

Assignment 1

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Problem Statement

Q.) Air pollution measurements available via multi-sensory system are PM10, PM2.5, SO₂, NO, NO₂, NO_x, CO, NH₃, O₃ and Benzene.

Now, given **dataset** depicts levels of these pollutants at given time intervals spread over a duration of approx. 3 months. On the basis of information provided through dataset, answer the following:

- **(a)Classification:** time series data classify mainly two categories: stock and flow time series. Find out if it identifies and assigns categories to the air pollution data.
- **(b)Curve fitting:** Plot the air pollution data along a curve to study the relationships of variables within the data.
- **(c)Descriptive analysis:** in coal India blasting effect time is 13:45 pm to 14:45 pm, find trends like cycles, or seasonal variation.
- **(d) Explanatory analysis:** The aim of this analysis is to gain insights into the air pollution data and explore the relationships within the data. Additionally, we aim to understand the impact of coal blasting on air pollution in the context of coal India.

- **(e)Forecasting:** Analyse the time series method used for forecasting i.e., which model (AR, MA, ARMA, ARIMA) needs to be used for forecasting?

-->Firstly, we will start by importing all the required libraries for our analysis.

```
In [1]:  import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error
from math import sqrt
from datetime import datetime
```

```
In [2]:  dataSet = pd.read_csv("Data.csv")
```

- **numpy** (imported as **np**): It is a popular numerical computing library in Python.
- **pandas** (imported as **pd**): It offers data structures and functions for efficiently handling and analysing structured data, such as data frames.
- **seaborn** (imported as **sns**): It is a data visualization library built on top of **matplotlib**.
- **matplotlib.pyplot** (imported as **plt**): It is a plotting library in Python that provides a wide range of functions for creating various types of plots, including line plots, scatter plots, bar plots, histograms, etc.
- **sklearn.metrics.mean_squared_error**: It calculates the mean squared error (MSE) between two arrays.
- **math.sqrt**: It is a function from the **math** module in Python. It calculates the square root of a number.

- **datetime.datetime**: It is a class from the **datetime** module in Python. In this case, it is imported to work with date and time-related operations.

dataSet													
	#	From	To (Interval: 15M)	Singrauli, Surya Kiran Bhawan Dudhichua PM10 (µg/m3)	Singrauli, Surya Kiran Bhawan Dudhichua PM2.5 (µg/m3)	Singrauli, Surya Kiran Bhawan Dudhichua NO (µg/m3)	Singrauli, Surya Kiran Bhawan Dudhichua NO2 (µg/m3)	Singrauli, Surya Kiran Bhawan Dudhichua NOX (ppb)	Singrauli, Surya Kiran Bhawan Dudhichua CO (mg/m3)	Singrauli, Surya Kiran Bhawan Dudhichua SO2 (µg/m3)	Singrauli, Surya Kiran Bhawan Dudhichua NH3 (µg/m3)	Singrauli, Surya Kiran Bhawan Dudhichua Ozone (µg/m3)	Singrauli, Surya Kiran Bhawan Dudhichua Benzene (µg/m3)
0	1	01-02-2023 00:00	01-02-2023 00:15	95.0	35.0	NaN	90.1	56.2	0.31	NaN	17.7	28.1	0.4
1	2	01-02-2023 00:15	01-02-2023 00:30	95.0	35.0	NaN	88.0	55.1	0.33	NaN	18.3	27.1	0.4
2	3	01-02-2023 00:30	01-02-2023 00:45	95.0	35.0	NaN	87.7	55.2	0.38	NaN	19.7	24.9	0.4
3	4	01-02-2023 00:45	01-02-2023 01:00	122.0	34.0	NaN	88.9	55.7	0.38	NaN	21.3	21.9	0.4
4	5	01-02-2023 01:00	01-02-2023 01:15	122.0	34.0	NaN	90.0	55.8	0.38	NaN	22.3	16.7	0.4

--> In our original dataset, there are many missing values in our data set. Now, we want to estimate the percentage of such missing values and the fill them by using interpolation.

```
columns=dataset.columns
date = columns[2]
columns=columns[3:]
columns
```

```
Index(['Singrauli, Surya Kiran Bhawan Dudhichua PM10 (µg/m3)',
      'Singrauli, Surya Kiran Bhawan Dudhichua PM2.5 (µg/m3)',
      'Singrauli, Surya Kiran Bhawan Dudhichua NO (µg/m3)',
      'Singrauli, Surya Kiran Bhawan Dudhichua NO2 (µg/m3)',
      'Singrauli, Surya Kiran Bhawan Dudhichua NOX (ppb)',
      'Singrauli, Surya Kiran Bhawan Dudhichua CO (mg/m3)',
      'Singrauli, Surya Kiran Bhawan Dudhichua SO2 (µg/m3)',
      'Singrauli, Surya Kiran Bhawan Dudhichua NH3 (µg/m3)',
      'Singrauli, Surya Kiran Bhawan Dudhichua Ozone (µg/m3)',
      'Singrauli, Surya Kiran Bhawan Dudhichua Benzene (µg/m3)'],
      dtype='object')
```

--> Now, we have eliminated 'Serial number', 'From' and 'To' columns and stored pollutant level columns.

```
In [5]: ➤ for col in columns:
          print((dataset[col].isna().sum() / len(dataset[col])) * 100)

19.45601851851852
2.6157407407407405
15.844907407407408
4.814814814814815
4.8032407407407405
5.7407407407407405
16.79398148148148
3.7731481481481484
5.243055555555555
71.70138888888889
```

--> Now, we have calculated percentage of missing values in each of the columns.

Q1) Updating NA Values By Interpolation (Cubic):

```
In [6]: ➤ for column in columns:
          x = pd.Series(dataset[column])
          dataset[column] = x.interpolate(limit_direction='both', kind='cubic')
```

-->Code updates the missing values of the current column in the **dataSet** Data Frame with the interpolated values.

-->Replacing NA values with 0 can distort the representation of the data. Depending on the context, assigning a value of 0 to missing data points can introduce bias or inaccurately portray the actual measurements.

By using cubic interpolation, the missing values are replaced with estimated values based on the surrounding data points, following a cubic interpolation curve. This helps to retain the overall shape and characteristics of the data while filling in the gaps caused by missing values.

```
In [7]: dataSet.describe()
```

Out[7]:

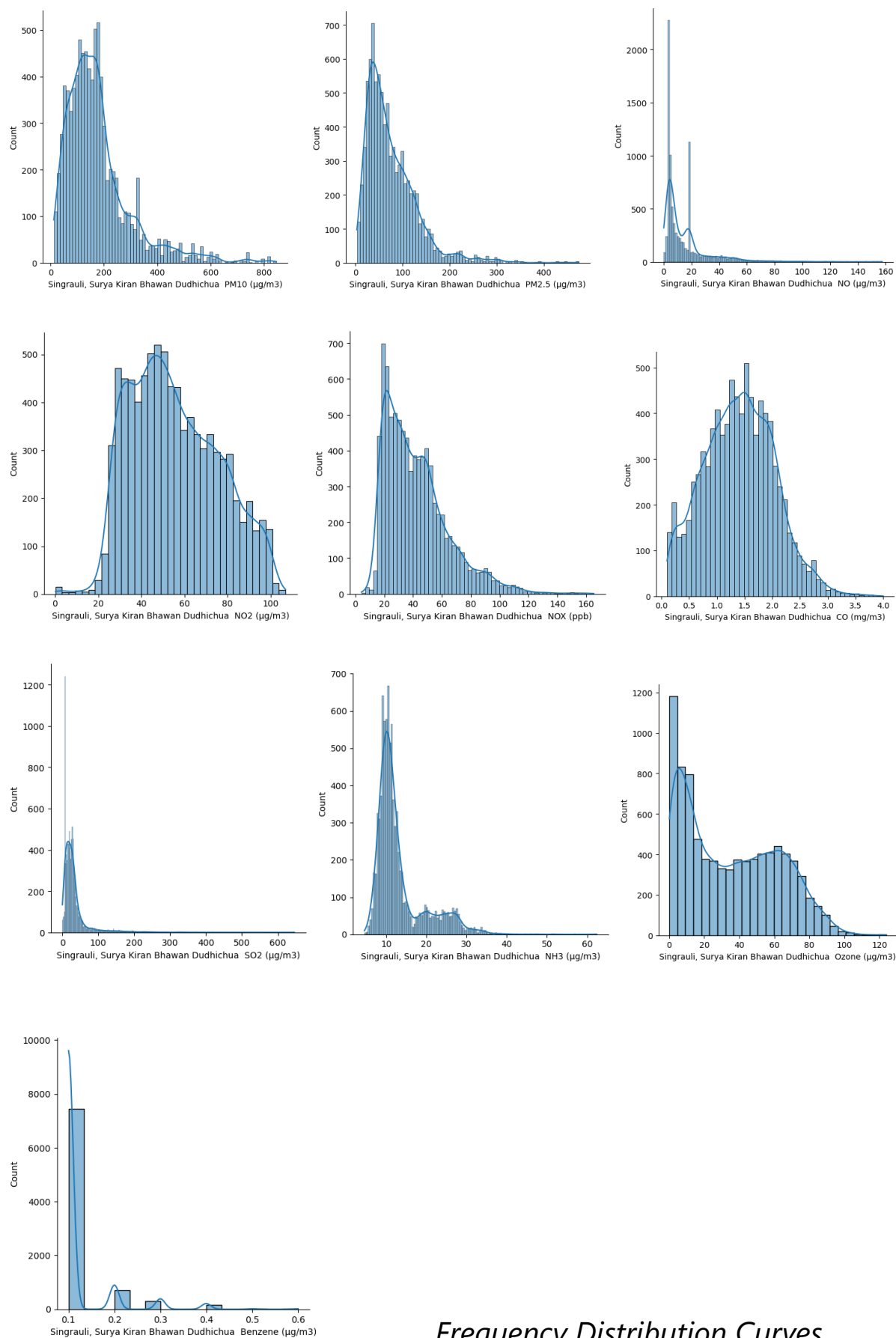
	#	Singrauli, Surya Kiran Bhawan Dudhichua PM10 (µg/m3)	Singrauli, Surya Kiran Bhawan Dudhichua PM2.5 (µg/m3)	Singrauli, Surya Kiran Bhawan Dudhichua NO (µg/m3)	Singrauli, Surya Kiran Bhawan Dudhichua NO2 (µg/m3)	Singrauli, Surya Kiran Bhawan Dudhichua NOX (ppb)	Singrauli, Surya Kiran Bhawan Dudhichua CO (mg/m3)	Singrauli, Surya Kiran Bhawan Dudhichua SO2 (µg/m3)	Singrauli, Surya Kiran Bhawan Dudhichua NH3 (µg/m3)	Singrauli, Surya Kiran Bhawan Dudhichua Ozone (µg/m3)	Singrauli, Surya Kiran Bhawan Dudhichua Benzene (µg/m3)
count	8640.000000	8640.000000	8640.000000	8640.000000	8640.000000	8640.000000	8640.000000	8640.000000	8640.000000	8640.000000	8640.000000
mean	4320.500000	177.463079	75.557350	14.940208	55.430689	42.328802	1.401927	31.923270	13.286956	35.193970	0.122002
std	2494.297496	124.773568	54.826850	17.862679	20.205531	22.181225	0.633087	39.028371	6.171697	26.867859	0.063168
min	1.000000	12.000000	3.000000	0.100000	0.200000	4.200000	0.100000	0.100000	4.600000	0.100000	0.100000
25%	2160.750000	97.000000	36.821429	4.000000	39.300000	24.900000	0.950000	12.300000	9.500000	10.300000	0.100000
50%	4320.500000	151.900794	61.000000	7.500000	52.800000	37.500000	1.410000	22.800000	11.000000	31.700000	0.100000
75%	6480.250000	215.000000	101.000000	18.100000	70.700000	53.200000	1.850000	33.400000	14.000000	58.100000	0.100000
max	8640.000000	847.000000	474.000000	157.500000	106.900000	165.200000	4.000000	645.600000	62.400000	123.800000	0.600000

-->Clearly, we have filled all the missing values by using cubic interpolation as can be seen from updated dataset.

Plotting Frequency Distribution Curves:

```
In [8]: for column in columns:
         sns.displot(dataSet[column], kde = True)
         plt.show()
```

-->Using the given code, we have plotted frequency distribution curves of various pollutant levels.



Frequency Distribution Curves

-->Classification (Flow Time Series Data) Q(3a),
Explanatory Analysis Q(3d) and
Statistical Inference (QQ Plot and Blasting Time) Q(2):

-->Results from graph plotted below indicate that *blasting time of coal in India is most likely occurring between 13:45 to 14:45 pm.*

```
avg_level = dataSet.groupby(dataSet.index % 90).mean(numeric_only=True)

plt.figure(figsize=(12, 8))

colors = ['red', 'green', 'blue', 'orange', 'purple']

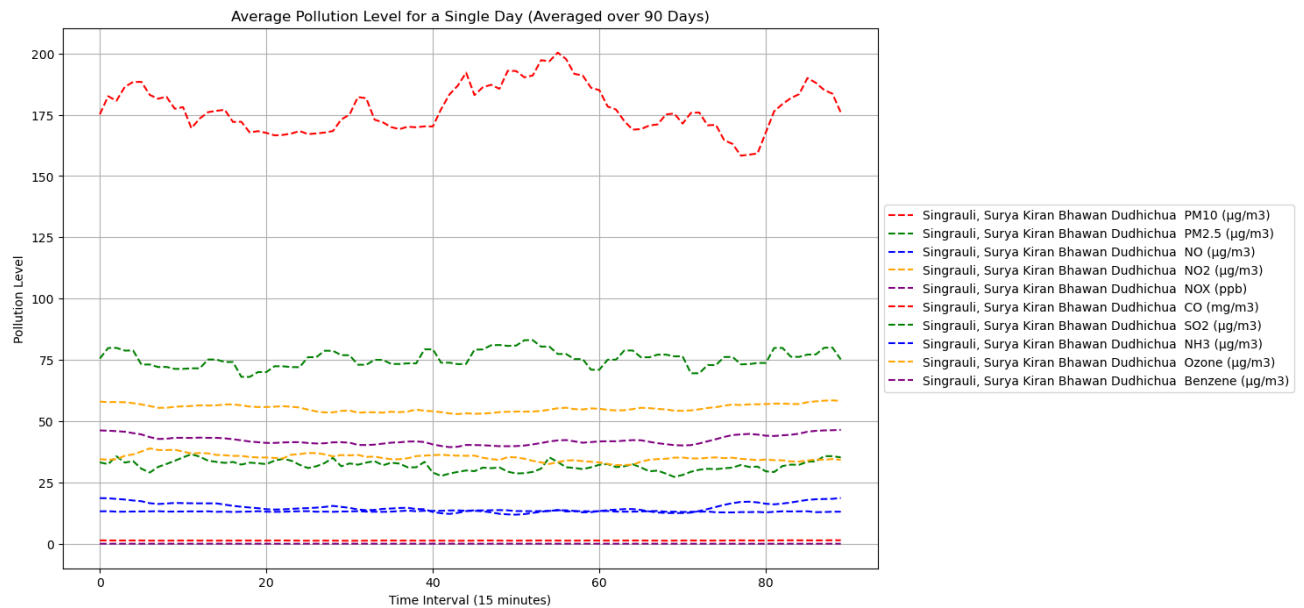
for i, column in enumerate(columns):
    plt.plot(avg_level[column], label=column, color=colors[i % len(colors)], linestyle='--')

plt.xlabel('Time Interval (15 minutes)')
plt.ylabel('Pollution Level')
plt.title('Average Pollution Level for a Single Day (Averaged over 90 Days)')

plt.legend(loc='center left', bbox_to_anchor=(1, 0.5))

plt.grid(True)
plt.show()
```

Plotted Graph (Flow Time Series):



The plotted graph shows the average pollution levels for different gases during a single day, averaged over the 90-day period.

The pollutants' levels exhibit noticeable increases specifically during and after the time interval of 13:45 to 14:45 (somewhere between 50th and 60th interval), suggesting a correlation with the blasting activities of coal in the region.

The graph provides a clear visual representation of the heightened pollution levels during and after the suspected blasting time. This observation supports the conclusion that the blasting time of coal in India is most likely occurring between 13:45 to 14:45 pm.

This inference is based on the analysis of average pollution levels and spikes during the specified time interval.

This indicates level of most pollutant gases spikes after blasting time of coal in India starts (i.e 13:45 pm to 14:45 pm).

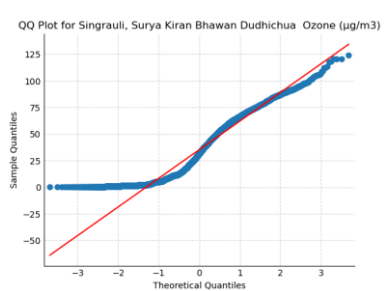
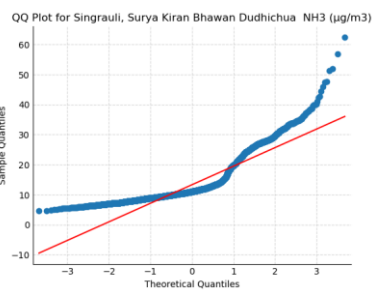
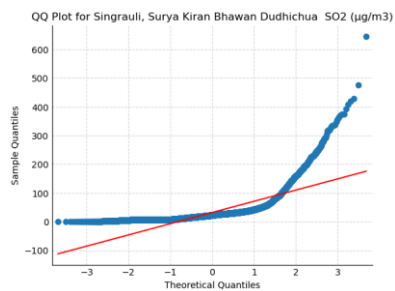
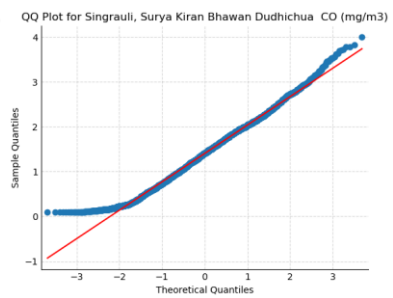
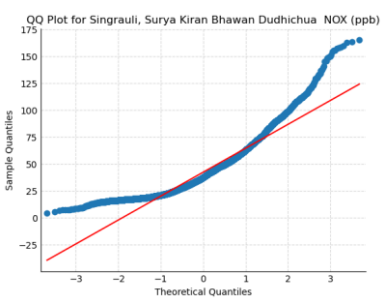
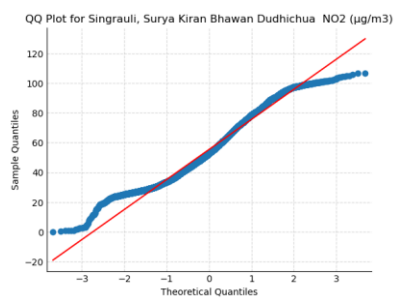
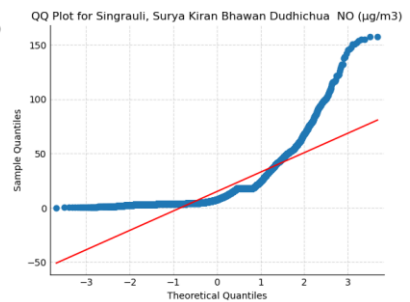
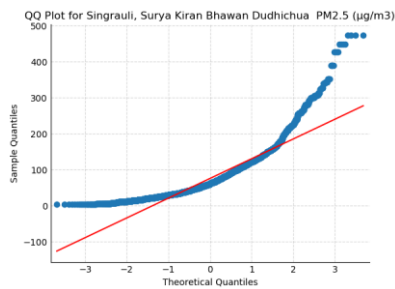
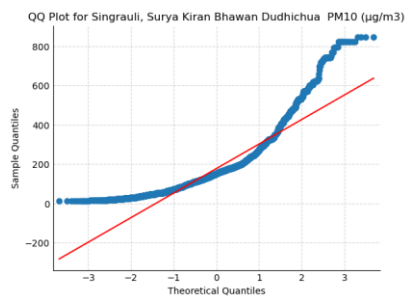
QQ Plots (Statistical Inference Q2):

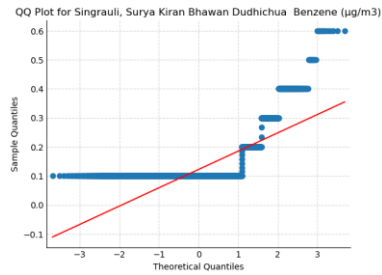

```

import statsmodels.api as sm
colors = ['red', 'green', 'blue', 'orange', 'purple'] # List of colors for each pollutant

for i, column in enumerate(columns):
    fig, ax = plt.subplots()
    sm.qqplot(dataSet[column], line='s', ax=ax)
    ax.set_title(f"QQ Plot for {column}")
    ax.spines['top'].set_visible(False) # Remove top spine
    ax.spines['right'].set_visible(False) # Remove right spine
    ax.grid(True, linestyle='--', alpha=0.5) # Add grid lines
    ax.tick_params(axis='both', which='both', length=0) # Remove tick marks
    ax.set_xlabel('Theoretical Quantiles')
    ax.set_ylabel('Sample Quantiles')
    ax.lines[0].set_color(colors[i % len(colors)]) # Set color for QQ plot line
    plt.show()

```





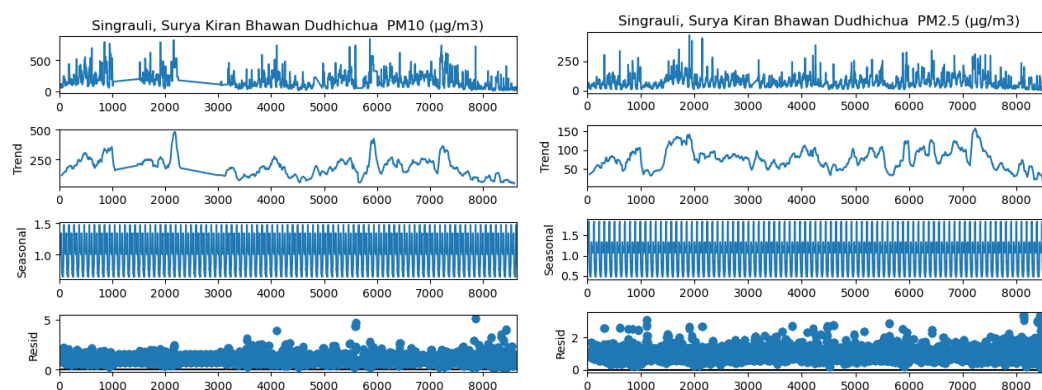
As we can infer from QQ plots, in general, the curves are positively skewed and *none of the curves resembles normal distribution*.

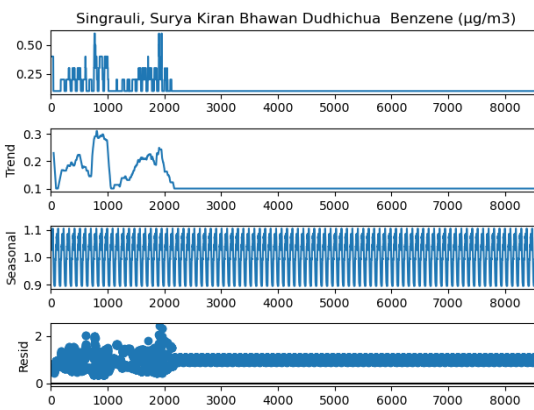
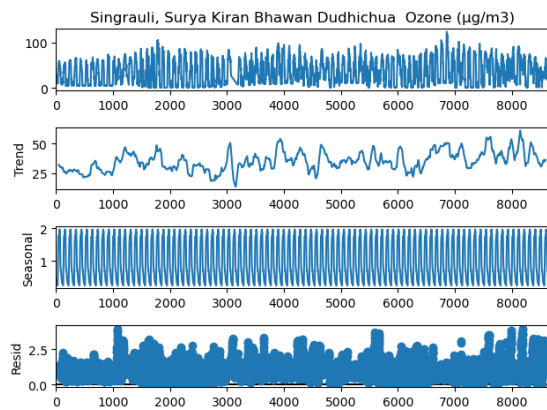
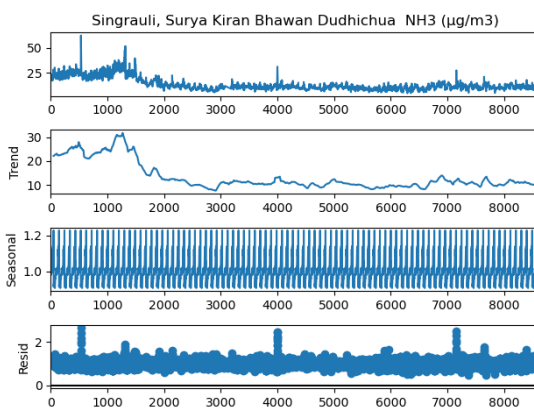
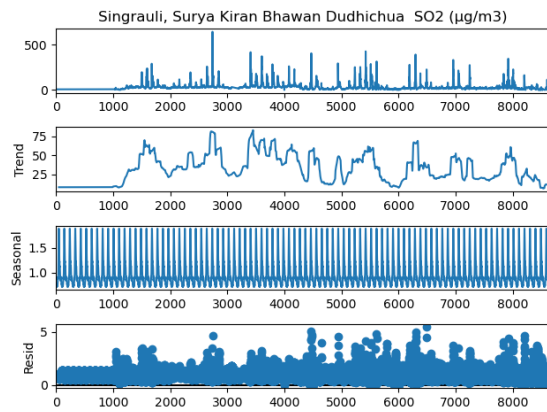
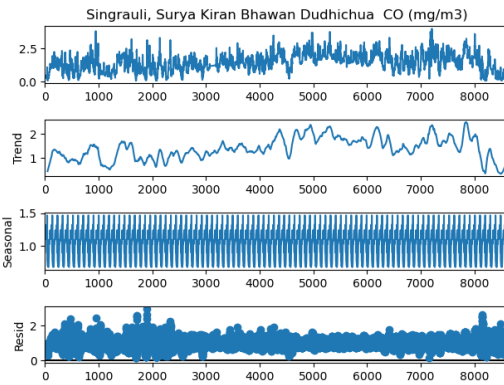
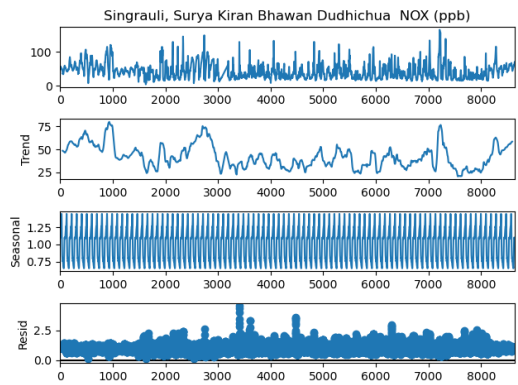
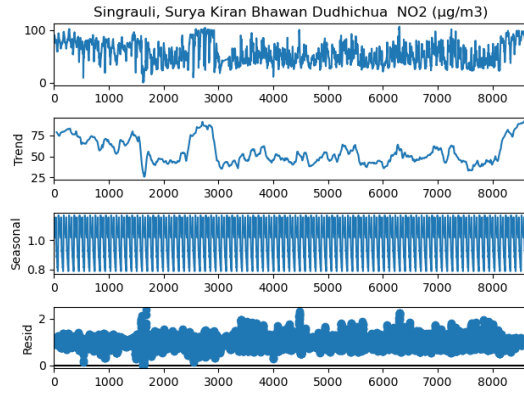
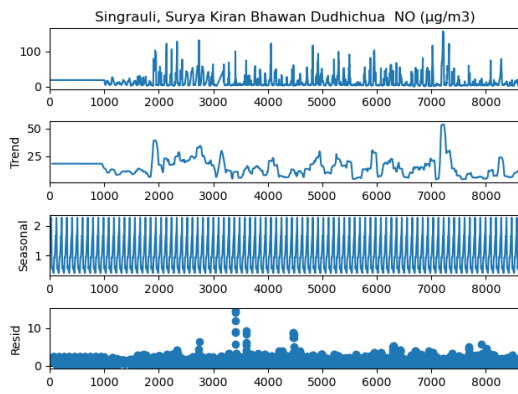
-->Descriptive Analysis (Trend and Seasonality) Q3(c):

I have used below code to decompose a time series into its trend, seasonal, and residual components.

```
from statsmodels.tsa.seasonal import seasonal_decompose
for column in columns:
    decompose_result_mult = seasonal_decompose(dataSet[column], period = 96, model="multiplicative")
    plt.figure(figsize=(30, 50))
    trend = decompose_result_mult.trend
    seasonal = decompose_result_mult.seasonal
    decompose_result_mult.plot()
```

-->Following are the plots of all the 3 components for all the pollutants:





--> Trend: By looking at these graphs, we can conclude that since trend graph is not continuously increasing or decreasing, *there is no trend in level of pollutant gases.*

--> Seasonality: Since duration in which data is available is 3 months and seasonality graphs repeat in very small duration of time, we can conclude *there is no seasonality in level of pollutant gases.*

--> ADF Test For Seasonality and Trend: Q3(C)

```
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
for column in columns:
    result = adfuller(dataSet[column])
    print('ADF Statistic: %f' % result[0])
    print('p-value: %f' % result[1])
    print('No. of Lags : %f' % result[2])
    print('No of Observation used for ADF regression and Critical Value Prediction : %f' % result[3])
    print('Critical Values:')
    for key, value in result[4].items():
        print('\t%s: %.3f' % (key, value))
```

--> In our context of analysing air pollution data and its relationship with coal blasting, the ADF test can help us assess the presence of trend and seasonality in the data.

In the ADF test, the null hypothesis assumes that the time series has a unit root, indicating that it is non-stationary and contains a trend. The alternative hypothesis suggests that the time series is stationary, meaning it does not contain a trend.

Below is the result of code:

ADF Statistic: -9.023314
p-value: 0.000000
No. of Lags : 36.000000
No of Observation used for ADF regression and Critical Value Prediction : 8603.000000
Critical Values:
1%: -3.431
5%: -2.862
10%: -2.567

ADF Statistic: -11.159054
p-value: 0.000000
No. of Lags : 36.000000
No of Observation used for ADF regression and Critical Value Prediction : 8603.000000
Critical Values:
1%: -3.431
5%: -2.862
10%: -2.567

ADF Statistic: -14.799960
p-value: 0.000000
No. of Lags : 11.000000
No of Observation used for ADF regression and Critical Value Prediction : 8628.000000
Critical Values:
1%: -3.431
5%: -2.862
10%: -2.567

ADF Statistic: -9.181725
p-value: 0.000000
No. of Lags : 21.000000
No of Observation used for ADF regression and Critical Value Prediction : 8618.000000
Critical Values:
1%: -3.431
5%: -2.862
10%: -2.567

```

ADF Statistic: -12.734220
p-value: 0.000000
No. of Lags : 24.000000
No of Observation used for ADF regression and Critical Value Prediction : 8615.000000
Critical Values:
    1%: -3.431
    5%: -2.862
    10%: -2.567
ADF Statistic: -9.976113
p-value: 0.000000
No. of Lags : 8.000000
No of Observation used for ADF regression and Critical Value Prediction : 8631.000000
Critical Values:
    1%: -3.431
    5%: -2.862
    10%: -2.567
ADF Statistic: -14.141881
p-value: 0.000000
No. of Lags : 20.000000
No of Observation used for ADF regression and Critical Value Prediction : 8619.000000
Critical Values:
    1%: -3.431
    5%: -2.862
    10%: -2.567
ADF Statistic: -3.059899
p-value: 0.029667
No. of Lags : 33.000000
No of Observation used for ADF regression and Critical Value Prediction : 8606.000000
Critical Values:
    1%: -3.431
    5%: -2.862
    10%: -2.567

ADF Statistic: -20.958946
p-value: 0.000000
No. of Lags : 34.000000
No of Observation used for ADF regression and Critical Value Prediction : 8605.000000
Critical Values:
    1%: -3.431
    5%: -2.862
    10%: -2.567
ADF Statistic: -9.037111
p-value: 0.000000
No. of Lags : 37.000000
No of Observation used for ADF regression and Critical Value Prediction : 8602.000000
Critical Values:
    1%: -3.431
    5%: -2.862
    10%: -2.567

```

-->Based on the ADF test results, we can make the following conclusions:

-
- p-value: The p-value is significantly lower than the significance level (e.g., 0.05), indicating strong evidence against the null hypothesis. By rejecting the

null hypothesis, we can conclude that the time series is stationary and does not exhibit a trend.

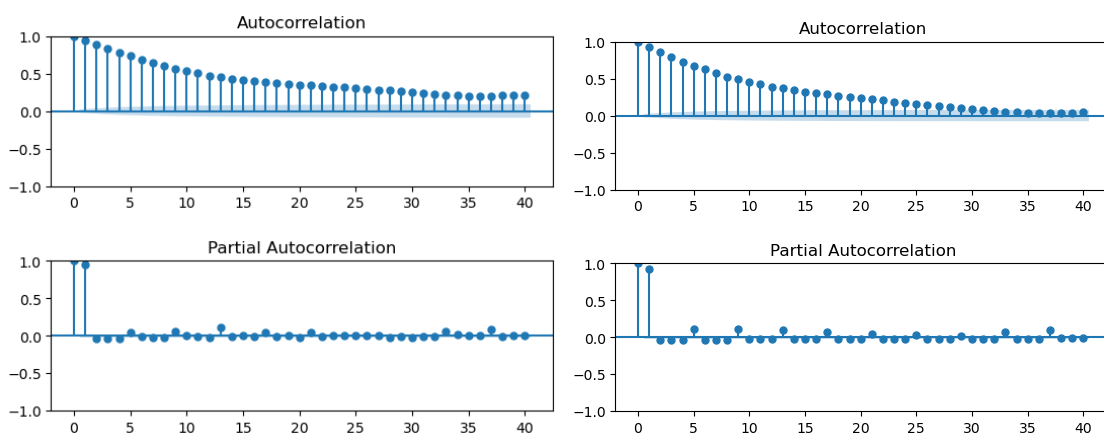
- ADF Statistic: The ADF statistic is significantly negative, lower than the critical values at 1%, 5%, and 10% significance levels. This further supports the rejection of the null hypothesis.

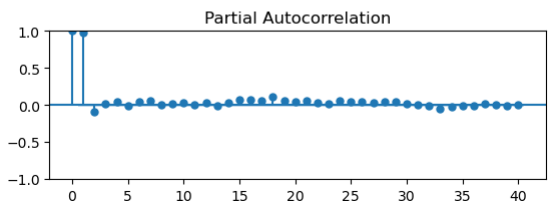
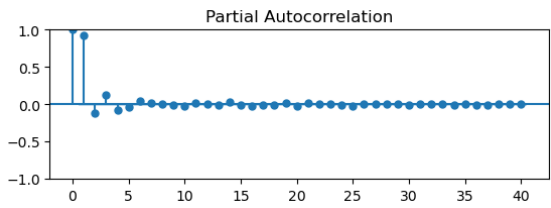
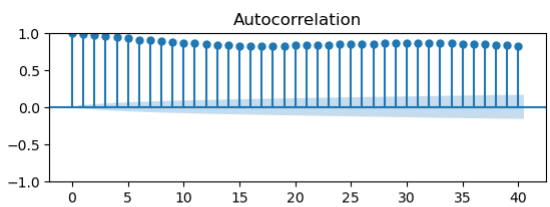
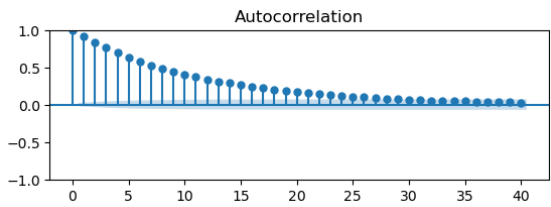
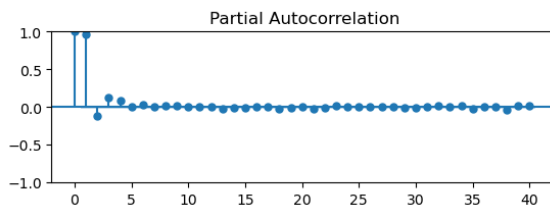
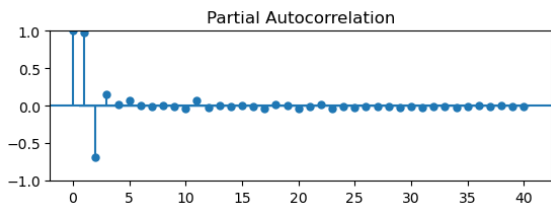
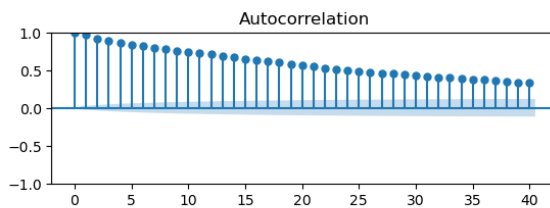
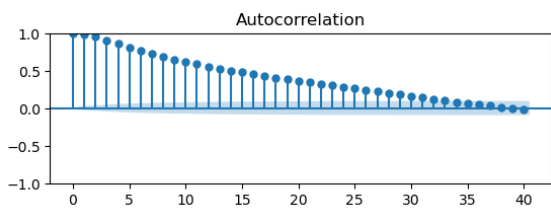
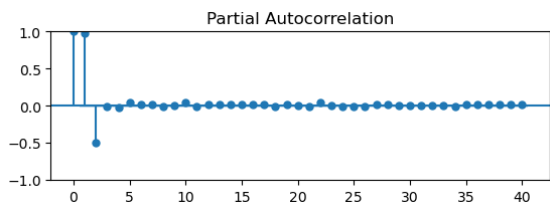
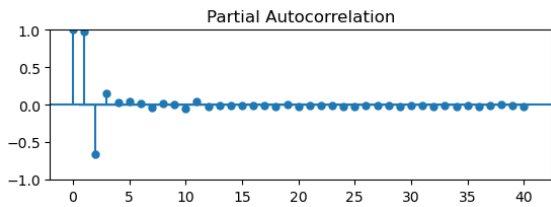
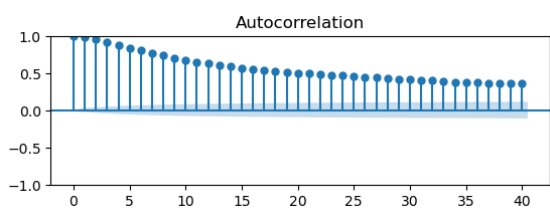
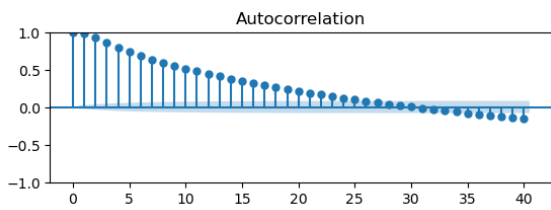
Based on these findings, we can confidently conclude that there is no presence of trend or seasonality in the pollutant levels.

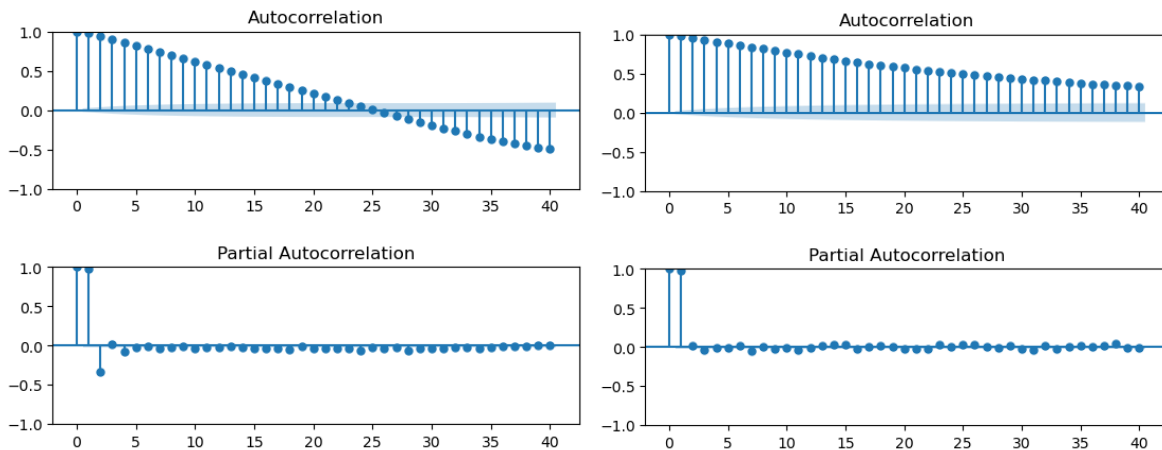
-->Forecasting Q3 (E):

```
In [15]: for column in columns:
          fig, (ax1, ax2) = plt.subplots(2)
          plot_acf(dataSet[column], ax = ax1)
          plot_pacf(dataSet[column], ax = ax2)
          plt.subplots_adjust(hspace=0.5)
          plt.show()
```

ACF (Autocorrelation) and PACF (Partial Autocorrelation) Plots:







Based on the autocorrelation function (ACF) and partial autocorrelation function (PACF) graphs, we can make the following observations:

- ACF: The ACF graph shows that the autocorrelation values do not decay fully after a certain lag. This indicates the presence of significant autocorrelation in the data. This behaviour is indicative of a time series that follows an autoregressive (AR) model.
- PACF: The PACF graph shows that the partial autocorrelation values decay after a lag of 2 or 3. This pattern is consistent with an **autoregressive model** with a lag of 2 or 3.

-->Based on these observations, we can infer that *the time series data follows an autoregressive model, specifically an AR (2) or AR (3) model*. The autocorrelation and partial autocorrelation patterns indicate the presence of a memory effect and direct influence of past values on the current value.

-->Autoregressive Model (AR): Stock Time Series Data Q3(A):

```

from statsmodels.tsa.ar_model import AutoReg
for column in columns:
    data = dataSet[column]
    train_data = data[:-80]
    test_data = data[-80:]
    ar_model = AutoReg(data, lags = 3).fit()
    print(ar_model.summary())
    pred = ar_model.predict(start = len(train_data), end = len(data) - 1, dynamic=False)
    plt.plot(pred, color = "blue")
    plt.plot(test_data, color = "red")
    plt.show()
    rmse = sqrt(mean_squared_error(pred, test_data))
    mean = data.mean()
    print("Mean : %f" % mean)
    print("Root Mean Squared Error : %f" %rmse)

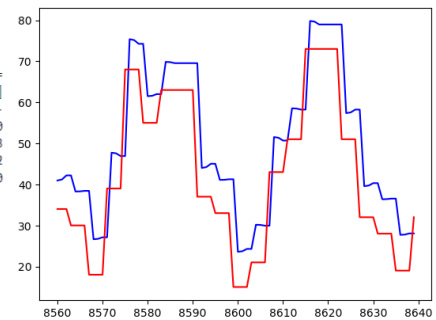
```

PM10

AutoReg Model Results									
=====									
Dep. Variable:	Singrauli, Surya Kiran Bhawan Dudhichua		PM10 (µg/m3)	No. Observations:	8640				
Model:			AutoReg(3)	Log Likelihood	-44157.239				
Method:			Conditional MLE	S.D. of innovations	40.190				
Date:			Tue, 27 Jun 2023	AIC	88324.479				
Time:			18:10:56	BIC	88359.798				
Sample:			3	HQIC	88336.522				
			8640						
=====									
			coef	std err	z	P> z	[0.025	0.975]	

const			10.1385	0.766	13.231	0.000	8.637	11.640	
Singrauli, Surya Kiran Bhawan Dudhichua	PM10 (µg/m3).L1		0.9816	0.011	91.272	0.000	0.961	1.003	
Singrauli, Surya Kiran Bhawan Dudhichua	PM10 (µg/m3).L2		-0.0075	0.015	-0.499	0.618	-0.037	0.022	
Singrauli, Surya Kiran Bhawan Dudhichua	PM10 (µg/m3).L3		-0.0312	0.011	-2.905	0.004	-0.052	-0.010	
Roots									
=====									
	Real	Imaginary	Modulus	Frequency					

AR.1	1.0660	+0.0000j	1.0660	0.0000					
AR.2	4.8645	+0.0000j	4.8645	0.0000					
AR.3	-6.1714	+0.0000j	6.1714	0.5000					



Mean : 177.463079
Root Mean Squared Error : 10.852239

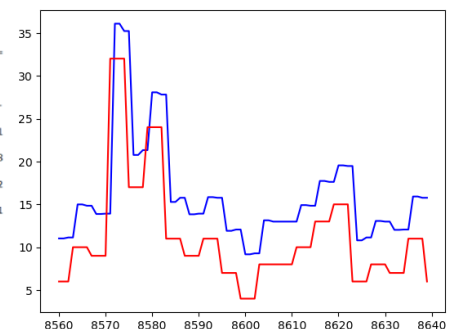
PM2.5

AutoReg Model Results							
Dep. Variable:	Singrauli, Surya Kiran Bhawan Dudhichua PM2.5 (µg/m3)	No. Observations:	8640				
Model:	AutoReg(3)	Log Likelihood	-38110.068				
Method:	Conditional MLE	S.D. of innovations	19.955				
Date:	Tue, 27 Jun 2023	AIC	76230.136				
Time:	18:10:56	BIC	76265.455				
Sample:	3	HQIC	76242.179				
	8640						
=====							
		coef	std err	z	P> z	[0.025	0.97

5)							

const		5.5796	0.374	14.901	0.000	4.846	6.31
3							
Singrauli, Surya Kiran Bhawan Dudhichua PM2.5 (µg/m3).L1		0.9635	0.011	89.609	0.000	0.942	0.98
5							
Singrauli, Surya Kiran Bhawan Dudhichua PM2.5 (µg/m3).L2	-2.203e-05	0.015	-0.001	0.999	-0.029	0.02	
9							
Singrauli, Surya Kiran Bhawan Dudhichua PM2.5 (µg/m3).L3	-0.0374	0.011	-3.477	0.001	-0.058	-0.01	
6							
=====							
Roots							
=====							
	Real	Imaginary	Modulus	Frequency			

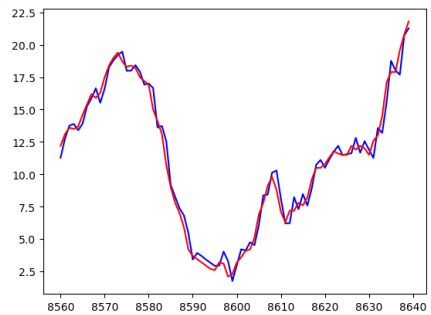
AR.1	1.0878	+0.0000j	1.0878	0.0000			
AR.2	4.4441	+0.0000j	4.4441	0.0000			
AR.3	-5.5325	+0.0000j	5.5325	0.5000			



Mean : 75.557350
Root Mean Squared Error : 6.033443

NO

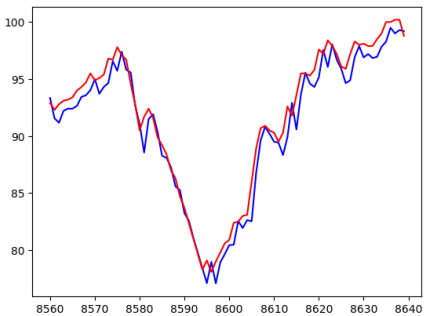
AutoReg Model Results						
Dep. Variable:	Singrauli, Surya Kiran Bhawan Dudhichua		NO ($\mu\text{g}/\text{m}^3$)	No. Observations:	8640	
Model:	AutoReg(3)			Log Likelihood	-21046.714	
Method:	Conditional MLE			S.D. of innovations	2.767	
Date:	Tue, 27 Jun 2023		AIC	42103.428		
Time:	18:10:56		BIC	42138.747		
Sample:	3		HQIC	42115.471		
	8640					
	coef	std err	z	P> z	[0.025	0.975]
const	0.4641	0.039	11.799	0.000	0.387	0.541
Singrauli, Surya Kiran Bhawan Dudhichua NO ($\mu\text{g}/\text{m}^3$).L1	1.7210	0.011	161.729	0.000	1.700	1.742
Singrauli, Surya Kiran Bhawan Dudhichua NO ($\mu\text{g}/\text{m}^3$).L2	-0.9002	0.019	-47.289	0.000	-0.937	-0.863
Singrauli, Surya Kiran Bhawan Dudhichua NO ($\mu\text{g}/\text{m}^3$).L3	0.1481	0.011	13.916	0.000	0.127	0.169
Roots						
	Real	Imaginary	Modulus	Frequency		
AR.1	1.0963	+0.0000j	1.0963	0.0000		
AR.2	2.2758	+0.0000j	2.2758	0.0000		
AR.3	2.7064	+0.0000j	2.7064	0.0000		



Mean : 14.940208
Root Mean Squared Error : 0.724277

NO2

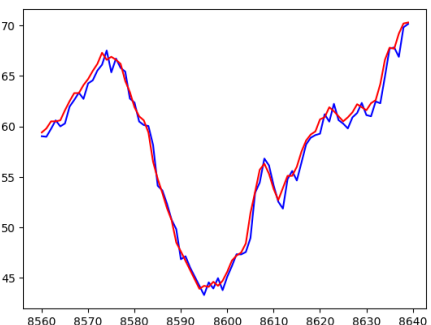
AutoReg Model Results						
Dep. Variable:	Singrauli, Surya Kiran Bhawan Dudhichua NO2 ($\mu\text{g}/\text{m}^3$)		No. Observations:	8640		
Model:	AutoReg(3)		Log Likelihood	-21774.830		
Method:	Conditional MLE		S.D. of innovations	3.011		
Date:	Tue, 27 Jun 2023		AIC	43559.661		
Time:	18:10:57		BIC	43594.980		
Sample:	3		HQIC	43571.704		
	8640					
	coef	std err	z	P> z	[0.025	0.975]
const	1.2417	0.096	12.952	0.000	1.054	1.430
Singrauli, Surya Kiran Bhawan Dudhichua NO2 ($\mu\text{g}/\text{m}^3$).L1	1.4797	0.011	137.515	0.000	1.459	1.501
Singrauli, Surya Kiran Bhawan Dudhichua NO2 ($\mu\text{g}/\text{m}^3$).L2	-0.5027	0.018	-27.264	0.000	-0.539	-0.467
Singrauli, Surya Kiran Bhawan Dudhichua NO2 ($\mu\text{g}/\text{m}^3$).L3	0.0007	0.011	0.062	0.950	-0.020	0.022
Roots						
	Real	Imaginary	Modulus	Frequency		
AR.1	1.0496	+0.0000j	1.0496	0.0000		
AR.2	1.9026	+0.0000j	1.9026	0.0000		
AR.3	746.5461	+0.0000j	746.5461	0.0000		



Mean : 55.430689
Root Mean Squared Error : 1.292297

NOX

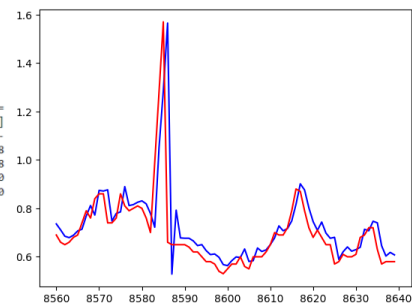
AutoReg Model Results									
Dep. Variable:	Singrauli, Surya Kiran Bhawan Dudhichua NOX (ppb)		No. Observations:		8640				
Model:	AutoReg(3)		Log Likelihood		-21068.541				
Method:	Conditional MLE		S.D. of innovations		2.774				
Date:	Tue, 27 Jun 2023		AIC		42147.081				
Time:	18:10:57		BIC		42182.400				
Sample:	3		HQIC		42159.124				
8640									
	coef	std err	z	P> z	[0.025	0.975]			
const	0.9017	0.065	13.767	0.000	0.773	1.030			
Singrauli, Surya Kiran Bhawan Dudhichua NOX (ppb).L1	1.7625	0.011	165.867	0.000	1.742	1.783			
Singrauli, Surya Kiran Bhawan Dudhichua NOX (ppb).L2	-0.9412	0.019	-48.931	0.000	-0.979	-0.904			
Singrauli, Surya Kiran Bhawan Dudhichua NOX (ppb).L3	0.1574	0.011	14.815	0.000	0.137	0.178			
Roots									
	Real	Imaginary	Modulus	Frequency					
AR.1	1.0661	+0.0000j	1.0661	0.0000					
AR.2	2.1829	+0.0000j	2.1829	0.0000					
AR.3	2.7294	+0.0000j	2.7294	0.0000					



Mean : 42.328802
Root Mean Squared Error : 0.888006

CO

AutoReg Model Results							
Dep. Variable:	Singrauli, Surya Kiran Bhawan Dudhichua		CO (mg/m3)	No. Observations:	8640		
Model:	AutoReg(3)		Log likelihood	3269.221			
Method:	Conditional MLE		S.D. of innovations	0.166			
Date:	Tue, 27 Jun 2023		AIC	-6528.441			
Time:	18:10:57		BIC	-6493.122			
Sample:	3		HQIC	-6516.398			
8640							
			coef	std err	z	P> z	[0.025 0.975]
const			0.0495	0.004	11.221	0.000	0.041 0.058
Singrauli, Surya Kiran Bhawan Dudhichua	CO	(mg/m3).L1	1.0969	0.011	102.796	0.000	1.076 1.118
Singrauli, Surya Kiran Bhawan Dudhichua	CO	(mg/m3).L2	-0.2610	0.016	-16.667	0.000	-0.292 -0.230
Singrauli, Surya Kiran Bhawan Dudhichua	CO	(mg/m3).L3	0.1289	0.011	12.080	0.000	0.108 0.150
Roots							
	Real	Imaginary	Modulus	Frequency			
AR.1	1.0365	-0.0000j	1.0365	-0.0000			
AR.2	0.4944	-2.6909j	2.7360	-0.2211			
AR.3	0.4944	+2.6909j	2.7360	0.2211			



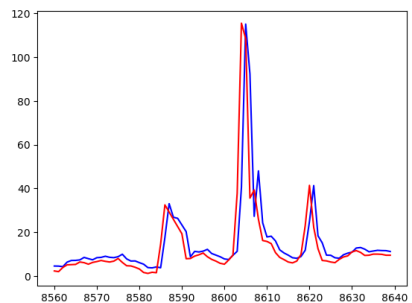
Mean : 1.401927
Root Mean Squared Error : 0.123370

SO2

AutoReg Model Results							
Dep. Variable:	Singrauli, Surya Kiran Bhawan Dudhichua		SO2 (µg/m3)	No. Observations:	8640		
Model:	AutoReg(3)		Log Likelihood	-35623.041			
Method:	Conditional MLE		S.D. of innovations	14.962			
Date:	Tue, 27 Jun 2023		AIC	71256.081			
Time:	18:10:58		BIC	71291.400			
Sample:	3		HQIC	71268.124			
8640							
			coef	std err	z	P> z	[0.025 0.975]

const			2.4705	0.212	11.661	0.000	2.055 2.886
Singrauli, Surya Kiran Bhawan Dudhichua SO2 (µg/m3).L1			1.0446	0.011	97.801	0.000	1.024 1.066
Singrauli, Surya Kiran Bhawan Dudhichua SO2 (µg/m3).L2			-0.2433	0.015	-15.920	0.000	-0.273 -0.213
Singrauli, Surya Kiran Bhawan Dudhichua SO2 (µg/m3).L3			0.1214	0.011	11.362	0.000	0.100 0.142
Roots							

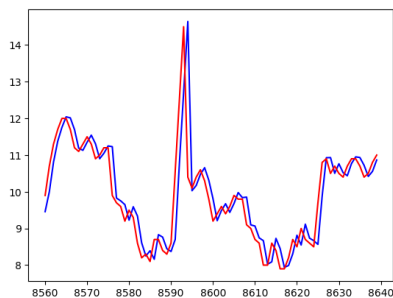
	Real	Imaginary	Modulus	Frequency			
AR.1	1.0829	-0.0000j	1.0829	-0.0000			
AR.2	0.4609	-2.7197j	2.7585	-0.2233			
AR.3	0.4609	+2.7197j	2.7585	0.2233			



Mean : 31.923270
Root Mean Squared Error : 12.248406

NH3

AutoReg Model Results						
Dep. Variable:	Singrauli, Surya Kiran Bhawan Dudhichua		NH3 (µg/m3)	No. Observations:	8640	
Model:	AutoReg(3)		Log Likelihood	-12623.571		
Method:	Conditional MLE		S.D. of innovations	1.044		
Date:	Tue, 27 Jun 2023		AIC	25257.142		
Time:	18:10:58		BIC	25292.461		
Sample:	3		HQIC	25269.185		
8640						
	coef	std err	z	P> z	[0.025	0.975]
const	0.2084	0.027	7.766	0.000	0.156	0.261
Singrauli, Surya Kiran Bhawan Dudhichua	NH3 (µg/m3).L1	1.0795	0.011	100.339	0.000	1.058 1.101
Singrauli, Surya Kiran Bhawan Dudhichua	NH3 (µg/m3).L2	-0.1078	0.016	-6.826	0.000	-0.139 -0.077
Singrauli, Surya Kiran Bhawan Dudhichua	NH3 (µg/m3).L3	0.0126	0.011	1.168	0.243	-0.009 0.034
Roots						
	Real	Imaginary	Modulus	Frequency		
AR.1	1.0175	-0.0000j	1.0175	-0.0000		
AR.2	3.7817	-7.9967j	8.8458	-0.1797		
AR.3	3.7817	+7.9967j	8.8458	0.1797		



Mean : 13.286956
Root Mean Squared Error : 0.701728

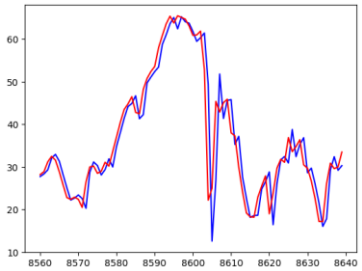
Ozone

AutoReg Model Results							
Dep. Variable:	Singrauli, Surya Kiran Bhawan Dudhichua Ozone ($\mu\text{g}/\text{m}^3$)		No. Observations:		8640		
Model:	AutoReg(3)		Log Likelihood		-26579.724		
Method:	Conditional MLE		S.D. of innovations		5.251		
Date:	Tue, 27 Jun 2023		AIC		53169.447		
Time:	18:10:58		BIC		53204.766		
Sample:	3		HQIC		53181.490		
	8640						
=====							
=							
		coef	std err	z	P> z	[0.025	0.97

5]							

const		0.9851	0.094	10.473	0.000	0.801	1.17
0							
Singrauli, Surya Kiran Bhawan Dudhichua Ozone ($\mu\text{g}/\text{m}^3$).L1		1.3038	0.011	121.196	0.000	1.283	1.32
5							
Singrauli, Surya Kiran Bhawan Dudhichua Ozone ($\mu\text{g}/\text{m}^3$).L2		-0.3546	0.017	-20.543	0.000	-0.388	-0.32
1							
Singrauli, Surya Kiran Bhawan Dudhichua Ozone ($\mu\text{g}/\text{m}^3$).L3		0.0229	0.011	2.128	0.033	0.002	0.04
4							
=====							
Roots							
=====							
	Real	Imaginary	Modulus	Frequency			

AR.1	1.0430	+0.0000j	1.0430	0.0000			
AR.2	4.0138	+0.0000j	4.0138	0.0000			
AR.3	10.4373	+0.0000j	10.4373	0.0000			



Mean : 35.193970
Root Mean Squared Error : 5.236985

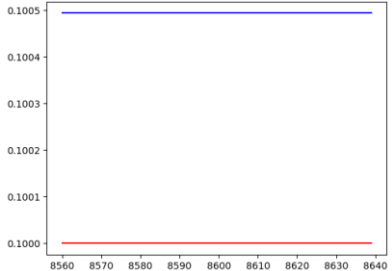
Benzene

AutoReg Model Results							
=====							
Dep. Variable:	Singrauli, Surya Kiran Bhawan Dudhichua Benzene ($\mu\text{g}/\text{m}^3$)		No. Observations:	8640			
Model:	AutoReg(3)		Log Likelihood	25044.425			
Method:	Conditional MLE		S.D. of innovations	0.013			
Date:	Tue, 27 Jun 2023		AIC	-50078.850			
Time:	18:10:58		BIC	-50043.531			
Sample:	3		HQIC	-50066.807			
	8640						
=====							
		coef	std err	z	P> z	[0.025	0.9

75]							

const		0.0029	0.000	9.209	0.000	0.002	0.
004							
Singrauli, Surya Kiran Bhawan Dudhichua Benzene ($\mu\text{g}/\text{m}^3$).L1		0.9524	0.011	88.582	0.000	0.931	0.
973							
Singrauli, Surya Kiran Bhawan Dudhichua Benzene ($\mu\text{g}/\text{m}^3$).L2		0.0625	0.015	4.210	0.000	0.033	0.
092							
Singrauli, Surya Kiran Bhawan Dudhichua Benzene ($\mu\text{g}/\text{m}^3$).L3		-0.0389	0.011	-3.625	0.000	-0.060	-0.
018							
=====							
Roots							
=====							
	Real	Imaginary	Modulus	Frequency			

AR.1	1.0251	+0.0000j	1.0251	0.0000			
AR.2	-4.7244	+0.0000j	4.7244	0.5000			
AR.3	5.3040	+0.0000j	5.3040	0.0000			



Mean : 0.122002
Root Mean Squared Error : 0.000493