# Measure of energy Consumption

## Introduction to Machine Learning for the Built Environment:

### Energy Consumption Forecasting:

It uses the Building Data Genome Project data set to analyze electrical meter data from non-residential buildings.

### Import relevant python package :

Let's use the electrical meter data to create clusters of typical load profiles for analysis. First we can load our conventional packages.

In [1] :

```
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib
```

Next let's load all the packages we will need for analysis

In [1] :

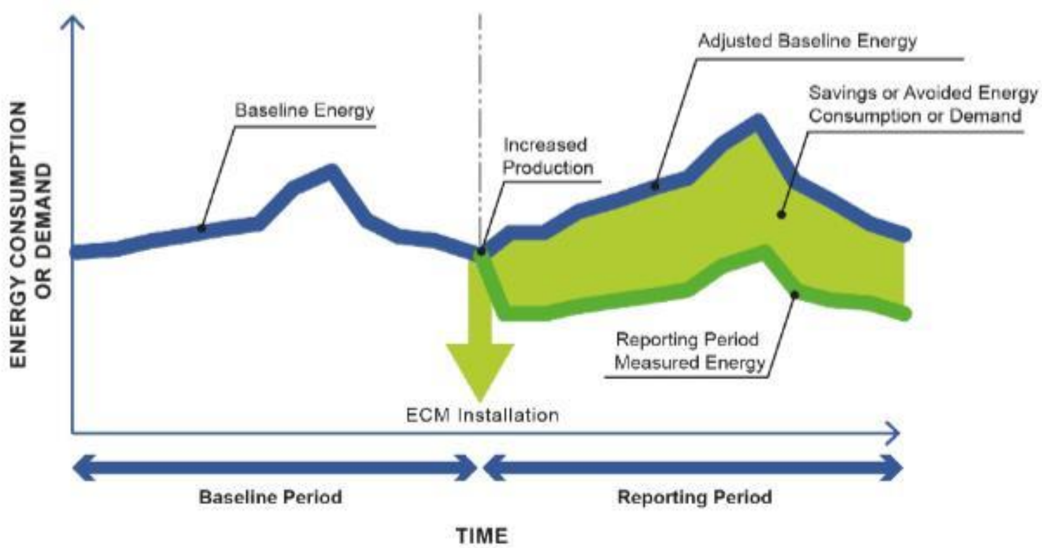
```
import sklearn
from sklearn import metrics
from sklearn.neighbors import KNeighborsRegressor
from scipy.cluster.vq import kmeans, vq, whiten
from scipy.spatial.distance import cdist
import numpy as np
from datetime import datetime
```

### Electricity Prediction for Measurement and Verification :

Prediction is a common machine learning (ML) technique used on building energy consumption data. This process is valuable for anomaly detection, load profile-based building control and measurement and verification procedures.

The graphic below comes from the IPMVP to show how prediction can be used for M&V to calculate how much energy **would have** been consumed if an energy savings intervention had not been implemented.

### Prediction for Measurement and Verification :




### Load electricity data and weather data

First we can load the data from the BDG in the same as our previous weather analysis influence notebook from the Construction Phase videos

In [1] :

```
elec_all_data = pd.read_csv("../input/buildingdatagenomeproject2/electricity_cleaned.csv", index_col='timestamp', parse_dates=True)
```

In [4] :

```
elec__data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 17544 entries, 2016-01-01 00:00:00 to 2017-12-31 23:00:00
Columns: 1578 entries, Panther_parking_Lorriane to Mouse_science_Micheal
dtypes: float64(1578)
memory usage: 211.3 MB
```

In [5] :

```
buildingname = 'Panther_office_Hannah'
```

In [6] :

```
office_example_prediction_data = pd.DataFrame(elec_all_data[buildingname].
truncate(before='2017-01-01')).fillna(method='ffill')
```

In [7] :

```
office_example_prediction_data.info()
```

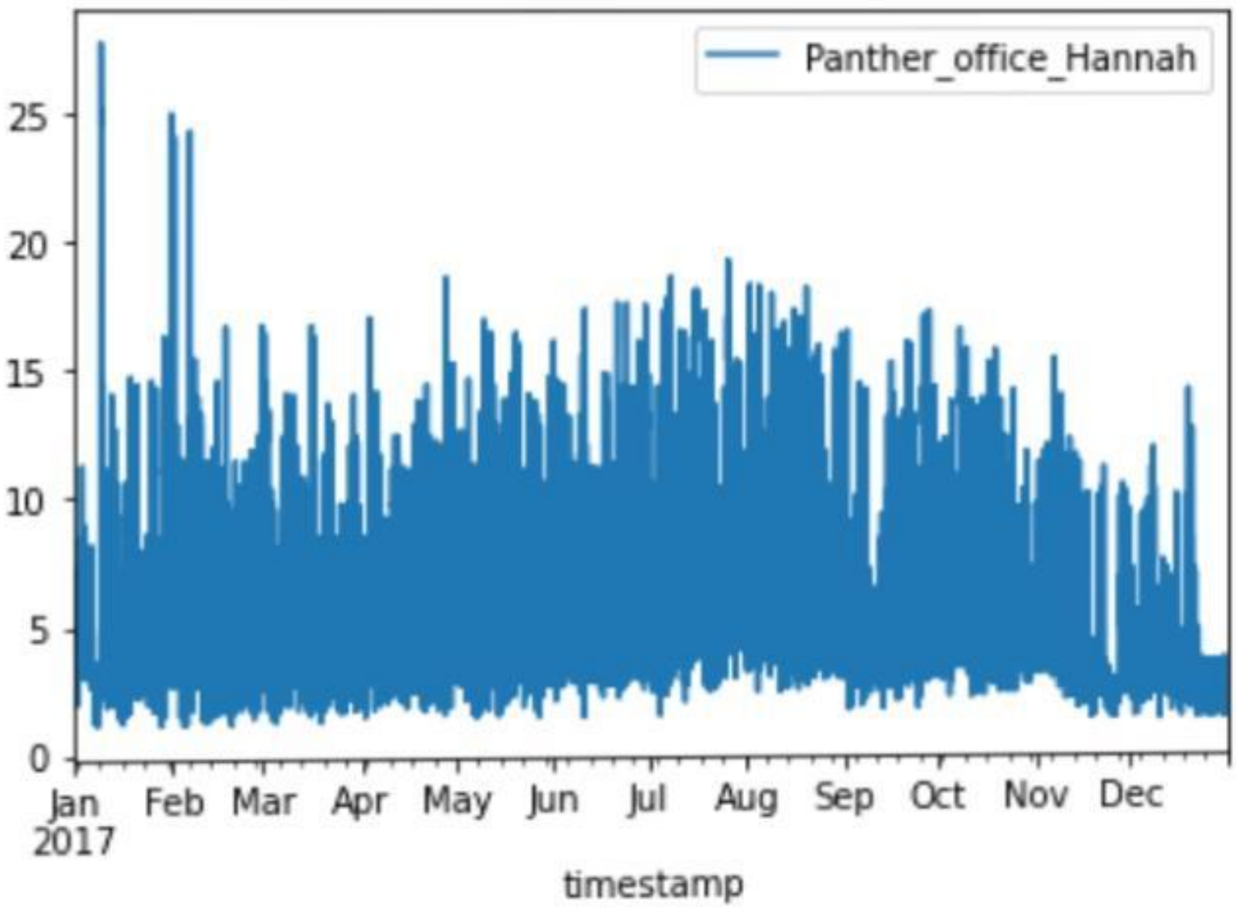
```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8760 entries, 2017-01-01 00:00:00 to 2017-12-31 23:00:00
Data columns (total 1 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Panther_office_Hannah  8760 non-null   float64
dtypes: float64(1)
memory usage: 136.9 KB
```

In [8] :

```
office_example_prediction_data.plot()
```

Out [8] :

```
<AxesSubplot:xlabel='timestamp'>
```




In [9] :

```
weather_data = pd.read_csv("../input/buildingdatagenomeproject2/weather.cs
v", index_col='timestamp', parse_dates=True)
```

In [10] :

```
weather_data_site = weather_data[weather_data.site_id == 'Panther'].truncate(
before='2017-01-01')
```

In [11] :

```
weather_data_site.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 8760 entries, 2017-01-01 00:00:00 to 2017-12-31 23:00:00
Data columns (total 9 columns):
 #   Column          Non-Null Count  Dtype
```

```
---  ------          --------------  -----
 0   site_id         8760 non-null   object
 1   airTemperature  8760 non-null   float64
 2   cloudCoverage   5047 non-null   float64
 3   dewTemperature  8760 non-null   float64
 4   precipDepth1HR  8752 non-null   float64
 5   precipDepth6HR  329 non-null    float64
 6   seaLvlPressure  8522 non-null   float64
 7   windDirection   8511 non-null   float64
 8   windSpeed       8760 non-null   float64
dtypes: float64(8), object(1)
memory usage: 684.4+ KB
```

In [12] :

```
weather_hourly = weather_data_site.resample("H").mean()
weather_hourly_nooutlier = weather_hourly[weather_hourly > -40]
weather_hourly_nooutlier_nogaps = weather_hourly_nooutlier.fillna(method='ffill')
```

In [13]:

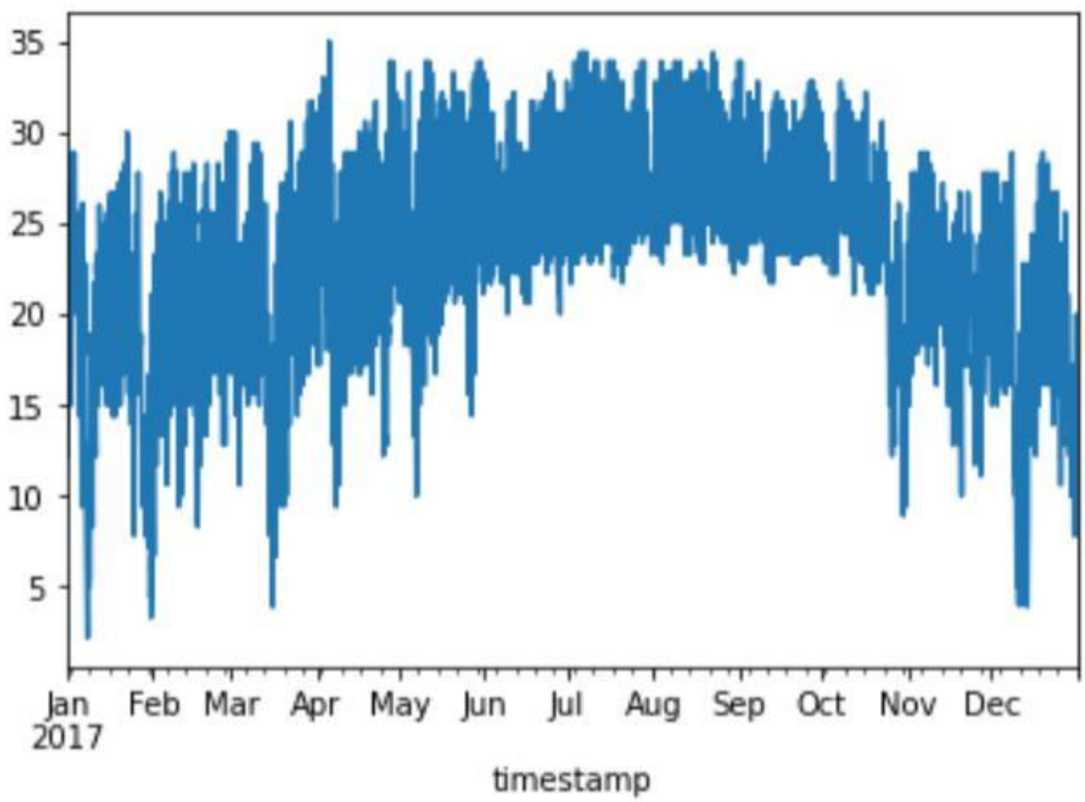
```
temperature = weather_hourly_nooutlier_nogaps["airTemperature"]
```

In [14]:

```
temperature.plot()
```

Out [14] :

```
<AxesSubplot:xlabel='timestamp'>
```




## Create Train and Test Datasets

The model is given a set of data that will be used to train the model to predict a specific objectice. In this case, we will use a few simple time series features as well as outdoor air temperature to predict how much energy a building uses.

For this demonstration, we will use three months of data from April, May, and June to prediction July.

In [15]:

```
training_months = [4,5,6]

test_months = [7]
```

We can divide the data set by using the `datetime index` of the data frame and a function knownas `.isin` to extract the months for the m`mode`

In [16]:

```
trainingdata = office_example_prediction_data[office_example_predicti
on_data.index.month.isin(training_months)]
```

```
testdata = office_example_prediction_data[office_example_prediction_data.index.month.isin(test_months)]
```

In [17]:

```
trainingdata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 2184 entries, 2017-04-01 00:00:00 to 2017-06-30 23:00:00
Data columns (total 1 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Panther_office_Hannah  2184 non-null   float64
dtypes: float64(1)
memory usage: 34.1 KB
```

In [18]:

```
testdata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 744 entries, 2017-07-01 00:00:00 to 2017-07-31 23:00:00
Data columns (total 1 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Panther_office_Hannah  744 non-null    float64
dtypes: float64(1)
memory usage: 11.6 KB
```

We can extract the training input data features that will go into the model and the training label data which is what are are targeting to predict.

## Encoding Categorical Variables

We use the pandas **`.get_dummies()`** function to change the temporal variables of time of day and day of week into categories that the model can use more effectively. This process is known as enconding

In [19]:

```
train_features = pd.concat([pd.get_dummies(trainingdata.index.hour)te
mperture    pd.get_dummies(trainingdata.index.dayofweek)

   pd.DataFrame(temperature[temperature.index.month.isin(training_mon
ths)].values)], axis=1).dropna()
```

In [20]:

```
train_features.head()
```

Out[20]:

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | ... | 22 | 23 | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 0 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 21.7 |
| 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 21.0 |
| 2 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 18.9 |
| 3 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 20.6 |
| 4 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | ... | 0 | | | | | | | | | |

## Conslusion :

So this project, we have known the how to enegy consumping, predicing and fore casting. Thank you.