# 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

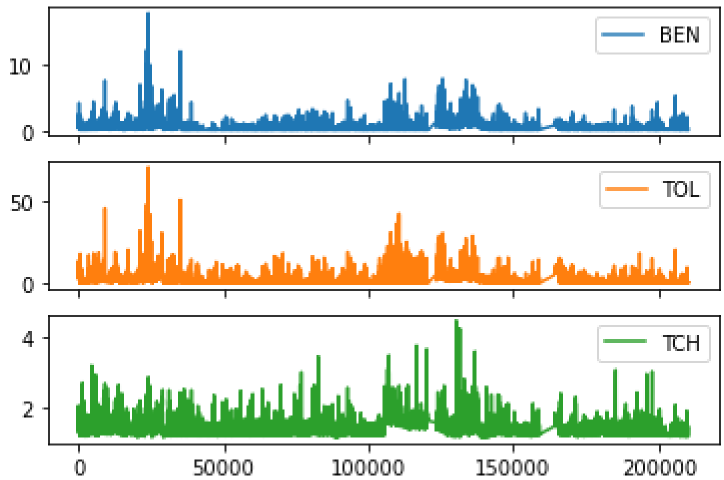
# Line chart

In [8]:

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

Out[8]:

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



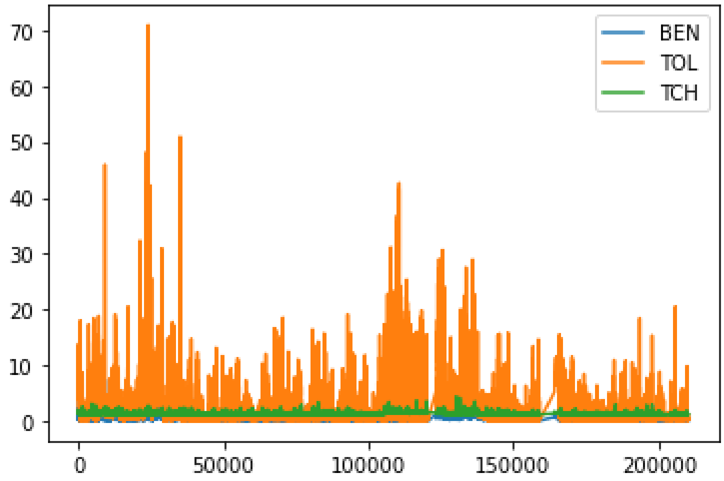

# Line chart

In [9]:

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

Out[9]:

<AxesSubplot:>




# Bar chart

In [10]:

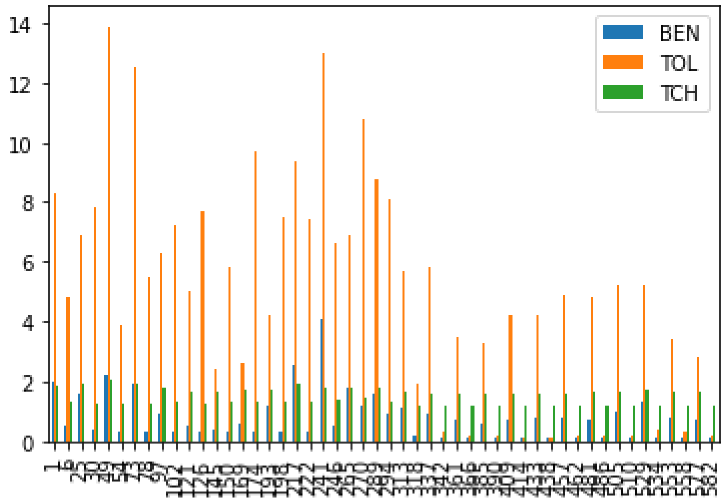
```
b=data[0:50]
```

In [11]:

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

Out[11]:

<AxesSubplot:>



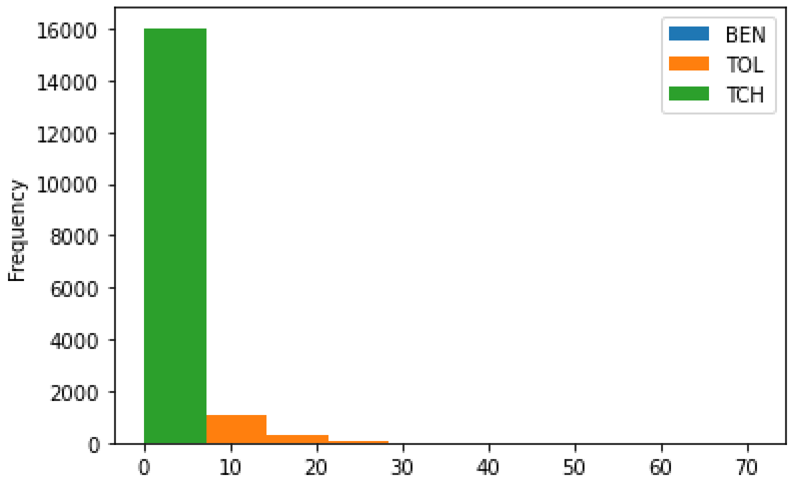

# Histogram

In [12]:

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

Out[12]:

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



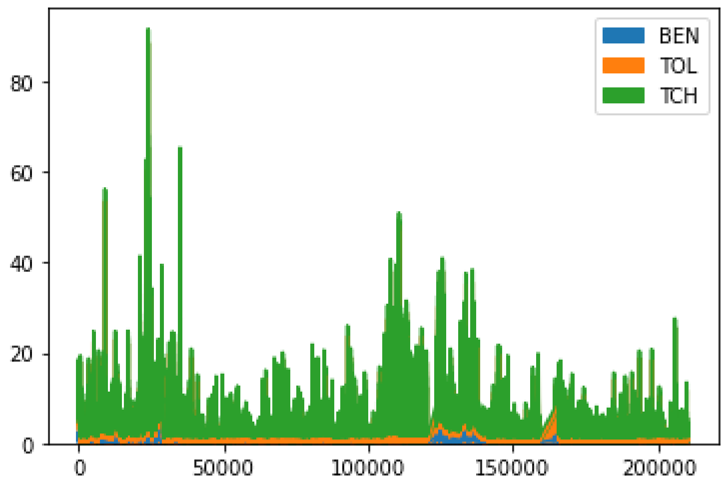

# Area chart

In [13]:

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

Out[13]:

```
<AxesSubplot:>
```



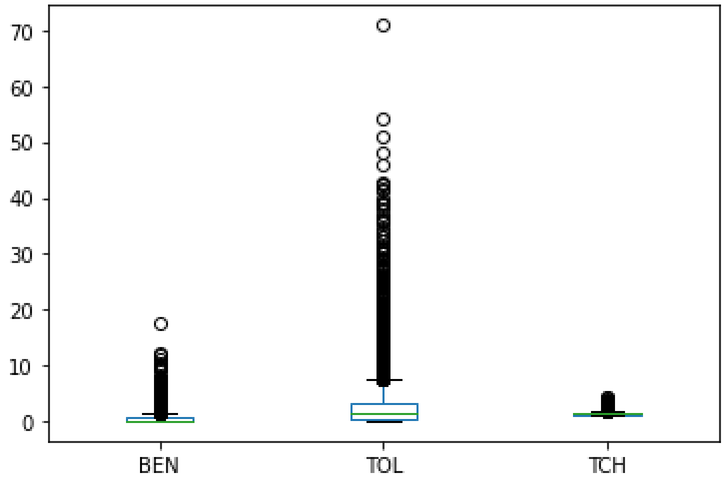

# Box chart

In [14]:

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

Out[14]:

<AxesSubplot:>



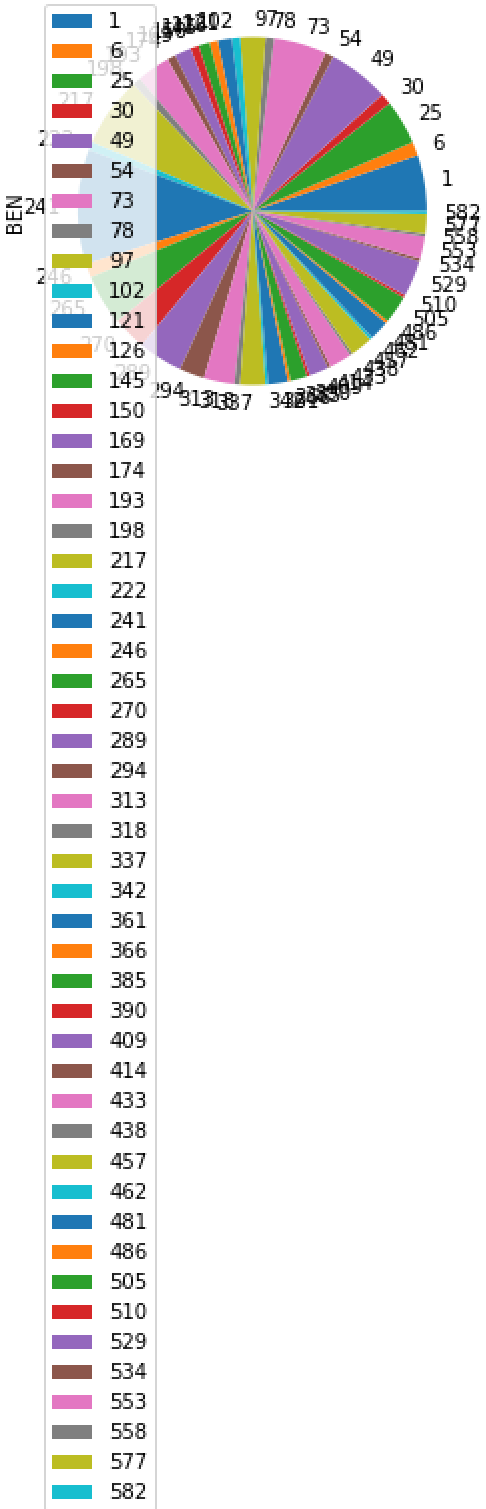

# Pie chart

In [15]:

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

Out[15]:

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



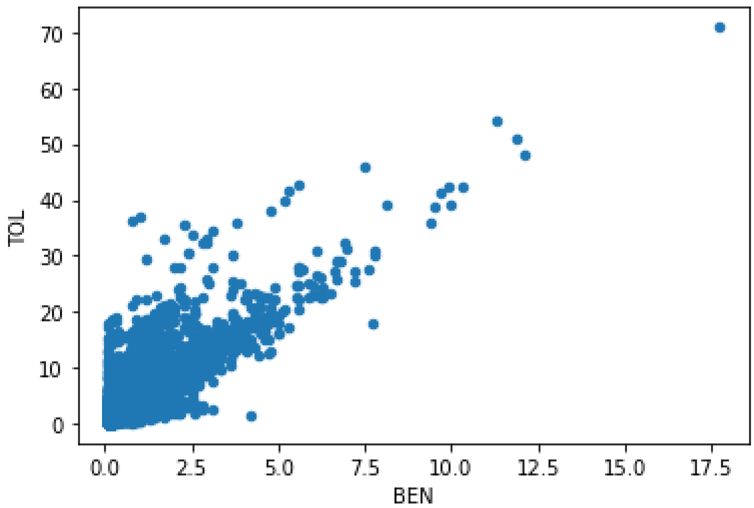

# Scatter chart

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']]
```

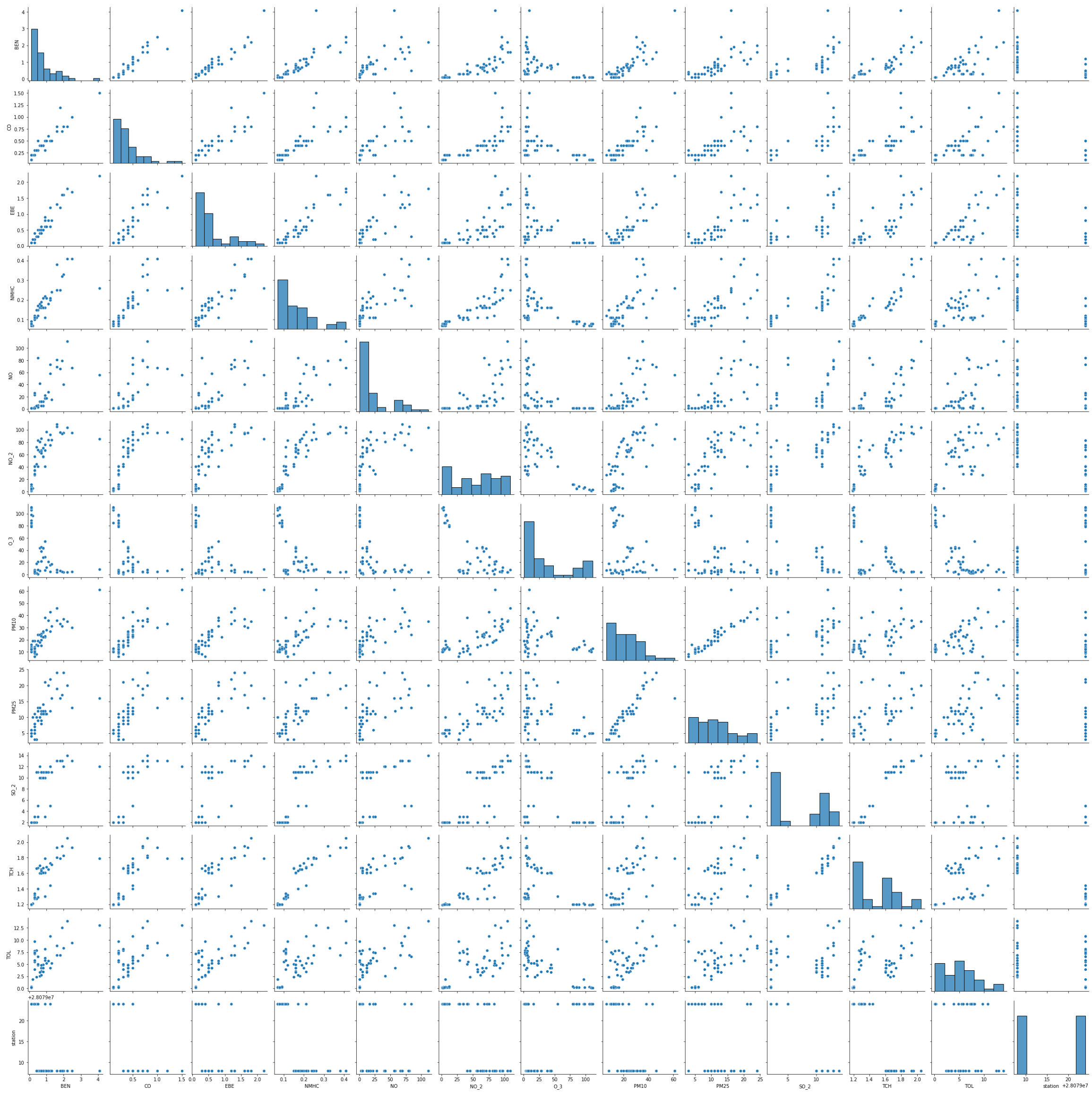
# EDA AND VISUALIZATION

In [20]:

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

Out[20]:

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



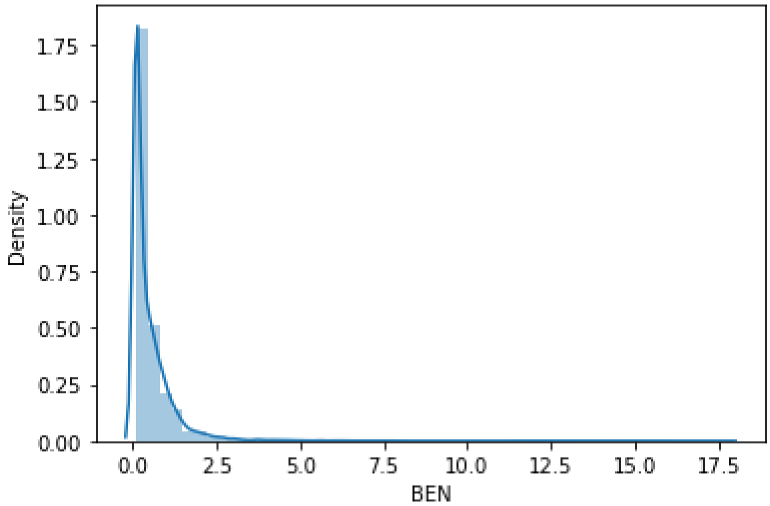
In [21]:

```
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'>

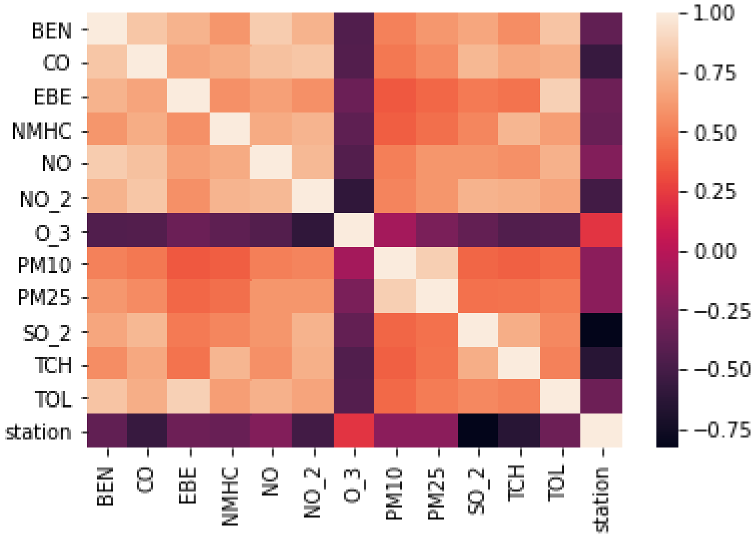



In [22]:

```
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]:

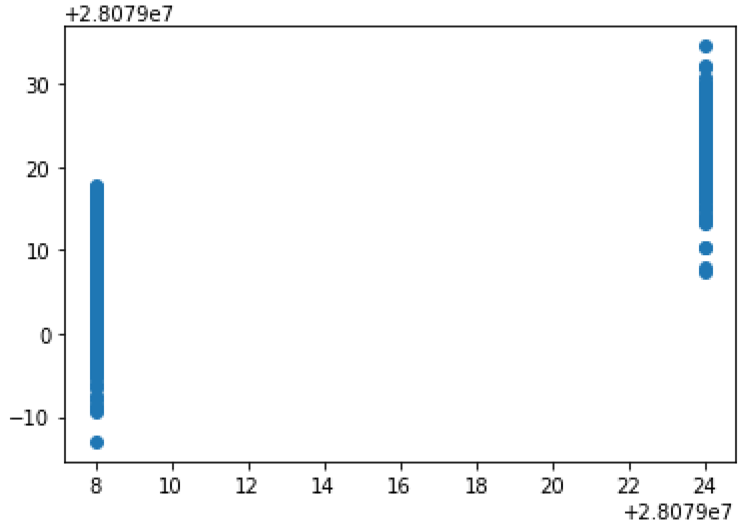
| | Co-efficient |
|---|---|
| **BEN** | 1.150938 |
| **CO** | -9.490519 |
| **EBE** | -0.493180 |
| **NMHC** | 13.263580 |
| **NO** | 0.079809 |
| **NO_2** | -0.018493 |
| **O_3** | -0.014573 |
| **PM10** | 0.010000 |
| **PM25** | 0.096769 |
| **SO_2** | -1.127079 |
| **TCH** | -9.503718 |
| **TOL**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

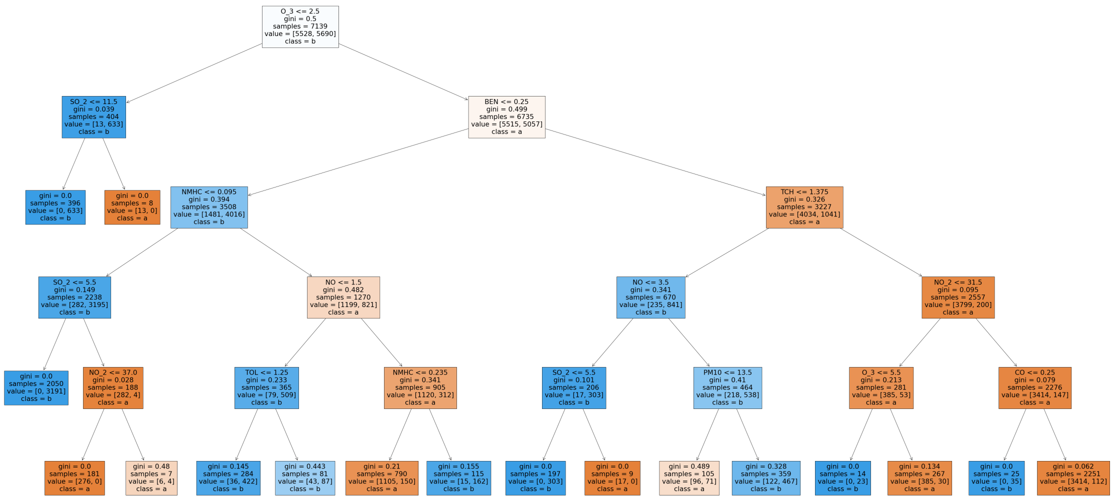
```
rfc_best=grid_search.best_estimator_
```

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
```

```
\nvalue = [0, 35]\nclass = b'),
 Text(4310.068965517242, 181.19999999999982, 'gini = 0.062\nsamples = 22
51\nvalue = [3414, 112]\nclass = a')]
```



# Conclusion

# Accuracy

#### *Linear Regression:0.871779860524847*

#### *Ridge Regression:0.8710049657009941*

#### *Lasso Regression:0.7320870681548695*

#### *ElasticNet Regression:0.818679035054062*

#### *Logistic Regression:0.9947585174092101*

#### *Random Forest:0.9940274558744875*

### Logistic Regression is suitable for this dataset