In [130]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
import re
from sklearn.datasets import load_digits
from sklearn.model_selection import train_test_split
```

In [215]:

```
a=pd.read_csv(r"C:\Users\user\Downloads\C10_air\madrid_2006.csv")
a
```

Out[215]:

date	BEN	СО	EBE	MXY	NMHC	NO_2	NOx	OXY	O_3	
2006- 02-01 01:00:00	NaN	1.84	NaN	NaN	NaN	155.100006	490.100006	NaN	4.880000	97
2006- 02-01 01:00:00	1.68	1.01	2.38	6.36	0.32	94.339996	229.699997	3.04	7.100000	25
2006- 02-01 01:00:00	NaN	1.25	NaN	NaN	NaN	66.800003	192.000000	NaN	4.430000	34
2006- 02-01 01:00:00	NaN	1.68	NaN	NaN	NaN	103.000000	407.799988	NaN	4.830000	28
2006- 02-01 01:00:00	NaN	1.31	NaN	NaN	NaN	105.400002	269.200012	NaN	6.990000	54
2006- 05-01 00:00:00	5.88	0.83	6.23	NaN	0.20	112.500000	218.000000	NaN	24.389999	93
2006- 05-01 00:00:00	0.76	0.32	0.48	1.09	0.08	51.900002	54.820000	0.61	48.410000	29
2006- 05-01 00:00:00	0.96	NaN	0.69	NaN	0.19	135.100006	179.199997	NaN	11.460000	64
2006- 05-01 00:00:00	0.50	NaN	0.67	NaN	0.10	82.599998	105.599998	NaN	NaN	94
2006- 05-01 00:00:00	1.95	0.74	1.99	4.00	0.24	107.300003	160.199997	2.01	17.730000	52
	2006- 02-01 01:00:00 2006- 02-01 01:00:00 2006- 02-01 01:00:00 2006- 02-01 01:00:00 2006- 02-01 01:00:00 2006- 05-01 00:00:00 2006- 05-01 00:00:00 2006- 05-01 00:00:00 2006- 05-01	2006- 02-01	2006- 02-01	2006- 02-01	2006- 02-01 01:00:00 NaN 1.84 1.01 NaN NaN 2006- 02-01 01:00:00 1.68 1.01 2.38 2.38 2.38 6.36 2006- 02-01 01:00:00 NaN 1.25 1.68 1.68 1.68 1.68 NaN NaN NaN 2006- 02-01 01:00:00 NaN 1.31	2006- 02-01 01:00:00 NaN 1.84 NaN NaN NaN NaN NaN NaN 2006- 02-01 02-01 01:00:00 1.68 1.01 2.38 6.36 0.32 0.32 2006- 02-01 02-01 01:00:00 NaN 1.25 NaN NaN NaN NaN NaN NaN 01:00:00 NaN 1.68 NaN NaN NaN NaN NaN NaN NaN 01:00:00 2006- 02-01 02-01 NaN 1.31 NaN NaN NaN 01:00:00 NaN 01:00:00 NaN 01:00:00 2006- 02-01 05-01 05-01 05-01 00:00:00 5.88 0.83 6.23 NaN 0.20 0.20 005-01 05-01 0.96 NaN 0:00:00:00 0.96 NaN 0.69 NaN 0.19 0.19 2006- 05-01 05-01 0.96 NaN 0:00:00:00 0.50 NaN 0.67 NaN 0.10 0.10 2006- 05-01 00:00:00 0.50 NaN 0.67 NaN 0.10 0.24	2006- 02-01 01:00:00 NaN 1.84 NaN NaN NaN 155.100006 2006- 02-01 01:00:00 1.68 1.01 2.38 6.36 0.32 94.339996 2006- 02-01 01:00:00 NaN 1.25 NaN NaN NaN 66.800003 2006- 02-01 01:00:00 NaN 1.68 NaN NaN NaN NaN 103.000000 2006- 02-01 01:00:00 NaN 1.31 NaN NaN NaN 105.400002 2006- 02-01 01:00:00 5.88 0.83 6.23 NaN 0.20 112.500000 2006- 05-01 00:00:00 0.76 0.32 0.48 1.09 0.08 51.900002 2006- 05-01 00:00:00 0.96 NaN 0.69 NaN 0.19 135.100006 2006- 05-01 00:00:00 0.50 NaN 0.67 NaN 0.10 82.599998 2006- 05-01 00:00:00 1.95 0.74 1.99 4.00 0.24 107.300003	2006- 02-01 01:00:00 NaN 1.84 NaN NaN NaN 155.100006 490.100006 2006- 02-01 01:00:00 1.68 1.01 2.38 6.36 0.32 94.339996 229.699997 2006- 02-01 01:00:00 NaN 1.25 NaN NaN NaN 66.800003 192.000000 2006- 02-01 01:00:00 NaN 1.68 NaN NaN NaN 103.000000 407.799988 2006- 02-01 01:00:00 NaN 1.31 NaN NaN NaN 105.400002 269.200012 2006- 05-01 00:00:00 5.88 0.83 6.23 NaN 0.20 112.500000 218.000000 2006- 05-01 00:00:00 0.76 0.32 0.48 1.09 0.08 51.900002 54.820000 2006- 05-01 00:00:00 0.50 NaN 0.69 NaN 0.19 135.100006 179.199997 2006- 05-01 00:00:00 0.50 NaN 0.67 NaN 0.10 82.599998 105.599998 2006- 05-01 00:00:00 1.95	2006- 02-01 01:00:00 NaN 1.84 NaN NaN NaN 155.100006 490.100006 NaN 2006- 02-01 01:00:00 1.68 1.01 2.38 6.36 0.32 94.339996 229.699997 3.04 2006- 02-01 01:00:00 NaN 1.25 NaN NaN NaN 66.800003 192.000000 NaN 2006- 02-01 01:00:00 NaN 1.68 NaN NaN NaN NaN 103.000000 407.799988 NaN 2006- 02-01 01:00:00 NaN 1.31 NaN NaN NaN 105.400002 269.200012 NaN 2006- 05-01 00:00:00 5.88 0.83 6.23 NaN 0.20 112.500000 218.000000 NaN 2006- 05-01 00:00:00 0.76 0.32 0.48 1.09 0.08 51.900002 54.820000 0.61 2006- 05-01 00:00:00 0.96 NaN 0.69 NaN 0.19 135.100006 179.199997 NaN 2006- 05-01 00:00:00 0.50 NaN	2006- 02-01 01:00:00 NaN 1.84 NaN NaN NaN 155.100006 490.100006 NaN 4.880000 2006- 02-01 01:00:00 1.68 1.01 2.38 6.36 0.32 94.339996 229.699997 3.04 7.100000 2006- 02-01 01:00:00 NaN 1.25 NaN NaN NaN 192.000000 NaN 4.430000 2006- 02-01 01:00:00 NaN 1.68 NaN NaN NaN NaN 103.00000 407.799988 NaN 4.830000 2006- 02-01 01:00:00 NaN 1.31 NaN NaN NaN 105.400002 269.200012 NaN 6.990000 2006- 02-01 00:00:00 5.88 0.83 6.23 NaN 0.20 112.500000 218.000000 NaN 24.389999 2006- 05-01 00:00:00 0.76 0.32 0.48 1.09 0.08 51.900002 54.820000 0.61 48.410000 2006- 05-01 00:00:00 0.50 NaN 0.67 NaN 0.10 82.599998 </th

230568 rows × 17 columns

◀

In [216]:

a.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 230568 entries, 0 to 230567
Data columns (total 17 columns):
    Column
             Non-Null Count
                             Dtype
---
    -----
             -----
                             ----
             230568 non-null object
0
    date
    BEN
 1
             73979 non-null
                             float64
 2
    CO
             211665 non-null float64
 3
    EBE
             73948 non-null float64
 4
             33422 non-null
                             float64
    MXY
 5
    NMHC
             90829 non-null
                             float64
 6
    NO_2
             228855 non-null float64
 7
    NOx
             228855 non-null float64
 8
    0XY
             33472 non-null
                             float64
             216511 non-null float64
 9
    0 3
             227469 non-null float64
 10 PM10
 11
    PM25
             61758 non-null
                             float64
             33447 non-null
                             float64
 12
    PXY
             229125 non-null float64
    S0_2
 13
 14
    TCH
             90887 non-null float64
15 TOL
             73840 non-null float64
 16 station 230568 non-null int64
dtypes: float64(15), int64(1), object(1)
memory usage: 29.9+ MB
```

In [217]:

```
b=a.fillna(value=104)
b
```

Out[217]:

	date	BEN	СО	EBE	MXY	NMHC	NO_2	NOx	OXY	
0	2006- 02-01 01:00:00	104.00	1.84	104.00	104.00	104.00	155.100006	490.100006	104.00	4.
1	2006- 02-01 01:00:00	1.68	1.01	2.38	6.36	0.32	94.339996	229.699997	3.04	7.
2	2006- 02-01 01:00:00	104.00	1.25	104.00	104.00	104.00	66.800003	192.000000	104.00	4.
3	2006- 02-01 01:00:00	104.00	1.68	104.00	104.00	104.00	103.000000	407.799988	104.00	4.
4	2006- 02-01 01:00:00	104.00	1.31	104.00	104.00	104.00	105.400002	269.200012	104.00	6.
230563	2006- 05-01 00:00:00	5.88	0.83	6.23	104.00	0.20	112.500000	218.000000	104.00	24.
230564	2006- 05-01 00:00:00	0.76	0.32	0.48	1.09	0.08	51.900002	54.820000	0.61	48.
230565	2006- 05-01 00:00:00	0.96	104.00	0.69	104.00	0.19	135.100006	179.199997	104.00	11.
230566	2006- 05-01 00:00:00	0.50	104.00	0.67	104.00	0.10	82.599998	105.599998	104.00	104.
230567	2006- 05-01 00:00:00	1.95	0.74	1.99	4.00	0.24	107.300003	160.199997	2.01	17.

230568 rows × 17 columns

In [218]:

```
b.columns
```

Out[218]:

In [219]:

c=b.head(10)
c

Out[219]:

	date	BEN	со	EBE	MXY	NMHC	NO_2	NOx	OXY	O_3	
0	2006- 02-01 01:00:00	104.00	1.84	104.00	104.000000	104.00	155.100006	490.100006	104.00	4.88	!
1	2006- 02-01 01:00:00	1.68	1.01	2.38	6.360000	0.32	94.339996	229.699997	3.04	7.10	1
2	2006- 02-01 01:00:00	104.00	1.25	104.00	104.000000	104.00	66.800003	192.000000	104.00	4.43	1
3	2006- 02-01 01:00:00	104.00	1.68	104.00	104.000000	104.00	103.000000	407.799988	104.00	4.83	
4	2006- 02-01 01:00:00	104.00	1.31	104.00	104.000000	104.00	105.400002	269.200012	104.00	6.99	;
5	2006- 02-01 01:00:00	9.41	1.69	9.98	19.959999	0.44	142.199997	453.500000	11.31	5.99	1
6	2006- 02-01 01:00:00	104.00	1.28	104.00	104.000000	0.57	94.320000	294.000000	104.00	6.77	;
7	2006- 02-01 01:00:00	0.27	1.51	0.28	104.000000	0.46	144.699997	385.299988	104.00	5.30	1
8	2006- 02-01 01:00:00	104.00	2.65	104.00	104.000000	104.00	197.100006	673.099976	104.00	2.64	1,
9	2006- 02-01 01:00:00	104.00	1.30	104.00	104.000000	104.00	130.899994	282.000000	104.00	5.14	į
4 (>

In [220]:

```
d=c[['BEN', 'CO', 'EBE', 'MXY', 'NMHC', 'NO_2', 'NOx', 'OXY', 'O_3',
    'PM10', 'PXY', 'SO_2', 'TCH', 'TOL', 'station']]
d
```

Out[220]:

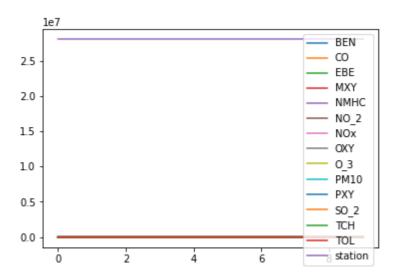
	BEN	СО	EBE	MXY	NMHC	NO_2	NOx	OXY	O_3	PM10
0	104.00	1.84	104.00	104.000000	104.00	155.100006	490.100006	104.00	4.88	97.570000
1	1.68	1.01	2.38	6.360000	0.32	94.339996	229.699997	3.04	7.10	25.820000
2	104.00	1.25	104.00	104.000000	104.00	66.800003	192.000000	104.00	4.43	34.419998
3	104.00	1.68	104.00	104.000000	104.00	103.000000	407.799988	104.00	4.83	28.260000
4	104.00	1.31	104.00	104.000000	104.00	105.400002	269.200012	104.00	6.99	54.180000
5	9.41	1.69	9.98	19.959999	0.44	142.199997	453.500000	11.31	5.99	89.190002
6	104.00	1.28	104.00	104.000000	0.57	94.320000	294.000000	104.00	6.77	55.130001
7	0.27	1.51	0.28	104.000000	0.46	144.699997	385.299988	104.00	5.30	80.150002
8	104.00	2.65	104.00	104.000000	104.00	197.100006	673.099976	104.00	2.64	142.500000
9	104.00	1.30	104.00	104.000000	104.00	130.899994	282.000000	104.00	5.14	49.029999
4 (•

In [221]:

```
d.plot.line()
```

Out[221]:

<AxesSubplot:>

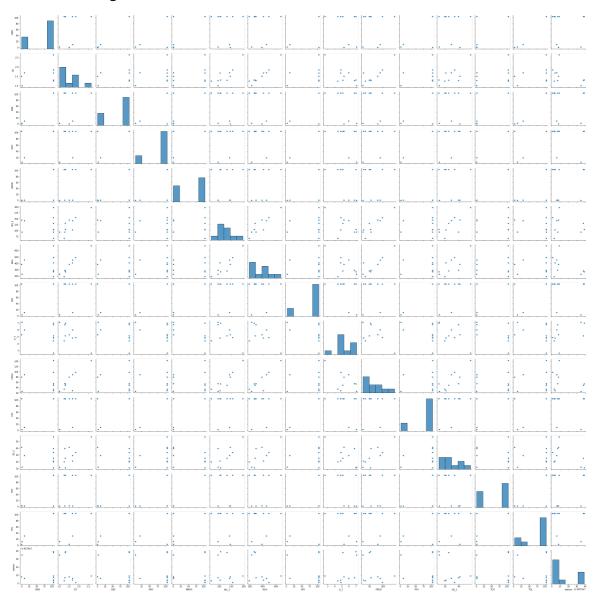


In [222]:

sns.pairplot(d)

Out[222]:

<seaborn.axisgrid.PairGrid at 0x1178a76efa0>



In [223]:

```
x=d[['BEN', 'CO', 'EBE', 'MXY', 'NMHC', 'NO_2', 'NOx', 'OXY']]
y=d['TCH']
```

In [224]:

```
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 [225]:
```

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

Out[225]:

LinearRegression()

In [226]:

```
print(lr.intercept_)
```

1.6366528371229805

In [227]:

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

Out[227]:

Co-efficient

BEN -1.584156e-03

CO -8.575021e-15

EBE -1.584003e-03

MXY 0.000000e+00

NMHC 9.874311e-01

NO_2 -4.906496e-16

NOx -5.630549e-18

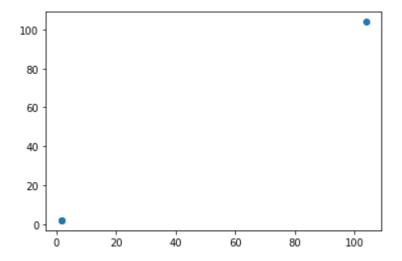
OXY 0.000000e+00

```
In [228]:
```

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

Out[228]:

<matplotlib.collections.PathCollection at 0x117972360d0>



In [229]:

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

0.9999771384355651

In [230]:

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

In [231]:

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

Out[231]:

Ridge(alpha=10)

In [232]:

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

Out[232]:

0.999977789448488

In [233]:

```
la=Lasso(alpha=10)
la.fit(x_train,y_train)
```

Out[233]:

Lasso(alpha=10)

In [234]:

la.score(x_test,y_test)

Out[234]:

0.9999348061232213

In [235]:

a1=b.head(7000) a1

Out[235]:

	date	BEN	со	EBE	MXY	NMHC	NO_2	NOx	OXY	O_3	
0	2006- 02-01 01:00:00	104.00	1.84	104.00	104.00	104.00	155.100006	490.100006	104.00	4.88	9
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	2
2	2006- 02-01 01:00:00	104.00	1.25	104.00	104.00	104.00	66.800003	192.000000	104.00	4.43	3,
3	2006- 02-01 01:00:00	104.00	1.68	104.00	104.00	104.00	103.000000	407.799988	104.00	4.83	2
4	2006- 02-01 01:00:00	104.00	1.31	104.00	104.00	104.00	105.400002	269.200012	104.00	6.99	5,
6995	2006- 02-12 06:00:00	1.54	0.44	2.80	7.86	0.19	61.410000	84.349998	2.85	8.77	1:
6996	2006- 02-12 06:00:00	104.00	0.46	104.00	104.00	104.00	53.340000	75.160004	104.00	7.88	11
6997	2006- 02-12 06:00:00	104.00	1.06	104.00	104.00	104.00	73.279999	231.899994	104.00	4.38	2:
6998	2006- 02-12 06:00:00	104.00	0.57	104.00	104.00	104.00	47.400002	52.240002	104.00	15.17	2
6999	2006- 02-12 06:00:00	2.12	0.66	2.39	4.76	0.11	74.879997	163.600006	2.69	8.16	2

7000 rows × 17 columns

```
In [236]:
e=a1[['BEN', 'CO', 'EBE', 'MXY', 'NMHC', 'NO_2', 'NOx', 'OXY', 'O_3',
 'PM10', 'PXY', 'SO_2', 'TCH', 'TOL', 'station']]
In [237]:
f=e.iloc[:,0:14]
g=e.iloc[:,-1]
In [238]:
h=StandardScaler().fit_transform(f)
In [239]:
logr=LogisticRegression(max_iter=10000)
logr.fit(h,g)
Out[239]:
LogisticRegression(max_iter=10000)
In [240]:
from sklearn.model_selection import train_test_split
h_train,h_test,g_train,g_test=train_test_split(h,g,test_size=0.3)
In [241]:
i=[[10,20,30,40,50,60,11,22,33,44,55,54,21,78]]
In [242]:
prediction=logr.predict(i)
print(prediction)
[28079039]
In [243]:
logr.classes_
Out[243]:
array([28079001, 28079003, 28079004, 28079006, 28079007, 28079008,
       28079009, 28079011, 28079012, 28079014, 28079015, 28079016,
       28079018, 28079019, 28079021, 28079022, 28079023, 28079024,
       28079026, 28079027, 28079035, 28079036, 28079038, 28079039,
       28079040, 28079099], dtype=int64)
In [244]:
logr.predict_proba(i)[0][0]
Out[244]:
1.9164523757870783e-126
```

```
In [245]:
logr.predict_proba(i)[0][1]
Out[245]:
1.0553514949951003e-174
In [246]:
logr.score(h_test,g_test)
Out[246]:
0.5476190476190477
In [247]:
from sklearn.linear_model import ElasticNet
en=ElasticNet()
en.fit(x_train,y_train)
Out[247]:
ElasticNet()
In [248]:
print(en.coef_)
9.86248953e-01 0.00000000e+00 5.12700660e-05 0.00000000e+00]
In [249]:
print(en.intercept_)
1.5801659139574014
In [250]:
prediction=en.predict(x_test)
print(en.score(x_test,y_test))
0.9999820518825869
In [251]:
from sklearn.ensemble import RandomForestClassifier
rfc=RandomForestClassifier()
rfc.fit(h_train,g_train)
Out[251]:
RandomForestClassifier()
```

```
In [252]:
```

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

In [253]:

```
from sklearn.model_selection import GridSearchCV
grid_search=GridSearchCV(estimator=rfc,param_grid=parameters,cv=2,scoring="accuracy")
grid_search.fit(h_train,g_train)
```

Out[253]:

In [254]:

```
grid_search.best_score_
```

Out[254]:

0.5751020408163265

In [255]:

```
rfc_best=grid_search.best_estimator_
```

In [256]:

```
from sklearn.tree import plot_tree
plt.figure(figsize=(80,50))
plot_tree(rfc_best.estimators_[2],filled=True)
```

```
e = [167, 195, 214, 179, 176, 178, 173, 179, 187, 187 \n176, 187, 179, 18
 0, 180, 229, 204, 177, 200, 186\n184, 196, 188, 196, 193, 210]'),
       Text(1249.92, 2038.5, X[2] <= -1.335 \ngini = 0.749\nsamples = 482\nvalu
e = [0, 0, 0, 179, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 177, 0, 0, 184,
 0, 0, 0, 0, 210]'),
       Text(714.24, 1585.5, 'X[10] <= -2.371 \setminus gini = 0.71 \setminus gini = 351 \setminus g
 = [0, 0, 0, 51, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 170, 0, 0, 127, 0, 0]
 0, 0, 0, 192]'),
       Text(357.12, 1132.5, 'X[4] <= -1.175 \setminus gini = 0.626 \setminus gini = 191 \setminus gini = 0.626 \setminus gini = 191 \setminus
 = [0, 0, 0, 30, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 165, 0, 0, 55, 0, 0]
0, 0, 0, 50]'),
      Text(178.56, 679.5, 'X[12] <= -1.177 \setminus gini = 0.49 \setminus gini = 88 \setminus gini = 88 \setminus gini = 88 \setminus gini = 188 \setminus gini 
 [0, 0, 0, 23, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 94, 0, 0, 0, 0, 0]
 0, 0, 22]'),
       Text(89.28, 226.5, 'gini = 0.408\nsamples = 12\nvalue = [0, 0, 0, 15, 0, 15]
 0, 0, 0, 0, 0, 0, 0, 0, 0 \setminus 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]'),
       Text(267.8400000000003, 226.5, 'gini = 0.404\nsamples = 76\nvalue = [0,
 0, 0, 8, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 88, 0, 0, 0, 0, 0, 0, 0,
 22]'),
        Text(535.6800000000001.679.5. 'X[9] <= -0.907 \ngini = 0.657 \nsamples =
```

In []:		