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_2016.csv")
df = df1.head(1000)
df
```

Out[2]:

	date	BEN	СО	EBE	NMHC	NO	NO_2	O_3	PM10	PM25	SO_2	тсн	TOL	
0	2016- 11-01 01:00:00	NaN	0.7	NaN	NaN	153.0	77.0	NaN	NaN	NaN	7.0	NaN	NaN	<u>'</u>
1	2016- 11-01 01:00:00	3.1	1.1	2.0	0.53	260.0	144.0	4.0	46.0	24.0	18.0	2.44	14.4	1
2	2016- 11-01 01:00:00	5.9	NaN	7.5	NaN	297.0	139.0	NaN	NaN	NaN	NaN	NaN	26.0	:
3	2016- 11-01 01:00:00	NaN	1.0	NaN	NaN	154.0	113.0	2.0	NaN	NaN	NaN	NaN	NaN	1
4	2016- 11-01 01:00:00	NaN	NaN	NaN	NaN	275.0	127.0	2.0	NaN	NaN	18.0	NaN	NaN	1
995	2016- 11-02 18:00:00	NaN	0.4	NaN	NaN	24.0	66.0	24.0	NaN	NaN	NaN	NaN	NaN	1
996	2016- 11-02 18:00:00	NaN	NaN	NaN	NaN	9.0	56.0	NaN	35.0	NaN	5.0	NaN	NaN	1
997	2016- 11-02 18:00:00	NaN	NaN	NaN	NaN	4.0	42.0	NaN	26.0	12.0	NaN	NaN	NaN	1
998	2016- 11-02 18:00:00	NaN	NaN	NaN	NaN	25.0	70.0	NaN	34.0	13.0	NaN	NaN	NaN	1
999	2016- 11-02 18:00:00	NaN	NaN	NaN	NaN	1.0	28.0	53.0	NaN	NaN	NaN	NaN	NaN	2

1000 rows × 14 columns

In [3]:

df=df.dropna()

In [4]:

```
df.columns
```

```
Out[4]:
```

In [5]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 84 entries, 1 to 990
Data columns (total 14 columns):
     Column
              Non-Null Count Dtype
     -----
              -----
---
                              ----
0
     date
              84 non-null
                              object
 1
     BEN
              84 non-null
                              float64
 2
     CO
              84 non-null
                              float64
                              float64
 3
     EBE
              84 non-null
 4
     NMHC
              84 non-null
                              float64
 5
              84 non-null
                              float64
     NO
                              float64
 6
     NO_2
              84 non-null
 7
                              float64
     0 3
              84 non-null
                              float64
 8
     PM10
              84 non-null
 9
              84 non-null
                              float64
     PM25
 10
    SO_2
              84 non-null
                              float64
                              float64
 11
    TCH
              84 non-null
 12
     TOL
              84 non-null
                              float64
     station 84 non-null
                              int64
dtypes: float64(12), int64(1), object(1)
memory usage: 9.8+ KB
```

In [6]:

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

Out[6]:

	СО	station
1	1.1	28079008
6	0.8	28079024
25	1.0	28079008
30	0.7	28079024
49	8.0	28079008
942	0.2	28079024
961	0.5	28079008
966	0.2	28079024
985	0.5	28079008
990	0.2	28079024

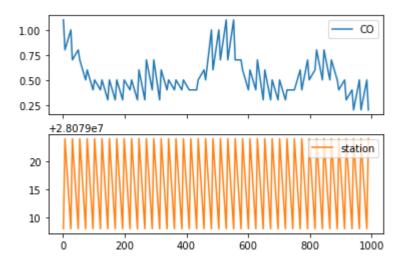
84 rows × 2 columns

In [7]:

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

Out[7]:

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

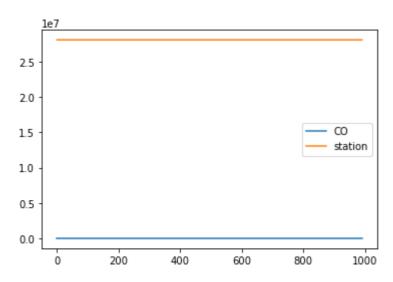


In [8]:

data.plot.line()

Out[8]:

<AxesSubplot:>



In [9]:

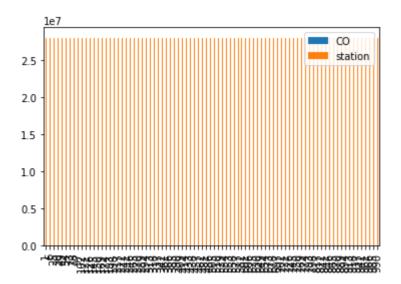
x = data[0:100]

In [10]:

x.plot.bar()

Out[10]:

<AxesSubplot:>

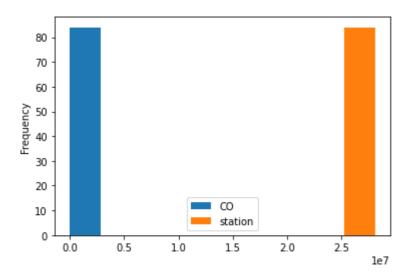


In [11]:

data.plot.hist()

Out[11]:

<AxesSubplot:ylabel='Frequency'>

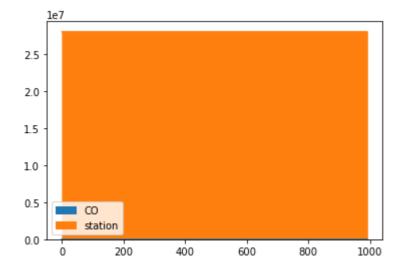


In [12]:

data.plot.area()

Out[12]:

<AxesSubplot:>

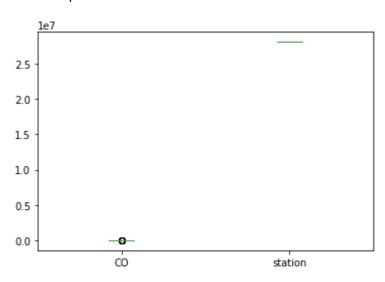


In [13]:

data.plot.box()

Out[13]:

<AxesSubplot:>



```
In [14]:
```

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

Out[14]:

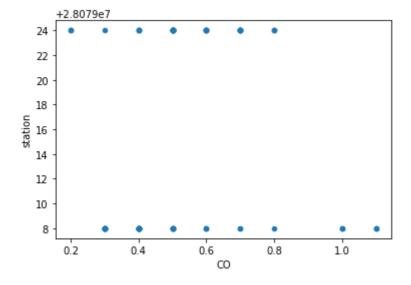
<AxesSubplot:ylabel='station'>

In [15]:

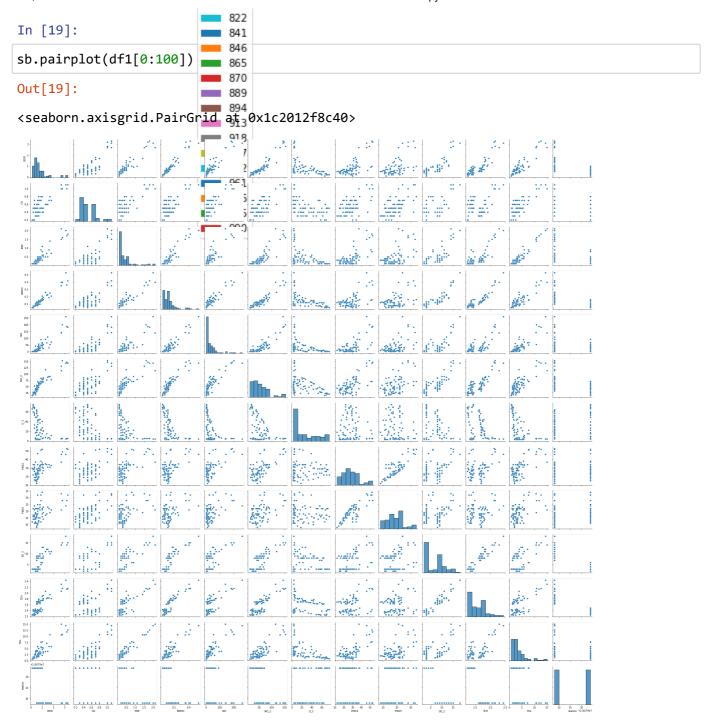
data.plot.scatter(x='CO' ,y='station')

Out[15]:

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



```
In [16]:
df.info()
                                25
                                30
<class 'pandas.core frame.Da@aFrame'>
Int64Index: 84 entries, 1 to 4990
Data columns (total 14 columns)
   20 Column
                Non-Null Count Ditype
                            102
                    non-null <sub>121</sub>object
 0
                   non-null 126float64
non-null 145float64
 1
         84 non-physical 150 float64 169 float64
 2
 3
     EBE
                84 non-nul 169 float 64
 4
     NMHC
                84 non-null <sup>174</sup>float64
 5
     NO
                84 non-null 193 float64
 6
     NO 2
                84 non-null 217 float64
 7
     0_3
 8
     PM10
                84 non-null 222float64
                84 non-null 241float64
 9
     PM25
                84 non-nul 246 float 64
 10
     SO 2
                84 non-nul 265 float 64
 11
     TCH
                84 non-nul <sup>270</sup>float64
 12
     TOL
     station 84 non-nul 289
                                   int64
 13
                            294
                            313
                                318
In [17]:
                                337
                                342
df.describe()
                                361
                                366
Out[17]:
                                385
                              ■ 39<del>0</del>BE
            BEN
                        CO
                                          NMHC
                                                        NO
                                                                  NO_2
                                                                              0_3
                                                                                       PΙ
                 84.000000 84.000000
count 84.000000
                                                  84.000000
                                                              84.000000 84.000000 84.000
                                       84.000000
                              433
                   0.533333 0.428571
        0.810714
                                        0.140000
                                                  34.940476
                                                              55.642857 24.726190 27.916
 mean
        0.696812
                   0.206131
   std
                                        0.089375
                                                  48.969711
                                                              31.532979 23.506652
                                                                                    9.406
                             0.100000
        0.100000
                   0.200000
                                        0.050000
                                                   1.000000
  min
                                                              14.000000
                                                                         3.000000 12.000
                               486
  25%
        0.400000
                   0.400000 -0.260500
                                        0.080000
                                                   8.000000
                                                              34.250000
                                                                         4.750000 22.000
                                510
  50%
        0.600000
                   0.500000
                                                              48.500000
                                        0.120000
                                                  15.500000
                                                                        15.000000 27.000
                             0.399900
  75%
                   0.625000
        0.900000
                                        0.150000
                                                  41.500000
                                                              69.000000
                                                                        43.250000
                                                                                   33.250
                             2.100000
                   1.100000
                                        0.530000
                                                             154.000000 75.000000 53.000
  max
        3.300000
                                                 260.000000
                                577
                                601
                                606
In [18]:
                                625
                              63NMHC', 'NO', 'NO_2', 'O_3', 'PM10', 'PM25',
df1=df[['BEN', 'CO', 'EBET
         'SO_2', 'TCH', 'TOL, 649 station']]
                                673
                                678
                                697
                                702
                                721
                                726
                                745
                                750
                                769
                                774
                                793
                                798
                                817
```



In [20]:

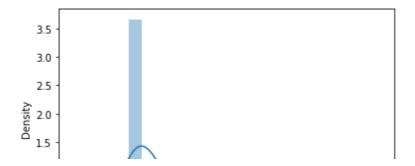
```
sb.distplot(df1['EBE'])
```

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='EBE', ylabel='Density'>

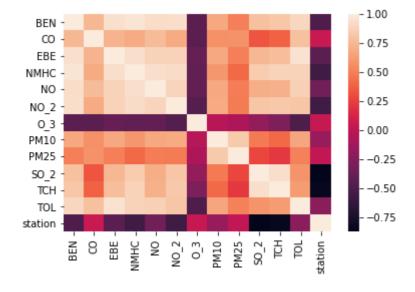


In [21]:

```
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]:

-1.862645149230957e-08

In [26]:

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

Out[26]:

Co-efficient

BEN -3.238009e-15

CO -4.990300e-15

EBE -6.489599e-15

NMHC 6.480721e-14

NO -1.834609e-17

NO_2 2.349135e-16

O_3 1.709426e-16

PM10 -8.613797e-17

PM25 1.505229e-16

SO_2 -2.153905e-16

TCH -1.158721e-15

TOL -9.261846e-17

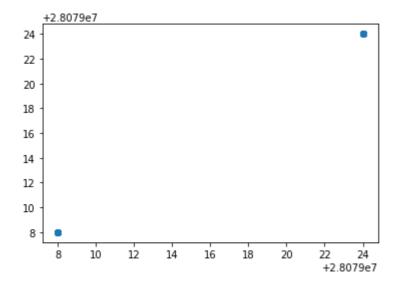
station 1.000000e+00

```
In [27]:
```

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

Out[27]:

<matplotlib.collections.PathCollection at 0x1c20bfc7f40>



In [28]:

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

Out[28]:

1.0

In [29]:

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

Out[29]:

1.0

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]:

0.999809337721146

```
In [33]:
r.score(x_train,y_train)
Out[33]:
0.99991459335366
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]:
0.9736271705434829
In [36]:
1.score(x_test,y_test)
Out[36]:
0.9758175842587881
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]:
array([-0.00000000e+00, 0.00000000e+00, -0.00000000e+00, -0.00000000e+00,
        0.00000000e+00, -2.70112598e-03, -7.62677321e-04,
                                                             0.00000000e+00,
        0.00000000e+00, -0.00000000e+00, -0.00000000e+00,
                                                             0.00000000e+00,
        9.79924041e-01])
In [39]:
e.intercept_
Out[39]:
563713.33394951
```

```
In [40]:
prediction=e.predict(x_test)
In [41]:
e.score(x_test,y_test)
Out[41]:
0.9997505655686159
In [42]:
from sklearn import metrics
In [43]:
print(metrics.mean_squared_error(y_test,prediction))
0.01445243758647134
In [44]:
print(np.sqrt(metrics.mean_squared_error(y_test,prediction)))
0.12021829139723847
In [45]:
print(metrics.mean_absolute_error(y_test,prediction))
0.11217871136390246
In [46]:
from sklearn.linear_model import LogisticRegression
In [47]:
feature_matrix=df[['BEN', 'CO', 'EBE', 'NMHC', 'NO', 'NO_2', 'O_3', 'PM10', 'PM25',
       'SO_2', 'TCH', 'TOL', 'station']]
target_vector=df['station']
In [48]:
feature_matrix.shape
Out[48]:
(84, 13)
In [49]:
target_vector.shape
Out[49]:
(84,)
```

```
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]]
In [54]:
prediction=logr.predict(observation)
print(prediction)
[28079008]
In [55]:
logr.classes_
Out[55]:
array([28079008, 28079024], dtype=int64)
In [56]:
logr.score(fs,target_vector)
Out[56]:
1.0
In [57]:
logr.predict_proba(observation)[0][0]
Out[57]:
0.8385094351160735
In [58]:
logr.predict_proba(observation)
Out[58]:
array([[0.83850944, 0.16149056]])
```

```
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]:

1.0

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, 1630.8000000000000, 'NMHC <= 0.11\ngini = 0.49\nsamples = 42
\nvalue = [25, 33]\nclass = b'),
    Text(1116.0, 543.59999999999, 'gini = 0.0\nsamples = 18\nvalue = [0, 2
5]\nclass = b'),
    Text(3348.0, 543.599999999999, 'gini = 0.367\nsamples = 24\nvalue = [25, 8]\nclass = a')]</pre>
```

NMHC <= 0.11 gini = 0.49 samples = 42 value = [25, 33] class = b

gini = 0.0 samples = 18 value = [0, 25] class = b gini = 0.367 samples = 24 value = [25, 8] class = a

random forest is the best suitable for this model

In []: