IoT - Power energy consumption predict

In [44]:

```
# Import packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.ensemble.forest import RandomForestRegressor
from sklearn.feature_selection import SelectFromModel
from sklearn.preprocessing import LabelEncoder
import seaborn as sns
from datetime import datetime
from sklearn.datasets import make_regression
from sklearn import ensemble
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.svm import SVR
```

Variables description

Appliances --> Power consumed

Lights --> Power appliance

Tx --> Temperatura

RH_x --> Umidade Relativa

T_out --> Temperatura fora da casa

Press_mm_hg --> Unidade de pressão

RH_out --> Umidade fora da casa

Visibility --> Visibilidade

Tdewpoint --> ponto de condensação

rvx --> variavel aleatória

In [3]:

```
#Import Train and Test dataset
df_train = pd.read_csv('projeto8-training.csv')
df_test = pd.read_csv('projeto8-testing.csv')
print(f'Train dataset has {df_train.shape[0]} lines and {df_train.shape[1]} variables')
print(f'Test dataset has {df_test.shape[0]} lines and {df_test.shape[1]} variables')
```

```
Train dataset has 14803 lines and 32 variables
Test dataset has 4932 lines and 32 variables
```

Both dataset have the same amount of columns. Thus, we can concatenate both datasets

In [4]:

```
df = pd.concat([df_train, df_test])
```

Exploratory Data Analysis

In [5]:

```
# Evaluate missing values in the dataset
df.isna().sum()
```

Out[5]:

```
date           0
Appliances     0
lights         0
T1             0
RH_1           0
T2             0
RH_2           0
T3             0
RH_3           0
T4             0
RH_4           0
T5             0
RH_5           0
T6             0
RH_6           0
T7             0
RH_7           0
T8             0
RH_8           0
T9             0
RH_9           0
T_out          0
Press_mm_hg    0
RH_out         0
Windspeed      0
Visibility     0
Tdewpoint      0
rv1            0
rv2            0
NSM            0
WeekStatus     0
Day_of_week    0
dtype: int64
```

In [6]:

```
# Evaluate the number of unique elements in the dataset
df.nunique()
```

Out[6]:

```
date           19735
Appliances        92
lights             8
T1               722
RH_1            2547
T2              1650
RH_2            3376
T3              1426
RH_3            2618
T4              1390
RH_4            2987
T5              2263
RH_5            7571
T6              4446
RH_6            9709
T7              1955
RH_7            5891
T8              2228
RH_8            6649
T9               924
RH_9            3388
T_out           1730
Press_mm_hg     2189
RH_out           566
Windspeed        189
Visibility       413
Tdewpoint       1409
rv1            19735
rv2            19735
NSM              144
WeekStatus         2
Day_of_week        7
dtype: int64
```

In [6]:

```
df.describe()
```

Out[6]:

	Appliances	lights	T1	RH_1	T2	RH_2
count	19735.000000	19735.000000	19735.000000	19735.000000	19735.000000	19735.000000
mean	97.694958	3.801875	21.686571	40.259739	20.341219	40.420420
std	102.524891	7.935988	1.606066	3.979299	2.192974	4.069813
min	10.000000	0.000000	16.790000	27.023333	16.100000	20.463333
25%	50.000000	0.000000	20.760000	37.333333	18.790000	37.900000
50%	60.000000	0.000000	21.600000	39.656667	20.000000	40.500000
75%	100.000000	0.000000	22.600000	43.066667	21.500000	43.260000
max	1080.000000	70.000000	26.260000	63.360000	29.856667	56.026667

8 rows × 29 columns

For a easily understand, let's separate the dataset as **numerical** and **categorical**. The criteria adopted was, if the variable has *less than 10 different values*, it will be considered categorical.

In [7]:

```
num = [name for name in df.columns if df[name].nunique() > 10]
cat = [name for name in df.columns if df[name].nunique() < 10]
df_num = df[num]
df_cat = df[cat]
```

In [8]:

```
#Formating columns Date and separate them into Month, Day and Hour
df_num = df_num.sort_values(['date'], ascending=True)
df_num['date'] = pd.to_datetime(df_num['date'], format='%Y-%m-%d %H:%M:%S')
df_num['Year'] = df_num['date'].dt.year
df_num['Month'] = df_num['date'].dt.month
df_num['Day'] = df_num['date'].dt.day
df_num['Hour'] = df_num['date'].dt.hour
```

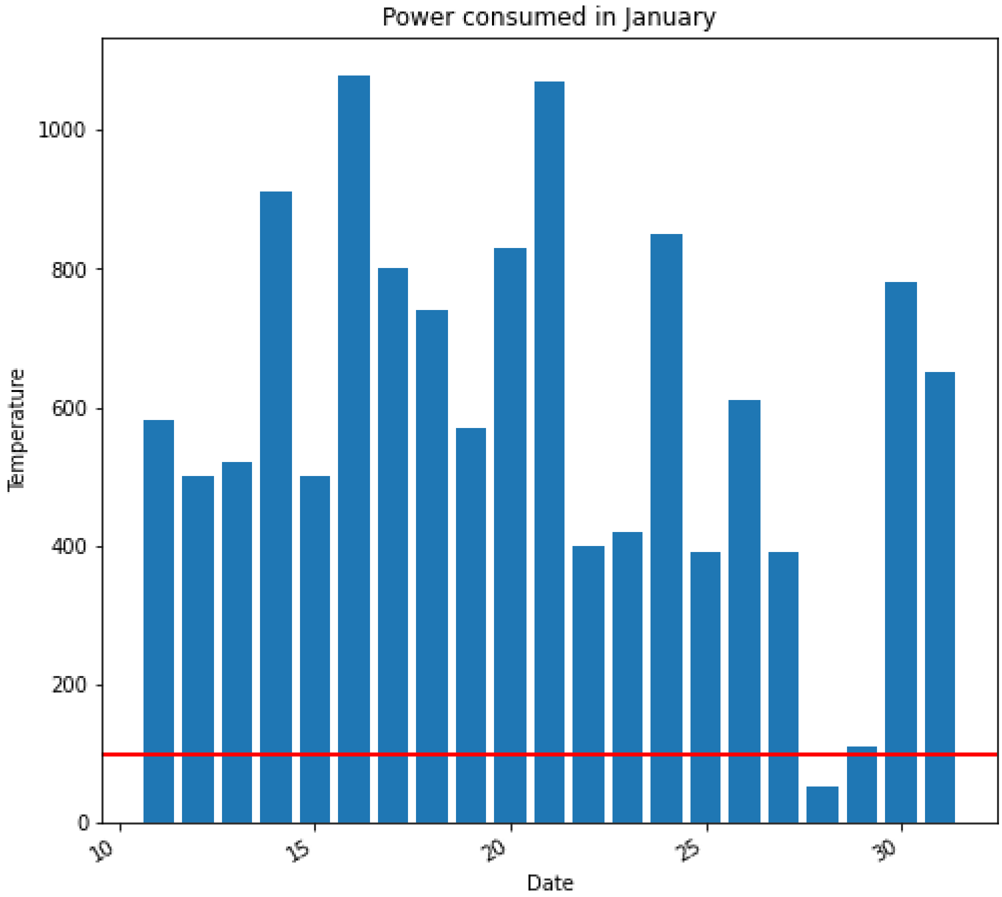
In [9]:

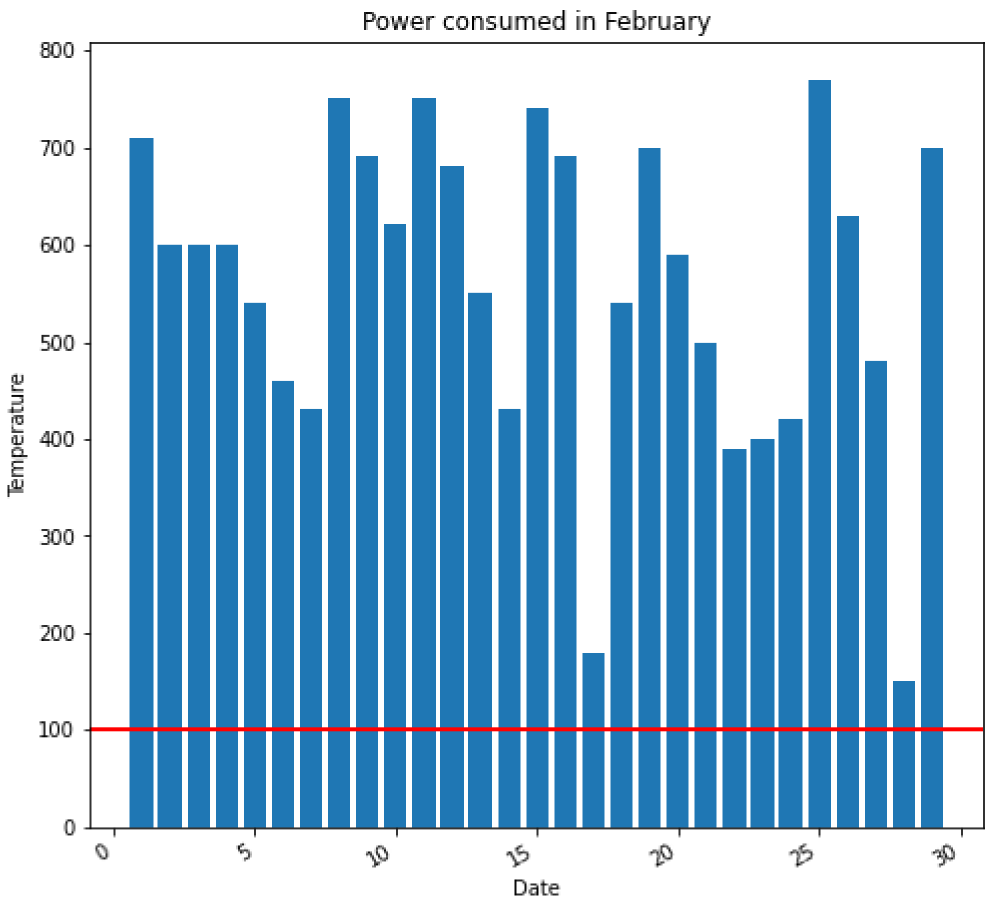
```
# Transform date column into index.
df_num.index = pd.DatetimeIndex(df_num['date'])
df_cat.index = pd.DatetimeIndex(df_num['date'])

# Adding colum 'Date' to future analysis
df_num['date'] = df_num['date'].copy()
```

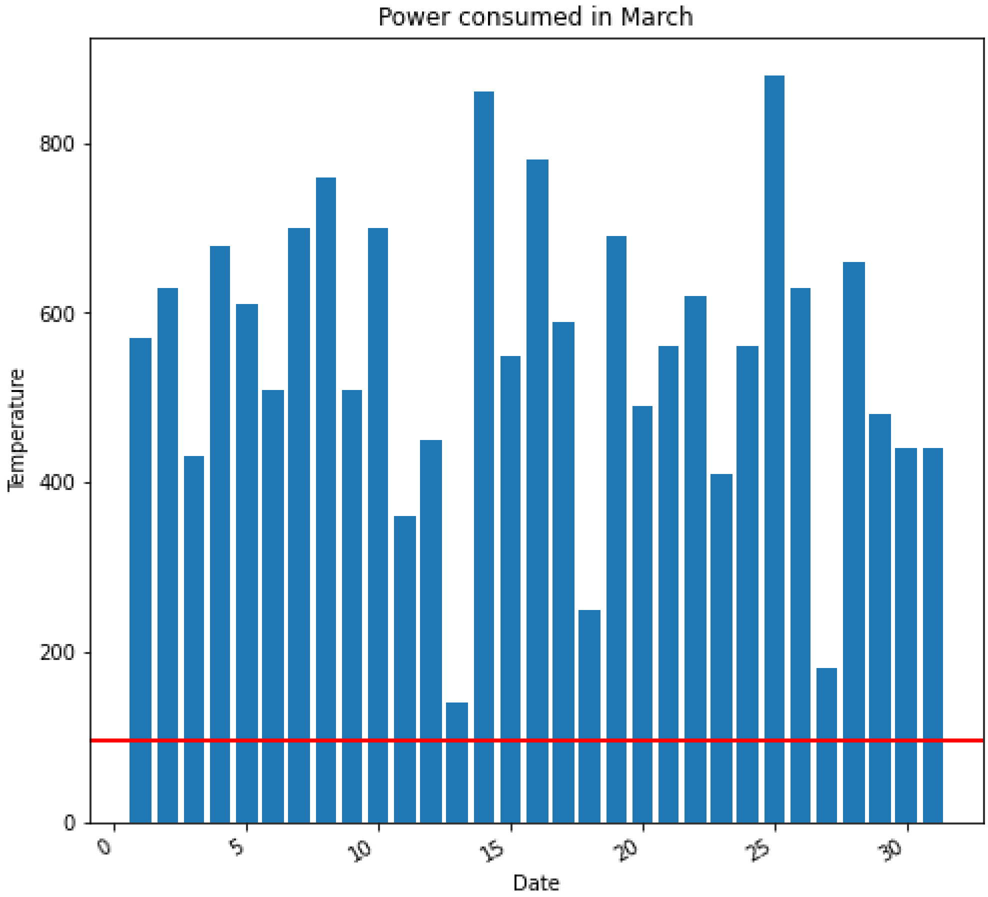
Plot power consumption by month

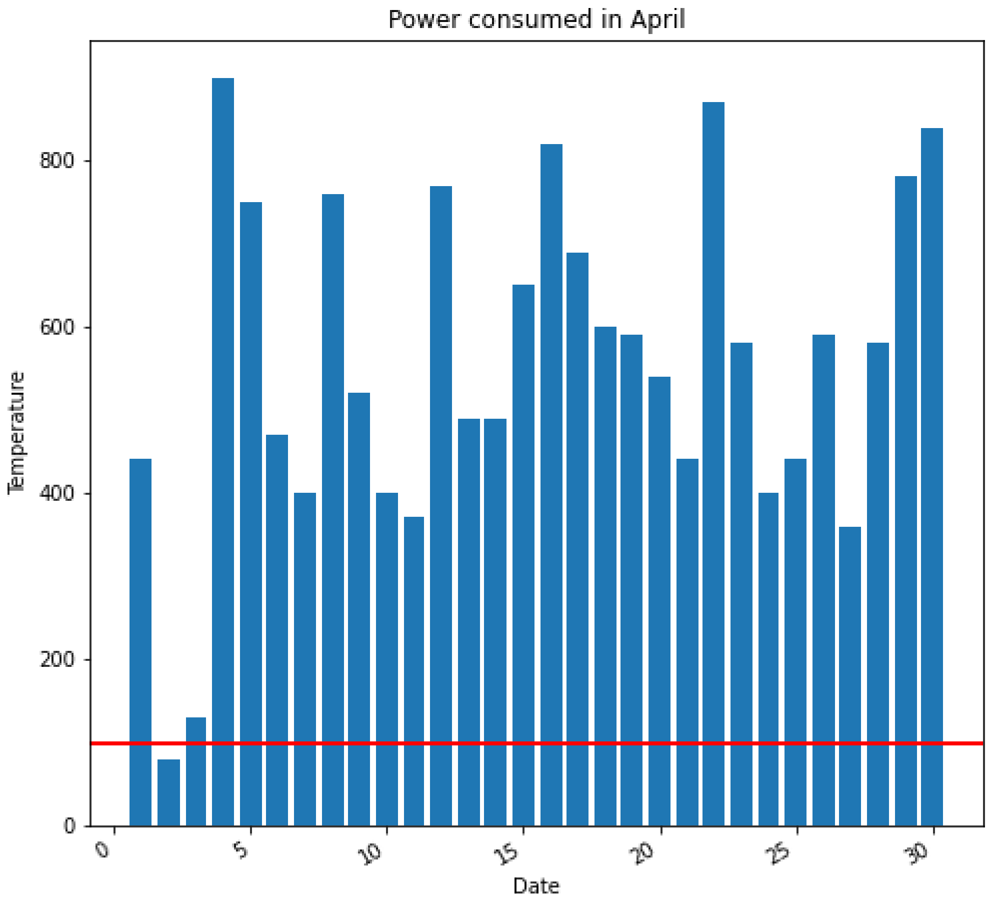
In [27]:

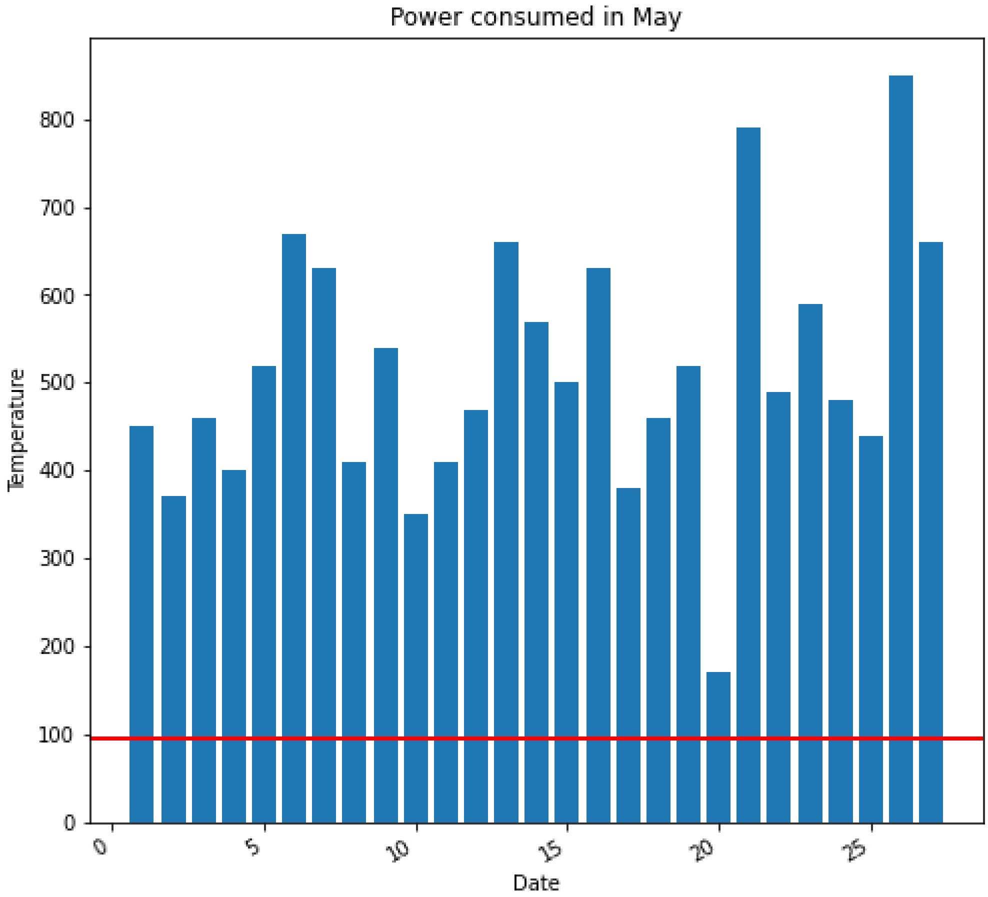
```
for i in range(6):
    if i == 1:
        fig, ax1 = plt.subplots(figsize=(8, 8))
        plot_1 = df_num[df_num['Month'] == 1]
        mean_1 = plot_1['Appliances'].mean()
        ax1.bar(plot_1['Day'], plot_1['Appliances'])
        ax1.set_title('Power consumed in January')
        ax1.axhline(mean_1, color='red', linewidth=2)
        plt.xlabel("Date")
        plt.ylabel("Temperature")
        fig.autofmt_xdate()

    if i == 2:
        fig, ax2 = plt.subplots(figsize=(8, 8))
        plot_2 = df_num[df_num['Month'] == 2]
        mean_2 = plot_2['Appliances'].mean()
        ax2.bar(plot_2['Day'], plot_2['Appliances'])
        ax2.set_title('Power consumed in February')
        ax2.axhline(mean_2, color='red', linewidth=2)
        plt.xlabel("Date")
        plt.ylabel("Temperature")
        fig.autofmt_xdate()

    if i == 3:
        fig, ax3 = plt.subplots(figsize=(8, 8))
        plot_3 = df_num[df_num['Month'] == 3]
        mean_3 = plot_3['Appliances'].mean()
        ax3.bar(plot_3['Day'], plot_3['Appliances'])
        ax3.set_title('Power consumed in March')
        ax3.axhline(mean_3, color='red', linewidth=2)
        plt.xlabel("Date")
        plt.ylabel("Temperature")
        fig.autofmt_xdate()

    if i == 4:
        fig, ax4 = plt.subplots(figsize=(8, 8))
        plot_4 = df_num[df_num['Month'] == 4]
        mean_4 = plot_4['Appliances'].mean()
        ax4.bar(plot_4['Day'], plot_4['Appliances'])
        ax4.set_title('Power consumed in April')
        ax4.axhline(mean_4, color='red', linewidth=2)
        plt.xlabel("Date")
        plt.ylabel("Temperature")
        fig.autofmt_xdate()

    if i == 5:
        fig, ax5 = plt.subplots(figsize=(8, 8))
        plot_5 = df_num[df_num['Month'] == 5]
        mean_5 = plot_5['Appliances'].mean()
        ax5.bar(plot_5['Day'], plot_5['Appliances'])
        ax5.set_title('Power consumed in May')
        ax5.axhline(mean_5, color='red', linewidth=2)
        plt.xlabel("Date")
        plt.ylabel("Temperature")
        fig.autofmt_xdate()
```


Power consumed in January
Temperature
Date
0
200
400
600
800
1000
10
15
20
25
30


Power consumed in February
Temperature
Date
0
100
200
300
400
500
600
700
800
0
5
10
15
20
25
30


Power consumed in March
Temperature
Date
0
200
400
600
800
0
5
10
15
20
25
30


Power consumed in April
Temperature
Date
0
200
400
600
800
0
5
10
15
20
25
30

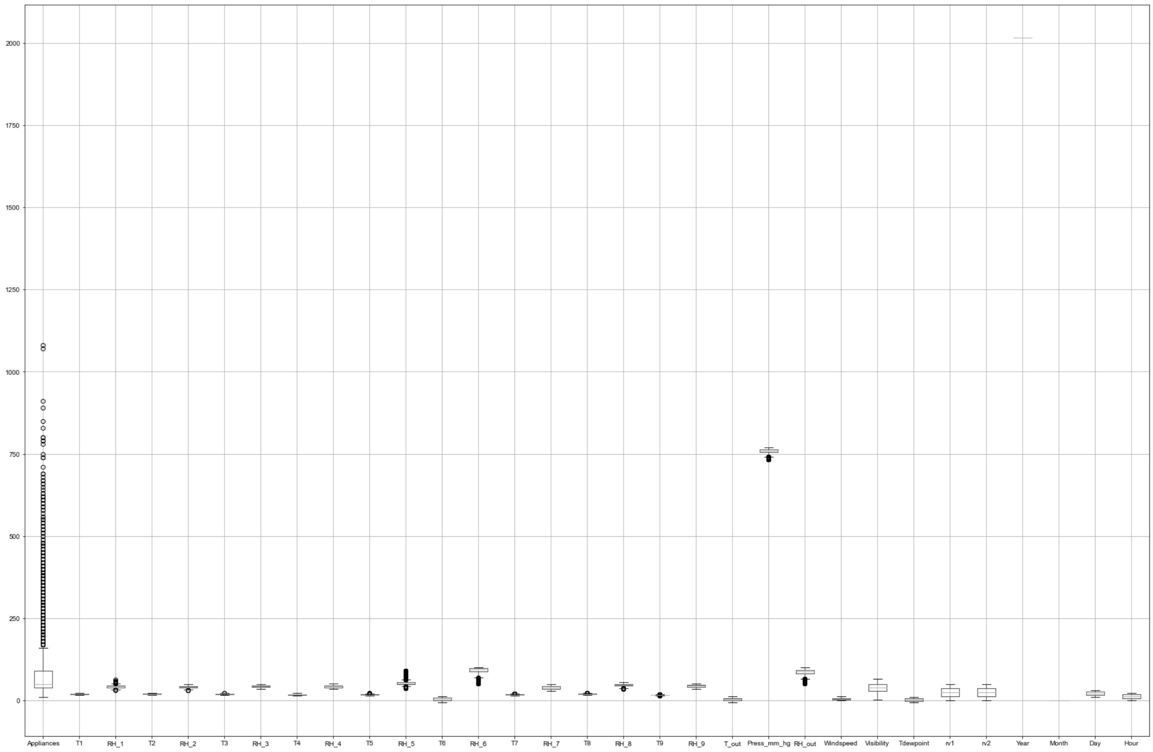


Plot to visualize the outliers

In [28]:

```
year_start = str(df_num['Year'].min())
month_start = str(df_num['Month'].min())
day = int('01')
# fim
year_end = str(df_num['Year'].max())
month_end = str(df_num['Month'].max())

if day < 10:
    date_start = year_start + '-' + month_start
    date_end = year_end + '-' + month_end + '-' + '0' + str(day) + ' 23:00:00'
else:
    date_start = year_start + '-' + month_start
    date_end = year_end + '-' + month_end + '-' + str(day) + ' 23:00:00'

print(f'{date_start} até {date_end} com {len(df_num[date_start])} pontos')

plt.subplots(figsize=(30, 20))
sns.set(style="ticks", color_codes=True)
df_filter = df_num[date_start]
df_filter = df_filter.drop(['date', 'NSM'], axis=1)
df_filter.boxplot()
plt.show()
```

2016-1 até 2016-5-01 23:00:00 com 2922 pontos



Analysing the outliers, we can remove data from "Appliances" that are greater than 150

In [29]:

```
df_num_v1 = df_num[df_num['Appliances'] < 150.0]
df_num_v1 = df_num_v1.drop(['Year', 'Month', 'Day', 'Hour', 'date'], axis=1)

# Reset index
df_num_v1.reset_index(drop=True, inplace=True)
df_num_v1.index

df_num_v1.head(2)
```

Out[29]:

	Appliances	T1	RH_1	T2	RH_2	T3	RH_3	T4	RH_4	T5	...
0	60	19.89	47.596667	19.2	44.7900	19.79	44.73	19.0	45.566667	17.166667	...
1	60	19.89	46.693333	19.2	44.7225	19.79	44.79	19.0	45.992500	17.166667	...

2 rows × 28 columns

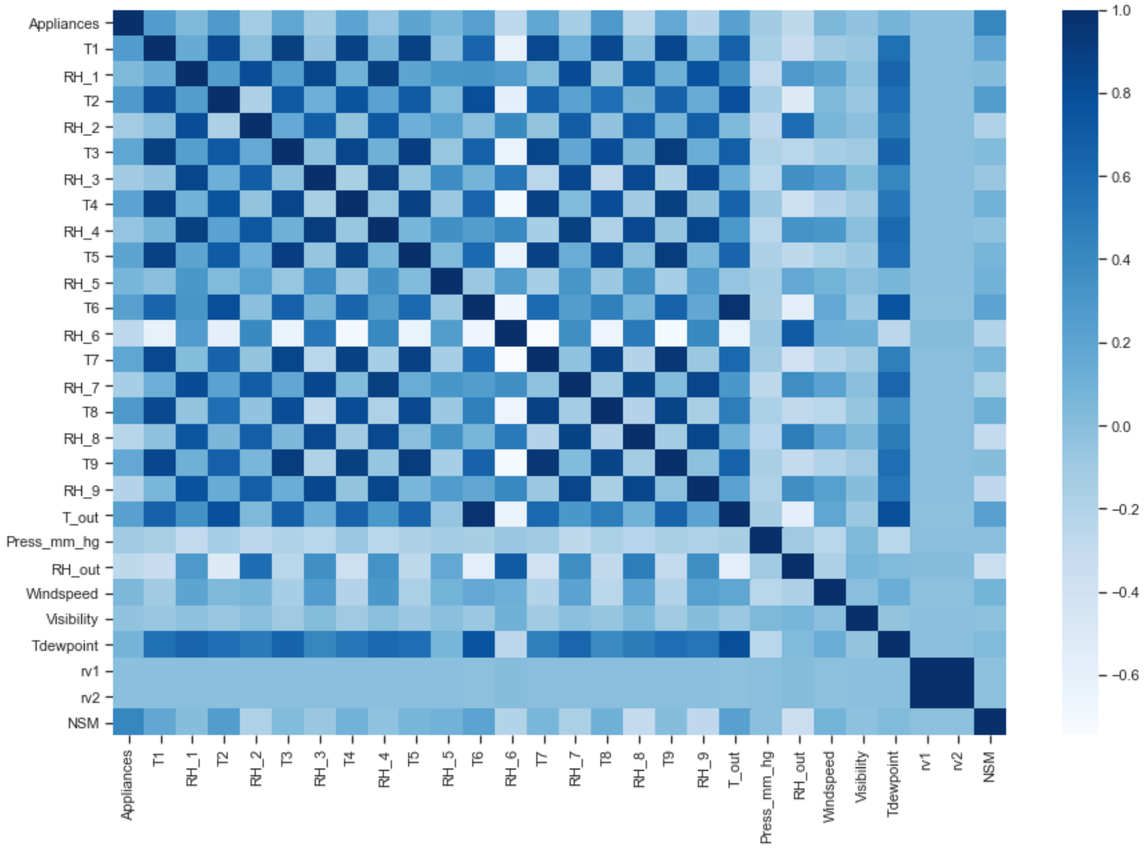
Correlation

In [30]:

```
plt.figure(figsize = (15,10))
sns.heatmap(df_num_v1.corr(), cmap="Blues")
```

Out[30]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2146c07b9e8>
```



In [31]:

```
#Correlation with output variable
cor_target = abs(df_num_v1.corr()["Appliances"])

#Selecting highly correlated features
relevant_features = cor_target[cor_target > 0.2]
relevant_features
```

Out[31]:

```
Appliances    1.000000
T1            0.266959
T2            0.277459
T4            0.211871
T5            0.205815
T6            0.233250
RH_6          0.255907
T8            0.288726
RH_8          0.229389
RH_9          0.212781
T_out         0.224154
RH_out        0.266875
NSM           0.426494
Name: Appliances, dtype: float64
```

In [32]:

```
# Encode the variables that are string
lb = LabelEncoder()

#Adjusting columns into categorical
df['WeekStatus'] = lb.fit_transform(df['WeekStatus'])
df['Day_of_week'] = lb.fit_transform(df['Day_of_week'])
df_v1 = df[df['Appliances'] < 150.0]
```

Normalizing data

In [33]:

```
#Separating target variable
df_v2_target = df_v1['Appliances']
df_v2 = df_v1.drop(['Appliances','date'], axis=1)
```

In [34]:

```
# Normalizing dataset
df_norm2 = (df_v2 - df_v2.mean()) / (df_v2.max() - df_v2.min())
```

Out[34]:

	lights	T1	RH_1	T2	RH_2	T3	RH_3	T4	RH_
0	0.533117	-0.192591	0.229042	-0.078426	0.121150	-0.20437	0.266728	-0.167153	0.28231
1	0.533117	-0.192591	0.201341	-0.078426	0.119252	-0.20437	0.269601	-0.167153	0.30055

2 rows × 30 columns

Feature Selection

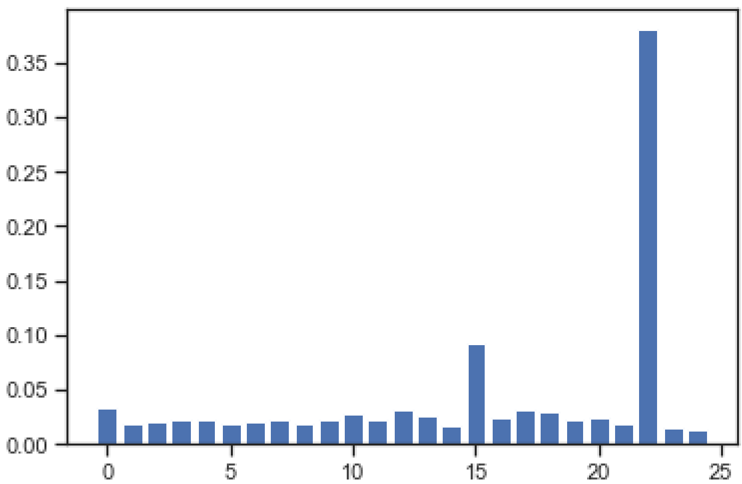
In [37]:

```
# Removing variables before fit the model
new_df_norm = df_norm2.drop(['rv1', 'rv2', 'Visibility', 'Press_mm_hg','Tdewpoint'], ax
is=1)

#Separating target variable for train dataframe
X_array = np.array(new_df_norm)
y_array = np.array(df_v2_target)

#Separating train and test data
X_train, X_test, y_train, y_test = train_test_split(X_array, y_array, train_size=0.7)
```

In [41]:

```
# random forest for feature importance on a regression problem
model = RandomForestRegressor()

# fit the model
model.fit(X_array, y_array)

# get importance
importance = model.feature_importances_

# summarize feature importance
for i,v in enumerate(importance):
    print('Feature: %0d, Score: %.5f' % (i,v))

# plot feature importance
plt.bar([x for x in range(len(importance))], importance)
plt.show()
```

```
Feature: 0, Score: 0.03302
Feature: 1, Score: 0.01811
Feature: 2, Score: 0.02112
Feature: 3, Score: 0.02180
Feature: 4, Score: 0.02321
Feature: 5, Score: 0.01899
Feature: 6, Score: 0.02117
Feature: 7, Score: 0.02258
Feature: 8, Score: 0.01877
Feature: 9, Score: 0.02209
Feature: 10, Score: 0.02900
Feature: 11, Score: 0.02180
Feature: 12, Score: 0.03195
Feature: 13, Score: 0.02626
Feature: 14, Score: 0.01794
Feature: 15, Score: 0.09208
Feature: 16, Score: 0.02473
Feature: 17, Score: 0.03125
Feature: 18, Score: 0.03002
Feature: 19, Score: 0.02223
Feature: 20, Score: 0.02448
Feature: 21, Score: 0.01882
Feature: 22, Score: 0.38054
Feature: 23, Score: 0.01451
Feature: 24, Score: 0.01352
```



Predictive Analysis

1) Gradient Boosting Regressor

In [45]:

```
params = {'n_estimators': 500, 'max_depth': 8, 'min_samples_split': 2,
          'learning_rate': 0.01, 'loss': 'ls'}
model_v1 = ensemble.GradientBoostingRegressor(**params)

model_v1.fit(X_train, y_train)
y_pred = model_v1.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
r2score = r2_score(y_test, y_pred)
print(f"R2 SCORE: {r2score}")
```

```
R2 SCORE: 0.7044533450383282
```

2) Support Vector Regression

In [47]:

```
model_v2 = SVR()
model_v2.fit(X_train, y_train)
y_pred = model_v2.predict(X_test)
r2score_v2 =  r2_score(y_test, y_pred)
print(f"R2 SCORE: {r2score_v2}")
```

```
R2 SCORE: 0.40585495932435556
```

3) Linear Regression

In [48]:

```
model_v3 = LinearRegression()
model_v3.fit(X_train, y_train)
y_pred = model_v3.predict(X_test)

r2score_v3 =  r2_score(y_test, y_pred)
print(f"R2 SCORE: {r2score_v3}")
```

```
R2 SCORE: 0.36847786034013674
```

Conclusion

- The best model for this dataset is Gradient Boosting Regressor. It has an accurancy of 70%
- It will be necessary more data to increase the accuracy of the model