Importing Libraries

In [2]:

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

Importing Datasets

In [3]:

```
df=pd.read_csv(r"C:\Users\user\Downloads\C10_air\csvs_per_year\csvs(Dataset)\madrid_2015.
df
```

Out[3]:

	date	BEN	CO	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	TCH	TOL
0	2015-10-01 01:00:00	NaN	0.8	NaN	NaN	90.0	82.0	NaN	NaN	NaN	10.0	NaN	NaN
1	2015-10-01 01:00:00	2.0	0.8	1.6	0.33	40.0	95.0	4.0	37.0	24.0	12.0	1.83	8.3
2	2015-10-01 01:00:00	3.1	NaN	1.8	NaN	29.0	97.0	NaN	NaN	NaN	NaN	NaN	7.1
3	2015-10-01 01:00:00	NaN	0.6	NaN	NaN	30.0	103.0	2.0	NaN	NaN	NaN	NaN	NaN
4	2015-10-01 01:00:00	NaN	NaN	NaN	NaN	95.0	96.0	2.0	NaN	NaN	9.0	NaN	NaN
...	...	...	...	...	...	...	...	...	...	...	...	...	...
210091	2015-08-01 00:00:00	NaN	0.2	NaN	NaN	11.0	33.0	53.0	NaN	NaN	NaN	NaN	NaN
210092	2015-08-01 00:00:00	NaN	0.2	NaN	NaN	1.0	5.0	NaN	26.0	NaN	10.0	NaN	NaN
210093	2015-08-01 00:00:00	NaN	NaN	NaN	NaN	1.0	7.0	74.0	NaN	NaN	NaN	NaN	NaN
210094	2015-08-01 00:00:00	NaN	NaN	NaN	NaN	3.0	7.0	65.0	NaN	NaN	NaN	NaN	NaN
210095	2015-08-01 00:00:00	NaN	NaN	NaN	NaN	1.0	9.0	54.0	29.0	NaN	NaN	NaN	NaN

210096 rows × 14 columns

Data Cleaning and Data Preprocessing

In [4]:

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

In [5]:

```
df.columns
```

Out[5]:

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

In [6]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 16026 entries, 1 to 210078
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   date     16026 non-null  object 
 1   BEN      16026 non-null  float64
 2   CO       16026 non-null  float64
 3   EBE      16026 non-null  float64
 4   NMHC     16026 non-null  float64
 5   NO       16026 non-null  float64
 6   NO_2     16026 non-null  float64
 7   O_3      16026 non-null  float64
 8   PM10     16026 non-null  float64
 9   PM25     16026 non-null  float64
 10  SO_2     16026 non-null  float64
 11  TCH      16026 non-null  float64
 12  TOL      16026 non-null  float64
 13  station  16026 non-null  int64  
dtypes: float64(12), int64(1), object(1)
memory usage: 1.8+ MB
```

In [7]:

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

Out[7]:

	BEN	TOL	TCH
1	2.0	8.3	1.83
6	0.5	4.8	1.29
25	1.6	6.9	1.93
30	0.4	7.8	1.27
49	2.2	13.9	2.05
...	...	...	...
210030	0.1	0.2	1.18
210049	0.4	1.2	1.45
210054	0.1	0.2	1.18
210073	0.1	0.6	1.44
210078	0.1	0.4	1.18

16026 rows × 3 columns

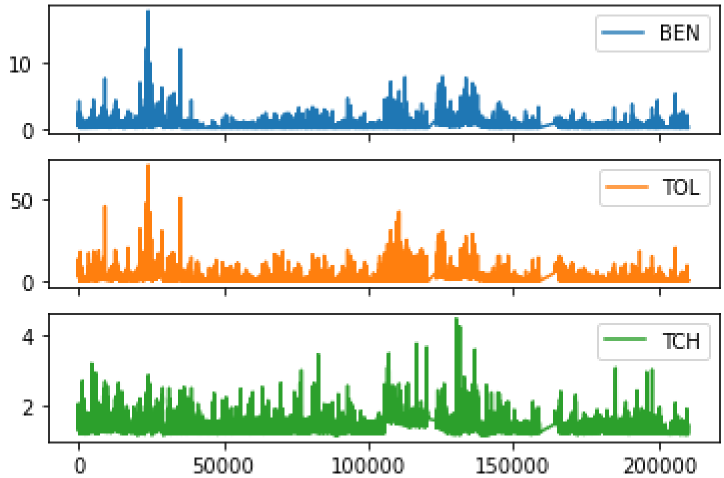
Line chart

In [8]:

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

Out[8]:

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



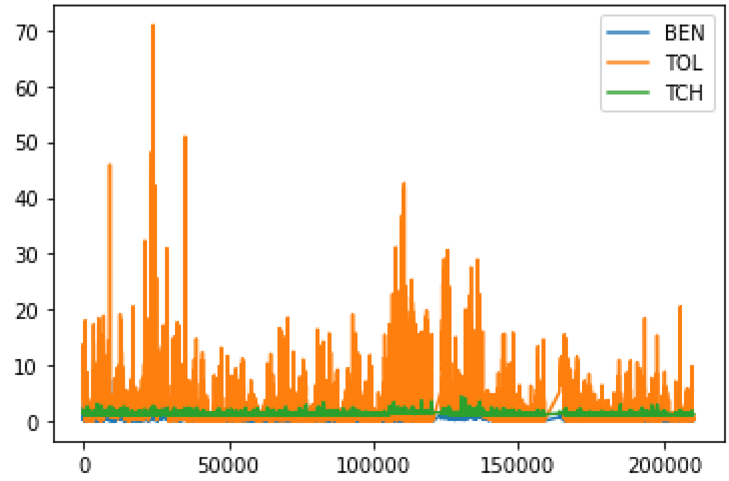
Line chart

In [9]:

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

Out[9]:

<AxesSubplot:>



Bar chart

In [10]:

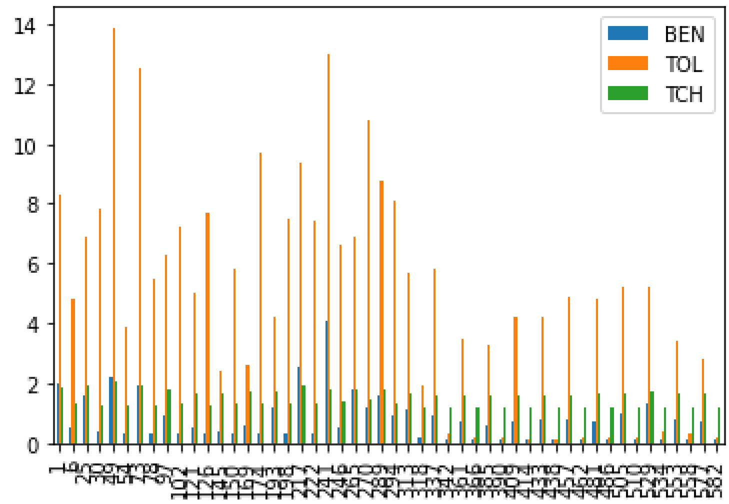
```
b=data[0:50]
```

In [11]:

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

Out[11]:

<AxesSubplot:>



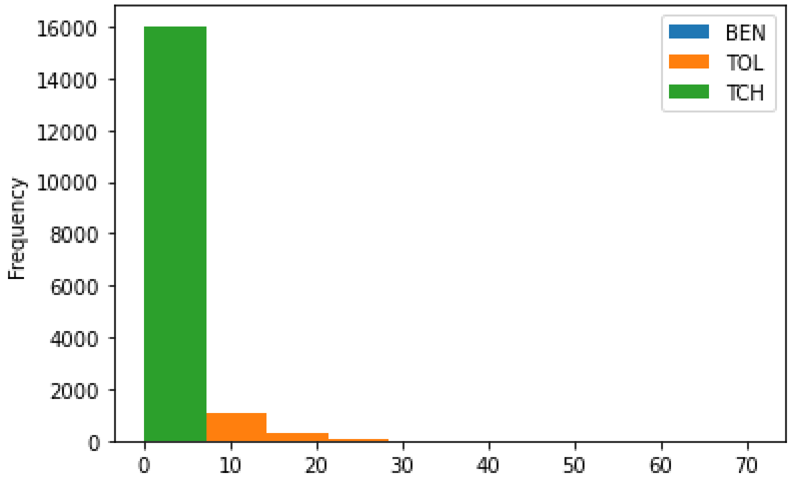
Histogram

In [12]:

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

Out[12]:

<AxesSubplot:ylabel='Frequency'>



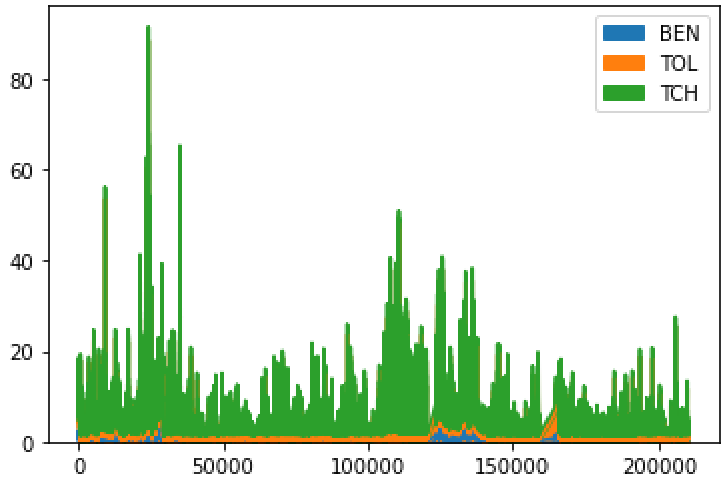
Area chart

In [13]:

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

Out[13]:

<AxesSubplot:>



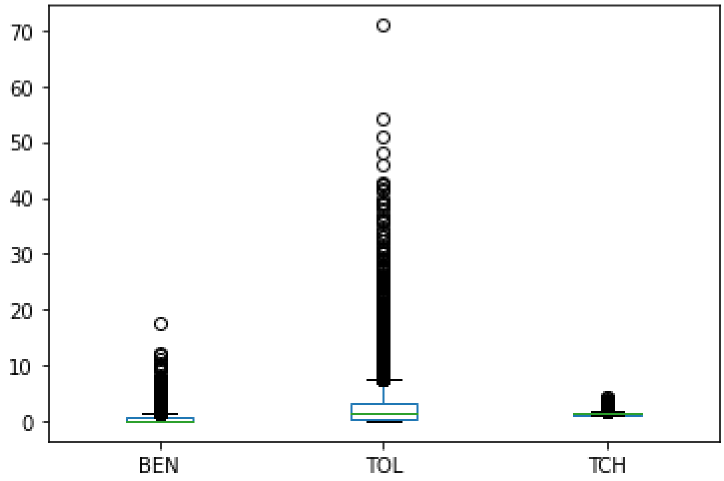
Box chart

In [14]:

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

Out[14]:

<AxesSubplot:>



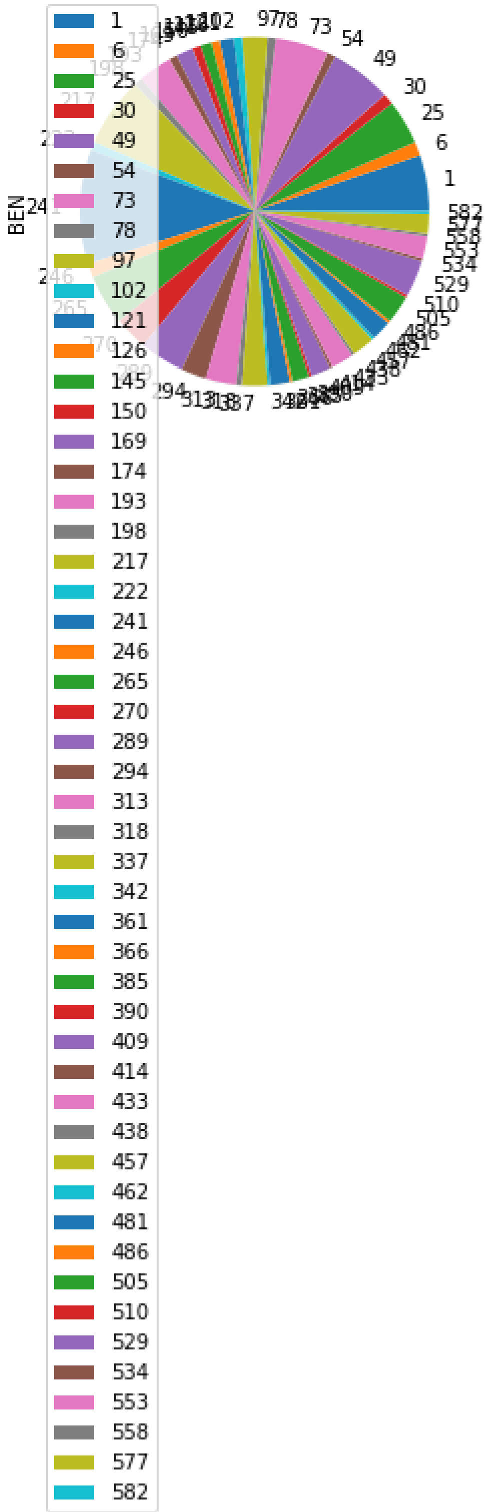
Pie chart

In [15]:

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

Out[15]:

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



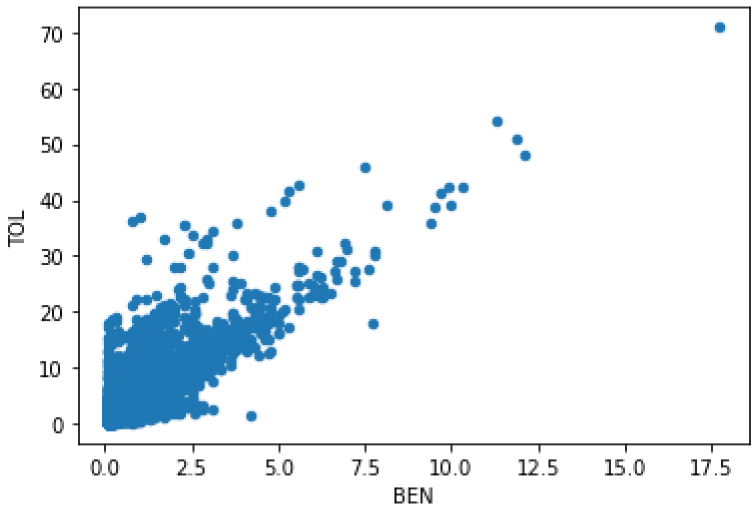
Scatter chart

In [16]:

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

Out[16]:

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



In [17]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 16026 entries, 1 to 210078
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   date     16026 non-null  object 
 1   BEN      16026 non-null  float64
 2   CO       16026 non-null  float64
 3   EBE      16026 non-null  float64
 4   NMHC     16026 non-null  float64
 5   NO       16026 non-null  float64
 6   NO_2     16026 non-null  float64
 7   O_3      16026 non-null  float64
 8   PM10     16026 non-null  float64
 9   PM25     16026 non-null  float64
 10  SO_2     16026 non-null  float64
 11  TCH      16026 non-null  float64
 12  TOL      16026 non-null  float64
 13  station  16026 non-null  int64  
dtypes: float64(12), int64(1), object(1)
memory usage: 1.8+ MB
```

In [18]:

```
df.describe()
```

Out[18]:

	BEN	CO	EBE	NMHC	NO	NO_2
count	16026.000000	16026.000000	16026.000000	16026.000000	16026.000000	16026.000000
mean	0.504823	0.380594	0.394247	0.123099	23.842256	40.948771
std	0.716896	0.260805	0.678592	0.092368	51.255660	33.236098
min	0.100000	0.100000	0.100000	0.000000	1.000000	1.000000
25%	0.100000	0.200000	0.100000	0.070000	1.000000	14.000000
50%	0.200000	0.300000	0.100000	0.100000	6.000000	35.000000
75%	0.700000	0.500000	0.400000	0.140000	24.000000	60.000000
max	17.700001	4.500000	12.100000	1.090000	960.000000	369.000000

In [19]:

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

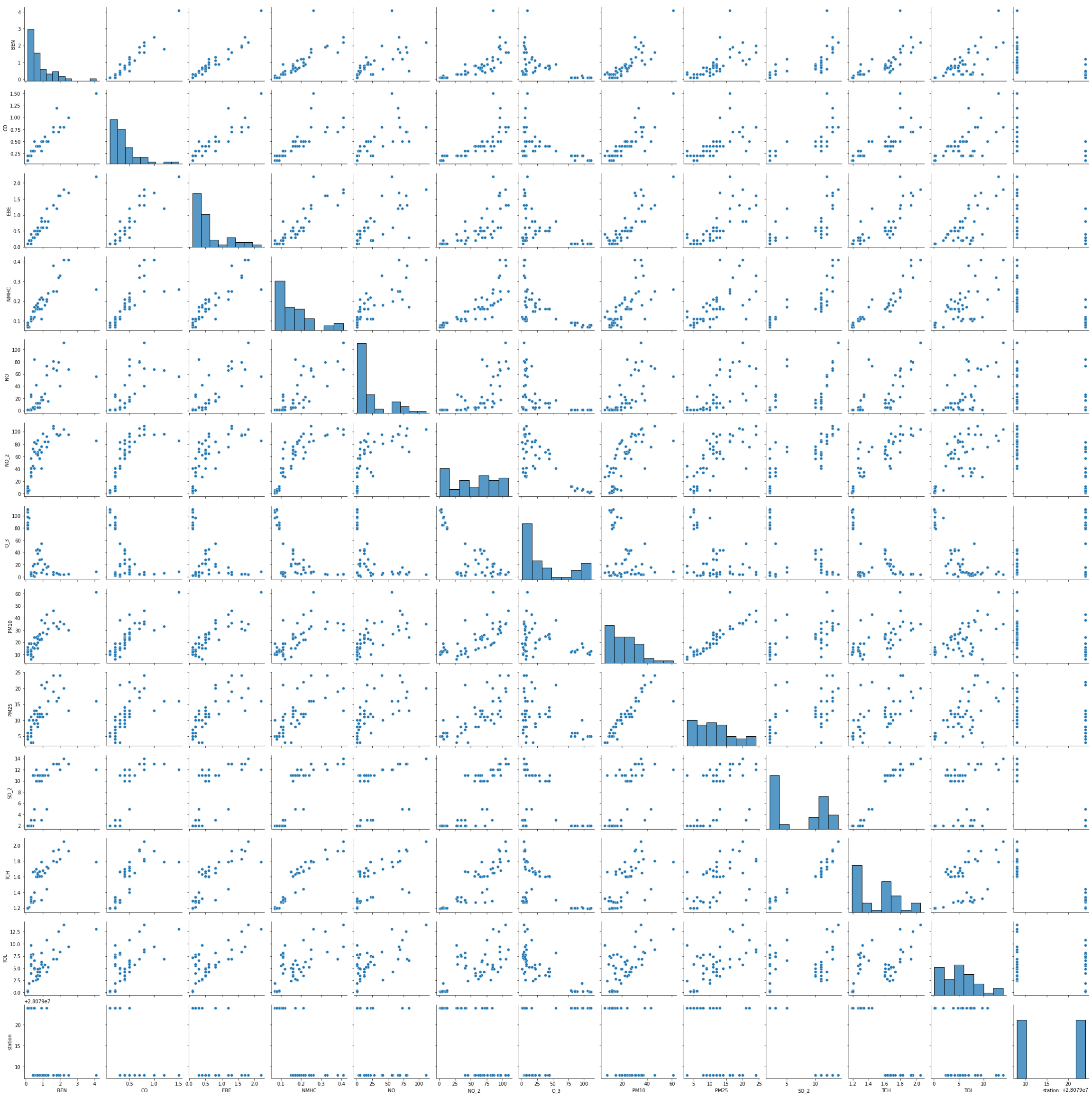
EDA AND VISUALIZATION

In [20]:

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

Out[20]:

```
<seaborn.axisgrid.PairGrid at 0x1ee9e9f0c40>
```



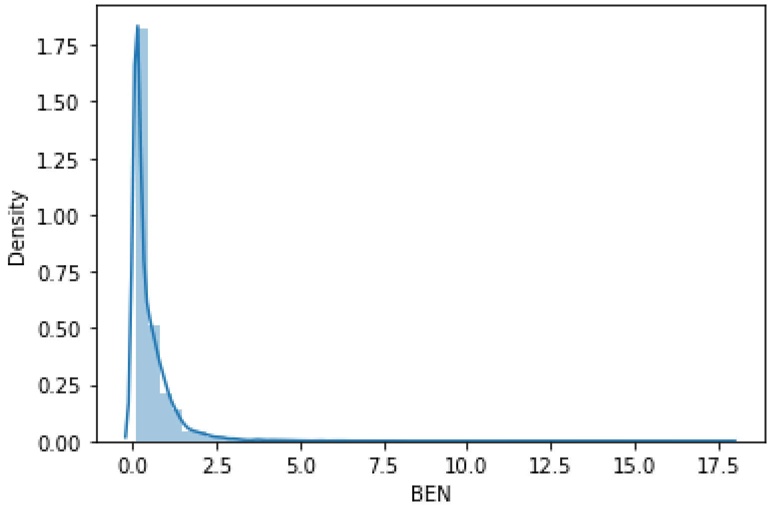
In [21]:

```
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[21]:

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

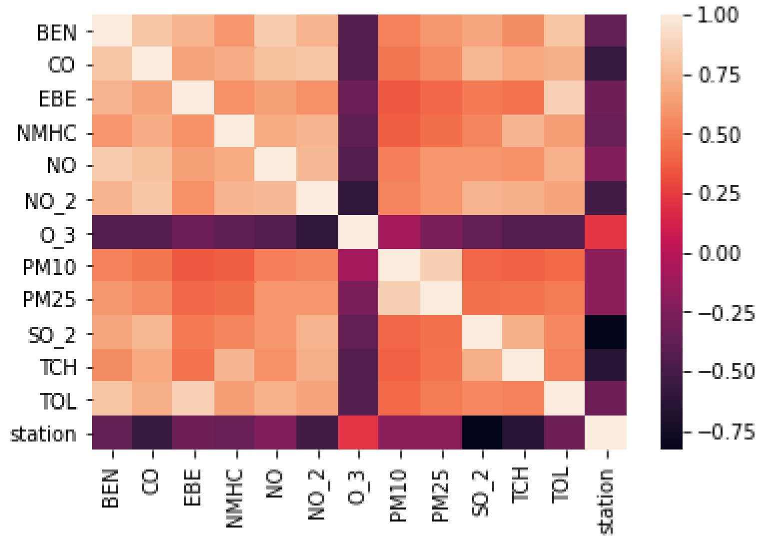


In [22]:

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

Out[22]:

<AxesSubplot:>



TO TRAIN THE MODEL AND MODEL BULDING

In [23]:

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

In [24]:

```
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 [25]:

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

Out[25]:

```
LinearRegression()
```

In [26]:

```
lr.intercept_
```

Out[26]:

```
28079038.123703483
```

In [27]:

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

Out[27]:

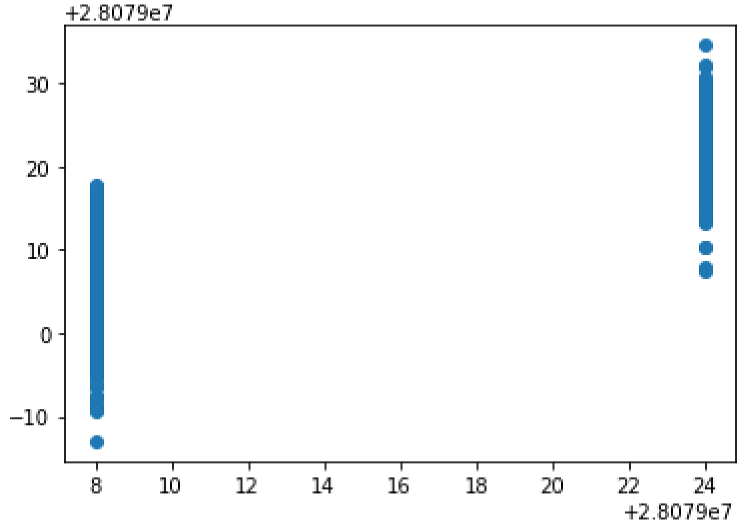
	Co-efficient
BEN	1.150938
CO	-9.490519
EBE	-0.493180
NMHC	13.263580
NO	0.079809
NO_2	-0.018493
O_3	-0.014573
PM10	0.010000
PM25	0.096769
SO_2	-1.127079
TCH	-9.503718
TOL	-0.115914

In [28]:

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

Out[28]:

```
<matplotlib.collections.PathCollection at 0x1eeabbee0d0>
```



ACCURACY

In [29]:

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

Out[29]:

```
0.8712230144436421
```

In [30]:

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

Out[30]:

```
0.871779860524847
```

Ridge and Lasso

In [31]:

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

In [32]:

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

Out[32]:

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

Accuracy(Ridge)

In [33]:

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

Out[33]:

```
0.8699290510221751
```

In [34]:

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

Out[34]:

```
0.8710049657009941
```

In [35]:

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

Out[35]:

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

In [36]:

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

Out[36]:

```
0.7297414144040693
```

Accuracy(Lasso)

In [37]:

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

Out[37]:

```
0.7320870681548695
```

Accuracy(Elastic Net)

In [38]:

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

Out[38]:

```
ElasticNet()
```

In [39]:

```
en.coef_
```

Out[39]:

```
array([-0.        , -0.        , -0.        , -0.        ,  0.07335022,
       -0.05194118, -0.01167171,  0.02182083,  0.05253284, -1.31766686,
       -0.        , -0.08100712])
```

In [40]:

```
en.intercept_
```

Out[40]:

```
28079025.950274505
```

In [41]:

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

In [42]:

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

Out[42]:

```
0.818679035054062
```

Evaluation Metrics

In [43]:

```
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)))
```

```
2.5316843413887313
11.604509628883251
3.406539245169979
```

Logistic Regression

In [44]:

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

In [45]:

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

In [46]:

```
feature_matrix.shape
```

Out[46]:

```
(16026, 10)
```

In [47]:

```
target_vector.shape
```

Out[47]:

```
(16026,)
```

In [48]:

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

In [49]:

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

In [50]:

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

Out[50]:

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

In [51]:

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

In [52]:

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

```
[28079008]
```

In [53]:

```
logr.classes_
```

Out[53]:

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

In [54]:

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

Out[54]:

```
0.9947585174092101
```

In [55]:

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

Out[55]:

```
1.0
```

In [56]:

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

Out[56]:

```
array([[1.00000000e+00, 5.69793111e-39]])
```

Random Forest

In [57]:

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

In [58]:

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

Out[58]:

```
RandomForestClassifier()
```

In [59]:

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

In [60]:

```
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[60]:

```
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 [61]:

```
grid_search.best_score_
```

Out[61]:

```
0.9940274558744875
```

In [62]:

```
rfc_best=grid_search.best_estimator_
```

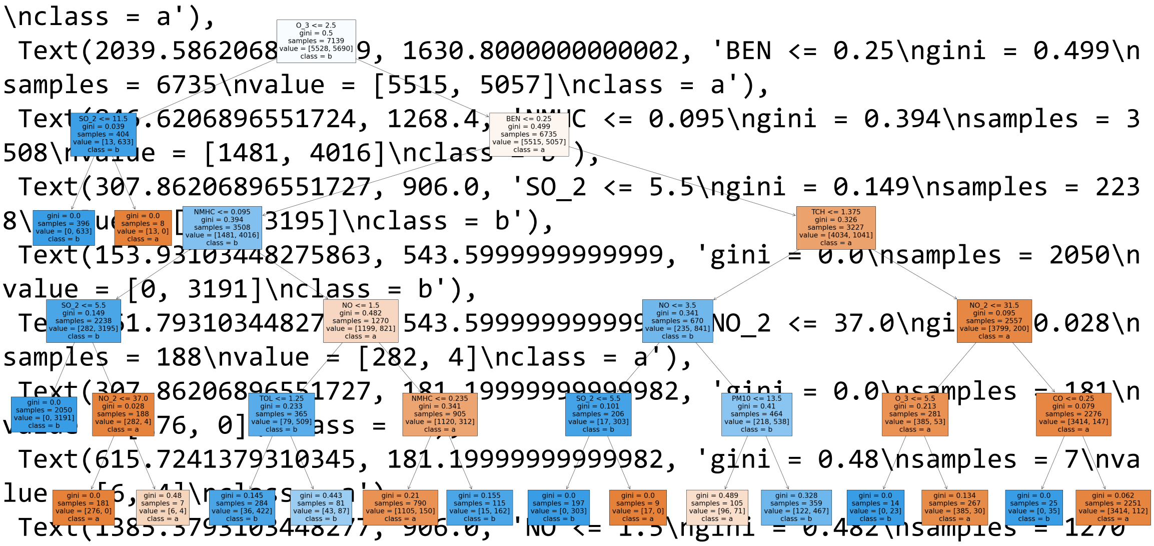
In [63]:

```
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[63]:

```
[Text(1212.2068965517242, 1993.2, 'O_3 <= 2.5\ngini = 0.5\nsamples = 7139\nvalue = [5528, 5690]\nclass = b'),
 Text(384.82758620689657, 1630.8000000000002, 'SO_2 <= 11.5\ngini = 0.039\nsamples = 404\nvalue = [13, 633]\nclass = b'),
 Text(230.89655172413796, 1268.4, 'gini = 0.0\nsamples = 396\nvalue = [0, 633]\nclass = b'),
 Text(538.7586206896552, 1268.4, 'gini = 0.0\nsamples = 8\nvalue = [13, 0]\nclass = a'),
 Text(2039.5862068965519, 1630.8000000000002, 'BEN <= 0.25\ngini = 0.499\nsamples = 6735\nvalue = [5515, 5057]\nclass = a'),
 Text(846.6206896551724, 1268.4, 'NMHC <= 0.095\ngini = 0.394\nsamples = 3508\nvalue = [1481, 4016]\nclass = b'),
 Text(307.86206896551727, 906.0, 'SO_2 <= 5.5\ngini = 0.149\nsamples = 2238\nvalue = [282, 3195]\nclass = b'),
 Text(153.93103448275863, 543.5999999999999, 'gini = 0.0\nsamples = 2050\nvalue = [0, 3191]\nclass = b'),
 Text(461.79310344827587, 543.5999999999999, 'NO_2 <= 37.0\ngini = 0.028\nsamples = 188\nvalue = [282, 4]\nclass = a'),
 Text(307.86206896551727, 181.19999999999982, 'gini = 0.0\nsamples = 181\nvalue = [276, 0]\nclass = a'),
 Text(615.7241379310345, 181.19999999999982, 'gini = 0.48\nsamples = 7\nvalue = [6, 4]\nclass = a'),
 Text(1385.3793103448277, 906.0, 'NO <= 1.5\ngini = 0.482\nsamples = 1270\nvalue = [1199, 821]\nclass = a'),
 Text(1077.5172413793105, 543.5999999999999, 'TOL <= 1.25\ngini = 0.233\nsamples = 365\nvalue = [79, 509]\nclass = b'),
 Text(923.5862068965519, 181.19999999999982, 'gini = 0.145\nsamples = 284\nvalue = [36, 422]\nclass = b'),
 Text(1231.448275862069, 181.19999999999982, 'gini = 0.443\nsamples = 81\nvalue = [43, 87]\nclass = b'),
 Text(1693.2413793103449, 543.5999999999999, 'NMHC <= 0.235\ngini = 0.341\nsamples = 905\nvalue = [1120, 312]\nclass = a'),
 Text(1539.3103448275863, 181.19999999999982, 'gini = 0.21\nsamples = 790\nvalue = [1105, 150]\nclass = a'),
 Text(1847.1724137931037, 181.19999999999982, 'gini = 0.155\nsamples = 115\nvalue = [15, 162]\nclass = b'),
 Text(3232.551724137931, 1268.4, 'TCH <= 1.375\ngini = 0.326\nsamples = 3227\nvalue = [4034, 1041]\nclass = a'),
 Text(2616.8275862068967, 906.0, 'NO <= 3.5\ngini = 0.341\nsamples = 670\nvalue = [235, 841]\nclass = b'),
 Text(2308.9655172413795, 543.5999999999999, 'SO_2 <= 5.5\ngini = 0.101\nsamples = 206\nvalue = [17, 303]\nclass = b'),
 Text(2155.0344827586205, 181.19999999999982, 'gini = 0.0\nsamples = 197\nvalue = [0, 303]\nclass = b'),
 Text(2462.896551724138, 181.19999999999982, 'gini = 0.0\nsamples = 9\nvalue = [17, 0]\nclass = a'),
 Text(2924.689655172414, 543.5999999999999, 'PM10 <= 13.5\ngini = 0.41\nsamples = 464\nvalue = [218, 538]\nclass = b'),
 Text(2770.7586206896553, 181.19999999999982, 'gini = 0.489\nsamples = 105\nvalue = [96, 71]\nclass = a'),
 Text(3078.6206896551726, 181.19999999999982, 'gini = 0.328\nsamples = 359\nvalue = [122, 467]\nclass = b'),
 Text(3848.275862068966, 906.0, 'NO_2 <= 31.5\ngini = 0.095\nsamples = 2557\nvalue = [3799, 200]\nclass = a'),
 Text(3540.4137931034484, 543.5999999999999, 'O_3 <= 5.5\ngini = 0.213\nsamples = 281\nvalue = [385, 53]\nclass = a'),
 Text(3386.4827586206898, 181.19999999999982, 'gini = 0.0\nsamples = 14\nv
```



Conclusion

Accuracy

Linear Regression:0.8717779860524847

Ridge Regression:0.8710049657009941

Lasso Regression:0.7320870681548695

ElasticNet Regression:0.8186790350540062

Logistic Regression:0.9947585174092101

Random Forest:0.9940274558744875

Logistic Regression is suitable for this dataset