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\madrid_2006.csv")
df
```

Out[2]:

	date	BEN	CO	EBE	MXY	NMHC	NO_2	NOx	OXY	O_3	PM10	
0	01-02-2006 01:00	NaN	1.84	NaN	NaN	NaN	155.100006	490.100006	NaN	4.880000	97.570000	40.2
1	01-02-2006 01:00	1.68	1.01	2.38	6.36	0.32	94.339996	229.699997	3.04	7.100000	25.820000	
2	01-02-2006 01:00	NaN	1.25	NaN	NaN	NaN	66.800003	192.000000	NaN	4.430000	34.419998	
3	01-02-2006 01:00	NaN	1.68	NaN	NaN	NaN	103.000000	407.799988	NaN	4.830000	28.260000	
4	01-02-2006 01:00	NaN	1.31	NaN	NaN	NaN	105.400002	269.200012	NaN	6.990000	54.180000	
...	...	...	...	...	...	...	...	...	...	...	...	...
230563	01-05-2006 00:00	5.88	0.83	6.23	NaN	0.20	112.500000	218.000000	NaN	24.389999	93.120003	
230564	01-05-2006 00:00	0.76	0.32	0.48	1.09	0.08	51.900002	54.820000	0.61	48.410000	29.469999	15.6
230565	01-05-2006 00:00	0.96	NaN	0.69	NaN	0.19	135.100006	179.199997	NaN	11.460000	64.680000	35.0

	date	BEN	CO	EBE	MXY	NMHC	NO_2	NOx	OXY	O_3	PM10	
230566	01-05-2006 00:00	0.50	NaN	0.67	NaN	0.10	82.599998	105.599998	NaN	NaN	94.360001	
230567	01-05-2006 00:00	1.95	0.74	1.99	4.00	0.24	107.300003	160.199997	2.01	17.730000	52.490002	27.9

230568 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: 24758 entries, 5 to 230567
Data columns (total 17 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   date     24758 non-null  object 
 1   BEN      24758 non-null  float64
 2   CO       24758 non-null  float64
 3   EBE      24758 non-null  float64
 4   MXY      24758 non-null  float64
 5   NMHC     24758 non-null  float64
 6   NO_2     24758 non-null  float64
 7   NOx      24758 non-null  float64
 8   OXY      24758 non-null  float64
 9   O_3      24758 non-null  float64
 10  PM10     24758 non-null  float64
 11  PM25     24758 non-null  float64
 12  PXY      24758 non-null  float64
 13  SO_2     24758 non-null  float64
 14  TCH      24758 non-null  float64
 15  TOL      24758 non-null  float64
 16  station  24758 non-null  int64  
dtypes: float64(15), int64(1), object(1)
memory usage: 3.4+ MB
```

In [6]:
```
data=df[['CO' ,'station']]
data
```

Out[6]:

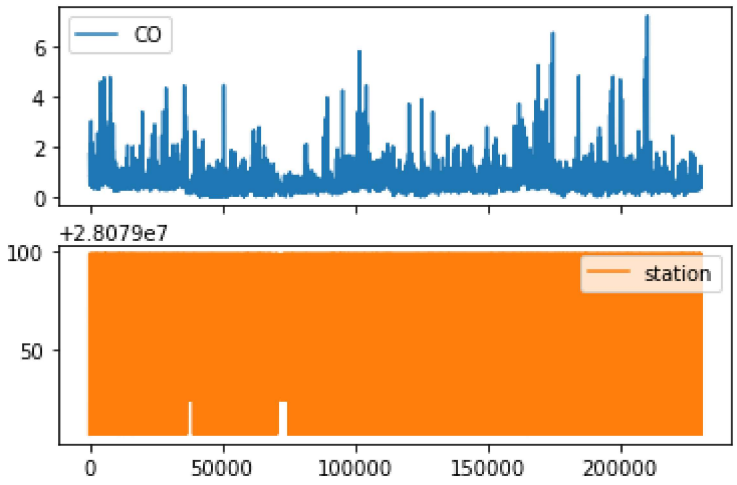
	CO	station
5	1.69	28079006
22	0.79	28079024
25	1.47	28079099
31	0.85	28079006
48	0.79	28079024
...	...	...
230538	0.40	28079024
230541	0.94	28079099
230547	1.06	28079006
230564	0.32	28079024
230567	0.74	28079099

24758 rows × 2 columns

Line chart

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

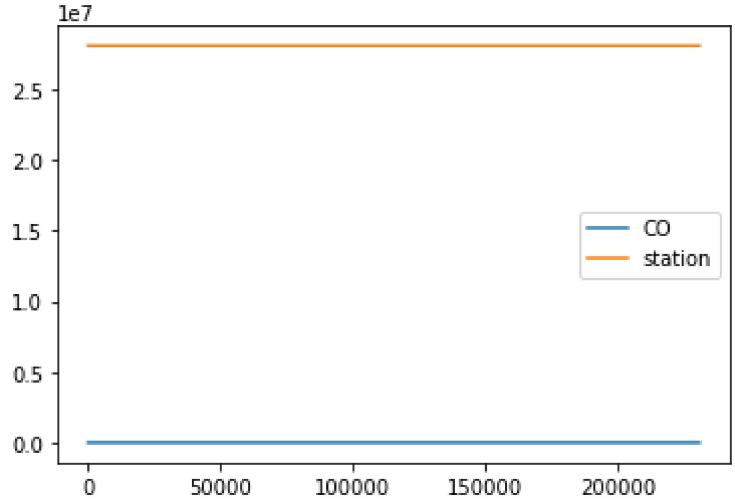
Out[7]:
```
array([<AxesSubplot:>, <AxesSubplot:>], dtype=object)
```



Line chart

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

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

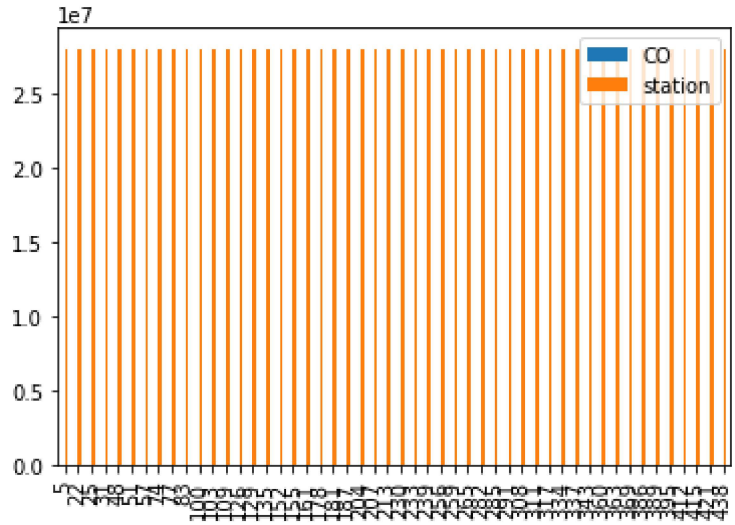


Bar chart

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

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

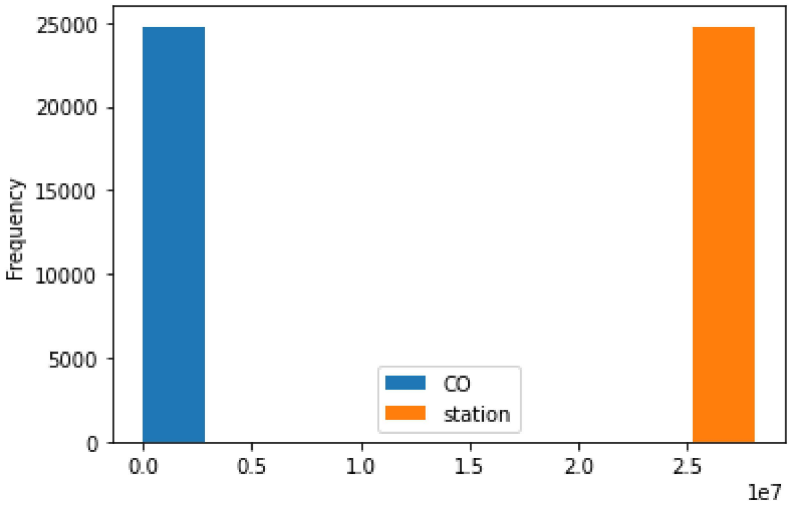
Out[10]: <AxesSubplot:>



Histogram

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

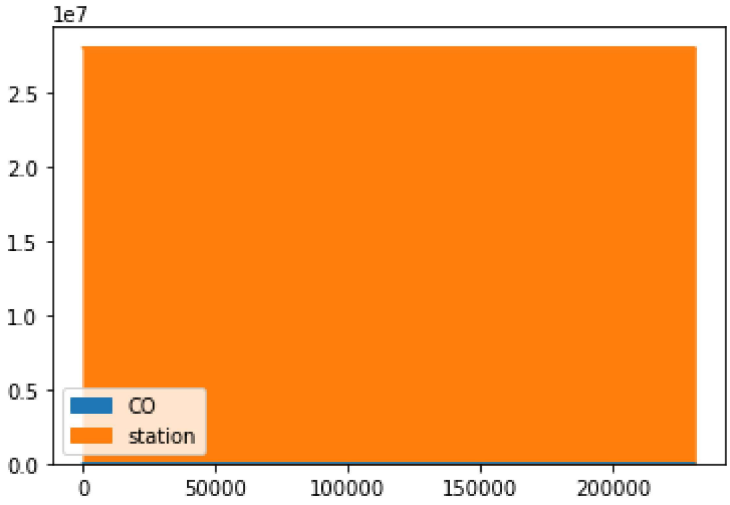
Out[11]: <AxesSubplot:ylabel='Frequency'>



Area chart

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

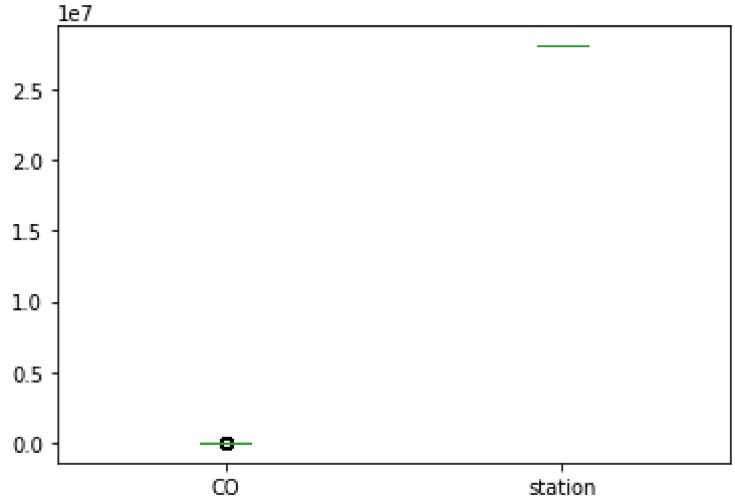
Out[12]: <AxesSubplot:>



Box chart

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

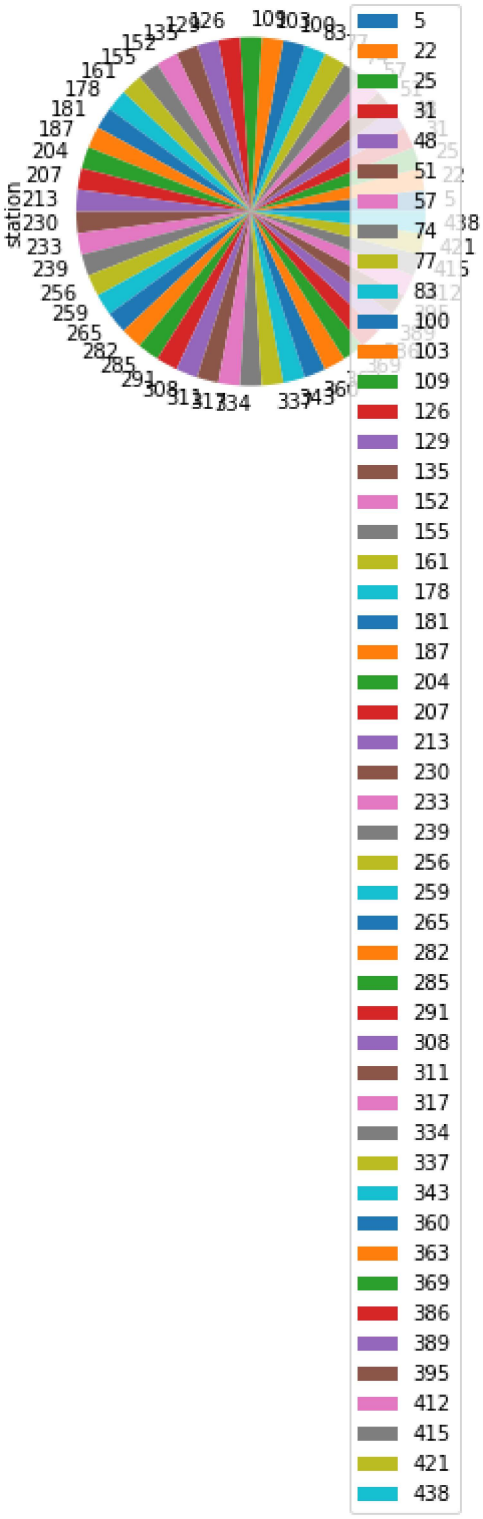
Out[13]: <AxesSubplot:>



Pie chart

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

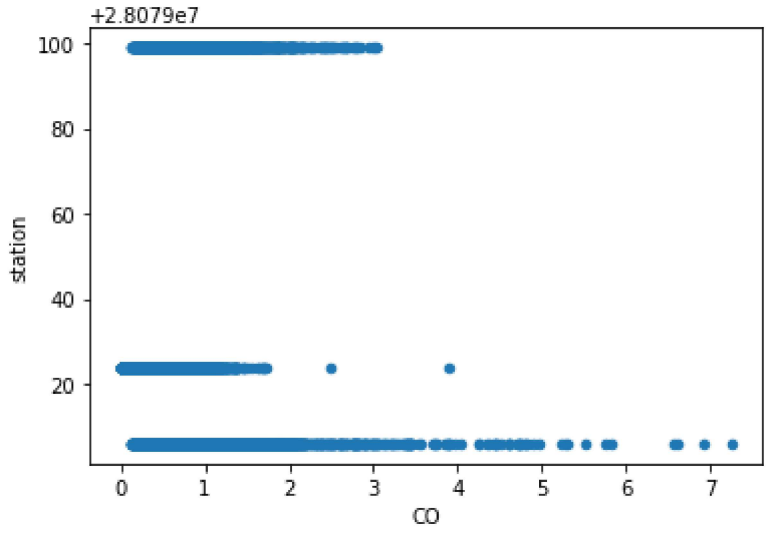
Out[14]:
```
<AxesSubplot:ylabel='station'>
```



Scatter chart

In [15]:
```
data.plot.scatter(x='CO' ,y='station')
```

Out[15]:
```
<AxesSubplot:xlabel='CO', ylabel='station'>
```



In [16]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 24758 entries, 5 to 230567
Data columns (total 17 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   date     24758 non-null  object 
 1   BEN      24758 non-null  float64
 2   CO       24758 non-null  float64
 3   EBE      24758 non-null  float64
 4   MXY      24758 non-null  float64
 5   NMHC     24758 non-null  float64
 6   NO_2     24758 non-null  float64
 7   NOx      24758 non-null  float64
 8   OXY      24758 non-null  float64
 9   O_3      24758 non-null  float64
 10  PM10     24758 non-null  float64
 11  PM25     24758 non-null  float64
 12  PXY      24758 non-null  float64
 13  SO_2     24758 non-null  float64
 14  TCH      24758 non-null  float64
 15  TOL      24758 non-null  float64
 16  station  24758 non-null  int64  
dtypes: float64(15), int64(1), object(1)
memory usage: 3.4+ MB
```

In [17]:
```
df.describe()
```

Out[17]:

	BEN	CO	EBE	MXY	NMHC	NO_2	NO
count	24758.000000	24758.000000	24758.000000	24758.000000	24758.000000	24758.000000	24758.00000
mean	1.350624	0.600713	1.824534	3.835034	0.176546	58.333481	116.41909
std	1.541636	0.419048	1.868939	4.069036	0.126683	40.529382	117.55706
min	0.110000	0.000000	0.170000	0.150000	0.000000	1.680000	2.02000
25%	0.450000	0.360000	0.810000	1.060000	0.100000	28.450001	36.88250
50%	0.850000	0.500000	1.130000	2.500000	0.150000	52.959999	85.18000

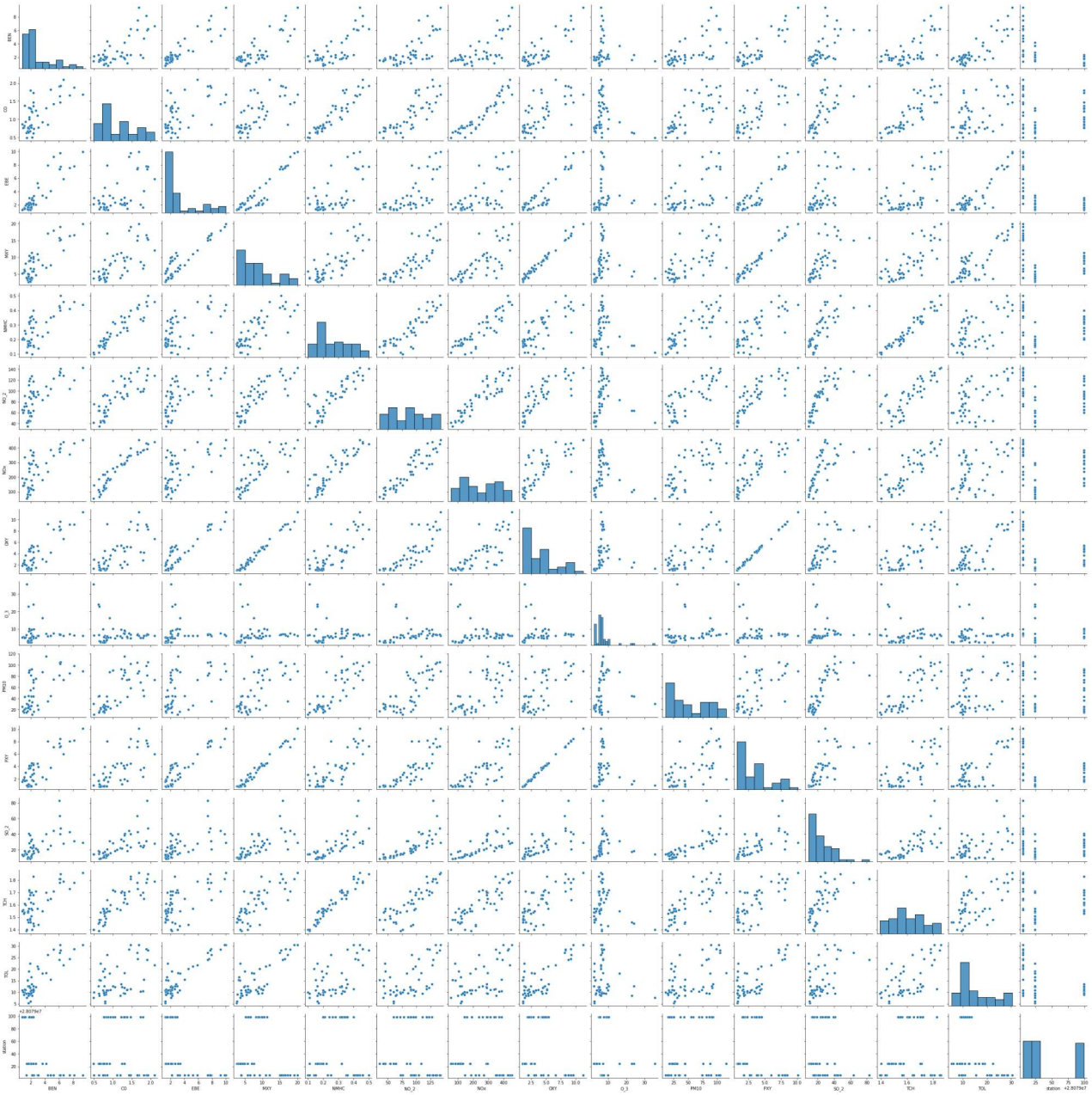
	BEN	CO	EBE	MXY	NMHC	NO_2	NO
75%	1.680000	0.720000	2.160000	5.090000	0.220000	79.347498	158.30000
max	45.430000	7.250000	57.799999	66.900002	2.020000	461.299988	1680.00000

In [18]:
```
df1=df[['BEN', 'CO', 'EBE', 'MXY', 'NMHC', 'NO_2', 'NOx', 'OXY', 'O_3',
       'PM10', 'PXY', 'SO_2', 'TCH', 'TOL', 'station']]
```

EDA AND VISUALIZATION

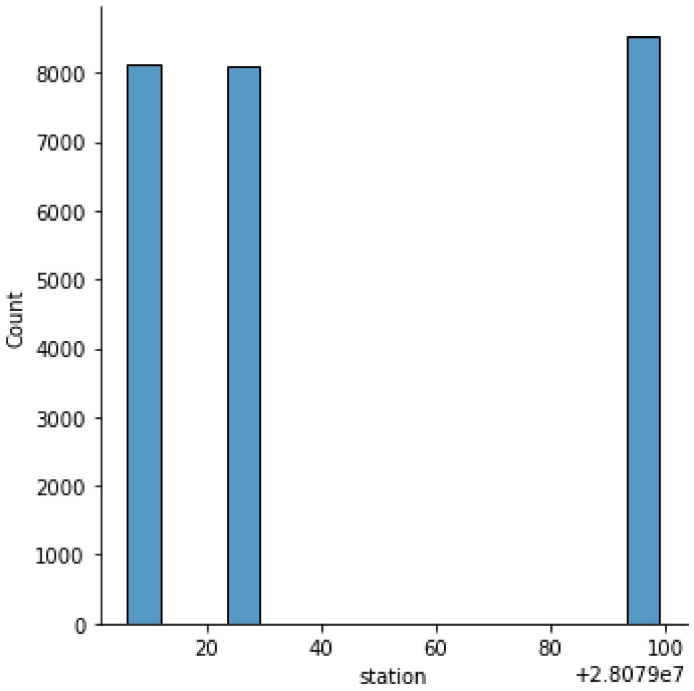
In [19]:
```
sns.pairplot(df1[0:50])
```

Out[19]: <seaborn.axisgrid.PairGrid at 0x17ec0337d90>



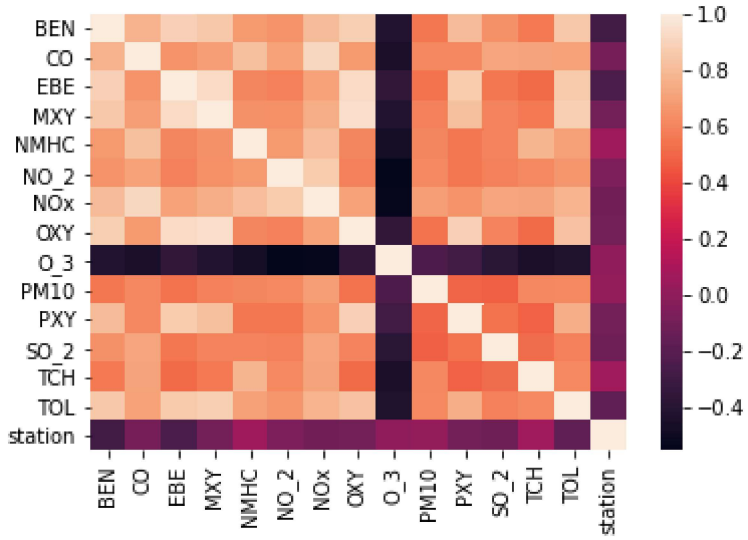
In [20]:
```
sns.displot(df1['station'])
```

Out[20]: <seaborn.axisgrid.FacetGrid at 0x17ecc064b80>



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

Out[21]: <AxesSubplot:>



TO TRAIN THE MODEL AND MODEL BULDING

In [22]:
```
x=df[['BEN', 'CO', 'EBE', 'MXY', 'NMHC', 'NO_2', 'NOx', 'OXY', 'O_3',
       'PM10', 'PXY', '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]:
```
28079015.645236906
```

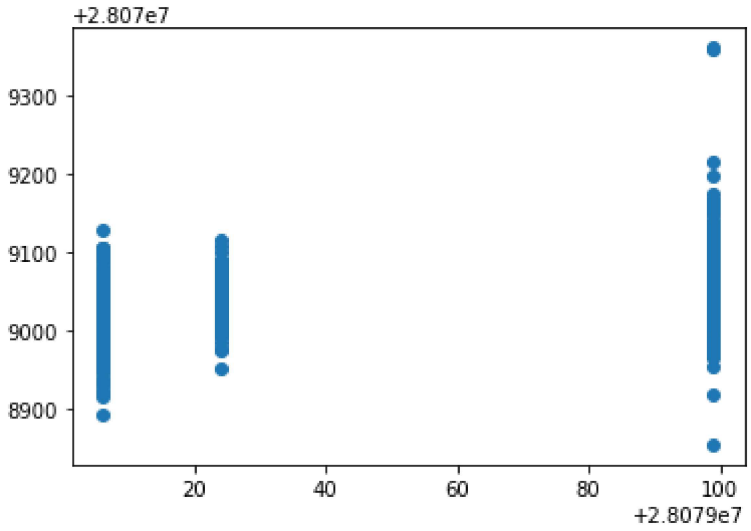
In [26]:
```
coeff=pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
coeff
```

Out[26]:

	Co-efficient
BEN	-18.705413
CO	-12.229780
EBE	-21.328150
MXY	2.550989
NMHC	123.225183
NO_2	-0.016937
NOx	-0.001274
OXY	18.751170
O_3	-0.076270
PM10	0.152285
PXY	5.956187
SO_2	-0.723212
TCH	22.618359
TOL	-0.683651

In [27]:
```
prediction =lr.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[27]:
```
<matplotlib.collections.PathCollection at 0x17ecedf76a0>
```



ACCURACY

In [28]:
```
lr.score(x_test,y_test)
```

Out[28]: 0.3942253498114515

In [29]:
```
lr.score(x_train,y_train)
```

Out[29]: 0.39194541363193647

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]: 0.3923734972503121

In [33]:
```
rr.score(x_train,y_train)
```

Out[33]: 0.39136386690973246

In [34]:
```
la=Lasso(alpha=10)
la.fit(x_train,y_train)
```

Out[34]:
```
Lasso(alpha=10)
```

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

Out[35]:
```
0.06316793635391815
```

Accuracy(Lasso)

In [36]:
```
la.score(x_test,y_test)
```

Out[36]:
```
0.05941509611611351
```

Elastic Net regression

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([-8.35533203e+00,  0.00000000e+00, -8.59840911e+00,  3.09185743e+00,
        4.01177598e-01, -8.28635026e-03,  4.04294315e-03,  3.99986179e+00,
       -1.35922657e-01,  3.11629520e-01,  2.88533244e+00, -5.01608944e-01,
        6.01762095e-01, -1.14802686e+00])
```

In [39]:
```
en.intercept_
```

Out[39]:
```
28079052.59413356
```

In [40]:
```
prediction=en.predict(x_test)
```

In [41]:
```
en.score(x_test,y_test)
```

Out[41]:
```
0.23414894775926287
```

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)))
```

```
32.23789819181627
1247.706497002361
35.32288913724868
```

Logistic Regression

In [43]:
```
from sklearn.linear_model import LogisticRegression
```

In [44]:
```
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 [45]:
```
feature_matrix.shape
```

Out[45]: (24758, 14)

In [46]:
```
target_vector.shape
```

Out[46]: (24758,)

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=[[1,2,3,4,5,6,7,8,9,10,11,12,13,14]]
```

In [51]:
```
prediction=logr.predict(observation)
print(prediction)
```

```
[28079099]
```

In [52]:
```
logr.classes_
```

Out[52]: array([28079006, 28079024, 28079099], dtype=int64)

In [53]:
```
logr.score(fs,target_vector)
```

Out[53]:
```
0.8741416915744405
```

In [54]:
```
logr.predict_proba(observation)[0][0]
```

Out[54]:
```
3.5470091844587883e-15
```

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

Out[55]:
```
array([[3.54700918e-15, 7.82458875e-29, 1.00000000e+00]])
```

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]:
```
0.8773225620311598
```

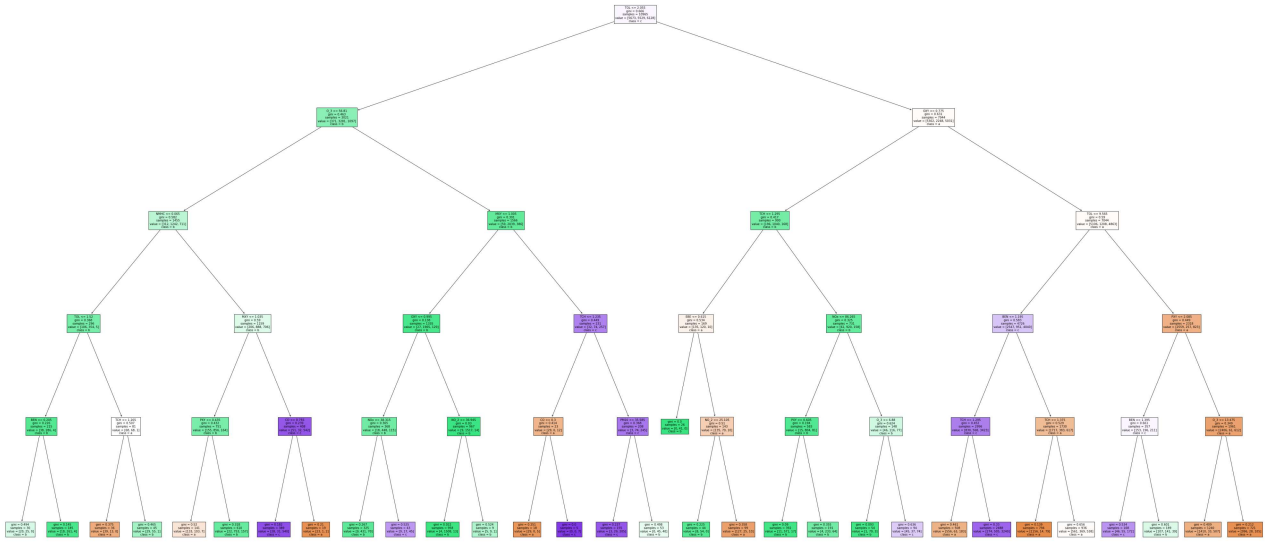
In [61]:
```
rfc_best=grid_search.best_estimator_
```

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']
```

Out[62]:
```
[Text(2241.3, 1993.2, 'TOL <= 2.055\ngini = 0.666\nsamples = 10965\nvalue = [5673, 5529,
6128]\nclass = c'),
 Text(1190.4, 1630.8000000000002, 'O_3 <= 56.81\ngini = 0.463\nsamples = 3021\nvalue =
[371, 3281, 1097]\nclass = b'),
 Text(595.2, 1268.4, 'NMHC <= 0.065\ngini = 0.582\nsamples = 1455\nvalue = [312, 1242, 7
11]\nclass = b'),
 Text(297.6, 906.0, 'TOL <= 1.52\ngini = 0.368\nsamples = 296\nvalue = [106, 354, 5]\ncl
ass = b'),
 Text(148.8, 543.5999999999999, 'BEN <= 0.205\ngini = 0.226\nsamples = 215\nvalue = [38,
286, 4]\nclass = b'),
 Text(74.4, 181.19999999999982, 'gini = 0.494\nsamples = 30\nvalue = [20, 25, 0]\nclass
= b'),
 Text(223.20000000000002, 181.19999999999982, 'gini = 0.145\nsamples = 185\nvalue = [18,
261, 4]\nclass = b'),
 Text(446.40000000000003, 543.5999999999999, 'TCH <= 1.265\ngini = 0.507\nsamples = 81\n
value = [68, 68, 1]\nclass = a'),
 Text(372.0, 181.19999999999982, 'gini = 0.375\nsamples = 36\nvalue = [39, 13, 0]\nclass
= a'),
 Text(520.8000000000001, 181.19999999999982, 'gini = 0.465\nsamples = 45\nvalue = [29, 5
5, 1]\nclass = b'),
 Text(892.8000000000001, 906.0, 'MXY <= 1.035\ngini = 0.59\nsamples = 1159\nvalue = [20
6, 888, 706]\nclass = b'),
 Text(744.0, 543.5999999999999, 'PXY <= 0.435\ngini = 0.432\nsamples = 751\nvalue = [15
5, 856, 164]\nclass = b'),
 Text(669.6, 181.19999999999982, 'gini = 0.52\nsamples = 141\nvalue = [133, 103, 7]\ncla
ss = a'),
 Text(818.4000000000001, 181.19999999999982, 'gini = 0.318\nsamples = 610\nvalue = [22,
753, 157]\nclass = b'),
 Text(1041.6000000000001, 543.5999999999999, 'CO <= 0.755\ngini = 0.239\nsamples = 408\n
value = [51, 32, 542]\nclass = c'),
 Text(967.2, 181.19999999999982, 'gini = 0.182\nsamples = 389\nvalue = [28, 31, 540]\ncl
ass = c'),
 Text(1116.0, 181.19999999999982, 'gini = 0.21\nsamples = 19\nvalue = [23, 1, 2]\nclass
= a'),
 Text(1785.6000000000001, 1268.4, 'MXY <= 1.005\ngini = 0.301\nsamples = 1566\nvalue =
[59, 2039, 386]\nclass = b'),
 Text(1488.0, 906.0, 'OXY <= 0.995\ngini = 0.138\nsamples = 1335\nvalue = [27, 1965, 12
9]\nclass = b'),
 Text(1339.2, 543.5999999999999, 'NOx <= 38.315\ngini = 0.365\nsamples = 368\nvalue = [1
8, 448, 115]\nclass = b'),
 Text(1264.8000000000002, 181.19999999999982, 'gini = 0.267\nsamples = 325\nvalue = [9,
431, 70]\nclass = b'),
 Text(1413.6000000000001, 181.19999999999982, 'gini = 0.525\nsamples = 43\nvalue = [9, 1
7, 45]\nclass = c'),
 Text(1636.8000000000002, 543.5999999999999, 'NO_2 <= 36.945\ngini = 0.03\nsamples = 967
\nvalue = [9, 1517, 14]\nclass = b'),
 Text(1562.4, 181.19999999999982, 'gini = 0.022\nsamples = 958\nvalue = [4, 1508, 13]\nc
lass = b'),
 Text(1711.2, 181.19999999999982, 'gini = 0.524\nsamples = 9\nvalue = [5, 9, 1]\nclass =
b'),
 Text(2083.2000000000003, 906.0, 'TCH <= 1.235\ngini = 0.449\nsamples = 231\nvalue = [3
2, 74, 257]\nclass = c'),
 Text(1934.4, 543.5999999999999, 'CO <= 0.3\ngini = 0.414\nsamples = 23\nvalue = [29, 0,
12]\nclass = a'),
 Text(1860.0000000000002, 181.19999999999982, 'gini = 0.251\nsamples = 18\nvalue = [29,
0, 5]\nclass = a'),
 Text(2008.8000000000002, 181.19999999999982, 'gini = 0.0\nsamples = 5\nvalue = [0, 0,
7]\nclass = c'),
 Text(2232.0, 543.5999999999999, 'PM10 <= 35.585\ngini = 0.368\nsamples = 208\nvalue =
[3, 74, 245]\nclass = c'),
 Text(2157.6000000000004, 181.19999999999982, 'gini = 0.237\nsamples = 155\nvalue = [3,
29, 205]\nclass = c'),
```

```
 Text(2306.4, 181.19999999999982, 'gini = 0.498\nsamples = 53\nvalue = [0, 45, 40]\nclas
s = b'),
 Text(3292.2000000000003, 1630.8000000000002, 'OXY <= 0.775\ngini = 0.631\nsamples = 794
4\nvalue = [5302, 2248, 5031]\nclass = a'),
 Text(2715.6000000000004, 1268.4, 'TCH <= 1.295\ngini = 0.417\nsamples = 900\nvalue = [1
96, 1040, 168]\nclass = b'),
 Text(2455.2000000000003, 906.0, 'EBE <= 0.615\ngini = 0.534\nsamples = 169\nvalue = [13
5, 120, 10]\nclass = a'),
 Text(2380.8, 543.5999999999999, 'gini = 0.0\nsamples = 26\nvalue = [0, 41, 0]\nclass =
b'),
 Text(2529.6000000000004, 543.5999999999999, 'NO_2 <= 25.105\ngini = 0.51\nsamples = 143
\nvalue = [135, 79, 10]\nclass = a'),
 Text(2455.2000000000003, 181.19999999999982, 'gini = 0.225\nsamples = 44\nvalue = [8, 5
4, 0]\nclass = b'),
 Text(2604.0, 181.19999999999982, 'gini = 0.358\nsamples = 99\nvalue = [127, 25, 10]\ncl
ass = a'),
 Text(2976.0, 906.0, 'NOx <= 86.265\ngini = 0.325\nsamples = 731\nvalue = [61, 920, 158]
\nclass = b'),
 Text(2827.2000000000003, 543.5999999999999, 'PXY <= 0.605\ngini = 0.194\nsamples = 583
\nvalue = [15, 804, 81]\nclass = b'),
 Text(2752.8, 181.19999999999982, 'gini = 0.09\nsamples = 392\nvalue = [11, 571, 17]\ncl
ass = b'),
 Text(2901.6000000000004, 181.19999999999982, 'gini = 0.355\nsamples = 191\nvalue = [4,
233, 64]\nclass = b'),
 Text(3124.8, 543.5999999999999, 'O_3 <= 6.88\ngini = 0.624\nsamples = 148\nvalue = [46,
116, 77]\nclass = b'),
 Text(3050.4, 181.19999999999982, 'gini = 0.093\nsamples = 54\nvalue = [1, 79, 3]\nclass
= b'),
 Text(3199.2000000000003, 181.19999999999982, 'gini = 0.636\nsamples = 94\nvalue = [45,
37, 74]\nclass = c'),
 Text(3868.8, 1268.4, 'TOL <= 9.565\ngini = 0.59\nsamples = 7044\nvalue = [5106, 1208, 4
863]\nclass = a'),
 Text(3571.2000000000003, 906.0, 'BEN <= 1.195\ngini = 0.583\nsamples = 4726\nvalue = [2
547, 951, 4040]\nclass = c'),
 Text(3422.4, 543.5999999999999, 'TCH <= 1.295\ngini = 0.452\nsamples = 2996\nvalue = [8
30, 568, 3423]\nclass = c'),
 Text(3348.0000000000005, 181.19999999999982, 'gini = 0.461\nsamples = 508\nvalue = [55
6, 63, 183]\nclass = a'),
 Text(3496.8, 181.19999999999982, 'gini = 0.33\nsamples = 2488\nvalue = [274, 505, 3240]
\nclass = c'),
 Text(3720.0000000000005, 543.5999999999999, 'TCH <= 1.375\ngini = 0.529\nsamples = 1730
\nvalue = [1717, 383, 617]\nclass = a'),
 Text(3645.6000000000004, 181.19999999999982, 'gini = 0.139\nsamples = 794\nvalue = [115
6, 14, 79]\nclass = a'),
 Text(3794.4, 181.19999999999982, 'gini = 0.656\nsamples = 936\nvalue = [561, 369, 538]
\nclass = a'),
 Text(4166.400000000001, 906.0, 'PXY <= 2.085\ngini = 0.449\nsamples = 2318\nvalue = [25
59, 257, 823]\nclass = a'),
 Text(4017.6000000000004, 543.5999999999999, 'BEN <= 1.395\ngini = 0.661\nsamples = 357
\nvalue = [153, 196, 211]\nclass = c'),
 Text(3943.2000000000003, 181.19999999999982, 'gini = 0.534\nsamples = 168\nvalue = [46,
55, 172]\nclass = c'),
 Text(4092.0000000000005, 181.19999999999982, 'gini = 0.601\nsamples = 189\nvalue = [10
7, 141, 39]\nclass = b'),
 Text(4315.200000000001, 543.5999999999999, 'O_3 <= 13.475\ngini = 0.349\nsamples = 1961
\nvalue = [2406, 61, 612]\nclass = a'),
 Text(4240.8, 181.19999999999982, 'gini = 0.409\nsamples = 1240\nvalue = [1410, 33, 507]
\nclass = a'),
 Text(4389.6, 181.19999999999982, 'gini = 0.212\nsamples = 721\nvalue = [996, 28, 105]\n
class = a')]
```



Conclusion

Accuracy

Linear Regression:0.3942253498114515

Ridge Regression:0.3923734972503121

Lasso Regression:0.05941509611611351

ElasticNet Regression:0.23414894775926287

Logistic Regression:0.8741416915744405

Random Forest:0.8773225620311598

Accuracy for random forest is higher so it is the best fit model