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("madrid_2011.csv")
```

In [3]:
```
df.head()
```

Out[3]:

	date	BEN	CO	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	TCH	TOL	stat
0	2011-11-01 01:00:00	NaN	1.0	NaN	NaN	154.0	84.0	NaN	NaN	NaN	6.0	NaN	NaN	28079
1	2011-11-01 01:00:00	2.5	0.4	3.5	0.26	68.0	92.0	3.0	40.0	24.0	9.0	1.54	8.7	28079
2	2011-11-01 01:00:00	2.9	NaN	3.8	NaN	96.0	99.0	NaN	NaN	NaN	NaN	NaN	7.2	28079
3	2011-11-01 01:00:00	NaN	0.6	NaN	NaN	60.0	83.0	2.0	NaN	NaN	NaN	NaN	NaN	28079
4	2011-11-01 01:00:00	NaN	NaN	NaN	NaN	44.0	62.0	3.0	NaN	NaN	3.0	NaN	NaN	28079

In [4]:
```
df=df.dropna()
```

In [5]:
```
df.columns
```

Out[5]:
```
Index(['date', 'BEN', 'CO', 'EBE', 'NMHC', 'NO', 'NO_2', 'O_3', 'PM10', 'PM2
5',
       'SO_2', 'TCH', 'TOL', 'station'],
      dtype='object')
```

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 16460 entries, 1 to 209910
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   date     16460 non-null  object 
 1   BEN      16460 non-null  float64
 2   CO       16460 non-null  float64
 3   EBE      16460 non-null  float64
 4   NMHC     16460 non-null  float64
 5   NO       16460 non-null  float64
 6   NO_2     16460 non-null  float64
 7   O_3      16460 non-null  float64
 8   PM10     16460 non-null  float64
 9   PM25     16460 non-null  float64
 10  SO_2     16460 non-null  float64
 11  TCH      16460 non-null  float64
 12  TOL      16460 non-null  float64
 13  station  16460 non-null  int64  
dtypes: float64(12), int64(1), object(1)
memory usage: 1.9+ MB
```

In [7]:
```
data=df[['CO','station']]
data
```

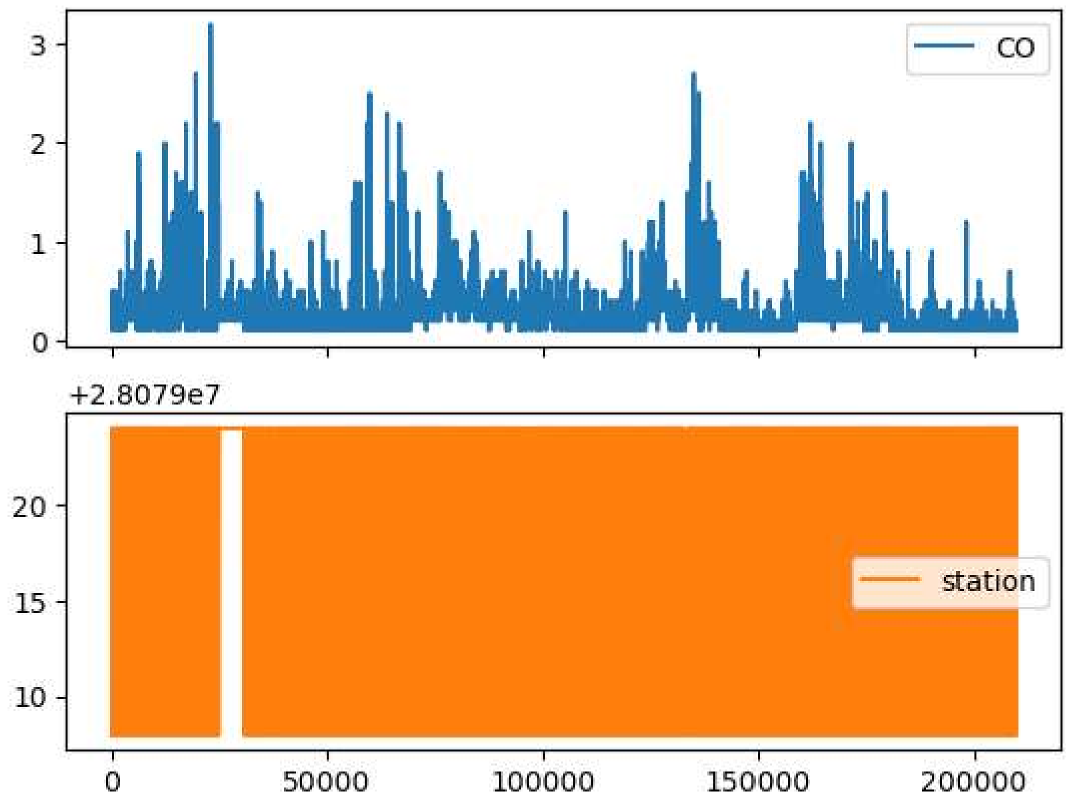
Out[7]:

	CO	station
1	0.4	28079008
6	0.3	28079024
25	0.3	28079008
30	0.4	28079024
49	0.2	28079008
...	...	...
209862	0.1	28079024
209881	0.1	28079008
209886	0.1	28079024
209905	0.1	28079008
209910	0.1	28079024

16460 rows × 2 columns

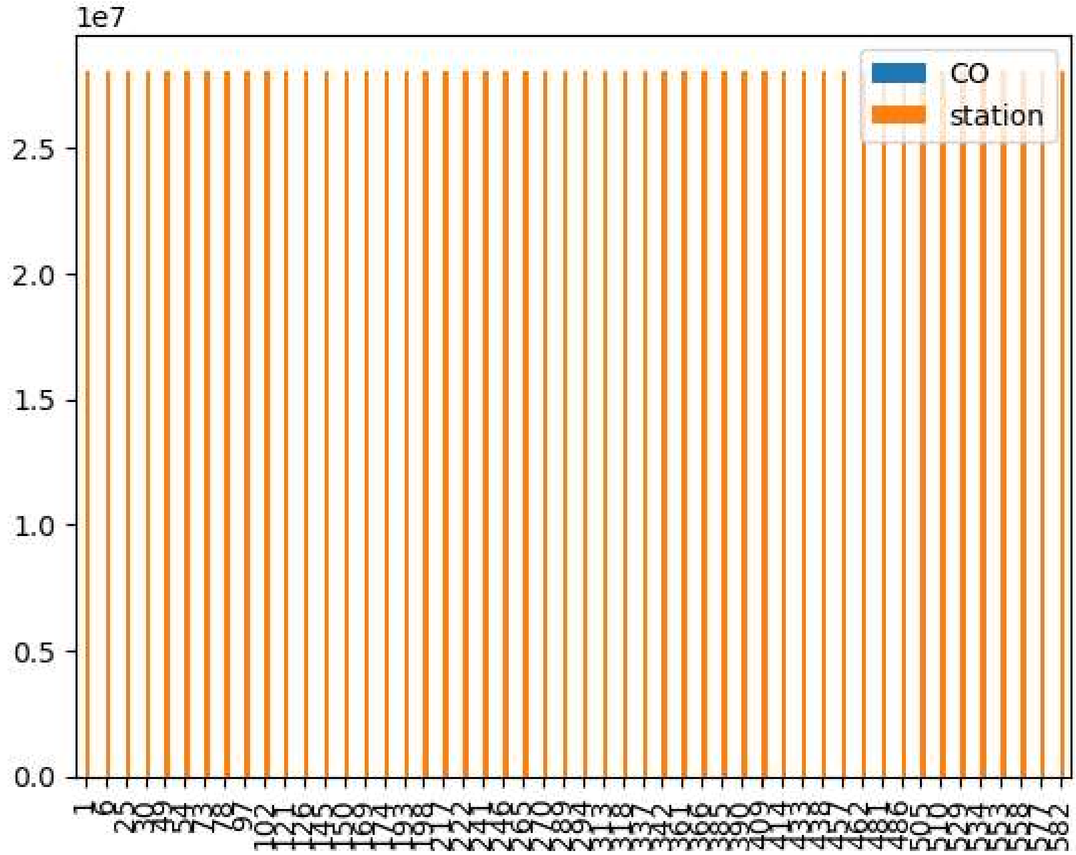
In [8]:
```
data.plot.line(subplots=True)
```

Out[8]:
```
array([<Axes: >, <Axes: >], dtype=object)
```



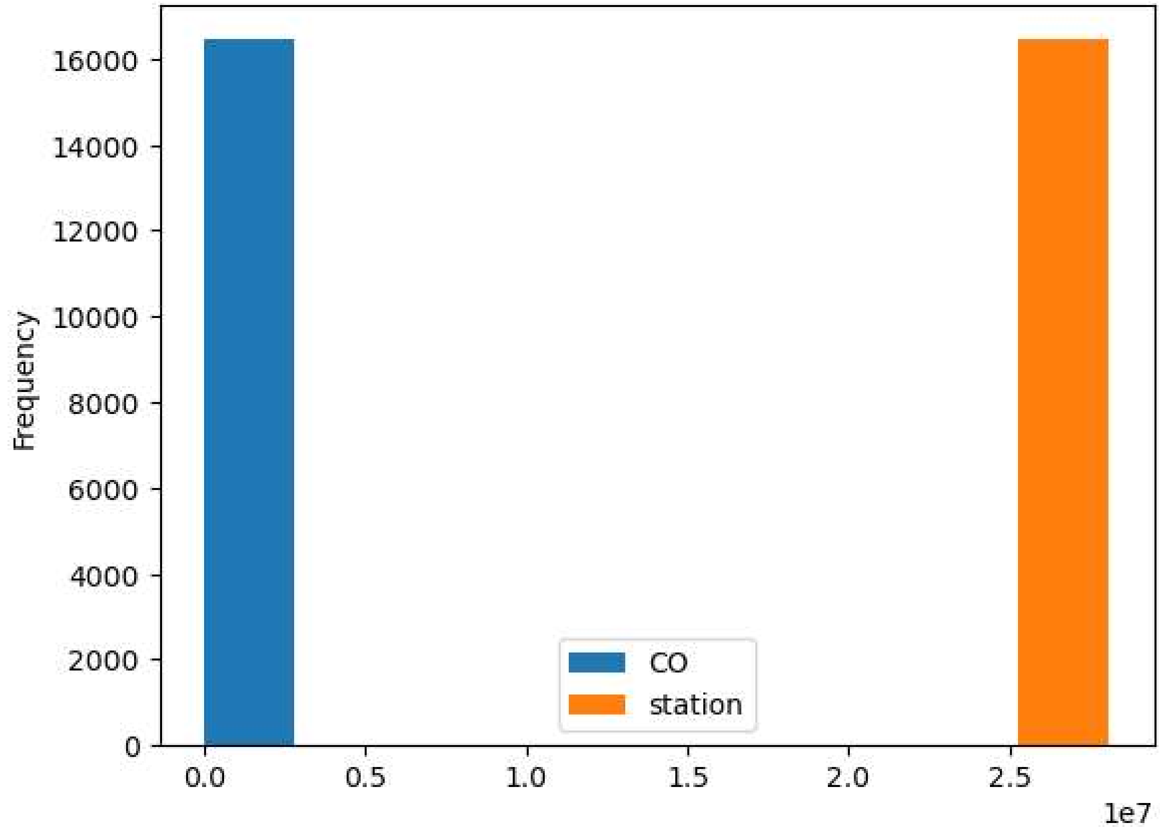
In [9]:
```
b=data[0:50]
b.plot.bar()
```

Out[9]:
```
<Axes: >
```



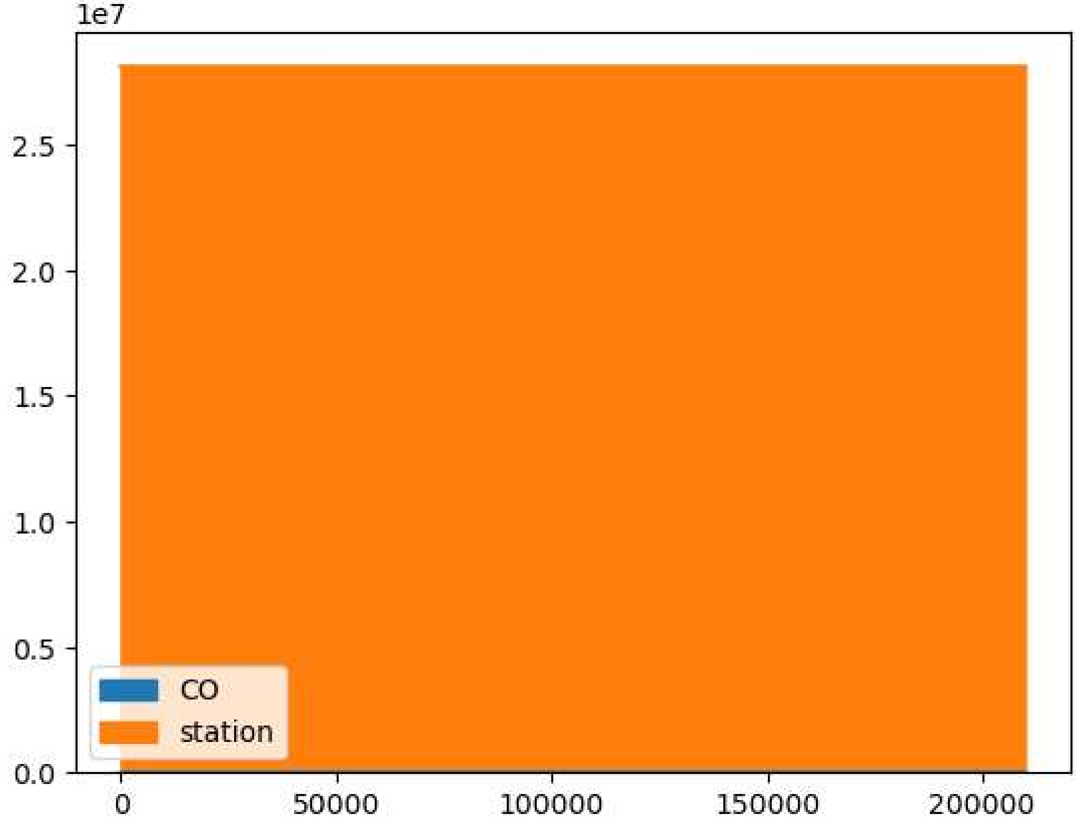
In [10]:
```
data.plot.hist()
```

Out[10]: <Axes: ylabel='Frequency'>



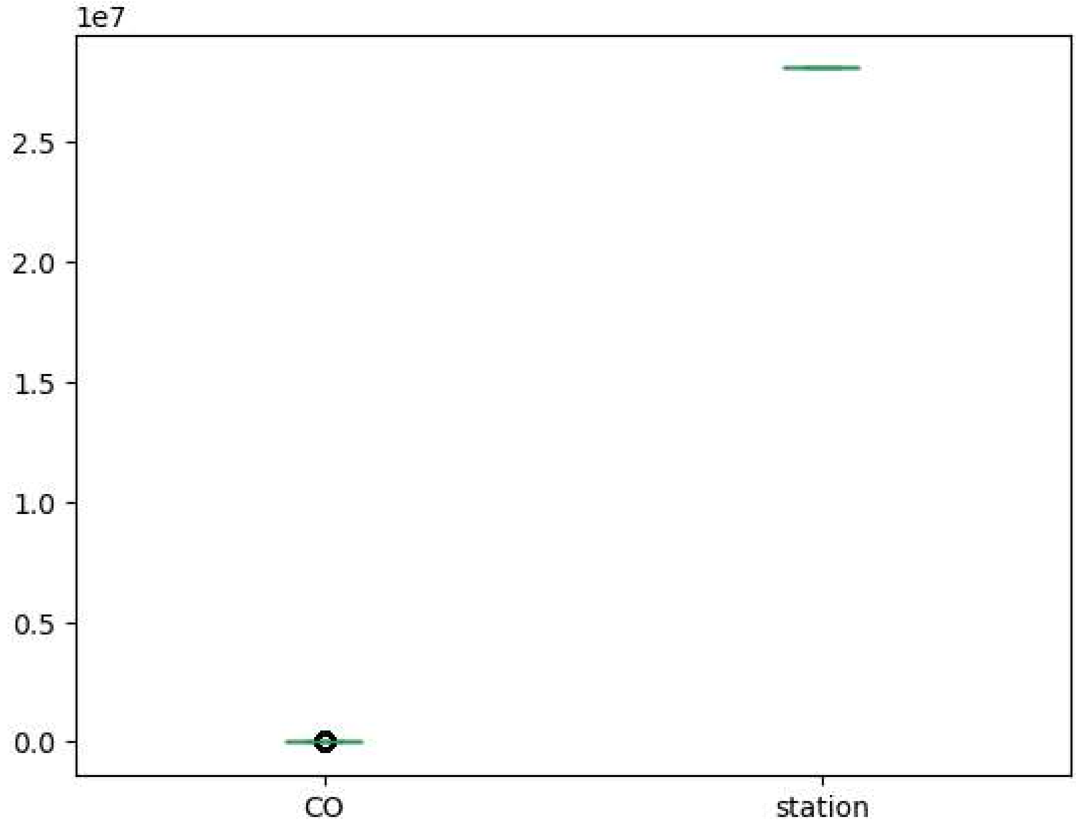
In [11]:
```
data.plot.area()
```

Out[11]: <Axes: >



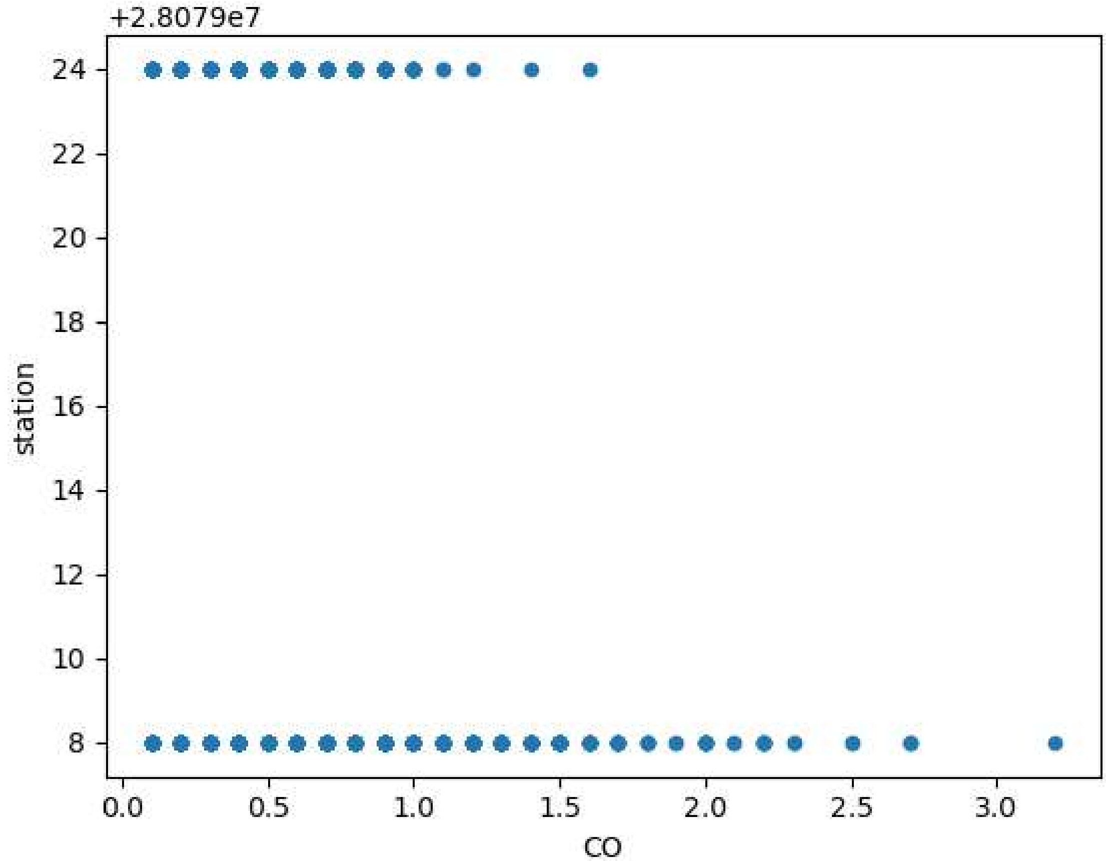
In [12]:
```
data.plot.box()
```

Out[12]: <Axes: >



In [13]:
```
data.plot.scatter(x='CO',y='station')
```

Out[13]: <Axes: xlabel='CO', ylabel='station'>



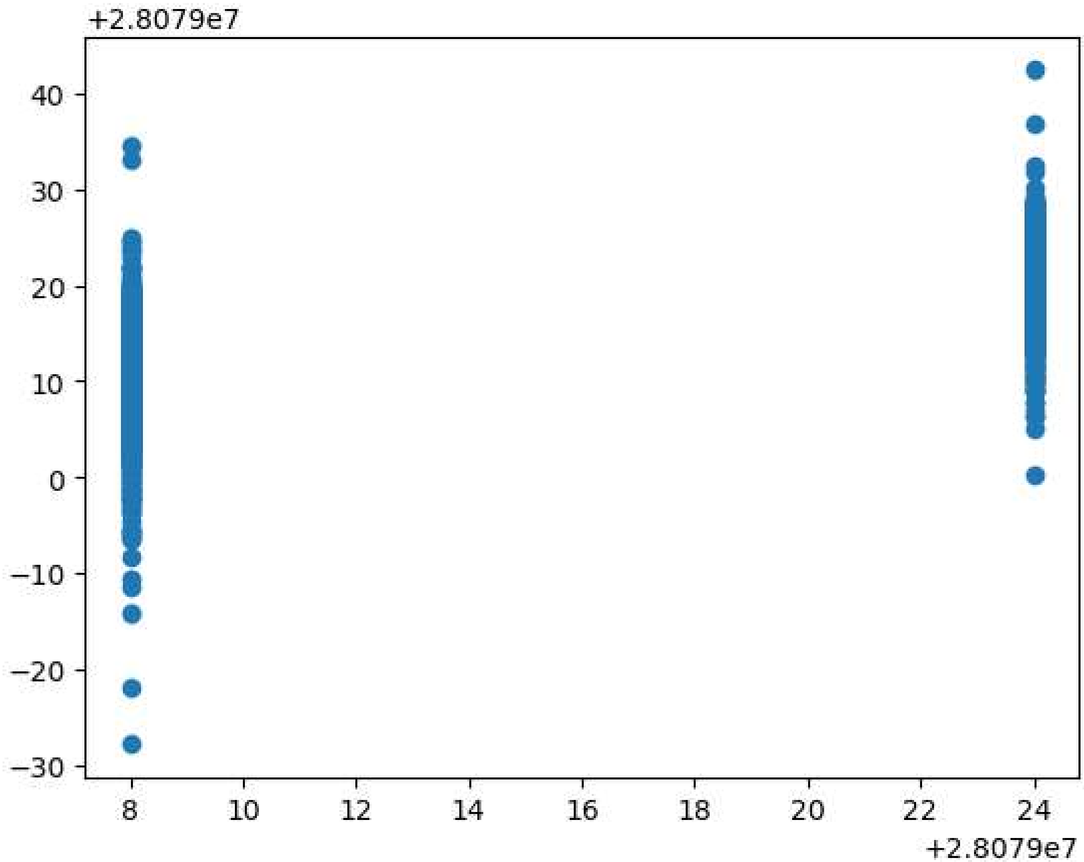
In [14]:
```
x=df[['BEN', 'CO', 'EBE', 'NMHC', 'NO_2', 'NO', 'O_3',
'PM10','PM25','SO_2', 'TCH', 'TOL']]
y=df['station']
```

In [15]:
```
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 [16]:
```
from sklearn.linear_model import LinearRegression
lr=LinearRegression()
lr.fit(x_train,y_train)
lr.intercept_
prediction =lr.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[16]: <matplotlib.collections.PathCollection at 0x21c55761190>



In [17]:
```
print(lr.score(x_test,y_test))
print(lr.score(x_train,y_train))
```

```
0.6259709949284429
0.6276479573022269
```

Ridge and Lasso

In [18]:
```
from sklearn.linear_model import Ridge,Lasso
rr=Ridge(alpha=10)
rr.fit(x_train,y_train)
print(rr.score(x_test,y_test))
print(rr.score(x_train,y_train))
la=Lasso(alpha=10)
la.fit(x_train,y_train)
```

```
0.5877091721395884
0.594469525578609
```

Out[18]:
```
Lasso
Lasso(alpha=10)
```

In [19]:
```
la.score(x_test,y_test)
```

Out[19]:
```
0.2273508727383743
```

ElasticNet

In [20]:
```
from sklearn.linear_model import ElasticNet
en=ElasticNet()
en.fit(x_train,y_train)
```

Out[20]:
```
ElasticNet
ElasticNet()
```

In [21]:
```
en.coef_
```

Out[21]:
```
array([ 0.2653043 ,  0.        , -0.        , -0.        , -0.14076021,
        0.05067364, -0.04412062,  0.02581064,  0.10485685, -0.16710751,
        0.        , -0.95067196])
```

In [22]:
```
en.intercept_
```

Out[22]:
```
28079025.14184462
```

In [23]:
```
prediction=en.predict(x_test)
```

In [24]:
```
en.score(x_test,y_test)
```

Out[24]:
```
0.3356452219334174
```

Evaluation Metrics

In [25]:
```
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)))
```

```
5.701842582725372
42.51283990709718
6.520187106755233
```

Logistics Regression

In [26]:
```
from sklearn.linear_model import LogisticRegression
```

In [27]:
```
feature_matrix=df[['BEN', 'CO', 'EBE', 'NMHC', 'NO_2', 'NO', 'O_3',
'PM10','PM25','SO_2', 'TCH', 'TOL']]
target_vector=df[ 'station']
```

In [28]:
```
from sklearn.preprocessing import StandardScaler
fs=StandardScaler().fit_transform(feature_matrix)
logr=LogisticRegression(max_iter=10000)
logr.fit(fs,target_vector)
```

Out[28]:
```
▾ LogisticRegression
LogisticRegression(max_iter=10000)
```

In [30]:
```
observation=[[1,2,3,4,5,6,7,8,9,10,11,12]]
logr.predict_proba(observation)
```

Out[30]:
```
array([[1.00000000e+00, 1.13637857e-16]])
```

Random Forest

In [31]:
```
from sklearn.ensemble import RandomForestClassifier
rfc=RandomForestClassifier()
rfc.fit(x_train,y_train)
```

Out[31]:
```
▾ RandomForestClassifier
RandomForestClassifier()
```

In [32]:
```
parameters={'max_depth':[1,2,3,4,5],
'min_samples_leaf':[5,10,15,20,25],
'n_estimators':[10,20,30,40,50]
}
```

In [33]:
```
from sklearn.model_selection import GridSearchCV
grid_search =GridSearchCV(estimator=rfc,param_grid=parameters,cv=2,scoring="ac
grid_search.fit(x_train,y_train)
```

Out[33]:
```
▸ GridSearchCV
▸ estimator: RandomForestClassifier
  ▸ RandomForestClassifier
```

In [34]:
```
rfc_best=grid_search.best_estimator_
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'
```

```
 Text(0.5813953488372093, 0.25, 'TOL <= 1.55\ngini = 0.017\nsamples = 769
\nvalue = [1239, 11]\nclass = a'),
 Text(0.5581395348837209, 0.08333333333333333, 'gini = 0.107\nsamples = 12
1\nvalue = [182, 11]\nclass = a'),
 Text(0.6046511627906976, 0.08333333333333333, 'gini = 0.0\nsamples = 648
\nvalue = [1057, 0]\nclass = a'),
 Text(0.813953488372093, 0.5833333333333334, 'NO_2 <= 39.5\ngini = 0.434\n
samples = 3589\nvalue = [3893, 1819]\nclass = a'),
 Text(0.7209302325581395, 0.4166666666666667, 'O_3 <= 23.5\ngini = 0.411\n
samples = 555\nvalue = [258, 634]\nclass = b'),
 Text(0.6744186046511628, 0.25, 'NO <= 15.5\ngini = 0.161\nsamples = 211\n
value = [30, 310]\nclass = b'),
 Text(0.6511627906976745, 0.08333333333333333, 'gini = 0.281\nsamples = 96
\nvalue = [27, 133]\nclass = b'),
 Text(0.6976744186046512, 0.08333333333333333, 'gini = 0.033\nsamples = 11
5\nvalue = [3, 177]\nclass = b'),
 Text(0.7674418604651163, 0.25, 'TOL <= 2.55\ngini = 0.485\nsamples = 344
\nvalue = [228, 324]\nclass = b'),
 Text(0.7441860465116279, 0.08333333333333333, 'gini = 0.32\nsamples = 209
```

Conclusion

In [35]:
```
print("Linear Regression:",lr.score(x_test,y_test))
print("Ridge Regression:",rr.score(x_test,y_test))
print("Lasso Regression",la.score(x_test,y_test))
print("ElasticNet Regression:",en.score(x_test,y_test))
print("Logistic Regression:",logr.score(fs,target_vector))
print("Random Forest:",grid_search.best_score_)
```

```
Linear Regression: 0.6259709949284429
Ridge Regression: 0.5877091721395884
Lasso Regression 0.2273508727383743
ElasticNet Regression: 0.3356452219334174
Logistic Regression: 0.9262454434993924
Random Forest: 0.935688248567957
```

Random Forest Is Better!!!