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_2004.csv")
df = df1.head(1000)
df
```

Out[2]:

	date	BEN	СО	EBE	MXY	NMHC	NO_2	NOx	OXY	O_3	PΝ
0	2004- 08-01 01:00:00	NaN	0.66	NaN	NaN	NaN	89.550003	118.900002	NaN	40.020000	39.990
1	2004- 08-01 01:00:00	2.66	0.54	2.99	6.08	0.18	51.799999	53.860001	3.28	51.689999	22.950
2	2004- 08-01 01:00:00	NaN	1.02	NaN	NaN	NaN	93.389999	138.600006	NaN	20.860001	49.4800
3	2004- 08-01 01:00:00	NaN	0.53	NaN	NaN	NaN	87.290001	105.000000	NaN	36.730000	31.070
4	2004- 08-01 01:00:00	NaN	0.17	NaN	NaN	NaN	34.910000	35.349998	NaN	86.269997	54.0800
995	2004- 08-02 13:00:00	NaN	0.47	NaN	NaN	NaN	84.260002	146.100006	NaN	39.549999	53.759!
996	2004- 08-02 13:00:00	NaN	0.22	NaN	NaN	0.54	51.709999	69.400002	NaN	62.310001	65.510
997	2004- 08-02 13:00:00	NaN	0.33	NaN	NaN	NaN	48.009998	64.550003	NaN	58.240002	38.389!
998	2004- 08-02 13:00:00	4.57	0.52	2.45	NaN	0.05	87.779999	138.199997	NaN	51.430000	53.259!
999	2004- 08-02 13:00:00	NaN	0.13	NaN	NaN	NaN	55.820000	75.260002	NaN	63.910000	49.150

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: 100 entries, 5 to 989
Data columns (total 17 columns):
     Column
              Non-Null Count Dtype
     -----
              -----
---
                              ----
0
     date
              100 non-null
                              object
     BEN
                              float64
 1
              100 non-null
 2
     CO
              100 non-null
                              float64
                              float64
 3
     EBE
              100 non-null
 4
     MXY
              100 non-null
                              float64
 5
              100 non-null
                              float64
     NMHC
                              float64
 6
     NO_2
              100 non-null
 7
                              float64
     NOx
              100 non-null
                              float64
 8
     OXY
              100 non-null
 9
     0 3
                              float64
              100 non-null
 10
    PM10
              100 non-null
                              float64
                              float64
 11
    PM25
              100 non-null
 12
     PXY
              100 non-null
                              float64
 13
     SO 2
              100 non-null
                              float64
                              float64
 14
    TCH
              100 non-null
 15
    TOL
              100 non-null
                              float64
 16 station 100 non-null
                              int64
dtypes: float64(15), int64(1), object(1)
memory usage: 14.1+ KB
```

In [6]:

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

Out[6]:

	СО	station
5	0.63	28079006
22	0.36	28079024
26	0.46	28079099
32	0.67	28079006
49	0.30	28079024
955	0.42	28079099
961	1.25	28079006
979	0.22	28079024
983	0.44	28079099
989	1.24	28079006

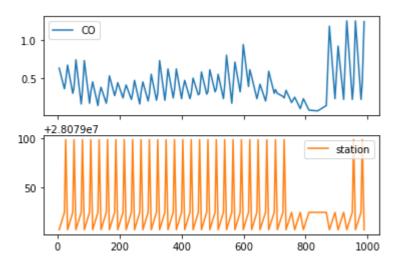
100 rows × 2 columns

In [7]:

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

Out[7]:

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

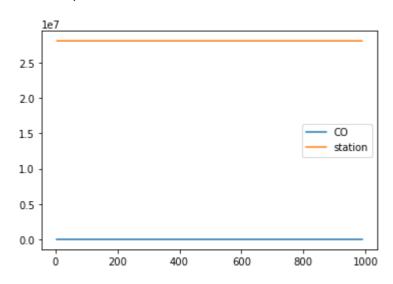


In [8]:

data.plot.line()

Out[8]:

<AxesSubplot:>



In [9]:

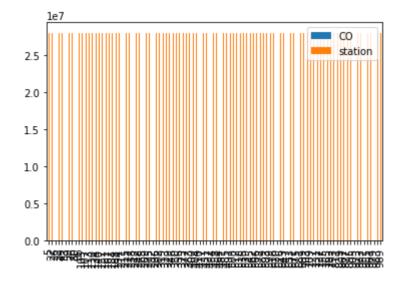
x = data[0:100]

In [10]:

x.plot.bar()

Out[10]:

<AxesSubplot:>

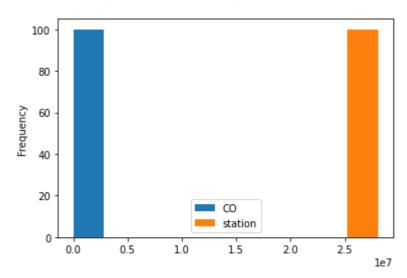


In [11]:

data.plot.hist()

Out[11]:

<AxesSubplot:ylabel='Frequency'>

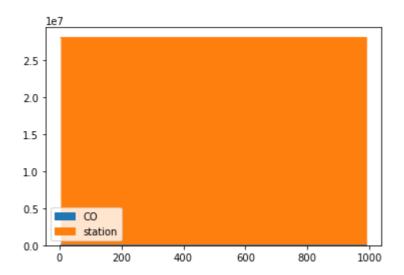


In [12]:

data.plot.area()

Out[12]:

<AxesSubplot:>

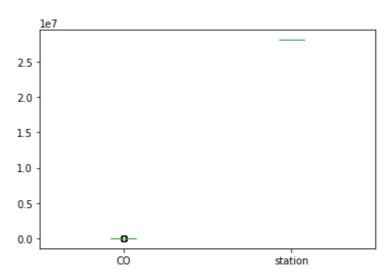


In [13]:

data.plot.box()

Out[13]:

<AxesSubplot:>



```
In [14]:
```

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

Out[14]:

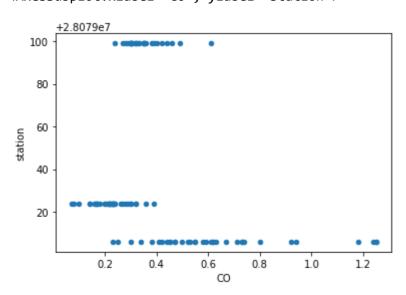
<AxesSubplot:ylabel='station'>

In [15]:

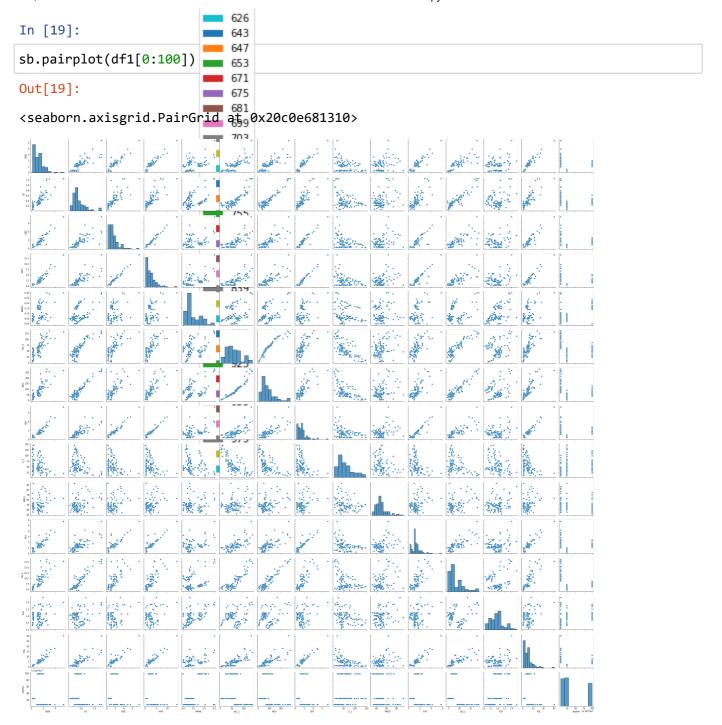
```
data.plot.scatter(x='CO' ,y='station')
```

Out[15]:

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



```
add 28 2215466
In [16]:
df.info()
                                26
                                32
<class 'pandas.core.frame.DataFrame'>
Int64Index: 100 entries, 5 to 989
Date columns (total 17 columns)
                Non-Null Count Dtype
     Column
                            00 5 Pe
                     non-null <sub>103</sub>object
 0
                100 non-null 107float64
 1
          100 non-null 130 float64
100 non-null 134 float64
 2
 3
     EBE
                100 non-null 134 float64
 4
     MXY
                100 non-null 140 float64
 5
     NMHC
                100 non-null 157 float64
 6
     NO 2
 7
                100 non-null 167 float64
     NOx
 8
     OXY
                100 non-null <sub>184</sub>float64
 9
     0_3
                100 non-null 188float64
 10
     PM10
                100 non-null 194float64
                100 non-null 211float64
 11
     PM25
                100 non-null 215 float 64
 12
     PXY
                100 non-null <sup>221</sup>float64
 13
     SO_2
                                238
                                242
                                248
In [17]:
                                265
                                269
df.describe()
                                275
                                292
Out[17]:
                                296
                                302
             BEN
                          CO
                                    EBE
                                                MXY
                                                          NMHC
                                                                      NO_2
                                                                                   NOx
count 100.000000
                   100.00000 100.000000
                                          100.000000
                                                      100.000000
                                                                 100.000000 100.000000
                              329
                     0.401900
          1.186700
                                34442300
                                            2.388100
                                                        0.093200
                                                                  58.240300
                                                                              82.661400
 mean
          0.905903
                     0.245849
                                                                              60.783607
   std
                                   247769
                                            2.270227
                                                        0.072389
                                                                  30.625082
                                7.250000
         0.190000
                                                        0.000000
  min
                     0.070000
                                            0.230000
                                                                   4.540000
                                                                               4.630000
  25%
          0.337500
                     0.237500
                                33.415000
                                            0.572500
                                                        0.040000
                                                                  35.147499
                                                                              41.542499
                     0.320000
                                40,040000
  50%
          1.195000
                                            1.935000
                                                        0.065000
                                                                  53.105001
                                                                              63.610001
                                410
1.832500
  75%
                     0.475000
          1.580000
                                            3.095000
                                                        0.150000
                                                                  74.535000
                                                                             108.750002
                                47.550000
                     1.250000
          5.400000
                                            14.080000
                                                                  135.000000
                                                                             279.799988
  max
                                                        0.300000
                                437
                                458
                                464
In [18]:
                                481
                                485
MXY', 'NMHC', 'NO_2', 'NOx', 'OXY', 'O_3',
df1=df[['BEN', 'CO', 'EBE
                                TCH', 'TOL', 'station']]
        'PM10', 'PXY',
                                512
                                518
                                535
                                539
                                545
                                562
                                566
                                572
                                589
                                593
                                599
                                616
                                620
```



In [20]:

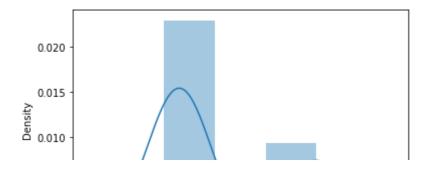
sb.distplot(df1['station'])

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'>

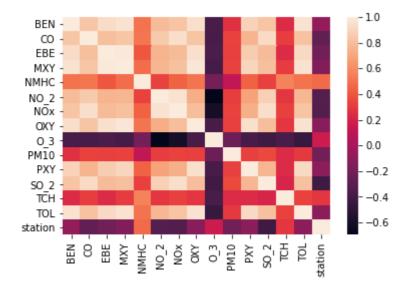


In [21]:

```
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]:

28078950.82491036

Co-efficient

In [26]:

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

Out[26]:

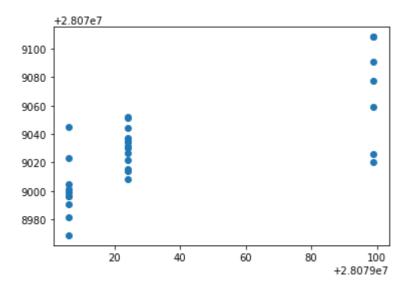
61.204819 **BEN** -25.447483 CO -13.844988 **EBE** MXY 4.489134 **NMHC** 352.403422 NO_2 -0.083407 NOx -0.468326 OXY -14.863733 O_3 -0.171765 **PM10** -0.167580 **PXY** 12.890044 SO_2 -1.868694 **TCH** 81.800858 TOL -6.188675

```
In [27]:
```

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

Out[27]:

<matplotlib.collections.PathCollection at 0x20c1d299eb0>



In [28]:

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

Out[28]:

0.45557467769186066

In [29]:

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

Out[29]:

0.791158550959588

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]:

0.02223624112412015

```
In [33]:
r.score(x_train,y_train)
Out[33]:
0.48343210561710614
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]:
0.2970261802948704
In [36]:
1.score(x_test,y_test)
Out[36]:
-0.2989841161260207
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]:
                               , -2.75673309, 0.81676049, 1.5259761,
array([ 4.1214755 , 0.
       -0.62194175, 0.31148644, 1.53679929, 0.31526474, -0.1891754,
        2.19191466, -8.99692726, 0.79847353,
                                                2.9275602 ])
In [39]:
e.intercept_
Out[39]:
28079094.52590053
```

```
In [40]:
prediction=e.predict(x_test)
In [41]:
e.score(x_test,y_test)
Out[41]:
-0.12667668616532257
In [42]:
from sklearn import metrics
In [43]:
print(metrics.mean_squared_error(y_test,prediction))
1451.4412409524768
In [44]:
print(np.sqrt(metrics.mean_squared_error(y_test,prediction)))
38.09778524996534
In [45]:
print(metrics.mean_absolute_error(y_test,prediction))
33.73625044661264
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]:
(100, 14)
In [49]:
target_vector.shape
Out[49]:
(100,)
```

```
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]:
0.9901352554131048
In [58]:
logr.predict_proba(observation)
Out[58]:
array([[9.90135255e-01, 4.89040800e-29, 9.86474459e-03]])
```

```
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]:

0.9857142857142858

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, 'TOL <= 2.51\ngini = 0.649\nsamples = 42 \nvalue = [31, 19, 20]\nclass = a'),

Text(1116.0, 543.59999999999, 'gini = 0.0\nsamples = 12\nvalue = [0, 1 9, 0]\nclass = b'),

Text(3348.0, 543.59999999999, 'gini = 0.477\nsamples = 30\nvalue = [31, 0, 20]\nclass = a')]
```

TOL <= 2.51 gini = 0.649 samples = 42 value = [31, 19, 20] class = a

gini = 0.0 samples = 12 value = [0, 19, 0] class = b gini = 0.477 samples = 30 value = [31, 0, 20] class = a

random forest is best suitable for this data set

In []: