## In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sb
import matplotlib.pyplot as pp
```

## In [2]:

```
df1 = pd.read_csv(r"C:\Users\user\Desktop\c10\madrid_2006.csv")
df = df1.head(1000)
df
```

## Out[2]:

	date	BEN	со	EBE	MXY	NMHC	NO_2	NOx	OXY	O_3	PM1
0	2006- 02-01 01:00:00	NaN	1.84	NaN	NaN	NaN	155.100006	490.100006	NaN	4.88	97.57000
1	2006- 02-01 01:00:00	1.68	1.01	2.38	6.36	0.32	94.339996	229.699997	3.04	7.10	25.820000
2	2006- 02-01 01:00:00	NaN	1.25	NaN	NaN	NaN	66.800003	192.000000	NaN	4.43	34.41999
3	2006- 02-01 01:00:00	NaN	1.68	NaN	NaN	NaN	103.000000	407.799988	NaN	4.83	28.260000
4	2006- 02-01 01:00:00	NaN	1.31	NaN	NaN	NaN	105.400002	269.200012	NaN	6.99	54.180000
995	2006- 02-02 15:00:00	0.20	0.92	0.13	NaN	0.32	135.000000	271.299988	NaN	12.48	98.87999
996	2006- 02-02 15:00:00	NaN	0.96	NaN	NaN	NaN	134.199997	230.300003	NaN	8.23	77.29000°
997	2006- 02-02 15:00:00	NaN	1.21	NaN	NaN	NaN	141.699997	251.399994	NaN	14.56	146.600000
998	2006- 02-02 15:00:00	NaN	1.38	NaN	NaN	0.35	83.239998	218.399994	NaN	8.91	94.309998
999	2006- 02-02 15:00:00	NaN	1.22	NaN	NaN	NaN	83.820000	237.500000	NaN	8.03	91.660004

## 1000 rows × 17 columns

## In [3]:

df=df.dropna()

#### In [4]:

```
df.columns
```

```
Out[4]:
```

#### In [5]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 114 entries, 5 to 993
Data columns (total 17 columns):
     Column
              Non-Null Count Dtype
     -----
              -----
---
                              ----
0
     date
              114 non-null
                              object
                              float64
 1
     BEN
              114 non-null
 2
     CO
              114 non-null
                              float64
                              float64
 3
     EBE
              114 non-null
 4
     MXY
              114 non-null
                              float64
 5
              114 non-null
                              float64
     NMHC
                              float64
 6
     NO_2
              114 non-null
 7
                              float64
     NOx
              114 non-null
                              float64
 8
     OXY
              114 non-null
 9
     0 3
              114 non-null
                              float64
 10
    PM10
              114 non-null
                              float64
                              float64
 11
    PM25
              114 non-null
 12
    PXY
              114 non-null
                              float64
 13
     SO 2
              114 non-null
                              float64
                              float64
 14
    TCH
              114 non-null
 15
    TOL
              114 non-null
                              float64
 16 station 114 non-null
                              int64
dtypes: float64(15), int64(1), object(1)
memory usage: 16.0+ KB
```

## In [6]:

```
data=df[['CO' ,'station']]
data
```

## Out[6]:

	СО	station			
5	1.69	28079006			
22	0.79	28079024			
25	1.47	28079099			
31	0.85	28079006			
48	0.79	28079024			
961	1.25	28079099			
967	1.40	28079006			
984	0.83	28079024			
987	1.02	28079099			
993	1.43	28079006			

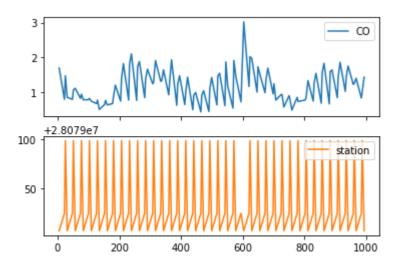
114 rows × 2 columns

## In [7]:

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

## Out[7]:

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

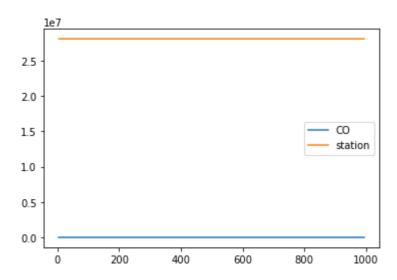


## In [8]:

data.plot.line()

## Out[8]:

## <AxesSubplot:>



## In [9]:

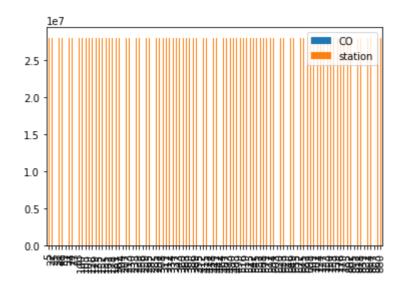
x = data[0:100]

## In [10]:

x.plot.bar()

## Out[10]:

## <AxesSubplot:>

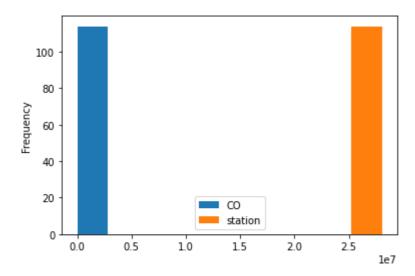


## In [11]:

data.plot.hist()

## Out[11]:

<AxesSubplot:ylabel='Frequency'>

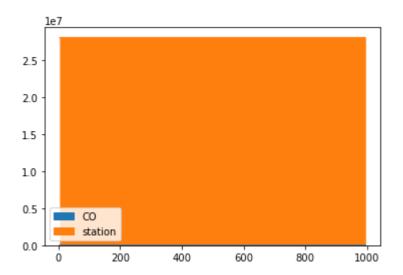


## In [12]:

data.plot.area()

## Out[12]:

# <AxesSubplot:>

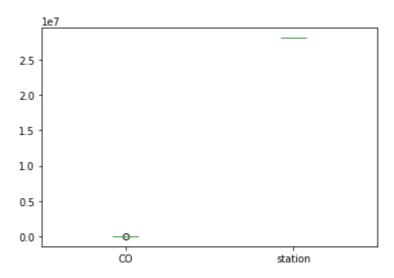


## In [13]:

data.plot.box()

## Out[13]:

## <AxesSubplot:>



```
In [14]:
```

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

## Out[14]:

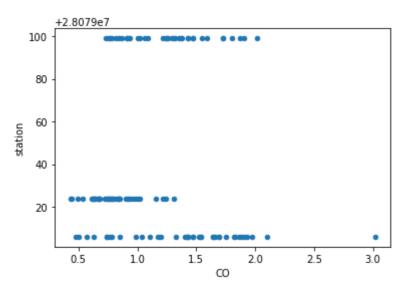
<AxesSubplot:ylabel='station'>

## In [15]:

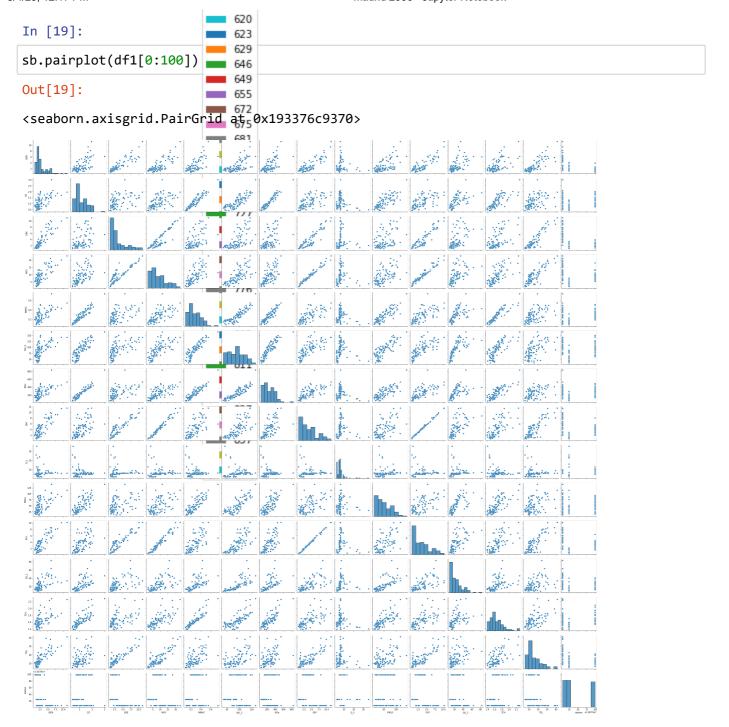
```
data.plot.scatter(x='CO' ,y='station')
```

## Out[15]:

<AxesSubplot:xlabel='CO', ylabel='station'>



```
222930 21294
In [16]:
df.info()
                                25
                                31
<class | pandas.core.frame.DataFrame'>
Int64Index: 114 entries, 5 to 993
Data columns (total 17 columns)
                Non-Null Count Dtype
     Column
                            83
                114 non-null 100 object
 0
                114 non-null 103float64
 1
          114 non-mull 126float64
114 non-null 129float64
 2
 3
     EBE
                114 non-null 129 float64
 4
     MXY
                114 non-null <sup>135</sup>float64
     NMHC
 5
                114 non-null 152 float64
 6
     NO 2
                114 non-null 161 float64
 7
     NOx
 8
     OXY
                114 non-null <sub>178</sub>float64
 9
     0_3
                114 non-null 181float64
 10
     PM10
                114 non-null 187float64
                114 non-null 204float64
 11
     PM25
                114 non-null 207 float64
 12
     PXY
                114 non-null <sup>213</sup>float64
 13
     SO_2
                                230
                                233
                                239
In [17]:
                                256
                                259
df.describe()
                                265
                                282
Out[17]:
                                285
                              <sup>291</sup> EBE
             BEN
                          CO
                                                MXY
                                                          NMHC
                                                                      NO_2
                                                                                   NOx
count 114.000000
                   114.000000 114.000000
                                          114.000000 114.000000
                                                                 114.000000
                                                                            114.000000 1
                                317
         3.007895
                     1.151930
                                3.650088
                                            9.002018
                                                       0.282018
                                                                  90.532982
                                                                            256.107017
 mean
                                 2<sub>4</sub>558025
         1.967359
                                            4.874614
   std
                     0.464977
                                                       0.119432
                                                                  30.213987
                                                                            128.404652
                                75080000
         0.760000
                     0.430000
                                            1.860000
                                                       0.090000
  min
                                                                  35.290001
                                                                              55.320000
  25%
         1.727500
                     0.772500
                                36820000
                                            5.097500
                                                       0.180000
                                                                  65.037500 144.549999
                                386
  50%
                     1.030000
                                2425000
         2.195000
                                            7.730000
                                                       0.270000
                                                                  92.469997
                                                                             239.650002
                                395
51045000
  75%
                     1.470000
         3.845000
                                           11.307500
                                                       0.360000
                                                                             337.174988
                                                                 112.775002
                     3.020000 11.070000
        11.230000
                                           22.920000
                                                                 164.500000 832.500000
  max
                                                       0.740000
                                421
                                441
                                447
In [18]:
                                464
                                46MXY', 'NMHC', 'NO_2', 'NOx', 'OXY', '0_3',
df1=df[['BEN', 'CO', 'EBET
                                TCH', 'TOL', 'station']]
        'PM10', 'PXY',
                                493
                                499
                                516
                                519
                                525
                                542
                                545
                                551
                                568
                                571
                                577
                                594
                                603
```



#### In [20]:

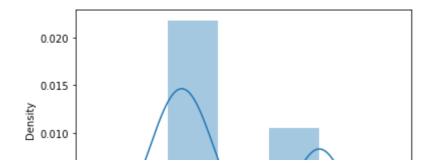
## sb.distplot(df1['station'])

C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:255
7: FutureWarning: `distplot` is a deprecated function and will be remove d in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

warnings.warn(msg, FutureWarning)

#### Out[20]:

<AxesSubplot:xlabel='station', ylabel='Density'>

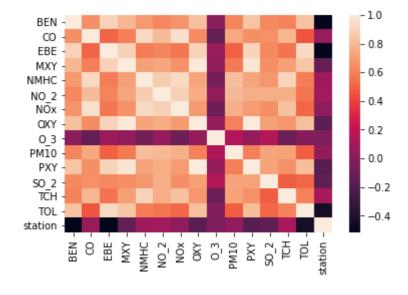


#### In [21]:

```
sb.heatmap(df1.corr())
```

#### Out[21]:

#### <AxesSubplot:>



#### In [22]:

```
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)
```

#### 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]:

28079094.969658807

#### In [26]:

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

## Out[26]:

#### Co-efficient

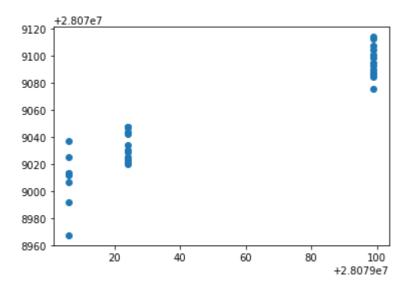
-10.748896 BEN CO -2.015224 **EBE** -29.410909 **MXY** 14.833981 **NMHC** 199.300105 NO\_2 -0.129263 -0.012314 NOx OXY -47.881637 O\_3 0.416031 **PM10** 0.113235 **PXY** 49.165460 SO\_2 -0.274870 **TCH** -46.015310 **TOL** 1.182023

```
In [27]:
```

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

## Out[27]:

<matplotlib.collections.PathCollection at 0x1934484cb50>



#### In [28]:

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

#### Out[28]:

0.8669452029017192

## In [29]:

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

## Out[29]:

0.9061843657440546

## In [30]:

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

## In [31]:

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

### Out[31]:

Ridge(alpha=10)

## In [32]:

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

## Out[32]:

0.8867524775822146

```
In [33]:
r.score(x_train,y_train)
Out[33]:
0.8664819679629829
In [34]:
l=Lasso(alpha=10)
1.fit(x_train,y_train)
Out[34]:
Lasso(alpha=10)
In [35]:
1.score(x_train,y_train)
Out[35]:
0.6923145899784232
In [36]:
1.score(x_test,y_test)
Out[36]:
0.5633408788029934
In [37]:
from sklearn.linear_model import ElasticNet
e=ElasticNet()
e.fit(x_train,y_train)
Out[37]:
ElasticNet()
In [38]:
e.coef_
Out[38]:
                                  , -11.59480875,
array([ -7.99133153,
                       0.
                                                     6.14978637,
                       0.52304156,
                                      0.01210836,
                                                     1.34122031,
         0.
        -0.05790393,
                                      0.81326317, -0.72421383,
                       0.20451887,
                      -1.85215883])
         0.
In [39]:
e.intercept_
Out[39]:
28079028.84873901
```

```
In [40]:
prediction=e.predict(x_test)
In [41]:
e.score(x_test,y_test)
Out[41]:
0.7754908047419946
In [42]:
from sklearn import metrics
In [43]:
print(metrics.mean_squared_error(y_test,prediction))
359.12930728220454
In [44]:
print(np.sqrt(metrics.mean_squared_error(y_test,prediction)))
18.95070730295322
In [45]:
print(metrics.mean_absolute_error(y_test,prediction))
16.161460589085305
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]:
(114, 14)
In [49]:
target_vector.shape
Out[49]:
(114,)
```

```
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)
[28079006]
In [55]:
logr.classes_
Out[55]:
array([28079006, 28079024, 28079099], dtype=int64)
In [56]:
logr.score(fs,target_vector)
Out[56]:
1.0
In [57]:
logr.predict_proba(observation)[0][0]
Out[57]:
0.9261448787367386
In [58]:
logr.predict_proba(observation)
Out[58]:
array([[9.26144879e-01, 3.39405518e-16, 7.38551213e-02]])
```

```
In [59]:
```

```
from sklearn.ensemble import RandomForestClassifier
```

```
In [60]:
```

```
rfc=RandomForestClassifier()
rfc.fit(x_train,y_train)
```

#### Out[60]:

RandomForestClassifier()

#### In [61]:

## 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]:

#### In [63]:

```
grid_search.best_score_
```

### Out[63]:

0.8733974358974359

#### In [64]:

```
rfc_best=grid_search.best_estimator_
```

#### In [65]:

```
from sklearn.tree import plot_tree

pp.figure(figsize=(80,40))
plot_tree(rfc_best.estimators_[5],feature_names=x.columns,class_names=['a','b','c','d'],f
Out[65]:
```

[Text(2232.0, 1630.8000000000002, 'OXY <= 5.24\ngini = 0.65\nsamples = 50 \nvalue = [31, 30, 18]\nclass = a'),

Text(1116.0, 543.59999999999, 'gini = 0.546\nsamples = 32\nvalue = [5, 30, 16]\nclass = b'),

Text(3348.0, 543.59999999999, 'gini = 0.133\nsamples = 18\nvalue = [26, 0, 2]\nclass = a')]

OXY <= 5.24 gini = 0.65 samples = 50 value = [31, 30, 18] class = a

gini = 0.546 samples = 32 value = [5, 30, 16] class = b gini = 0.133 samples = 18 value = [26, 0, 2] class = a

# random forest is best suitable for this dataset

#### In [ ]: