untitled1

July 28, 2023

[2]:
```python
#importing the libraries

import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

import warnings
warnings.filterwarnings('ignore')
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.stattools import acf, pacf
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
```

[43]:
```python
#Loading the dataset
data = pd.read_csv("Complete_Blasting_info.csv")
```

[44]:
```python
data.head()
```

[44]:
```
   Unnamed: 0  PM10 (µg/m3)      Time        Date  NO (µg/m3)  PM2.5 (µg/m3)
0           0          95.0  00:00:00  2023-02-01   14.484070           35.0  \
1           1          95.0  00:15:00  2023-02-01   14.484070           35.0
2           2          95.0  00:30:00  2023-02-01   15.835914           35.0
3           3         122.0  00:45:00  2023-02-01   15.914518           34.0
4           4         122.0  01:00:00  2023-02-01   16.035640           34.0

   NO2 (µg/m3)  NOX (ppb)  CO (mg/m3)  SO2 (µg/m3)  NH3 (µg/m3)
0         90.1       56.2        0.31    11.986833         17.7  \
1         88.0       55.1        0.33    11.986833         18.3
2         87.7       55.2        0.38    10.912796         19.7
3         88.9       55.7        0.38    10.613291         21.3
4         90.0       55.8        0.38     7.362361         22.3

   Ozone (µg/m3)  Benzene (µg/m3)
0           28.1              0.4
1           27.1              0.4
```

```
2           24.9              0.4
3           21.9              0.4
4           16.7              0.4
```

[45]:
```python
# Combine 'Date' and 'Time' columns into a single datetime column
data['DateTime'] = pd.to_datetime(data['Date'] + ' ' + data['Time'])
```

[46]:
```python
# Drop the separate 'Date' and 'Time' columns
data.drop(['Date', 'Time'], axis=1, inplace=True)
```

[47]:
```python
# Set 'DateTime' column as the index
data.set_index('DateTime', inplace=True)
```

[63]:
```python
data.head(10)
```

[63]:
```
                     PM10 (µg/m3)  NO (µg/m3)  PM2.5 (µg/m3)  NO2 (µg/m3)  \
DateTime
2023-02-01 00:00:00          95.0   14.484070           35.0         90.1
2023-02-01 00:15:00          95.0   14.484070           35.0         88.0
2023-02-01 00:30:00          95.0   15.835914           35.0         87.7
2023-02-01 00:45:00         122.0   15.914518           34.0         88.9
2023-02-01 01:00:00         122.0   16.035640           34.0         90.0
2023-02-01 01:15:00         122.0   17.497777           34.0         90.2
2023-02-01 01:30:00         122.0   17.121285           34.0         88.9
2023-02-01 01:45:00          90.0   15.532830           35.0         88.9
2023-02-01 02:00:00          90.0   19.465702           35.0         88.9
2023-02-01 02:15:00          90.0   22.215146           35.0         88.9

                     NOX (ppb)  CO (mg/m3)  SO2 (µg/m3)  NH3 (µg/m3)  \
DateTime
2023-02-01 00:00:00       56.2        0.31    11.986833         17.7
2023-02-01 00:15:00       55.1        0.33    11.986833         18.3
2023-02-01 00:30:00       55.2        0.38    10.912796         19.7
2023-02-01 00:45:00       55.7        0.38    10.613291         21.3
2023-02-01 01:00:00       55.8        0.38     7.362361         22.3
2023-02-01 01:15:00       55.9        0.37     8.494481         22.7
2023-02-01 01:30:00       55.4        0.34     8.326684         23.1
2023-02-01 01:45:00       55.2        0.35     8.612863         23.5
2023-02-01 02:00:00       55.9        0.34     9.272343         23.1
2023-02-01 02:15:00       55.3        0.35     9.457114         22.9

                     Ozone (µg/m3)  Benzene (µg/m3)
DateTime
2023-02-01 00:00:00           28.1              0.4
2023-02-01 00:15:00           27.1              0.4
2023-02-01 00:30:00           24.9              0.4
2023-02-01 00:45:00           21.9              0.4
```

```
2023-02-01 01:00:00          16.7             0.4
2023-02-01 01:15:00          16.1             0.4
2023-02-01 01:30:00          22.5             0.4
2023-02-01 01:45:00          20.5             0.4
2023-02-01 02:00:00          22.8             0.4
2023-02-01 02:15:00          19.0             0.4
```

[49]:
```
data.shape
```

[49]:
```
(8640, 11)
```

[50]:
```
data = data.drop(['Unnamed: 0']  , axis = 1)
```

[51]:
```
data.isnull().sum()
```

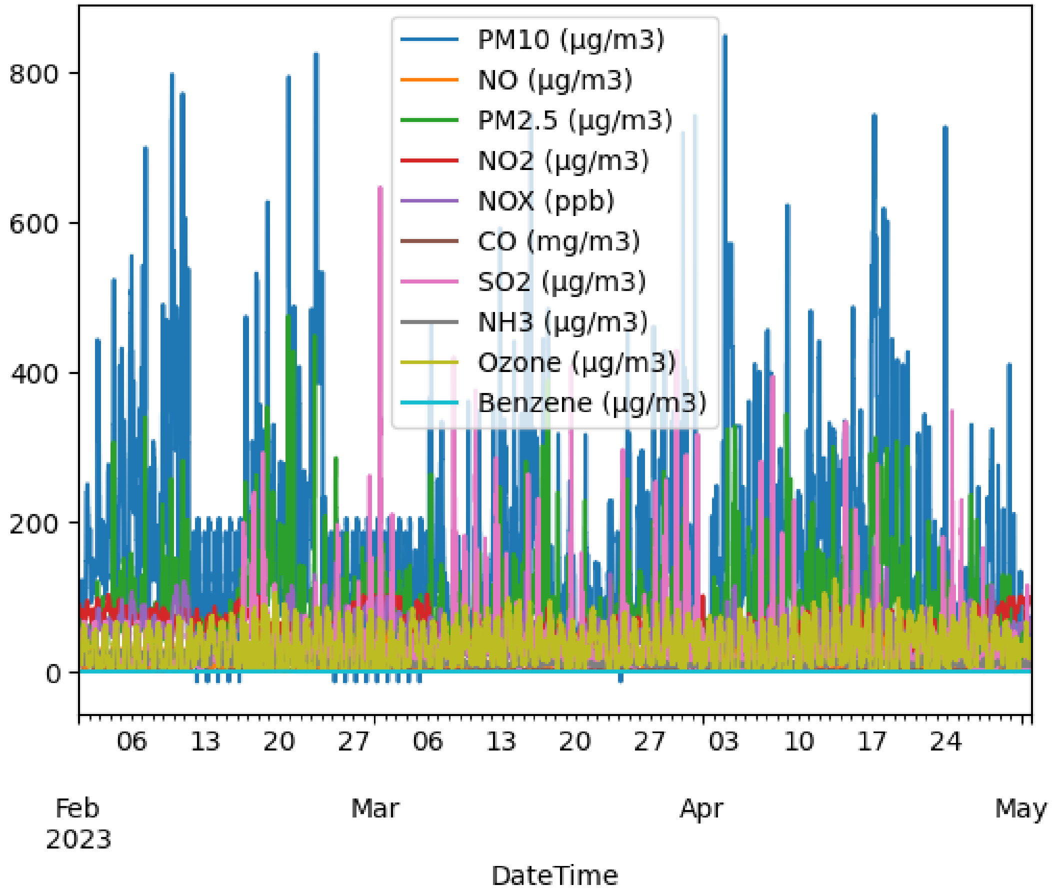
[51]:
```
PM10 (µg/m3)       0
NO (µg/m3)         0
PM2.5 (µg/m3)      0
NO2 (µg/m3)        0
NOX (ppb)          0
CO (mg/m3)         0
SO2 (µg/m3)        0
NH3 (µg/m3)        0
Ozone (µg/m3)      0
Benzene (µg/m3)    0
dtype: int64
```

0.1 Visualizing the Multivariate Time Series Data

0.1.1 1) Plotting all the observations in a single graph

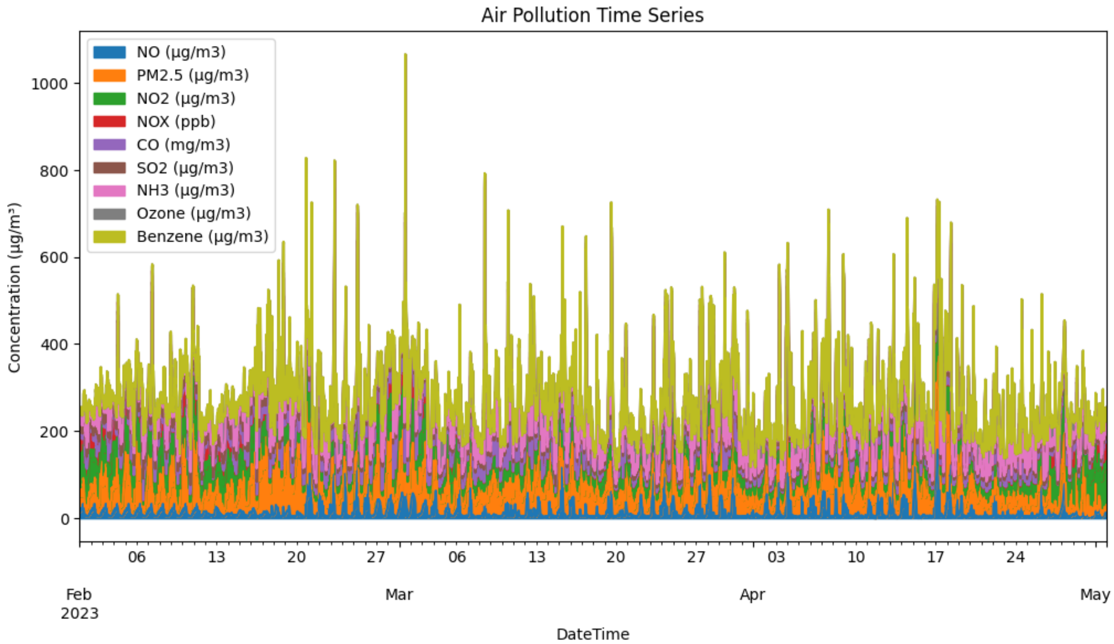
[55]:
```
data.plot()
```

[55]:
```
<Axes: xlabel='DateTime'>
```



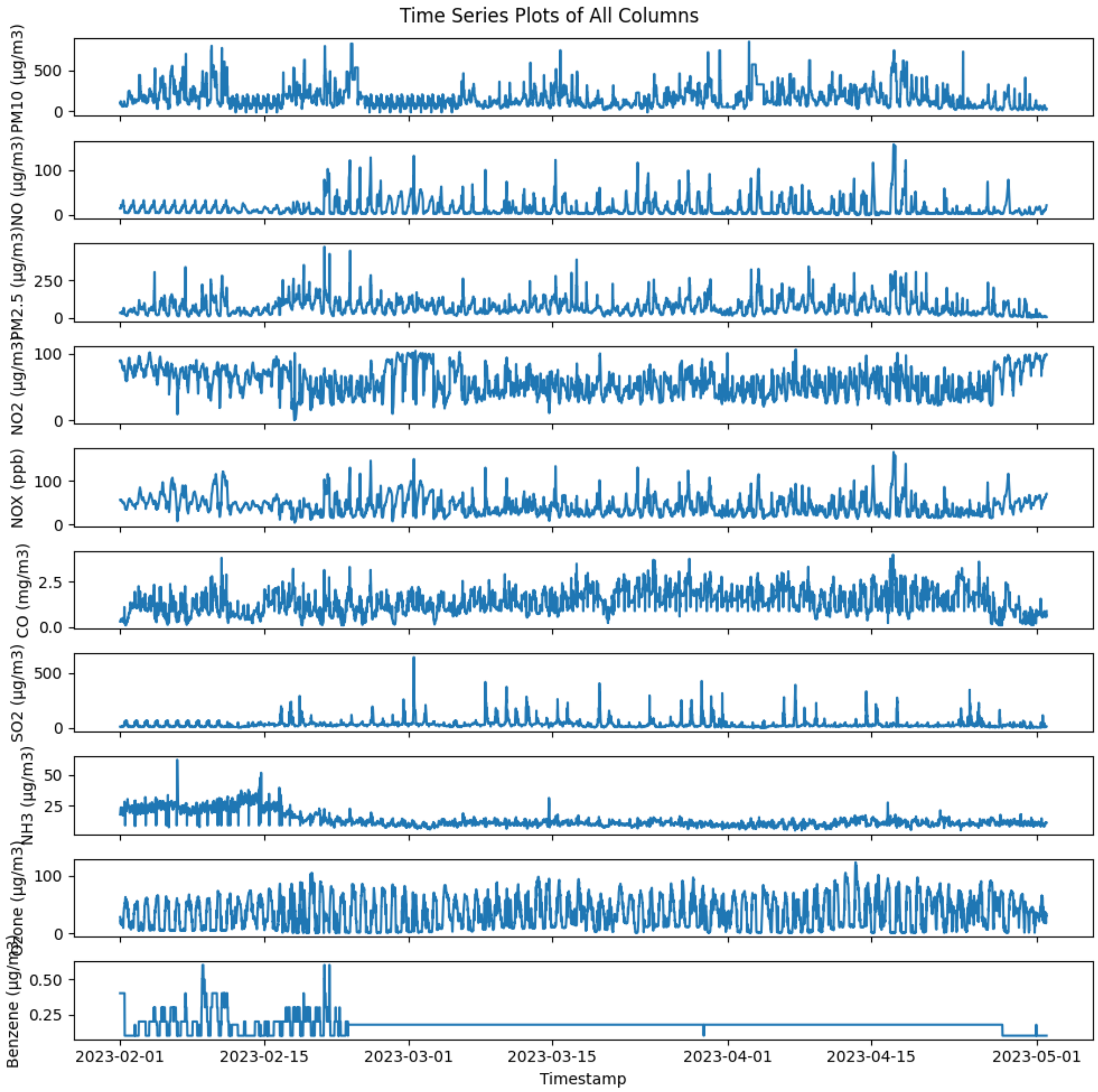
0.1.2 2) Stacked Area Plot for Time Series:

[80]:
```
data.drop('PM10 (µg/m3)' , axis = 1).plot.area(figsize=(12, 6),␣
↪xlabel='DateTime', ylabel='Concentration (µg/m³)', title='Air Pollution Time␣
↪Series')
plt.show()
```



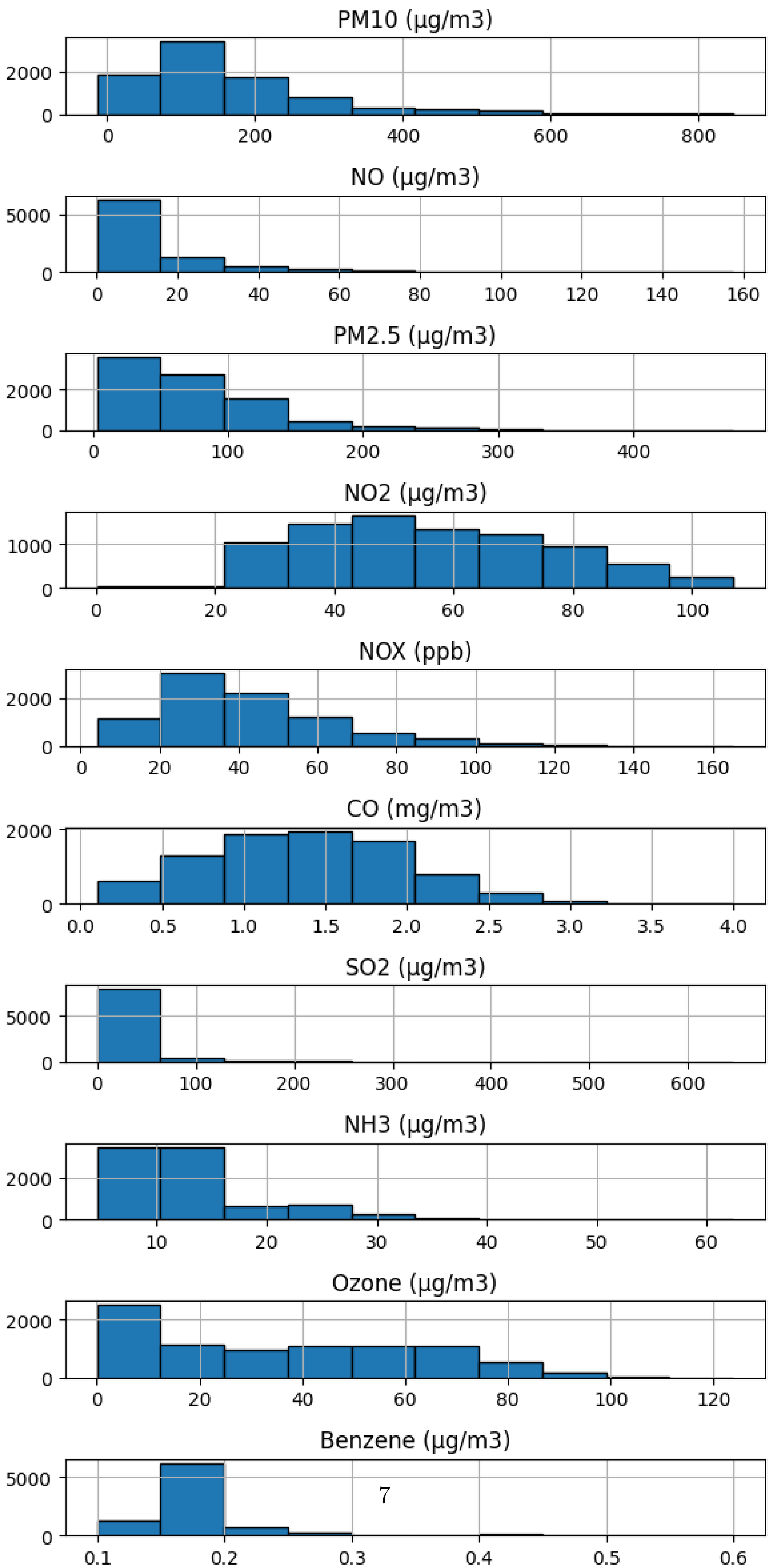
0.1.3 3) Grid Plot

[59]:
```
fig, axes = plt.subplots(nrows=len(data.columns), ncols=1, figsize=(10, 10),␣
↪sharex=True)

for i, column in enumerate(data.columns):
    axes[i].plot(data.index, data[column])
    axes[i].set_ylabel(column)

axes[-1].set_xlabel('Timestamp')
plt.suptitle('Time Series Plots of All Columns')
plt.tight_layout()
plt.show()
```



0.1.4 4) Histogram plot of all the columns

[62]:
```python
# Create a grid of histograms for all columns
fig, axes = plt.subplots(nrows=len(data.columns), ncols=1, figsize=(6, 12))

for i, column in enumerate(data.columns):
    data[column].hist(ax=axes[i], bins=10, edgecolor='black')
    axes[i].set_title(column)

plt.tight_layout()
plt.show()
```

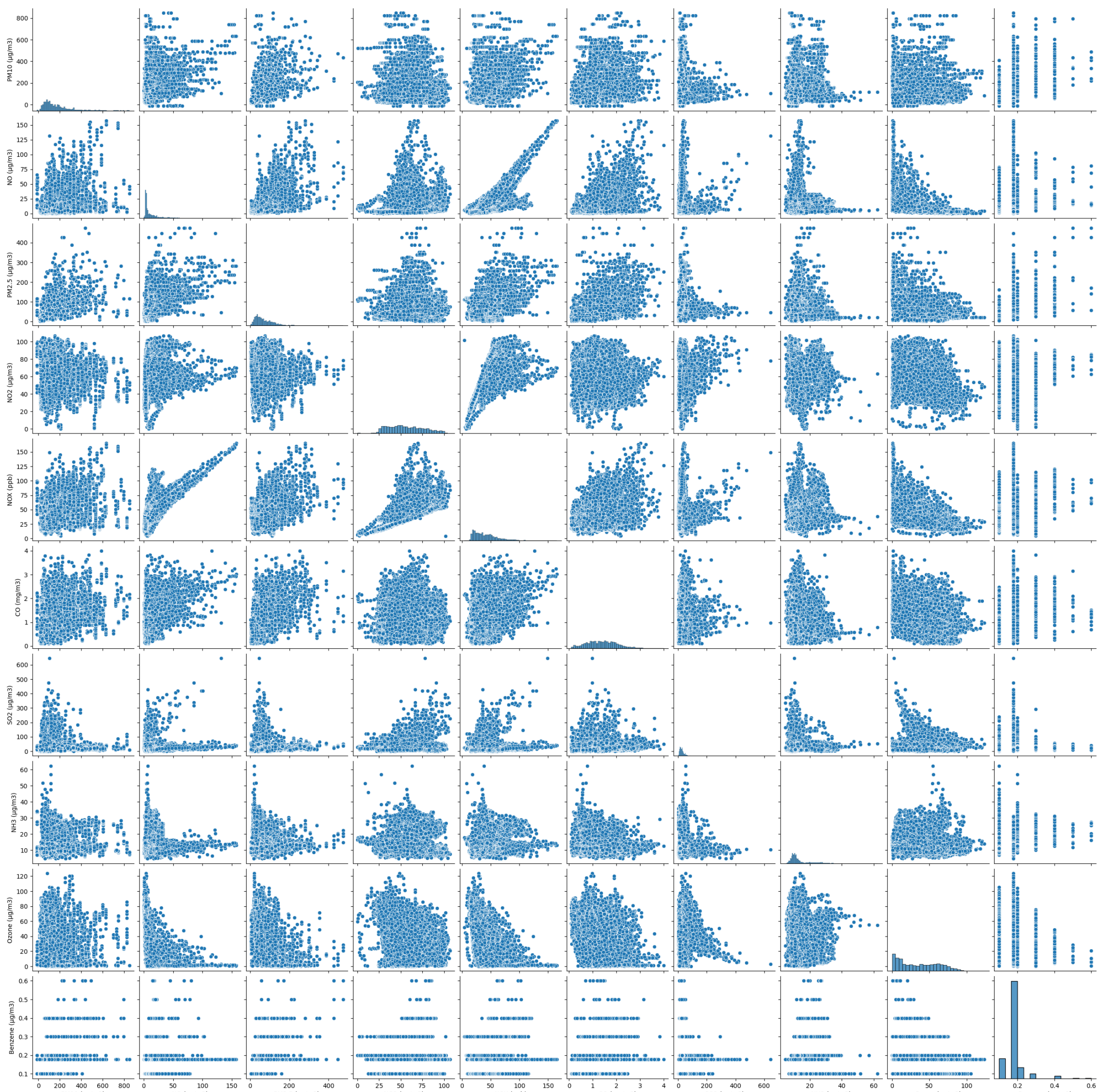

PM10 (µg/m3)
0
2000
0
200
400
600
800
NO (µg/m3)
0
5000
0
20
40
60
80
100
120
140
160
PM2.5 (µg/m3)
0
2000
0
100
200
300
400
NO2 (µg/m3)
0
1000
0
20
40
60
80
100
NOX (ppb)
0
2000
0
20
40
60
80
100
120
140
160
CO (mg/m3)
0
2000
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
SO2 (µg/m3)
0
5000
0
100
200
300
400
500
600
NH3 (µg/m3)
0
2000
10
20
30
40
50
60
Ozone (µg/m3)
0
2000
0
20
40
60
80
100
120
Benzene (µg/m3)
0
5000
0.1
0.2
0.3
0.4
0.5
0.6

0.1.5 Let us see the relationship between the air pollutants with each other by visualtizations

0.1.6 1) Pair-wise Plotting the different pollutants

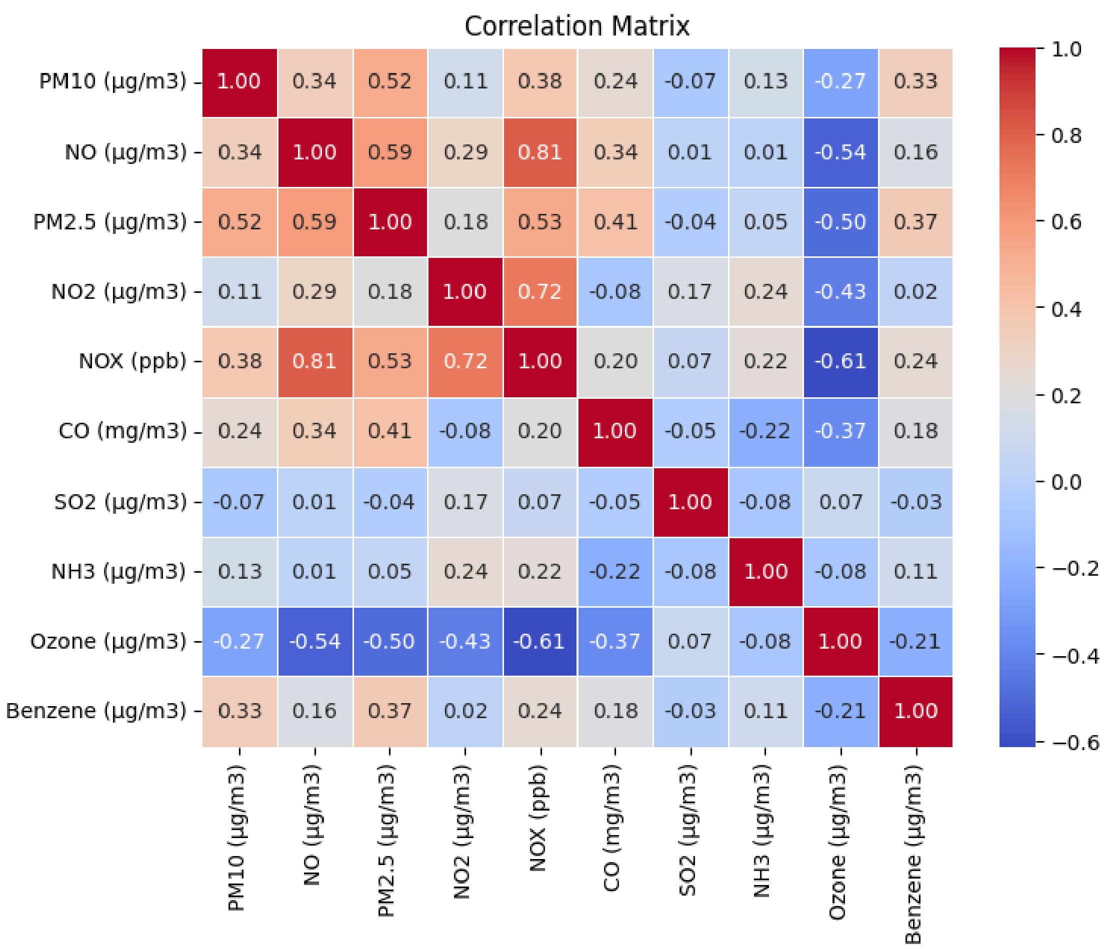
[86]:
```
sns.pairplot(data)
```

[86]:
```
<seaborn.axisgrid.PairGrid at 0x16206639750>
```



0.1.7 2) Correlation Matrix:

[87]:
```python
# Calculate the correlation matrix
correlation_matrix = data.corr()

# Plot the correlation matrix using seaborn
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f',␣
 ↪linewidths=0.5)
plt.title('Correlation Matrix')
plt.show()
```



	PM10 (µg/m3)	NO (µg/m3)	PM2.5 (µg/m3)	NO2 (µg/m3)	NOX (ppb)	CO (mg/m3)	SO2 (µg/m3)	NH3 (µg/m3)	Ozone (µg/m3)	Benzene (µg/m3)
PM10 (µg/m3)	1.00	0.34	0.52	0.11	0.38	0.24	-0.07	0.13	-0.27	0.33
NO (µg/m3)	0.34	1.00	0.59	0.29	0.81	0.34	0.01	0.01	-0.54	0.16
PM2.5 (µg/m3)	0.52	0.59	1.00	0.18	0.53	0.41	-0.04	0.05	-0.50	0.37
NO2 (µg/m3)	0.11	0.29	0.18	1.00	0.72	-0.08	0.17	0.24	-0.43	0.02
NOX (ppb)	0.38	0.81	0.53	0.72	1.00	0.20	0.07	0.22	-0.61	0.24
CO (mg/m3)	0.24	0.34	0.41	-0.08	0.20	1.00	-0.05	-0.22	-0.37	0.18
SO2 (µg/m3)	-0.07	0.01	-0.04	0.17	0.07	-0.05	1.00	-0.08	0.07	-0.03
NH3 (µg/m3)	0.13	0.01	0.05	0.24	0.22	-0.22	-0.08	1.00	-0.08	0.11
Ozone (µg/m3)	-0.27	-0.54	-0.50	-0.43	-0.61	-0.37	0.07	-0.08	1.00	-0.21
Benzene (µg/m3)	0.33	0.16	0.37	0.02	0.24	0.18	-0.03	0.11	-0.21	1.00

0.1.8 We observe that there is a strong positive association between NOX and NO, indicating multicollinearity.

.

0.1.9 Blasting time in coal India generally occurs around 13:45 pm to 14:45 pm and put a major effect on air pollution. So let us compare the two datasets and try to get some conclusions from it

[64]:
```python
# Extract rows between 13:45 PM and 14:45 PM

new_data = data.between_time('13:45', '14:45')
new_data.head()
```

[64]:
```
                     PM10 (µg/m3)  NO (µg/m3)  PM2.5 (µg/m3)  NO2 (µg/m3)  \
DateTime
2023-02-01 13:45:00          73.0    4.647741           18.0         59.9
2023-02-01 14:00:00          73.0    4.854775           18.0         62.4
2023-02-01 14:15:00          73.0    5.469984           18.0         61.1
2023-02-01 14:30:00          73.0    5.736887           18.0         59.0
2023-02-01 14:45:00          63.0    6.123021           14.0         59.2

                     NOX (ppb)  CO (mg/m3)  SO2 (µg/m3)  NH3 (µg/m3)  \
DateTime
2023-02-01 13:45:00       34.8        0.31    49.421488         20.5
2023-02-01 14:00:00       36.2        0.30    53.211752         20.7
2023-02-01 14:15:00       35.0        0.31    36.971376         21.5
2023-02-01 14:30:00       34.0        0.34    29.556898         22.0
2023-02-01 14:45:00       34.0        0.38    27.448166         20.8

                     Ozone (µg/m3)  Benzene (µg/m3)
DateTime
2023-02-01 13:45:00           56.9              0.1
2023-02-01 14:00:00           56.8              0.1
2023-02-01 14:15:00           57.1              0.1
2023-02-01 14:30:00           55.0              0.1
2023-02-01 14:45:00           56.3              0.1
```

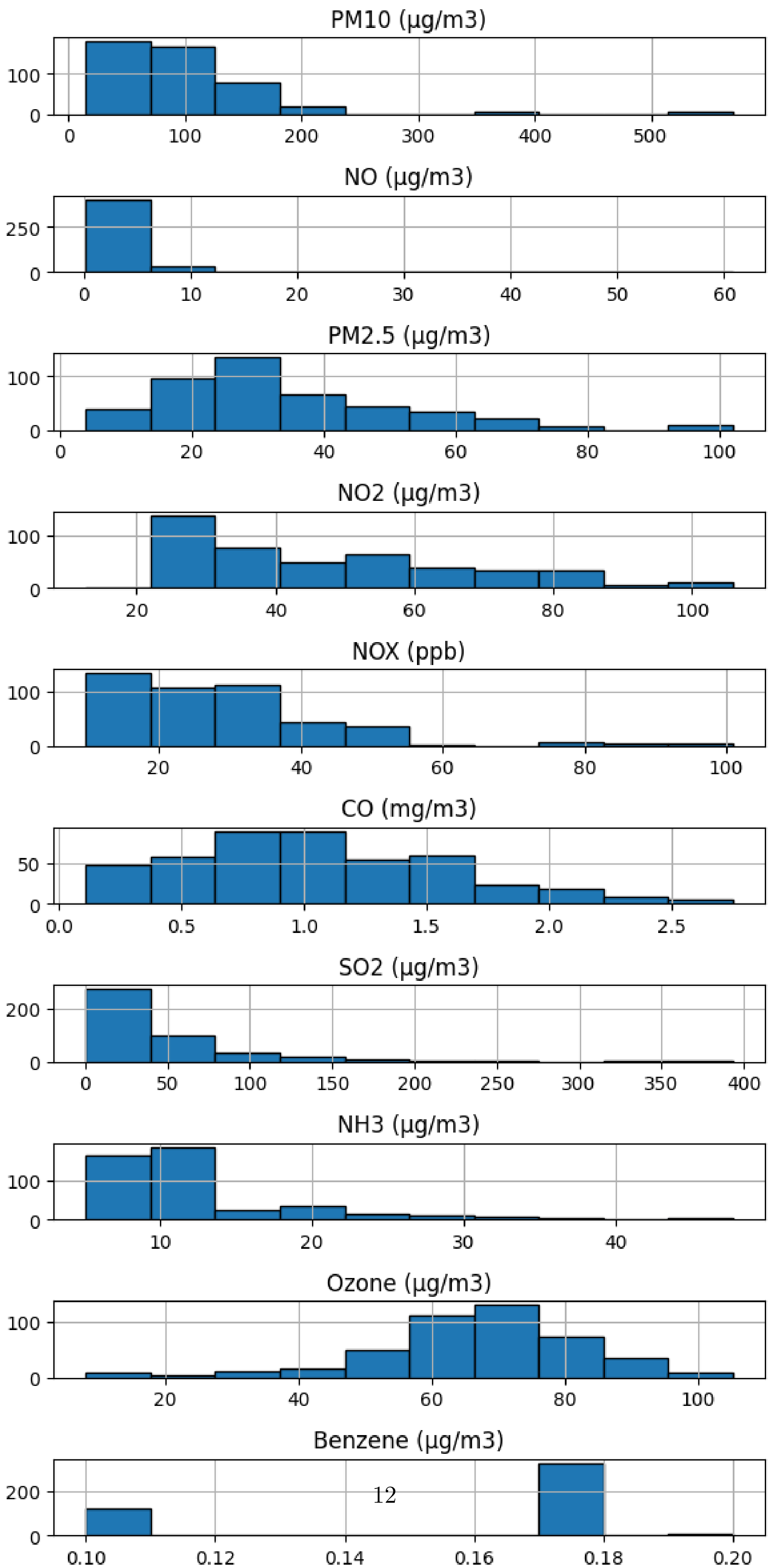
[118]:
```python
# Observations for the rest of the time
new_data_1 = data.between_time('14:46' , '13:44')
new_data_1.head()
```

[118]:
```
                     PM10 (µg/m3)  NO (µg/m3)  PM2.5 (µg/m3)  NO2 (µg/m3)  \
DateTime
2023-02-01 00:00:00          95.0   14.484070           35.0         90.1
2023-02-01 00:15:00          95.0   14.484070           35.0         88.0
2023-02-01 00:30:00          95.0   15.835914           35.0         87.7
2023-02-01 00:45:00         122.0   15.914518           34.0         88.9
2023-02-01 01:00:00         122.0   16.035640           34.0         90.0

                     NOX (ppb)  CO (mg/m3)  SO2 (µg/m3)  NH3 (µg/m3)
DateTime
```

```
2023-02-01 00:00:00       56.2        0.31    11.986833         17.7  \
2023-02-01 00:15:00       55.1        0.33    11.986833         18.3
2023-02-01 00:30:00       55.2        0.38    10.912796         19.7
2023-02-01 00:45:00       55.7        0.38    10.613291         21.3
2023-02-01 01:00:00       55.8        0.38     7.362361         22.3

                     Ozone (µg/m3)  Benzene (µg/m3)
DateTime
2023-02-01 00:00:00           28.1              0.4
2023-02-01 00:15:00           27.1              0.4
2023-02-01 00:30:00           24.9              0.4
2023-02-01 00:45:00           21.9              0.4
2023-02-01 01:00:00           16.7              0.4
```

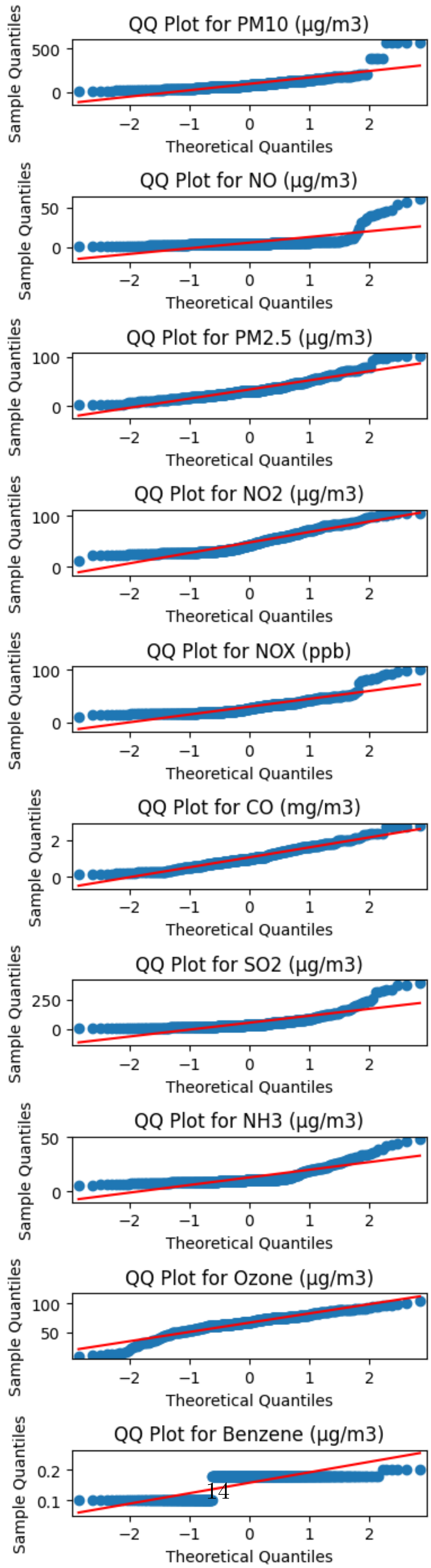
0.2 Visualizing the new dataset of observations b/w 13:45 to 14:45

[65]:
```python
# Create a grid of histograms for all columns
fig, axes = plt.subplots(nrows=len(new_data.columns), ncols=1, figsize=(6, 12))

for i, column in enumerate(new_data.columns):
    new_data[column].hist(ax=axes[i], bins=10, edgecolor='black')
    axes[i].set_title(column)

plt.tight_layout()
plt.show()
```


PM10 (µg/m3)
0
100
0
100
200
300
400
500
NO (µg/m3)
0
250
0
10
20
30
40
50
60
PM2.5 (µg/m3)
0
100
0
20
40
60
80
100
NO2 (µg/m3)
0
100
20
40
60
80
100
NOX (ppb)
0
100
20
40
60
80
100
CO (mg/m3)
0
50
0.0
0.5
1.0
1.5
2.0
2.5
SO2 (µg/m3)
0
200
0
50
100
150
200
250
300
350
400
NH3 (µg/m3)
0
100
10
20
30
40
Ozone (µg/m3)
0
100
20
40
60
80
100
Benzene (µg/m3)
0
200
0.10
0.12
0.14
0.16
0.18
0.20

0.2.1 Let us look at the Q-Q Plots to determine if the columns follow a normal distribution.

[78]:
```
import statsmodels.api as sm
# Create QQ plots for all columns
fig, axes = plt.subplots(nrows=len(new_data.columns), ncols=1, figsize=(4, 14))

for i, column in enumerate(new_data.columns):
    sm.qqplot(new_data[column], line='s', ax=axes[i])
    axes[i].set_title(f'QQ Plot for {column}')

plt.tight_layout()
plt.show()
```



QQ Plot for PM10 (µg/m3)
Sample Quantiles
Theoretical Quantiles
QQ Plot for NO (µg/m3)
Sample Quantiles
Theoretical Quantiles
QQ Plot for PM2.5 (µg/m3)
Sample Quantiles
Theoretical Quantiles
QQ Plot for NO2 (µg/m3)
Sample Quantiles
Theoretical Quantiles
QQ Plot for NOX (ppb)
Sample Quantiles
Theoretical Quantiles
QQ Plot for CO (mg/m3)
Sample Quantiles
Theoretical Quantiles
QQ Plot for SO2 (µg/m3)
Sample Quantiles
Theoretical Quantiles
QQ Plot for NH3 (µg/m3)
Sample Quantiles
Theoretical Quantiles
QQ Plot for Ozone (µg/m3)
Sample Quantiles
Theoretical Quantiles
QQ Plot for Benzene (µg/m3)
Sample Quantiles
Theoretical Quantiles

from the Q-Q Plots and the Histograms, we can conclude that only PM2.5 pollutant, CO pollutant and Ozone pollutant approximately follows a normal distribution. .

0.2.2 Now, we would compare the Descriptive Statistics of the two datasets

[88]:
```
new_data.describe()
```

[88]:

	PM10 (µg/m3)	NO (µg/m3)	PM2.5 (µg/m3)	NO2 (µg/m3)	NOX (ppb)
count	450.000000	450.000000	450.000000	450.000000	450.000000
mean	97.693250	5.490348	34.181804	47.803924	29.993426
std	73.507027	7.259741	18.551560	20.433826	14.951182
min	15.000000	0.200000	4.000000	12.700000	9.700000
25%	58.250000	3.300000	21.000000	29.500000	18.225000
50%	84.000000	3.900000	31.000000	42.150000	25.950000
75%	123.000000	5.200000	43.750000	61.175000	36.075000
max	570.000000	60.800000	102.000000	105.800000	100.900000

	CO (mg/m3)	SO2 (µg/m3)	NH3 (µg/m3)	Ozone (µg/m3)	Benzene (µg/m3)
count	450.000000	450.000000	450.000000	450.000000	450.000000
mean	1.055087	51.798855	12.715081	66.428793	0.157137
std	0.542093	59.394849	7.076697	16.337413	0.034589
min	0.110000	0.500000	5.100000	8.100000	0.100000
25%	0.660000	17.750000	8.700000	60.125000	0.100000
50%	0.965000	30.300000	10.100000	67.850000	0.177505
75%	1.440000	63.550000	12.275000	76.400000	0.177505
max	2.750000	393.200000	47.700000	105.200000	0.200000

[89]:
```
new_data_1.describe()
```

[89]:

	PM10 (µg/m3)	NO (µg/m3)	PM2.5 (µg/m3)	NO2 (µg/m3)	NOX (ppb)
count	8190.000000	8190.000000	8190.000000	8190.000000	8190.000000
mean	168.846521	14.752009	76.848693	56.585740	43.141974
std	129.415702	18.273803	55.467537	20.224937	22.257075
min	-13.488183	0.100000	3.000000	0.200000	4.200000
25%	82.000000	4.100000	37.000000	40.300000	25.600000
50%	130.644482	7.090766	62.000000	54.300000	38.600000
75%	216.750000	17.900000	103.000000	71.900000	54.200000
max	847.000000	157.500000	474.000000	106.900000	165.200000

	CO (mg/m3)	SO2 (µg/m3)	NH3 (µg/m3)	Ozone (µg/m3)	Benzene (µg/m3)
count	8190.000000	8190.000000	8190.000000	8190.000000	8190.000000
mean	1.411416	32.734539	13.184968	34.080895	0.178624
std	0.626088	37.178138	6.036831	25.970518	0.053191
min	0.100000	0.100000	4.600000	0.100000	0.100000

```
25%        0.950000    14.899626     9.400000     10.400000          0.177505
50%        1.410000    23.800000    11.000000     30.200000          0.177505
75%        1.850000    35.400000    14.000000     55.500000          0.177505
max        4.000000   645.600000    62.400000    123.800000          0.600000
```

[90]:
```
new_data.median()
```

[90]:
```
PM10 (µg/m3)        84.000000
NO (µg/m3)           3.900000
PM2.5 (µg/m3)       31.000000
NO2 (µg/m3)         42.150000
NOX (ppb)           25.950000
CO (mg/m3)           0.965000
SO2 (µg/m3)         30.300000
NH3 (µg/m3)         10.100000
Ozone (µg/m3)       67.850000
Benzene (µg/m3)      0.177505
dtype: float64
```

[91]:
```
new_data_1.median()
```

[91]:
```
PM10 (µg/m3)        130.644482
NO (µg/m3)            7.090766
PM2.5 (µg/m3)        62.000000
NO2 (µg/m3)          54.300000
NOX (ppb)            38.600000
CO (mg/m3)            1.410000
SO2 (µg/m3)          23.800000
NH3 (µg/m3)          11.000000
Ozone (µg/m3)        30.200000
Benzene (µg/m3)       0.177505
dtype: float64
```

0.2.3 We can observe that the median value of SO2 and Ozone pollutant during 13:45 to 14:45 is significancly greater than rest of the day. This gives us a clear indication that, during the open pit-blasting, Ozone and Sulphur Oxide levels in air rises.

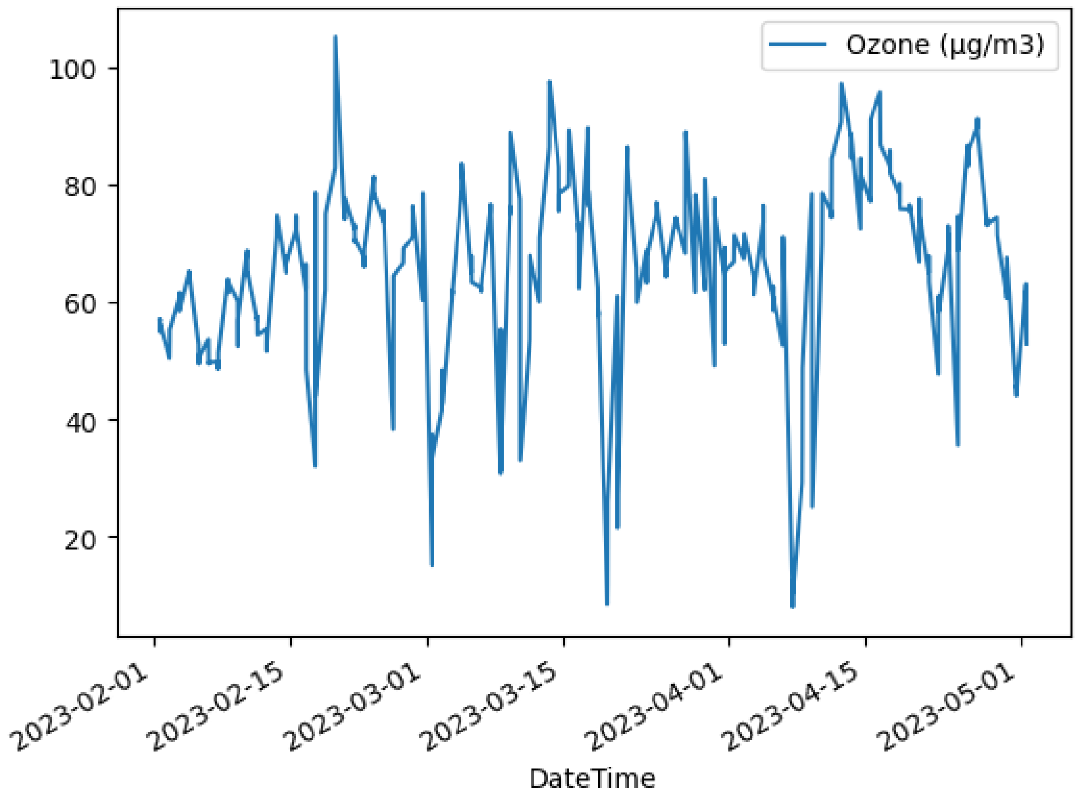
0.3 Decomposition of Time Series

Let us study the time series data of Ozone Pollutant

[124]:
```
univ_data = pd.DataFrame(new_data['Ozone (µg/m3)'])
```

[125]:
```
univ_data.plot()
```

[125]: <Axes: xlabel='DateTime'>



Checking for Stationarity by adfuller Test

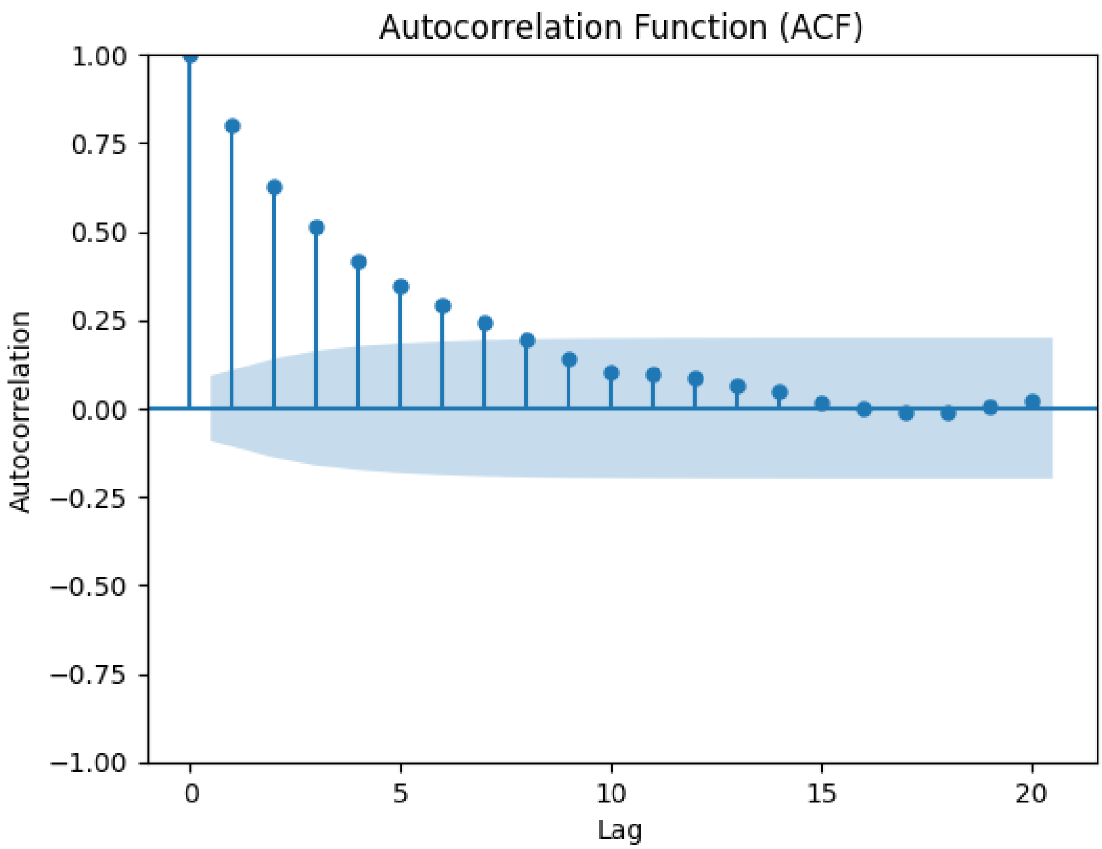
[99]:
```
def adfuller_test(x):
    result = adfuller(x)
    labels = ['ADF Test Statistic' , 'p-value' , '#Lags Used' , 'Number of␣
↪Observations Used']
    for value,label in zip(result , labels):
        print(label+' : '+str(value) )
    if result[1] <= 0.05:
        print("reject null hypothesis")
    else:
        print("accept null hypothesis")
```

[100]:
```
adfuller_test(new_data['Ozone (µg/m3)'])
```

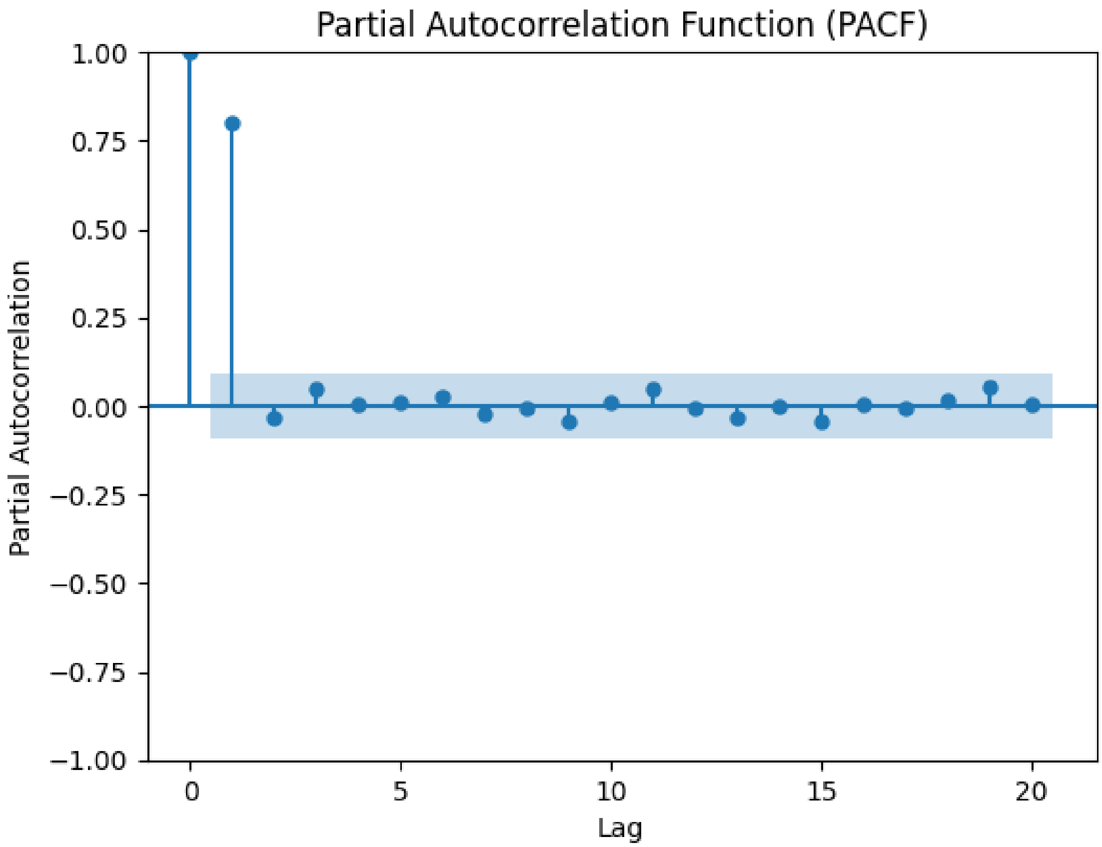
```
ADF Test Statistic : -7.005429322242349
p-value : 7.142548345098416e-10
#Lags Used : 0
Number of Observations Used : 449
reject null hypothesis
```

Thus, by adfuller test, the time series is stationary.

[101]:
```
#plot of ACF

plot_acf(new_data['Ozone (μg/m3)'], lags=20)
plt.xlabel('Lag')
plt.ylabel('Autocorrelation')
plt.title('Autocorrelation Function (ACF)')
plt.show()
```



[102]:
```
#plot of PACF

plot_pacf(new_data['Ozone (μg/m3)'], lags=20)
plt.xlabel('Lag')
plt.ylabel('Partial Autocorrelation')
plt.title('Partial Autocorrelation Function (PACF)')
plt.show()
```

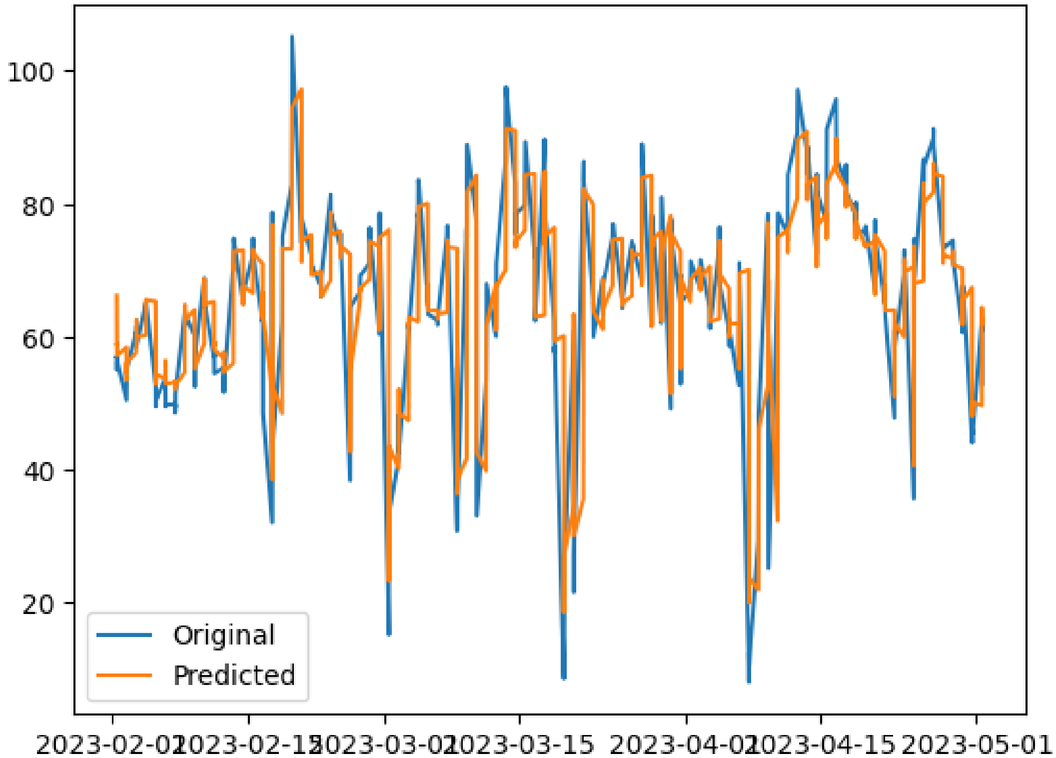


0.4 Fitting of ARMA Model

[107]:
```
# Create an instance of the ARMA model with appropriate order values
model = ARIMA(new_data['Ozone (µg/m3)'], order=(1, 0 , 1))  # Replace p and q␣
↪with desired order values

# Fit the model to the data
model_fit = model.fit()
```

[116]:
```
predictions = model_fit.predict()
```

[126]:
```
plt.plot(new_data['Ozone (µg/m3)'], label='Original')
plt.plot(predictions, label='Predicted')
plt.legend()
plt.show()
```



We can apply similar ARMA modeling techniques for other pollutants as well.

0.5 Conclusion:

0.5.1 Air pollution due to coal open pit blasting is a significant environmental concern that arises from the mining and extraction processes in coalfields. The blasting activities release large quantities of particulate matter, including suspended particulate matter (SPM) and reparable particulate matter (RPM), into the atmosphere. These pollutants pose severe health and environmental hazards, impacting both the immediate vicinity and the surrounding regions. We performed the Data Visualization of the several air pollutants. We observed that there is a positive correlation among some of the pollutants.

0.5.2 We have plotted the pollutant levels during the blasting periods which generally lasts between 13:45 and 14:45. Ozone and Sulphates concentration in the atmosphere rises rapidly during this time. During coal open pit blasting, the concentration of ozone (O3) and sulfur oxides (SOx), such as sulfur dioxide (SO2), can increase in the atmosphere due to various chemical and physical processes that take place during the blasting activity. These increases in O3 and SOx concentrations are primarily attributed to the following factors:

1) Chemical Reactions:

2) Dispersion and Transport:

3) Inefficient Combustion:

4) Meteorological Conditions:

0.5.3 Overall, coal open pit blasting contributes to the release of various pollutants, including nitrogen oxides and sulfur dioxide, which can subsequently lead to increased ozone and sulfur oxide concentrations in the atmosphere. These pollutants have adverse effects on air quality, human health, and the environment, emphasizing the importance of implementing emission control measures and adopting cleaner technologies to mitigate air pollution during coal mining activities.