Vijay(P17) 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_2017.csv")
df
```

Out[2]:

	date	BEN	CH4	CO	EBE	NMHC	NO	NO_2	NOx	O_3	PM10	PM25	SO_2	TCH	TOL	station
0	2017-06-01 01:00:00	NaN	NaN	0.3	NaN	NaN	4.0	38.0	NaN	NaN	NaN	NaN	5.0	NaN	NaN	28079004
1	2017-06-01 01:00:00	0.6	NaN	0.3	0.4	0.08	3.0	39.0	NaN	71.0	22.0	9.0	7.0	1.4	2.9	28079008
2	2017-06-01 01:00:00	0.2	NaN	NaN	0.1	NaN	1.0	14.0	NaN	NaN	NaN	NaN	NaN	NaN	0.9	28079011
3	2017-06-01 01:00:00	NaN	NaN	0.2	NaN	NaN	1.0	9.0	NaN	91.0	NaN	NaN	NaN	NaN	NaN	28079016
4	2017-06-01 01:00:00	NaN	NaN	NaN	NaN	NaN	1.0	19.0	NaN	69.0	NaN	NaN	2.0	NaN	NaN	28079017
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
210115	2017-08-01 00:00:00	NaN	NaN	0.2	NaN	NaN	1.0	27.0	NaN	65.0	NaN	NaN	NaN	NaN	NaN	28079056
210116	2017-08-01 00:00:00	NaN	NaN	0.2	NaN	NaN	1.0	14.0	NaN	NaN	73.0	NaN	7.0	NaN	NaN	28079057
210117	2017-08-01 00:00:00	NaN	NaN	NaN	NaN	NaN	1.0	4.0	NaN	83.0	NaN	NaN	NaN	NaN	NaN	28079058
210118	2017-08-01 00:00:00	NaN	NaN	NaN	NaN	NaN	1.0	11.0	NaN	78.0	NaN	NaN	NaN	NaN	NaN	28079059
210119	2017-08-01 00:00:00	NaN	NaN	NaN	NaN	NaN	1.0	14.0	NaN	77.0	60.0	NaN	NaN	NaN	NaN	28079060

210120 rows × 16 columns

In [3]:
```
df=df.dropna()
```

In [4]:
```
df.columns
```

Out[4]:
```
Index(['date', 'BEN', 'CH4', 'CO', 'EBE', 'NMHC', 'NO', 'NO_2', 'NOx', 'O_3',
       'PM10', 'PM25', 'SO_2', 'TCH', 'TOL', 'station'],
      dtype='object')
```

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

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4127 entries, 87457 to 158286
Data columns (total 16 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   date     4127 non-null   object 
 1   BEN      4127 non-null   float64
 2   CH4      4127 non-null   float64
 3   CO       4127 non-null   float64
 4   EBE      4127 non-null   float64
 5   NMHC     4127 non-null   float64
 6   NO       4127 non-null   float64
 7   NO_2     4127 non-null   float64
 8   NOx      4127 non-null   float64
 9   O_3      4127 non-null   float64
 10  PM10     4127 non-null   float64
 11  PM25     4127 non-null   float64
 12  SO_2     4127 non-null   float64
 13  TCH      4127 non-null   float64
 14  TOL      4127 non-null   float64
 15  station  4127 non-null   int64  
dtypes: float64(14), int64(1), object(1)
memory usage: 548.1+ KB
```

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

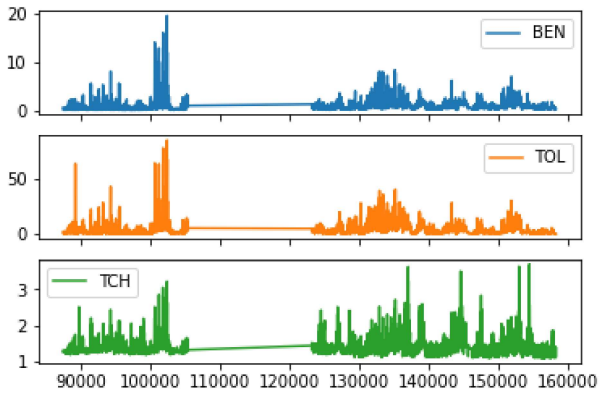
Out[6]:

	BEN	TOL	TCH
87457	0.6	2.3	1.31
87462	0.2	1.1	1.27
87481	0.4	1.3	1.28
87486	0.2	0.8	1.26
87505	0.3	1.0	1.29
...	...	...	...
158238	0.3	0.2	1.14
158257	0.6	0.9	1.41
158262	0.3	0.2	1.14
158281	0.5	0.6	1.39
158286	0.3	0.2	1.14

4127 rows × 3 columns

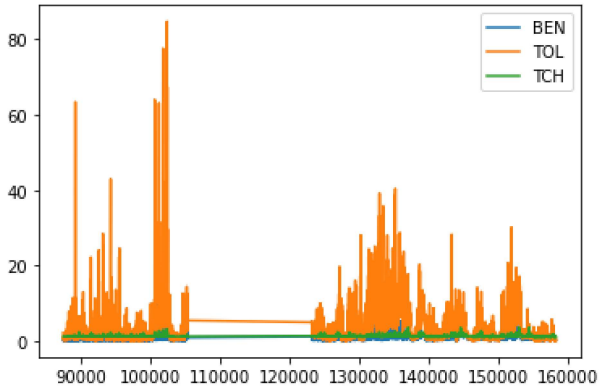
In [7]:
```
1 data.plot.line(subplots=True)
```

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



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

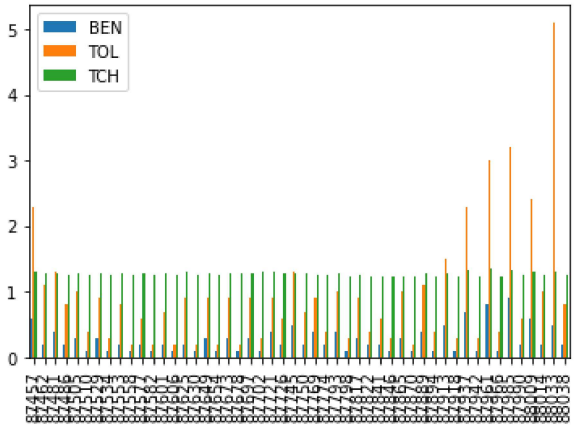
Out[8]:
```
<AxesSubplot:>
```



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

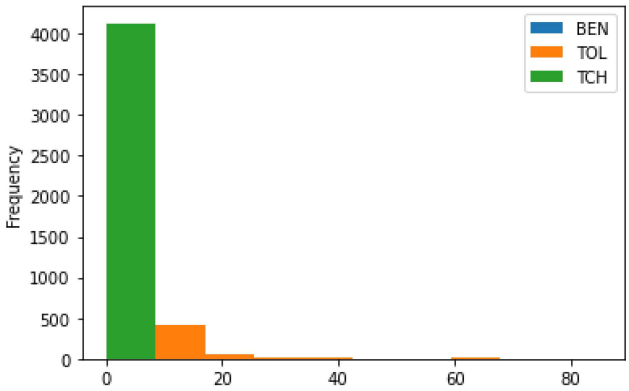
In [10]:
```
1 b.plot.bar()
```

Out[10]: <AxesSubplot:>



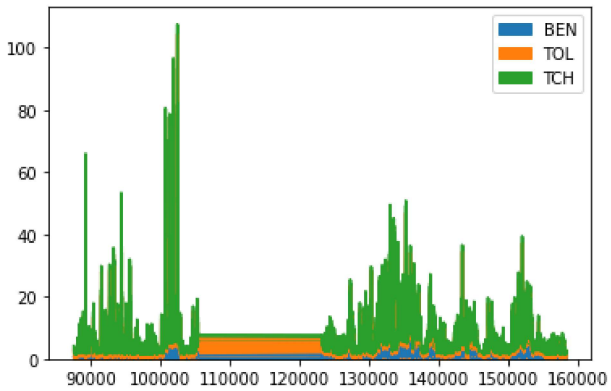
In [11]:
```
1 data.plot.hist()
```

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



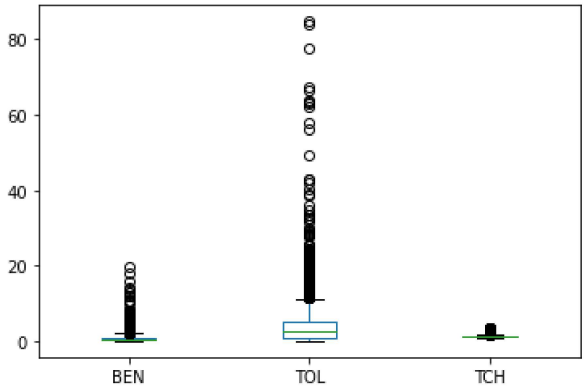
In [12]:
```
1 data.plot.area()
```

Out[12]: <AxesSubplot:>



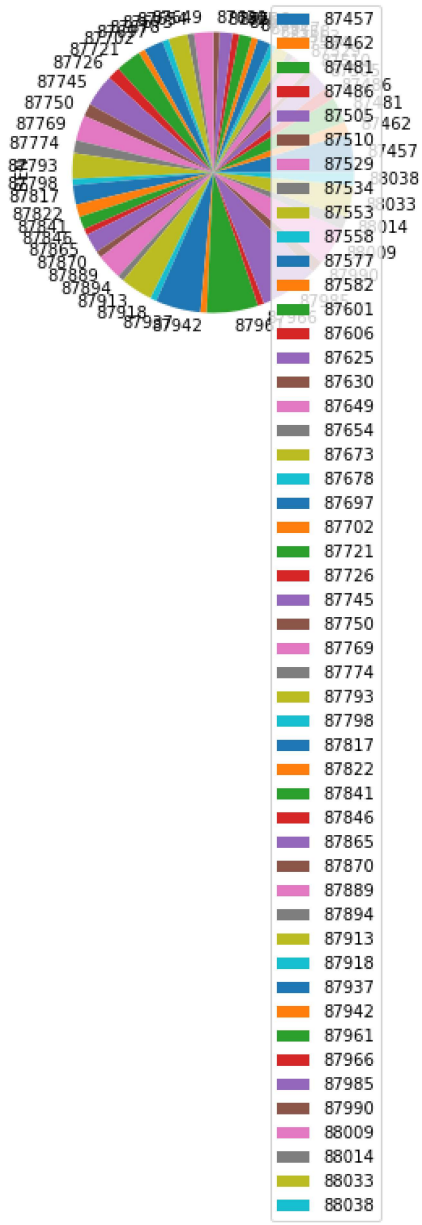
In [13]:
```
1 data.plot.box()
```

Out[13]: <AxesSubplot:>



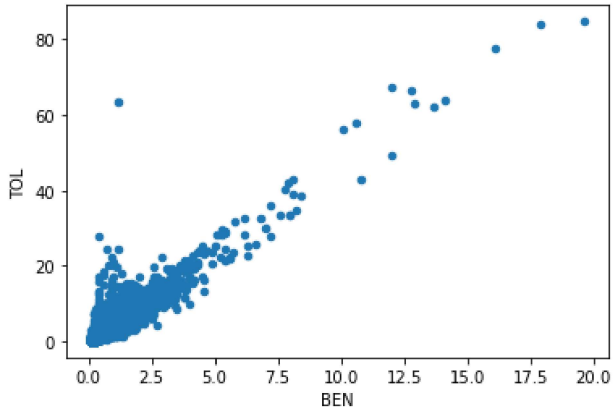
In [14]:
```
1 b.plot.pie(y='BEN' )
```

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()
```

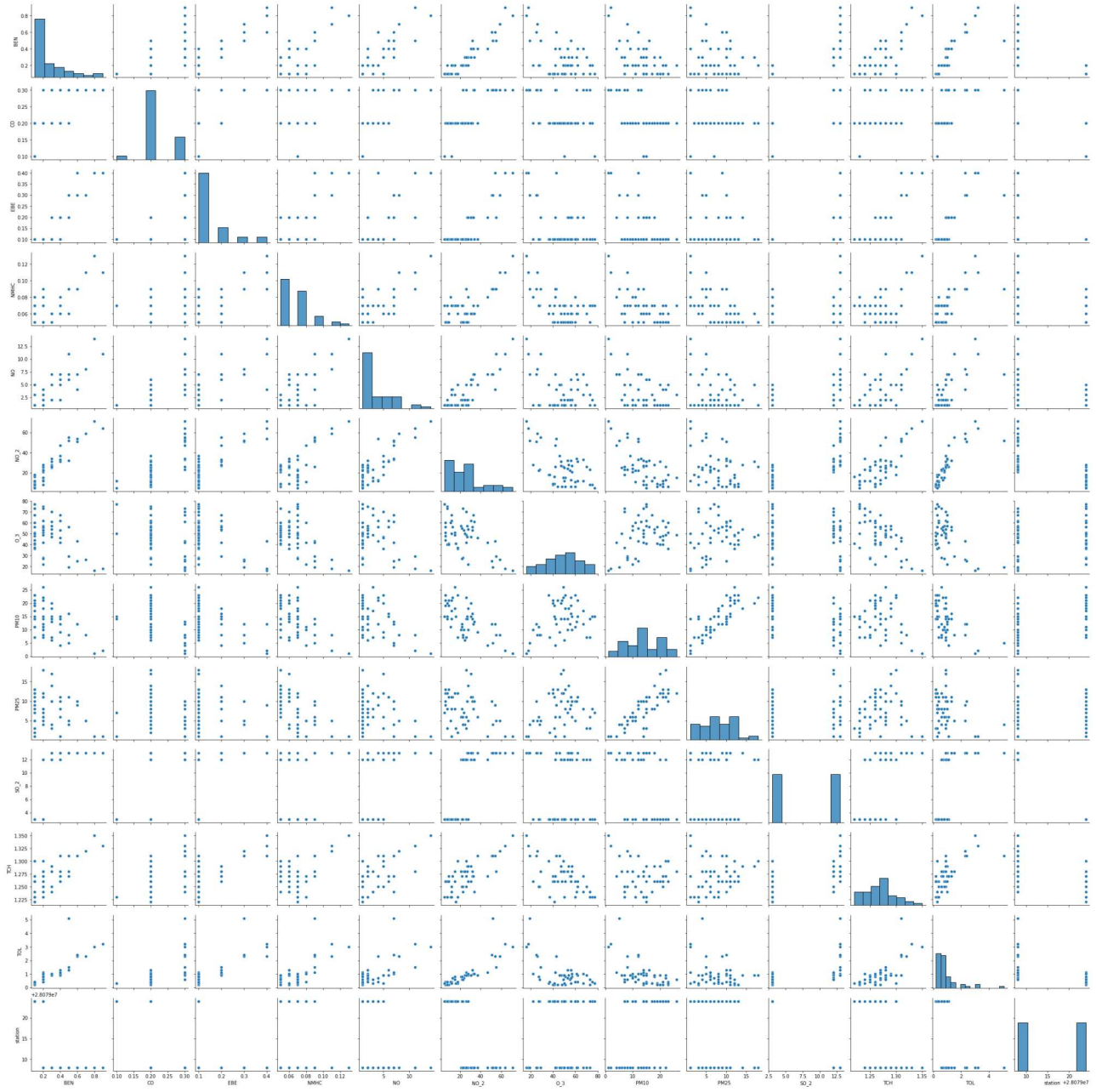
Out[16]:

	BEN	CH4	CO	EBE	NMHC	NO	NO_2	NOx	O_3	
count	4127.000000	4127.000000	4127.000000	4127.000000	4127.000000	4127.000000	4127.000000	4127.000000	4127.000000	4
mean	0.919918	1.323732	0.417858	0.578168	0.097269	41.785316	58.069057	122.125515	28.716501	
std	1.123078	0.215742	0.342871	0.962000	0.094035	71.118499	38.974112	142.828344	25.304909	
min	0.100000	1.100000	0.100000	0.100000	0.000000	1.000000	1.000000	2.000000	1.000000	
25%	0.300000	1.180000	0.200000	0.100000	0.050000	3.000000	30.000000	37.000000	6.000000	
50%	0.600000	1.270000	0.300000	0.300000	0.080000	16.000000	54.000000	80.000000	22.000000	
75%	1.100000	1.400000	0.500000	0.700000	0.110000	50.000000	78.000000	153.000000	46.000000	
max	19.600000	3.630000	4.900000	16.700001	1.420000	879.000000	349.000000	1681.000000	140.000000	

In [17]:
```
1 df1=df[['date', 'BEN', 'CO', 'EBE', 'NMHC', 'NO', 'NO_2', 'O_3', 'PM10', 'PM25',
2 'SO_2', 'TCH', 'TOL', 'station']]
```

In [18]:
```
1 sns.pairplot(df1[0:50])
```

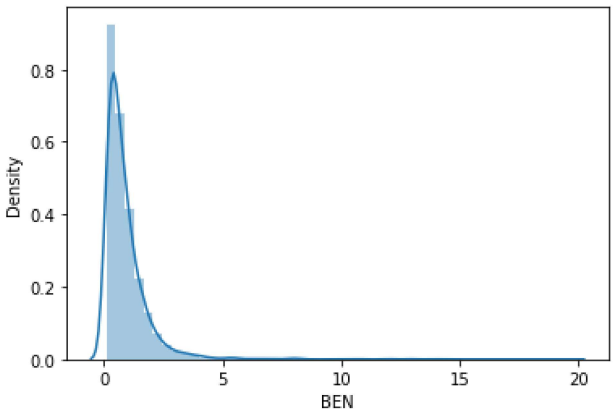
Out[18]: <seaborn.axisgrid.PairGrid at 0x2135c7472b0>



In [19]:
```
1 sns.distplot(df1['BEN'])
```

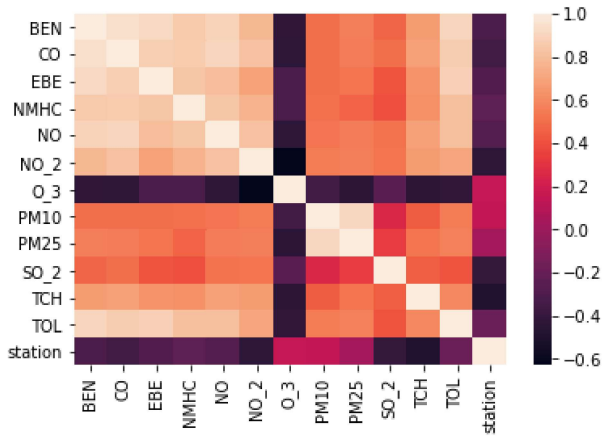
```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is
a deprecated function and will be removed in a future version. Please adapt your code to use either `di
splot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function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

Out[19]: <AxesSubplot:xlabel='BEN', ylabel='Density'>



In [20]:
```
1 sns.heatmap(df1.corr())
```

Out[20]: <AxesSubplot:>



In [21]:
```
1 x=df[['BEN', 'CO', 'EBE', 'NMHC', 'NO', 'NO_2', 'O_3', 'PM10', 'PM25',
2 'SO_2', 'TCH', 'TOL']]
3 y=df['station']
```

In [22]:
```
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 [23]:
```
1 from sklearn.linear_model import LinearRegression
2 lr=LinearRegression()
3 lr.fit(x_train,y_train)
```

Out[23]: LinearRegression()

In [24]:
```
1 lr.intercept_
```

Out[24]: 28079042.124266382

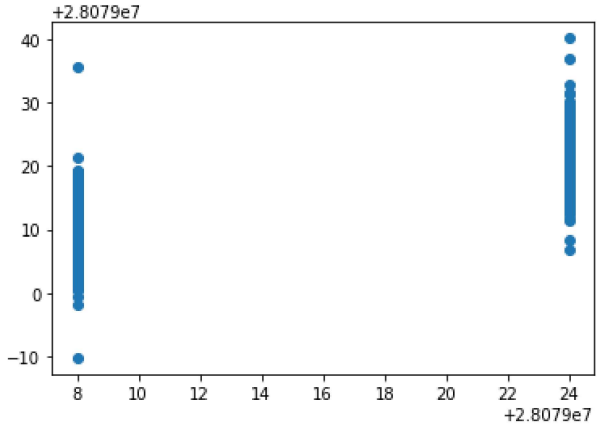
In [25]:
```
coeff=pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
coeff
```

Out[25]:

	Co-efficient
BEN	-0.582697
CO	-4.505782
EBE	-1.900084
NMHC	25.454120
NO	0.050906
NO_2	-0.183283
O_3	-0.090455
PM10	0.418976
PM25	-0.153112
SO_2	-0.249782
TCH	-13.825667
TOL	0.312383

In [26]:
```
prediction =lr.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[26]: <matplotlib.collections.PathCollection at 0x21367703a90>



In [27]:
```
lr.score(x_test,y_test)
```

Out[27]: 0.6509798297639944

In [28]:
```
lr.score(x_train,y_train)
```

Out[28]: 0.6277182624521873

In [29]:
```
from sklearn.linear_model import Ridge,Lasso
```

In [30]:
```
rr=Ridge(alpha=10)
rr.fit(x_train,y_train)
```

Out[30]: Ridge(alpha=10)

In [31]:
```
rr.score(x_test,y_test)
```

Out[31]: 0.6388430689805904

In [32]:
```
rr.score(x_train,y_train)
```

Out[32]: 0.6191897548217457

In [33]:
```
la=Lasso(alpha=10)
la.fit(x_train,y_train)
```

Out[33]:
```
Lasso(alpha=10)
```

In [34]:
```
la.score(x_test,y_test)
```

Out[34]:
```
0.4106090579902061
```

In [35]:
```
la.score(x_train,y_train)
```

Out[35]:
```
0.3977464968218405
```

In [36]:
```
from sklearn.linear_model import ElasticNet
en=ElasticNet()
en.fit(x_train,y_train)
```

Out[36]:
```
ElasticNet()
```

In [37]:
```
en.coef_
```

Out[37]:
```
array([-0.        , -0.        , -0.        ,  0.        ,  0.03190586,
       -0.20368023, -0.08462839,  0.55000139, -0.40450207, -0.30078072,
       -0.        ,  0.        ])
```

In [38]:
```
en.intercept_
```

Out[38]:
```
28079025.257014
```

In [39]:
```
prediction=en.predict(x_test)
```

In [40]:
```
en.score(x_test,y_test)
```

Out[40]:
```
0.5205114372790913
```

In [41]:
```
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)))
```

```
4.723383129836693
30.683889682205763
5.539304079232856
```

In [42]:
```
from sklearn.linear_model import LogisticRegression
```

In [43]:
```
feature_matrix=df[['BEN', 'CO', 'EBE', 'NMHC', 'NO_2', 'O_3',
'PM10', 'SO_2', 'TCH', 'TOL']]
target_vector=df[ 'station']
```

In [44]:
```
feature_matrix.shape
```

Out[44]:
```
(4127, 10)
```

In [45]:
```
target_vector.shape
```

Out[45]:
```
(4127,)
```

In [46]:
```
from sklearn.preprocessing import StandardScaler
```

In [47]:
```
fs=StandardScaler().fit_transform(feature_matrix)
```

In [48]:
```
logr=LogisticRegression(max_iter=10000)
logr.fit(fs,target_vector)
```

Out[48]:
```
LogisticRegression(max_iter=10000)
```

In [49]:
```
observation=[[1,2,3,4,5,6,7,8,9,10]]
```

In [50]:
```
prediction=logr.predict(observation)
print(prediction)
```

```
[28079008]
```

In [51]:
```
logr.classes_
```

Out[51]:
```
array([28079008, 28079024], dtype=int64)
```

In [52]:
```
logr.score(fs,target_vector)
```

Out[52]:
```
0.9437848315968016
```

In [53]:
```
logr.predict_proba(observation)[0][0]
```

Out[53]:
```
0.9999999999725541
```

In [54]:
```
logr.predict_proba(observation)
```

Out[54]:
```
array([[1.00000000e+00, 2.74458959e-11]])
```

In [55]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [56]:
```
rfc=RandomForestClassifier()
rfc.fit(x_train,y_train)
```

Out[56]:
```
RandomForestClassifier()
```

In [57]:
```
parameters={'max_depth':[1,2,3,4,5],
'min_samples_leaf':[5,10,15,20,25],
'n_estimators':[10,20,30,40,50]
}
```

In [58]:
```
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[58]:
```
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 [59]:
```
grid_search.best_score_
```

Out[59]:
```
0.9653739612188366
```

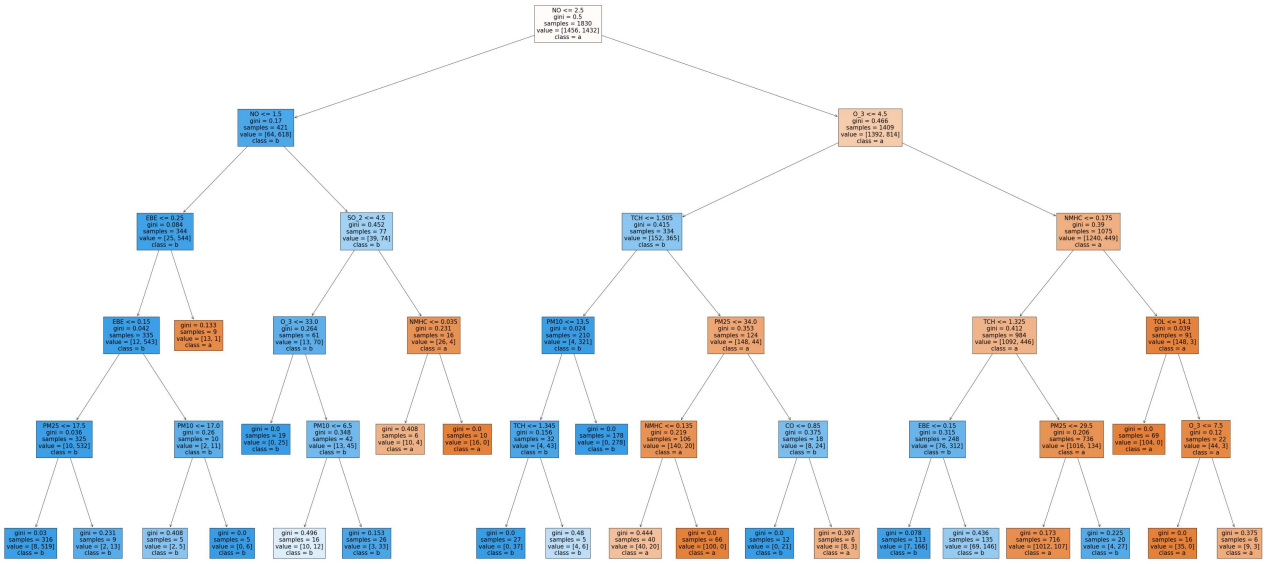
In [60]:
```
rfc_best=grid_search.best_estimator_
```

In [61]:

```
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'],filled=True
```

Out[61]:
```
[Text(1997.0526315789473, 1993.2, 'NO <= 2.5\ngini = 0.5\nsamples = 1830\nvalue = [1456, 1432]\nclass =
a'),
 Text(939.7894736842105, 1630.8000000000002, 'NO <= 1.5\ngini = 0.17\nsamples = 421\nvalue = [64, 618]
\nclass = b'),
 Text(587.3684210526316, 1268.4, 'EBE <= 0.25\ngini = 0.084\nsamples = 344\nvalue = [25, 544]\nclass =
b'),
 Text(469.89473684210526, 906.0, 'EBE <= 0.15\ngini = 0.042\nsamples = 335\nvalue = [12, 543]\nclass =
b'),
 Text(234.94736842105263, 543.5999999999999, 'PM25 <= 17.5\ngini = 0.036\nsamples = 325\nvalue = [10, 5
32]\nclass = b'),
 Text(117.47368421052632, 181.19999999999982, 'gini = 0.03\nsamples = 316\nvalue = [8, 519]\nclass =
b'),
 Text(352.42105263157896, 181.19999999999982, 'gini = 0.231\nsamples = 9\nvalue = [2, 13]\nclass = b'),
 Text(704.8421052631579, 543.5999999999999, 'PM10 <= 17.0\ngini = 0.26\nsamples = 10\nvalue = [2, 11]\n
class = b'),
 Text(587.3684210526316, 181.19999999999982, 'gini = 0.408\nsamples = 5\nvalue = [2, 5]\nclass = b'),
 Text(822.3157894736842, 181.19999999999982, 'gini = 0.0\nsamples = 5\nvalue = [0, 6]\nclass = b'),
 Text(704.8421052631579, 906.0, 'gini = 0.133\nsamples = 9\nvalue = [13, 1]\nclass = a'),
 Text(1292.2105263157894, 1268.4, 'SO_2 <= 4.5\ngini = 0.452\nsamples = 77\nvalue = [39, 74]\nclass =
b'),
 Text(1057.2631578947369, 906.0, 'O_3 <= 33.0\ngini = 0.264\nsamples = 61\nvalue = [13, 70]\nclass =
b'),
 Text(939.7894736842105, 543.5999999999999, 'gini = 0.0\nsamples = 19\nvalue = [0, 25]\nclass = b'),
 Text(1174.7368421052631, 543.5999999999999, 'PM10 <= 6.5\ngini = 0.348\nsamples = 42\nvalue = [13, 45]
\nclass = b'),
 Text(1057.2631578947369, 181.19999999999982, 'gini = 0.496\nsamples = 16\nvalue = [10, 12]\nclass =
b'),
 Text(1292.2105263157894, 181.19999999999982, 'gini = 0.153\nsamples = 26\nvalue = [3, 33]\nclass =
b'),
 Text(1527.157894736842, 906.0, 'NMHC <= 0.035\ngini = 0.231\nsamples = 16\nvalue = [26, 4]\nclass =
a'),
 Text(1409.6842105263158, 543.5999999999999, 'gini = 0.408\nsamples = 6\nvalue = [10, 4]\nclass = a'),
 Text(1644.6315789473683, 543.5999999999999, 'gini = 0.0\nsamples = 10\nvalue = [16, 0]\nclass = a'),
 Text(3054.315789473684, 1630.8000000000002, 'O_3 <= 4.5\ngini = 0.466\nsamples = 1409\nvalue = [1392,
814]\nclass = a'),
 Text(2290.7368421052633, 1268.4, 'TCH <= 1.505\ngini = 0.415\nsamples = 334\nvalue = [152, 365]\nclass
= b'),
 Text(1997.0526315789473, 906.0, 'PM10 <= 13.5\ngini = 0.024\nsamples = 210\nvalue = [4, 321]\nclass =
b'),
 Text(1879.578947368421, 543.5999999999999, 'TCH <= 1.345\ngini = 0.156\nsamples = 32\nvalue = [4, 43]
\nclass = b'),
 Text(1762.1052631578948, 181.19999999999982, 'gini = 0.0\nsamples = 27\nvalue = [0, 37]\nclass = b'),
 Text(1997.0526315789473, 181.19999999999982, 'gini = 0.48\nsamples = 5\nvalue = [4, 6]\nclass = b'),
 Text(2114.5263157894738, 543.5999999999999, 'gini = 0.0\nsamples = 178\nvalue = [0, 278]\nclass = b'),
 Text(2584.4210526315787, 906.0, 'PM25 <= 34.0\ngini = 0.353\nsamples = 124\nvalue = [148, 44]\nclass =
a'),
 Text(2349.4736842105262, 543.5999999999999, 'NMHC <= 0.135\ngini = 0.219\nsamples = 106\nvalue = [140,
20]\nclass = a'),
 Text(2232.0, 181.19999999999982, 'gini = 0.444\nsamples = 40\nvalue = [40, 20]\nclass = a'),
 Text(2466.9473684210525, 181.19999999999982, 'gini = 0.0\nsamples = 66\nvalue = [100, 0]\nclass = a'),
 Text(2819.3684210526317, 543.5999999999999, 'CO <= 0.85\ngini = 0.375\nsamples = 18\nvalue = [8, 24]\n
class = b'),
 Text(2701.8947368421054, 181.19999999999982, 'gini = 0.0\nsamples = 12\nvalue = [0, 21]\nclass = b'),
 Text(2936.842105263158, 181.19999999999982, 'gini = 0.397\nsamples = 6\nvalue = [8, 3]\nclass = a'),
 Text(3817.8947368421054, 1268.4, 'NMHC <= 0.175\ngini = 0.39\nsamples = 1075\nvalue = [1240, 449]\ncla
ss = a'),
 Text(3524.2105263157896, 906.0, 'TCH <= 1.325\ngini = 0.412\nsamples = 984\nvalue = [1092, 446]\nclass
= a'),
 Text(3289.2631578947367, 543.5999999999999, 'EBE <= 0.15\ngini = 0.315\nsamples = 248\nvalue = [76, 31
2]\nclass = b'),
 Text(3171.7894736842104, 181.19999999999982, 'gini = 0.078\nsamples = 113\nvalue = [7, 166]\nclass =
b'),
 Text(3406.7368421052633, 181.19999999999982, 'gini = 0.436\nsamples = 135\nvalue = [69, 146]\nclass =
b'),
 Text(3759.157894736842, 543.5999999999999, 'PM25 <= 29.5\ngini = 0.206\nsamples = 736\nvalue = [1016,
134]\nclass = a'),
 Text(3641.684210526316, 181.19999999999982, 'gini = 0.173\nsamples = 716\nvalue = [1012, 107]\nclass =
a'),
 Text(3876.6315789473683, 181.19999999999982, 'gini = 0.225\nsamples = 20\nvalue = [4, 27]\nclass =
b'),
 Text(4111.578947368421, 906.0, 'TOL <= 14.1\ngini = 0.039\nsamples = 91\nvalue = [148, 3]\nclass =
```

```
a'),
 Text(3994.1052631578946, 543.5999999999999, 'gini = 0.0\nsamples = 69\nvalue = [104, 0]\nclass = a'),
 Text(4229.0526315789475, 543.5999999999999, 'O_3 <= 7.5\ngini = 0.12\nsamples = 22\nvalue = [44, 3]\nc
lass = a'),
 Text(4111.578947368421, 181.19999999999982, 'gini = 0.0\nsamples = 16\nvalue = [35, 0]\nclass = a'),
 Text(4346.526315789473, 181.19999999999982, 'gini = 0.375\nsamples = 6\nvalue = [9, 3]\nclass = a')]
```



Conclusion

Linear Regression=0.6277182624521873

Ridge Regression=0.6191897548217457

Lasso Regression=0.3977464968218405

ElasticNet Regression=0.5205114372790913

Logistic Regression=0.9437848315968016

Random Forest=0.9653739612188366

Random Forest is suitable for this dataset