mk 03/08/2023

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

In [2]:
```
df=pd.read_csv(r"C:\Users\user\Downloads\C10_air\csvs_per_year\csvs_per_year\madrid_200
df
```

Out[2]:

	date	BEN	CO	EBE	MXY	NMHC	NO_2	NOx	OXY	O_3	PM10	PXY	SO_2
0	2002-04-01 01:00:00	NaN	1.39	NaN	NaN	NaN	145.100006	352.100006	NaN	6.54	41.990002	NaN	21.320000
1	2002-04-01 01:00:00	1.93	0.71	2.33	6.20	0.15	98.150002	153.399994	2.67	6.85	20.980000	2.53	11.660000
2	2002-04-01 01:00:00	NaN	0.80	NaN	NaN	NaN	103.699997	134.000000	NaN	13.01	28.440001	NaN	13.670000
3	2002-04-01 01:00:00	NaN	1.61	NaN	NaN	NaN	97.599998	268.000000	NaN	5.12	42.180000	NaN	16.990000
4	2002-04-01 01:00:00	NaN	1.90	NaN	NaN	NaN	92.089996	237.199997	NaN	7.28	76.330002	NaN	15.260000
...	...	...	...	...	...	...	...	...	...	...	...	...	..
217291	2002-11-01 00:00:00	4.16	1.14	NaN	NaN	NaN	81.080002	265.700012	NaN	7.21	36.750000	NaN	13.210000
217292	2002-11-01 00:00:00	3.67	1.73	2.89	NaN	0.38	113.900002	373.100006	NaN	5.66	63.389999	NaN	15.640000
217293	2002-11-01 00:00:00	1.37	0.58	1.17	2.37	0.15	65.389999	107.699997	1.30	9.11	9.640000	0.94	5.620000
217294	2002-11-01 00:00:00	4.51	0.91	4.83	10.99	NaN	149.800003	202.199997	1.00	5.75	NaN	5.52	24.219999
217295	2002-11-01 00:00:00	3.11	1.17	3.00	7.77	0.26	80.110001	180.300003	2.25	7.38	29.240000	3.35	12.910000

217296 rows × 16 columns

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', 'PXY', 'SO_2', 'TCH', 'TOL', 'station'],
      dtype='object')
```

In [5]:
```
1 df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 32381 entries, 1 to 217295
Data columns (total 16 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   date     32381 non-null  object 
 1   BEN      32381 non-null  float64
 2   CO       32381 non-null  float64
 3   EBE      32381 non-null  float64
 4   MXY      32381 non-null  float64
 5   NMHC     32381 non-null  float64
 6   NO_2     32381 non-null  float64
 7   NOx      32381 non-null  float64
 8   OXY      32381 non-null  float64
 9   O_3      32381 non-null  float64
 10  PM10     32381 non-null  float64
 11  PXY      32381 non-null  float64
 12  SO_2     32381 non-null  float64
 13  TCH      32381 non-null  float64
 14  TOL      32381 non-null  float64
 15  station  32381 non-null  int64  
dtypes: float64(14), int64(1), object(1)
memory usage: 4.2+ MB
```

In [6]:
```
1 data=df[['BEN', 'TOL', 'TCH']]
2 data
```

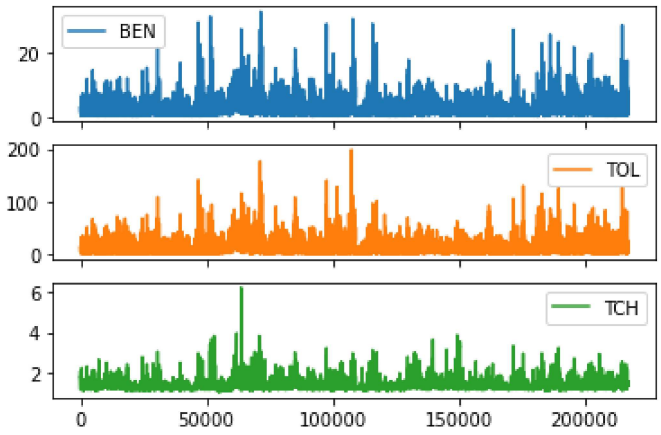
Out[6]:

	BEN	TOL	TCH
1	1.93	10.98	1.82
5	3.19	15.60	1.83
22	2.02	7.32	1.54
24	3.02	11.42	1.79
26	2.02	10.60	2.08
...	...	...	...
217269	1.24	4.45	1.36
217271	3.13	15.10	1.53
217273	2.50	16.65	1.34
217293	1.37	4.33	1.43
217295	3.11	15.51	1.54

32381 rows × 3 columns

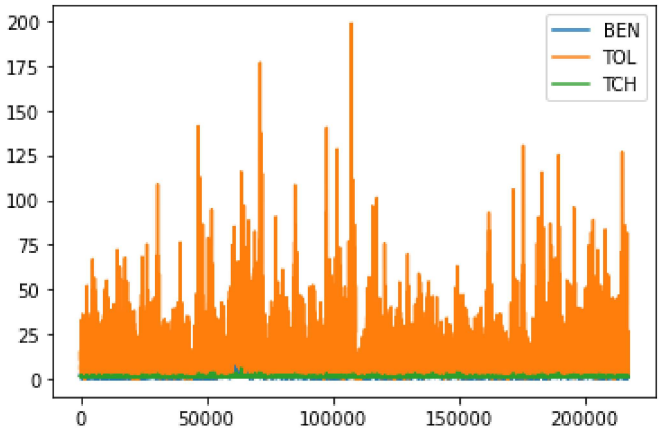
In [7]:
```
1 data.plot.line(subplots=True)
```

Out[7]:
```
array([<AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>], dtype=object)
```



In [8]:
```
1 data.plot.line()
```

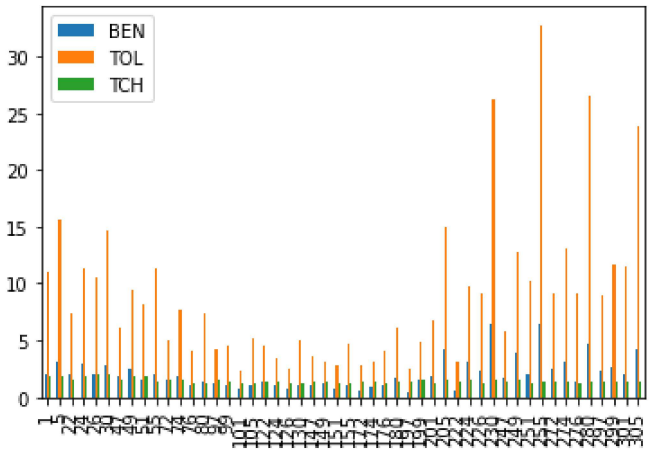
Out[8]:
```
<AxesSubplot:>
```



In [9]:
```
1 b=data[0:50]
```

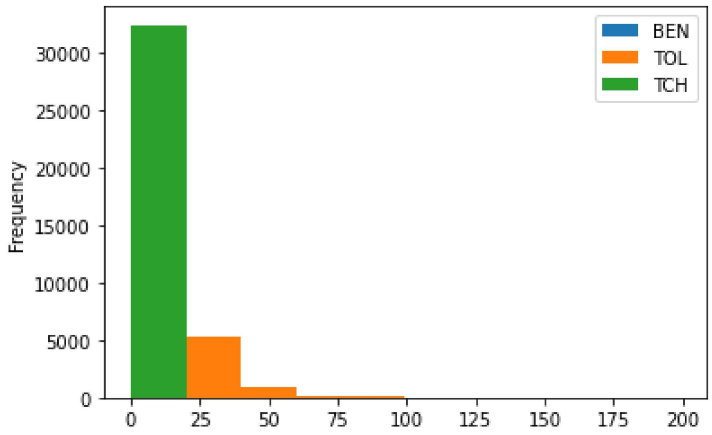
In [10]:
```
1 b.plot.bar()
```

Out[10]:
```
<AxesSubplot:>
```



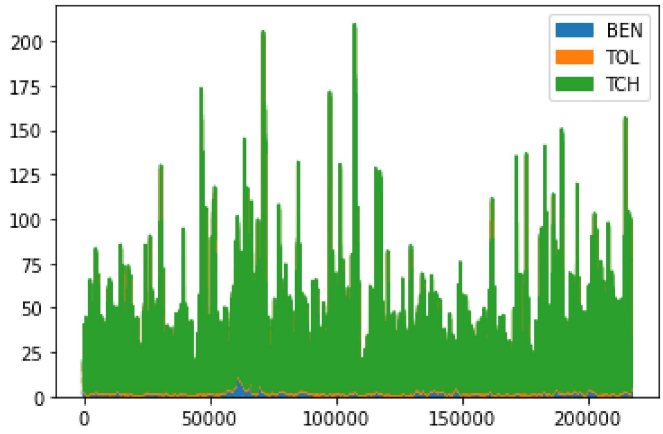
In [11]:
```
1 data.plot.hist()
```

Out[11]: <AxesSubplot:ylabel='Frequency'>



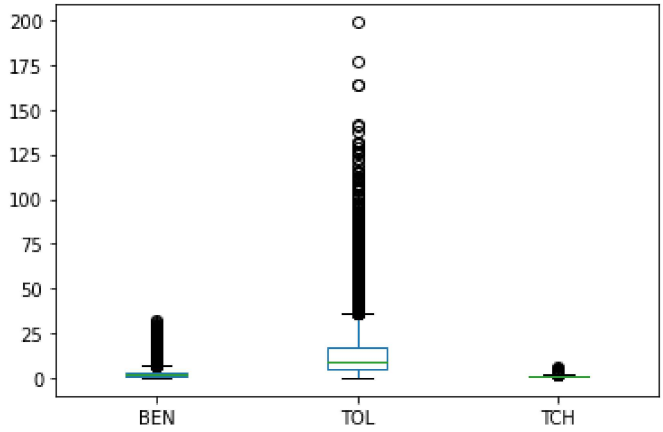
In [12]:
```
1 data.plot.area()
```

Out[12]: <AxesSubplot:>



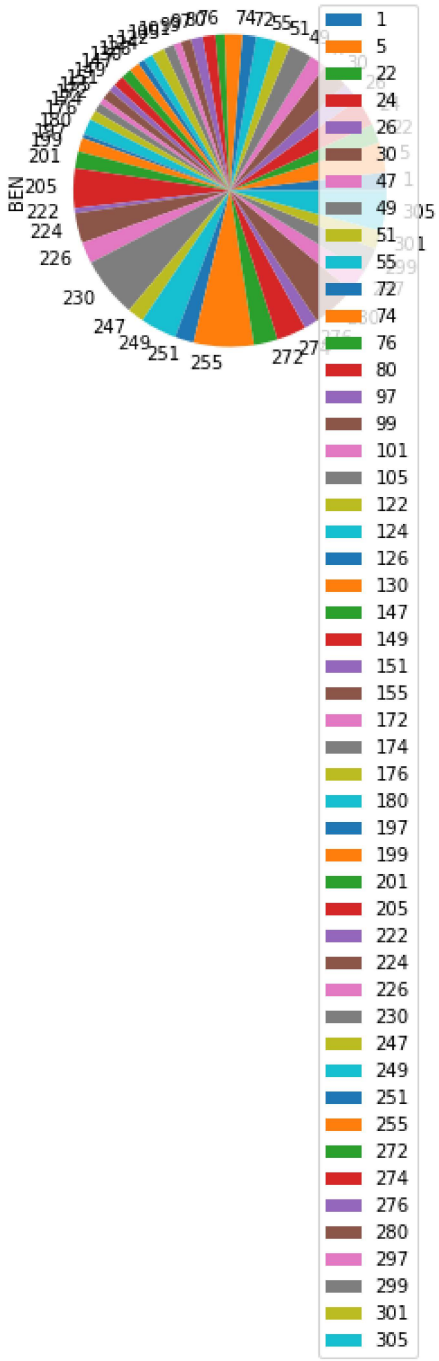
In [13]:
```
1 data.plot.box()
```

Out[13]: <AxesSubplot:>



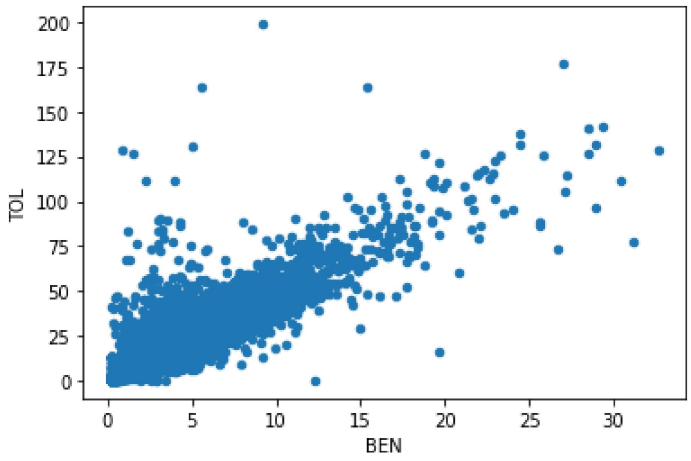
In [14]:
```
1 b.plot.pie(y='BEN' )
```

Out[14]: <AxesSubplot:ylabel='BEN'>



In [15]:
```
1 data.plot.scatter(x='BEN' ,y='TOL')
```

Out[15]: <AxesSubplot:xlabel='BEN', ylabel='TOL'>



In [16]:
```
1 df.describe()
```

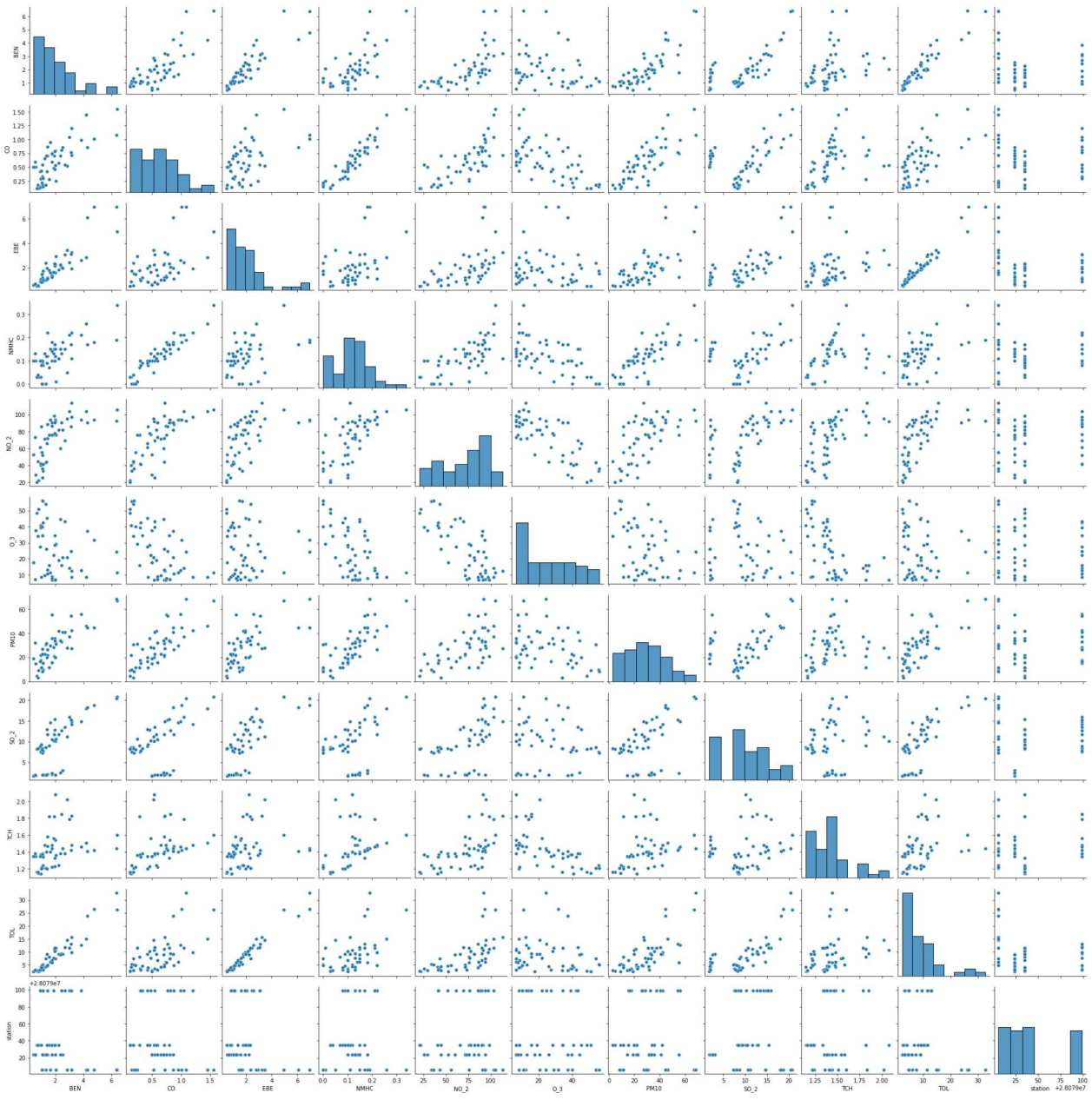
Out[16]:

	BEN	CO	EBE	MXY	NMHC	NO_2	NOx	
count	32381.000000	32381.000000	32381.000000	32381.000000	32381.000000	32381.000000	32381.000000	32381
mean	2.479155	0.787323	2.914004	7.013636	0.155827	58.936796	126.009340	3
std	2.280959	0.610810	2.667881	6.774365	0.135731	31.472733	114.035078	2
min	0.180000	0.000000	0.180000	0.190000	0.000000	0.890000	1.710000	0
25%	0.970000	0.420000	1.140000	2.420000	0.080000	35.660000	48.720001	1
50%	1.840000	0.620000	2.130000	5.140000	0.130000	57.160000	96.830002	2
75%	3.250000	0.980000	3.830000	9.420000	0.200000	78.769997	167.500000	4
max	32.660000	8.460000	41.740002	99.879997	2.700000	263.600006	1336.000000	76

In [18]:
```
1 df1=df[['date', 'BEN', 'CO', 'EBE', 'NMHC', 'NO_2', 'O_3', 'PM10',
2 'SO_2', 'TCH', 'TOL', 'station']]
```

In [19]:
```
1 sns.pairplot(df1[0:50])
```

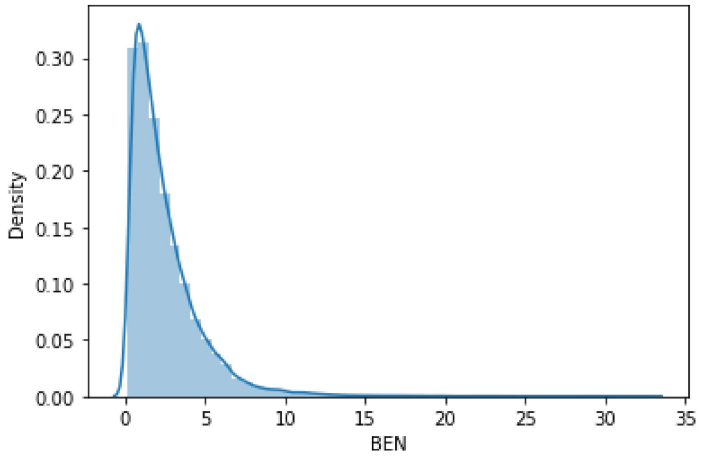
Out[19]: <seaborn.axisgrid.PairGrid at 0x260f3977520>



In [20]:
```
1 sns.distplot(df1['BEN'])
```

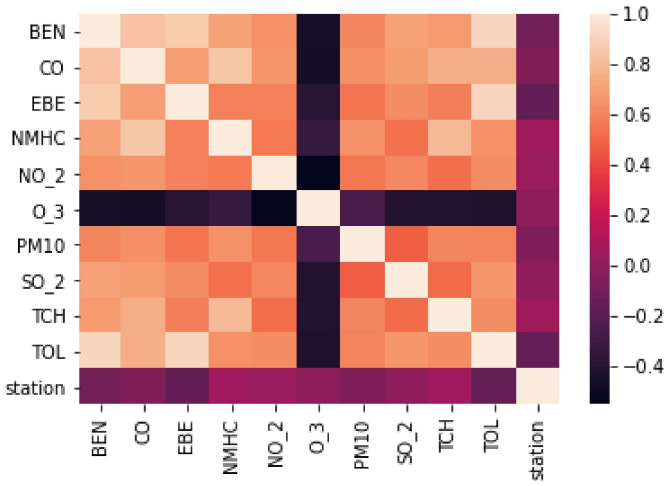
```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `
distplot` is a deprecated function and will be removed in a future version. Please adapt y
our code to use either `displot` (a figure-level function with similar flexibility) or `hi
stplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[20]: <AxesSubplot:xlabel='BEN', ylabel='Density'>



In [21]:
```
1 sns.heatmap(df1.corr())
```

Out[21]: <AxesSubplot:>



In [23]:
```
1 x=df[['BEN', 'CO', 'EBE', 'NMHC','NO_2', 'O_3', 'PM10',
2 'SO_2', 'TCH', 'TOL']]
3 y=df['station']
```

In [24]:
```
1 from sklearn.model_selection import train_test_split
2 x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
```

In [25]:
```
1 from sklearn.linear_model import LinearRegression
2 lr=LinearRegression()
3 lr.fit(x_train,y_train)
```

Out[25]: LinearRegression()

In [26]:
```
1 lr.intercept_
```

Out[26]: 28079002.638303623

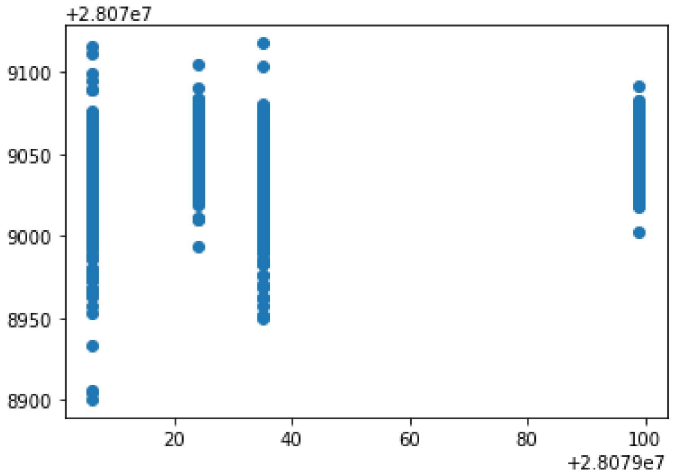
In [27]:
```
1 coeff=pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
2 coeff
```

Out[27]:

	Co-efficient
BEN	2.594159
CO	-21.875852
EBE	-2.073236
NMHC	78.858291
NO_2	0.229989
O_3	0.000040
PM10	-0.160225
SO_2	0.467244
TCH	31.525011
TOL	-0.998069

In [28]:
```
1 prediction =lr.predict(x_test)
2 plt.scatter(y_test,prediction)
```

Out[28]: <matplotlib.collections.PathCollection at 0x26081c04190>



In [29]:
```
1 lr.score(x_test,y_test)
```

Out[29]: 0.1362998219995376

In [30]:
```
1 lr.score(x_train,y_train)
```

Out[30]: 0.12314091359623547

In [31]:
```
1 from sklearn.linear_model import Ridge,Lasso
```

In [32]:
```
rr=Ridge(alpha=10)
rr.fit(x_train,y_train)
```

Out[32]:
```
Ridge(alpha=10)
```

In [33]:
```
rr.score(x_test,y_test)
```

Out[33]:
```
0.1353672419009878
```

In [34]:
```
rr.score(x_train,y_train)
```

Out[34]:
```
0.122953205809053
```

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]:
```
0.05884379733131284
```

In [37]:
```
la.score(x_train,y_train)
```

Out[37]:
```
0.056550800067747375
```

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([ 0.80360807,  0.        , -1.04511452,  0.05341397,  0.22009593,
       -0.00419588, -0.0224454 ,  0.33499834,  0.85961246, -0.89121427])
```

In [40]:
```
en.intercept_
```

Out[40]:
```
28079038.08829956
```

In [41]:
```
prediction=en.predict(x_test)
```

In [42]:
```
en.score(x_test,y_test)
```

Out[42]:
```
0.06896982483407044
```

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)))
```

```
29.19207120339817
1163.9954947718343
34.117378193112
```

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]: (32381, 10)

In [47]:
```
target_vector.shape
```

Out[47]: (32381,)

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)
```

```
[28079006]
```

In [53]:
```
logr.classes_
```

Out[53]: array([28079006, 28079024, 28079035, 28079099], dtype=int64)

In [54]:
```
logr.score(fs,target_vector)
```

Out[54]: 0.7608782928260399

In [55]:
```
logr.predict_proba(observation)[0][0]
```

Out[55]: 0.9998759853067379

In [56]:
```
logr.predict_proba(observation)
```

Out[56]: array([[9.99875985e-01, 2.34979379e-50, 1.24014421e-04, 2.71856788e-10]])

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]:
```
0.7857584046589605
```

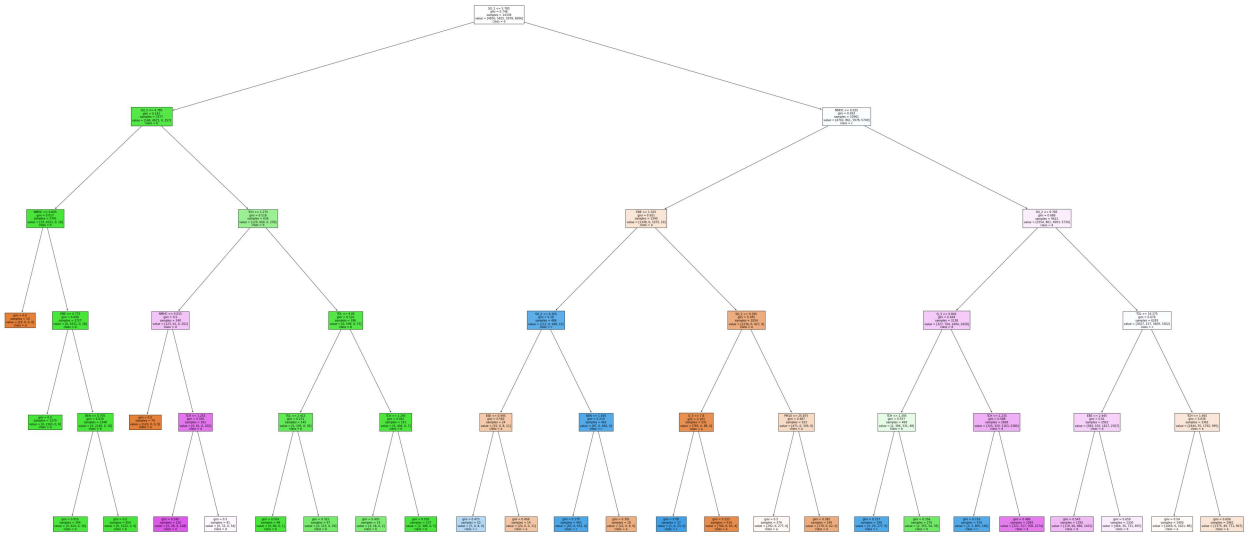
In [62]:
```
rfc_best=grid_search.best_estimator_
```

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']
```

Out[63]:
```
[Text(1796.76, 1993.2, 'SO_2 <= 5.785\ngini = 0.748\nsamples = 14338\nvalue = [4850, 5832,
5978, 6006]\nclass = d'),
 Text(558.0, 1630.8000000000002, 'SO_2 <= 4.785\ngini = 0.142\nsamples = 3377\nvalue = [14
8, 4971, 0, 257]\nclass = b'),
 Text(178.56, 1268.4, 'NMHC <= 0.005\ngini = 0.017\nsamples = 2741\nvalue = [19, 4311, 0,
18]\nclass = b'),
 Text(89.28, 906.0, 'gini = 0.0\nsamples = 14\nvalue = [19, 0, 0, 0]\nclass = a'),
 Text(267.84000000000003, 906.0, 'EBE <= 0.775\ngini = 0.008\nsamples = 2727\nvalue = [0,
4311, 0, 18]\nclass = b'),
 Text(178.56, 543.5999999999999, 'gini = 0.0\nsamples = 1379\nvalue = [0, 2165, 0, 0]\ncla
ss = b'),
 Text(357.12, 543.5999999999999, 'BEN <= 0.705\ngini = 0.016\nsamples = 1348\nvalue = [0,
2146, 0, 18]\nclass = b'),
 Text(267.84000000000003, 181.19999999999982, 'gini = 0.055\nsamples = 394\nvalue = [0, 62
4, 0, 18]\nclass = b'),
 Text(446.4, 181.19999999999982, 'gini = 0.0\nsamples = 954\nvalue = [0, 1522, 0, 0]\nclas
s = b'),
 Text(937.44, 1268.4, 'TCH <= 1.275\ngini = 0.518\nsamples = 636\nvalue = [129, 660, 0, 23
9]\nclass = b'),
 Text(624.96, 906.0, 'NMHC <= 0.015\ngini = 0.6\nsamples = 240\nvalue = [123, 61, 0, 202]
\nclass = d'),
 Text(535.6800000000001, 543.5999999999999, 'gini = 0.0\nsamples = 79\nvalue = [123, 0, 0,
0]\nclass = a'),
 Text(714.24, 543.5999999999999, 'TCH <= 1.255\ngini = 0.356\nsamples = 161\nvalue = [0, 6
1, 0, 202]\nclass = d'),
 Text(624.96, 181.19999999999982, 'gini = 0.245\nsamples = 120\nvalue = [0, 28, 0, 168]\nc
lass = d'),
 Text(803.52, 181.19999999999982, 'gini = 0.5\nsamples = 41\nvalue = [0, 33, 0, 34]\nclass
= d'),
 Text(1249.92, 906.0, 'TOL <= 4.85\ngini = 0.126\nsamples = 396\nvalue = [6, 599, 0, 37]\n
class = b'),
 Text(1071.3600000000001, 543.5999999999999, 'TOL <= 2.415\ngini = 0.231\nsamples = 145\nv
alue = [0, 195, 0, 30]\nclass = b'),
 Text(982.08, 181.19999999999982, 'gini = 0.024\nsamples = 48\nvalue = [0, 80, 0, 1]\nclas
s = b'),
 Text(1160.64, 181.19999999999982, 'gini = 0.322\nsamples = 97\nvalue = [0, 115, 0, 29]\nc
lass = b'),
 Text(1428.48, 543.5999999999999, 'TCH <= 1.295\ngini = 0.061\nsamples = 251\nvalue = [6,
404, 0, 7]\nclass = b'),
 Text(1339.2, 181.19999999999982, 'gini = 0.403\nsamples = 14\nvalue = [4, 18, 0, 2]\nclas
s = b'),
 Text(1517.76, 181.19999999999982, 'gini = 0.035\nsamples = 237\nvalue = [2, 386, 0, 5]\nc
lass = b'),
 Text(3035.52, 1630.8000000000002, 'NMHC <= 0.035\ngini = 0.693\nsamples = 10961\nvalue =
[4702, 861, 5978, 5749]\nclass = c'),
 Text(2321.28, 1268.4, 'EBE <= 1.325\ngini = 0.501\nsamples = 1540\nvalue = [1348, 0, 107
5, 19]\nclass = a'),
 Text(1964.16, 906.0, 'SO_2 <= 6.365\ngini = 0.28\nsamples = 486\nvalue = [112, 0, 648, 1
5]\nclass = c'),
 Text(1785.6, 543.5999999999999, 'EBE <= 0.995\ngini = 0.582\nsamples = 24\nvalue = [25,
0, 8, 11]\nclass = a'),
 Text(1696.32, 181.19999999999982, 'gini = 0.473\nsamples = 10\nvalue = [5, 0, 8, 0]\nclas
s = c'),
 Text(1874.88, 181.19999999999982, 'gini = 0.458\nsamples = 14\nvalue = [20, 0, 0, 11]\ncl
ass = a'),
 Text(2142.7200000000003, 543.5999999999999, 'BEN <= 1.695\ngini = 0.219\nsamples = 462\nv
alue = [87, 0, 640, 4]\nclass = c'),
 Text(2053.44, 181.19999999999982, 'gini = 0.179\nsamples = 443\nvalue = [65, 0, 632, 4]\n
class = c'),
 Text(2232.0, 181.19999999999982, 'gini = 0.391\nsamples = 19\nvalue = [22, 0, 8, 0]\nclas
s = a'),
 Text(2678.4, 906.0, 'SO_2 <= 9.395\ngini = 0.385\nsamples = 1054\nvalue = [1236, 0, 427,
4]\nclass = a'),
```

```
 Text(2499.84, 543.5999999999999, 'O_3 <= 7.8\ngini = 0.193\nsamples = 531\nvalue = [765,
0, 88, 4]\nclass = a'),
 Text(2410.56, 181.19999999999982, 'gini = 0.08\nsamples = 17\nvalue = [1, 0, 23, 0]\nclas
s = c'),
 Text(2589.12, 181.19999999999982, 'gini = 0.153\nsamples = 514\nvalue = [764, 0, 65, 4]\n
class = a'),
 Text(2856.96, 543.5999999999999, 'PM10 <= 25.875\ngini = 0.487\nsamples = 523\nvalue = [4
71, 0, 339, 0]\nclass = a'),
 Text(2767.68, 181.19999999999982, 'gini = 0.5\nsamples = 374\nvalue = [292, 0, 277, 0]\nc
lass = a'),
 Text(2946.2400000000002, 181.19999999999982, 'gini = 0.382\nsamples = 149\nvalue = [179,
0, 62, 0]\nclass = a'),
 Text(3749.76, 1268.4, 'SO_2 <= 9.785\ngini = 0.688\nsamples = 9421\nvalue = [3354, 861, 4
903, 5730]\nclass = d'),
 Text(3392.64, 906.0, 'O_3 <= 9.845\ngini = 0.644\nsamples = 3138\nvalue = [327, 704, 149
4, 2428]\nclass = d'),
 Text(3214.08, 543.5999999999999, 'TCH <= 1.395\ngini = 0.557\nsamples = 469\nvalue = [2,
384, 331, 48]\nclass = b'),
 Text(3124.8, 181.19999999999982, 'gini = 0.217\nsamples = 199\nvalue = [0, 29, 277, 9]\nc
lass = c'),
 Text(3303.36, 181.19999999999982, 'gini = 0.356\nsamples = 270\nvalue = [2, 355, 54, 39]
\nclass = b'),
 Text(3571.2, 543.5999999999999, 'TCH <= 1.235\ngini = 0.588\nsamples = 2669\nvalue = [32
5, 320, 1163, 2380]\nclass = d'),
 Text(3481.92, 181.19999999999982, 'gini = 0.216\nsamples = 576\nvalue = [3, 3, 805, 106]
\nclass = c'),
 Text(3660.48, 181.19999999999982, 'gini = 0.486\nsamples = 2093\nvalue = [322, 317, 358,
2274]\nclass = d'),
 Text(4106.88, 906.0, 'TOL <= 16.275\ngini = 0.676\nsamples = 6283\nvalue = [3027, 157, 34
09, 3302]\nclass = c'),
 Text(3928.32, 543.5999999999999, 'EBE <= 2.445\ngini = 0.61\nsamples = 2922\nvalue = [58
3, 102, 1617, 2307]\nclass = d'),
 Text(3839.04, 181.19999999999982, 'gini = 0.543\nsamples = 1592\nvalue = [119, 66, 886, 1
452]\nclass = d'),
 Text(4017.6, 181.19999999999982, 'gini = 0.659\nsamples = 1330\nvalue = [464, 36, 731, 85
5]\nclass = d'),
 Text(4285.4400000000005, 543.5999999999999, 'TCH <= 1.465\ngini = 0.636\nsamples = 3361\n
value = [2444, 55, 1792, 995]\nclass = a'),
 Text(4196.16, 181.19999999999982, 'gini = 0.54\nsamples = 1400\nvalue = [1069, 6, 1021, 8
8]\nclass = a'),
 Text(4374.72, 181.19999999999982, 'gini = 0.656\nsamples = 1961\nvalue = [1375, 49, 771,
907]\nclass = a')]
```



Conclusion

Linear Regression=0.8069102549582842

Ridge Regression=0.709408577546153

Lasso Regression=0.4113700257643299

ElasticNet Regression=0.4901906715101415

Logistic Regression=0.9888206926786497

Random Forest=0.9921700776675565

Random Forest is suitable for this dataset