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_2014.
df
```

Out[2]:

	date	BEN	CO	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	TCH	TOL
0	2014-06-01 01:00:00	NaN	0.2	NaN	NaN	3.0	10.0	NaN	NaN	NaN	3.0	NaN	NaN
1	2014-06-01 01:00:00	0.2	0.2	0.1	0.11	3.0	17.0	68.0	10.0	5.0	5.0	1.36	1.3
2	2014-06-01 01:00:00	0.3	NaN	0.1	NaN	2.0	6.0	NaN	NaN	NaN	NaN	NaN	1.1
3	2014-06-01 01:00:00	NaN	0.2	NaN	NaN	1.0	6.0	79.0	NaN	NaN	NaN	NaN	NaN
4	2014-06-01 01:00:00	NaN	NaN	NaN	NaN	1.0	6.0	75.0	NaN	NaN	4.0	NaN	NaN
...	...	...	...	...	...	...	...	...	...	...	...	...	...
210019	2014-09-01 00:00:00	NaN	0.5	NaN	NaN	20.0	84.0	29.0	NaN	NaN	NaN	NaN	NaN
210020	2014-09-01 00:00:00	NaN	0.3	NaN	NaN	1.0	22.0	NaN	15.0	NaN	6.0	NaN	NaN
210021	2014-09-01 00:00:00	NaN	NaN	NaN	NaN	1.0	13.0	70.0	NaN	NaN	NaN	NaN	NaN
210022	2014-09-01 00:00:00	NaN	NaN	NaN	NaN	3.0	38.0	42.0	NaN	NaN	NaN	NaN	NaN
210023	2014-09-01 00:00:00	NaN	NaN	NaN	NaN	1.0	26.0	65.0	11.0	NaN	NaN	NaN	NaN

210024 rows × 14 columns

Data Cleaning and Data Preprocessing

In [3]:

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

In [4]:

```
df.columns
```

Out[4]:

```
Index(['date', 'BEN', 'CO', 'EBE', 'NMHC', 'NO', 'NO_2', 'O_3', 'PM10', 'P
M25',
       'SO_2', 'TCH', 'TOL', 'station'],
      dtype='object')
```

In [5]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 13946 entries, 1 to 210006
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   date     13946 non-null  object 
 1   BEN      13946 non-null  float64
 2   CO       13946 non-null  float64
 3   EBE      13946 non-null  float64
 4   NMHC     13946 non-null  float64
 5   NO       13946 non-null  float64
 6   NO_2     13946 non-null  float64
 7   O_3      13946 non-null  float64
 8   PM10     13946 non-null  float64
 9   PM25     13946 non-null  float64
 10  SO_2     13946 non-null  float64
 11  TCH      13946 non-null  float64
 12  TOL      13946 non-null  float64
 13  station  13946 non-null  int64  
dtypes: float64(12), int64(1), object(1)
memory usage: 1.6+ MB
```

In [6]:

```
data=df[['BEN', 'TOL', 'TCH']]
data
```

Out[6]:

	BEN	TOL	TCH
1	0.2	1.3	1.36
6	0.1	0.1	1.21
25	0.2	0.8	1.36
30	0.2	0.1	1.21
49	0.1	0.9	1.36
...	...	...	...
209958	0.2	0.1	1.28
209977	1.1	6.5	1.27
209982	0.2	0.2	1.27
210001	0.6	4.1	1.19
210006	0.2	0.1	1.30

13946 rows × 3 columns

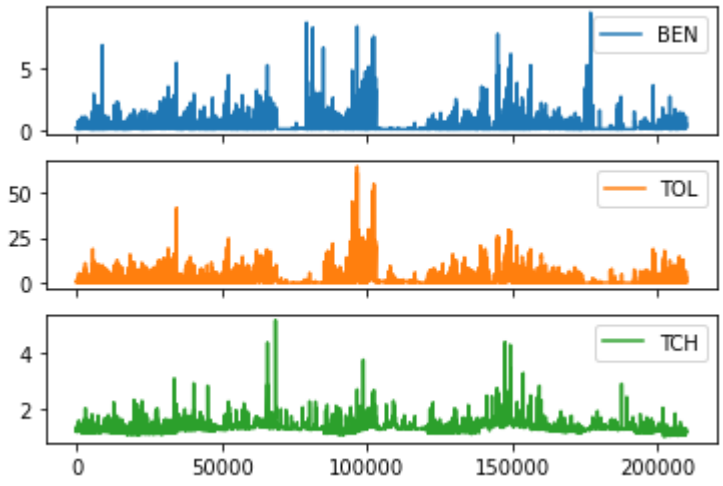
Line chart

In [7]:

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

Out[7]:

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



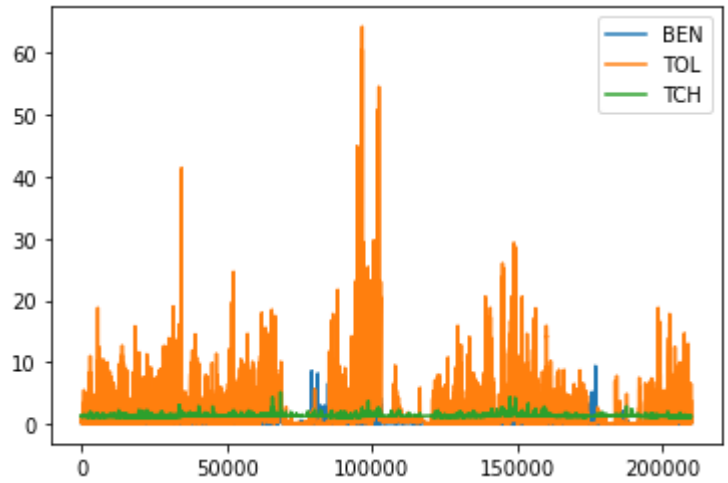
Line chart

In [8]:

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

Out[8]:

<AxesSubplot:>



Bar chart

In [9]:

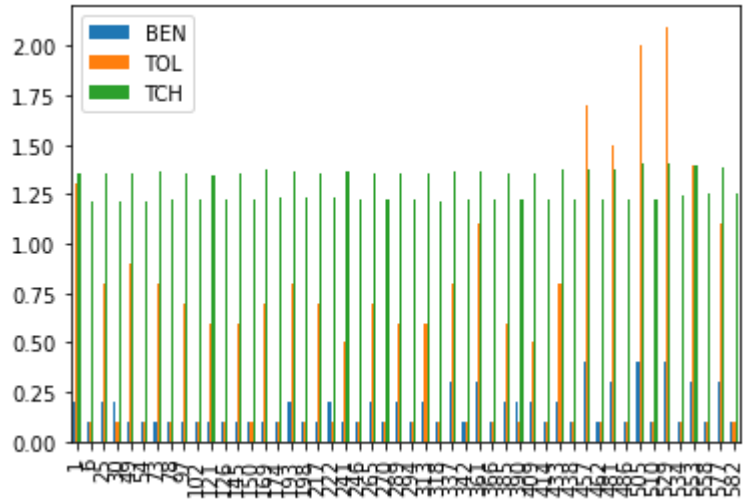
```
b=data[0:50]
```

In [10]:

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

Out[10]:

<AxesSubplot:>



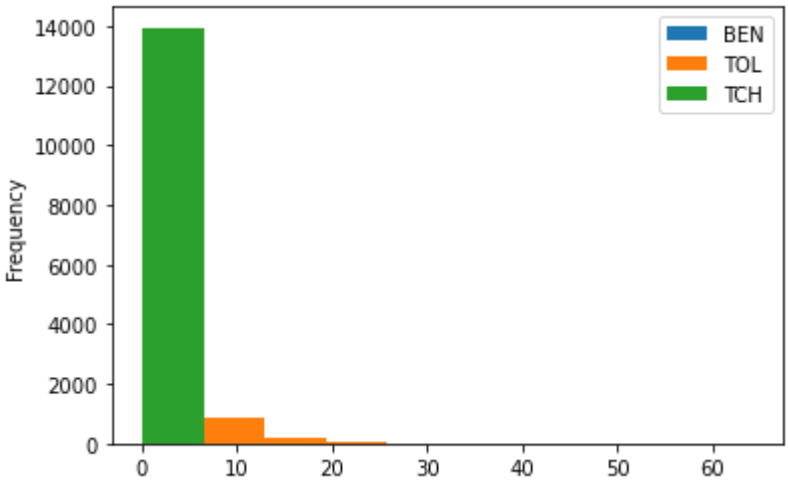
Histogram

In [11]:

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

Out[11]:

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



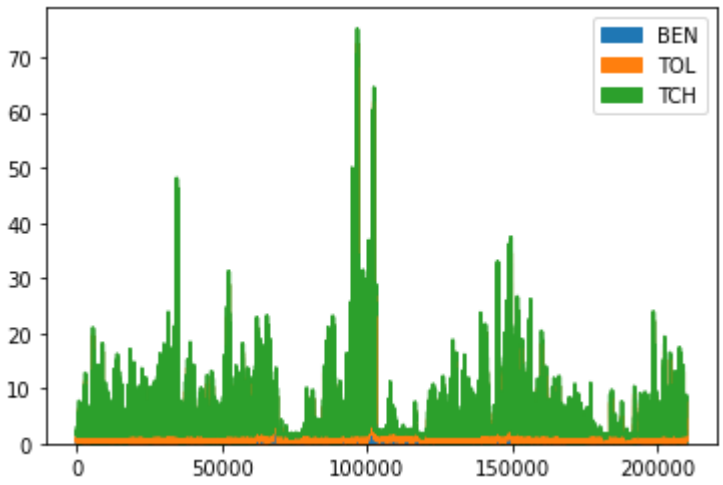
Area chart

In [12]:

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

Out[12]:

```
<AxesSubplot:>
```



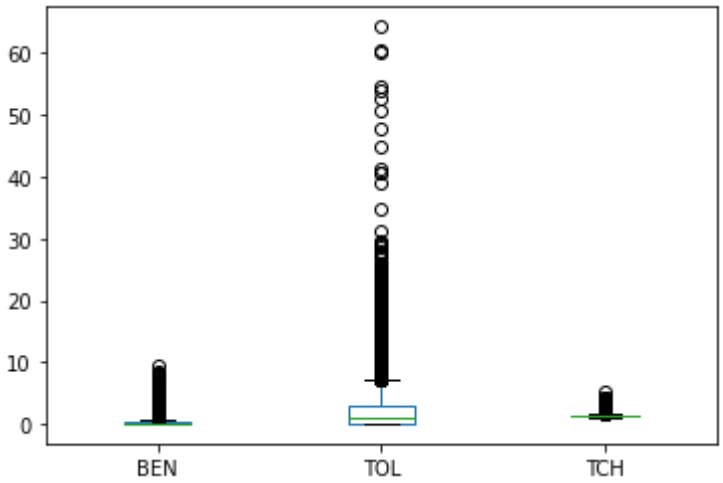
Box chart

In [13]:

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

Out[13]:

<AxesSubplot:>



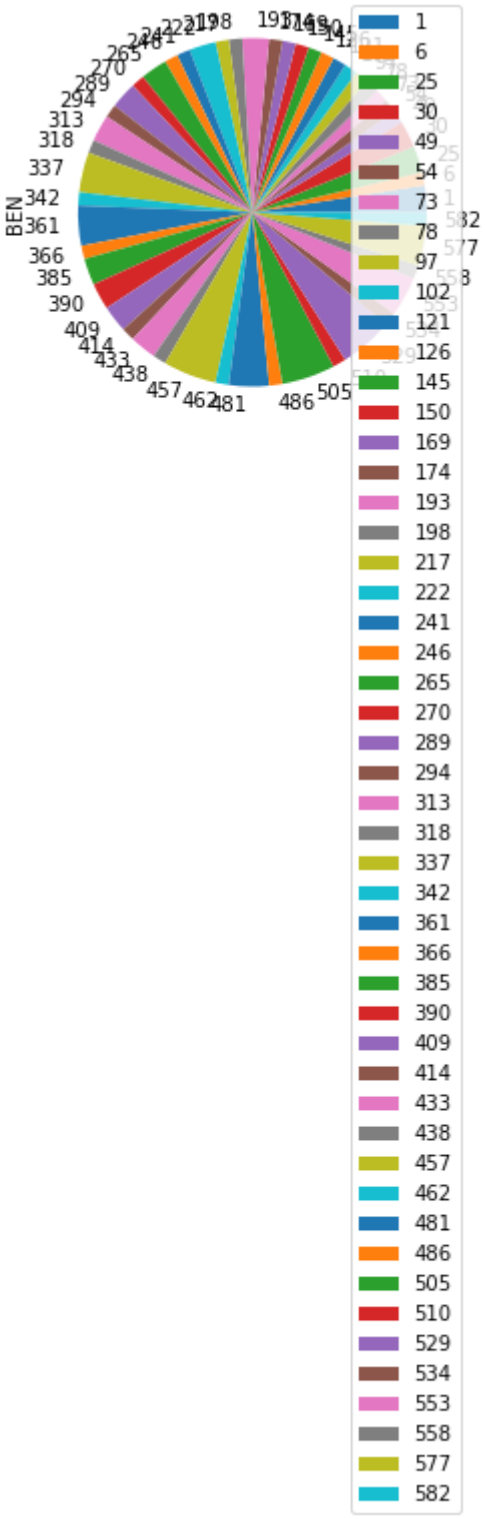
Pie chart

In [14]:

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

Out[14]:

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



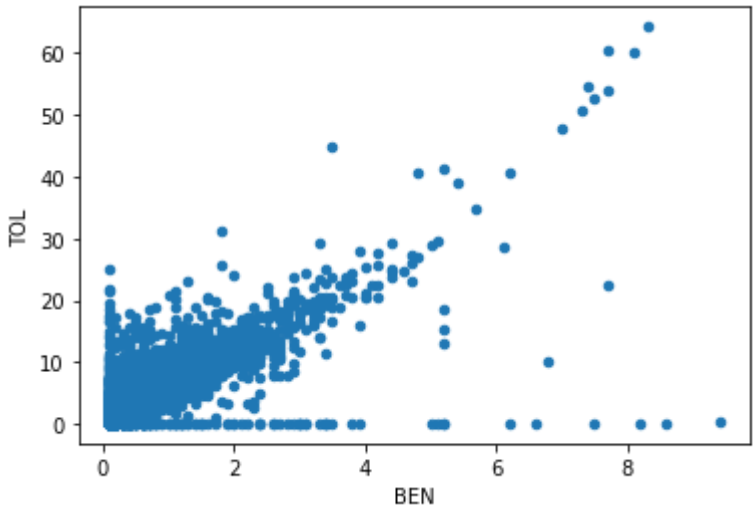
Scatter chart

In [15]:

```
data.plot.scatter(x='BEN' ,y='TOL')
```

Out[15]:

```
<AxesSubplot:xlabel='BEN', ylabel='TOL'>
```



In [16]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 13946 entries, 1 to 210006
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   date     13946 non-null  object 
 1   BEN      13946 non-null  float64
 2   CO       13946 non-null  float64
 3   EBE      13946 non-null  float64
 4   NMHC     13946 non-null  float64
 5   NO       13946 non-null  float64
 6   NO_2     13946 non-null  float64
 7   O_3      13946 non-null  float64
 8   PM10     13946 non-null  float64
 9   PM25     13946 non-null  float64
 10  SO_2     13946 non-null  float64
 11  TCH      13946 non-null  float64
 12  TOL      13946 non-null  float64
 13  station  13946 non-null  int64  
dtypes: float64(12), int64(1), object(1)
memory usage: 1.6+ MB
```

In [17]:

```
df.describe()
```

Out[17]:

	BEN	CO	EBE	NMHC	NO	NO_2
count	13946.000000	13946.000000	13946.000000	13946.000000	13946.000000	13946.000000
mean	0.375921	0.314793	0.306016	0.222302	17.589129	34.240929
std	0.555093	0.207375	0.635475	0.082403	39.432216	30.654229
min	0.100000	0.100000	0.100000	0.060000	1.000000	1.000000
25%	0.100000	0.200000	0.100000	0.160000	1.000000	10.000000
50%	0.200000	0.300000	0.100000	0.230000	4.000000	27.000000
75%	0.400000	0.400000	0.300000	0.260000	18.000000	51.000000
max	9.400000	4.400000	16.200001	1.290000	725.000000	346.000000

In [18]:

```
df1=df[['date', 'BEN', 'CO', 'EBE', 'NMHC', 'NO', 'NO_2', 'O_3', 'PM10', 'PM25',
       'SO_2', 'TCH', 'TOL', 'station']]
```

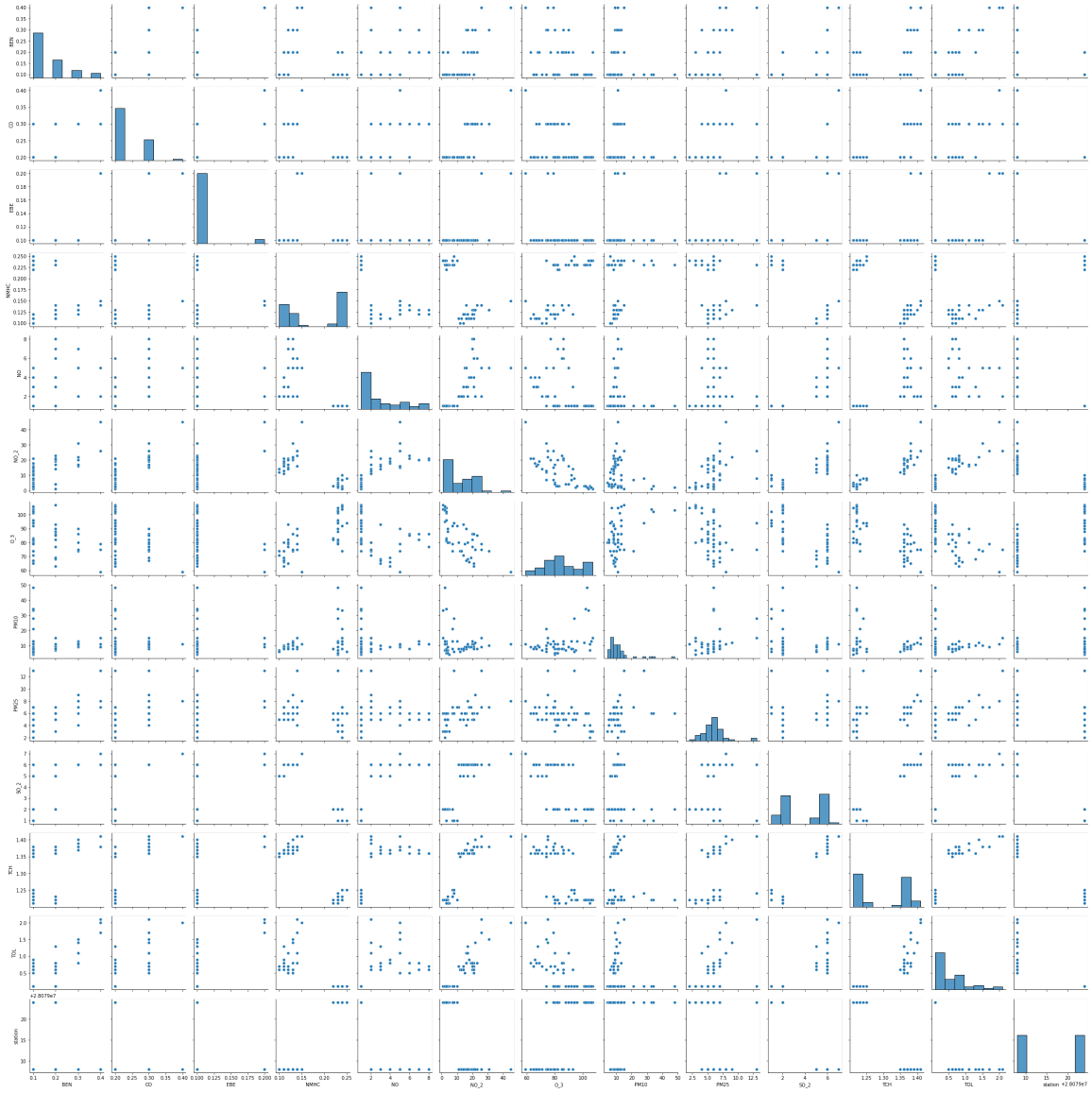
EDA AND VISUALIZATION

In [19]:

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

Out[19]:

```
<seaborn.axisgrid.PairGrid at 0x22581899c10>
```



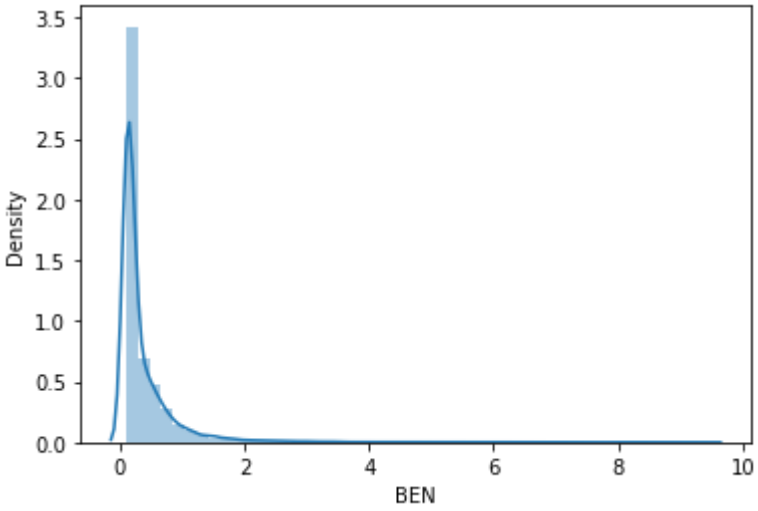
In [20]:

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

```
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[20]:

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

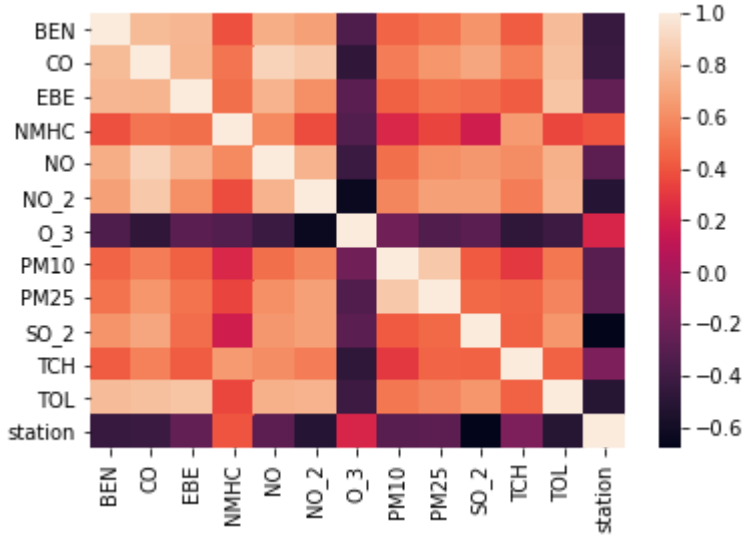


In [21]:

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

Out[21]:

```
<AxesSubplot:>
```



TO TRAIN THE MODEL AND MODEL BULDING

In [22]:

```
x=df[['BEN', 'CO', 'EBE', 'NMHC', 'NO', 'NO_2', 'O_3', 'PM10', 'PM25',
       'SO_2', 'TCH', 'TOL']]
y=df['station']
```

In [23]:

```
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 [24]:

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

Out[24]:

```
LinearRegression()
```

In [25]:

```
lr.intercept_
```

Out[25]:

```
28079024.75309375
```

In [26]:

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

Out[26]:

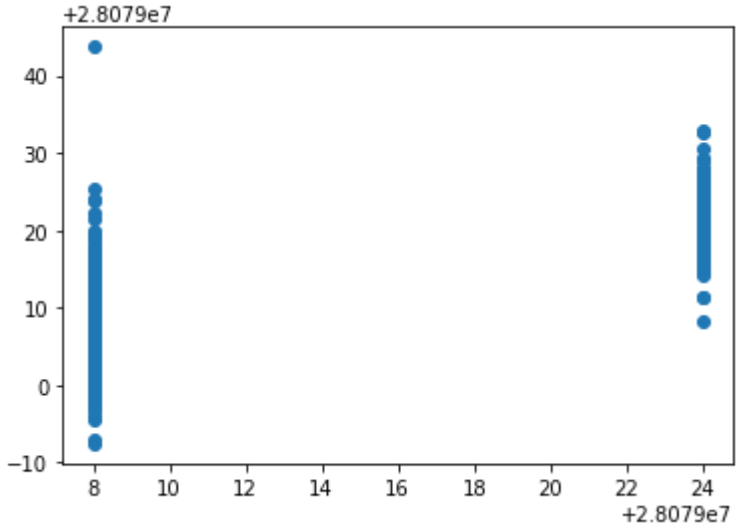
	Co-efficient
BEN	-1.526053
CO	-9.582083
EBE	0.169485
NMHC	81.813711
NO	0.027040
NO_2	-0.039069
O_3	0.001044
PM10	-0.021125
PM25	0.135383
SO_2	-0.886189
TCH	-12.883515
TOL	-0.399896

In [27]:

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

Out[27]:

```
<matplotlib.collections.PathCollection at 0x2258d91ddf0>
```



ACCURACY

In [28]:

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

Out[28]:

```
0.8856068356416521
```

In [29]:

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

Out[29]:

```
0.8933824684760232
```

Ridge and Lasso

In [30]:

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

In [31]:

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

Out[31]:

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

Accuracy(Ridge)

In [32]:

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

Out[32]:

```
0.8685900527611394
```

In [33]:

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

Out[33]:

```
0.8700021760005732
```

In [34]:

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

Out[34]:

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

In [35]:

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

Out[35]:

```
0.2984542671759195
```

Accuracy(Lasso)

In [36]:

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

Out[36]:

```
0.29803877281876634
```

Accuracy(Elastic Net)

In [37]:

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

Out[37]:

```
ElasticNet()
```

In [38]:

```
en.coef_
```

Out[38]:

```
array([-0.        , -0.        ,  0.        ,  0.        ,  0.10487826,
       -0.10952204, -0.01681879, -0.00967349,  0.09959627, -1.41820342,
        0.        , -0.5323858 ])
```

In [39]:

```
en.intercept_
```

Out[39]:

```
28079026.65375127
```

In [40]:

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

In [41]:

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

Out[41]:

```
0.5963524316522861
```

Evaluation Metrics

In [42]:

```
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)))
```

```
4.1518782354627755
25.440529593890414
5.043860584303497
```

Logistic Regression

In [43]:

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

In [44]:

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

In [45]:

```
feature_matrix.shape
```

Out[45]:

```
(13946, 10)
```

In [46]:

```
target_vector.shape
```

Out[46]:

```
(13946,)
```

In [47]:

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

In [48]:

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

In [49]:

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

Out[49]:

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

In [50]:

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

In [51]:

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

```
[28079008]
```

In [52]:

```
logr.classes_
```

Out[52]:

```
array([28079008, 28079024], dtype=int64)
```

In [53]:

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

Out[53]:

```
0.9926143697117453
```

In [54]:

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

Out[54]:

```
1.0
```

In [55]:

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

Out[55]:

```
array([[1.00000000e+00, 5.27113072e-18]])
```

Random Forest

In [56]:

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

In [57]:

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

Out[57]:

```
RandomForestClassifier()
```

In [58]:

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

In [59]:

```
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[59]:

```
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 [60]:

```
grid_search.best_score_
```

Out[60]:

```
0.99580004097521
```

In [61]:

```
rfc_best=grid_search.best_estimator_
```

In [62]:

```
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
```

Out[62]:

```
[Text(1825.125, 1993.2, 'TOL <= 1.05\ngini = 0.494\nsamples = 6211\nvalue
= [4366, 5396]\nclass = b'),
 Text(651.0, 1630.8000000000002, 'NMHC <= 0.165\ngini = 0.179\nsamples = 3
392\nvalue = [528, 4782]\nclass = b'),
 Text(186.0, 1268.4, 'NO_2 <= 7.5\ngini = 0.029\nsamples = 299\nvalue = [4
68, 7]\nclass = a'),
 Text(93.0, 906.0, 'gini = 0.48\nsamples = 6\nvalue = [6, 4]\nclass = a'),
 Text(279.0, 906.0, 'SO_2 <= 2.5\ngini = 0.013\nsamples = 293\nvalue = [46
2, 3]\nclass = a'),
 Text(186.0, 543.5999999999999, 'gini = 0.397\nsamples = 7\nvalue = [8, 3]
\nclass = a'),
 Text(372.0, 543.5999999999999, 'gini = 0.0\nsamples = 286\nvalue = [454,
0]\nclass = a'),
 Text(1116.0, 1268.4, 'SO_2 <= 5.5\ngini = 0.025\nsamples = 3093\nvalue =
[60, 4775]\nclass = b'),
 Text(744.0, 906.0, 'NO_2 <= 18.5\ngini = 0.003\nsamples = 3032\nvalue =
[8, 4728]\nclass = b'),
 Text(558.0, 543.5999999999999, 'NMHC <= 0.195\ngini = 0.001\nsamples = 20
95\nvalue = [1, 3256]\nclass = b'),
 Text(465.0, 181.19999999999982, 'gini = 0.014\nsamples = 90\nvalue = [1,
138]\nclass = b'),
 Text(651.0, 181.19999999999982, 'gini = 0.0\nsamples = 2005\nvalue = [0,
3118]\nclass = b'),
 Text(930.0, 543.5999999999999, 'BEN <= 0.25\ngini = 0.009\nsamples = 937
\nvalue = [7, 1472]\nclass = b'),
 Text(837.0, 181.19999999999982, 'gini = 0.004\nsamples = 925\nvalue = [3,
1460]\nclass = b'),
 Text(1023.0, 181.19999999999982, 'gini = 0.375\nsamples = 12\nvalue = [4,
12]\nclass = b'),
 Text(1488.0, 906.0, 'O_3 <= 30.5\ngini = 0.499\nsamples = 61\nvalue = [5
2, 47]\nclass = a'),
 Text(1302.0, 543.5999999999999, 'PM10 <= 24.0\ngini = 0.061\nsamples = 19
\nvalue = [1, 31]\nclass = b'),
 Text(1209.0, 181.19999999999982, 'gini = 0.0\nsamples = 14\nvalue = [0, 2
5]\nclass = b'),
 Text(1395.0, 181.19999999999982, 'gini = 0.245\nsamples = 5\nvalue = [1,
6]\nclass = b'),
 Text(1674.0, 543.5999999999999, 'TOL <= 0.45\ngini = 0.364\nsamples = 42
\nvalue = [51, 16]\nclass = a'),
 Text(1581.0, 181.19999999999982, 'gini = 0.0\nsamples = 8\nvalue = [0, 1
1]\nclass = b'),
 Text(1767.0, 181.19999999999982, 'gini = 0.163\nsamples = 34\nvalue = [5
1, 5]\nclass = a'),
 Text(2999.25, 1630.8000000000002, 'NMHC <= 0.235\ngini = 0.238\nsamples =
2819\nvalue = [3838, 614]\nclass = a'),
 Text(2278.5, 1268.4, 'SO_2 <= 2.5\ngini = 0.041\nsamples = 1859\nvalue =
[2877, 61]\nclass = a'),
 Text(1953.0, 906.0, 'TCH <= 1.21\ngini = 0.371\nsamples = 43\nvalue = [1
7, 52]\nclass = b'),
 Text(1860.0, 543.5999999999999, 'gini = 0.0\nsamples = 6\nvalue = [9, 0]
\nclass = a'),
 Text(2046.0, 543.5999999999999, 'CO <= 0.2\ngini = 0.1\nsamples = 37\n
value = [8, 52]\nclass = b'),
 Text(1953.0, 181.19999999999982, 'gini = 0.074\nsamples = 31\nvalue = [2,
50]\nclass = b'),
 Text(2139.0, 181.19999999999982, 'gini = 0.375\nsamples = 6\nvalue = [6,
2]\nclass = a'),
 Text(2604.0, 906.0, 'NO <= 5.5\ngini = 0.006\nsamples = 1816\nvalue = [28
60, 9]\nclass = a'),
 Text(2418.0, 543.5999999999999, 'SO_2 <= 4.5\ngini = 0.025\nsamples = 373
\nvalue = [556, 7]\nclass = a'),
```

```
 Text(2325.0, 181.19999999999982, 'gini = 0.198\nsamples = 46\nvalue = [5
6, 7]\nclass = a'),
 Text(2511.0, 181.19999999999982, 'gini = 0.0\nsamples = 327\nvalue = [50
0, 0]\nclass = a'),
 Text(2790.0, 543.5999999999999, 'NMHC <= 0.215\ngini = 0.002\nsamples = 1
443\nvalue = [2304, 2]\nclass = a'),
 Text(2697.0, 181.19999999999982, 'gini = 0.0\nsamples = 1302\nvalue = [20
85, 0]\nclass = a'),
 Text(2883.0, 181.19999999999982, 'gini = 0.018\nsamples = 141\nvalue = [2
19, 2]\nclass = a'),
 Text(3720.0, 1268.4, 'SO_2 <= 5.5\ngini = 0.464\nsamples = 960\nvalue =
[903, 353]\nclass = a'),
 Text(3348.0, 906.0, 'O_3 <= 5.5\ngini = 0.181\nsamples = 345\nvalue = [5
3, 473]\nclass = b'),
 Text(3162.0, 543.5999999999999, 'BEN <= 0.65\ngini = 0.01\nsamples = 121
\nvalue = [1, 194]\nclass = b'),
 Text(3069.0, 181.19999999999982, 'gini = 0.0\nsamples = 116\nvalue = [0,
188]\nclass = b'),
 Text(3255.0, 181.19999999999982, 'gini = 0.245\nsamples = 5\nvalue = [1,
6]\nclass = b'),
 Text(3534.0, 543.5999999999999, 'EBE <= 0.25\ngini = 0.265\nsamples = 224
\nvalue = [52, 279]\nclass = b'),
 Text(3441.0, 181.19999999999982, 'gini = 0.079\nsamples = 147\nvalue =
[9, 209]\nclass = b'),
 Text(3627.0, 181.19999999999982, 'gini = 0.444\nsamples = 77\nvalue = [4
3, 70]\nclass = b'),
 Text(4092.0, 906.0, 'PM10 <= 21.5\ngini = 0.149\nsamples = 615\nvalue =
[908, 80]\nclass = a'),
 Text(3906.0, 543.5999999999999, 'PM10 <= 16.5\ngini = 0.02\nsamples = 197
\nvalue = [301, 3]\nclass = a'),
 Text(3813.0, 181.19999999999982, 'gini = 0.0\nsamples = 110\nvalue = [16
4, 0]\nclass = a'),
 Text(3999.0, 181.19999999999982, 'gini = 0.042\nsamples = 87\nvalue = [13
```

Conclusion

Accuracy

Linear Regression:0.8933824684760232

Ridge Regression:0.8700021760005732

Lasso Regression:0.29803877281876634

ElasticNet Regression:0.5963524316522861

Logistic Regression:0.9926143697117453

Random Forest:0.9958004097521

Random Forest is suitable for this dataset