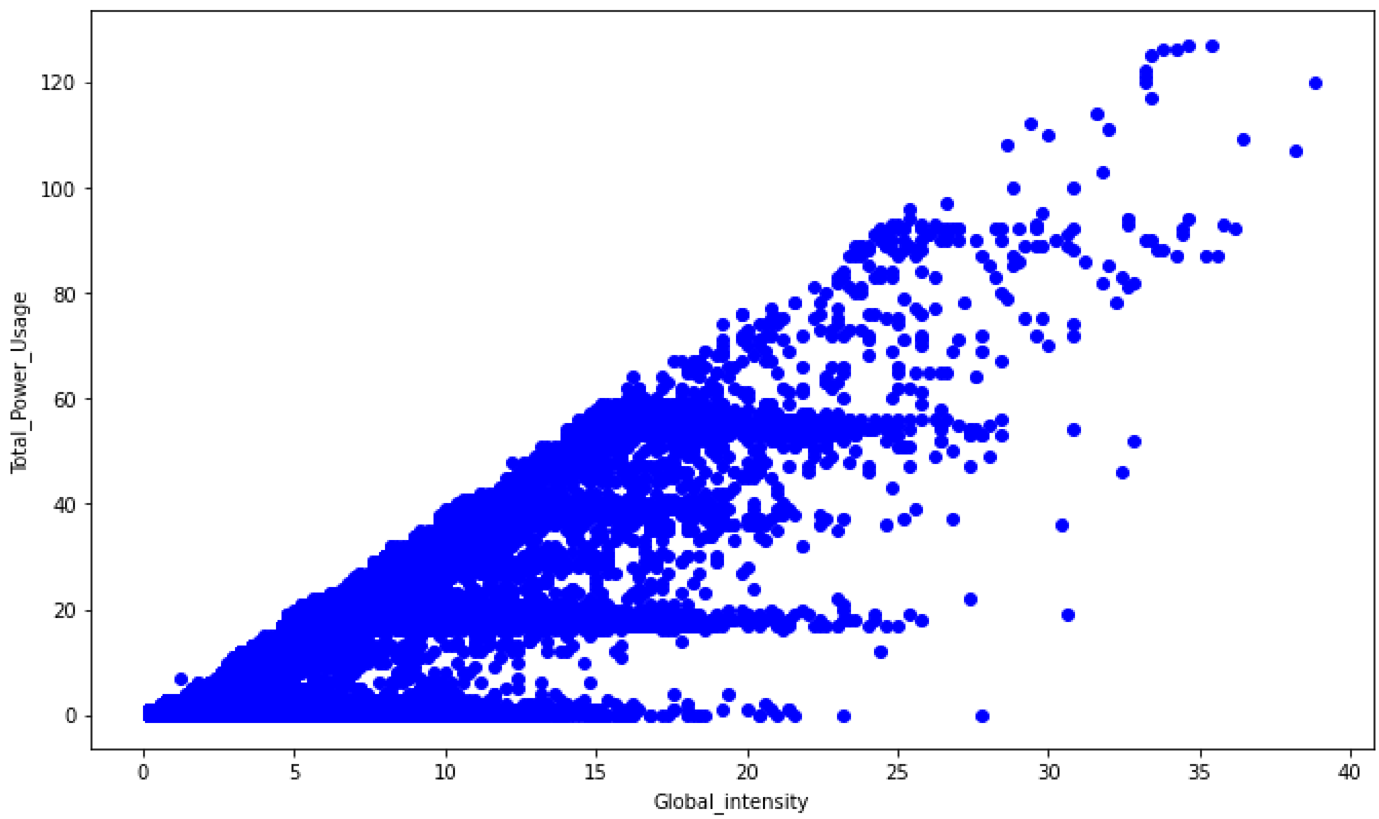
```
#### Comaparing the features against dependant feature 'Total_Power_Usage'
for features in data:
    plot_num=1
    if features!='Total_Power_Usage':
        plt.figure(figsize=(10,6))
        plt.scatter(x=data[features],y=data['Total_Power_Usage'],c='blue')
        plt.xlabel(features)
        plt.ylabel('Total_Power_Usage')
        plt.tight_layout()
        plot_num+=1
```



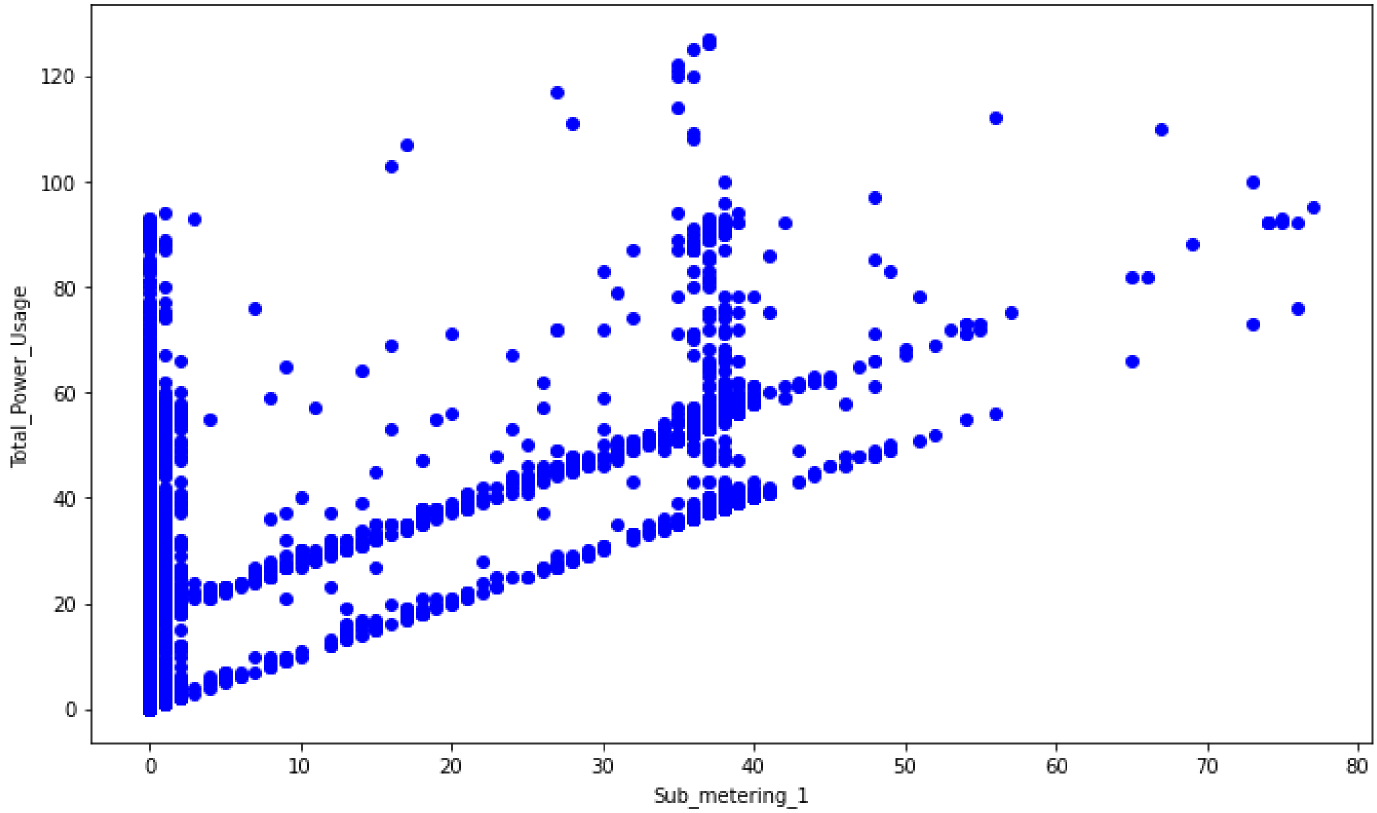




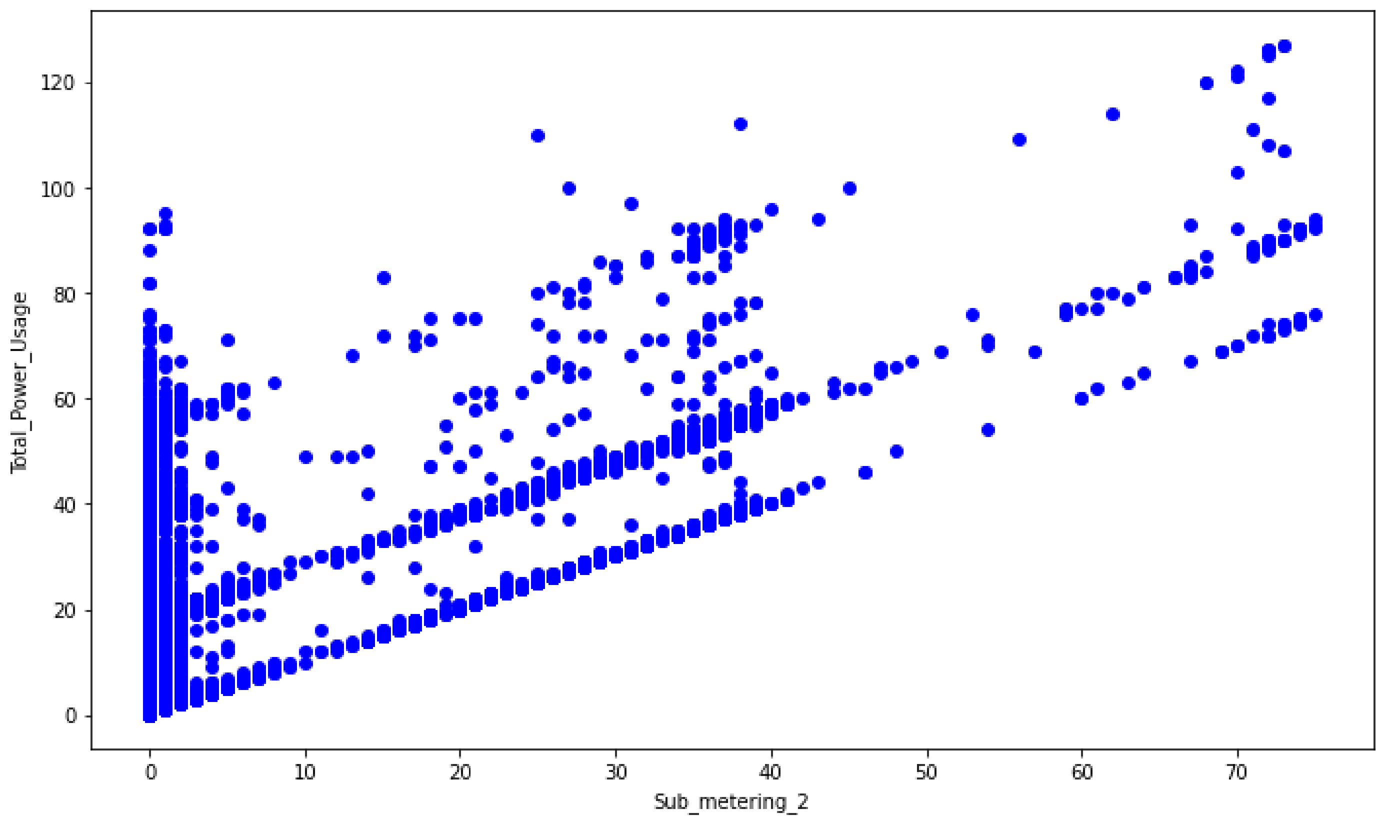
Total_Power_Usage
Voltage



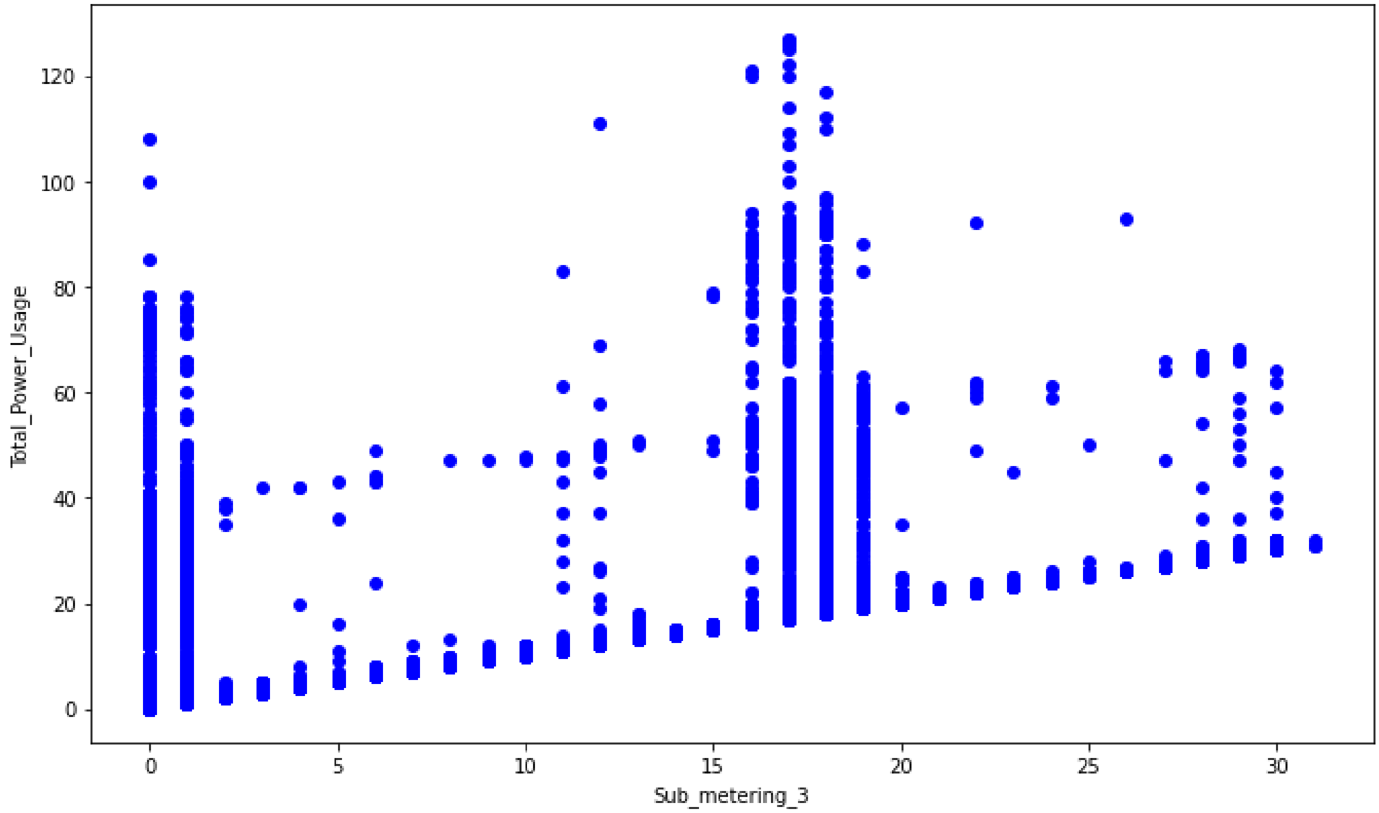
Total_Power_Usage
Global_intensity



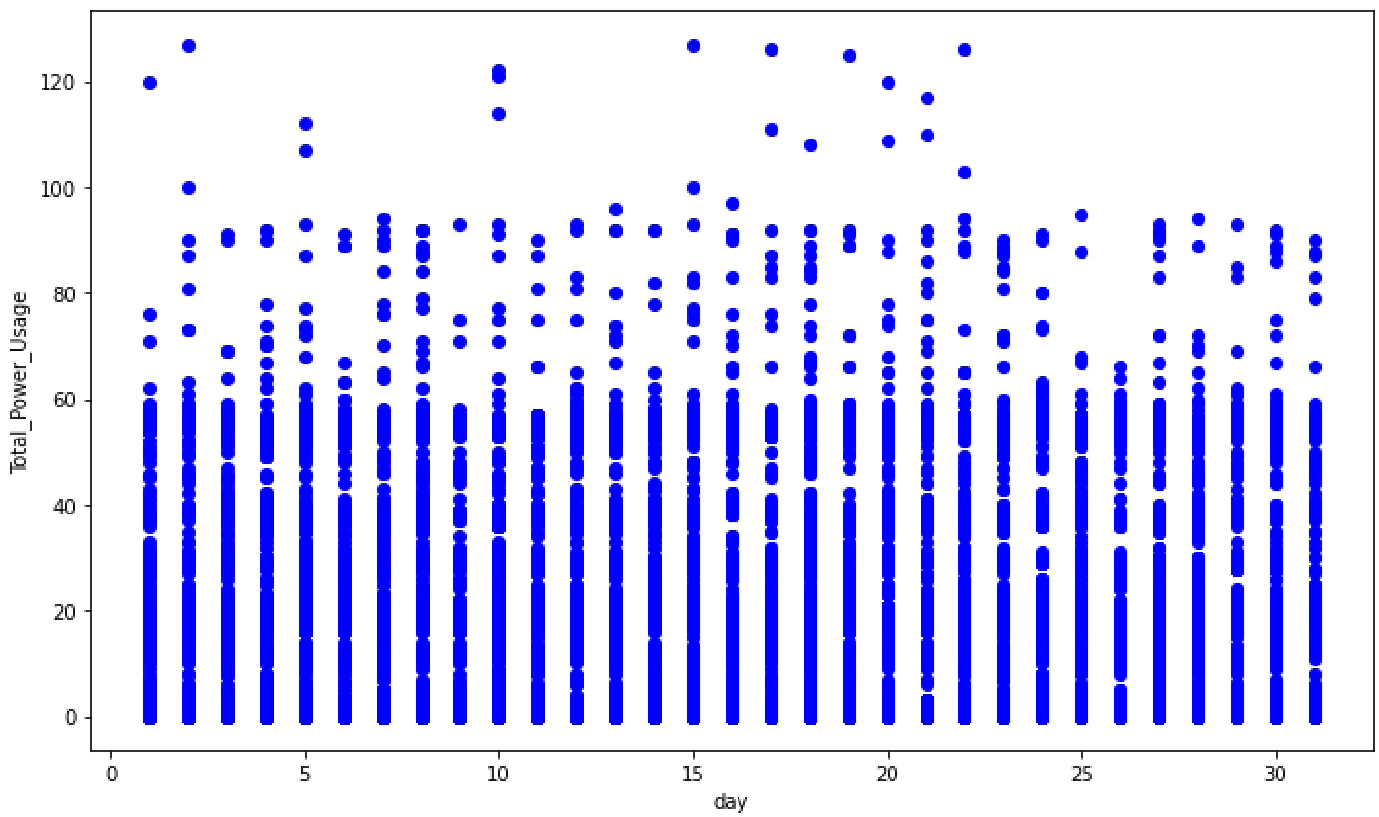
Total_Power_Usage
Sub_metering_1



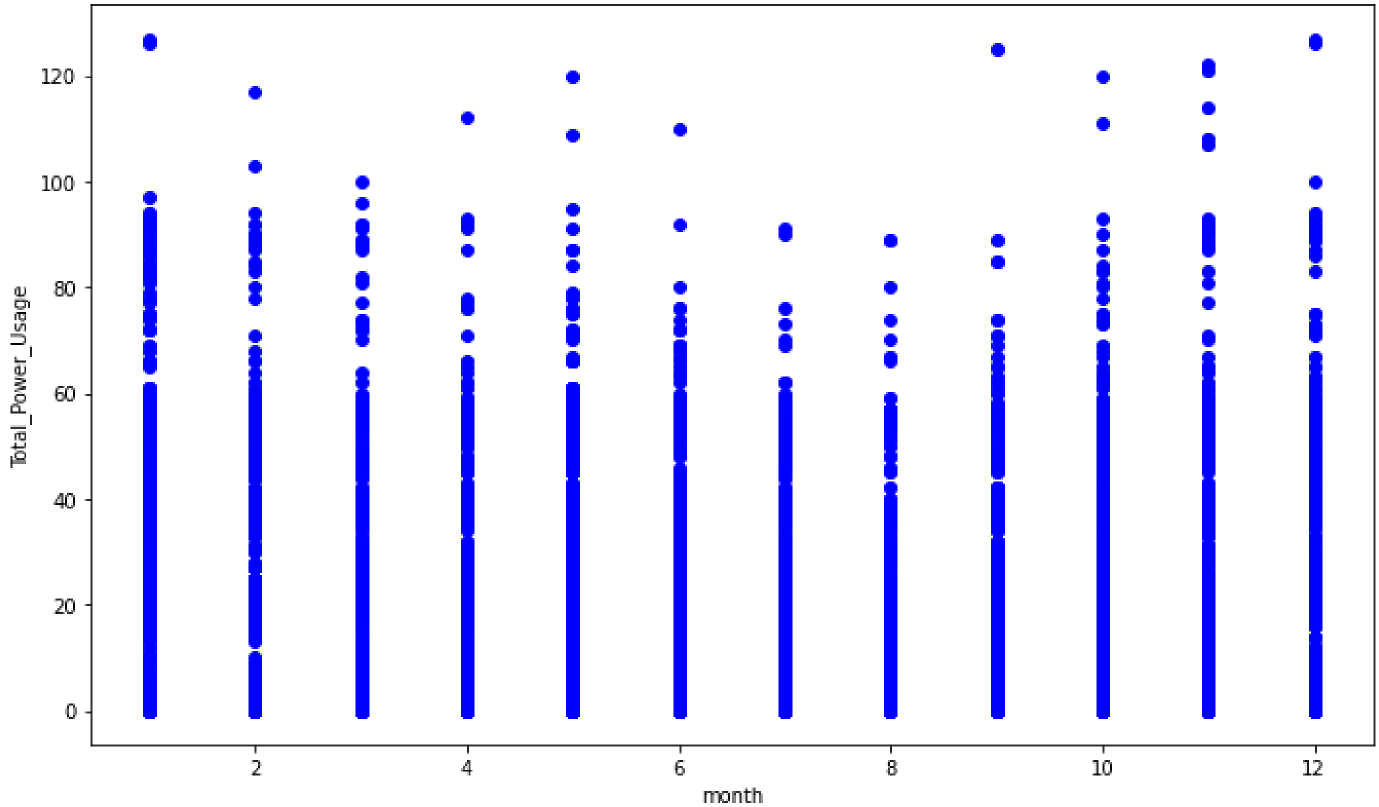
Total_Power_Usage
Sub_metering_2

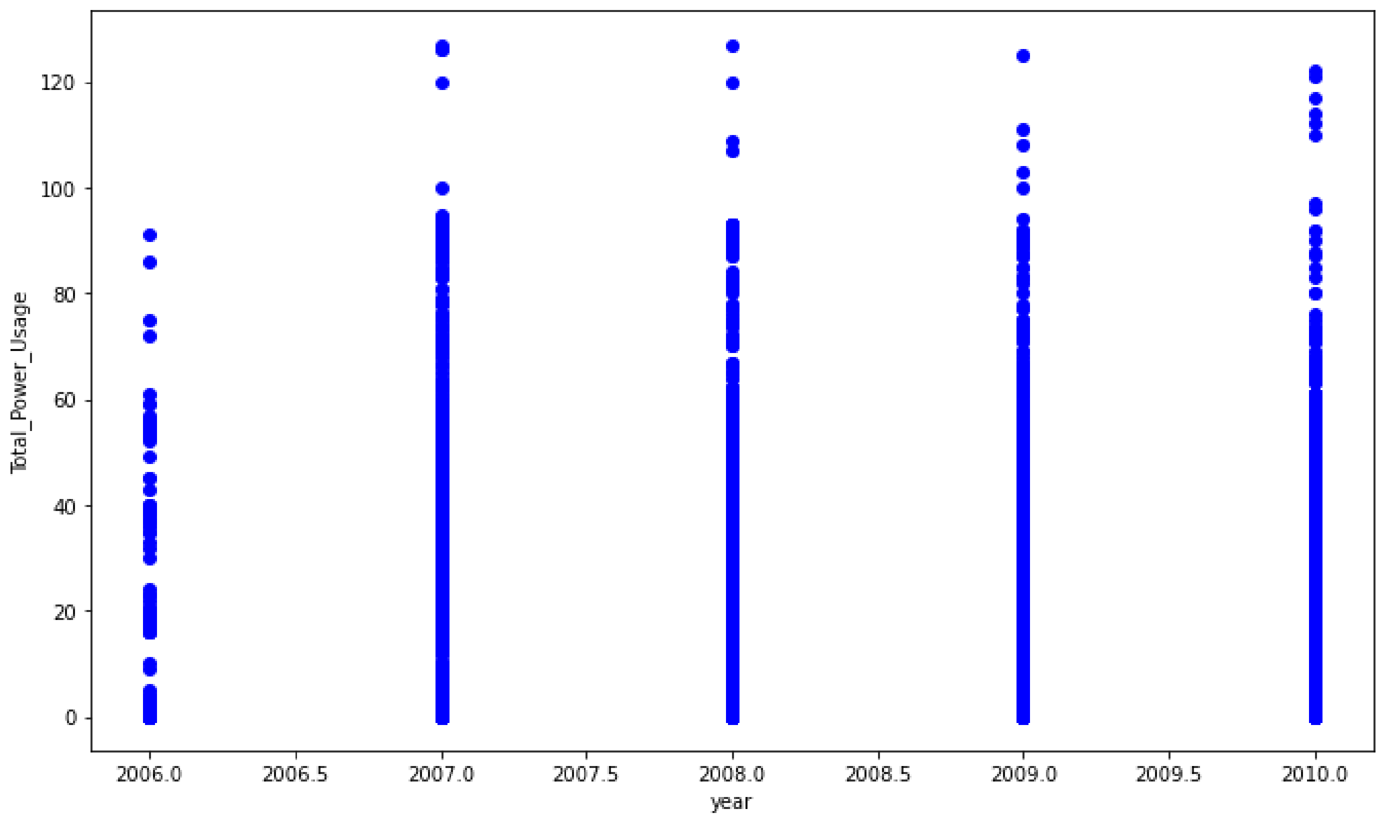


Total_Power_Usage
Sub_metering_3



Total_Power_Usage
day





In [65]:
```
#### Checking correlation between the features
data.corr()
```

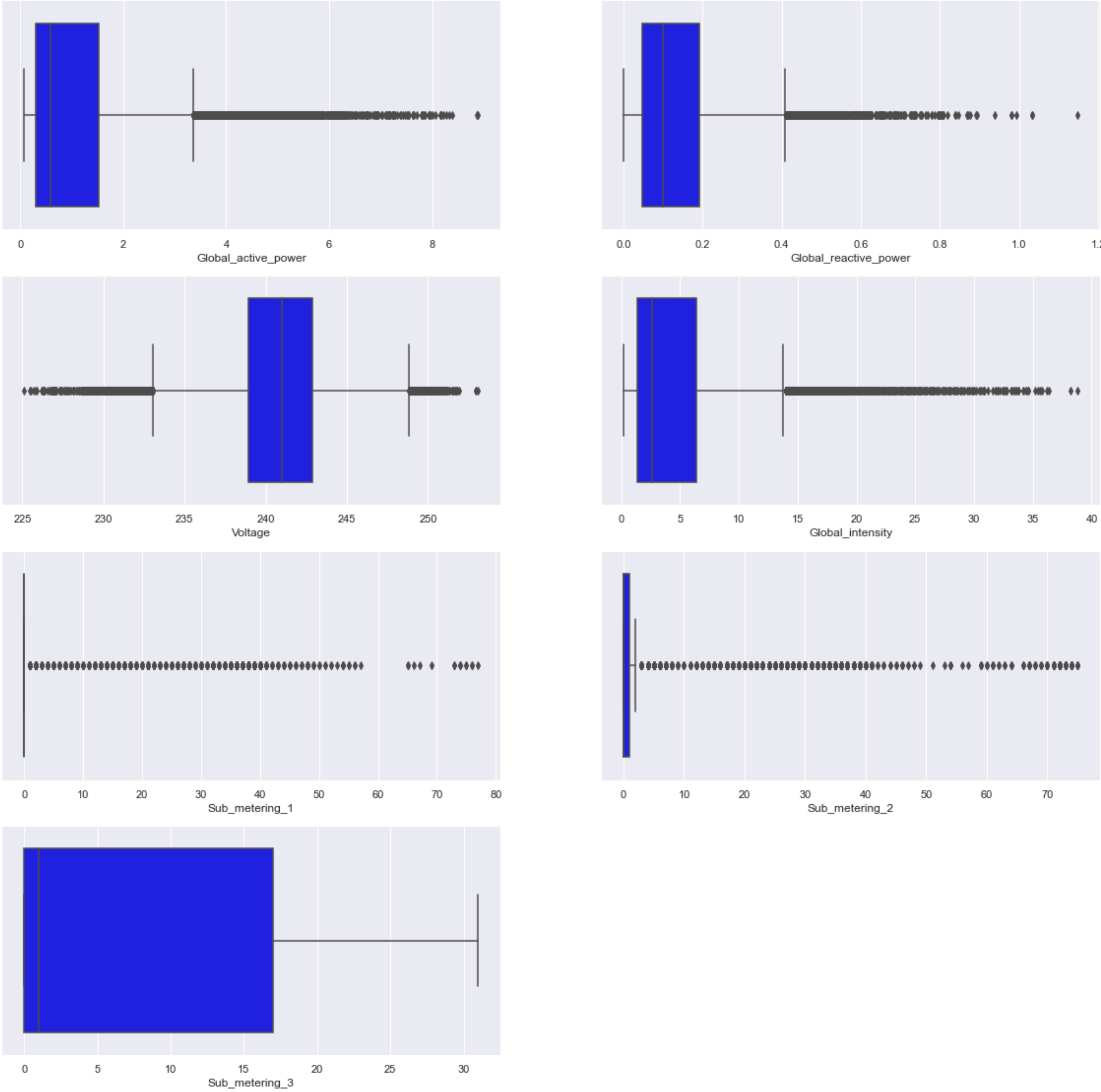
Out[65]:

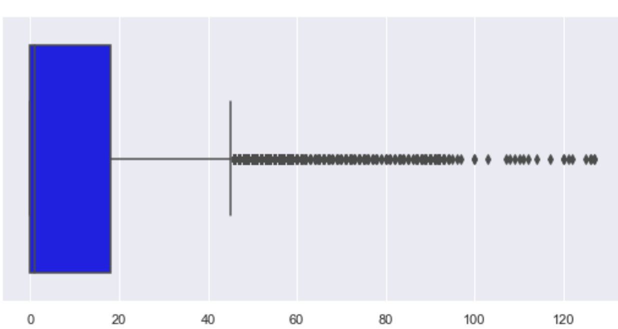
	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1
Global_active_power	1.000000	0.247642	-0.403876	0.998900	0.492156
Global_reactive_power	0.247642	1.000000	-0.114857	0.266809	0.134770
Voltage	-0.403876	-0.114857	1.000000	-0.415413	-0.196462
Global_intensity	0.998900	0.266809	-0.415413	1.000000	0.496834
Sub_metering_1	0.492156	0.134770	-0.196462	0.496834	1.000000
Sub_metering_2	0.438064	0.138916	-0.170027	0.444213	0.072243
Sub_metering_3	0.641381	0.085111	-0.277035	0.629476	0.106653
day	0.006372	0.000947	0.023519	0.005849	-0.002583
month	-0.031237	0.023582	-0.018293	-0.029994	-0.006605
year	-0.036686	0.040599	0.256456	-0.041184	-0.014463
Total_Power_Usage	0.848660	0.182044	-0.350258	0.845913	0.579077

Handling outliers

In [85]:

```
#### Visualising outliers using boxplot
plt.figure(figsize=(20,30))
for features in enumerate(data.columns):
        if features[1] not in ['day','month','year']:
            plt.subplot(6,2,features[0]+1)
            sns.set(rc={'figure.figsize':(10,8)})
            sns.boxplot(data=data,x=features[1],color='blue')
            plt.xlabel(features[1])
```


Global_active_power
Global_reactive_power
Voltage
Global_intensity
Sub_metering_1
Sub_metering_2
Sub_metering_3


Total_Power_Usage

In [102…

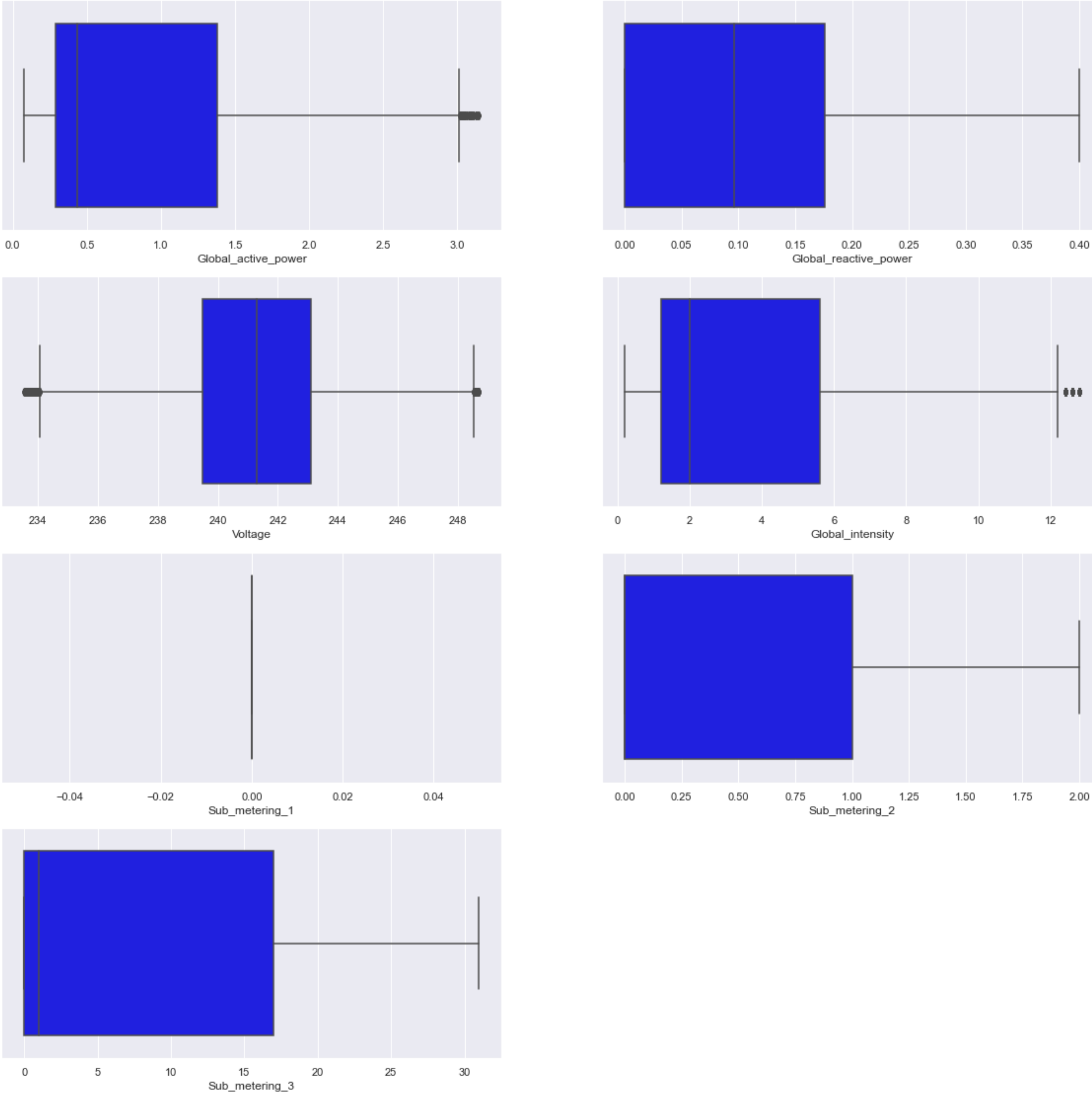
```
#### From the above plot it is very evident that the data contains a lot of out liers. W
def outlier_handle(feature):
    q1=data[feature].quantile(0.25)
    q3=data[feature].quantile(0.75)
    IQR=q3-q1
    lower_limit=q1-1.5*IQR
    upper_limit=q3+1.5*IQR
    index_to_drop=list(data[(data[feature]<lower_limit)|(data[feature]>upper_limit)].ind
    data.drop(index_to_drop,inplace=True)
    return 'Outliers Removed'
```

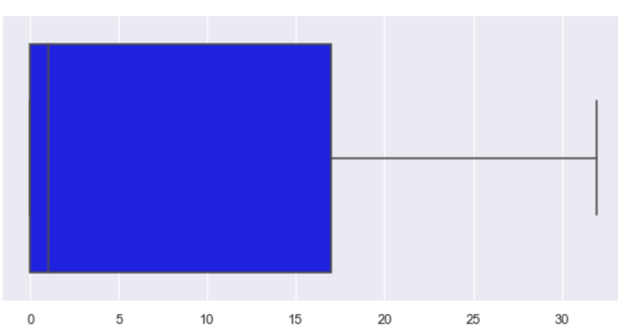
In [105…

```
#### We are going to pass the features one by one to our function to remove outliers
for features in data.columns:
        if features not in ['day','month','year']:
            outlier_handle(features)
```

In [106…

```
#### Checking the boxplot post outlier removal
plt.figure(figsize=(20,30))
for features in enumerate(data.columns):
        if features[1] not in ['day','month','year']:
            plt.subplot(6,2,features[0]+1)
            sns.set(rc={'figure.figsize':(10,8)})
            sns.boxplot(data=data,x=features[1],color='blue')
            plt.xlabel(features[1])
```


0.0 0.5 1.0 1.5 2.0 2.5 3.0
Global_active_power
0.00 0.05 0.10 0.15 0.20 0.25 0.30 0.35 0.40
Global_reactive_power
234 236 238 240 242 244 246 248
Voltage
0 2 4 6 8 10 12
Global_intensity
−0.04 −0.02 0.00 0.02 0.04
Sub_metering_1
0.00 0.25 0.50 0.75 1.00 1.25 1.50 1.75 2.00
Sub_metering_2
0 5 10 15 20 25 30
Sub_metering_3


0 5 10 15 20 25 30
Total_Power_Usage

In [107…
```
#### The plots look much better now. We can focus on model building now.
```

In [110…
```
#### Removing duplicate data
data.duplicated().sum()
```

Out[110]:
```
17
```

In [111…
```
data.drop_duplicates(inplace=True)
data.reset_index(inplace=True)
data.duplicated().sum()
```

Out[111]:
```
0
```

In [113…
```
data.drop('index',axis=1,inplace=True)
data.head()
```

Out[113]:

	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Su
0	0.272	0.000	244.34	1.2	0.0	0.0	
1	0.342	0.208	239.76	1.6	0.0	1.0	
2	1.440	0.106	243.86	5.8	0.0	0.0	
3	0.250	0.000	244.30	1.0	0.0	0.0	
4	0.288	0.156	243.65	1.4	0.0	2.0	

Model Building

In [114…
```
#### Splitting Dependent and Independent columns
X=data.drop('Total_Power_Usage',axis=1)
y=data['Total_Power_Usage']
X.head()
```

Out[114]:

	Global_active_power	Global_reactive_power	Voltage	Global_intensity	Sub_metering_1	Sub_metering_2	Su
0	0.272	0.000	244.34	1.2	0.0	0.0	
1	0.342	0.208	239.76	1.6	0.0	1.0	
2	1.440	0.106	243.86	5.8	0.0	0.0	
3	0.250	0.000	244.30	1.0	0.0	0.0	
4	0.288	0.156	243.65	1.4	0.0	2.0	

In [115…
```
y.head()
```

Out[115]:
```
0     1.0
1     2.0
2    19.0
3     1.0
4     2.0
Name: Total_Power_Usage, dtype: float64
```

In [116…
```
#### Splitting the training and test data
from sklearn.model_selection import train_test_split,GridSearchCV
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.33,random_state=10)
```

In [117…
```
from sklearn.tree import DecisionTreeRegressor
model=DecisionTreeRegressor()
```

```
train,y_train)
```

Loading [MathJax]/extensions/Safe.js

Out[118]:

▼ DecisionTreeRegressor

DecisionTreeRegressor()

In [120…

```
model.score(X_train,y_train)
```

Out[120]:

1.0

In [121…

```
from sklearn import tree
import matplotlib.pyplot as plt
fig=plt.figure(figsize=(25,15))
tree.plot_tree(model, max_depth=4,filled=True)
```

Out[121]:

```
[Text(0.4774590163934426, 0.9166666666666666, 'X[6] <= 9.5\nsquared_error = 65.346\nsamples = 27697\nvalue = 5.818'),
 Text(0.21721311475409835, 0.75, 'X[5] <= 0.5\nsquared_error = 1.04\nsamples = 19702\nvalue = 0.764'),
 Text(0.09016393442622951, 0.5833333333333334, 'X[6] <= 3.5\nsquared_error = 0.557\nsamples = 14463\nvalue = 0.393'),
 Text(0.03278688524590164, 0.4166666666666667, 'X[6] <= 0.5\nsquared_error = 0.235\nsamples = 14354\nvalue = 0.345'),
 Text(0.01639344262295082, 0.25, 'squared_error = 0.0\nsamples = 9454\nvalue = 0.0'),
 Text(0.04918032786885246, 0.25, 'X[6] <= 1.5\nsquared_error = 0.016\nsamples = 4900\nvalue = 1.011'),
 Text(0.03278688524590164, 0.08333333333333333, '\n  (...)  \n'),
 Text(0.06557377049180328, 0.08333333333333333, '\n  (...)  \n'),
 Text(0.14754098360655737, 0.4166666666666667, 'X[6] <= 6.5\nsquared_error = 3.288\nsamples = 109\nvalue = 6.661'),
 Text(0.11475409836065574, 0.25, 'X[6] <= 5.5\nsquared_error = 0.774\nsamples = 57\nvalue = 5.123'),
 Text(0.09836065573770492, 0.08333333333333333, '\n  (...)  \n'),
 Text(0.13114754098360656, 0.08333333333333333, '\n  (...)  \n'),
 Text(0.18032786885245902, 0.25, 'X[6] <= 8.5\nsquared_error = 0.611\nsamples = 52\nvalue = 8.346'),
 Text(0.16393442622950818, 0.08333333333333333, '\n  (...)  \n'),
 Text(0.19672131147540983, 0.08333333333333333, '\n  (...)  \n'),
 Text(0.3442622950819672, 0.5833333333333334, 'X[6] <= 3.5\nsquared_error = 0.943\nsamples = 5239\nvalue = 1.789'),
 Text(0.2786885245901639, 0.4166666666666667, 'X[6] <= 0.5\nsquared_error = 0.472\nsamples = 5181\nvalue = 1.719'),
 Text(0.2459016393442623, 0.25, 'X[5] <= 1.5\nsquared_error = 0.21\nsamples = 3055\nvalue = 1.3'),
 Text(0.22950819672131148, 0.08333333333333333, '\n  (...)  \n'),
 Text(0.26229508196721313, 0.08333333333333333, '\n  (...)  \n'),
 Text(0.3114754098360656, 0.25, 'X[5] <= 1.5\nsquared_error = 0.232\nsamples = 2126\nvalue = 2.322'),
 Text(0.29508196721311475, 0.08333333333333333, '\n  (...)  \n'),
 Text(0.32786885245901637, 0.08333333333333333, '\n  (...)  \n'),
 Text(0.4098360655737705, 0.4166666666666667, 'X[6] <= 6.5\nsquared_error = 3.133\nsamples = 58\nvalue = 8.069'),
 Text(0.3770491803278688, 0.25, 'X[6] <= 5.5\nsquared_error = 0.957\nsamples = 24\nvalue = 6.292'),
 Text(0.36065573770491804, 0.08333333333333333, '\n  (...)  \n'),
 Text(0.39344262295081966, 0.08333333333333333, '\n  (...)  \n'),
 Text(0.4426229508196721, 0.25, 'X[6] <= 7.5\nsquared_error = 0.866\nsamples = 34\nvalue = 9.324'),
 Text(0.4262295081967213, 0.08333333333333333, '\n  (...)  \n'),
 Text(0.45901639344262296, 0.08333333333333333, '\n  (...)  \n'),
 Text(0.7377049180327869, 0.75, 'X[6] <= 22.5\nsquared_error = 5.798\nsamples = 7995\nvalue = 18.271'),
 Text(0.6065573770491803, 0.5833333333333334, 'X[6] <= 14.5\nsquared_error = 3.047\nsamples = 7786\nvalue = 18.001'),
 Text(0.5409836065573771, 0.4166666666666667, 'X[6] <= 11.5\nsquared_error = 1.169\nsamples = 439\nvalue = 11.993'),
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 Text(0.5245901639344263, 0.08333333333333333, '\n  (...)  \n'),
 Text(0.5737704918032787, 0.25, 'X[5] <= 0.5\nsquared_error = 0.657\nsamples = 258\nvalue = 12.609'),
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 Text(0.6229508196721312, 0.08333333333333333, '\n  (...)  \n'),
```

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```
 Text(0.6557377049180327, 0.08333333333333333, '\n  (...)  \n'),
 Text(0.7049180327868853, 0.25, 'X[5] <= 0.5\nsquared_error = 0.455\nsamples = 1667\nva
lue = 19.394'),
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 Text(0.8688524590163934, 0.5833333333333334, 'X[6] <= 26.5\nsquared_error = 4.082\nsam
ples = 209\nvalue = 28.344'),
 Text(0.8032786885245902, 0.4166666666666667, 'X[6] <= 24.5\nsquared_error = 1.383\nsam
ples = 35\nvalue = 24.6'),
 Text(0.7704918032786885, 0.25, 'X[5] <= 0.5\nsquared_error = 0.372\nsamples = 21\nvalu
e = 23.762'),
 Text(0.7540983606557377, 0.08333333333333333, '\n  (...)  \n'),
 Text(0.7868852459016393, 0.08333333333333333, '\n  (...)  \n'),
 Text(0.8360655737704918, 0.25, 'X[0] <= 1.852\nsquared_error = 0.265\nsamples = 14\nva
lue = 25.857'),
 Text(0.819672131147541, 0.08333333333333333, '\n  (...)  \n'),
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ples = 174\nvalue = 29.098'),
 Text(0.9016393442622951, 0.25, 'X[5] <= 0.5\nsquared_error = 0.334\nsamples = 59\nvalu
e = 27.932'),
 Text(0.8852459016393442, 0.08333333333333333, '\n  (...)  \n'),
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ue = 29.696'),
 Text(0.9508196721311475, 0.08333333333333333, '\n  (...)  \n'),
 Text(0.9836065573770492, 0.08333333333333333, '\n  (...)  \n')]
```

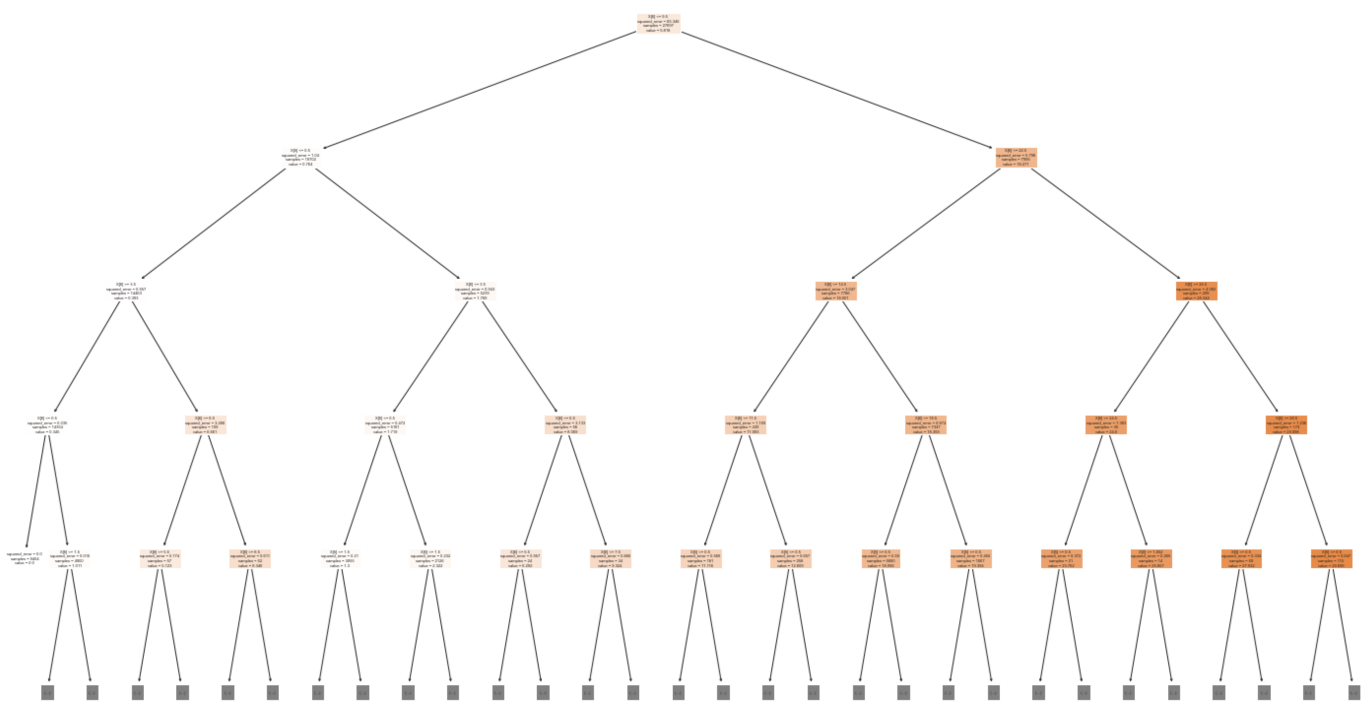

In [122…
```
y_predict=model.predict(X_test)
```

In [123…
```
from sklearn.metrics import r2_score
```

In [128…
```
r2=r2_score(y_test,y_predict)
print('Our model has', round(r2*100,3),'% accuracy')
```

```
Our model has 99.998 % accuracy
```

In [ ]: