Importing Libraries

In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

Importing Datasets

In [2]:

```
df=pd.read_csv(r"C:\Users\user\Downloads\C10_air\csvs_per_year\csvs(Dataset)\madrid_2003.
df
```

Out[2]:

	date	BEN	CO	EBE	MXY	NMHC	NO_2	NOx	OXY	O_3	
0	2003-03-01 01:00:00	NaN	1.72	NaN	NaN	NaN	73.900002	316.299988	NaN	10.550000	55.
1	2003-03-01 01:00:00	NaN	1.45	NaN	NaN	0.26	72.110001	250.000000	0.73	6.720000	52.
2	2003-03-01 01:00:00	NaN	1.57	NaN	NaN	NaN	80.559998	224.199997	NaN	21.049999	63.
3	2003-03-01 01:00:00	NaN	2.45	NaN	NaN	NaN	78.370003	450.399994	NaN	4.220000	67.
4	2003-03-01 01:00:00	NaN	3.26	NaN	NaN	NaN	96.250000	479.100006	NaN	8.460000	95.
...	...	...	...	...	...	...	...	...	...	...	
243979	2003-10-01 00:00:00	0.20	0.16	2.01	3.17	0.02	31.799999	32.299999	1.68	34.049999	7.
243980	2003-10-01 00:00:00	0.32	0.08	0.36	0.72	NaN	10.450000	14.760000	1.00	34.610001	7.
243981	2003-10-01 00:00:00	NaN	NaN	NaN	NaN	0.07	34.639999	50.810001	NaN	32.160000	16.
243982	2003-10-01 00:00:00	NaN	NaN	NaN	NaN	0.07	32.580002	41.020000	NaN	NaN	13.
243983	2003-10-01 00:00:00	1.00	0.29	2.15	6.41	0.07	37.150002	56.849998	2.28	21.480000	12.

243984 rows × 16 columns

Data Cleaning and Data Preprocessing

In [3]:

```
df=df.dropna()
```

In [4]:

```
df.columns
```

Out[4]:

```
Index(['date', 'BEN', 'CO', 'EBE', 'MXY', 'NMHC', 'NO_2', 'NOx', 'OXY', 'O
_3',
       'PM10', 'PXY', 'SO_2', 'TCH', 'TOL', 'station'],
      dtype='object')
```

In [5]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 33010 entries, 5 to 243983
Data columns (total 16 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   date     33010 non-null  object 
 1   BEN      33010 non-null  float64
 2   CO       33010 non-null  float64
 3   EBE      33010 non-null  float64
 4   MXY      33010 non-null  float64
 5   NMHC     33010 non-null  float64
 6   NO_2     33010 non-null  float64
 7   NOx      33010 non-null  float64
 8   OXY      33010 non-null  float64
 9   O_3      33010 non-null  float64
 10  PM10     33010 non-null  float64
 11  PXY      33010 non-null  float64
 12  SO_2     33010 non-null  float64
 13  TCH      33010 non-null  float64
 14  TOL      33010 non-null  float64
 15  station  33010 non-null  int64  
dtypes: float64(14), int64(1), object(1)
memory usage: 4.3+ MB
```

In [7]:

```
data=df[['EBE', 'MXY', 'PXY']]
data
```

Out[7]:

	EBE	MXY	PXY
5	9.83	21.49	7.94
23	3.43	7.08	2.62
27	5.75	10.88	4.24
33	10.63	24.73	8.93
51	3.20	7.08	2.70
...	...	...	...
243955	3.07	9.38	3.48
243957	3.88	10.86	3.89
243961	4.53	10.88	4.13
243979	2.01	3.17	1.20
243983	2.15	6.41	2.43

33010 rows × 3 columns

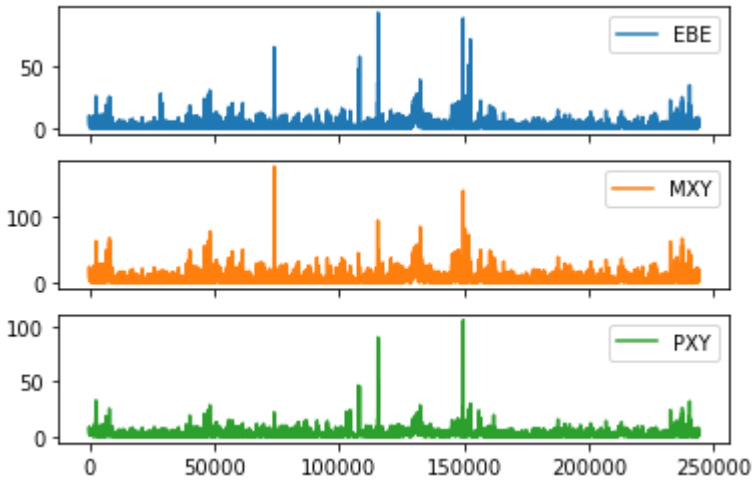
Line chart

In [8]:

```
data.plot.line(subplots=True)
```

Out[8]:

```
array([<AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>], dtype=object)
```



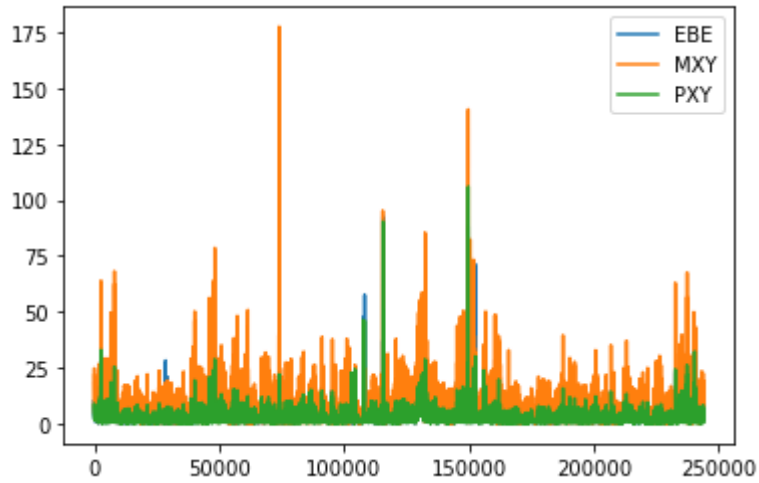
Line chart

In [9]:

```
data.plot.line()
```

Out[9]:

<AxesSubplot:>



Bar chart

In [10]:

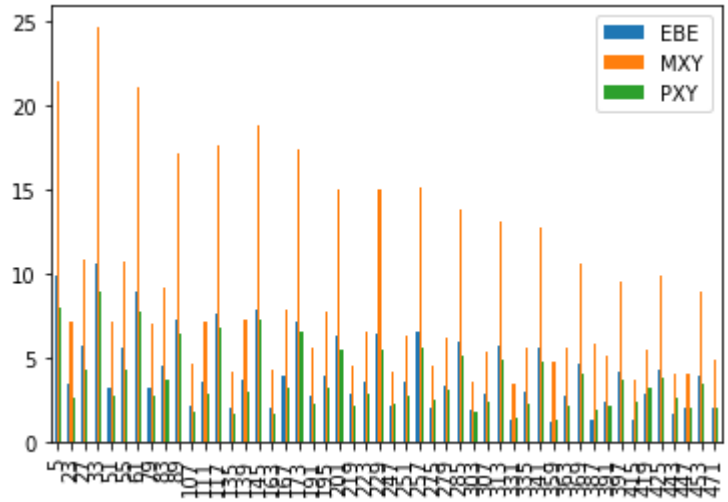
```
b=data[0:50]
```

In [11]:

```
b.plot.bar()
```

Out[11]:

<AxesSubplot:>



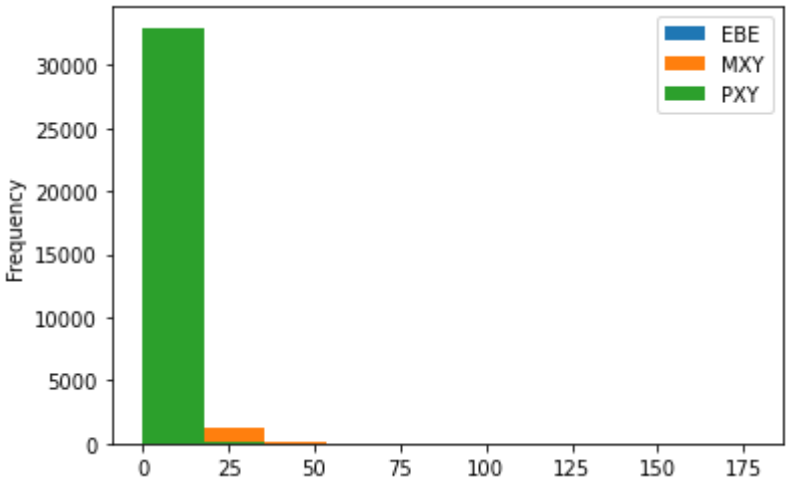
Histogram

In [12]:

```
data.plot.hist()
```

Out[12]:

```
<AxesSubplot:ylabel='Frequency'>
```



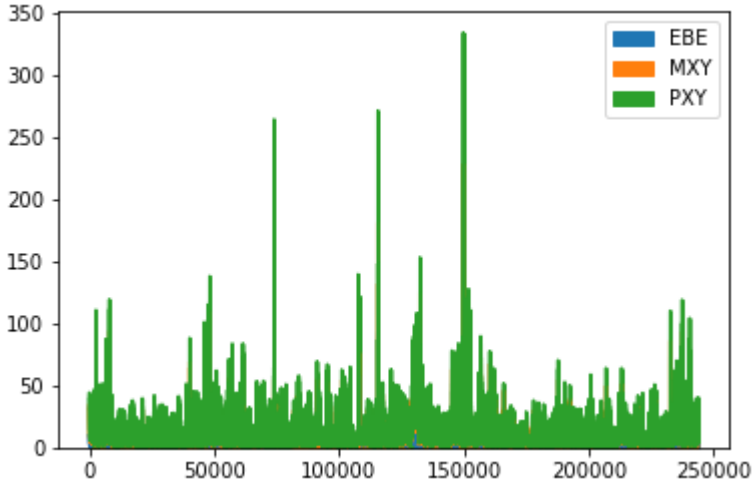
Area chart

In [13]:

```
data.plot.area()
```

Out[13]:

```
<AxesSubplot:>
```



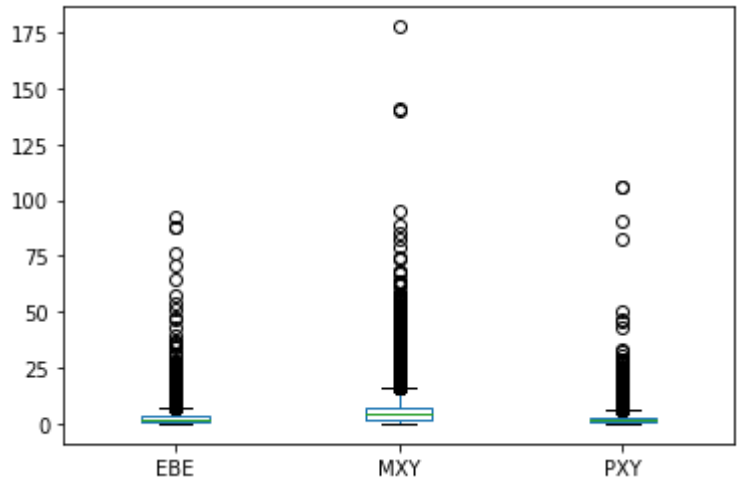
Box chart

In [14]:

```
data.plot.box()
```

Out[14]:

<AxesSubplot:>



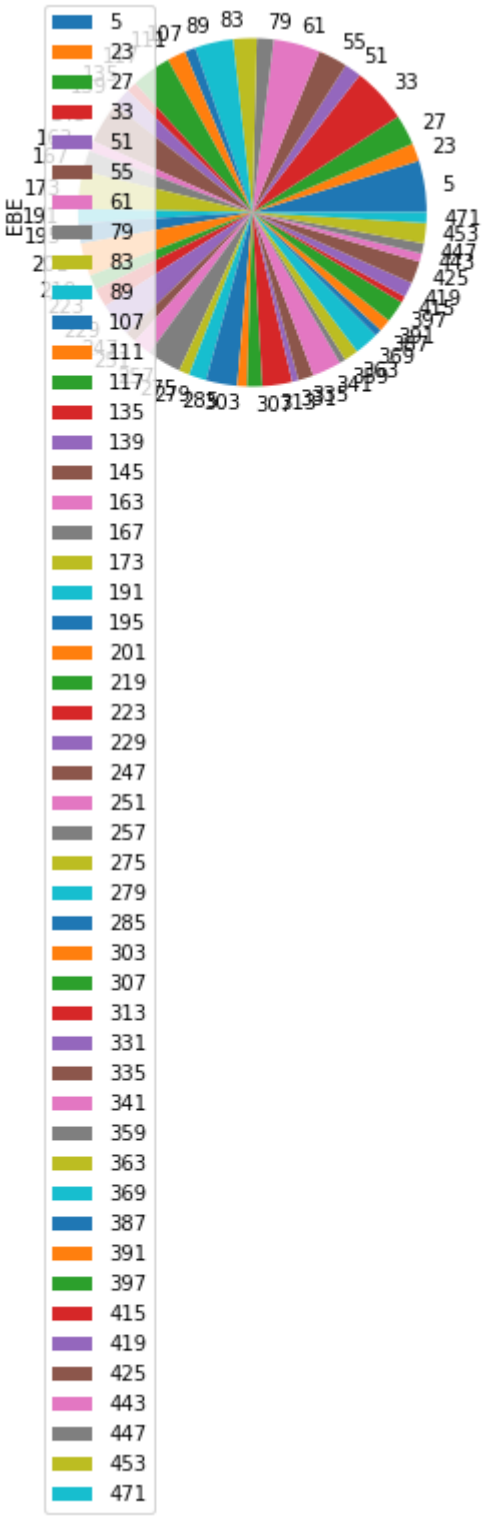
Pie chart

In [16]:

```
b.plot.pie(y='EBE' )
```

Out[16]:

```
<AxesSubplot:ylabel='EBE'>
```



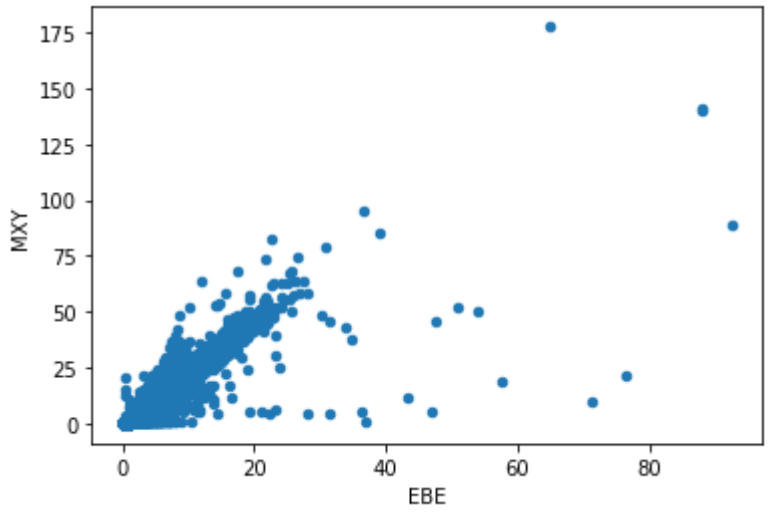
Scatter chart

In [17]:

```
data.plot.scatter(x='EBE' ,y='MXY')
```

Out[17]:

```
<AxesSubplot:xlabel='EBE', ylabel='MXY'>
```



In [18]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 33010 entries, 5 to 243983
Data columns (total 16 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   date     33010 non-null  object 
 1   BEN      33010 non-null  float64
 2   CO       33010 non-null  float64
 3   EBE      33010 non-null  float64
 4   MXY      33010 non-null  float64
 5   NMHC     33010 non-null  float64
 6   NO_2     33010 non-null  float64
 7   NOx      33010 non-null  float64
 8   OXY      33010 non-null  float64
 9   O_3      33010 non-null  float64
 10  PM10     33010 non-null  float64
 11  PXY      33010 non-null  float64
 12  SO_2     33010 non-null  float64
 13  TCH      33010 non-null  float64
 14  TOL      33010 non-null  float64
 15  station  33010 non-null  int64  
dtypes: float64(14), int64(1), object(1)
memory usage: 4.3+ MB
```

In [19]:

```
df.describe()
```

Out[19]:

	BEN	CO	EBE	MXY	NMHC	NO_2
count	33010.000000	33010.000000	33010.000000	33010.000000	33010.000000	33010.000000
mean	2.192633	0.759868	2.639726	5.838414	0.137177	57.328049
std	2.064160	0.545999	2.825194	6.267296	0.127863	31.811082
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.900000	0.430000	1.010000	1.880000	0.060000	34.529999
50%	1.610000	0.620000	1.890000	4.070000	0.110000	55.105000
75%	2.810000	0.930000	3.300000	7.530000	0.170000	76.160004
max	66.389999	7.920000	92.589996	177.600006	2.180000	342.700012

In [20]:

```
df1=df[['BEN', 'CO', 'EBE', 'MXY', 'NMHC', 'NO_2', 'NOx', 'OXY', 'O_3',
       'PM10', 'PXY', 'SO_2', 'TCH', 'TOL', 'station']]
```

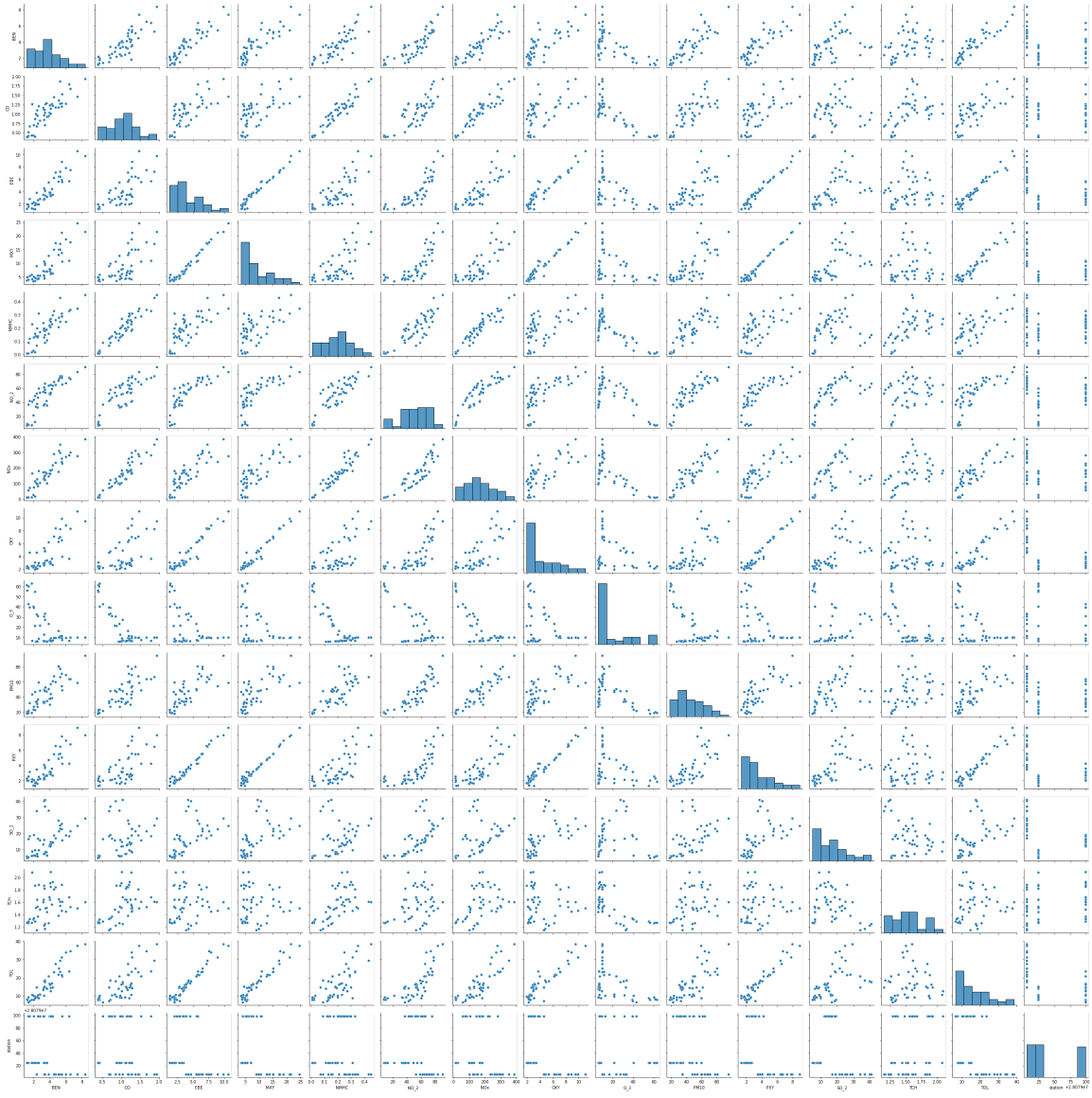
EDA AND VISUALIZATION

In [21]:

```
sns.pairplot(df1[0:50])
```

Out[21]:

```
<seaborn.axisgrid.PairGrid at 0x18dd3ef6b50>
```



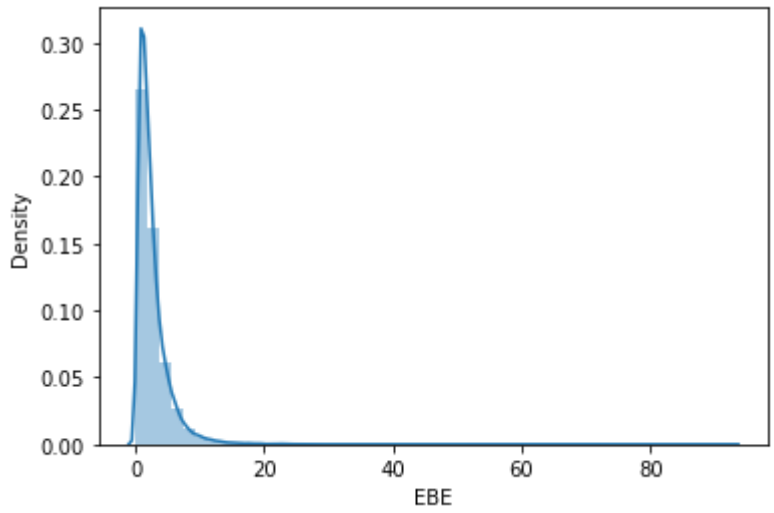
In [22]:

```
sns.distplot(df1['EBE'])
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in
a future version. Please adapt your code to use either `displot` (a figure
-level function with similar flexibility) or `histplot` (an axes-level fun
ction for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[22]:

```
<AxesSubplot:xlabel='EBE', ylabel='Density'>
```

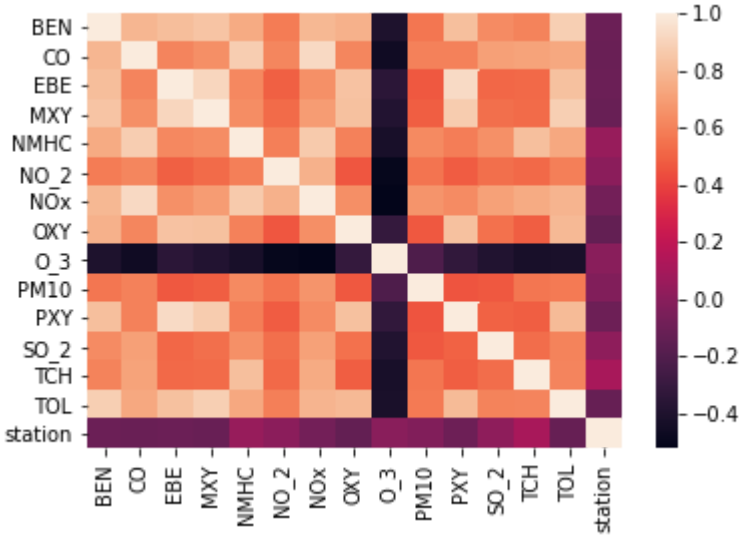


In [23]:

```
sns.heatmap(df1.corr())
```

Out[23]:

```
<AxesSubplot:>
```



TO TRAIN THE MODEL AND MODEL BULDING

In [24]:

```
x=df[['BEN', 'CO', 'EBE', 'MXY', 'NMHC', 'NO_2', 'NOx', 'OXY', 'O_3',
       'PM10', 'PXY', 'SO_2', 'TCH', 'TOL']]
y=df['station']
```

In [25]:

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
```

Linear Regression

In [26]:

```
from sklearn.linear_model import LinearRegression
lr=LinearRegression()
lr.fit(x_train,y_train)
```

Out[26]:

```
LinearRegression()
```

In [27]:

```
lr.intercept_
```

Out[27]:

```
28079000.88287165
```

In [28]:

```
coeff=pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
coeff
```

Out[28]:

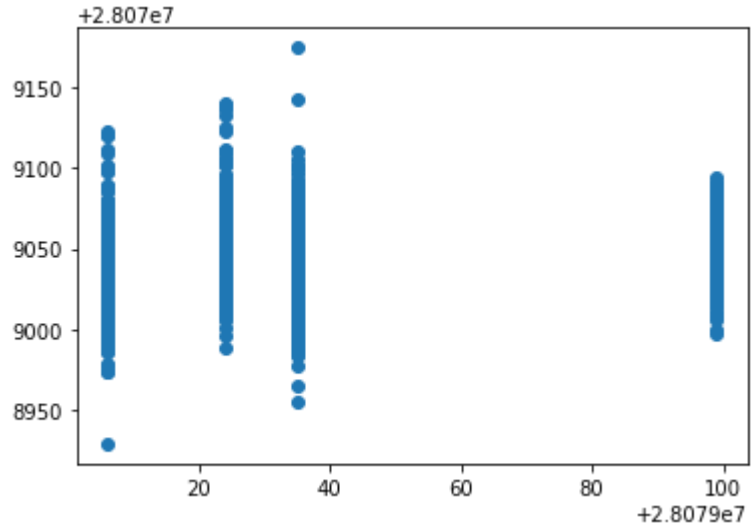
	Co-efficient
BEN	1.692702
CO	-38.977600
EBE	-1.867924
MXY	0.174105
NMHC	152.722698
NO_2	0.163994
NOx	-0.071702
OXY	-1.299032
O_3	-0.014141
PM10	-0.050933
PXY	2.076299
SO_2	0.865766
TCH	35.557182
TOL	-0.922173

In [29]:

```
prediction =lr.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[29]:

```
<matplotlib.collections.PathCollection at 0x18de1c99c70>
```



ACCURACY

In [30]:

```
lr.score(x_test,y_test)
```

Out[30]:

```
0.1724179923348299
```

In [31]:

```
lr.score(x_train,y_train)
```

Out[31]:

```
0.1775053138791619
```

Ridge and Lasso

In [32]:

```
from sklearn.linear_model import Ridge,Lasso
```

In [33]:

```
rr=Ridge(alpha=10)
rr.fit(x_train,y_train)
```

Out[33]:

```
Ridge(alpha=10)
```

Accuracy(Ridge)

In [34]:

```
rr.score(x_test,y_test)
```

Out[34]:

```
0.17104202048880912
```

In [35]:

```
rr.score(x_train,y_train)
```

Out[35]:

```
0.17647021880331226
```

In [36]:

```
la=Lasso(alpha=10)
la.fit(x_train,y_train)
```

Out[36]:

```
Lasso(alpha=10)
```

In [37]:

```
la.score(x_train,y_train)
```

Out[37]:

```
0.03743296904759286
```

Accuracy(Lasso)

In [38]:

```
la.score(x_test,y_test)
```

Out[38]:

```
0.03248687905869285
```

Accuracy(Elastic Net)

In [40]:

```
from sklearn.linear_model import ElasticNet
en=ElasticNet()
en.fit(x_train,y_train)
```

Out[40]:

```
ElasticNet()
```

In [41]:

```
en.coef_
```

Out[41]:

```
array([ 0.        , -0.22243934,  0.        , -0.01685342,  0.14109596,
        0.15774441, -0.07187445, -1.12341392, -0.04543365,  0.08531711,
        0.33830415,  0.7394519 ,  1.57593375, -0.47188519])
```

In [42]:

```
en.intercept_
```

Out[42]:

```
28079037.19291707
```

In [43]:

```
prediction=en.predict(x_test)
```

In [44]:

```
en.score(x_test,y_test)
```

Out[44]:

```
0.04581467200955813
```

Evaluation Metrics

In [45]:

```
from sklearn import metrics
print(metrics.mean_absolute_error(y_test,prediction))
print(metrics.mean_squared_error(y_test,prediction))
print(np.sqrt(metrics.mean_squared_error(y_test,prediction)))
```

```
29.119161570718372
1184.5346313544042
34.41706889545367
```

Logistic Regression

In [46]:

```
from sklearn.linear_model import LogisticRegression
```

In [47]:

```
feature_matrix=df[['BEN', 'CO', 'EBE', 'MXY', 'NMHC', 'NO_2', 'NOx', 'OXY', 'O_3',
       'PM10', 'PXY', 'SO_2', 'TCH', 'TOL']]
target_vector=df[ 'station']
```

In [48]:

```
feature_matrix.shape
```

Out[48]:

```
(33010, 14)
```

In [49]:

```
target_vector.shape
```

Out[49]:

```
(33010,)
```

In [50]:

```
from sklearn.preprocessing import StandardScaler
```

In [51]:

```
fs=StandardScaler().fit_transform(feature_matrix)
```

In [52]:

```
logr=LogisticRegression(max_iter=10000)
logr.fit(fs,target_vector)
```

Out[52]:

```
LogisticRegression(max_iter=10000)
```

In [53]:

```
observation=[[1,2,3,4,5,6,7,8,9,10,11,12,13,14]]
```

In [54]:

```
prediction=logr.predict(observation)
print(prediction)
```

```
[28079035]
```

In [55]:

```
logr.classes_
```

Out[55]:

```
array([28079006, 28079024, 28079035, 28079099], dtype=int64)
```

In [56]:

```
logr.score(fs,target_vector)
```

Out[56]:

```
0.7584974250227204
```

In [57]:

```
logr.predict_proba(observation)[0][0]
```

Out[57]:

```
2.3306153265290618e-23
```

In [58]:

```
logr.predict_proba(observation)
```

Out[58]:

```
array([[2.33061533e-23, 1.44436075e-55, 1.00000000e+00, 6.68457491e-16]])
```

Random Forest

In [59]:

```
from sklearn.ensemble import RandomForestClassifier
```

In [60]:

```
rfc=RandomForestClassifier()
rfc.fit(x_train,y_train)
```

Out[60]:

```
RandomForestClassifier()
```

In [61]:

```
parameters={'max_depth':[1,2,3,4,5],
            'min_samples_leaf':[5,10,15,20,25],
            'n_estimators':[10,20,30,40,50]
}
```

In [62]:

```
from sklearn.model_selection import GridSearchCV
grid_search =GridSearchCV(estimator=rfc,param_grid=parameters,cv=2,scoring="accuracy")
grid_search.fit(x_train,y_train)
```

Out[62]:

```
GridSearchCV(cv=2, estimator=RandomForestClassifier(),
             param_grid={'max_depth': [1, 2, 3, 4, 5],
                         'min_samples_leaf': [5, 10, 15, 20, 25],
                         'n_estimators': [10, 20, 30, 40, 50]},
             scoring='accuracy')
```

In [63]:

```
grid_search.best_score_
```

Out[63]:

```
0.7254074069545836
```

In [64]:

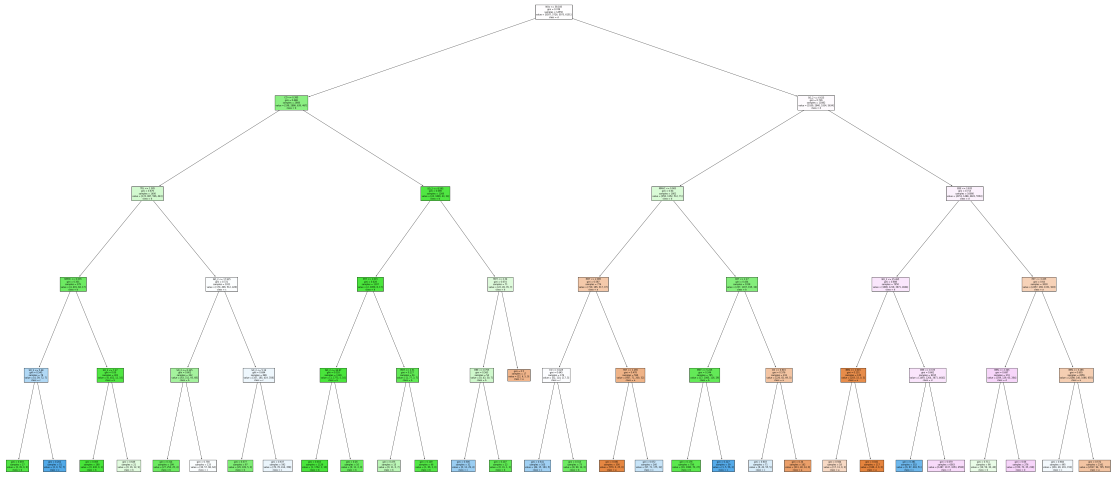
```
rfc_best=grid_search.best_estimator_
```

In [65]:

```
from sklearn.tree import plot_tree

plt.figure(figsize=(80,40))
plot_tree(rfc_best.estimators_[5],feature_names=x.columns,class_names=['a','b','c','d'],f
```

```
[261, 46, 291, 153]\nclass = c'),
 Text(4389.6, 181.19999999999982, 'gini = 0.572\nsamples = 2161\nvalue =
[2027, 94, 795, 502]\nclass = a')]
```



Conclusion

Accuracy

Linear Regression:0.1775053138791619

Ridge Regression:0.03743296904759286

Lasso Regression:0.03248687905869285

ElasticNet Regression:0.04581467200955813

Logistic Regression:0.7584974250227204

Random Forest:0.0.7254074069545836

Logistic Regression is suitable for this dataset