In [2]:

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

In [3]:

```
df1 = pd.read_csv(r"C:\Users\user\Desktop\c10\madrid_2018.csv")
df = df1.head(1000)
df
```

Out[3]:

	date	BEN	CH4	СО	EBE	NMHC	NO	NO_2	NOx	0_3	PM10	PM25	SO_2	1
0	2018- 03-01 01:00:00	NaN	NaN	0.3	NaN	NaN	1.0	29.0	31.0	NaN	NaN	NaN	2.0	1
1	2018- 03-01 01:00:00	0.5	1.39	0.3	0.2	0.02	6.0	40.0	49.0	52.0	5.0	4.0	3.0	,
2	2018- 03-01 01:00:00	0.4	NaN	NaN	0.2	NaN	4.0	41.0	47.0	NaN	NaN	NaN	NaN	1
3	2018- 03-01 01:00:00	NaN	NaN	0.3	NaN	NaN	1.0	35.0	37.0	54.0	NaN	NaN	NaN	1
4	2018- 03-01 01:00:00	NaN	NaN	NaN	NaN	NaN	1.0	27.0	29.0	49.0	NaN	NaN	3.0	1
995	2018- 03-02 18:00:00	NaN	NaN	0.4	NaN	NaN	13.0	62.0	83.0	31.0	NaN	NaN	NaN	1
996	2018- 03-02 18:00:00	NaN	NaN	NaN	NaN	NaN	19.0	70.0	99.0	NaN	9.0	NaN	4.0	1
997	2018- 03-02 18:00:00	NaN	NaN	NaN	NaN	NaN	42.0	88.0	152.0	NaN	3.0	2.0	NaN	1
998	2018- 03-02 18:00:00	NaN	NaN	NaN	NaN	NaN	20.0	69.0	100.0	NaN	11.0	10.0	NaN	1
999	2018- 03-02 18:00:00	NaN	NaN	NaN	NaN	NaN	19.0	76.0	105.0	14.0	NaN	NaN	NaN	1

1000 rows × 16 columns

In [4]:

df=df.dropna()

In [5]:

```
df.columns
```

```
Out[5]:
```

In [6]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 83 entries, 1 to 990
Data columns (total 16 columns):
              Non-Null Count Dtype
     Column
     -----
              -----
---
                              ----
0
     date
              83 non-null
                              object
              83 non-null
                              float64
 1
     BEN
 2
     CH4
              83 non-null
                              float64
                              float64
 3
              83 non-null
     CO
 4
              83 non-null
                              float64
     EBE
 5
              83 non-null
                              float64
     NMHC
 6
     NO
              83 non-null
                              float64
 7
     NO 2
              83 non-null
                              float64
                              float64
 8
     NOx
              83 non-null
 9
     0 3
              83 non-null
                              float64
 10
    PM10
              83 non-null
                              float64
                              float64
 11
     PM25
              83 non-null
 12
     S0_2
              83 non-null
                              float64
 13
     TCH
              83 non-null
                              float64
              83 non-null
                              float64
 14
    TOL
15 station 83 non-null
                              int64
dtypes: float64(14), int64(1), object(1)
memory usage: 11.0+ KB
```

In [7]:

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

Out[7]:

	СО	station
1	0.3	28079008
6	0.2	28079024
25	0.2	28079008
30	0.2	28079024
49	0.2	28079008
942	0.3	28079024
961	0.6	28079008
966	0.2	28079024
985	0.5	28079008
990	0.2	28079024

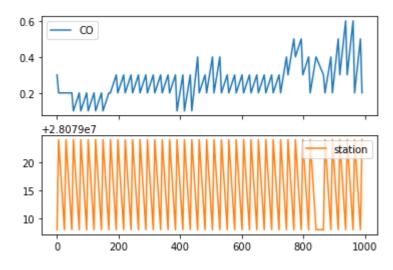
83 rows × 2 columns

In [8]:

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

Out[8]:

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

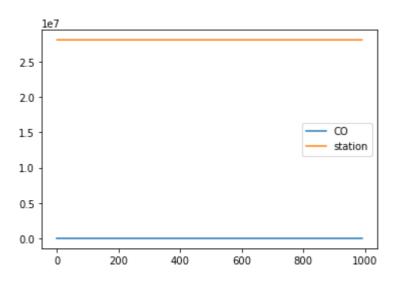


In [9]:

data.plot.line()

Out[9]:

<AxesSubplot:>



In [10]:

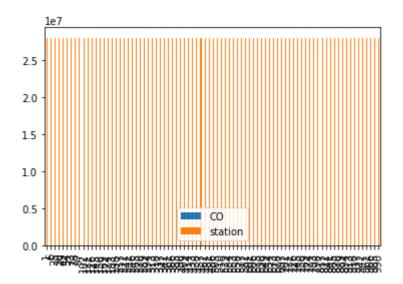
x = data[0:100]

In [11]:

x.plot.bar()

Out[11]:

<AxesSubplot:>

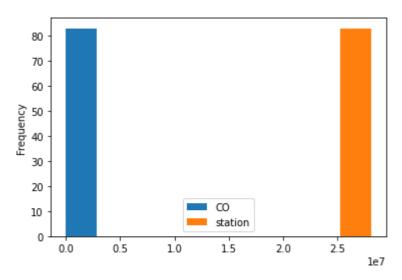


In [12]:

data.plot.hist()

Out[12]:

<AxesSubplot:ylabel='Frequency'>

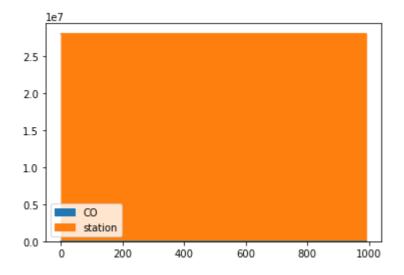


In [13]:

data.plot.area()

Out[13]:

<AxesSubplot:>

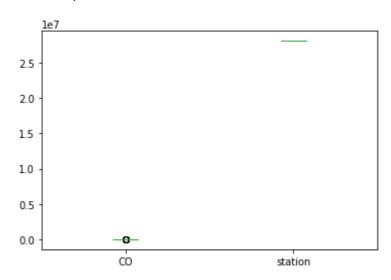


In [14]:

data.plot.box()

Out[14]:

<AxesSubplot:>



```
In [15]:
```

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

Out[15]:

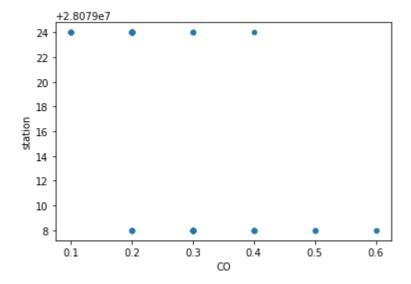
<AxesSubplot:ylabel='station'>

In [16]:

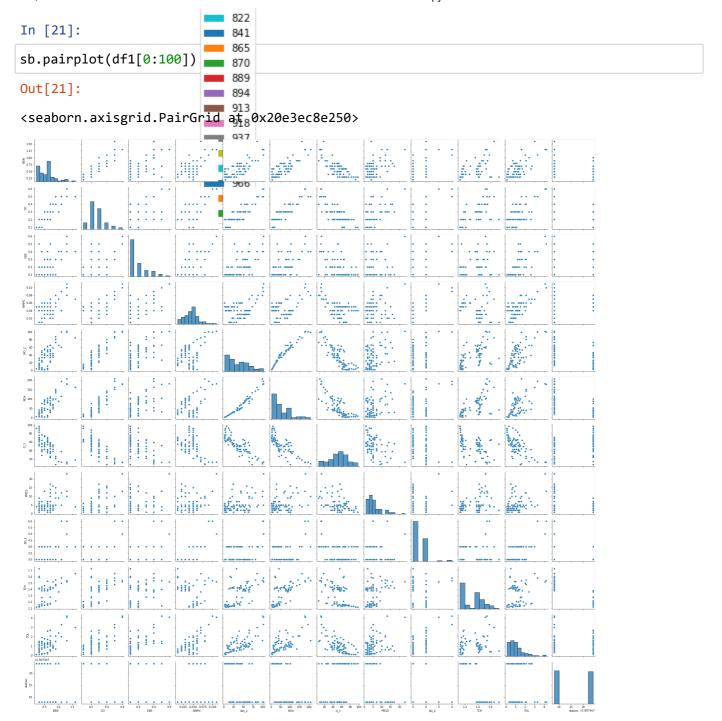
```
data.plot.scatter(x='CO' ,y='station')
```

Out[16]:

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



```
242198
In [17]:
df.info()
                               30
<class 'pandas.core.frame.DataFrame'>
Int64Index: 83 entries, 1 to 4990
Data columns (total 16 columns)
 #锐《Column
                Non-Null Count Dtype
                              102 7----
                             ∎ <sub>121</sub>object
 0
               83 non-null 126float64
 1
     2
 3
               83 non-nul 169float64
 4
               83 non-null <sup>174</sup>float64
 5
     NMHC
               83 non-null 193 float64
 6
     NO
               83 non-null 217 float64
 7
     NO_2
 8
     NOx
               83 non-null 222float64
               83 non-null 241float64
 9
     0_3
               83 non-nul 246 float 64
 10
     PM10
               83 non-nul 265 float 64
 11
     PM25
               83 non-nul 270 float64
 12
     SO 2
                             289
float64
               83 non-null
 13
     TCH
                               294
                              313
                               318
In [18]:
                               337
                               342
df.describe()
                               361
                               366
Out[18]:
                               385
                             ■ 390co
            BEN
                      CH4
                                          EBE
                                                  NMHC
                                                               NO
                                                                        NO_2
                 83.000000 83.000000
count 83.000000
                                     83.000000 83.000000 83.000000
                                                                     83.000000
                                                                                83.000
                             433
        0.589157
                  1.275301
                                      0.185542
                                                0.044096
                                                         12.783133
                                                                     36.843373
                                                                                56.385
 mean
                          0.265060
        0.276305
                  0.169010
                                      0.123103
  std
                                                0.020184
                                                         15.798308
                                                                     27.034974
                                                                                50.024
                            0.100000
        0.200000
                  1.080000
                                      0.100000
                                                0.010000
                                                                                 3.000
  min
                                                          1.000000
                                                                      2.000000
                              486
  25%
        0.400000
                  1.100000 -0.260000
                                      0.100000
                                                0.030000
                                                           1.000000
                                                                     14.000000
                                                                                17.000
                              510
  50%
        0.600000
                  1.350000
                                      0.100000
                                                0.040000
                                                           4.000000
                                                                     34.000000
                                                                                40.000
                            0.200000
  75%
                  1.400000
        0.700000
                                      0.200000
                                                0.050000
                                                          19.500000
                                                                     55.000000
                                                                                89.000
                            0.655500
                  1.720000
                                      0.600000
                                                 0.110000 71.000000
                                                                    102.000000
                                                                               208.000
  max
        1.600000
                              577
                               601
                               606
In [20]:
                               625
                             63NMHC', 'NO_2', 'NOx', 'O_3',
df1=df[['BEN', 'CO', 'EBE
                              TOL', 'station']]
        'PM10', 'SO_2',
                               673
                               678
                               697
                               702
                               721
                               726
                               745
                               750
                               769
                               774
                               793
                               798
                               817
```



```
In [22]:
```

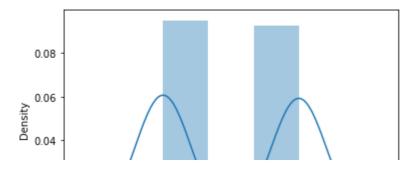
```
sb.distplot(df1['station'])
```

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[22]:

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



In []:

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

In [23]:

In [24]:

```
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 [25]:

```
from sklearn.linear_model import LinearRegression
lr=LinearRegression()
lr.fit(x_train,y_train)
```

Out[25]:

LinearRegression()

In [26]:

```
lr.intercept_
```

Out[26]:

28079031.416664694

In [27]:

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

Out[27]:

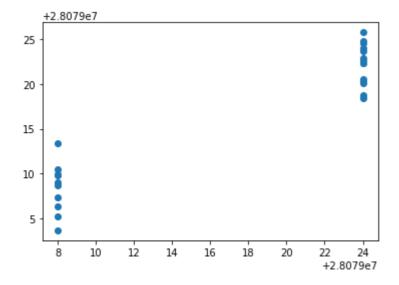
	Co-efficient		
BEN	2.850632		
со	-33.764002		
EBE	2.894612		
NMHC	263.064382		
NO_2	0.093230		
NOx	-0.121530		
O_3	-0.043294		
PM10	0.019408		
SO_2	-0.305820		
тсн	-10.166375		
TOL	-0.616478		

In [28]:

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

Out[28]:

<matplotlib.collections.PathCollection at 0x20e47e3f070>



In [29]:

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

Out[29]:

0.8593006551325477

```
In [30]:
lr.score(x_train,y_train)
Out[30]:
0.9685777662792087
In [31]:
from sklearn.linear_model import Ridge,Lasso
In [32]:
r=Ridge(alpha=10)
r.fit(x_train,y_train)
Out[32]:
Ridge(alpha=10)
In [33]:
r.score(x_test,y_test)
Out[33]:
0.6843527368959668
In [34]:
r.score(x_train,y_train)
Out[34]:
0.6805566756117155
In [35]:
l=Lasso(alpha=10)
1.fit(x_train,y_train)
Out[35]:
Lasso(alpha=10)
In [36]:
1.score(x_train,y_train)
Out[36]:
0.43550728759496293
In [37]:
1.score(x_test,y_test)
Out[37]:
0.3738345569498982
```

```
In [38]:
from sklearn.linear_model import ElasticNet
e=ElasticNet()
e.fit(x_train,y_train)
Out[38]:
ElasticNet()
In [39]:
e.coef_
Out[39]:
                                                          , -0.05044841,
array([ 0.
                  , -0.
       -0.14127213, -0.16530384, -0.21242968, 1.74123806, -0.0257283,
        0.640385 ])
In [40]:
e.intercept_
Out[40]:
28079028.52312789
In [41]:
prediction=e.predict(x_test)
In [42]:
e.score(x_test,y_test)
Out[42]:
0.5566407016409418
In [43]:
from sklearn import metrics
In [44]:
print(metrics.mean_squared_error(y_test,prediction))
27.239995291180534
In [45]:
print(np.sqrt(metrics.mean_squared_error(y_test,prediction)))
5.219194889174051
```

localhost:8888/notebooks/madrid 2018.ipynb

```
In [46]:
print(metrics.mean_absolute_error(y_test,prediction))
4.456924369931221
In [47]:
from sklearn.linear_model import LogisticRegression
In [49]:
feature_matrix=df[['BEN', 'CO', 'EBE', 'NMHC', 'NO_2', 'NOx', '0_3',
       'PM10', 'SO_2', 'TCH', 'TOL']]
target_vector=df[ 'station']
In [50]:
feature_matrix.shape
Out[50]:
(83, 11)
In [51]:
target_vector.shape
Out[51]:
(83,)
In [52]:
from sklearn.preprocessing import StandardScaler
In [53]:
fs=StandardScaler().fit_transform(feature_matrix)
In [54]:
logr=LogisticRegression(max iter=10000)
logr.fit(fs,target_vector)
Out[54]:
LogisticRegression(max_iter=10000)
In [60]:
observation=[[1,2,3,4,5,6,7,8,9,10,11]]
In [61]:
prediction=logr.predict(observation)
print(prediction)
[28079008]
```

```
In [62]:
logr.classes_
Out[62]:
array([28079008, 28079024], dtype=int64)
In [63]:
logr.score(fs,target_vector)
Out[63]:
1.0
In [64]:
logr.predict_proba(observation)[0][0]
Out[64]:
0.9999999988636115
In [65]:
logr.predict_proba(observation)
Out[65]:
array([[9.9999999e-01, 1.13638856e-09]])
In [66]:
from sklearn.ensemble import RandomForestClassifier
In [67]:
rfc=RandomForestClassifier()
rfc.fit(x_train,y_train)
Out[67]:
RandomForestClassifier()
In [68]:
parameters={'max_depth':[1,2,3,4,5],
            'min_samples_leaf':[5,10,15,20,25],
            'n_estimators':[10,20,30,40,50]
}
```

```
In [69]:
```

```
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[69]:

In [70]:

```
grid_search.best_score_
```

Out[70]:

0.9827586206896552

In [71]:

```
rfc_best=grid_search.best_estimator_
```

In [72]:

```
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[72]:

```
[Text(2232.0, 1630.8000000000002, 'NO_2 <= 14.0\ngini = 0.5\nsamples = 38 \nvalue = [29, 29]\nclass = a'),

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

Text(3348.0, 543.599999999999, 'gini = 0.466\nsamples = 29\nvalue = [29, 17]\nclass = a')]
```

NO_2 <= 14.0 gini = 0.5 samples = 38 value = [29, 29] class = a

```
gini = 0.0
samples = 9
value = [0, 12]
class = b
```

gini = 0.466 samples = 29 value = [29, 17] class = a

random forest is best suitable for this dataset

In []:		