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_2011.
df
```

Out[2]:

	date	BEN	CO	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	TCH	TO
0	2011-11-01 01:00:00	NaN	1.0	NaN	NaN	154.0	84.0	NaN	NaN	NaN	6.0	NaN	Na
1	2011-11-01 01:00:00	2.5	0.4	3.5	0.26	68.0	92.0	3.0	40.0	24.0	9.0	1.54	8.
2	2011-11-01 01:00:00	2.9	NaN	3.8	NaN	96.0	99.0	NaN	NaN	NaN	NaN	NaN	7.
3	2011-11-01 01:00:00	NaN	0.6	NaN	NaN	60.0	83.0	2.0	NaN	NaN	NaN	NaN	Na
4	2011-11-01 01:00:00	NaN	NaN	NaN	NaN	44.0	62.0	3.0	NaN	NaN	3.0	NaN	Na
...	...	...	...	...	...	...	...	...	...	...	...	...	.
209923	2011-09-01 00:00:00	NaN	0.2	NaN	NaN	5.0	19.0	44.0	NaN	NaN	NaN	NaN	Na
209924	2011-09-01 00:00:00	NaN	0.1	NaN	NaN	6.0	29.0	NaN	11.0	NaN	7.0	NaN	Na
209925	2011-09-01 00:00:00	NaN	NaN	NaN	0.23	1.0	21.0	28.0	NaN	NaN	NaN	1.44	Na
209926	2011-09-01 00:00:00	NaN	NaN	NaN	NaN	3.0	15.0	48.0	NaN	NaN	NaN	NaN	Na
209927	2011-09-01 00:00:00	NaN	NaN	NaN	NaN	4.0	33.0	38.0	13.0	NaN	NaN	NaN	Na

209928 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: 16460 entries, 1 to 209910
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   date     16460 non-null  object 
 1   BEN      16460 non-null  float64
 2   CO       16460 non-null  float64
 3   EBE      16460 non-null  float64
 4   NMHC     16460 non-null  float64
 5   NO       16460 non-null  float64
 6   NO_2     16460 non-null  float64
 7   O_3      16460 non-null  float64
 8   PM10     16460 non-null  float64
 9   PM25     16460 non-null  float64
 10  SO_2     16460 non-null  float64
 11  TCH      16460 non-null  float64
 12  TOL      16460 non-null  float64
 13  station  16460 non-null  int64  
dtypes: float64(12), int64(1), object(1)
memory usage: 1.9+ MB
```

In [6]:

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

Out[6]:

	BEN	TOL	TCH
1	2.5	8.7	1.54
6	0.7	1.7	1.36
25	1.8	7.4	1.71
30	1.0	2.9	1.40
49	1.3	6.2	1.75
...	...	...	...
209862	0.4	0.7	1.26
209881	0.9	4.9	1.34
209886	0.6	0.9	1.26
209905	0.6	3.8	1.32
209910	0.7	0.9	1.25

16460 rows × 3 columns

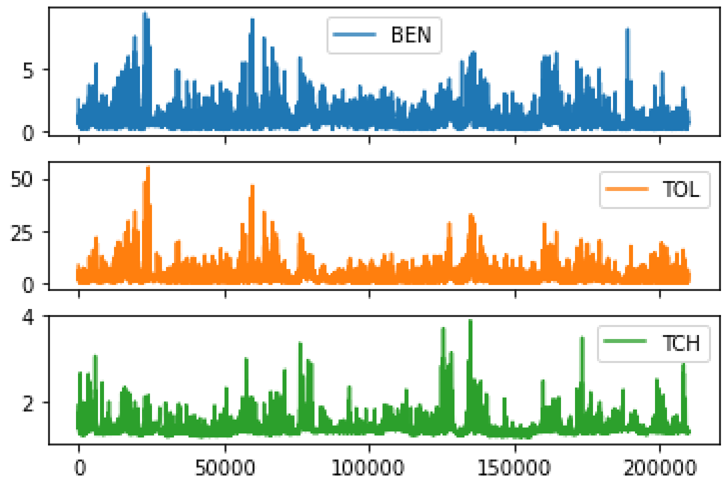
Line chart

In [7]:

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

Out[7]:

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



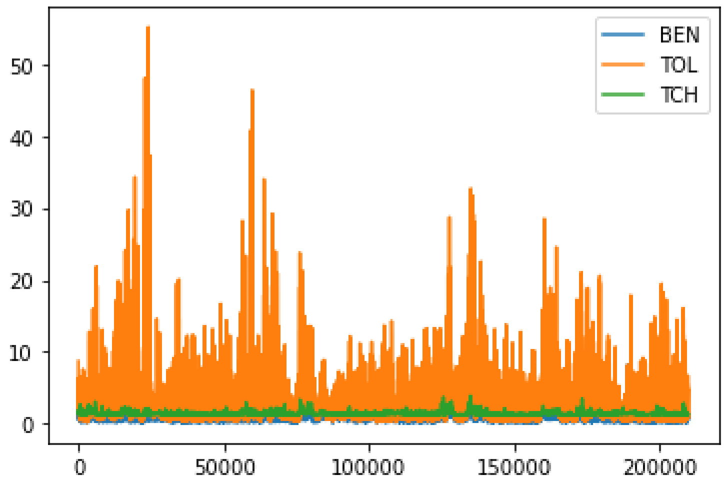
Line chart

In [8]:

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

Out[8]:

<AxesSubplot:>



Bar chart

In [9]:

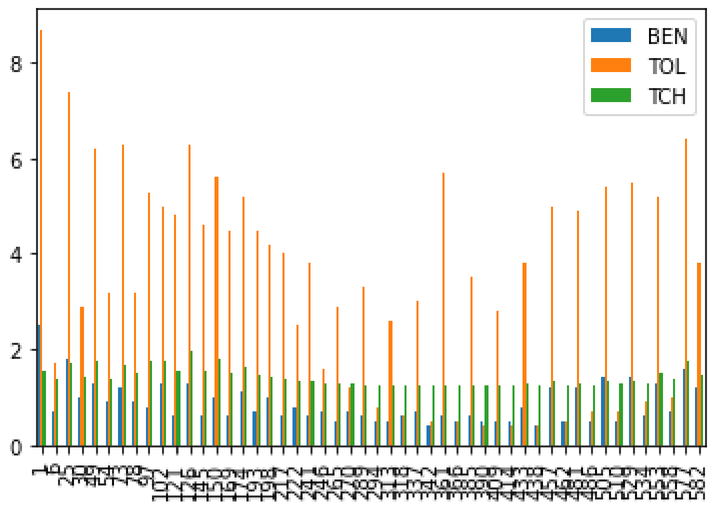
```
b=data[0:50]
```

In [10]:

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

Out[10]:

<AxesSubplot:>



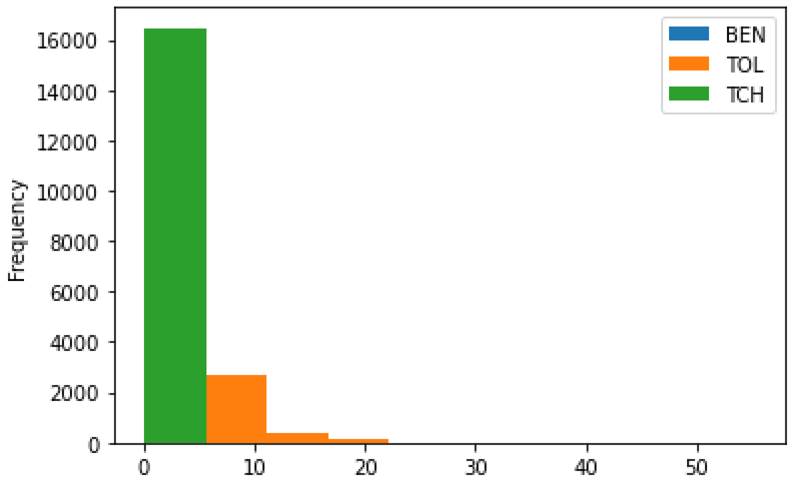
Histogram

In [11]:

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

Out[11]:

<AxesSubplot:ylabel='Frequency'>



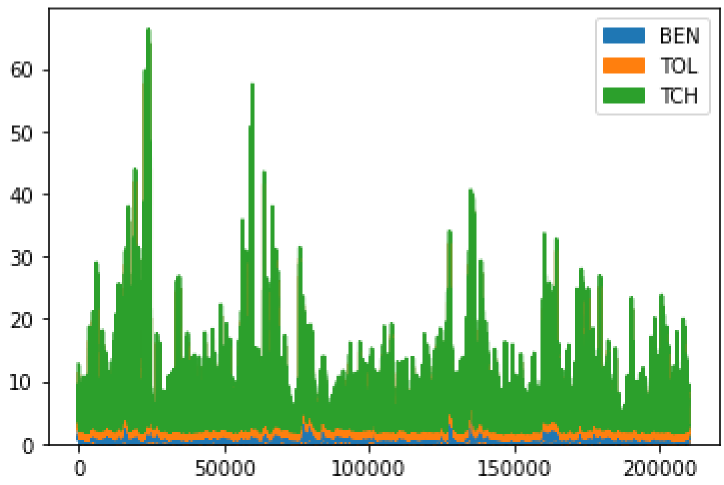
Area chart

In [12]:

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

Out[12]:

<AxesSubplot:>



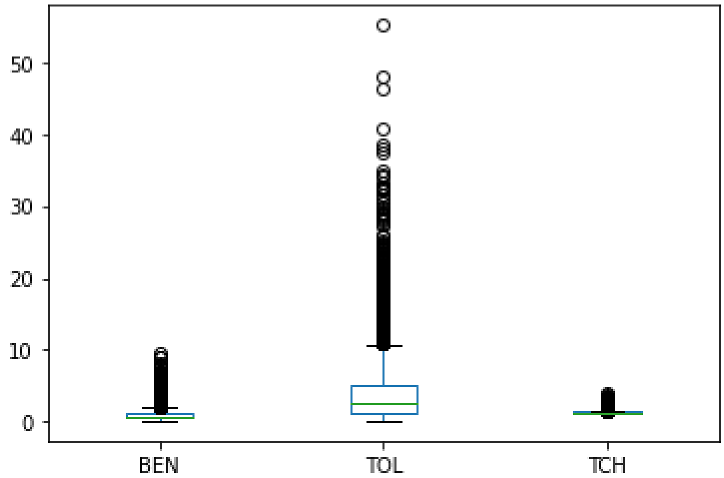
Box chart

In [13]:

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

Out[13]:

```
<AxesSubplot:>
```



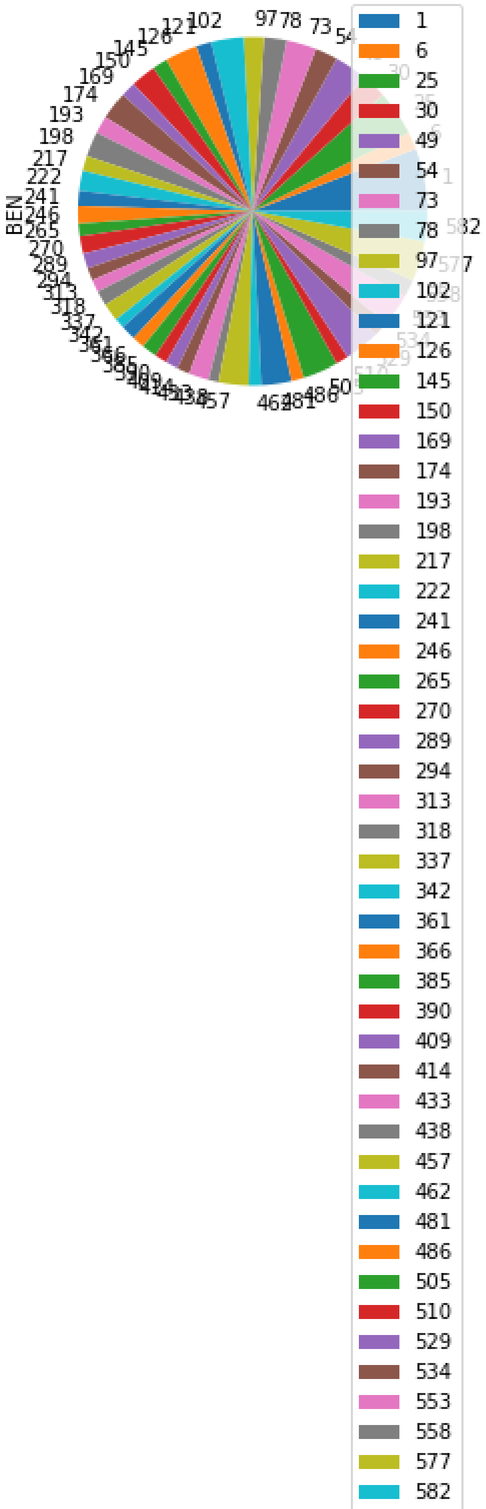
Pie chart

In [14]:

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

Out[14]:

<AxesSubplot:ylabel='BEN'>



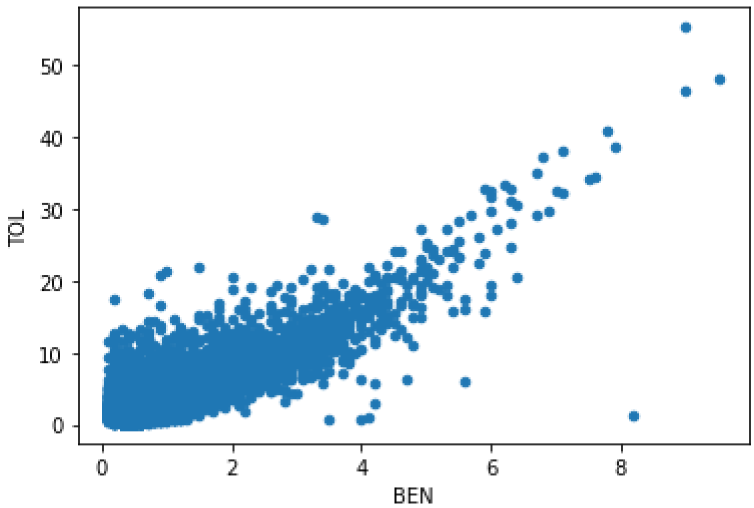
Scatter chart

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: 16460 entries, 1 to 209910
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   date     16460 non-null  object 
 1   BEN      16460 non-null  float64
 2   CO       16460 non-null  float64
 3   EBE      16460 non-null  float64
 4   NMHC     16460 non-null  float64
 5   NO       16460 non-null  float64
 6   NO_2     16460 non-null  float64
 7   O_3      16460 non-null  float64
 8   PM10     16460 non-null  float64
 9   PM25     16460 non-null  float64
 10  SO_2     16460 non-null  float64
 11  TCH      16460 non-null  float64
 12  TOL      16460 non-null  float64
 13  station  16460 non-null  int64  
dtypes: float64(12), int64(1), object(1)
memory usage: 1.9+ MB
```

In [17]:

```
df.describe()
```

Out[17]:

	BEN	CO	EBE	NMHC	NO	NO_2
count	16460.000000	16460.000000	16460.000000	16460.000000	16460.000000	16460.000000
mean	0.900680	0.277758	1.471871	0.167043	23.671810	44.583961
std	0.768892	0.206143	1.051004	0.075068	44.362859	31.569185
min	0.100000	0.100000	0.200000	0.010000	1.000000	1.000000
25%	0.500000	0.200000	0.800000	0.120000	2.000000	19.000000
50%	0.700000	0.200000	1.200000	0.160000	7.000000	40.000000
75%	1.100000	0.300000	1.700000	0.200000	25.000000	63.000000
max	9.500000	3.200000	12.800000	0.840000	615.000000	289.000000

In [18]:

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

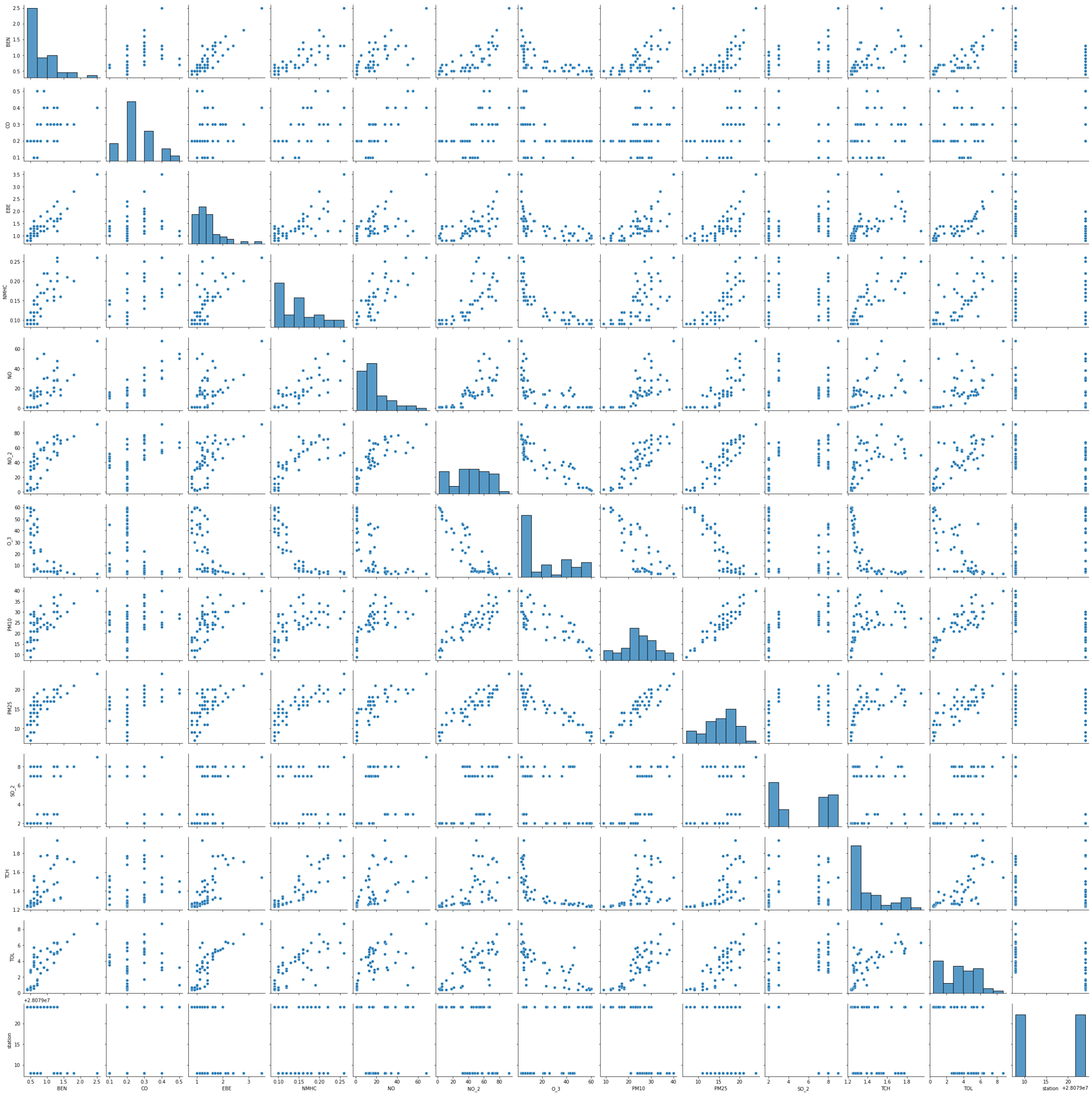
EDA AND VISUALIZATION

In [19]:

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

Out[19]:

<seaborn.axisgrid.PairGrid at 0x1bb2a70d7f0>



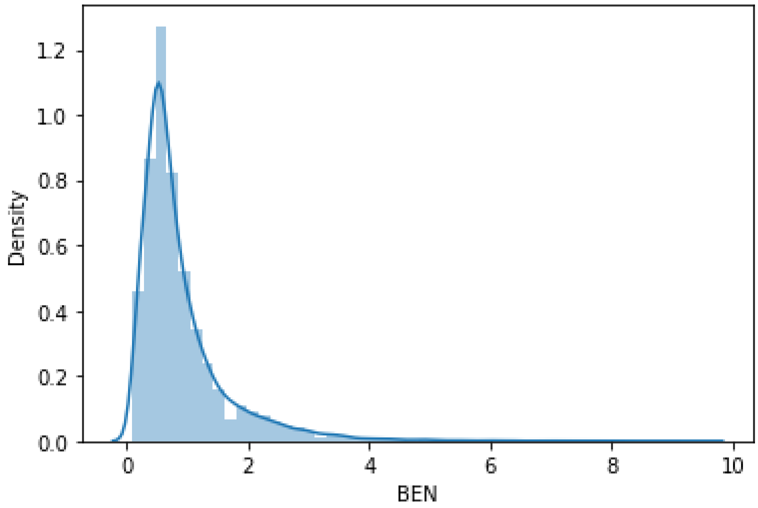
In [20]:

```
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'>
```

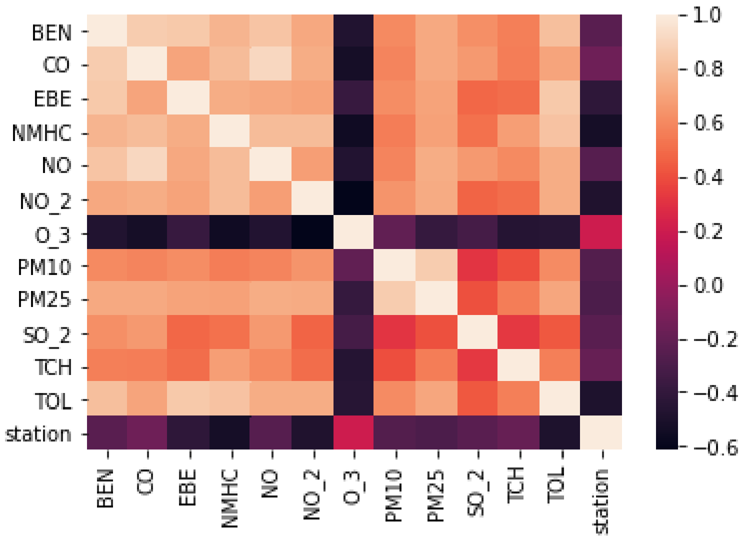


In [21]:

```
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]:

```
28079015.223056305
```

In [26]:

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

Out[26]:

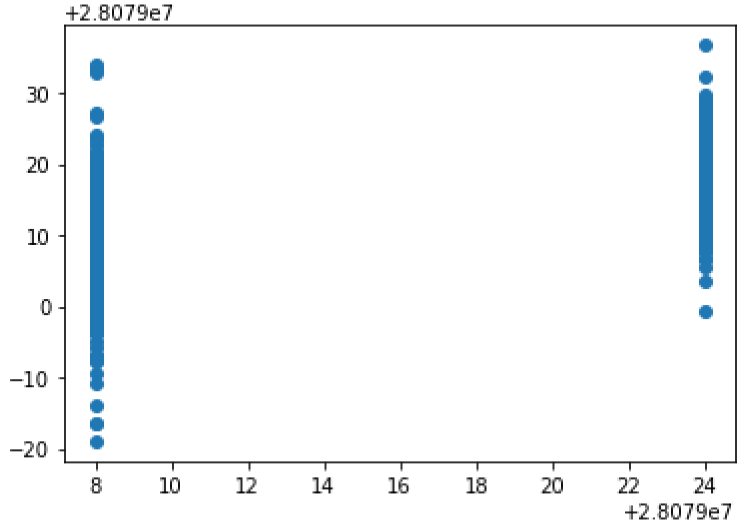
	Co-efficient
BEN	3.805170
CO	37.603729
EBE	-1.858668
NMHC	-93.094409
NO	-0.036306
NO_2	-0.089968
O_3	-0.015230
PM10	0.014540
PM25	-0.035677
SO_2	-0.474032
TCH	11.074567
TOL	-0.415248

In [27]:

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

Out[27]:

```
<matplotlib.collections.PathCollection at 0x1bb36eccac0>
```



ACCURACY

In [28]:

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

Out[28]:

```
0.6176242622614179
```

In [29]:

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

Out[29]:

```
0.6312376538837546
```

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]:

```
0.580321441574621
```

In [33]:

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

Out[33]:

```
0.5979243288685172
```

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]:

```
0.24603868232736525
```

Accuracy(Lasso)

In [36]:

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

Out[36]:

```
0.23241032291592945
```

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([ 0.30437437,  0.        , -0.        , -0.        ,  0.05117634,
       -0.13281545, -0.04260736,  0.02915675,  0.09360197, -0.1808079 ,
        0.        , -1.00493552])
```

In [39]:

```
en.intercept_
```

Out[39]:

```
28079025.017157324
```

In [40]:

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

In [41]:

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

Out[41]:

```
0.3502416888161278
```

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)))
```

```
5.604138864118284
41.58278557254639
6.448471568716605
```

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]:

```
(16460, 10)
```

In [46]:

```
target_vector.shape
```

Out[46]:

```
(16460,)
```

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]:

```
0.9237545565006076
```

In [54]:

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

Out[54]:

```
0.9999999999999966
```

In [55]:

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

Out[55]:

```
array([[1.00000000e+00, 3.47334507e-15]])
```

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]:

```
0.9395938205172714
```

In [61]:

```
rfc_best=grid_search.best_estimator_
```

In [62]:

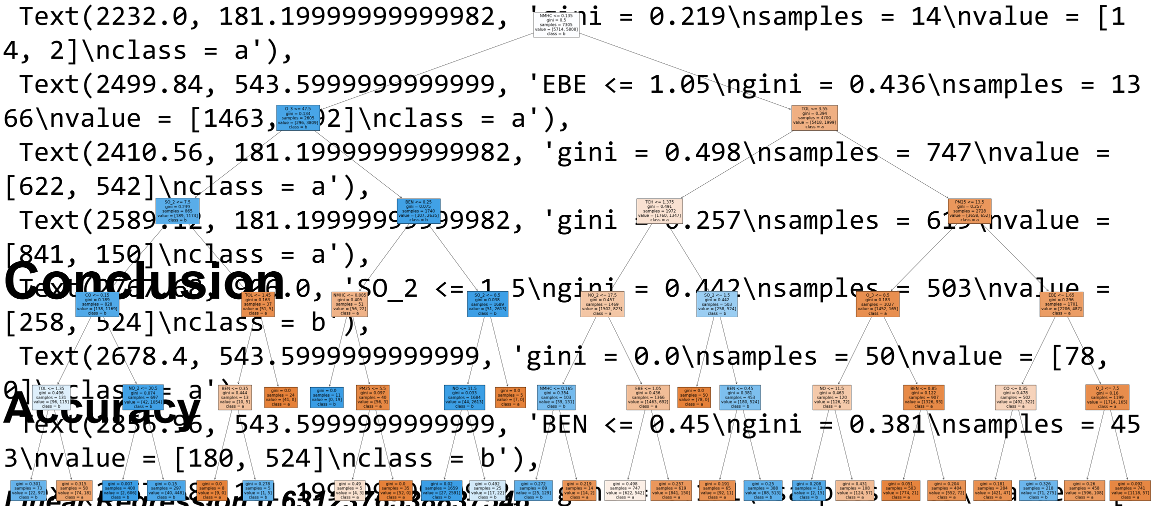
```
from sklearn.tree import plot_tree

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(2142.7200000000003, 1993.2, 'NMHC <= 0.135\ngini = 0.5\nsamples = 73
05\nvalue = [5714, 5808]\nclass = b'),
 Text(1138.32, 1630.8000000000002, 'O_3 <= 47.5\ngini = 0.134\nsamples = 2
605\nvalue = [296, 3809]\nclass = b'),
 Text(669.6, 1268.4, 'SO_2 <= 7.5\ngini = 0.239\nsamples = 865\nvalue = [1
89, 1174]\nclass = b'),
 Text(357.12, 906.0, 'CO <= 0.15\ngini = 0.189\nsamples = 828\nvalue = [13
8, 1169]\nclass = b'),
 Text(178.56, 543.5999999999999, 'TOL <= 1.35\ngini = 0.496\nsamples = 131
\nvalue = [96, 115]\nclass = b'),
 Text(89.28, 181.19999999999982, 'gini = 0.301\nsamples = 73\nvalue = [22,
97]\nclass = b'),
 Text(267.84000000000003, 181.19999999999982, 'gini = 0.315\nsamples = 58
\nvalue = [74, 18]\nclass = a'),
 Text(535.6800000000001, 543.5999999999999, 'NO_2 <= 30.5\ngini = 0.074\ns
amples = 697\nvalue = [42, 1054]\nclass = b'),
 Text(446.4, 181.19999999999982, 'gini = 0.007\nsamples = 400\nvalue = [2,
606]\nclass = b'),
 Text(624.96, 181.19999999999982, 'gini = 0.15\nsamples = 297\nvalue = [4
0, 448]\nclass = b'),
 Text(982.08, 906.0, 'TOL <= 1.45\ngini = 0.163\nsamples = 37\nvalue = [5
1, 5]\nclass = a'),
 Text(892.8, 543.5999999999999, 'BEN <= 0.35\ngini = 0.444\nsamples = 13\n
value = [10, 5]\nclass = a'),
 Text(803.52, 181.19999999999982, 'gini = 0.0\nsamples = 8\nvalue = [9, 0]
\nclass = a'),
 Text(982.08, 181.19999999999982, 'gini = 0.278\nsamples = 5\nvalue = [1,
5]\nclass = b'),
 Text(1071.3600000000001, 543.5999999999999, 'gini = 0.0\nsamples = 24\nva
lue = [41, 0]\nclass = a'),
 Text(1607.04, 1268.4, 'BEN <= 0.25\ngini = 0.075\nsamples = 1740\nvalue =
[107, 2635]\nclass = b'),
 Text(1339.2, 906.0, 'NMHC <= 0.085\ngini = 0.405\nsamples = 51\nvalue =
[56, 22]\nclass = a'),
 Text(1249.92, 543.5999999999999, 'gini = 0.0\nsamples = 11\nvalue = [0, 1
9]\nclass = b'),
 Text(1428.48, 543.5999999999999, 'PM25 <= 5.5\ngini = 0.097\nsamples = 40
\nvalue = [56, 3]\nclass = a'),
 Text(1339.2, 181.19999999999982, 'gini = 0.49\nsamples = 5\nvalue = [4,
3]\nclass = a'),
 Text(1517.76, 181.19999999999982, 'gini = 0.0\nsamples = 35\nvalue = [52,
0]\nclass = a'),
 Text(1874.88, 906.0, 'SO_2 <= 8.5\ngini = 0.038\nsamples = 1689\nvalue =
[51, 2613]\nclass = b'),
 Text(1785.6, 543.5999999999999, 'NO <= 11.5\ngini = 0.033\nsamples = 1684
\nvalue = [44, 2613]\nclass = b'),
 Text(1696.32, 181.19999999999982, 'gini = 0.02\nsamples = 1659\nvalue =
[27, 2591]\nclass = b'),
 Text(1874.88, 181.19999999999982, 'gini = 0.492\nsamples = 25\nvalue = [1
7, 22]\nclass = b'),
 Text(1964.16, 543.5999999999999, 'gini = 0.0\nsamples = 5\nvalue = [7, 0]
\nclass = a'),
 Text(3147.12, 1630.8000000000002, 'TOL <= 3.55\ngini = 0.394\nsamples = 4
700\nvalue = [5418, 1999]\nclass = a'),
 Text(2544.48, 1268.4, 'TCH <= 1.375\ngini = 0.491\nsamples = 1972\nvalue
= [1760, 1347]\nclass = a'),
 Text(2321.28, 906.0, 'NO_2 <= 17.5\ngini = 0.457\nsamples = 1469\nvalue =
[1502, 823]\nclass = a'),
 Text(2142.7200000000003, 543.5999999999999, 'NMHC <= 0.165\ngini = 0.354
\nsamples = 103\nvalue = [39, 131]\nclass = b'),
 Text(2053.44, 181.19999999999982, 'gini = 0.272\nsamples = 89\nvalue = [2
```

```
5, 129]\nclass = b'),
 Text(2232.0, 181.19999999999982, 'gini = 0.219\nsamples = 14\nvalue = [1
4, 2]\nclass = a'),
 Text(2499.84, 543.5999999999999, 'EBE <= 1.05\ngini = 0.436\nsamples = 13
66\nvalue = [1463, ?92]\nclass = a'),
 Text(2410.56, 181.19999999999982, 'gini = 0.498\nsamples = 747\nvalue =
[622, 542]\nclass = a'),
 Text(2589.12, 181.19999999999982, 'gini = 0.257\nsamples = 619\nvalue =
[841, 150]\nclass = a'),
 Text(27??.?, 906.0, 'SO_2 <= 1.5\ngini = 0.442\nsamples = 503\nvalue =
[258, 524]\nclass = b'),
 Text(2678.4, 543.5999999999999, 'gini = 0.0\nsamples = 50\nvalue = [78,
0]\nclass = a'),
 Text(2856.96, 543.5999999999999, 'BEN <= 0.45\ngini = 0.381\nsamples = 45
3\nvalue = [180, 524]\nclass = b'),
 [illegible]
2, 11]\nclass = a'),
 Text(2946.2400000000002, 181.19999999999982, 'gini = 0.25\nsamples = 388
\nvalue = [88, 513]\nclass = b'),
 Text(3749.76, 1268.4, 'PM25 <= 13.5\ngini = 0.257\nsamples = 2728\nvalue
= [3658, 652]\nclass = a'),
 Text(3392.64, 906.0, 'O_3 <= 8.5\ngini = 0.183\nsamples = 1027\nvalue =
[1452, 165]\nclass = a'),
 Text(3214.08, 543.5999999999999, 'NO <= 11.5\ngini = 0.463\nsamples = 120
\nvalue = [126, 72]\nclass = a'),
 Text(3124.8, 181.19999999999982, 'gini = 0.208\nsamples = 12\nvalue = [2,
15]\nclass = b'),
 Text(3303.36, 181.19999999999982, 'gini = 0.431\nsamples = 108\nvalue =
[124, 57]\nclass = a'),
 Text(3571.2, 543.5999999999999, 'BEN <= 0.85\ngini = 0.122\nsamples = 907
\nvalue = [1326, 93]\nclass = a'),
 Text(3481.92, 181.19999999999982, 'gini = 0.0??\nsamples = 503\nvalue =
[774, 21]\nclass = a'),
 Text(3660.48, 181.19999999999982, 'gini = 0.204\nsamples = 404\nvalue =
[552, 72]\nclass = a'),
 Text(4106.88, 906.0, 'EBE <= 1.65\ngini = 0.296\nsamples = 1701\nvalue =
[2206, 487]\nclass = a'),
 Text(3928.32, 543.5999999999999, 'CO <= 0.35\ngini = 0.478\nsamples = 502
\nvalue = [492, 322]\nclass = a'),
 Text(3839.04, 181.19999999999982, 'gini = 0.181\nsamples = 284\nvalue =
```



Conclusion

Accuracy

Linear Regression:0.6312370538837546

Ridge Regression:0.5979243288685172

Lasso Regression:0.23241032291592945

ElasticNet Regression:0.3502416888161278

Logistic Regression:0.9999999999999966

Random Forest:0.9395938205172714

Logistic Regression is suitable for this dataset