# 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_2007.
df
```

Out[2]:

| | date | BEN | CO | EBE | MXY | NMHC | NO_2 | NOx | OXY | O_3 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 2007-12-01 01:00:00 | NaN | 2.86 | NaN | NaN | NaN | 282.200012 | 1054.000000 | NaN | 4.030000 | 1 |
| **1** | 2007-12-01 01:00:00 | NaN | 1.82 | NaN | NaN | NaN | 86.419998 | 354.600006 | NaN | 3.260000 | |
| **2** | 2007-12-01 01:00:00 | NaN | 1.47 | NaN | NaN | NaN | 94.639999 | 319.000000 | NaN | 5.310000 | |
| **3** | 2007-12-01 01:00:00 | NaN | 1.64 | NaN | NaN | NaN | 127.900002 | 476.700012 | NaN | 4.500000 | 1 |
| **4** | 2007-12-01 01:00:00 | 4.64 | 1.86 | 4.26 | 7.98 | 0.57 | 145.100006 | 573.900024 | 3.49 | 52.689999 | 1 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| **225115** | 2007-03-01 00:00:00 | 0.30 | 0.45 | 1.00 | 0.30 | 0.26 | 8.690000 | 11.690000 | 1.00 | 42.209999 | |
| **225116** | 2007-03-01 00:00:00 | NaN | 0.16 | NaN | NaN | NaN | 46.820000 | 51.480000 | NaN | 22.150000 | |
| **225117** | 2007-03-01 00:00:00 | 0.24 | NaN | 0.20 | NaN | 0.09 | 51.259998 | 66.809998 | NaN | 18.540001 | |
| **225118** | 2007-03-01 00:00:00 | 0.11 | NaN | 1.00 | NaN | 0.05 | 24.240000 | 36.930000 | NaN | NaN | |
| **225119** | 2007-03-01 00:00:00 | 0.53 | 0.40 | 1.00 | 1.70 | 0.12 | 32.360001 | 47.860001 | 1.37 | 24.150000 | |

225120 rows × 17 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', 'PM25', 'PXY', 'SO_2', 'TCH', 'TOL', 'station'],
      dtype='object')
```

In [5]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 25443 entries, 4 to 225119
Data columns (total 17 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   date     25443 non-null  object 
 1   BEN      25443 non-null  float64
 2   CO       25443 non-null  float64
 3   EBE      25443 non-null  float64
 4   MXY      25443 non-null  float64
 5   NMHC     25443 non-null  float64
 6   NO_2     25443 non-null  float64
 7   NOx      25443 non-null  float64
 8   OXY      25443 non-null  float64
 9   O_3      25443 non-null  float64
 10  PM10     25443 non-null  float64
 11  PM25     25443 non-null  float64
 12  PXY      25443 non-null  float64
 13  SO_2     25443 non-null  float64
 14  TCH      25443 non-null  float64
 15  TOL      25443 non-null  float64
 16  station  25443 non-null  int64  
dtypes: float64(15), int64(1), object(1)
memory usage: 3.5+ MB
```

In [8]:

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

Out[8]:

| | station | TCH | TOL |
|---|---|---|---|
| **4** | 28079006 | 1.94 | 21.200001 |
| **21** | 28079024 | 1.54 | 8.440000 |
| **25** | 28079099 | 1.84 | 15.010000 |
| **30** | 28079006 | 2.23 | 21.330000 |
| **47** | 28079024 | 1.53 | 8.400000 |
| **...** | ... | ... | ... |
| **225073** | 28079006 | 1.28 | 7.850000 |
| **225094** | 28079099 | 1.33 | 3.340000 |
| **225098** | 28079006 | 1.28 | 4.560000 |
| **225115** | 28079024 | 1.44 | 0.510000 |
| **225119** | 28079099 | 1.32 | 2.410000 |

25443 rows × 3 columns

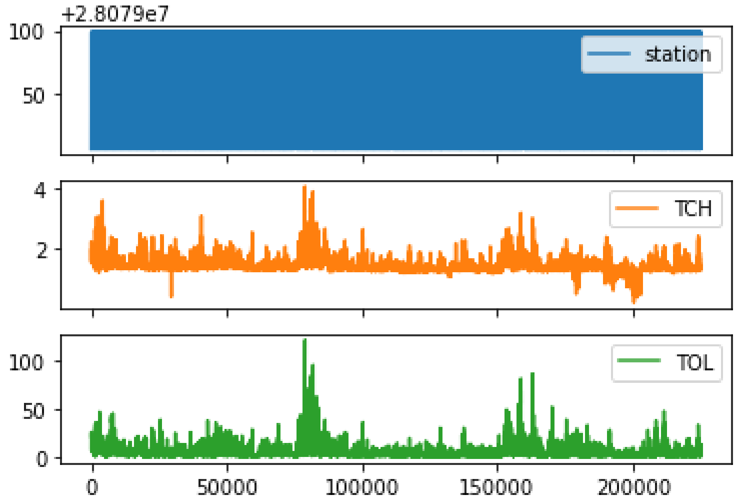
# Line chart

In [9]:

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

Out[9]:

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



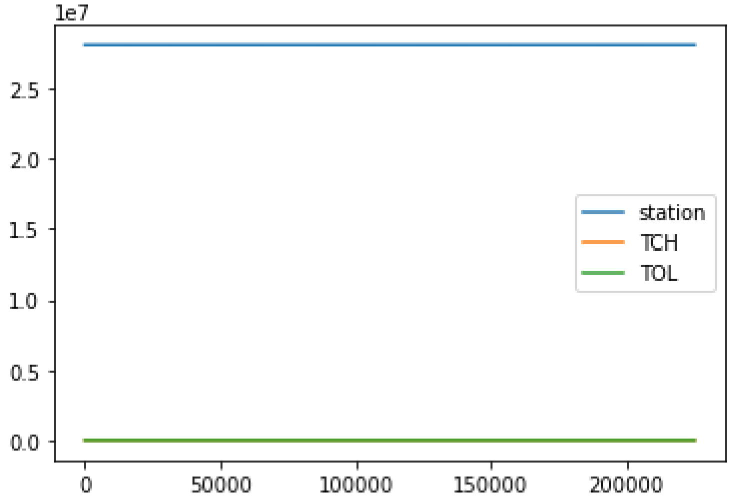

# Line chart

In [10]:

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

Out[10]:

<AxesSubplot:>




# Bar chart

In [11]:

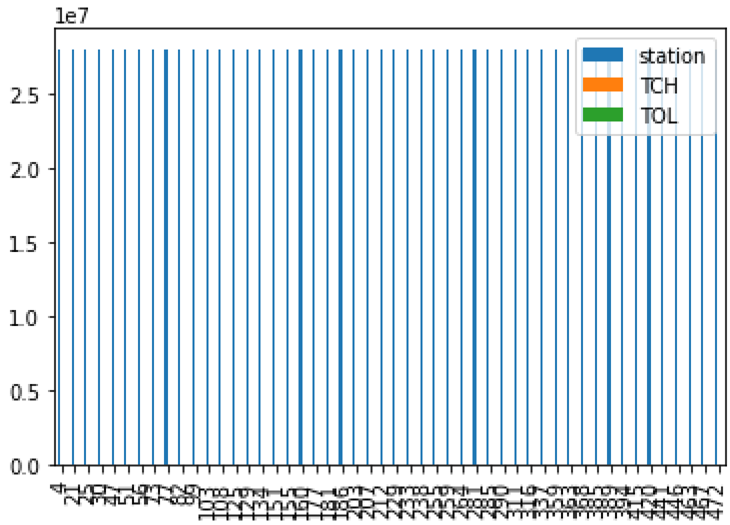
```
b=data[0:50]
```

In [12]:

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

Out[12]:

<AxesSubplot:>



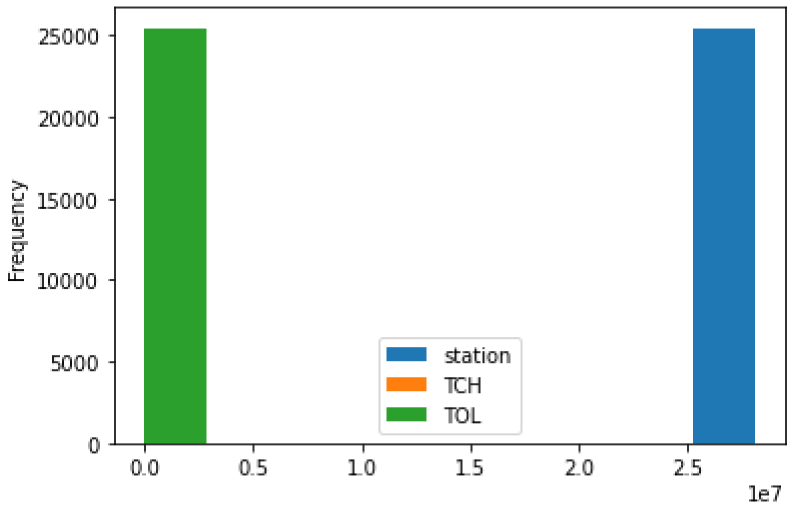

# Histogram

In [13]:

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

Out[13]:

<AxesSubplot:ylabel='Frequency'>



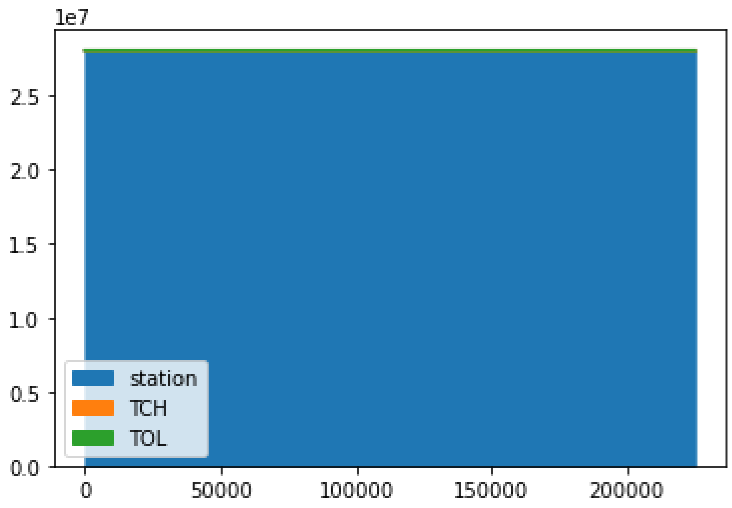

# Area chart

In [14]:

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

Out[14]:

<AxesSubplot:>



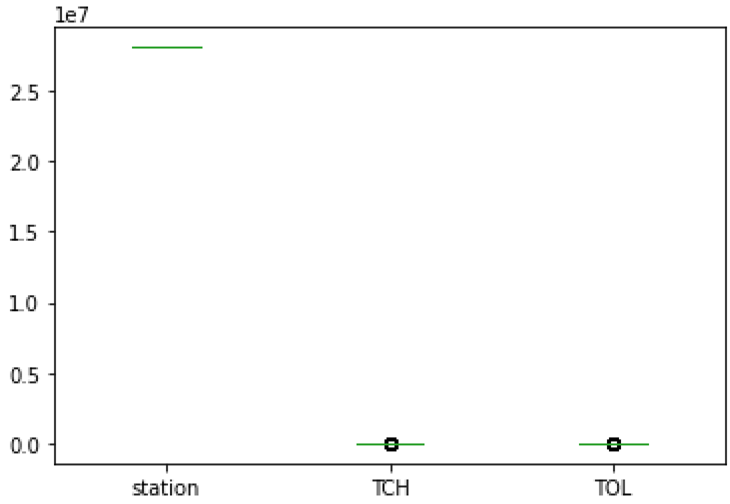

# Box chart

In [15]:

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

Out[15]:

<AxesSubplot:>



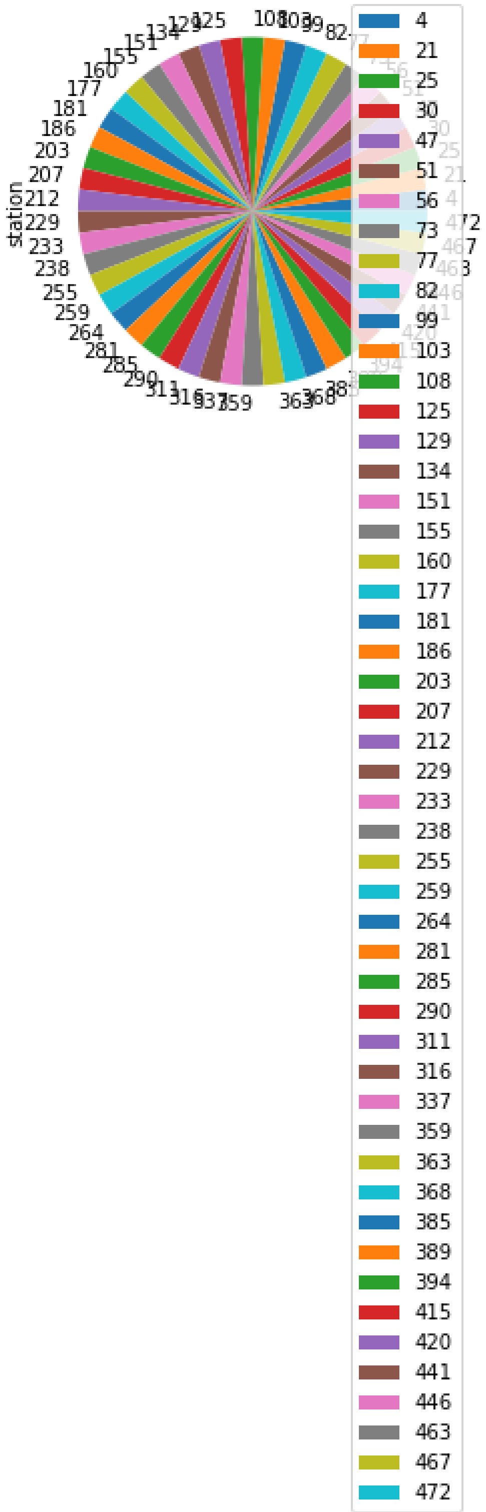

# Pie chart

In [17]:

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

Out[17]:

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



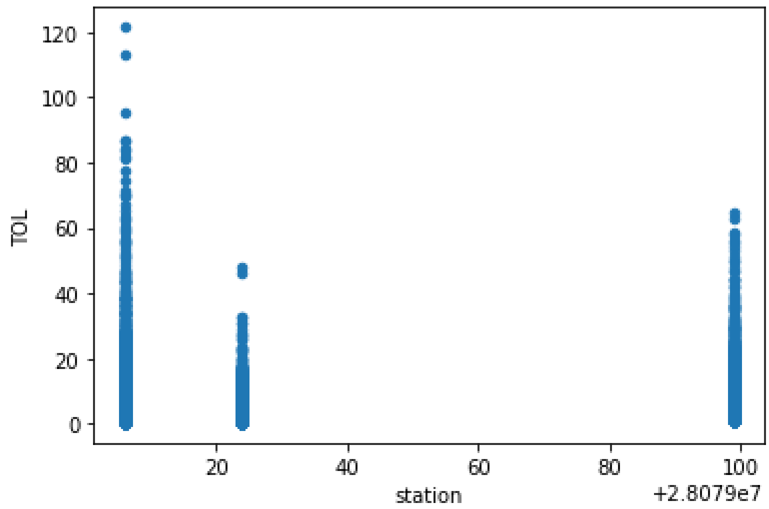

# Scatter chart

In [18]:

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

Out[18]:

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




In [19]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 25443 entries, 4 to 225119
Data columns (total 17 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   date     25443 non-null  object 
 1   BEN      25443 non-null  float64
 2   CO       25443 non-null  float64
 3   EBE      25443 non-null  float64
 4   MXY      25443 non-null  float64
 5   NMHC     25443 non-null  float64
 6   NO_2     25443 non-null  float64
 7   NOx      25443 non-null  float64
 8   OXY      25443 non-null  float64
 9   O_3      25443 non-null  float64
 10  PM10     25443 non-null  float64
 11  PM25     25443 non-null  float64
 12  PXY      25443 non-null  float64
 13  SO_2     25443 non-null  float64
 14  TCH      25443 non-null  float64
 15  TOL      25443 non-null  float64
 16  station  25443 non-null  int64  
dtypes: float64(15), int64(1), object(1)
memory usage: 3.5+ MB
```

In [20]:

```
df.describe()
```

Out[20]:

| | BEN | CO | EBE | MXY | NMHC | NO_2 |
|---|---|---|---|---|---|---|
| **count** | 25443.000000 | 25443.000000 | 25443.000000 | 25443.000000 | 25443.000000 | 25443.000000 |
| **mean** | 1.146744 | 0.505120 | 1.394071 | 2.392008 | 0.249967 | 58.532683 |
| **std** | 1.278733 | 0.423231 | 1.268265 | 2.784302 | 0.142627 | 37.755029 |
| **min** | 0.130000 | 0.000000 | 0.120000 | 0.150000 | 0.000000 | 1.690000 |
| **25%** | 0.450000 | 0.260000 | 0.780000 | 0.960000 | 0.160000 | 31.285001 |
| **50%** | 0.770000 | 0.400000 | 1.000000 | 1.500000 | 0.220000 | 54.080002 |
| **75%** | 1.390000 | 0.640000 | 1.580000 | 2.855000 | 0.300000 | 79.230003 |
| **max** | 30.139999 | 9.660000 | 31.680000 | 65.480003 | 2.570000 | 430.299988 |

In [21]:

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

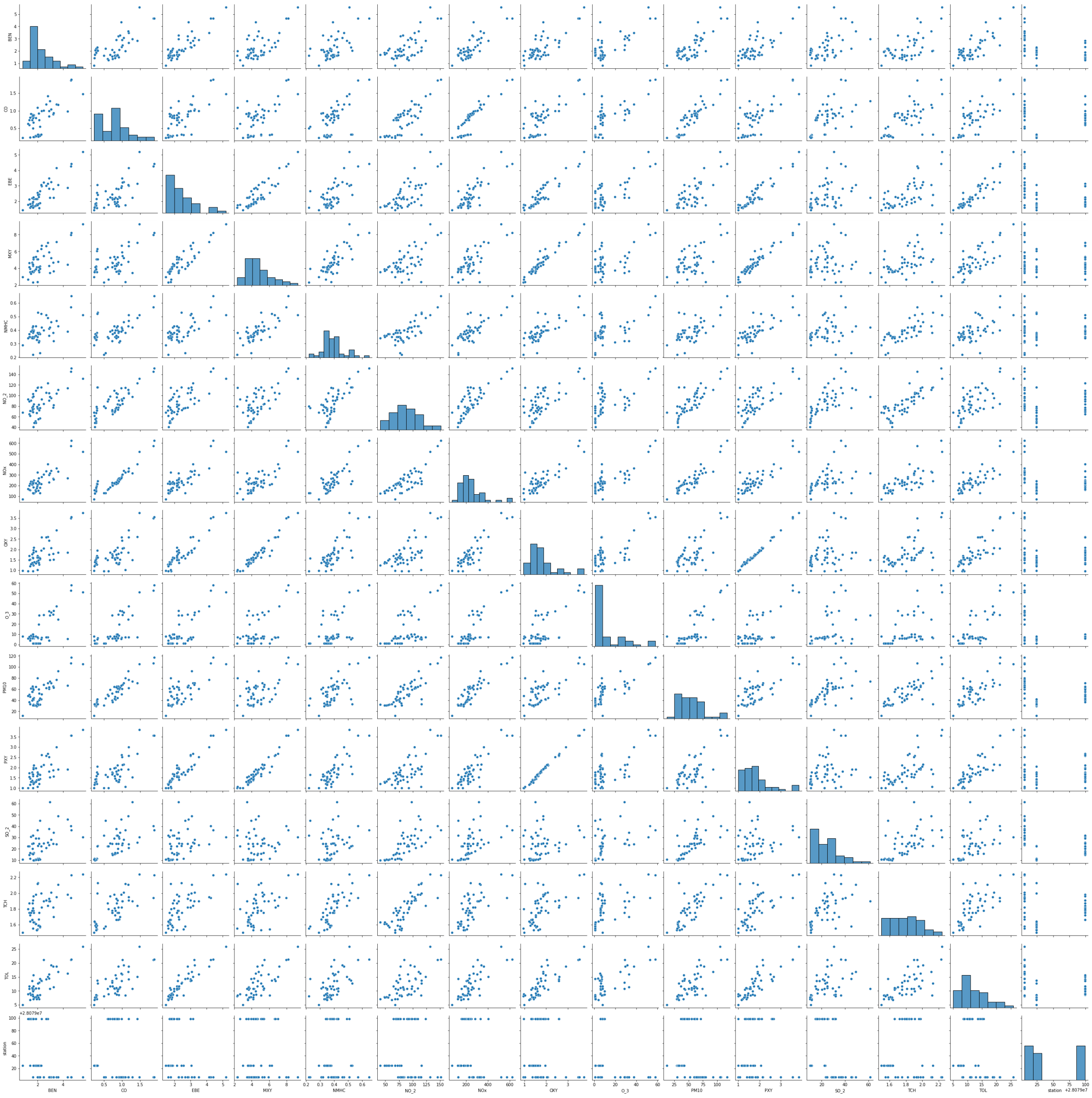
# EDA AND VISUALIZATION

In [22]:

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

Out[22]:

<seaborn.axisgrid.PairGrid at 0x220851bf4f0>



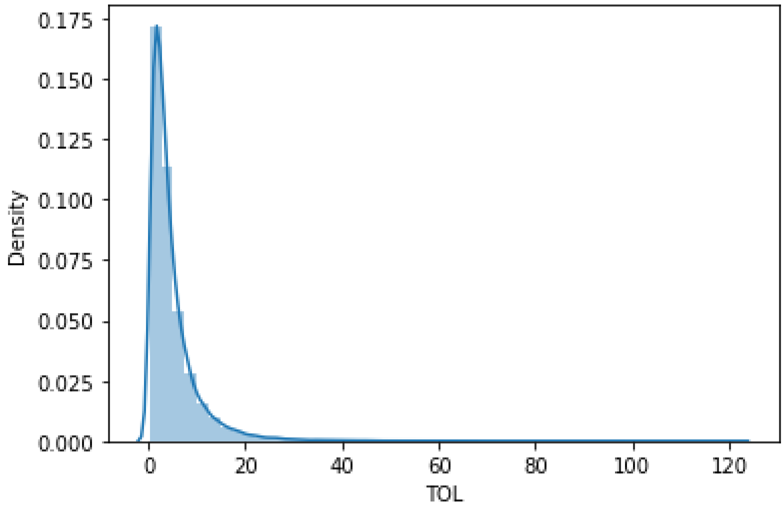
In [23]:

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

```
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[23]:

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

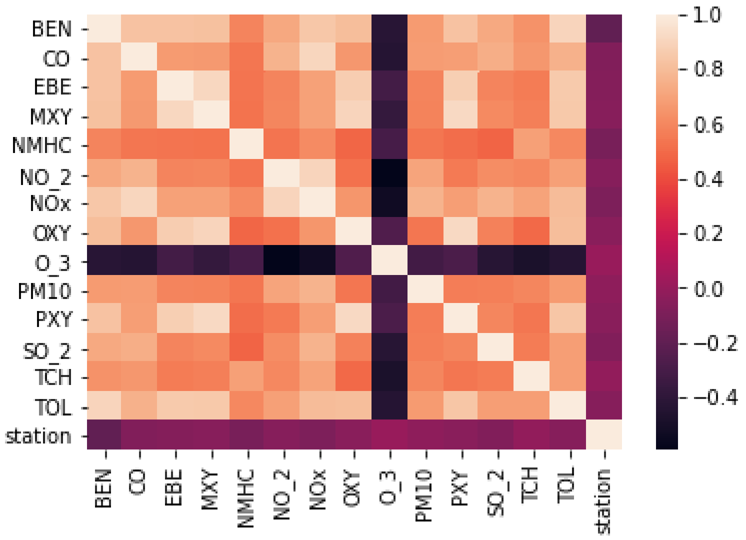



In [24]:

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

Out[24]:

```
<AxesSubplot:>
```




# TO TRAIN THE MODEL AND MODEL BULDING

In [25]:

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

In [26]:

```
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 [27]:

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

Out[27]:

```
LinearRegression()
```

In [28]:

```
lr.intercept_
```

Out[28]:

```
28079009.445346206
```

In [29]:

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

Out[29]:

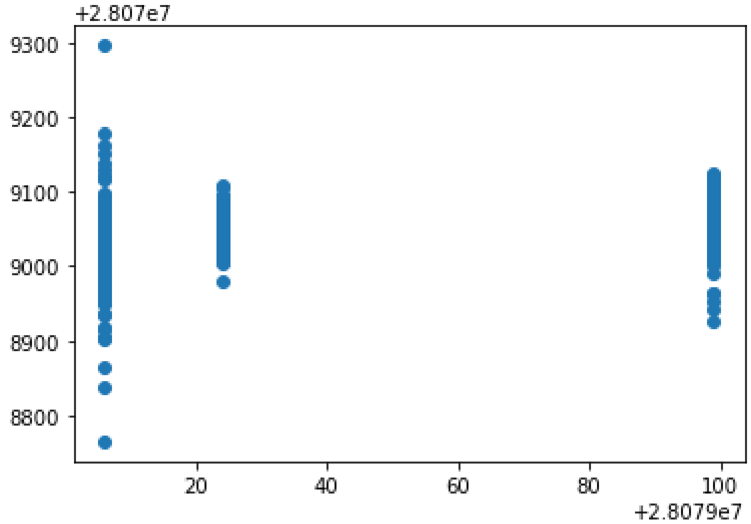
| | Co-efficient |
|---|---|
| BEN | -33.295002 |
| CO | 18.460482 |
| EBE | 0.804154 |
| MXY | -1.028983 |
| NMHC | -39.893319 |
| NO_2 | 0.107691 |
| NOx | -0.033843 |
| OXY | 5.073755 |
| O_3 | -0.026383 |
| PM10 | 0.148810 |
| PXY | 7.137987 |
| SO_2 | 0.184490 |
| TCH | 25.579256 |
| TOL | 3.013003 |

In [30]:

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

Out[30]:

<matplotlib.collections.PathCollection at 0x22094aff3a0>




# ACCURACY

In [31]:

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

Out[31]:

```
0.15658034817295796
```

In [32]:

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

Out[32]:

```
0.16040101066333845
```

# Ridge and Lasso

In [33]:

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

In [34]:

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

Out[34]:

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

# Accuracy(Ridge)

In [35]:

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

Out[35]:

```
0.15651166203018474
```

In [36]:

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

Out[36]:

```
0.1603509695403328
```

In [37]:

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

Out[37]:

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

In [38]:

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

Out[38]:

```
0.011348336385610946
```

# Accuracy(Lasso)

In [39]:

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

Out[39]:

```
0.014633893408507292
```

# 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([-7.99120661,  0.        , -0.        ,  0.09725735, -0.        ,
        0.05781774, -0.05434256,  0.61204634, -0.05206503,  0.17822584,
        0.7630782 , -0.        ,  0.        ,  0.92763063])
```

In [42]:

```
en.intercept_
```

Out[42]:

```
28079045.32997434
```

In [43]:

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

In [44]:

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

Out[44]:

```
0.06558933566008651
```

# 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)))
```

```
36.73147362190291
1543.4894917284475
39.28726882500803
```

# 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]:

```
(25443, 14)
```

In [49]:

```
target_vector.shape
```

Out[49]:

```
(25443,)
```

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)
```

```
[28079099]
```

In [55]:

```
logr.classes_
```

Out[55]:

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

In [56]:

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

Out[56]:

```
0.8146838030106512
```

In [57]:

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

Out[57]:

```
1.082753977181323e-19
```

In [58]:

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

Out[58]:

```
array([[1.08275398e-19, 1.80383815e-19, 1.00000000e+00]])
```

# 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]:

```
0.8256597417181359
```

In [64]:

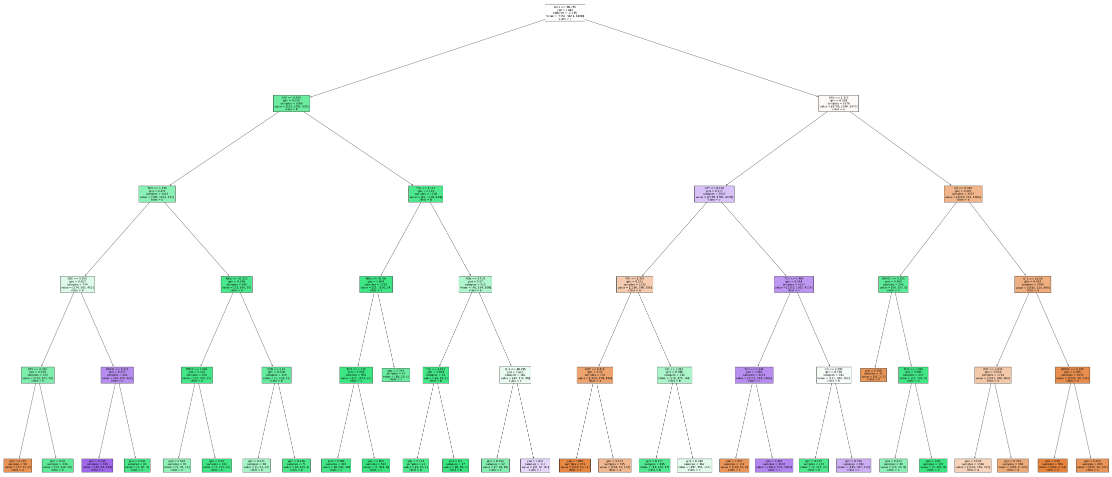
```
rfc_best=grid_search.best_estimator_
```

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
```

```
\nvalue = [609, 2, 14]\nclass = a'),
 Text(4384.285714285714, 181.19999999999982, 'gini = 0.254\nsamples = 69
5\nvalue = [932, 36, 121]\nclass = a')]
```



# Conclusion

## Accuracy

#### ***Linear Regression:0.16040101066333845***

#### ***Ridge Regression:0.1603509695403328***

#### ***Lasso Regression:0.014633893408507292***

#### ***ElasticNet Regression:0.06558933566008651***

#### ***Logistic Regression:0.8146838030106512***

#### ***Random Forest:0.8256597417181359***

### Random Forest is suitable for this dataset