TSF -PROJECT

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- Compare the performance of all the models built - Choose the best model with proper rationale - Rebuild the best model using the entire data - Make a forecast for the next 12 months

7-Actionable Insights & Recommendations

- Conclude with the key takeaways (actionable insights and recommendations) for the business

ROSE

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Problem Statement - TSF Project

Context

As an analyst at ABC Estate Wines, we are presented with historical data encompassing the sales of different types of wines throughout the 20th century. These datasets originate from the same company but represent sales figures for distinct wine varieties. Our objective is to delve into the data, analyze trends, patterns, and factors influencing wine sales over the course of the century. By leveraging data analytics and forecasting techniques, we aim to gain actionable insights that can inform strategic decision-making and optimize sales strategies for the future.

Objective

The primary objective of this project is to analyze and forecast wine sales trends for the 20th century based on historical data provided by ABC Estate Wines. We aim to equip ABC Estate Wines with the necessary insights and foresight to enhance sales performance, capitalize on emerging market opportunities, and maintain a competitive edge in the wine industry.

Sparkling wine sale

QUESTION-1

Define the problem and perform Exploratory Data Analysis

- Read the data as an appropriate time series data - Plot the data - Perform EDA - Perform Decomposition

```
#import the libaries
#read Data Set
#first 5 rows of the dataSet
```

	YearMonth	Sparkling
0	1980-01	1686

	YearMonth	Sparkling
1	1980-02	1591
2	1980-03	2304
3	1980-04	1712
4	1980-05	1471

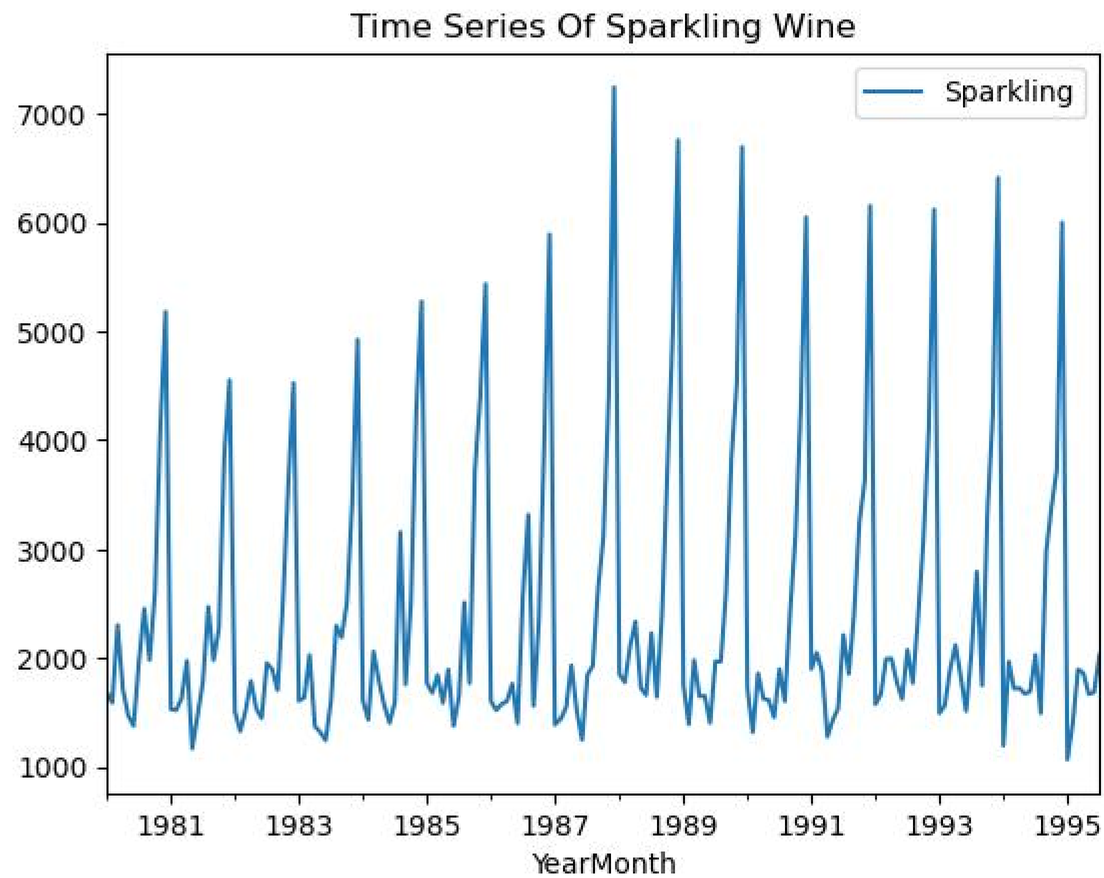
#Read the data as an appropriate time series data

#first 5 rows of the Data set

	Sparkling
YearMonth	
1980-01-01	1686
1980-02-01	1591
1980-03-01	2304
1980-04-01	1712
1980-05-01	1471

Plot the data

#Time Series Of Sparkling Wine



Time series have strong Seasonality

Perform EDA

#check information about the data set

)

<class 'pandas.core.frame.DataFrame'>

DatetimeIndex: 187 entries, 1980-01-01 to 1995-07-01

Data columns (total 1 columns):

```
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Sparkling  187 non-null    int64
```

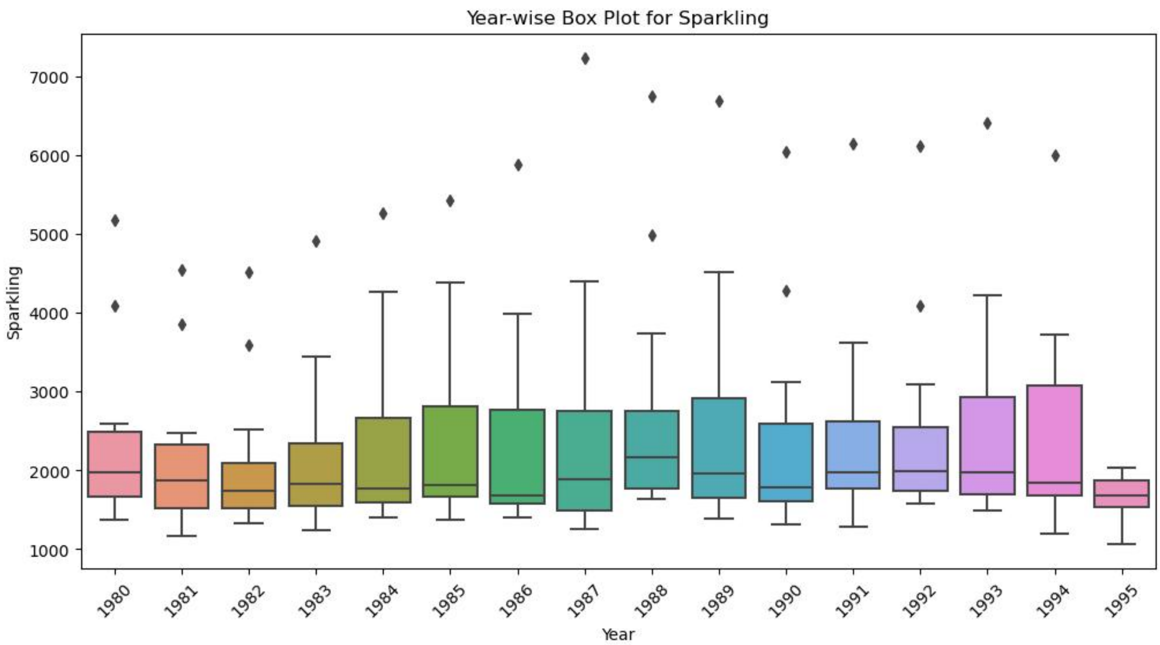
dtypes: int64(1)

memory usage: 2.9 KB

No missing value in tis Data Set

#statical summary of the data set

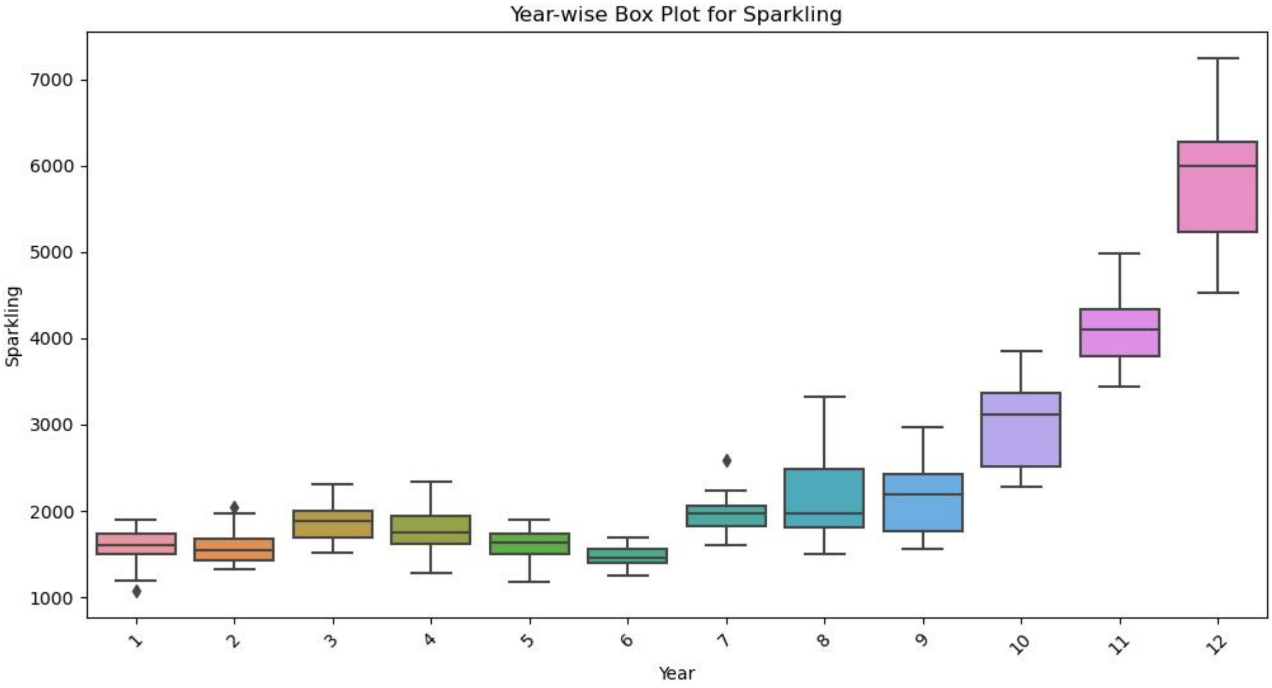
	Sparkling
count	187.000000
mean	2402.417112
std	1295.111540
min	1070.000000
25%	1605.000000
50%	1874.000000
75%	2549.000000
max	7242.000000



#Year-wise Box Plot for Sparkling wine sale

- From the above year wise box plot it is clearly visile all the year have outliers

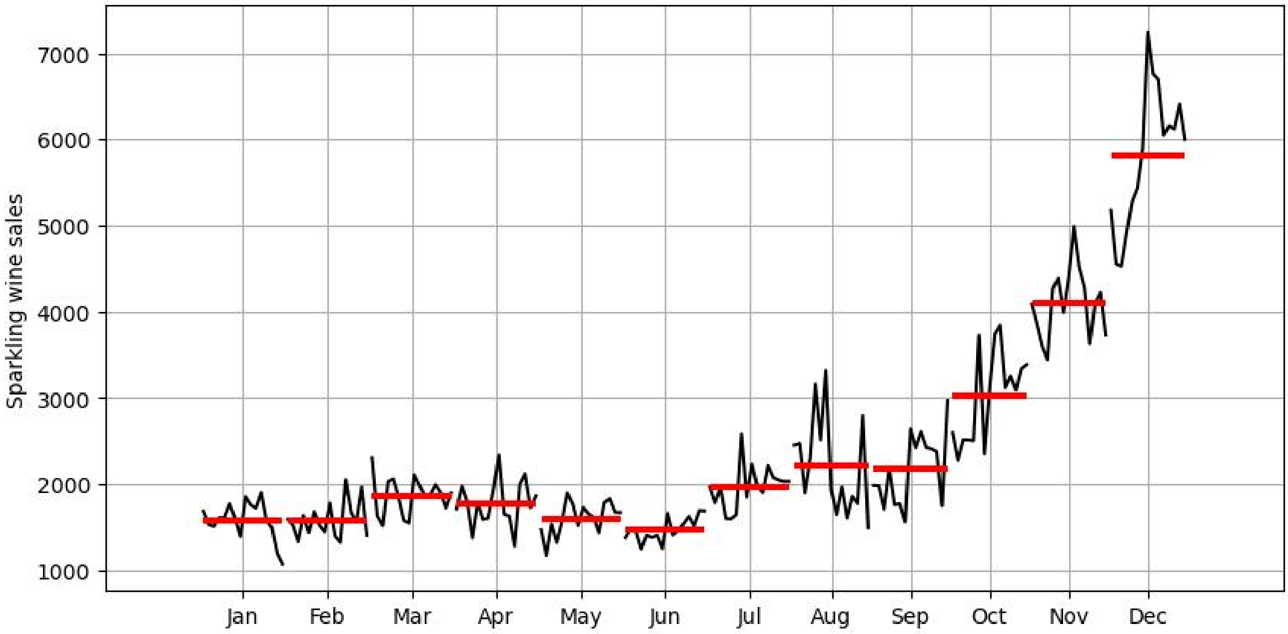
- year 1995 alone doesn't have outliers



- from the above Month wise box plot across the year it is clearly visible January ,February & july month has outliers
- Across the year December month shows highest sale
- june month shows the lowest sale across the year

Throug this boxplot we could understand seasonality present in the sparkling dataset

#monthly plot of Sparkling wine sales



- This plot shows the behavior of the Time series ("Sparkling wine sales") across various month.The red line is the median value.
- As already seen Decemer month has highest sale.

Pivot Table

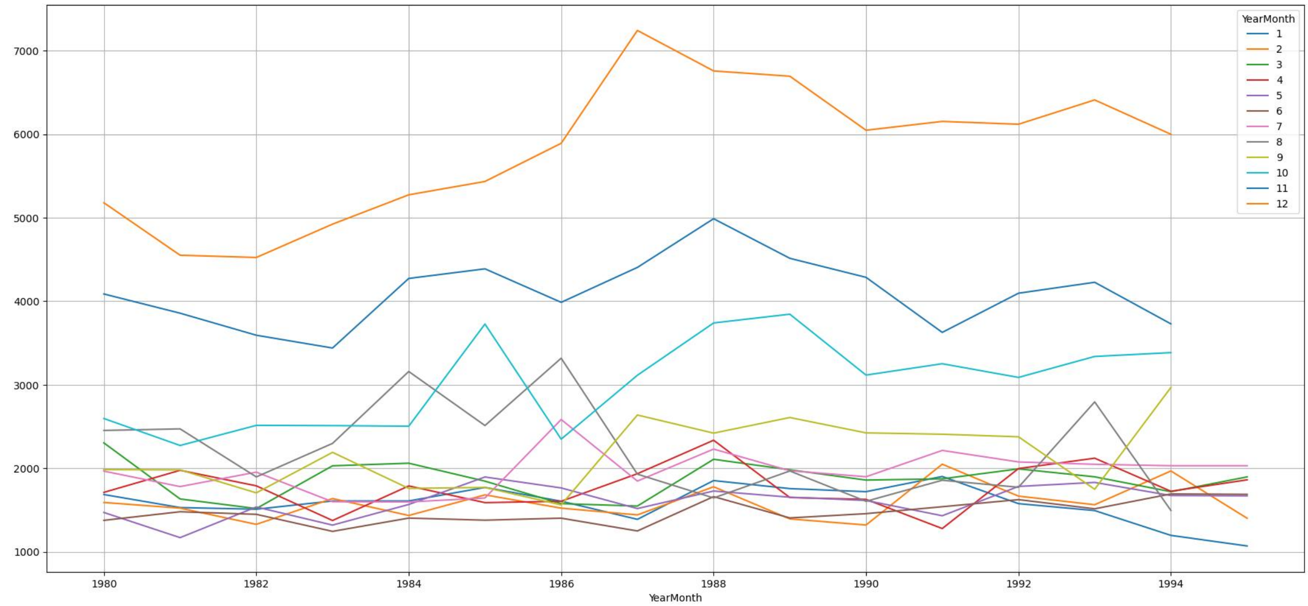
#pivot table

YearMonth	1	2	3	4	5	6	7	8	9	10	11	12
YearMonth												
1980	1686.0	1591.0	2304.0	1712.0	1471.0	1377.0	1966.0	2453.0	1984.0	2596.0	4087.0	5179.0
1981	1530.0	1523.0	1633.0	1976.0	1170.0	1480.0	1781.0	2472.0	1981.0	2273.0	3857.0	4551.0
1982	1510.0	1329.0	1518.0	1790.0	1537.0	1449.0	1954.0	1897.0	1706.0	2514.0	3593.0	4524.0
1983	1609.0	1638.0	2030.0	1375.0	1320.0	1245.0	1600.0	2298.0	2191.0	2511.0	3440.0	4923.0
1984	1609.0	1435.0	2061.0	1789.0	1567.0	1404.0	1597.0	3159.0	1759.0	2504.0	4273.0	5274.0
1985	1771.0	1682.0	1846.0	1589.0	1896.0	1379.0	1645.0	2512.0	1771.0	3727.0	4388.0	5434.0
1986	1606.0	1523.0	1577.0	1605.0	1765.0	1403.0	2584.0	3318.0	1562.0	2349.0	3987.0	5891.0
1987	1389.0	1442.0	1548.0	1935.0	1518.0	1250.0	1847.0	1930.0	2638.0	3114.0	4405.0	7242.0
1988	1853.0	1779.0	2108.0	2336.0	1728.0	1661.0	2230.0	1645.0	2421.0	3740.0	4988.0	6757.0
1989	1757.0	1394.0	1982.0	1650.0	1654.0	1406.0	1971.0	1968.0	2608.0	3845.0	4514.0	6694.0
1990	1720.0	1321.0	1859.0	1628.0	1615.0	1457.0	1899.0	1605.0	2424.0	3116.0	4286.0	6047.0
1991	1902.0	2049.0	1874.0	1279.0	1432.0	1540.0	2214.0	1857.0	2408.0	3252.0	3627.0	6153.0
1992	1577.0	1667.0	1993.0	1997.0	1783.0	1625.0	2076.0	1773.0	2377.0	3088.0	4096.0	6119.0
1993	1494.0	1564.0	1898.0	2121.0	1831.0	1515.0	2048.0	2795.0	1749.0	3339.0	4227.0	6410.0
1994	1197.0	1968.0	1720.0	1725.0	1674.0	1693.0	2031.0	1495.0	2968.0	3385.0	3729.0	5999.0
1995	1070.0	1402.0	1897.0	1862.0	1670.0	1688.0	2031.0	NaN	NaN	NaN	NaN	NaN

- Sparkling data are grouped in month wise.

- Month are represented in numbers 1 to 12
- The largest sales of the year occur in December.
- The best sales month was December in 1987with 7242 units of sparkling wine

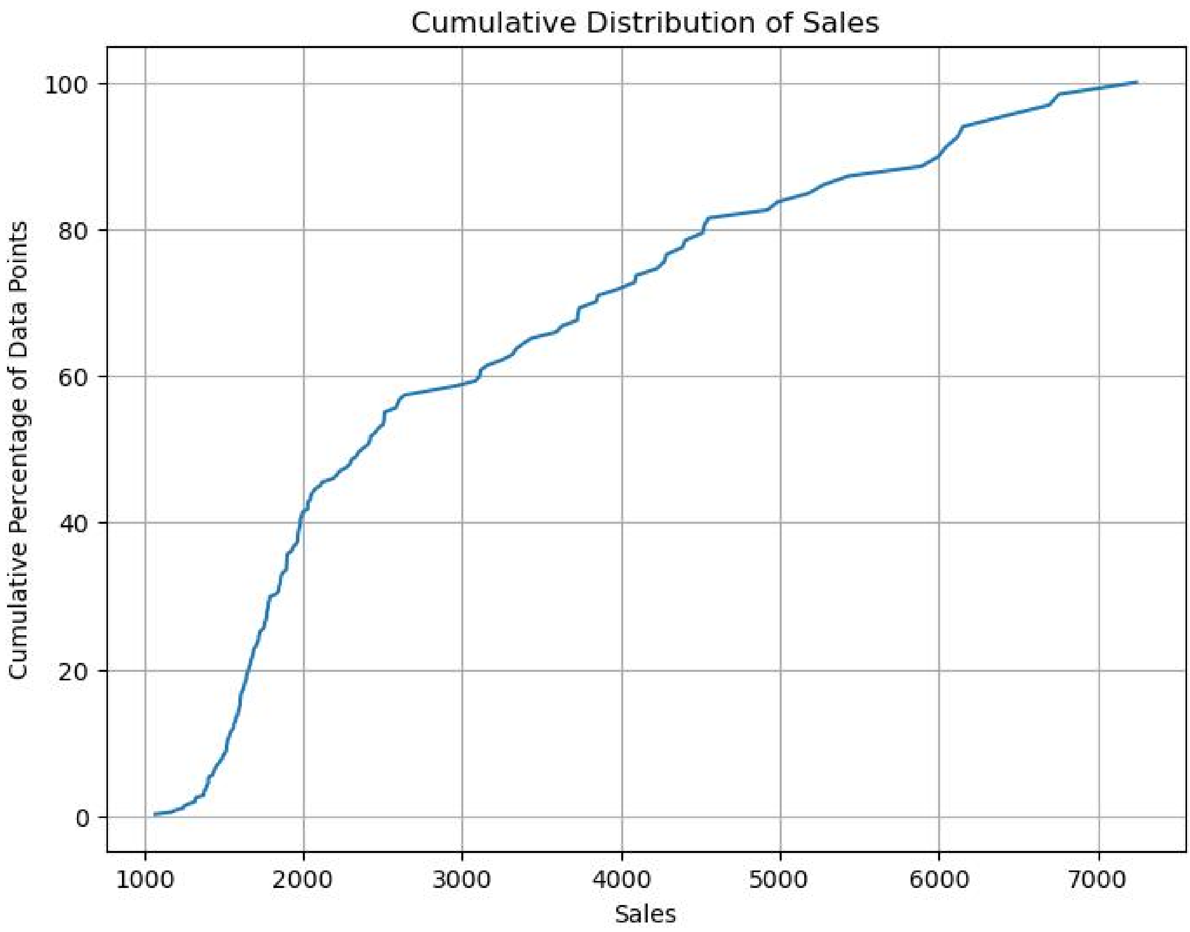
#plot of yearly_sales_across_months



sale in december is highest the the rest of the year

 # Calculate cumulative distribution

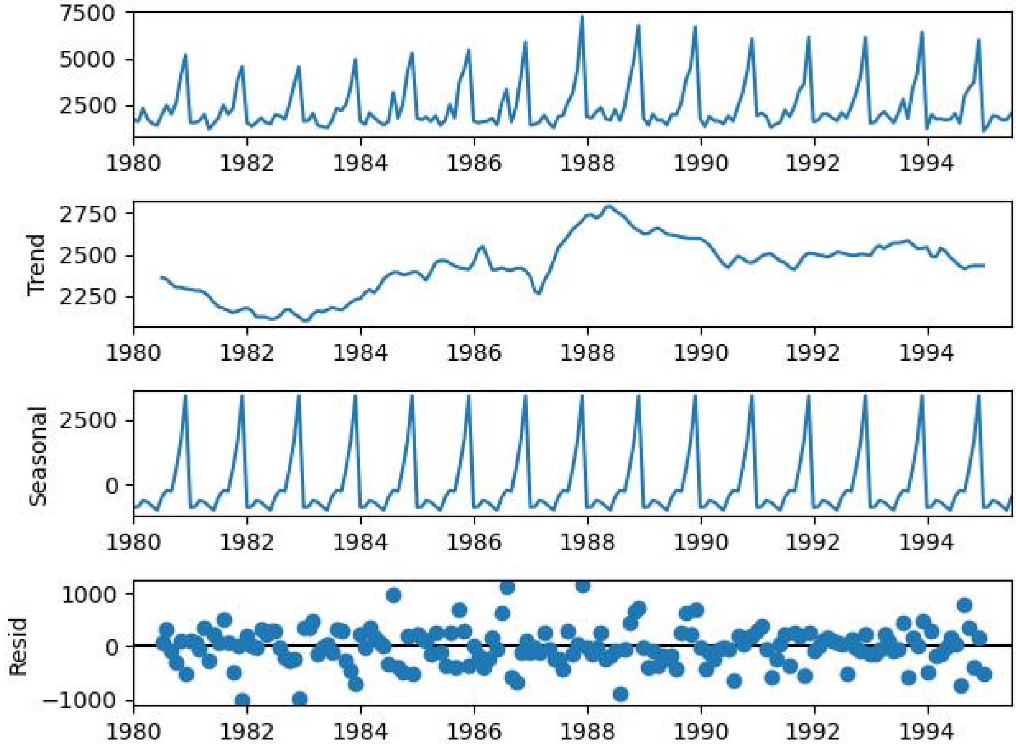
 # Plot the cumulative distribution



cumulative graph tells us what percentage of data points refer to what number of sales

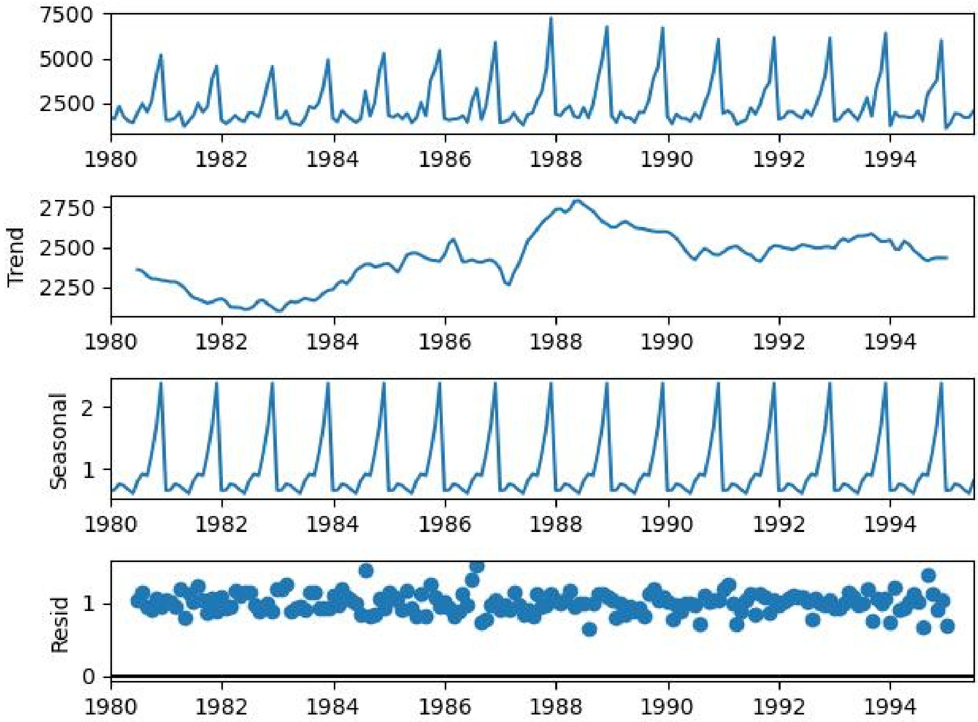
Perform Decomposition

#additive decomposition



Strong Seasonality is present
Trend is fluctuating
trend--------------------------------
YearMonth
1980-01-01   NaN
1980-02-01   NaN
1980-03-01   NaN
1980-04-01   NaN
1980-05-01   NaN
Name: trend, dtype: float64
seasonality---------------------------------
YearMonth
1980-01-01   -854.260599
1980-02-01   -830.350678
1980-03-01   -592.356630
1980-04-01   -658.490559
1980-05-01   -824.416154
Name: seasonal, dtype: float64
residual------------------------------------
YearMonth
1980-01-01   NaN
1980-02-01   NaN
1980-03-01   NaN
1980-04-01   NaN
1980-05-01   NaN
Name: resid, dtype: float64

#multiplicative decomposition



for all residuals are locate around 1
trend--------------------------
YearMonth
1980-01-01 NaN
1980-02-01 NaN
1980-03-01 NaN
1980-04-01 NaN
1980-05-01 NaN
Name: trend, dtype: float64
seasonality------------------------
YearMonth
1980-01-01 0.649843
1980-02-01 0.659214
1980-03-01 0.757440
1980-04-01 0.730351
1980-05-01 0.660609
Name: seasonal, dtype: float64
residual------------------------------
YearMonth
1980-01-01 NaN
1980-02-01 NaN
1980-03-01 NaN
1980-04-01 NaN
1980-05-01 NaN
Name: resid, dtype: float64

QUESTION-2

Data Pre-processing

- Missing value treatment - Visualize the processed data - Train-test split

#Missing value treatment

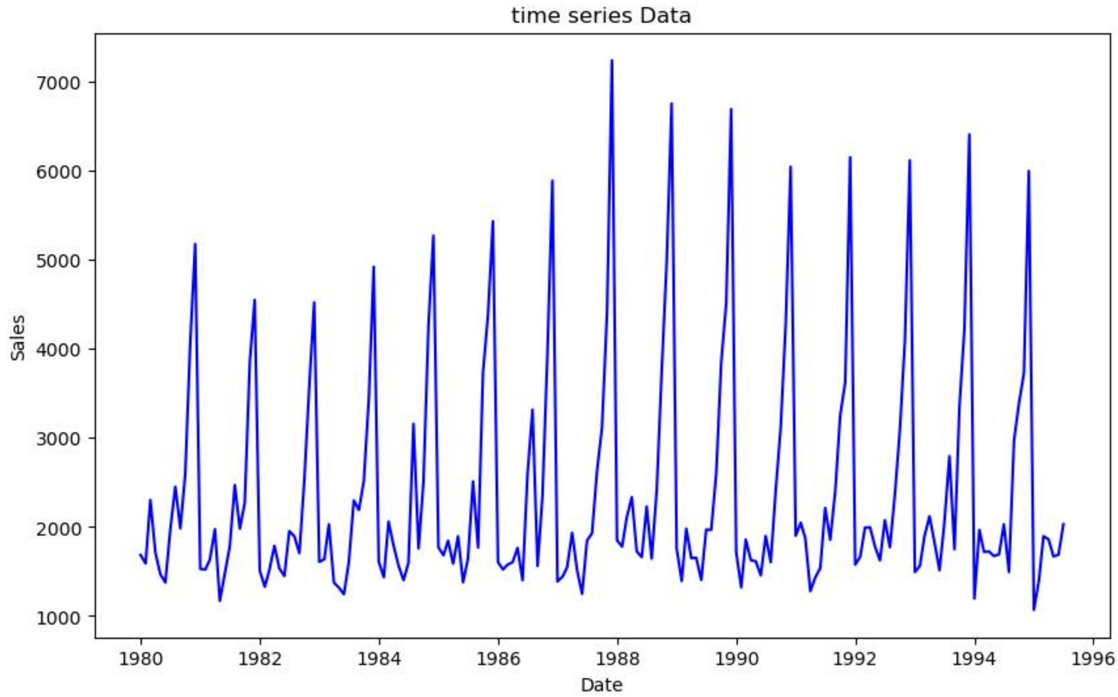
#checking missing value

Sparkling   0

dtype: int64

- no missing value

 # Visualize the Processed Data



#Train-test split

First few rows of Training Data

	Sparkling
YearMonth	
1980-01-01	1686
1980-02-01	1591
1980-03-01	2304
1980-04-01	1712
1980-05-01	1471

Last few rows of Training Data

	Sparkling
YearMonth	
1990-06-01	1457
1990-07-01	1899

	Sparkling
YearMonth	
1990-08-01	1605
1990-09-01	2424
1990-10-01	3116

First few rows of Test Data

	Sparkling
YearMonth	
1990-11-01	4286
1990-12-01	6047
1991-01-01	1902
1991-02-01	2049
1991-03-01	1874

Last few rows of Test Data

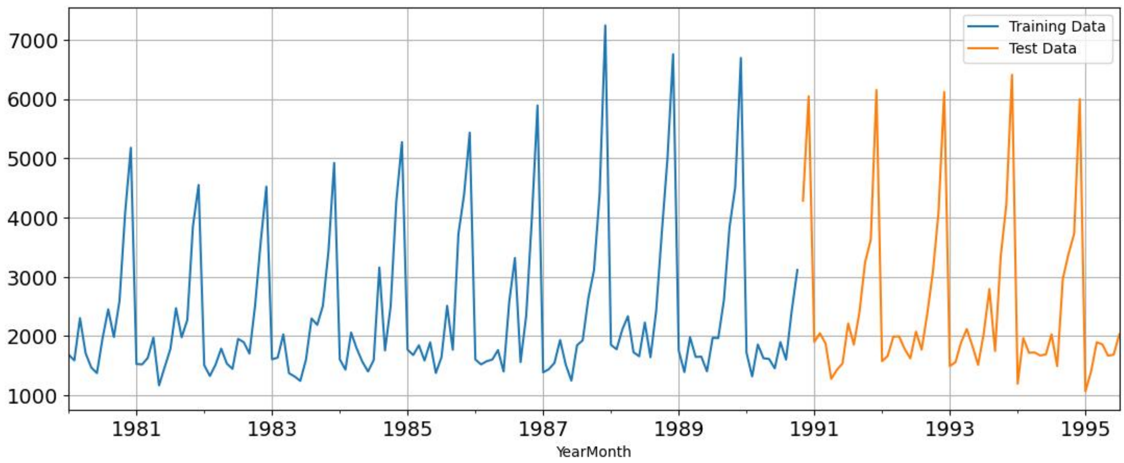
	Sparkling
YearMonth	
1995-03-01	1897
1995-04-01	1862
1995-05-01	1670
1995-06-01	1688
1995-07-01	2031

```
#shape of Train,Test
```

(130, 1)
(57, 1)

In [30]:

```
#plot train,test data
```



QUESTION- 3

Model Building - Original Data

- Build forecasting models - Linear regression - Simple Average - Moving Average - Exponential Models (Single, Double, Triple) - Check the performance of the models built

ANSWER

#Build forecasting models

Linear regression model

For this particular linear regression, we are going to regress the 'Sparkling ' variable against the order of the occurrence. For this we need to modify our training data before fitting it into a linear regression.¶

We see that we have successfully the generated the numerical time instance order for both the training and test set. Now we will add these values in the training and test set.

First few rows of Training Data

YearMonth	Sparkling	time
1980-01-01	1686	1
1980-02-01	1591	2
1980-03-01	2304	3
1980-04-01	1712	4
1980-05-01	1471	5

Last few rows of Training Data

YearMonth	Sparkling	time
1990-06-01	1457	126
1990-07-01	1899	127
1990-08-01	1605	128
1990-09-01	2424	129
1990-10-01	3116	130

First few rows of Test Data

YearMonth	Sparkling	time
1990-11-01	4286	131

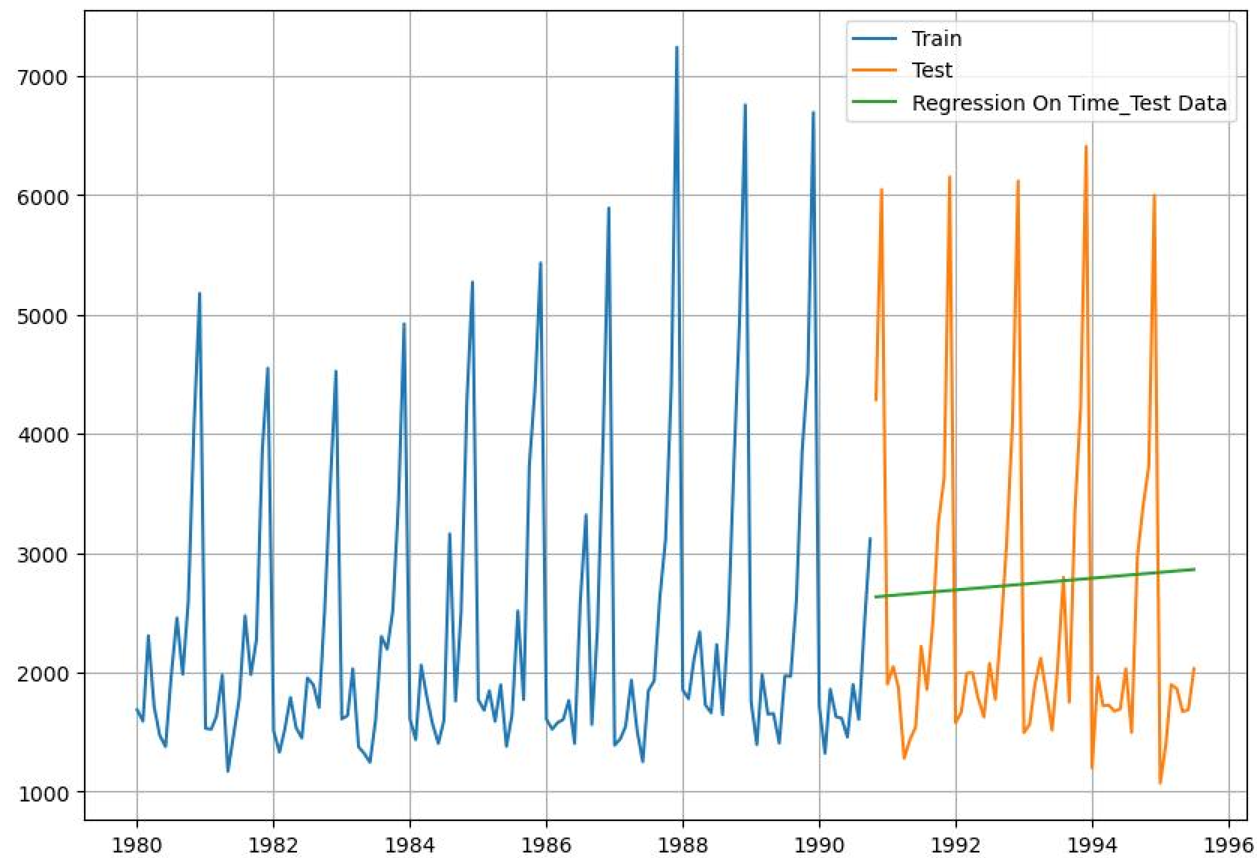
1990-12-01	6047	132
1991-01-01	1902	133
1991-02-01	2049	134
1991-03-01	1874	135

Last few rows of Test Data

	Sparkling	time
YearMonth		
1995-03-01	1897	183
1995-04-01	1862	184
1995-05-01	1670	185
1995-06-01	1688	186
1995-07-01	2031	187

Now that our training and test data has been modified, let us go ahead use
_ _
to build the model on the training data and test the model on the test data.

#plot linear Regression On Time_Test Data



#Defining the accuracy metrics.
Test Data - RMSE
For RegressionOnTime forecast on the Test Data, RMSE is 1392.44
#Test_RMSE table

Test_RMSE

	Test_RMSE
Linear_Regression	1392.438305

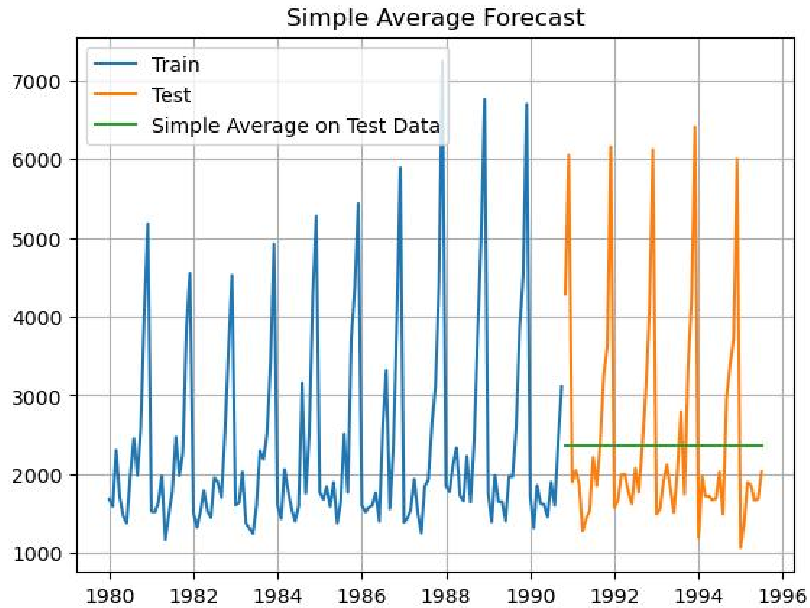
Simple Average

For this particular simple average method, we will forecast by using the average of the training values.

SIMPLE AVG TABLE

	Sparkling	mean_forecast
YearMonth		
1990-11-01	4286	2361.276923
1990-12-01	6047	2361.276923
1991-01-01	1902	2361.276923
1991-02-01	2049	2361.276923
1991-03-01	1874	2361.276923

 # Simple Average on Test Data



For Simple Average forecast on the Test Data, RMSE is 1368.747

#Test_RMSE table

	Test_RMSE
Linear_Regression	1392.438305
SimpleAverageModel	1368.746717

Method 3: Moving Average(MA)

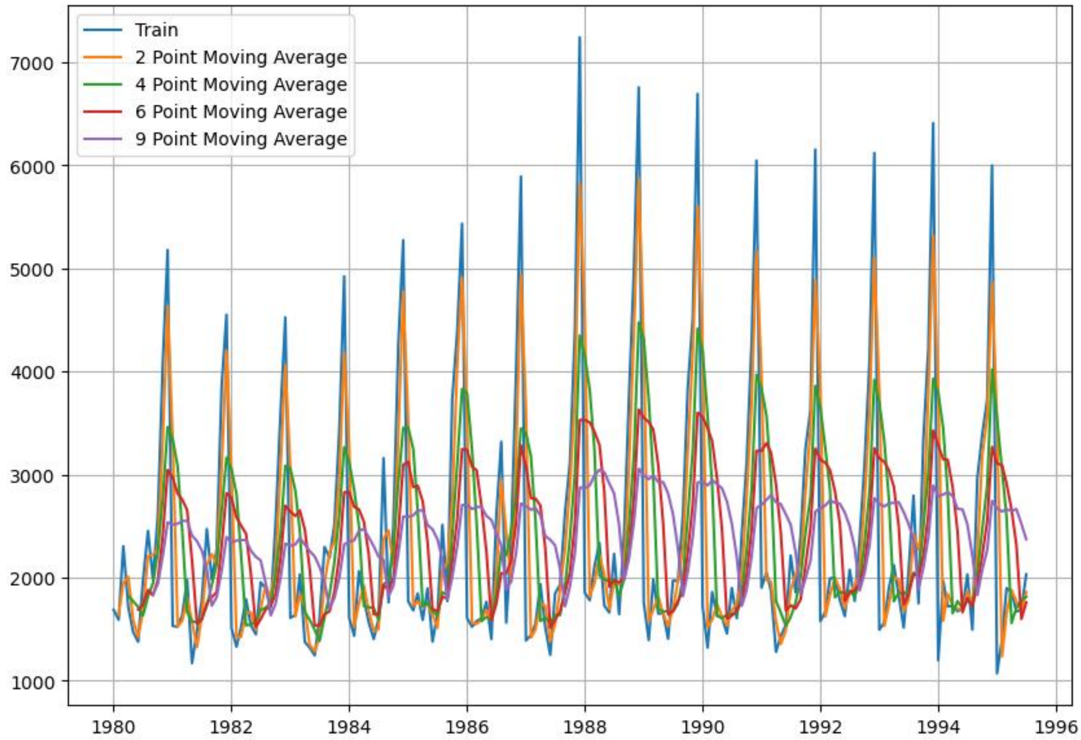
For the moving average model, we are going to calculate rolling means (or moving averages) for different intervals. The best interval can be determined by the maximum accuracy (or the minimum error) over here. For Moving Average, we are going to average over the entire data.

	Sparkling
YearMonth	
1980-01-01	1686
1980-02-01	1591
1980-03-01	2304
1980-04-01	1712
1980-05-01	1471

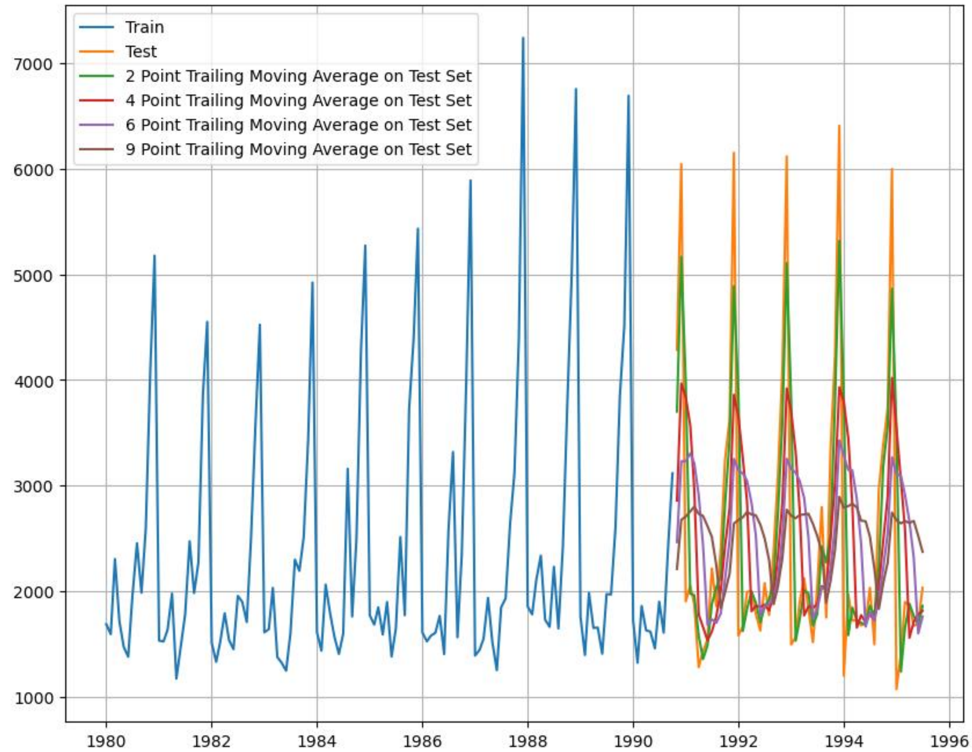
Moving_avg.head

	Sparkling	Trailing_2	Trailing_4	Trailing_6	Trailing_9
YearMonth					
1980-01-01	1686	NaN	NaN	NaN	NaN
1980-02-01	1591	1638.5	NaN	NaN	NaN
1980-03-01	2304	1947.5	NaN	NaN	NaN
1980-04-01	1712	2008.0	1823.25	NaN	NaN
1980-05-01	1471	1591.5	1769.50	NaN	NaN

Plotting on the whole data



#Creating train and test set
Plotting on both the Training and Test data



Model Evaluation

Done only on the test data.
Test Data - RMSE --> 2 point Trailing MA
Test Data - RMSE --> 4 point Trailing MA
Test Data - RMSE --> 6 point Trailing MA

Test Data - RMSE --> 9 point Trailing MA
For 2 point Moving Average Model forecast on the Training Data, RMSE is 811.179
For 4 point Moving Average Model forecast on the Training Data, RMSE is 1184.213
For 6 point Moving Average Model forecast on the Training Data, RMSE is 1337.201
For 9 point Moving Average Model forecast on the Training Data, RMSE is 1422.653
#Test_RMSE table

	Test_RMSE
Linear_Regression	1392.438305
SimpleAverageModel	1368.746717
2pointTrailingMovingAverage	811.178937
4pointTrailingMovingAverage	1184.213295
6pointTrailingMovingAverage	1337.200524
9pointTrailingMovingAverage	1422.653281

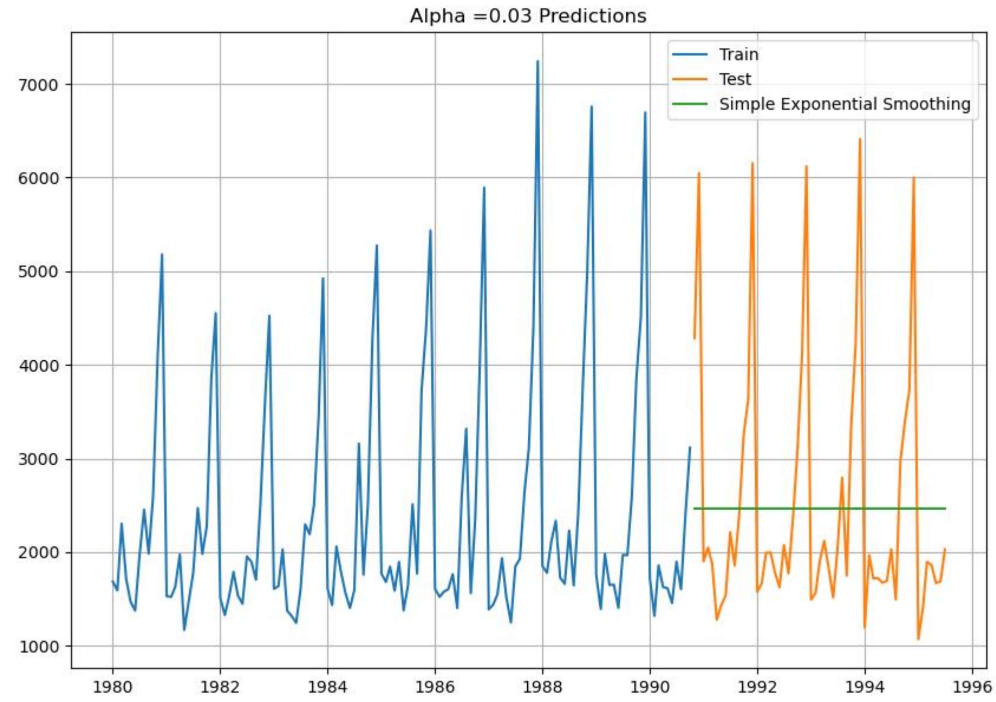
Exponential Models (Single, Double, Triple)

Single Exponential Smoothing Model

#build SimpleExpSmoothing model
#summary of SimpleExpSmoothing model
#forcast model

	Sparkling	predict
YearMonth		
1990-11-01	4286	2468.649492
1990-12-01	6047	2468.649492
1991-01-01	1902	2468.649492
1991-02-01	2049	2468.649492
1991-03-01	1874	2468.649492

#Simple Exponential Smoothing plot



For Alpha =0.03 Simple Exponential Smoothing Model forecast on the Test Data, RMSE is 136 2.356

#Test_RMSE table

Out[64]:

	Test_RMSE
Linear_Regression	1392.438305
SimpleAverageModel	1368.746717
2pointTrailingMovingAverage	811.178937

	Test_RMSE
4pointTrailingMovingAverage	1184.213295
6pointTrailingMovingAverage	1337.200524
9pointTrailingMovingAverage	1422.653281
Alpha=0.03,SimpleExponentialSmoothing	1362.355524

Setting different alpha values. Remember, the higher the alpha value more weightage is given to the more recent observation. That means, what happened recently will happen again. We will run a loop with different alpha values to understand which particular value works best for alpha on the test set.¶

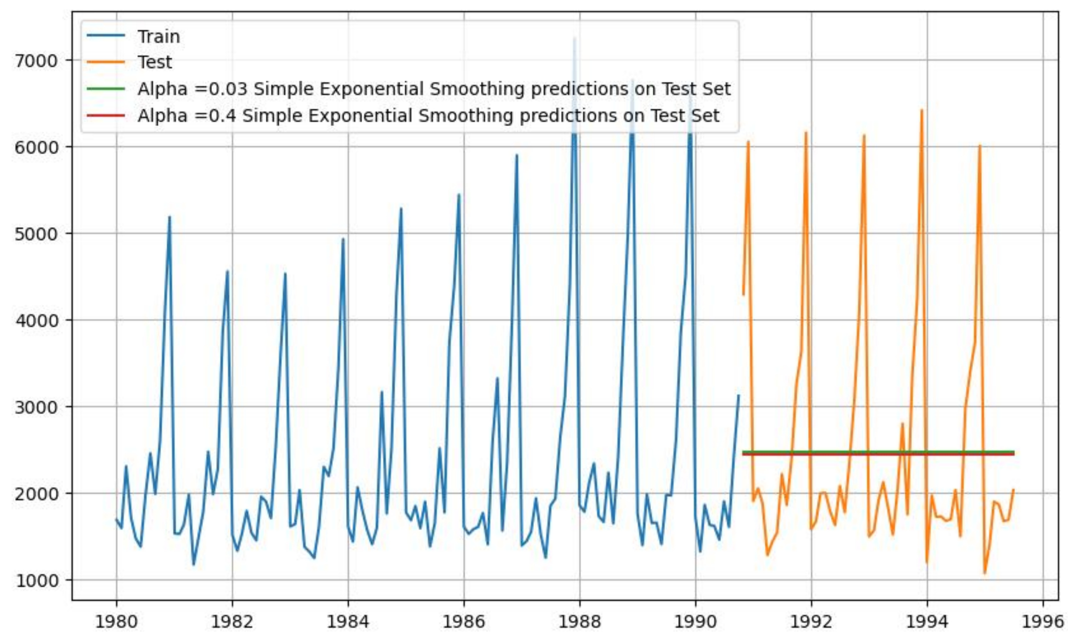
Alpha Values	Train RMSE	Test RMSE

#sort by Test rmse value

	Alpha Values	Train RMSE	Test RMSE
1	0.4	1329.814823	1363.037803
2	0.5	1326.403864	1364.863549
0	0.3	1331.102204	1372.323705
3	0.6	1325.588422	1379.988733
4	0.7	1329.257530	1404.659104
5	0.8	1337.879425	1434.578214
6	0.9	1351.645478	1466.179706

Alpha=0.4 have less Test RMSE

Plotting Simple Exponential Smoothing model



#Test_RMSE table

	Test_RMSE
Linear_Regression	1392.438305
SimpleAverageModel	1368.746717
2pointTrailingMovingAverage	811.178937
4pointTrailingMovingAverage	1184.213295
6pointTrailingMovingAverage	1337.200524
9pointTrailingMovingAverage	1422.653281
Alpha=0.03,SimpleExponentialSmoothing	1362.355524
Alpha=0.4,SimpleExponentialSmoothing	1363.037803

Double Exponential Smoothing (Holt's Model)

Two parameters and are estimated in this model. Level and Trend are accounted for in this model

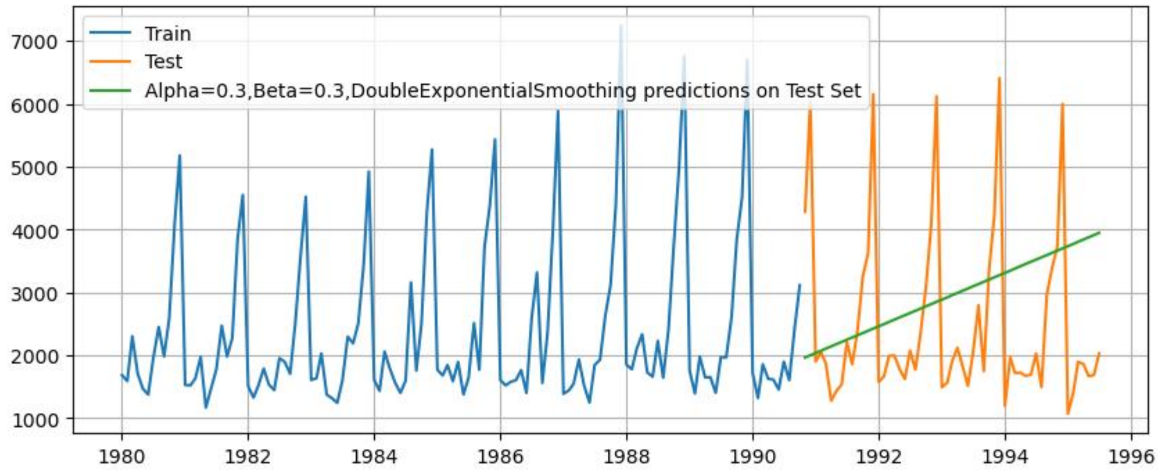
#build model
First we will define an empty dataframe to store our values from the loop

Alpha Values	Beta Values	Train RMSE	Test RMSE

#sort values by test_rmse

	Alpha Values	Beta Values	Train RMSE	Test RMSE
0	0.3	0.3	1567.524066	1597.853999
1	0.3	0.4	1662.549225	4023.672164
8	0.4	0.3	1556.795694	5049.478887
16	0.5	0.3	1525.615506	7817.569799
2	0.3	0.5	1758.543876	8879.172380
...	...	...	...	...
39	0.7	1.0	1829.175506	26841.074837
47	0.8	1.0	1885.669827	27176.057077
5	0.3	0.8	1925.999079	29603.277989
7	0.3	1.0	1883.511575	33015.522624
6	0.3	0.9	1915.332971	33043.719889

64 rows × 4 columns
Alpha=0.3,beta=0.3 have low test RMSE
##DoubleExponentialSmoothing



In [77]:

```
#Test_RMSE table
resultsDf_7_1 = pd.DataFrame({'Test_RMSE': [resultsDf_7.sort_values(by=['Test RMSE']).values[0][3]]}
                            ,index=['Alpha=0.3,Beta=0.3,DoubleExponentialSmoothing'])

resultsDf = pd.concat([resultsDf, resultsDf_7_1])
resultsDf
```

Out[77]:

	Test_RMSE
Linear_Regression	1392.438305
SimpleAverageModel	1368.746717
2pointTrailingMovingAverage	811.178937
4pointTrailingMovingAverage	1184.213295
6pointTrailingMovingAverage	1337.200524
9pointTrailingMovingAverage	1422.653281
Alpha=0.03,SimpleExponentialSmoothing	1362.355524
Alpha=0.4,SimpleExponentialSmoothing	1363.037803
Alpha=0.3,Beta=0.3,DoubleExponentialSmoothing	1597.853999

Triple Exponential Smoothing (Holt - Winter's Model)

Three parameters , and are estimated in this model. Level, Trend and Seasonality are accounted for in this model.¶

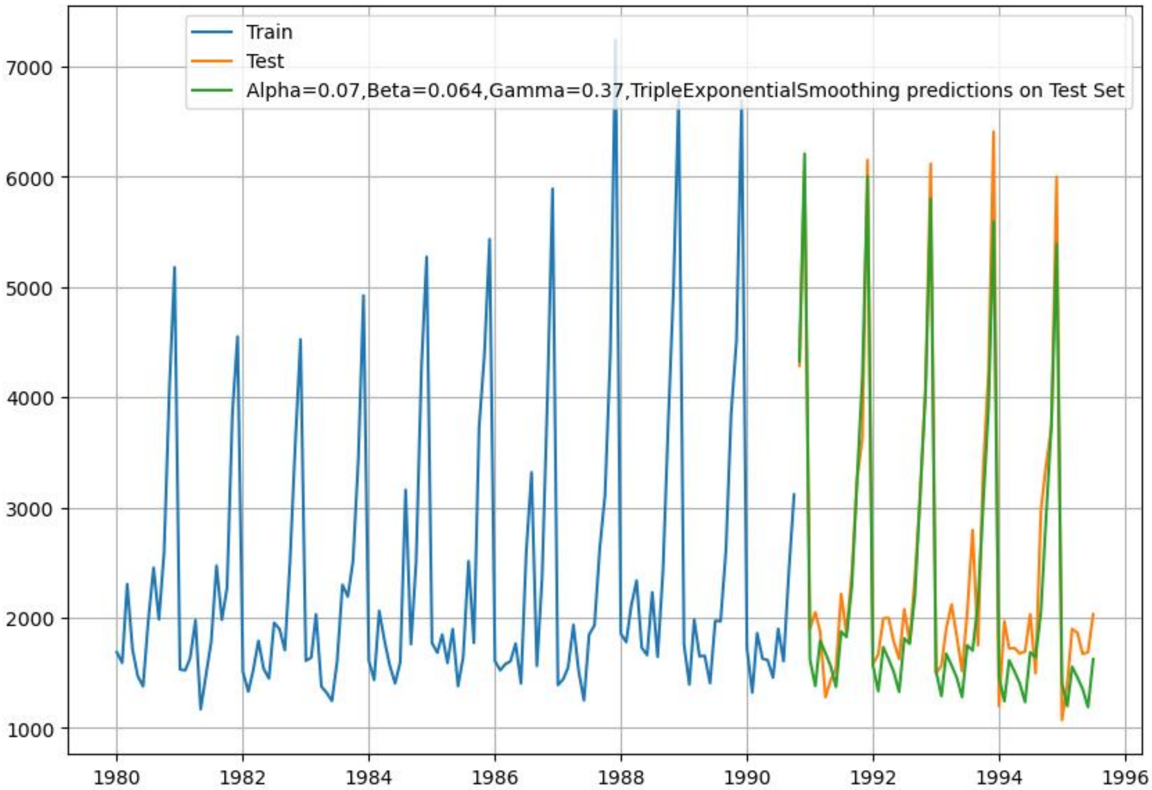
```
## Prediction on the test data
```

	Sparkling	auto_predict
YearMonth		
1990-11-01	4286	4327.606504
1990-12-01	6047	6208.854292
1991-01-01	1902	1621.602282
1991-02-01	2049	1379.868255
1991-03-01	1874	1791.914776

#summary of TES

```
{'smoothing_level': 0.07571432471504627,
 'smoothing_trend': 0.06489794789923221,
 'smoothing_seasonal': 0.3765611795178487,
 'damping_trend': nan,
 'initial_level': 2356.5416847960546,
 'initial_trend': -9.182360270735833,
 'initial_seasons': array([0.71216394, 0.67829895, 0.89649052, 0.79723125, 0.64100433,
        0.63985644, 0.86674058, 1.1133546 , 0.89819179, 1.18511974,
        1.83459596, 2.32779881]),
 'use_boxcox': False,
 'lamda': None,
 'remove_bias': False}
```

#TripleExponentialSmoothing model



For Alpha=0.07,Beta=0.064,Gamma=0.37, Triple Exponential Smoothing Model forecast on the Test Data, RMSE is 381.655

#rmse Table

Out[85]:

	Test_RMSE
Linear_Regression	1392.438305
SimpleAverageModel	1368.746717
2pointTrailingMovingAverage	811.178937
4pointTrailingMovingAverage	1184.213295
6pointTrailingMovingAverage	1337.200524
9pointTrailingMovingAverage	1422.653281
Alpha=0.03,SimpleExponentialSmoothing	1362.355524
Alpha=0.4,SimpleExponentialSmoothing	1363.037803
Alpha=0.3,Beta=0.3,DoubleExponentialSmoothing	1597.853999
Alpha=0.07,Beta=0.064,Gamma=0.37,TripleExponentialSmoothing	381.655272

#setting diferent Alpa,beta,gamma values

Out[86]:

Alpha Values	Beta Values	Gamma Values	Train RMSE	Test RMSE

```
  resultsDf_8_1 = resultsDf_8_1.append({'Alpha Values':i,'Beta Values':j,'Gamma Values':k,
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\868923985.py:5: PerformanceWarning: DataFrame is highly fragmented.  This is usually the result of calling `frame.insert` many times, which has poor performance.  Consider joining all columns at once using pd.concat(axis=1) instead. To get a de-fragmented frame, use `newframe = frame.copy()`
  TES_train['predict',i,j,k] = model_TES_alpha_i_j_k.fittedvalues
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\868923985.py:6: PerformanceWarning: DataFrame is highly fragmented.  This is usually the result of calling `frame.insert` many times, which has poor performance.  Consider joining all columns at once using pd.concat(axis=1) instead. To get a de-fragmented frame, use `newframe = frame.copy()`
  TES_test['predict',i,j,k] = model_TES_alpha_i_j_k.forecast(steps=57)
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\868923985.py:12: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  resultsDf_8_1 = resultsDf_8_1.append({'Alpha Values':i,'Beta Values':j,'Gamma Values':k,
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\868923985.py:5: PerformanceWarning: DataFrame is highly fragmented.  This is usually the result of calling `frame.insert` many times, which has poor performance.  Consider joining all columns at once using pd.concat(axis=1) instead. To get a de-fragmented frame, use `newframe = frame.copy()`
  TES_train['predict',i,j,k] = model_TES_alpha_i_j_k.fittedvalues
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\868923985.py:6: PerformanceWarning: DataFrame is highly fragmented.  This is usually the result of calling `frame.insert` many times, which has poor performance.  Consider joining all columns at once using pd.concat(axis=1) instead. To get a de-fragmented frame, use `newframe = frame.copy()`
```

```
#sort values by test_rmse
resultsDf_8_1.sort_values(by=['Test RMSE']).head()
```

Out[88]:

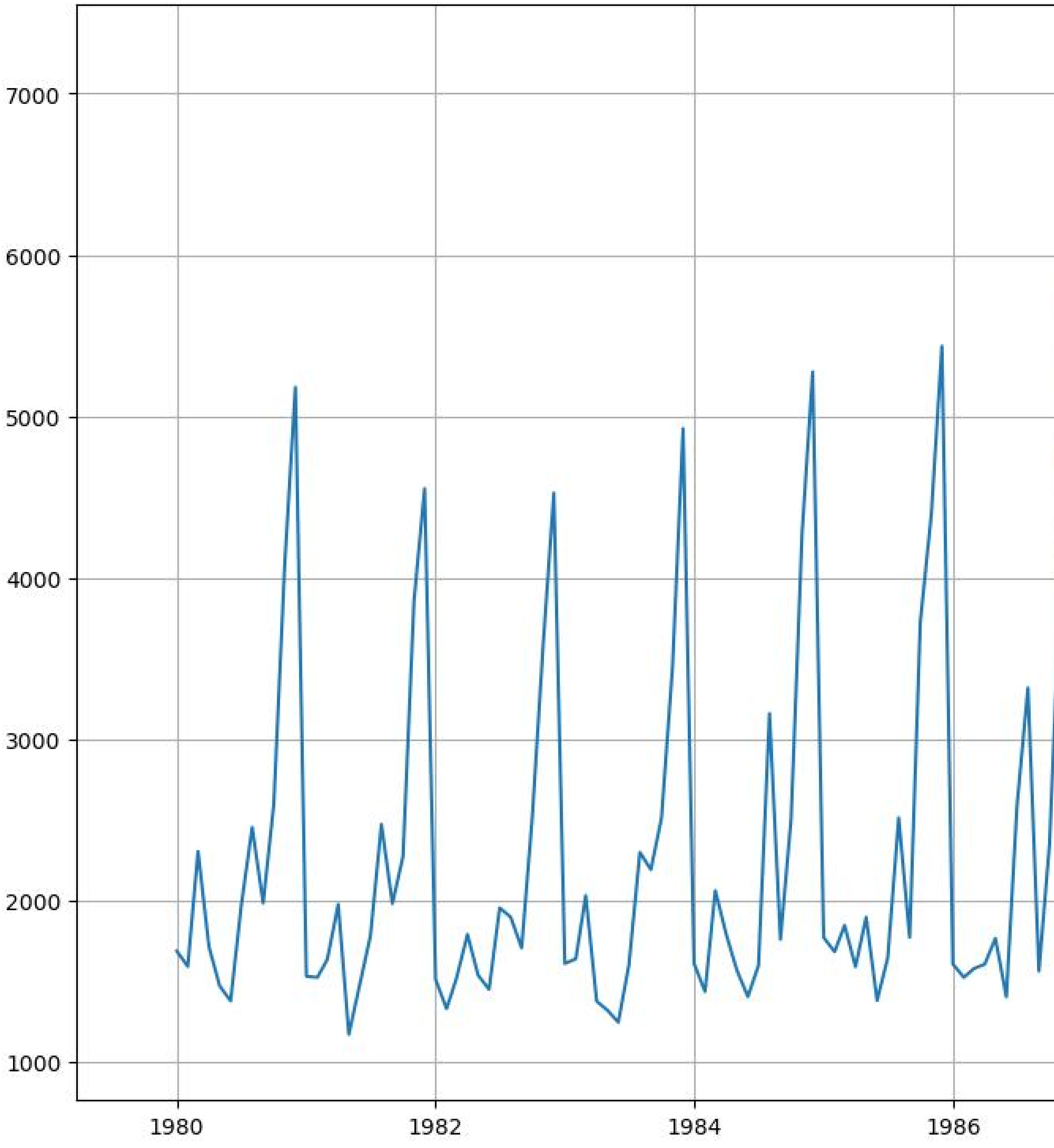
	Alpha Values	Beta Values	Gamma Values	Train RMSE	Test RMSE
264	0.7	0.4	0.3	512.023844	422.908833
144	0.5	0.5	0.3	472.088500	451.601686
169	0.5	0.8	0.4	625.557444	481.151676
200	0.6	0.4	0.3	479.344459	498.796626
328	0.8	0.4	0.3	544.126424	502.371290

In [89]:

```
#TripleExponentialSmoothing
plt.figure(figsize=(18,9))
plt.plot(TES_train['Sparkling'], label='Train')
plt.plot(TES_test['Sparkling'], label='Test')

#The value of alpha and beta is taken like that by python
plt.plot(TES_test['predict', 0.7000000000000002,0.4, 0.3], label='Alpha=0.7,Beta=0.4,Gamma=0.3,TripleExponentialSmoothing predictions on Test Set')


plt.legend(loc='best')
plt.grid();
```



In [90]:

```
#rmse Table
resultsDf_8_3 = pd.DataFrame({'Test_RMSE': [resultsDf_8_1.sort_values(by=['Test RMSE']).values[0]
[4]]}
                    ,index=['Alpha=0.7,Beta=0.4,Gamma=0.3,TripleExponentialSmoothing'])
```

```
resultsDf = pd.concat([resultsDf, resultsDf_8_3])
resultsDf
```

Out[90]:

	Test_RMSE
Linear_Regression	1392.438305
SimpleAverageModel	1368.746717
2pointTrailingMovingAverage	811.178937
4pointTrailingMovingAverage	1184.213295
6pointTrailingMovingAverage	1337.200524
9pointTrailingMovingAverage	1422.653281
Alpha=0.03,SimpleExponentialSmoothing	1362.355524
Alpha=0.4,SimpleExponentialSmoothing	1363.037803
Alpha=0.3,Beta=0.3,DoubleExponentialSmoothing	1597.853999
Alpha=0.07,Beta=0.064,Gamma=0.37,TripleExponentialSmoothing	381.655272
Alpha=0.7,Beta=0.4,Gamma=0.3,TripleExponentialSmoothing	422.908833

In [91]:

```
#rmse table sort by rmse value
resultsDf.sort_values(by=['Test_RMSE'])
```

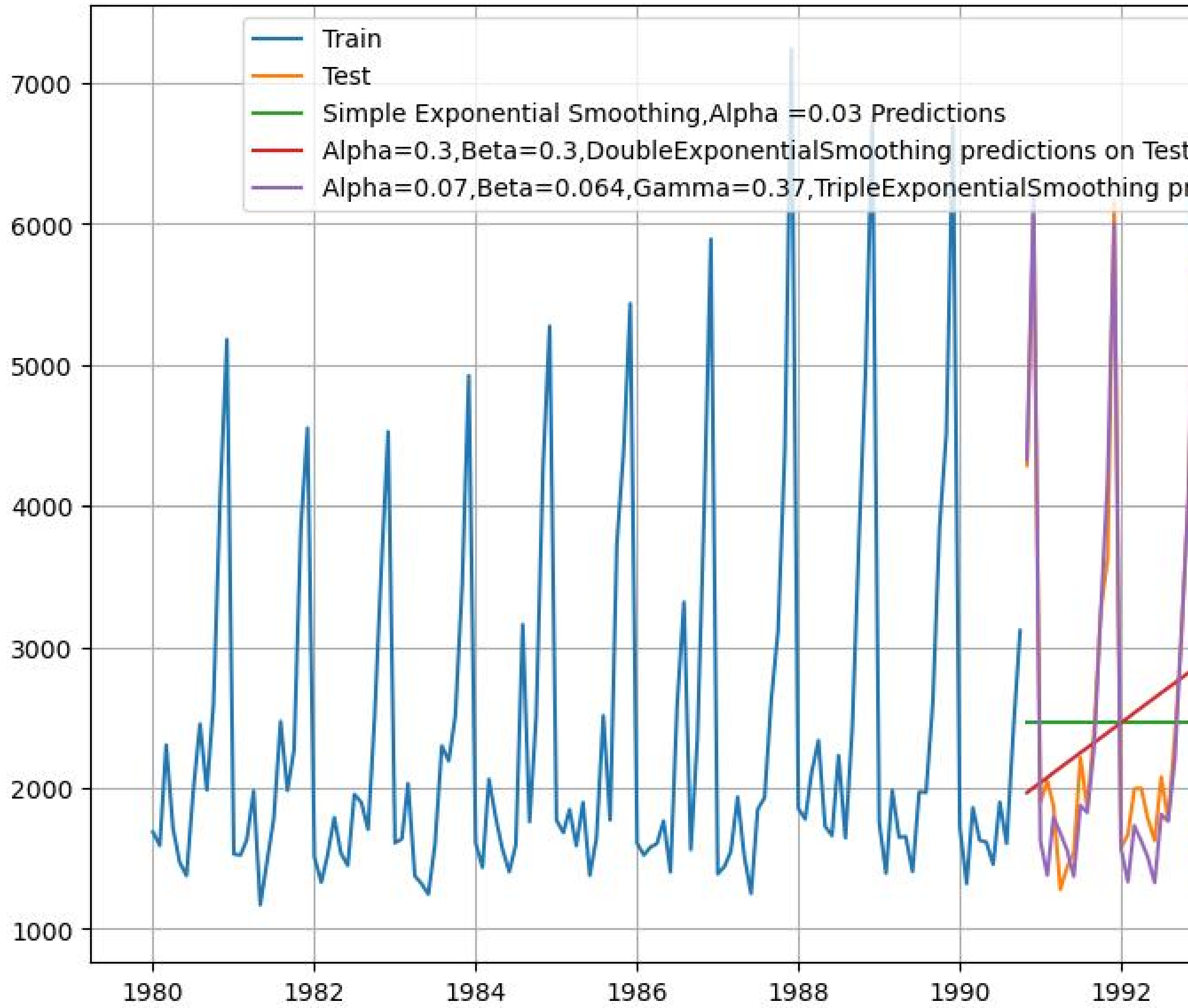
Out[91]:

	Test_RMSE
Alpha=0.07,Beta=0.064,Gamma=0.37,TripleExponentialSmoothing	381.655272
Alpha=0.7,Beta=0.4,Gamma=0.3,TripleExponentialSmoothing	422.908833
2pointTrailingMovingAverage	811.178937
4pointTrailingMovingAverage	1184.213295
6pointTrailingMovingAverage	1337.200524
Alpha=0.03,SimpleExponentialSmoothing	1362.355524
Alpha=0.4,SimpleExponentialSmoothing	1363.037803
SimpleAverageModel	1368.746717

	Test_RMSE
Linear_Regression	1392.438305
9pointTrailingMovingAverage	1422.653281
Alpha=0.3,Beta=0.3,DoubleExponentialSmoothing	1597.853999

In [92]:

```
#plot all ExponentialSmoothing
plt.figure(figsize=(10,7))
plt.plot(train,label="Train")
plt.plot(test,label="Test")
plt.plot(SES_test["predict"],label="Simple Exponential Smoothing,Alpha =0.03 Predictions")
plt.plot(DES_test['predict', 0.3, 0.3], label='Alpha=0.3,Beta=0.3,DoubleExponentialSmoothing predicti
ons on Test Set')
plt.plot(TES_test['auto_predict'], label='Alpha=0.07,Beta=0.064,Gamma=0.37,TripleExponentialSmoo
thing predictions on Test set')
plt.legend(loc='best')
plt.grid()
```



QUESTION-4

Check for Stationarity

- Check for stationarity - Make the data stationary (if needed)

Dicky Fuller Test

H0:Time series is not stationary

H1:Time series is stationary

In [93]:

```
from statsmodels.tsa.stattools import adfuller
def test_stationarity(time_series):
```

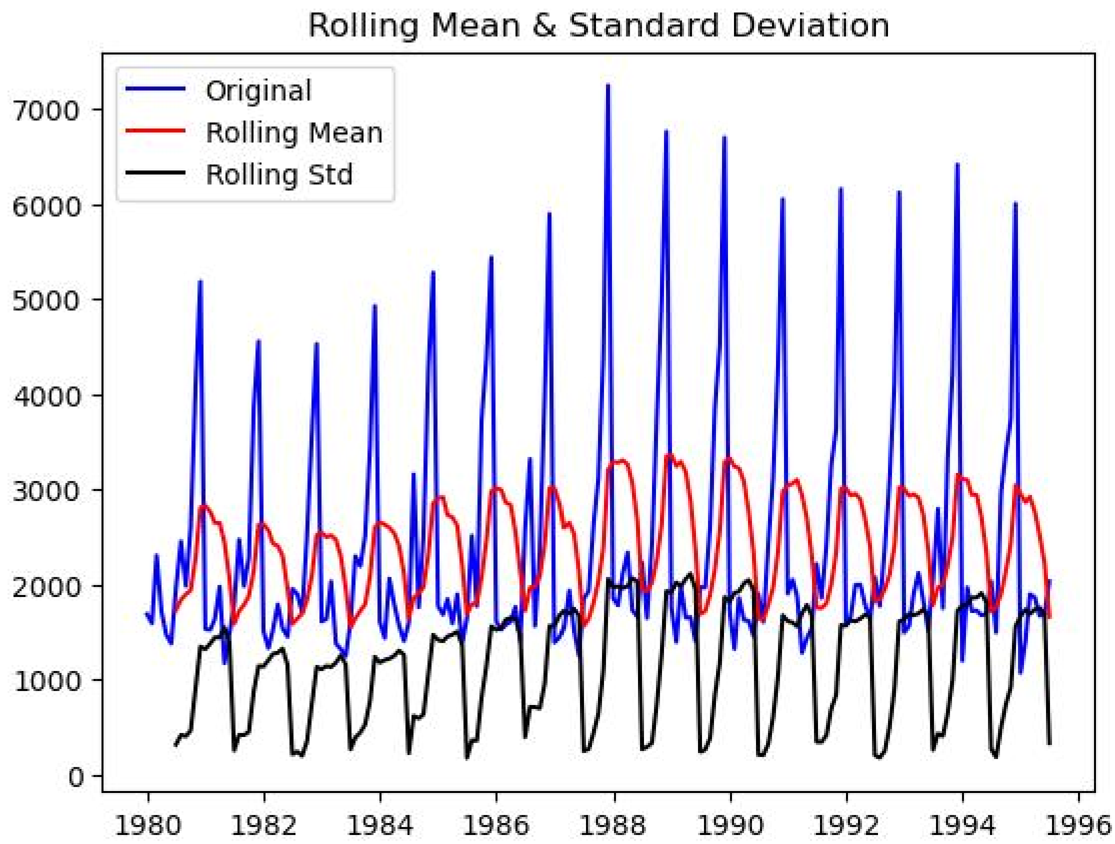
```
    #Determing rolling statistics
    rolmean=time_series.rolling(window=7).mean()
    rolstd=time_series.rolling(window=7).std()

    #Plot rolling statistics:
    orig = plt.plot(time_series, color='blue',label='Original')
    mean = plt.plot(rolmean, color='red', label='Rolling Mean')
    std = plt.plot(rolstd, color='black', label = 'Rolling Std')
    plt.legend(loc='best')
    plt.title('Rolling Mean & Standard Deviation')
    plt.show(block=False)

    #Perform Dickey-Fuller test:
    print ('Results of Dickey-Fuller Test:')
    dftest=adfuller(time_series, autolag='AIC')
    dfoutput=pd.Series(dftest[0:4],index=['Test Statistic','p-value','#Lags Used','Number of Observations Used'])
    for key,value in dftest[4].items():
        dfoutput['Critical Value (%s)'%key] = value
    print (dfoutput,'\n')
```

In [94]:

```
#checking stationarity plot of orginal data set
test_stationarity(df_1['Sparkling'])
```

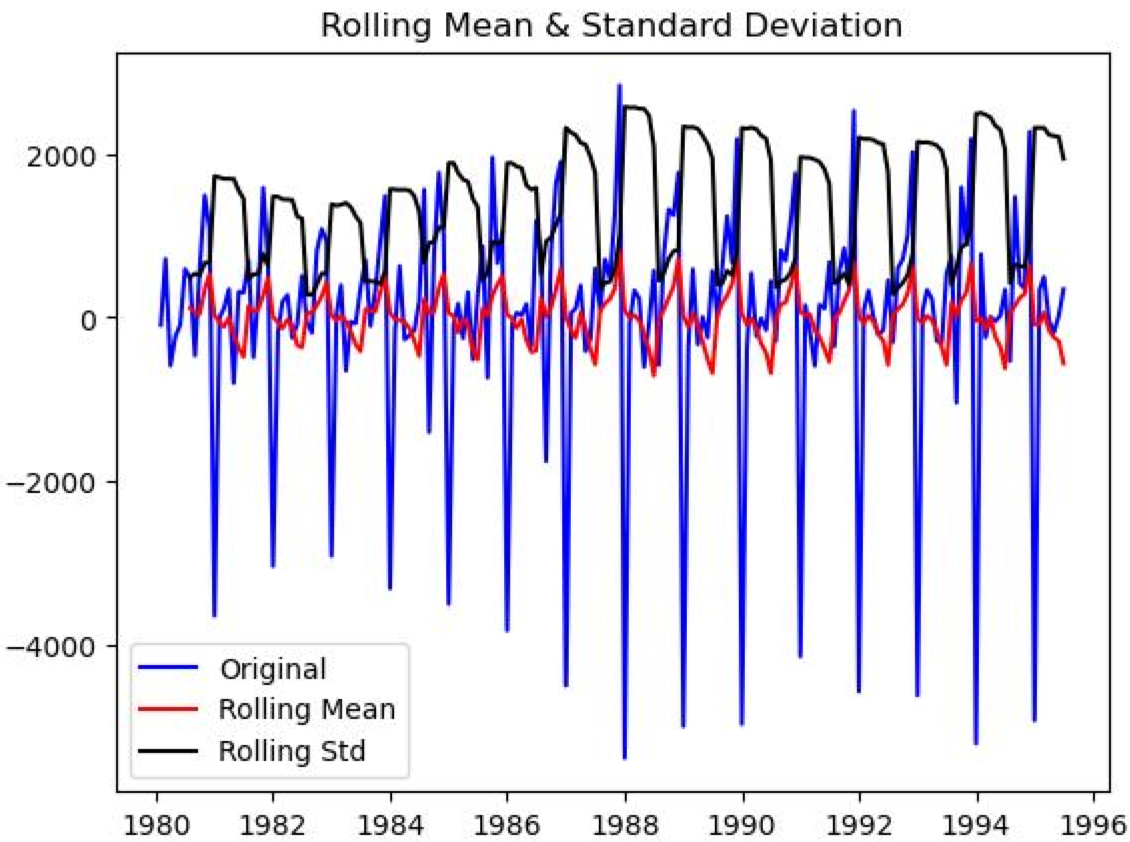



```
Results of Dickey-Fuller Test:
Test Statistic                -1.360497
p-value                        0.601061
#Lags Used                    11.000000
Number of Observations Used  175.000000
Critical Value (1%)           -3.468280
Critical Value (5%)           -2.878202
Critical Value (10%)          -2.575653
dtype: float64
```

p-value greater than 0.05 so the Time series is not stationary
Let us take a difference of order 1 and check whether the Time Series is stationary or not.

In [95]:

```
##checking stationarity plot of 1 difference series
test_stationarity(df_1['Sparkling'].diff().dropna())
```



Results of Dickey-Fuller Test:
Test Statistic   -45.050301
p-value   0.000000
#Lags Used   10.000000
Number of Observations Used   175.000000
Critical Value (1%)   -3.468280
Critical Value (5%)   -2.878202
Critical Value (10%)   -2.575653
dtype: float64

p-value less than 0.05 so null hypothesis is reject so this time series is stationary

QUESTION-5

Model Building - Stationary Data

- Generate ACF & PACF Plot and find the AR, MA values. - Build different ARIMA models - Auto ARIMA - Manual ARIMA - Build different SARIMA models - Auto SARIMA - Manual SARIMA - Check the performance of the models built

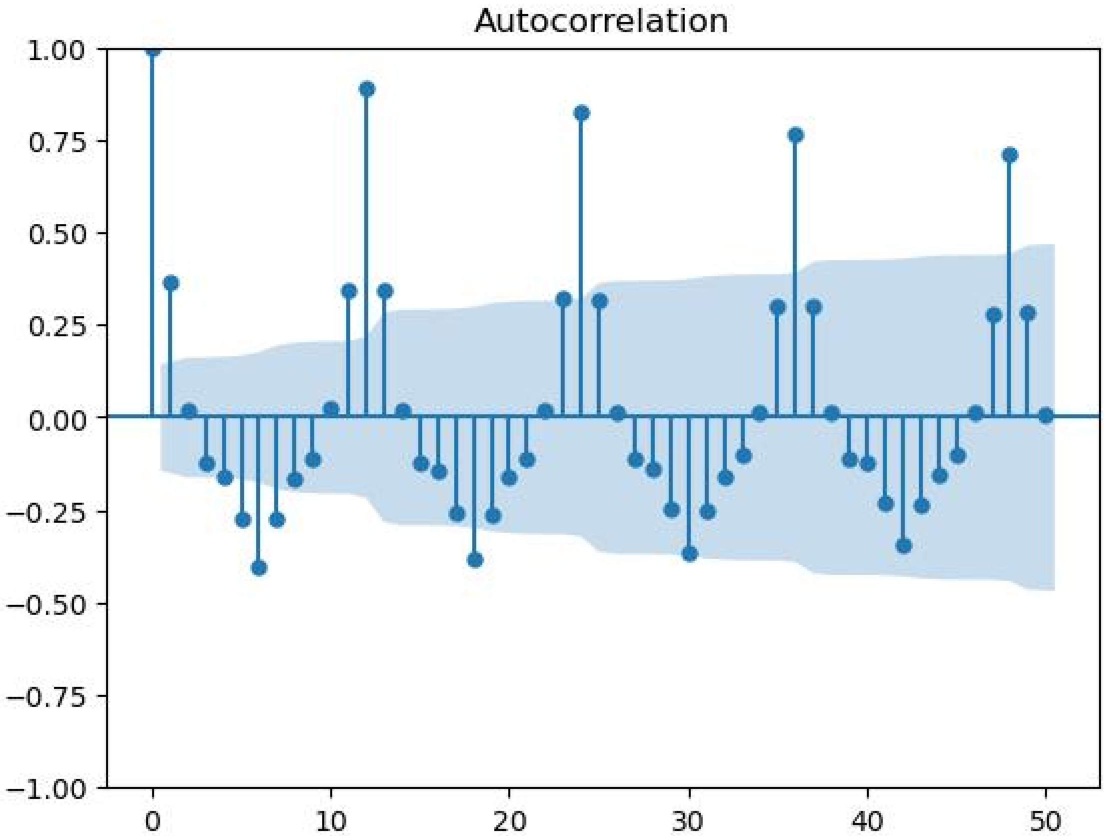
Generate ACF

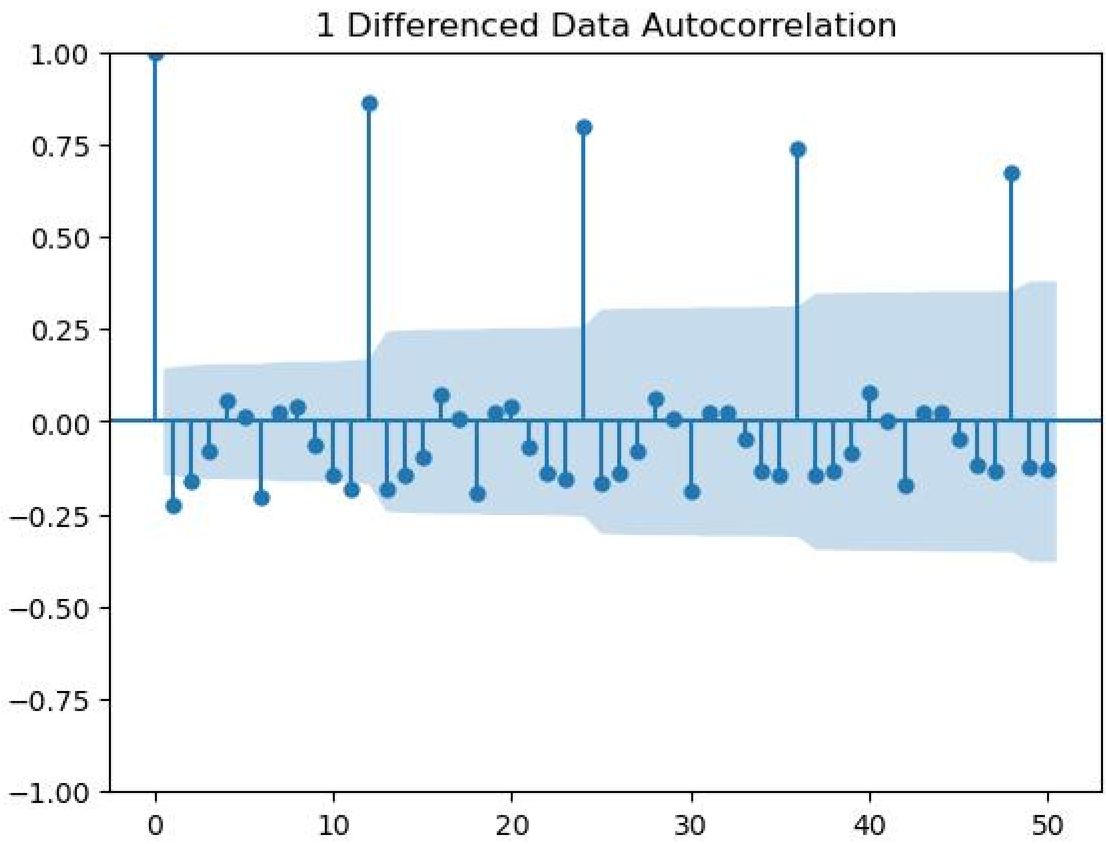
In [96]:

```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
```

In [97]:

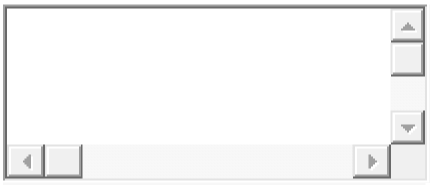
```
#plot acf,pacf
plot_acf(df_1['Sparkling'],lags=50)
plot_acf(df_1['Sparkling'].diff().dropna(),lags=50,title='1 Differenced Data Autocorrelation')
plt.show()
```





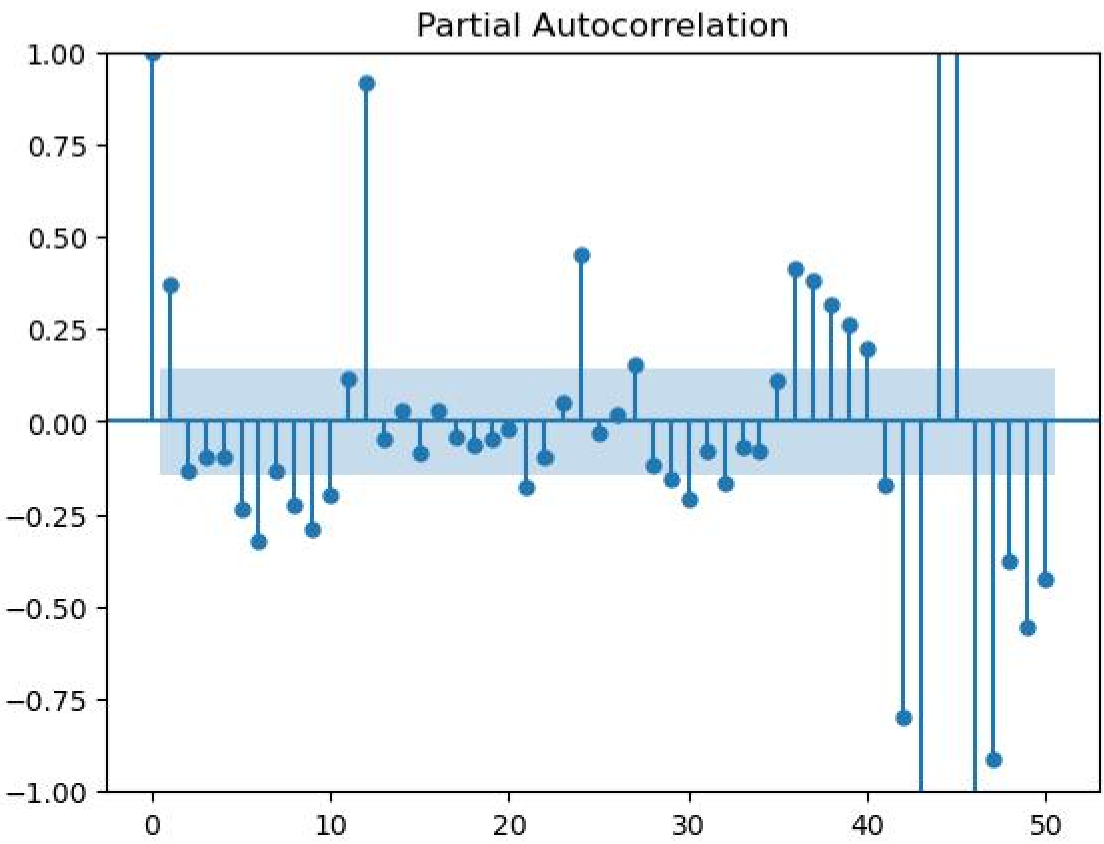
In [ ]:

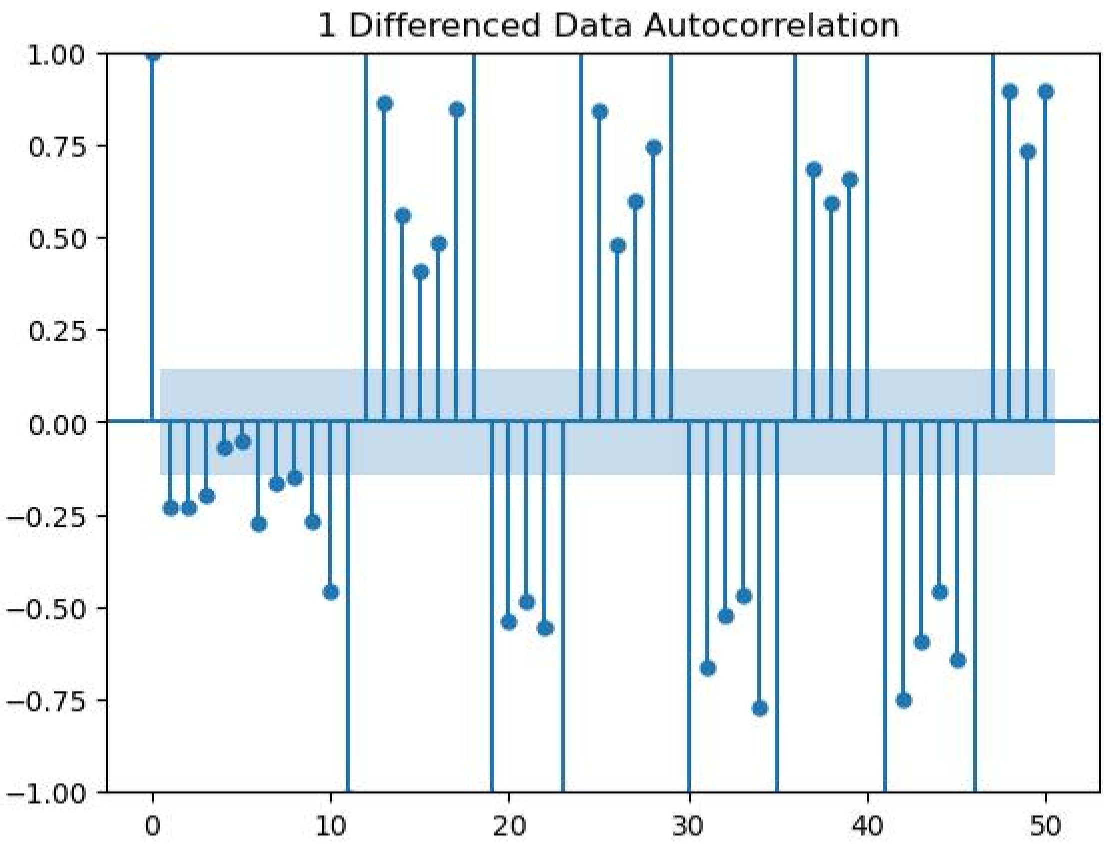
In [98]:



```
plot_pacf(df_1['Sparkling'],lags=50)
plot_pacf(df_1['Sparkling'].diff().dropna(),lags=50,title=' 1 Differenced Data Autocorrelation')
plt.show()
```

```
c:\Users\SABIR\anaconda3\Lib\site-packages\statsmodels\graphics\tsaplots.py:348: Future
Warning: The default method 'yw' can produce PACF values outside of the [-1,1] interval. Aft
er 0.13, the default will change tounadjusted Yule-Walker ('ywm'). You can use this method
now by setting method='ywm'.
  warnings.warn(
```





AR=0 (from PACF) MA=1 (from ACF)
for 1 difference time series

AR=0 (FROM PACF) MA=1 (FROM ACF)

Build different ARIMA models - Auto ARIMA - Manual ARIMA -

#Auto ARIMA

In [99]:

```
import itertools
p=q=range(0,3)
d= range(1,2)
pdq=list(itertools.product(p,d,q))
print('Some parameter combinations for the Model...')
for i in range(1,len(pdq)):
   print("model:  {}".format(pdq[i]))
```

```
Some parameter combinations for the Model...
model:  (0, 1, 1)
model:  (0, 1, 2)
model:  (1, 1, 0)
model:  (1, 1, 1)
model:  (1, 1, 2)
model:  (2, 1, 0)
model:  (2, 1, 1)
model:  (2, 1, 2)
```

In [100]:

```
ARIMA_AIC=pd.DataFrame(columns=["param","AIC"])
ARIMA_AIC
```

Out[100]:

param	AIC

#setting values

In [101]:

```
from statsmodels.tsa.arima.model import ARIMA
for param in pdq:
   ARIMA_MODEL=ARIMA(train["Sparkling"].values,order=param).fit()
   print("ARIMA{}-AIC:{}".format(param, ARIMA_MODEL.aic))
   ARIMA_AIC= ARIMA_AIC.append({"param":param,"AIC":ARIMA_MODEL.aic},ignore_index=True)
```

```
ARIMA(0, 1, 0)-AIC:2232.719438106631
ARIMA(0, 1, 1)-AIC:2217.9392215777407
```

```
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\2387515056.py:5: FutureWarning: T
he frame.append method is deprecated and will be removed from pandas in a future version.
 Use pandas.concat instead.
  ARIMA_AIC= ARIMA_AIC.append({"param":param,"AIC":ARIMA_MODEL.aic},ignore_index=
True)
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\2387515056.py:5: FutureWarning: T
he frame.append method is deprecated and will be removed from pandas in a future version.
 Use pandas.concat instead.
  ARIMA_AIC= ARIMA_AIC.append({"param":param,"AIC":ARIMA_MODEL.aic},ignore_index=
True)
ARIMA(0, 1, 2)-AIC:2194.034361361615
ARIMA(1, 1, 0)-AIC:2231.137663012458
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\2387515056.py:5: FutureWarning: T
he frame.append method is deprecated and will be removed from pandas in a future version.
 Use pandas.concat instead.
  ARIMA_AIC= ARIMA_AIC.append({"param":param,"AIC":ARIMA_MODEL.aic},ignore_index=
True)
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\2387515056.py:5: FutureWarning: T
he frame.append method is deprecated and will be removed from pandas in a future version.
 Use pandas.concat instead.
  ARIMA_AIC= ARIMA_AIC.append({"param":param,"AIC":ARIMA_MODEL.aic},ignore_index=
True)
c:\Users\SABIR\anaconda3\Lib\site-packages\statsmodels\tsa\statespace\sarimax.py:978: U
serWarning: Non-invertible starting MA parameters found. Using zeros as starting parameter
s.
  warn('Non-invertible starting MA parameters found.'
ARIMA(1, 1, 1)-AIC:2196.050085997568
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\2387515056.py:5: FutureWarning: T
he frame.append method is deprecated and will be removed from pandas in a future version.
 Use pandas.concat instead.
  ARIMA_AIC= ARIMA_AIC.append({"param":param,"AIC":ARIMA_MODEL.aic},ignore_index=
True)
ARIMA(1, 1, 2)-AIC:2194.959653392053
ARIMA(2, 1, 0)-AIC:2223.899470277437
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\2387515056.py:5: FutureWarning: T
he frame.append method is deprecated and will be removed from pandas in a future version.
 Use pandas.concat instead.
  ARIMA_AIC= ARIMA_AIC.append({"param":param,"AIC":ARIMA_MODEL.aic},ignore_index=
True)
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\2387515056.py:5: FutureWarning: T
he frame.append method is deprecated and will be removed from pandas in a future version.
 Use pandas.concat instead.
  ARIMA_AIC= ARIMA_AIC.append({"param":param,"AIC":ARIMA_MODEL.aic},ignore_index=
True)
ARIMA(2, 1, 1)-AIC:2193.9749624358974
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\2387515056.py:5: FutureWarning: T
he frame.append method is deprecated and will be removed from pandas in a future version.
 Use pandas.concat instead.
  ARIMA_AIC= ARIMA_AIC.append({"param":param,"AIC":ARIMA_MODEL.aic},ignore_index=
True)
ARIMA(2, 1, 2)-AIC:2178.1097266792094
```

```
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\2387515056.py:5: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  ARIMA_AIC= ARIMA_AIC.append({"param":param,"AIC":ARIMA_MODEL.aic},ignore_index=True)
```

In [102]:

```
## Sort the above AIC values in the ascending order to get the parameters for the minimum AIC value

ARIMA_AIC.sort_values(by='AIC',ascending=True)
```

Out[102]:

	param	AIC
8	(2, 1, 2)	2178.109727
7	(2, 1, 1)	2193.974962
2	(0, 1, 2)	2194.034361
5	(1, 1, 2)	2194.959653
4	(1, 1, 1)	2196.050086
1	(0, 1, 1)	2217.939222
6	(2, 1, 0)	2223.899470
3	(1, 1, 0)	2231.137663
0	(0, 1, 0)	2232.719438

In [103]:

```
#set (2,1,2) model
auto_ARIMA = ARIMA(train['Sparkling'], order=(2, 1, 2), freq="MS")
```

```
c:\Users\SABIR\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
```

In [104]:

```
results_auto_ARIMA = auto_ARIMA.fit()
```

```
print(results_auto_ARIMA.summary())
                               SARIMAX Results
==============================================================================
===
Dep. Variable:              Sparkling   No. Observations:                  130
Model:                 ARIMA(2, 1, 2)   Log Likelihood               -1084.055
Date:                Sun, 21 Apr 2024   AIC                           2178.110
Time:                        21:12:52   BIC                           2192.409
Sample:                    01-01-1980   HQIC                          2183.920
                         - 10-01-1990
Covariance Type:                  opg
==============================================================================
===
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          1.3020      0.046     28.547      0.000       1.213       1.391
ar.L2         -0.5360      0.079     -6.765      0.000      -0.691      -0.381
ma.L1         -1.9916      0.109    -18.214      0.000      -2.206      -1.777
ma.L2          0.9998      0.110      9.104      0.000       0.785       1.215
sigma2      1.085e+06   2.03e-07   5.35e+12      0.000    1.08e+06    1.08e+06
==============================================================================
========
Ljung-Box (L1) (Q):                   0.10   Jarque-Bera (JB):                19.53
Prob(Q):                              0.75   Prob(JB):                         0.00
Heteroskedasticity (H):               2.30   Skew:                             0.71
Prob(H) (two-sided):                  0.01   Kurtosis:                         4.27
==============================================================================
========

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 7.93e+27. Standard
 errors may be unstable.
```

In [105]:

```
predicted_auto_ARIMA = results_auto_ARIMA.forecast(steps=len(test))
```

In [106]:

```
from sklearn.metrics import mean_squared_error
rmse = mean_squared_error(test['Sparkling'],predicted_auto_ARIMA,squared=False)
print(rmse)
1325.1542678968494
```

In [107]:

```
#rmse table
resultsDf0 = pd.DataFrame({'Test_RMSE': [rmse]}
                         ,index=['ARIMA(2,1,2)'])

resultsDf0
```

Out[107]:

	Test_RMSE
ARIMA(2,1,2)	1325.154268

Manual ARIMA

In [108]:

```
#set(2,1,1)
manual_ARIMA= ARIMA(train['Sparkling'], order=(2, 1, 1), freq="MS")
```

```
c:\Users\SABIR\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: Valu
eWarning: No frequency information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
```

In [109]:

```
#manual_ARIMA summary
results_manual_ARIMA = manual_ARIMA.fit()

print(results_manual_ARIMA.summary())
```

```
                               SARIMAX Results
==============================================================================
===
Dep. Variable:            Sparkling   No. Observations:               130
Model:                ARIMA(2, 1, 1)   Log Likelihood              -1092.987
Date:               Sun, 21 Apr 2024   AIC                          2193.975
Time:                       21:12:55   BIC                          2205.414
Sample:                   01-01-1980   HQIC                         2198.623
                        - 10-01-1990
Covariance Type:                 opg
==============================================================================
===
              coef    std err          z      P>|z|      [0.025      0.975]
```

```
------------------------------------------------------------------------------
ar.L1        0.4862     0.104     4.660     0.000      0.282      0.691
ar.L2       -0.1764     0.190    -0.929     0.353     -0.548      0.196
ma.L1       -0.9999     0.098   -10.225     0.000     -1.192     -0.808
sigma2     1.292e+06  7.62e-08   1.7e+13     0.000   1.29e+06   1.29e+06
==============================================================================
========
Ljung-Box (L1) (Q):              0.06   Jarque-Bera (JB):             19.61
Prob(Q):                         0.80   Prob(JB):                      0.00
Heteroskedasticity (H):          2.45   Skew:                          0.67
Prob(H) (two-sided):             0.00   Kurtosis:                      4.37
==============================================================================
========

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 1.85e+28. Standard
 errors may be unstable.
```

In [110]:

```
predicted_manual_ARIMA = results_manual_ARIMA.forecast(steps=len(test))
```

In [111]:

```
from sklearn.metrics import  mean_squared_error
rmse = mean_squared_error(test['Sparkling'],predicted_manual_ARIMA,squared=False)
print(rmse)
```

1359.6498379449822

In [112]:

```
resultsDf_3= pd.DataFrame({'Test_RMSE': [rmse]}
                          ,index=['manual ARIMA(2,1,1)'])


resultsDf0=pd.concat([resultsDf0,resultsDf_3])
resultsDf0
```

Out[112]:

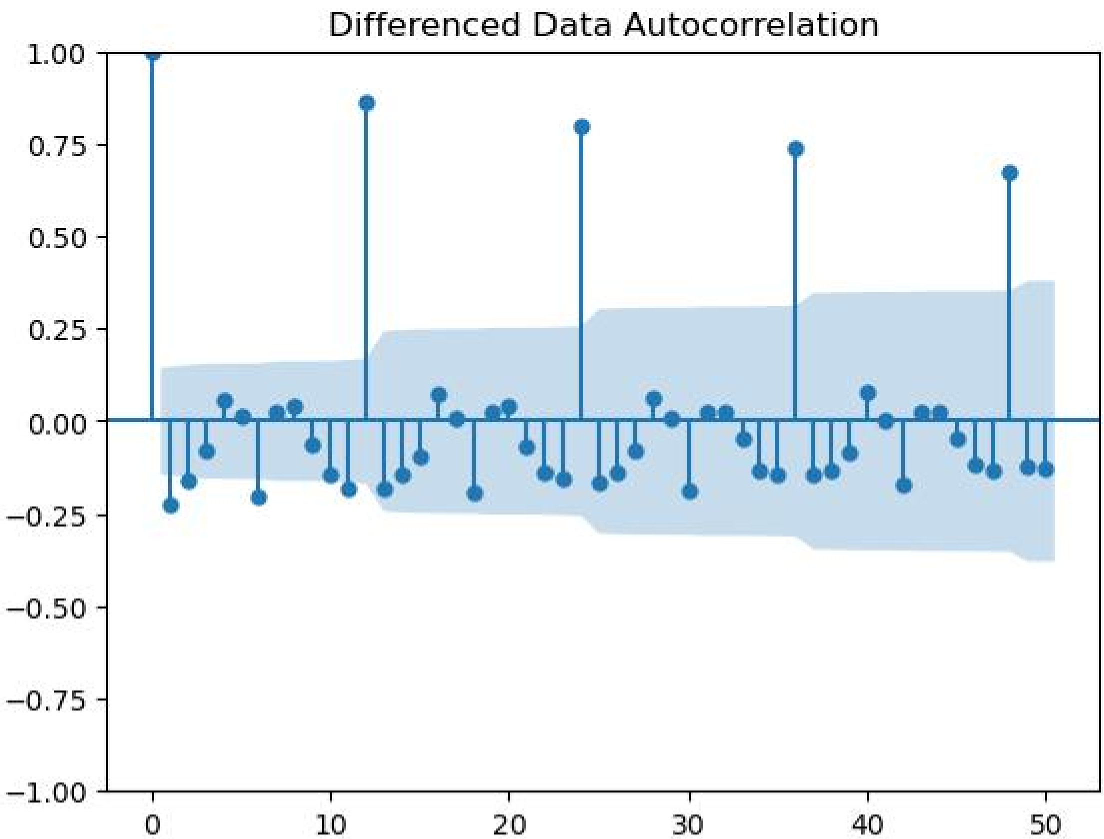
	Test_RMSE
ARIMA(2,1,2)	1325.154268

	Test_RMSE
manual ARIMA(2,1,1)	1359.649838

Build an Automated version of a SARIMA model for which the best parameters are selected in accordance with the lowest Akaike Information Criteria (AIC).¶

In [113]:

```
plot_acf(df_1['Sparkling'].diff().dropna(),lags=50,title='Differenced Data Autocorrelation')
plt.show()
```



We see that there can be a seasonality of 6 as well as 12. But from the decompostion at the start we ascertained that visually it looks like the seasonality =6 and thus using the same

Setting the seasonality as 6 to estimate parametrs using auto SARIMA model.

In [114]:

```
import itertools
p = q = range(0, 3)
d= range(1,2)
```

```
D = range(0,1)
pdq = list(itertools.product(p, d, q))
model_pdq = [(x[0], x[1], x[2], 12) for x in list(itertools.product(p, D, q))]
print('Examples of some parameter combinations for Model...')
for i in range(1,len(pdq)):
  print('Model: {}{}'.format(pdq[i], model_pdq[i]))
```

```
Examples of some parameter combinations for Model...
Model: (0, 1, 1)(0, 0, 1, 12)
Model: (0, 1, 2)(0, 0, 2, 12)
Model: (1, 1, 0)(1, 0, 0, 12)
Model: (1, 1, 1)(1, 0, 1, 12)
Model: (1, 1, 2)(1, 0, 2, 12)
Model: (2, 1, 0)(2, 0, 0, 12)
Model: (2, 1, 1)(2, 0, 1, 12)
Model: (2, 1, 2)(2, 0, 2, 12)
```

In [115]:

```
#setting different values
SARIMA_AIC = pd.DataFrame(columns=['param','seasonal', 'AIC'])
SARIMA_AIC
```

Out[115]:

param	seasonal	AIC

In [116]:

```
import statsmodels.api as sm
```

In [117]:

```
for param in pdq:
  for parm_seasonal in model_pdq:
    SARIMA_model = sm.tsa.statespace.SARIMAX(train['Sparkling'].values,
                                             order=param,
                                             seasonal_order=parm_seasonal,
                                             enforce_stationarity=False,
                                             enforce_invertibility=False)
    results_SARIMA = SARIMA_model.fit(maxiter=1000)
    print('SARIMA{}x{} - AIC:{}'.format(param, parm_seasonal, results_SARIMA.aic))
    SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results_SAR
IMA.aic}, ignore_index=True)
```

```
SARIMA(0, 1, 0)x(0, 0, 0, 12) - AIC:2216.4189020489616
```

```
SARIMA(0, 1, 0)x(0, 0, 1, 12) - AIC:1921.5151801498844
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results_SARIMA.aic}, ignore_index=True)
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results_SARIMA.aic}, ignore_index=True)
SARIMA(0, 1, 0)x(0, 0, 2, 12) - AIC:1691.5049017310976
SARIMA(0, 1, 0)x(1, 0, 0, 12) - AIC:1807.2950161665542
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results_SARIMA.aic}, ignore_index=True)
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results_SARIMA.aic}, ignore_index=True)
SARIMA(0, 1, 0)x(1, 0, 1, 12) - AIC:1777.6492913876366
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results_SARIMA.aic}, ignore_index=True)
SARIMA(0, 1, 0)x(1, 0, 2, 12) - AIC:1601.281534210607
SARIMA(0, 1, 0)x(2, 0, 0, 12) - AIC:1618.9670228363275
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results_SARIMA.aic}, ignore_index=True)
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results_SARIMA.aic}, ignore_index=True)
SARIMA(0, 1, 0)x(2, 0, 1, 12) - AIC:1617.7268547329668
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results_SARIMA.aic}, ignore_index=True)
SARIMA(0, 1, 0)x(2, 0, 2, 12) - AIC:1602.062365958758
SARIMA(0, 1, 1)x(0, 0, 0, 12) - AIC:2193.281680181417
```

```
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: 
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results
_SARIMA.aic}, ignore_index=True)
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: 
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_SARIMA.aic}, ignore_index=True)
SARIMA(0, 1, 1)x(0, 0, 1, 12) - AIC:1888.5868794008513
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: 
The frame.append method is deprecated and will be removed from pandas in a future versio
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_SARIMA.aic}, ignore_index=True)
SARIMA(0, 1, 1)x(0, 0, 2, 12) - AIC:1658.7576059581322
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: 
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
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_SARIMA.aic}, ignore_index=True)
SARIMA(0, 1, 1)x(1, 0, 0, 12) - AIC:1768.1554049142383
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: 
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
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_SARIMA.aic}, ignore_index=True)
SARIMA(0, 1, 1)x(1, 0, 1, 12) - AIC:1704.8427340697406
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: 
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_SARIMA.aic}, ignore_index=True)
SARIMA(0, 1, 1)x(1, 0, 2, 12) - AIC:1536.3191139350608
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: 
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_SARIMA.aic}, ignore_index=True)
SARIMA(0, 1, 1)x(2, 0, 0, 12) - AIC:1575.249693559518
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: 
The frame.append method is deprecated and will be removed from pandas in a future versio
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  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results
_SARIMA.aic}, ignore_index=True)
SARIMA(0, 1, 1)x(2, 0, 1, 12) - AIC:1564.9149381065015
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: 
The frame.append method is deprecated and will be removed from pandas in a future versio
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```

```
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results
_SARIMA.aic}, ignore_index=True)
SARIMA(0, 1, 1)x(2, 0, 2, 12) - AIC:1536.411010133245
SARIMA(0, 1, 2)x(0, 0, 0, 12) - AIC:2143.9209005621547
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
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_SARIMA.aic}, ignore_index=True)
SARIMA(0, 1, 2)x(0, 0, 1, 12) - AIC:1853.674716438678
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a future versio
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_SARIMA.aic}, ignore_index=True)
SARIMA(0, 1, 2)x(0, 0, 2, 12) - AIC:1624.757310552475
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a future versio
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_SARIMA.aic}, ignore_index=True)
SARIMA(0, 1, 2)x(1, 0, 0, 12) - AIC:1760.7216575033397
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a future versio
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_SARIMA.aic}, ignore_index=True)
SARIMA(0, 1, 2)x(1, 0, 1, 12) - AIC:1691.3744541840751
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a future versio
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_SARIMA.aic}, ignore_index=True)
SARIMA(0, 1, 2)x(1, 0, 2, 12) - AIC:1524.522125089718
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
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_SARIMA.aic}, ignore_index=True)
SARIMA(0, 1, 2)x(2, 0, 0, 12) - AIC:1573.2338748356217
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a future versio
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_SARIMA.aic}, ignore_index=True)
SARIMA(0, 1, 2)x(2, 0, 1, 12) - AIC:1566.7494024673133
```

```
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a future versio
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_SARIMA.aic}, ignore_index=True)
SARIMA(0, 1, 2)x(2, 0, 2, 12) - AIC:1523.7072972160424
SARIMA(1, 1, 0)x(0, 0, 0, 12) - AIC:2214.8516264604455
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
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SARIMA(1, 1, 0)x(0, 0, 1, 12) - AIC:1919.1580486803139
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
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SARIMA(1, 1, 0)x(0, 0, 2, 12) - AIC:1689.8880118556967
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
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_SARIMA.aic}, ignore_index=True)
SARIMA(1, 1, 0)x(1, 0, 0, 12) - AIC:1782.024250138347
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
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_SARIMA.aic}, ignore_index=True)
SARIMA(1, 1, 0)x(1, 0, 1, 12) - AIC:1759.3455844991136
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
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_SARIMA.aic}, ignore_index=True)
SARIMA(1, 1, 0)x(1, 0, 2, 12) - AIC:1587.2527635497665
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
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_SARIMA.aic}, ignore_index=True)
SARIMA(1, 1, 0)x(2, 0, 0, 12) - AIC:1593.015124187761
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
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```

```
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results
_SARIMA.aic}, ignore_index=True)
SARIMA(1, 1, 0)x(2, 0, 1, 12) - AIC:1587.7818267352864
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
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_SARIMA.aic}, ignore_index=True)
SARIMA(1, 1, 0)x(2, 0, 2, 12) - AIC:1587.0474358182623
SARIMA(1, 1, 1)x(0, 0, 0, 12) - AIC:2165.914890109132
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
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C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
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SARIMA(1, 1, 1)x(0, 0, 1, 12) - AIC:1872.2057291078409
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
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_SARIMA.aic}, ignore_index=True)
SARIMA(1, 1, 1)x(0, 0, 2, 12) - AIC:1645.119035211755
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
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SARIMA(1, 1, 1)x(1, 0, 0, 12) - AIC:1746.0411803412817
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
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_SARIMA.aic}, ignore_index=True)
SARIMA(1, 1, 1)x(1, 0, 1, 12) - AIC:1706.6940980082393
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
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  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results
_SARIMA.aic}, ignore_index=True)
c:\Users\SABIR\anaconda3\Lib\site-packages\statsmodels\base\model.py:604: Convergence
Warning: Maximum Likelihood optimization failed to converge. Check mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a future versio
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```

```
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results
_SARIMA.aic}, ignore_index=True)
SARIMA(1, 1, 1)x(1, 0, 2, 12) - AIC:1537.9253340950597
SARIMA(1, 1, 1)x(2, 0, 0, 12) - AIC:1560.2276828197046
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
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_SARIMA.aic}, ignore_index=True)
SARIMA(1, 1, 1)x(2, 0, 1, 12) - AIC:1552.2403936956653
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
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_SARIMA.aic}, ignore_index=True)
SARIMA(1, 1, 1)x(2, 0, 2, 12) - AIC:1538.0472362362943
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
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  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results
_SARIMA.aic}, ignore_index=True)
SARIMA(1, 1, 2)x(0, 0, 0, 12) - AIC:2145.0969765927966
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results
_SARIMA.aic}, ignore_index=True)
SARIMA(1, 1, 2)x(0, 0, 1, 12) - AIC:1855.5409901543958
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results
_SARIMA.aic}, ignore_index=True)
SARIMA(1, 1, 2)x(0, 0, 2, 12) - AIC:1626.6068224318342
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results
_SARIMA.aic}, ignore_index=True)
SARIMA(1, 1, 2)x(1, 0, 0, 12) - AIC:1741.939708760783
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results
_SARIMA.aic}, ignore_index=True)
SARIMA(1, 1, 2)x(1, 0, 1, 12) - AIC:1690.7620851584074
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results
_SARIMA.aic}, ignore_index=True)
```

```
SARIMA(1, 1, 2)x(1, 0, 2, 12) - AIC:1526.1482232821686
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results_SARIMA.aic}, ignore_index=True)
SARIMA(1, 1, 2)x(2, 0, 0, 12) - AIC:1562.2382505165879
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results_SARIMA.aic}, ignore_index=True)
SARIMA(1, 1, 2)x(2, 0, 1, 12) - AIC:1551.3914065831564
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results_SARIMA.aic}, ignore_index=True)
SARIMA(1, 1, 2)x(2, 0, 2, 12) - AIC:1521.7379550255532
SARIMA(2, 1, 0)x(0, 0, 0, 12) - AIC:2190.8338694577515
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results_SARIMA.aic}, ignore_index=True)
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results_SARIMA.aic}, ignore_index=True)
SARIMA(2, 1, 0)x(0, 0, 1, 12) - AIC:1913.107023045554
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results_SARIMA.aic}, ignore_index=True)
SARIMA(2, 1, 0)x(0, 0, 2, 12) - AIC:1678.6510971328044
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results_SARIMA.aic}, ignore_index=True)
SARIMA(2, 1, 0)x(1, 0, 0, 12) - AIC:1751.4274988003995
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results_SARIMA.aic}, ignore_index=True)
SARIMA(2, 1, 0)x(1, 0, 1, 12) - AIC:1726.338133900166
```

```
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results_SARIMA.aic}, ignore_index=True)
SARIMA(2, 1, 0)x(1, 0, 2, 12) - AIC:1570.2465435892427
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results_SARIMA.aic}, ignore_index=True)
SARIMA(2, 1, 0)x(2, 0, 0, 12) - AIC:1563.2068573875492
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results_SARIMA.aic}, ignore_index=True)
SARIMA(2, 1, 0)x(2, 0, 1, 12) - AIC:1556.407845021267
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results_SARIMA.aic}, ignore_index=True)
SARIMA(2, 1, 0)x(2, 0, 2, 12) - AIC:1554.951253385322
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results_SARIMA.aic}, ignore_index=True)
SARIMA(2, 1, 1)x(0, 0, 0, 12) - AIC:2160.2483044779
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results_SARIMA.aic}, ignore_index=True)
SARIMA(2, 1, 1)x(0, 0, 1, 12) - AIC:1870.9922931385008
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results_SARIMA.aic}, ignore_index=True)
SARIMA(2, 1, 1)x(0, 0, 2, 12) - AIC:1642.5176683267248
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results_SARIMA.aic}, ignore_index=True)
SARIMA(2, 1, 1)x(1, 0, 0, 12) - AIC:1730.2218368538113
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.
```

```
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results
_SARIMA.aic}, ignore_index=True)
SARIMA(2, 1, 1)x(1, 0, 1, 12) - AIC:1706.7535525260807
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: 
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results
_SARIMA.aic}, ignore_index=True)
SARIMA(2, 1, 1)x(1, 0, 2, 12) - AIC:1538.345097493133
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: 
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results
_SARIMA.aic}, ignore_index=True)
SARIMA(2, 1, 1)x(2, 0, 0, 12) - AIC:1546.7290693790144
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: 
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results
_SARIMA.aic}, ignore_index=True)
SARIMA(2, 1, 1)x(2, 0, 1, 12) - AIC:1538.7173774511689
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: 
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results
_SARIMA.aic}, ignore_index=True)
SARIMA(2, 1, 1)x(2, 0, 2, 12) - AIC:1538.2657002089788
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: 
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results
_SARIMA.aic}, ignore_index=True)
SARIMA(2, 1, 2)x(0, 0, 0, 12) - AIC:2140.6693960014036
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: 
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results
_SARIMA.aic}, ignore_index=True)
SARIMA(2, 1, 2)x(0, 0, 1, 12) - AIC:1857.4627148532304
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: 
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results
_SARIMA.aic}, ignore_index=True)
SARIMA(2, 1, 2)x(0, 0, 2, 12) - AIC:1631.3963012278175
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning: 
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results
_SARIMA.aic}, ignore_index=True)
SARIMA(2, 1, 2)x(1, 0, 0, 12) - AIC:1727.5761548970236
```

```
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results
_SARIMA.aic}, ignore_index=True)
SARIMA(2, 1, 2)x(1, 0, 1, 12) - AIC:1691.6106392736092
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results
_SARIMA.aic}, ignore_index=True)
SARIMA(2, 1, 2)x(1, 0, 2, 12) - AIC:1523.5249458580122
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results
_SARIMA.aic}, ignore_index=True)
SARIMA(2, 1, 2)x(2, 0, 0, 12) - AIC:1545.387546985494
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results
_SARIMA.aic}, ignore_index=True)
SARIMA(2, 1, 2)x(2, 0, 1, 12) - AIC:1539.0422082396763
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results
_SARIMA.aic}, ignore_index=True)
SARIMA(2, 1, 2)x(2, 0, 2, 12) - AIC:1523.2178331168238
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\3714483348.py:10: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
  SARIMA_AIC = SARIMA_AIC.append({'param':param,'seasonal':parm_seasonal ,'AIC': results
_SARIMA.aic}, ignore_index=True)
```

In [118]:

```python
#sort values by AIC of SARIMA
SARIMA_AIC.sort_values(by="AIC",ascending=True)
```

Out[118]:

	param	seasonal	AIC
53	(1, 1, 2)	(2, 0, 2, 12)	1521.737955
80	(2, 1, 2)	(2, 0, 2, 12)	1523.217833
77	(2, 1, 2)	(1, 0, 2, 12)	1523.524946

	param	seasonal	AIC
26	(0, 1, 2)	(2, 0, 2, 12)	1523.707297
23	(0, 1, 2)	(1, 0, 2, 12)	1524.522125
...	...	...	...
36	(1, 1, 1)	(0, 0, 0, 12)	2165.914890
54	(2, 1, 0)	(0, 0, 0, 12)	2190.833869
9	(0, 1, 1)	(0, 0, 0, 12)	2193.281680
27	(1, 1, 0)	(0, 0, 0, 12)	2214.851626
0	(0, 1, 0)	(0, 0, 0, 12)	2216.418902

81 rows × 3 columns

In [119]:

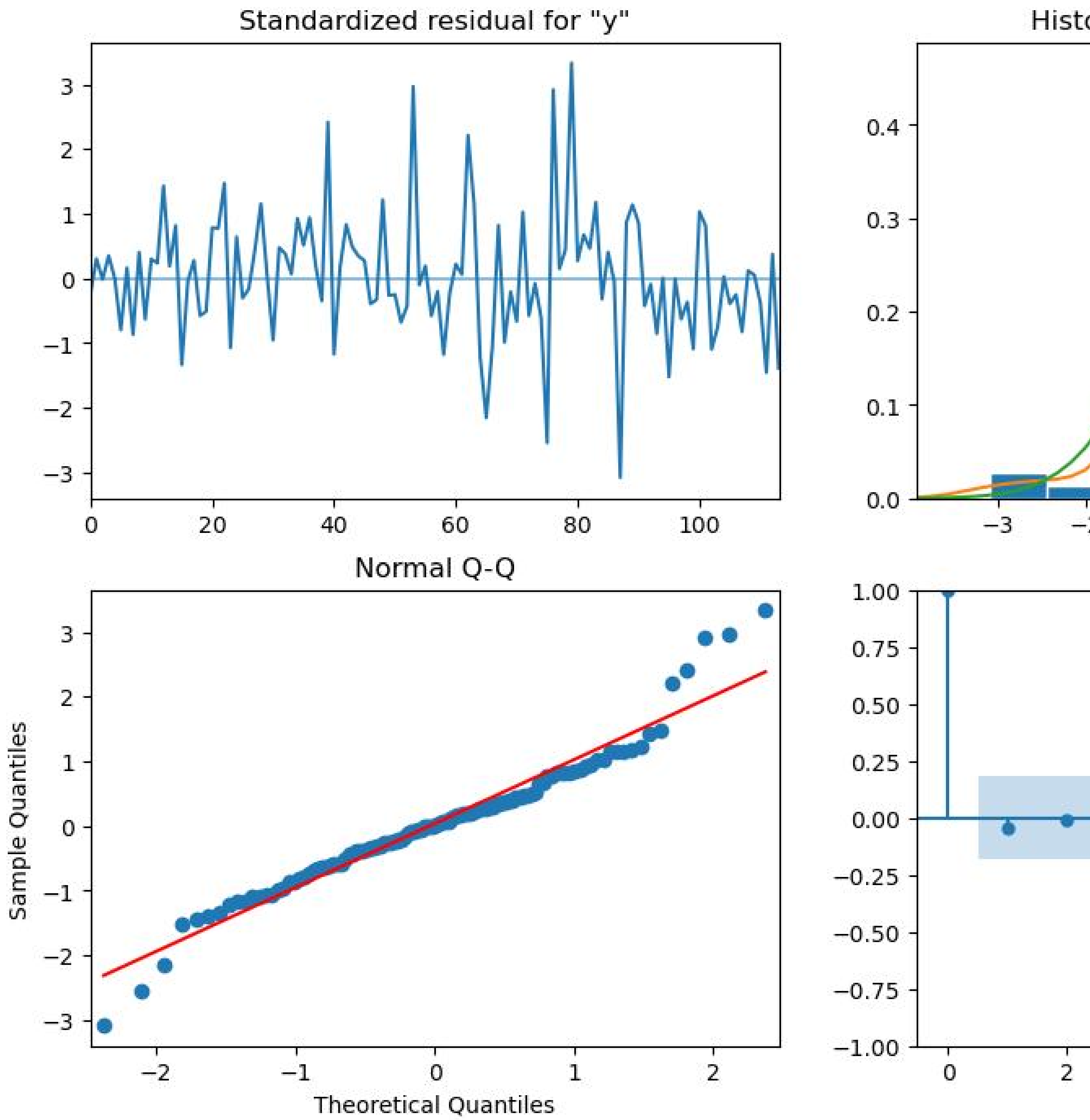
```
#auto_SARIMA summary
import statsmodels.api as sm

auto_SARIMA_6 = sm.tsa.statespace.SARIMAX(train['Sparkling'].values,
                    order=(1, 1, 2),
                    seasonal_order=(2, 0, 2, 6),
                    enforce_stationarity=False,
                    enforce_invertibility=False)
results_auto_SARIMA_6 = auto_SARIMA_6.fit(maxiter=1000)
print(results_auto_SARIMA_6.summary())
```

```
                              SARIMAX Results
==============================================================================
==============
Dep. Variable:                     y   No. Observations:              130
Model:          SARIMAX(1, 1, 2)x(2, 0, 2, 6)   Log Likelihood          -839.175
Date:                  Sun, 21 Apr 2024   AIC                    1694.351
Time:                          21:15:20   BIC                    1716.240
Sample:                               0   HQIC                   1703.235
                                 - 130
Covariance Type:                    opg
==============================================================================
===
              coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1      -0.6517      0.277     -2.349      0.019      -1.195      -0.108
ma.L1      -0.1335      0.241     -0.554      0.580      -0.606       0.339
ma.L2      -0.7232      0.218     -3.322      0.001      -1.150      -0.296
ar.S.L6    -0.0001      0.025     -0.006      0.996      -0.048       0.048
```

```
ar.S.L12      1.0526      0.018     57.001      0.000       1.016       1.089
ma.S.L6       0.0636      0.152      0.419      0.675      -0.234       0.361
ma.S.L12     -0.6545      0.087     -7.509      0.000      -0.825      -0.484
sigma2     1.391e+05   1.76e+04      7.890      0.000    1.05e+05    1.74e+05
==============================================================================
========
Ljung-Box (L1) (Q):                   0.26   Jarque-Bera (JB):                21.00
Prob(Q):                              0.61   Prob(JB):                         0.00
Heteroskedasticity (H):               2.75   Skew:                             0.37
Prob(H) (two-sided):                  0.00   Kurtosis:                         4.97
==============================================================================
========

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

In [120]:

```
#diagnostics plot of SARIMA
results_auto_SARIMA_6.plot_diagnostics(figsize=(12, 8))
plt.show()
```



From the model diagnostics plot, we can see that all the individual diagnostics plots almost follow the theoretical numbers and thus we cannot develop any pattern from these plots.

Predict on the Test Set using this model and evaluate the model.

In [121]:

```
predicted_auto_SARIMA_6 =results_auto_SARIMA_6.get_forecast(steps=len(test))
```

In [122]:

```
predicted_auto_SARIMA_6.summary_frame(alpha=0.05).head()
```

Out[122]:

y	mean	mean_se	mean_ci_lower	mean_ci_upper
0	4672.709251	373.039086	3941.566077	5403.852424
1	7093.670708	381.548387	6345.849612	7841.491805
2	1539.952786	381.550368	792.127806	2287.777766
3	1257.122908	385.158309	502.226493	2012.019323
4	1806.925454	385.631633	1051.101342	2562.749566

In [123]:

```
rmse = mean_squared_error(test['Sparkling'],predicted_auto_SARIMA_6.predicted_mean,squared=F
alse)
print(rmse)
```

642.8246418918768

In [124]:

```
#rmse tale
temp_resultsDf = pd.DataFrame({'Test_RMSE': [rmse]}
                       ,index=['SARIMA(1,1,2)(2,0,2,6)'])


resultsDf0 = pd.concat([resultsDf0,temp_resultsDf])

resultsDf0
```

Out[124]:

	Test_RMSE
ARIMA(2,1,2)	1325.154268
manual ARIMA(2,1,1)	1359.649838
SARIMA(1,1,2)(2,0,2,6)	642.824642

manual_SARIMA

In [125]:

```
#manual_SARIMA.summary
manual_SARIMA_6= sm.tsa.statespace.SARIMAX(train['Sparkling'].values,
                        order=(0, 1, 2),
                        seasonal_order=(2, 0, 2, 6),
                        enforce_stationarity=False,
                        enforce_invertibility=False)
results_manual_SARIMA_6= manual_SARIMA_6.fit(maxiter=1000)
print(results_manual_SARIMA_6.summary())
```

```
                               SARIMAX Results
============================================================================
==============
Dep. Variable:                         y   No. Observations:           130
Model:        SARIMAX(0, 1, 2)x(2, 0, 2, 6)   Log Likelihood         -840.420
Date:                   Sun, 21 Apr 2024   AIC                   1694.840
Time:                           21:15:24   BIC                   1713.993
Sample:                                0   HQIC                  1702.613
                                   - 130
Covariance Type:                     opg
============================================================================
===
              coef    std err        z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1       -0.8398      0.102     -8.223      0.000      -1.040      -0.640
ma.L2       -0.0691      0.104     -0.662      0.508      -0.274       0.135
ar.S.L6      0.0073      0.022      0.326      0.744      -0.036       0.051
ar.S.L12     1.0571      0.017     62.711      0.000       1.024       1.090
ma.S.L6      0.0333      0.142      0.234      0.815      -0.245       0.312
ma.S.L12    -0.6723      0.086     -7.819      0.000      -0.841      -0.504
sigma2    1.418e+05   1.51e+04      9.403      0.000    1.12e+05    1.71e+05
============================================================================
========
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):              30.24
Prob(Q):                              0.95   Prob(JB):                       0.00
Heteroskedasticity (H):               2.99   Skew:                           0.44
Prob(H) (two-sided):                  0.00   Kurtosis:                       5.37
============================================================================
========

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

In [126]:

```
predicted_manual_SARIMA_6 =results_manual_SARIMA_6.get_forecast(steps=len(test))
```

In [127]:

```
predicted_manual_SARIMA_6.summary_frame(alpha=0.05).head()
```

Out[127]:

y	mean	mean_se	mean_ci_lower	mean_ci_upper
0	4756.021732	376.544905	4018.007280	5494.036183
1	7041.957045	381.348431	6294.527856	7789.386235
2	1568.982872	382.890365	818.531546	2319.434198
3	1246.209239	384.426018	492.748088	1999.670389
4	1805.400485	385.945857	1048.960506	2561.840464

In [128]:

```
rmse = mean_squared_error(test['Sparkling'],predicted_manual_SARIMA_6.predicted_mean,squared=False)
print(rmse)
```

646.8865073481762

In [129]:

```
temp_resultsDf = pd.DataFrame({'Test_RMSE': [rmse]}
                              ,index=['manual SARIMA(0,1,2)(2,0,2,6)'])


resultsDf0 = pd.concat([resultsDf0,temp_resultsDf])

resultsDf0
```

Out[129]:

	Test_RMSE
ARIMA(2,1,2)	1325.154268
manual ARIMA(2,1,1)	1359.649838
SARIMA(1,1,2)(2,0,2,6)	642.824642

	Test_RMSE
manual SARIMA(0,1,2)(2,0,2,6)	646.886507

6- Compare the performance of the models

- Compare the performance of all the models built - Choose the best model with proper rationale - Rebuild the best model using the entire data - Make a forecast for the next 12 months

In [130]:

```
resultsDf0
```

Out[130]:

	Test_RMSE
ARIMA(2,1,2)	1325.154268
manual ARIMA(2,1,1)	1359.649838
SARIMA(1,1,2)(2,0,2,6)	642.824642
manual SARIMA(0,1,2)(2,0,2,6)	646.886507

In [131]:

```
resultsDf=pd.concat([resultsDf,resultsDf0])
```

In [132]:

```
#rmse Table
resultsDf
```

Out[132]:

	Test_RMSE
Linear_Regression	1392.438305
SimpleAverageModel	1368.746717
2pointTrailingMovingAverage	811.178937
4pointTrailingMovingAverage	1184.213295
6pointTrailingMovingAverage	1337.200524

	Test_RMSE
9pointTrailingMovingAverage	1422.653281
Alpha=0.03,SimpleExponentialSmoothing	1362.355524
Alpha=0.4,SimpleExponentialSmoothing	1363.037803
Alpha=0.3,Beta=0.3,DoubleExponentialSmoothing	1597.853999
Alpha=0.07,Beta=0.064,Gamma=0.37,TripleExponentialSmoothing	381.655272
Alpha=0.7,Beta=0.4,Gamma=0.3,TripleExponentialSmoothing	422.908833
ARIMA(2,1,2)	1325.154268
manual ARIMA(2,1,1)	1359.649838
SARIMA(1,1,2)(2,0,2,6)	642.824642
manual SARIMA(0,1,2)(2,0,2,6)	646.886507

In [133]:

```
#rmse tale sort by test rmse value
resultsDf.sort_values(by="Test_RMSE",ascending=True)
```

Out[133]:

	Test_RMSE
Alpha=0.07,Beta=0.064,Gamma=0.37,TripleExponentialSmoothing	381.655272
Alpha=0.7,Beta=0.4,Gamma=0.3,TripleExponentialSmoothing	422.908833
SARIMA(1,1,2)(2,0,2,6)	642.824642
manual SARIMA(0,1,2)(2,0,2,6)	646.886507
2pointTrailingMovingAverage	811.178937
4pointTrailingMovingAverage	1184.213295
ARIMA(2,1,2)	1325.154268
6pointTrailingMovingAverage	1337.200524
manual ARIMA(2,1,1)	1359.649838
Alpha=0.03,SimpleExponentialSmoothing	1362.355524
Alpha=0.4,SimpleExponentialSmoothing	1363.037803

	Test_RMSE
SimpleAverageModel	1368.746717
Linear_Regression	1392.438305
9pointTrailingMovingAverage	1422.653281
Alpha=0.3,Beta=0.3,DoubleExponentialSmoothing	1597.853999

best model is Alpha=0.07,Beta=0.064,Gamma=0.37,TripleExponentialSmoothing (Test_rmse value 381.655272)

Rebuild the best model using the entire data - Make a forecast for the next 12 months

In [134]:

```
#full_data_model summary
full_data_model = sm.tsa.ExponentialSmoothing(df_1['Sparkling'],trend='additive',seasonal='multipli
cative')
results_full_data_model = full_data_model.fit()
print(results_full_data_model.summary())
```

```
c:\Users\SABIR\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: Valu
eWarning: No frequency information was provided, so inferred frequency MS will be used.
 self._init_dates(dates, freq)
                ExponentialSmoothing Model Results
================================================================================
=====
Dep. Variable:              Sparkling   No. Observations:              187
Model:          ExponentialSmoothing   SSE                    22325913.148
Optimized:                       True   AIC                        2218.058
Trend:                       Additive   BIC                        2269.756
Seasonal:              Multiplicative   AICC                       2222.129
Seasonal Periods:                  12   Date:              Sun, 21 Apr 2024
Box-Cox:                        False   Time:                      21:15:25
Box-Cox Coeff.:                  None
================================================================================
======
                     coeff              code          optimized
--------------------------------------------------------------------------------
smoothing_level           0.0756735          alpha           True
smoothing_trend           0.0648689           beta           True
smoothing_seasonal        0.2737263          gamma           True
initial_level             2356.2037            l.0           True
initial_trend            -17.101169            b.0           True
initial_seasons.0         0.7131224            s.0           True
initial_seasons.1         0.6756548            s.1           True
initial_seasons.2         0.8830167            s.2           True
initial_seasons.3         0.7897935            s.3           True
initial_seasons.4         0.6534282            s.4           True
```

initial_seasons.5	0.6379082	s.5	True
initial_seasons.6	0.8715216	s.6	True
initial_seasons.7	1.1323447	s.7	True
initial_seasons.8	0.9117161	s.8	True
initial_seasons.9	1.2496749	s.9	True
initial_seasons.10	1.8964959	s.10	True
initial_seasons.11	2.4627512	s.11	True

In [ ]:

Evaluate the model on the whole and predict 12 months into the future (till the end of next year).

In [135]:

```
# Forecast the next 12 months
forecast_12_months = results_full_data_model.forecast(steps=12)

print("Forecast for the next 12 months:")
print(forecast_12_months)
```

```
Forecast for the next 12 months:
1995-08-01    1931.948827
1995-09-01    2351.014431
1995-10-01    3178.501530
1995-11-01    3916.626178
1995-12-01    5982.802931
1996-01-01    1356.447923
1996-02-01    1597.725021
1996-03-01    1828.530596
1996-04-01    1788.993714
1996-05-01    1639.705581
1996-06-01    1553.839348
1996-07-01    1962.350245
Freq: MS, dtype: float64
```

In [136]:

```
rmse = mean_squared_error(df_1['Sparkling'],results_full_data_model.fittedvalues,squared=False)
```

In [137]:

```
print('RMSE of the Full Model',rmse)
```

RMSE of the Full Model 345.52845018024107

In [138]:

```
#forcasted Table
forecast_df = pd.DataFrame(forecast_12_months, columns=['sale'])
forecast_df
```

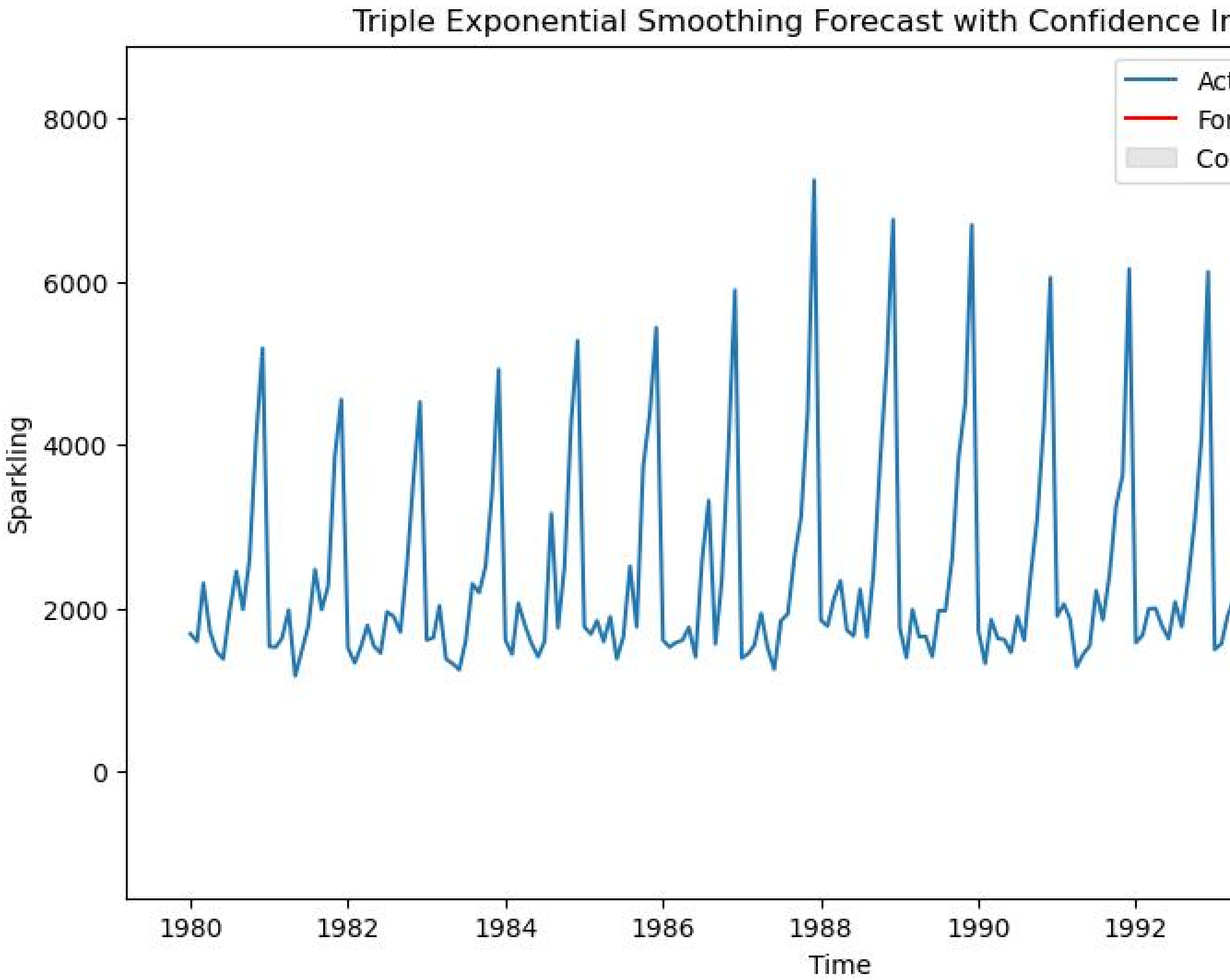
Out[138]:

	sale
1995-08-01	1931.948827
1995-09-01	2351.014431
1995-10-01	3178.501530
1995-11-01	3916.626178
1995-12-01	5982.802931
1996-01-01	1356.447923
1996-02-01	1597.725021
1996-03-01	1828.530596
1996-04-01	1788.993714
1996-05-01	1639.705581
1996-06-01	1553.839348
1996-07-01	1962.350245

In [139]:

```
# Plot the forecast
plt.figure(figsize=(10, 6))
```

```
plt.plot(df_1['Sparkling'], label='Actual')
plt.plot(forecast_12_months, color='red', label='Forecast')
plt.fill_between(
    forecast_12_months.index,
    forecast_12_months - 1.96 * results_full_data_model.fittedvalues.std(),
    forecast_12_months + 1.96 * results_full_data_model.fittedvalues.std(),
    color='gray', alpha=0.2, label='Confidence Interval (95%)'
)
plt.legend()
plt.title('Triple Exponential Smoothing Forecast with Confidence Interval')
plt.xlabel('Time')
plt.ylabel('Sparkling')
plt.show()
```



Actionable Insights & Recommendations

- Conclude with the key takeaways (actionable insights and recommendations) for the business

Inference

- for the given Sparkling data set there is not much compared to previous year.
- December month has the highest sales in a year.

- Model plot was build based on trend and seasonality.we see the future prediction is inline with the previous year prediction.

Recommendation

- Sparkling wine sale are seasonal
- Company should plan a head and keep enough stock from september till december to captlize on the demand
- In order to increase the sales company should plan some promotional offers from january till june so that there will be steady sales throughout the year

##

Rose wine sale

QUESTION -1

Define the problem and perform Exploratory Data Analysis- Read the data as an appropriate time series data - Plot the data - Perform EDA - Perform Decomposition

In [ ]:

In [140]:

```
#READ DATA SET
df_2=pd.read_csv("Rose (1).csv")
```

In [141]:

```
#first 5 rows of data set
df_2.head()
```

KB

In [143]:

```
#convert YearMonth column as index,and change YearMonth column to date time type
df_2=pd.read_csv("Rose (1).csv",parse_dates=True,index_col="YearMonth")
```

In [144]:

```
#first 5 rows
df_2.head()
```

Out[144]:

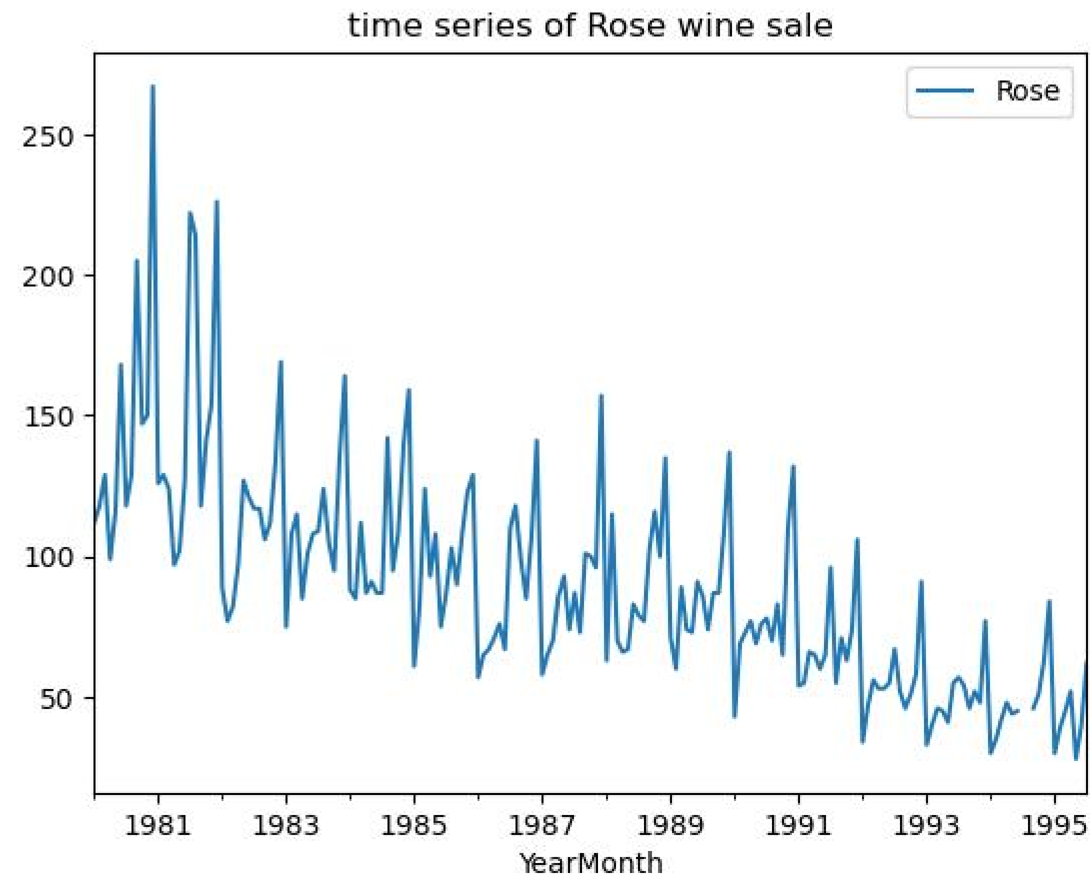
	Rose
YearMonth	
1980-01-01	112.0
1980-02-01	118.0
1980-03-01	129.0
1980-04-01	99.0
1980-05-01	116.0

In [145]:

```
#time series of Rose wine sale
df_2.plot()
plt.title("time series of Rose wine sale")
```

Out[145]:

Text(0.5, 1.0, 'time series of Rose wine sale')



we can see the trend is downward trend.

Perform EDA

In [146]:

#check information about the Data Set
df_2.info()
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 187 entries, 1980-01-01 to 1995-07-01
Data columns (total 1 columns):
 #   Column Non-Null Count Dtype
--- ------ -------------- -----
 0   Rose   185 non-null   float64

dtypes: float64(1)
memory usage: 2.9 KB

this dataset have 2 missing value.

In [147]:

```
#check null values
df_2.isnull().sum()
```

Out[147]:

```
Rose    2
dtype: int64
```

there no null values after interploation treatment

In [148]:

```
missing_rows = df_2[df_2.isnull().any(axis=1)]

# Print or view the rows with missing values
print(missing_rows)
```

```
            Rose
YearMonth
1994-07-01   NaN
1994-08-01   NaN
```

In [149]:

```
## Interpolate missing values using spline interpolation
df_2['Rose'] = df_2['Rose'].interpolate(method='spline', order=3)

# Print the DataFrame with missing values removed and interpolated
print(df_2)
```

```
             Rose
YearMonth
1980-01-01  112.0
1980-02-01  118.0
1980-03-01  129.0
1980-04-01   99.0
1980-05-01  116.0
```

```
...         ...
1995-03-01   45.0
1995-04-01   52.0
1995-05-01   28.0
1995-06-01   40.0
1995-07-01   62.0

[187 rows x 1 columns]
```

In [150]:

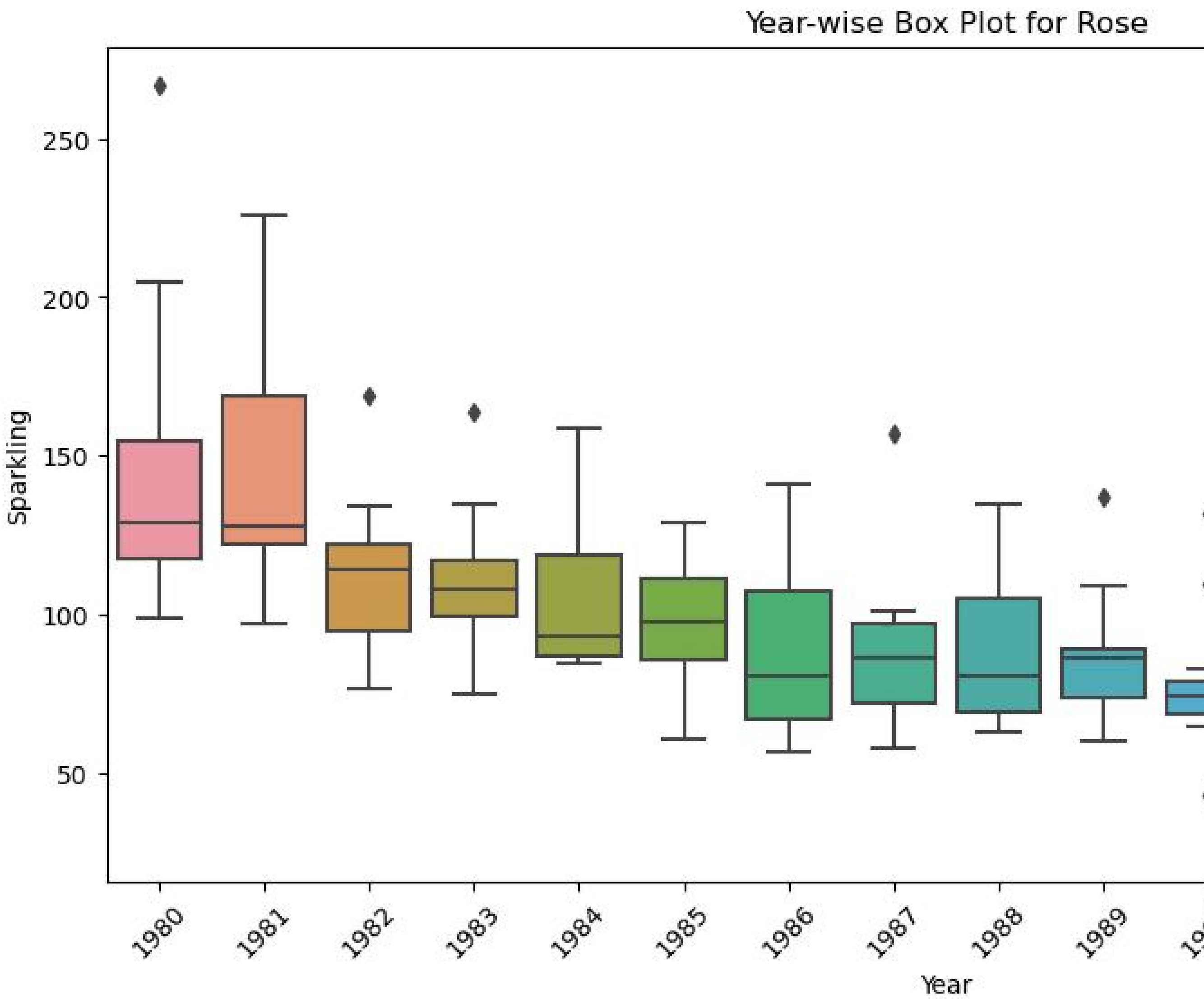
```python
#print statical summary of the data set
df_2.describe()
```

Out[150]:

	Rose
count	187.000000
mean	89.898722
std	39.256515
min	28.000000
25%	62.500000
50%	85.000000
75%	111.000000
max	267.000000

In [151]:

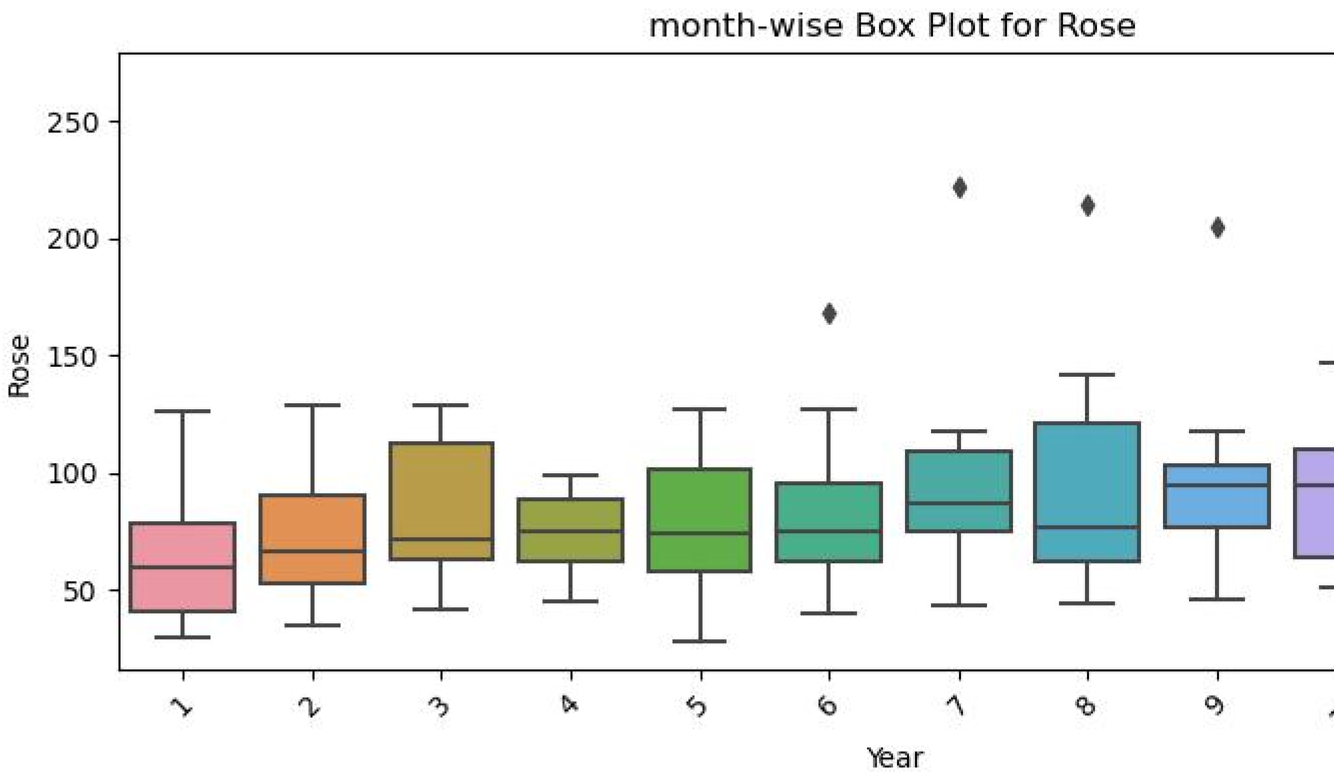
```python
#Year-wise Box Plot for Rose
import seaborn as sns
plt.figure(figsize=(12, 6))
sns.boxplot(data=df_2, x=df_2.index.year, y='Rose')
plt.title('Year-wise Box Plot for Rose')
plt.xlabel('Year')
plt.ylabel('Sparkling')
plt.xticks(rotation=45)
plt.show()
```



Sales have decreased towards the last few years
Year 1981 seems to be having highest sales and lowest seems to be year 1994

In [152]:

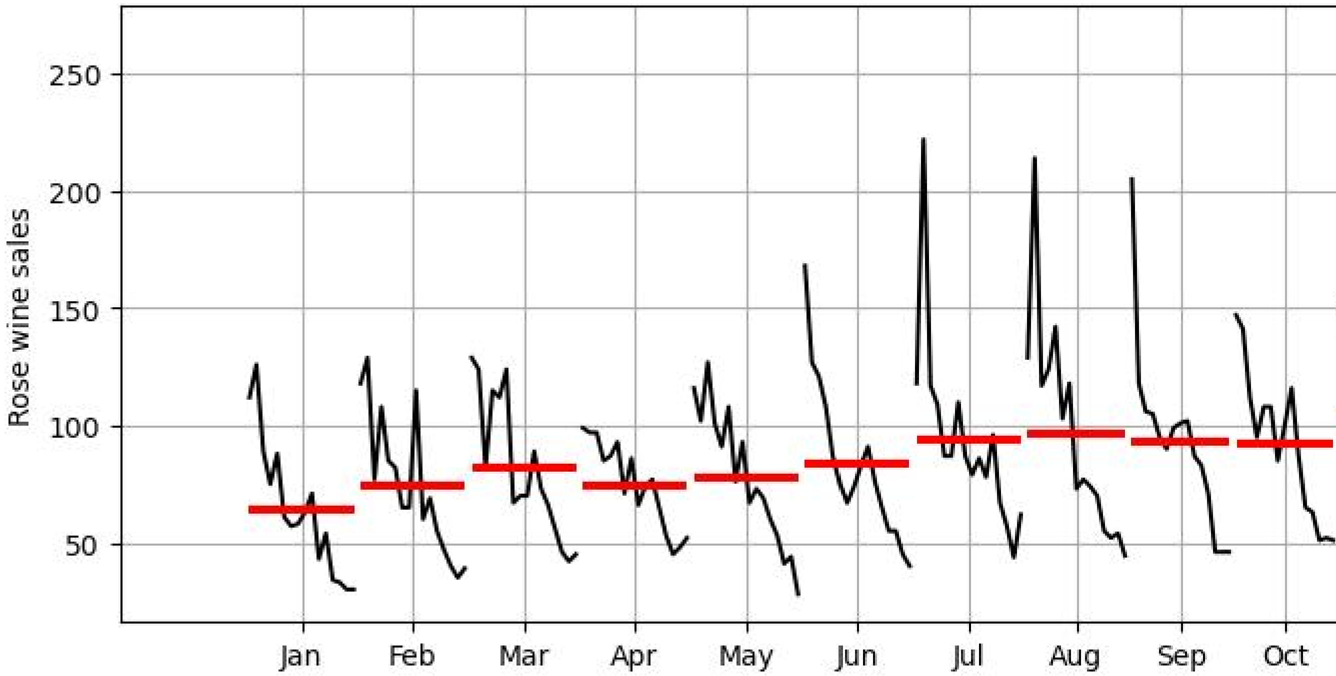
```
#month-wise Box Plot for Rose
plt.figure(figsize=(10,4))
sns.boxplot(data=df_2,x=df_2.index.month,y="Rose")
plt.title("month-wise Box Plot for Rose")
plt.xlabel('Year')
plt.ylabel('Rose')
plt.xticks(rotation=45)
plt.show()
```



outliers present in the dataset for month june,july,August,september and december
december month has highest sales in a year

In [153]:

```
#month wise sale
from statsmodels.graphics.tsaplots import month_plot
fig,ax=plt.subplots(figsize=(10,4))
month_plot(df_2,ylabel="Rose wine sales",ax=ax)
plt.grid();
```



low sale in April

In [154]:

```
#pivot table yearly_sales_across_months
yearly_sales_across_months=pd.pivot_table(data=df_2,values="Rose",index=df_2.index.year,columns=df_2.index.month)
yearly_sales_across_months
```

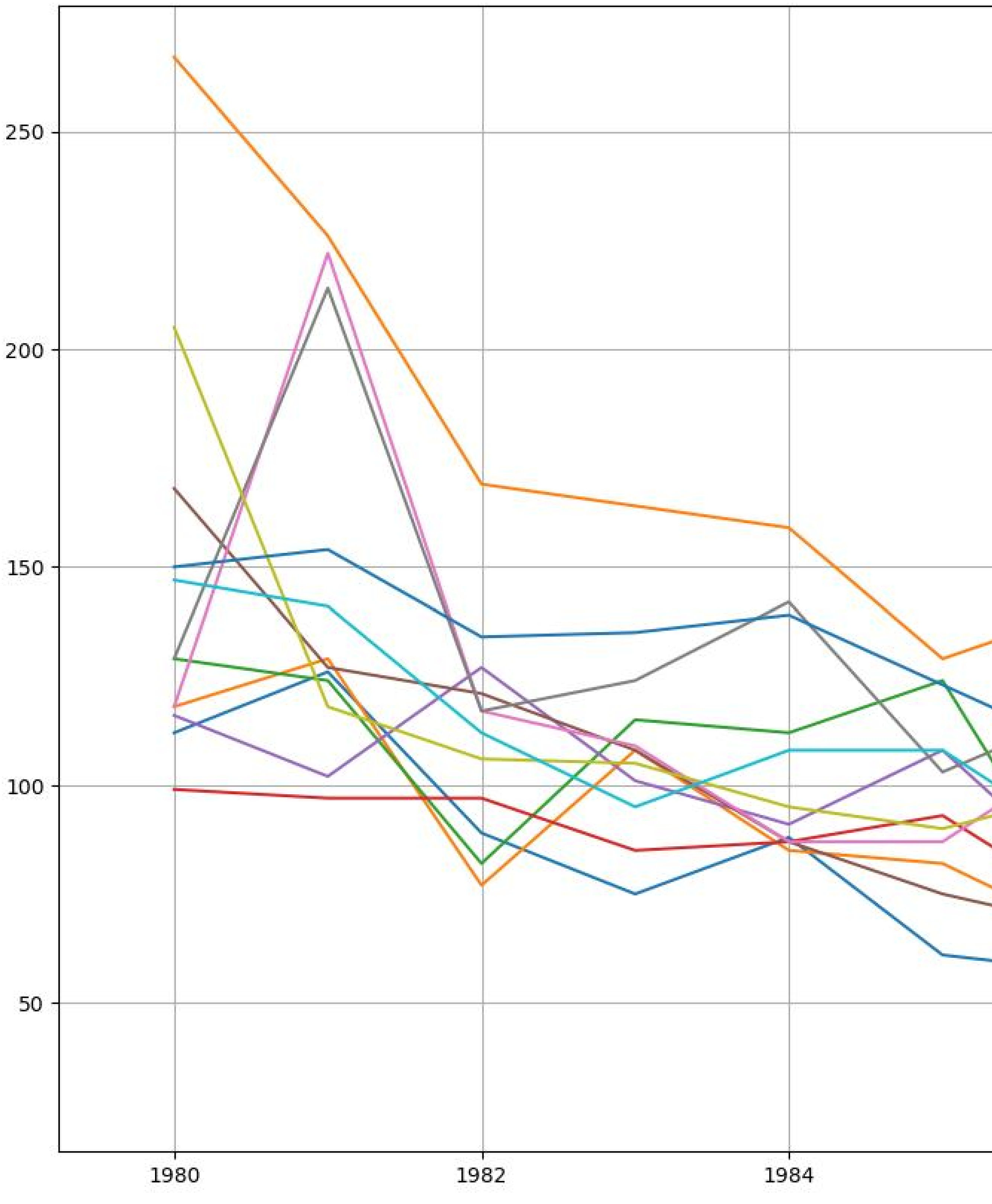
Out[154]:

YearMonth	1	2	3	4	5	6	7	8	9	10	11	12
YearMonth												
1980	112.0	118.0	129.0	99.0	116.0	168.0	118.000000	129.000000	205.0	147.0	150.0	267.0
1981	126.0	129.0	124.0	97.0	102.0	127.0	222.000000	214.000000	118.0	141.0	154.0	226.0
1982	89.0	77.0	82.0	97.0	127.0	121.0	117.000000	117.000000	106.0	112.0	134.0	169.0
1983	75.0	108.0	115.0	85.0	101.0	108.0	109.000000	124.000000	105.0	95.0	135.0	164.0
1984	88.0	85.0	112.0	87.0	91.0	87.0	87.000000	142.000000	95.0	108.0	139.0	159.0

YearMonth	1	2	3	4	5	6	7	8	9	10	11	12
YearMonth												
1985	61.0	82.0	124.0	93.0	108.0	75.0	87.000000	103.000000	90.0	108.0	123.0	129.0
1986	57.0	65.0	67.0	71.0	76.0	67.0	110.000000	118.000000	99.0	85.0	107.0	141.0
1987	58.0	65.0	70.0	86.0	93.0	74.0	87.000000	73.000000	101.0	100.0	96.0	157.0
1988	63.0	115.0	70.0	66.0	67.0	83.0	79.000000	77.000000	102.0	116.0	100.0	135.0
1989	71.0	60.0	89.0	74.0	73.0	91.0	86.000000	74.000000	87.0	87.0	109.0	137.0
1990	43.0	69.0	73.0	77.0	69.0	76.0	78.000000	70.000000	83.0	65.0	110.0	132.0
1991	54.0	55.0	66.0	65.0	60.0	65.0	96.000000	55.000000	71.0	63.0	74.0	106.0
1992	34.0	47.0	56.0	53.0	53.0	55.0	67.000000	52.000000	46.0	51.0	58.0	91.0
1993	33.0	40.0	46.0	45.0	41.0	55.0	57.000000	54.000000	46.0	52.0	48.0	77.0
1994	30.0	35.0	42.0	48.0	44.0	45.0	43.656385	44.404582	46.0	51.0	63.0	84.0
1995	30.0	39.0	45.0	52.0	28.0	40.0	62.000000	NaN	NaN	NaN	NaN	NaN

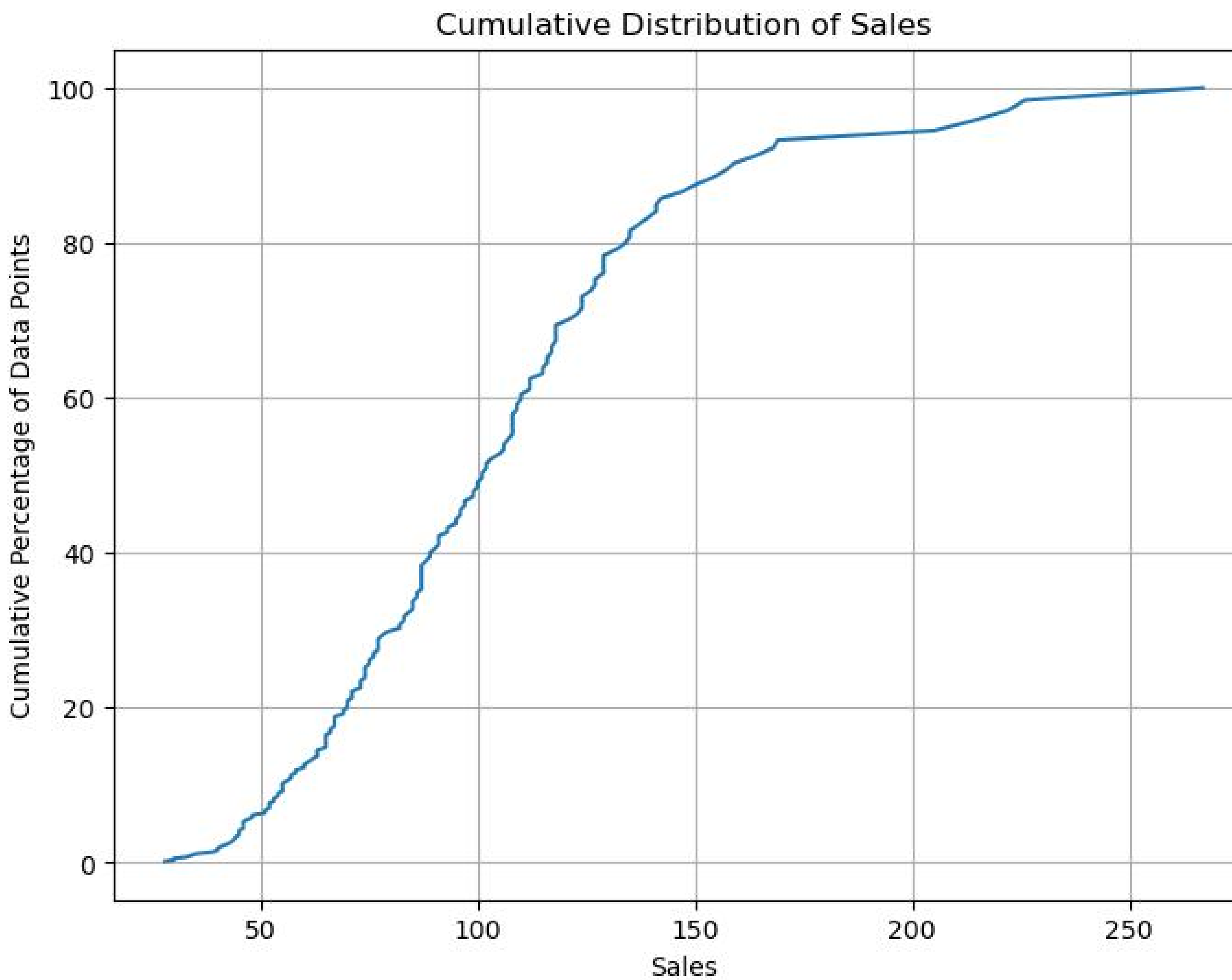
In [155]:

```
#yearly_sales_across_months
fig,ax=plt.subplots(figsize=(22,10))
yearly_sales_across_months.plot(ax=ax)
plt.grid();
```



In [156]:

```
df_sorted = df_2.sort_values(by='Rose')

# Calculate cumulative distribution
total_sales = df_sorted['Rose'].sum()
df_sorted['Cumulative_Percentage'] = (df_sorted['Rose'].cumsum() / total_sales) * 100

# Plot the cumulative distribution
plt.figure(figsize=(8, 6))
plt.plot(df_sorted['Rose'], df_sorted['Cumulative_Percentage'])
plt.title('Cumulative Distribution of Sales')
plt.xlabel('Sales')
plt.ylabel('Cumulative Percentage of Data Points')
plt.grid(True)
plt.show()
```



cumulative graph tells us what percentage of data points refer to what number of sales

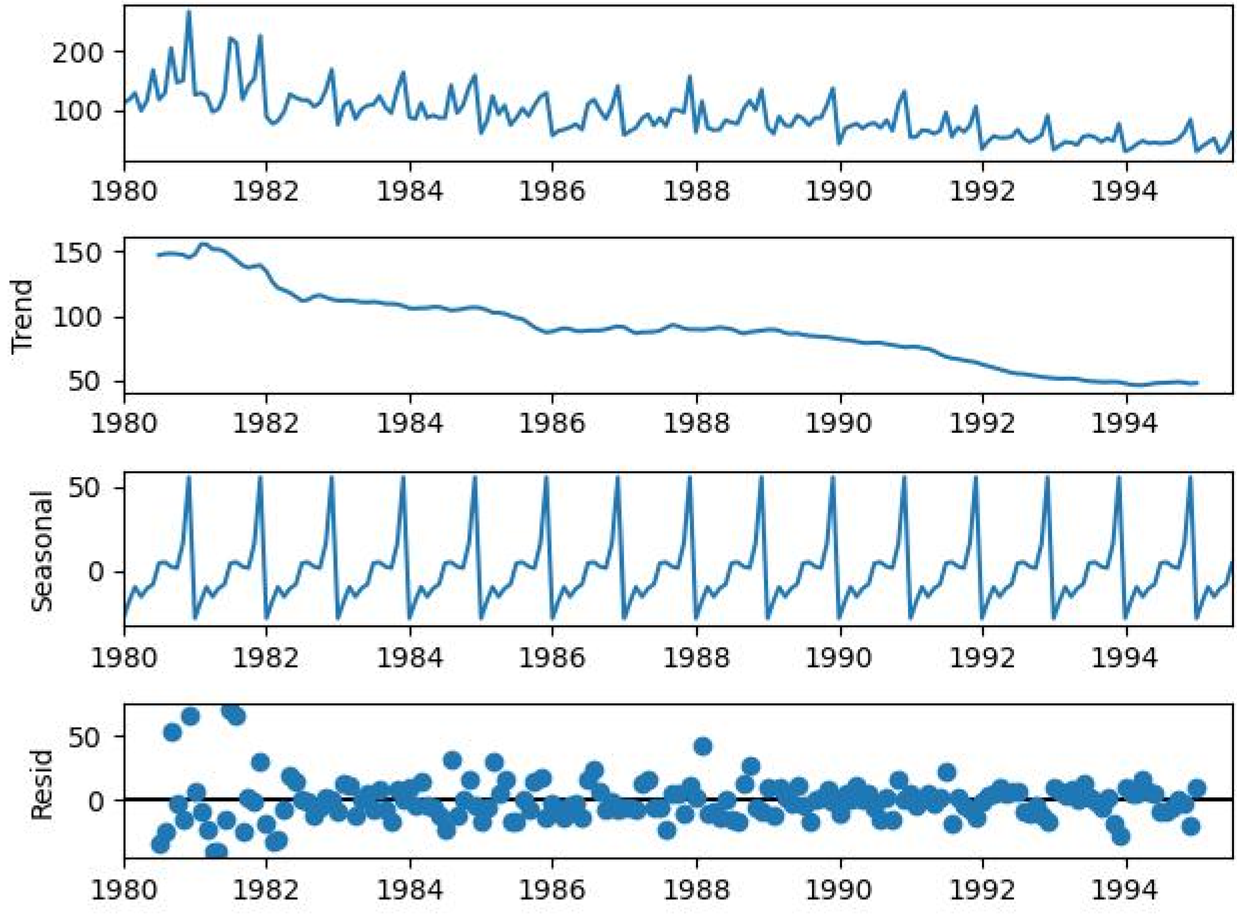
Perform Decomposition¶

In [157]:

```
from statsmodels.tsa.seasonal import seasonal_decompose
```

In [158]:

```
#additive decomposition
decomposition = seasonal_decompose(df_2,model='additive')
decomposition.plot();
```



strong strong seasonality present.
decreasing trend

In [159]:

```
trend = decomposition.trend
seasonality = decomposition.seasonal
residual = decomposition.resid
```

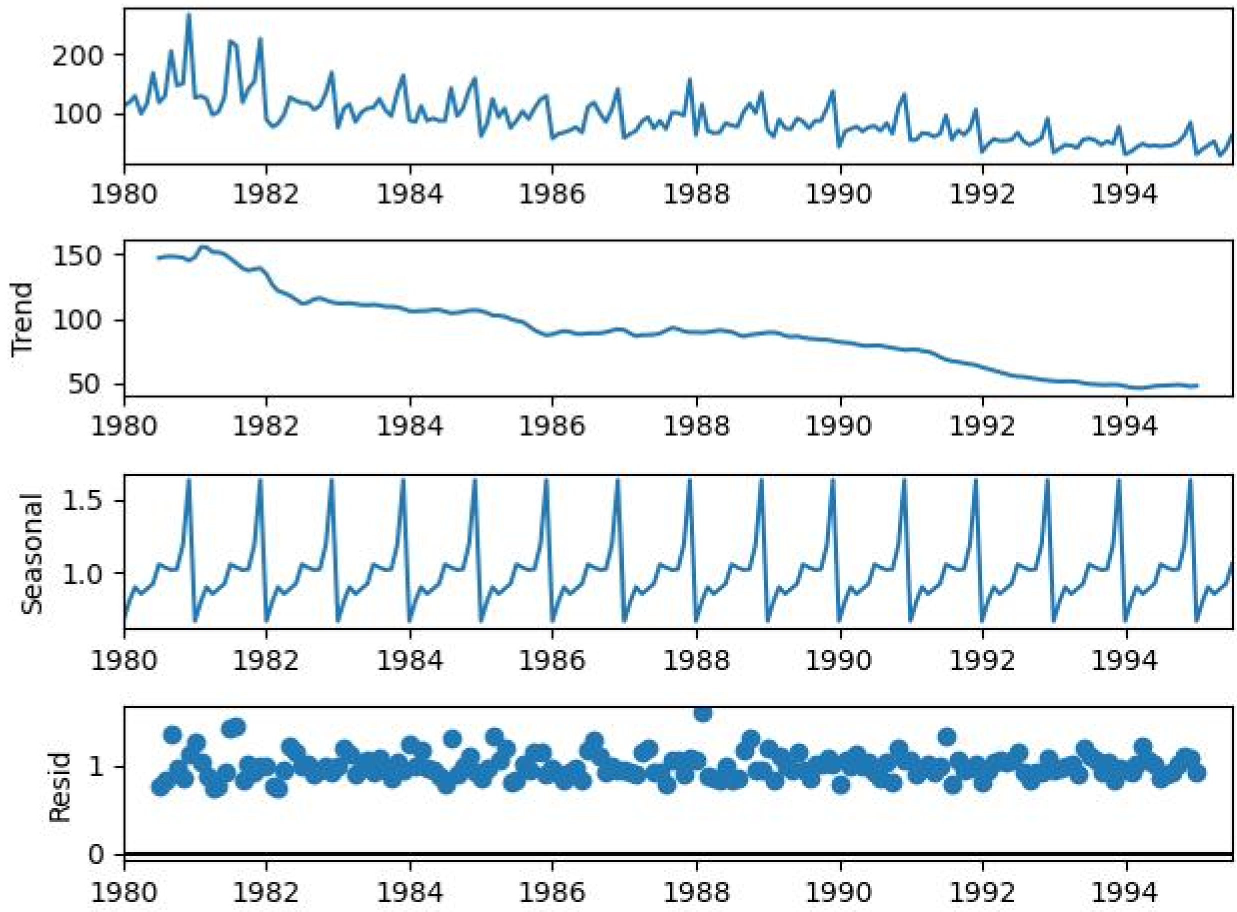
In [160]:

```
print("trend-------------------------------")
print(trend.head())
print("seasonality---------------------------------")
print(seasonality.head())
print("residual-----------------------------------")
print(residual.head())
```

```
trend-------------------------------
YearMonth
1980-01-01   NaN
1980-02-01   NaN
1980-03-01   NaN
1980-04-01   NaN
1980-05-01   NaN
Name: trend, dtype: float64
seasonality---------------------------------
YearMonth
1980-01-01   -27.892492
1980-02-01   -17.422067
1980-03-01    -9.268509
1980-04-01   -15.081009
1980-05-01   -10.179223
Name: seasonal, dtype: float64
residual-----------------------------------
YearMonth
1980-01-01   NaN
1980-02-01   NaN
1980-03-01   NaN
1980-04-01   NaN
1980-05-01   NaN
Name: resid, dtype: float64
```

In [161]:

```
#multiplicative decomposition
decomposition = seasonal_decompose(df_2,model='multiplicative')
decomposition.plot();
```



residual is more in 1
for all residuals are locate around 1

In [162]:

```
trend = decomposition.trend
seasonality = decomposition.seasonal
residual = decomposition.resid
```

In [163]:

```
print("trend--------------------------")
print(trend.head())
print("seasonality------------------------")
print(seasonality.head())
print("residual-------------------------------")
print(residual.head())
```

trend--------------------------
YearMonth

```
1980-01-01   NaN
1980-02-01   NaN
1980-03-01   NaN
1980-04-01   NaN
1980-05-01   NaN
Name: trend, dtype: float64
seasonality-----------------------
YearMonth
1980-01-01    0.670317
1980-02-01    0.806374
1980-03-01    0.901496
1980-04-01    0.854406
1980-05-01    0.889755
Name: seasonal, dtype: float64
residual-----------------------------
YearMonth
1980-01-01   NaN
1980-02-01   NaN
1980-03-01   NaN
1980-04-01   NaN
1980-05-01   NaN
Name: resid, dtype: float64
```

QUESTION-2

Data Pre-processing

- Missing value treatment - Visualize the processed data - Train-test split

In [164]:

```python
#checking missing values
df_2.isnull().sum()
```

Out[164]:

```
Rose    0
dtype: int64
```

In [165]:

```python
#checking missing values
missing_rows = df_2[df_2.isnull().any(axis=1)]

# Print or view the rows with missing values
print(missing_rows)
```

```
Empty DataFrame
```

Columns: [Rose]
Index: []

In [166]:

```
## Interpolate missing values using spline interpolation
df_2['Rose'] = df_2['Rose'].interpolate(method='spline', order=3)

# Print the DataFrame with missing values removed and interpolated
print(df_2)
```

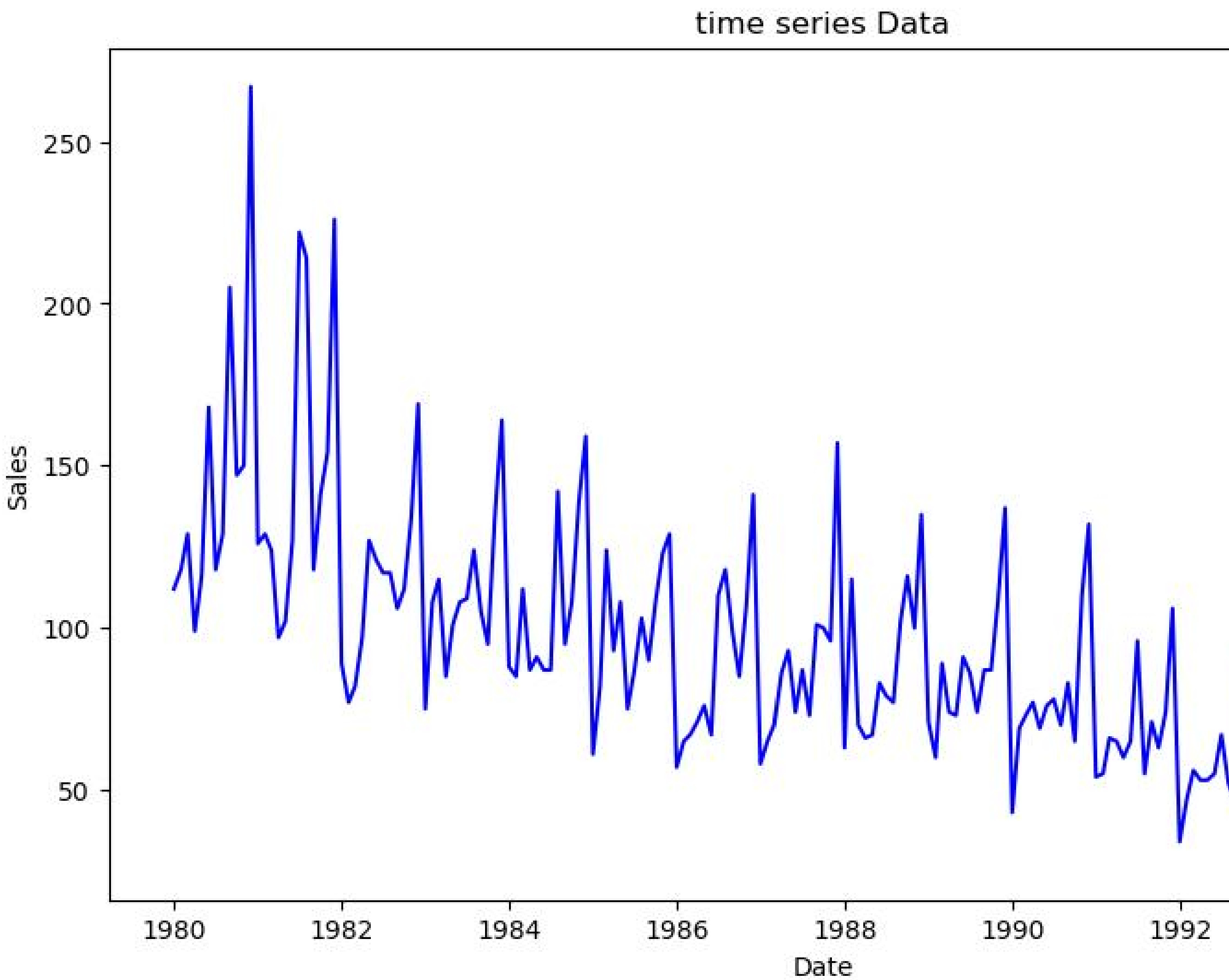
```
             Rose
YearMonth
1980-01-01  112.0
1980-02-01  118.0
1980-03-01  129.0
1980-04-01   99.0
1980-05-01  116.0
...           ...
1995-03-01   45.0
1995-04-01   52.0
1995-05-01   28.0
1995-06-01   40.0
1995-07-01   62.0

[187 rows x 1 columns]
```

we already treated the missing values.

Visualize the processed data

In [167]:

```
# Visualize the Processed Data
plt.figure(figsize=(10, 6))
plt.plot(df_2.index, df_2['Rose'], color='blue')
plt.title('time series Data')
plt.xlabel('Date')
plt.ylabel('Sales')
plt.show()
```



In [168]:

#Train-test split

In [169]:

```
train=df_2[:int(len(df_2)*0.7)]
test   =   df_2[int(len(df_2)*0.7):]
```

In [170]:

```python
print('First few rows of Training Data')
display(train.head())
print('Last few rows of Training Data')
display(train.tail())
print('First few rows of Test Data')
display(test.head())
print('Last few rows of Test Data')
display(test.tail())
```

First few rows of Training Data

	Rose
YearMonth	
1980-01-01	112.0
1980-02-01	118.0
1980-03-01	129.0
1980-04-01	99.0
1980-05-01	116.0

Last few rows of Training Data

	Rose
YearMonth	
1990-06-01	76.0
1990-07-01	78.0
1990-08-01	70.0
1990-09-01	83.0
1990-10-01	65.0

First few rows of Test Data

	Rose
YearMonth	
1990-11-01	110.0
1990-12-01	132.0
1991-01-01	54.0
1991-02-01	55.0
1991-03-01	66.0

Last few rows of Test Data

Rose

YearMonth	
1995-03-01	45.0
1995-04-01	52.0
1995-05-01	28.0
1995-06-01	40.0
1995-07-01	62.0

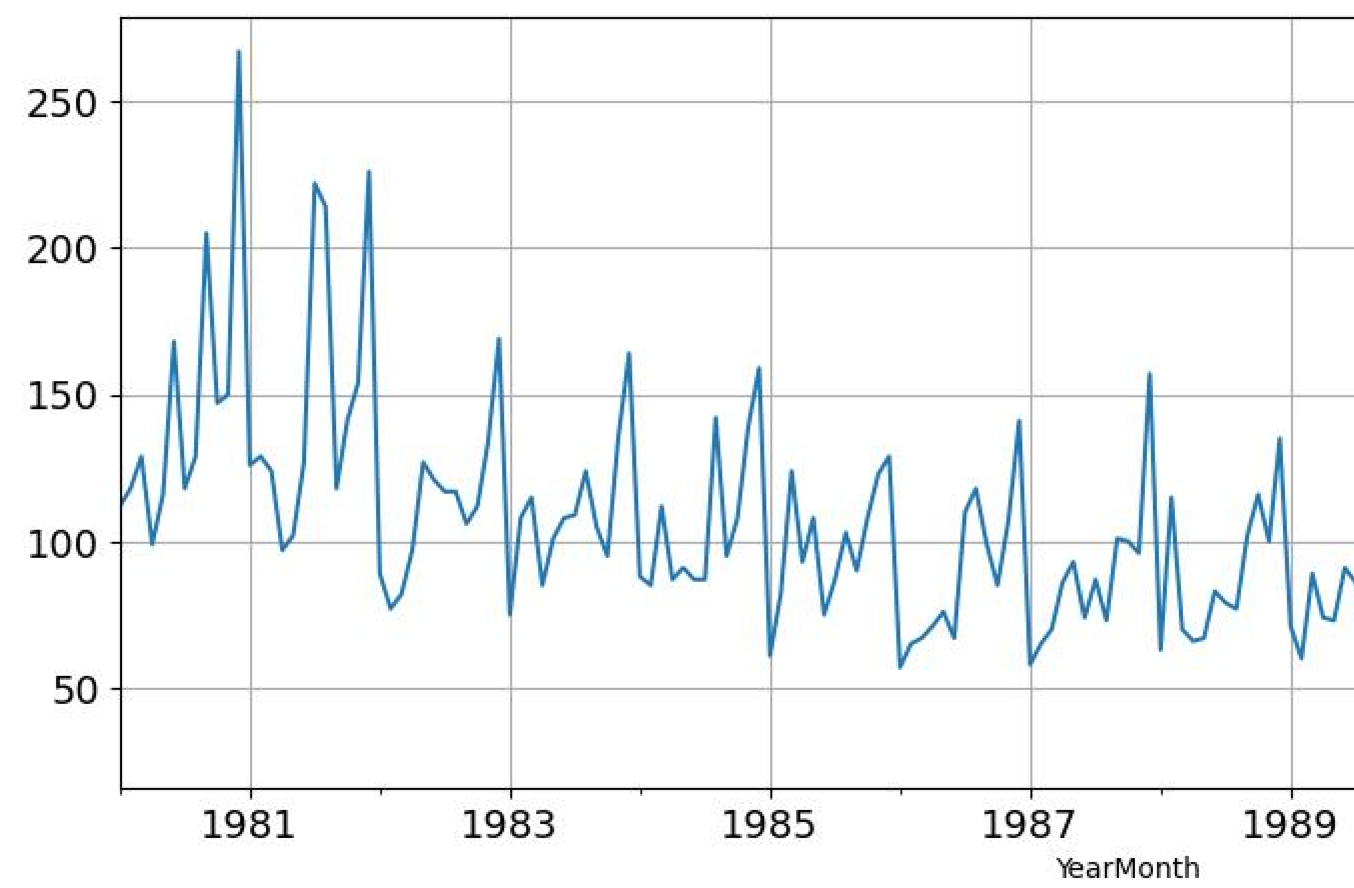
In [171]:

```
print(train.shape)
print(test.shape)
```

(130, 1)
(57, 1)

In [172]:

```
train['Rose'].plot(figsize=(13,5), fontsize=14)
test['Rose'].plot(figsize=(13,5), fontsize=14)
plt.grid()
plt.legend(['Training Data','Test Data'])
plt.show()
```



QUESTION- 3

Model Building - Original Data

- Build forecasting models - Linear regression - Simple Average - Moving Average - Exponential Models (Single, Double, Triple) - Check the performance of the models built

ANSWER

In [173]:

#Build forecasting models

Linear regression

For this particular linear regression, we are going to regress the 'Rose ' variable against the order of the occurrence. For this we need to modify our training data before fitting it into a linear regression.¶

In [174]:

```
train_time=[i+1 for i in range(len(train))]
test_time=[i+131 for i in range(len(test))]
```

In [175]:

```
print('Training Time instance','\n',train_time)
print('Test Time instance','\n',test_time)
```

Training Time instance
 [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101, 102, 103, 104, 105, 106, 107, 108, 109, 110, 111, 112, 113, 114, 115, 116, 117, 118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 130]
Test Time instance
 [131, 132, 133, 134, 135, 136, 137, 138, 139, 140, 141, 142, 143, 144, 145, 146, 147, 148, 149, 150, 151, 152, 153, 154, 155, 156, 157, 158, 159, 160, 161, 162, 163, 164, 165, 166, 167, 168, 169, 170, 171, 172, 173, 174, 175, 176, 177, 178, 179, 180, 181, 182, 183, 184, 185, 186, 187]

We see that we have successfully the generated the numerical time instance order for both the training and test set. Now we will add these values in the training and test set.

In [176]:

```
LinearRegression_train = train.copy()
LinearRegression_test = test.copy()
```

In [177]:

```
LinearRegression_train['time'] = train_time
LinearRegression_test['time'] = test_time

print('First few rows of Training Data','\n',LinearRegression_train.head(),'\n')
print('Last few rows of Training Data','\n',LinearRegression_train.tail(),'\n')
print('First few rows of Test Data','\n',LinearRegression_test.head(),'\n')
print('Last few rows of Test Data','\n',LinearRegression_test.tail(),'\n')
```

First few rows of Training Data
            Rose time

```
YearMonth
1980-01-01  112.0     1
1980-02-01  118.0     2
1980-03-01  129.0     3
1980-04-01   99.0     4
1980-05-01  116.0     5

Last few rows of Training Data
            Rose  time
YearMonth
1990-06-01  76.0   126
1990-07-01  78.0   127
1990-08-01  70.0   128
1990-09-01  83.0   129
1990-10-01  65.0   130

First few rows of Test Data
             Rose  time
YearMonth
1990-11-01  110.0   131
1990-12-01  132.0   132
1991-01-01   54.0   133
1991-02-01   55.0   134
1991-03-01   66.0   135

Last few rows of Test Data
            Rose  time
YearMonth
1995-03-01  45.0   183
1995-04-01  52.0   184
1995-05-01  28.0   185
1995-06-01  40.0   186
1995-07-01  62.0   187
```

Now that our training and test data has been modified, let us go ahead use
_ _
to build the model on the training data and test the model on the test data.

In [178]:

```
from sklearn.linear_model import LinearRegression
```

In [179]:

```
lr = LinearRegression()
```

In [180]:

```
lr.fit(LinearRegression_train[['time']],LinearRegression_train['Rose'].values)
```

Out[180]:

LinearRegression

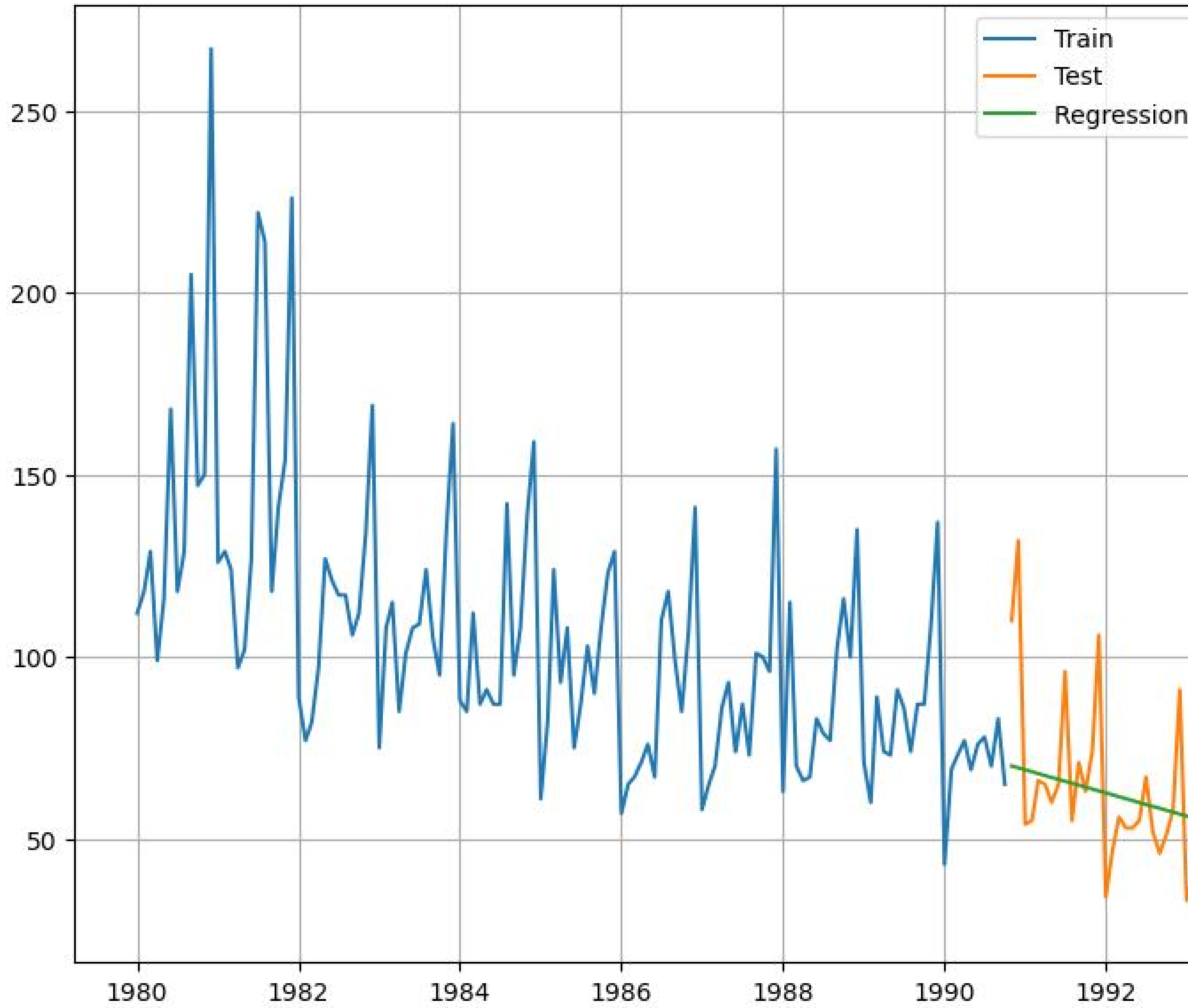
LinearRegression()

In [181]:

```
test_pred_lr=lr.predict(LinearRegression_test[['time']])
LinearRegression_test["RegOnTime"] =test_pred_lr
```

In [182]:

```
plt.figure(figsize=(10,7))
plt.plot(train["Rose"],label="Train")
plt.plot(test["Rose"],label="Test")
plt.plot(LinearRegression_test["RegOnTime"],label='Regression On Time_Test Data')
plt.legend(loc='best')
plt.grid();
```



In [183]:

```
#Defining the accuracy metrics.
from sklearn import metrics
```

In [184]:

```
rmse_lr_test=metrics.mean_squared_error(test["Rose"],test_pred_lr,squared=False)
```

In [185]:

```
print("For RegressionOnTime forecast on the Test Data,  RMSE is %3.2f" %(rmse_lr_test))
```

For RegressionOnTime forecast on the Test Data, RMSE is 17.36

In [186]:

```
#rmse table
resultsDf=pd.DataFrame({"Test_RMSE":[rmse_lr_test]},index=["Linear_Regression"])
resultsDf
```

Out[186]:

	Test_RMSE
Linear_Regression	17.361118

Simple Average

In [187]:

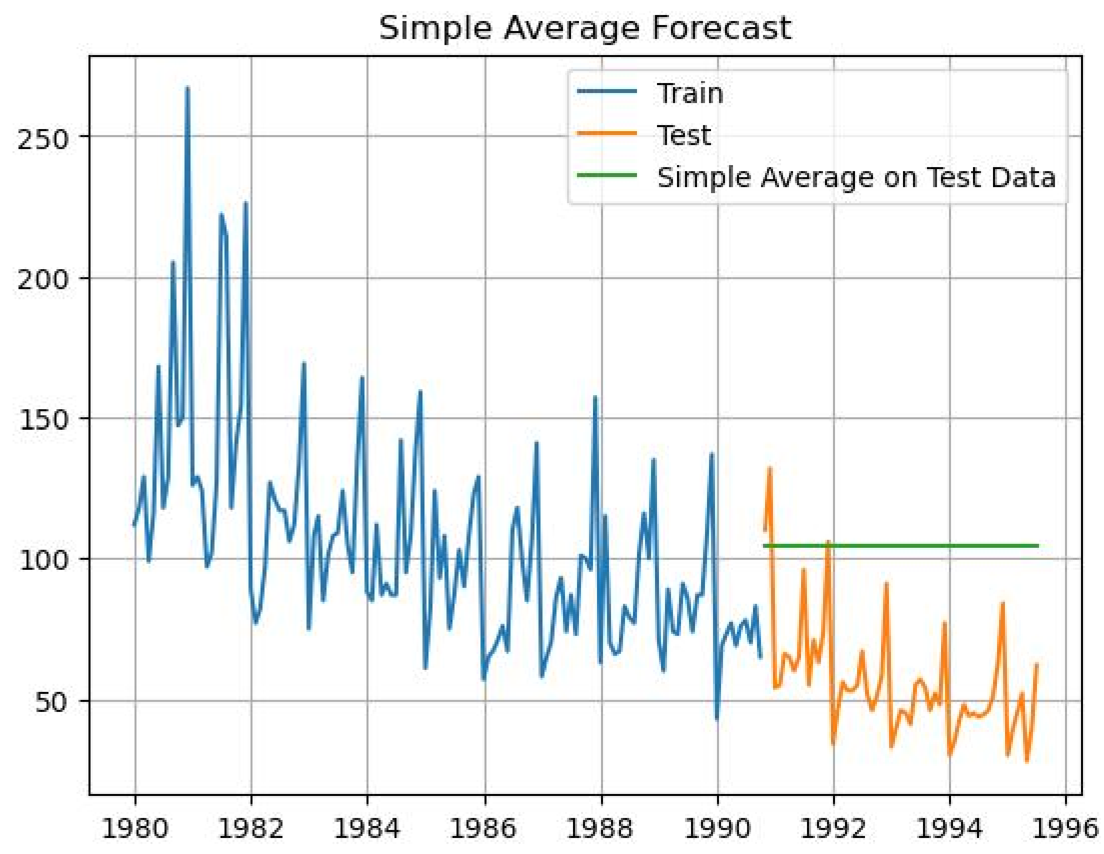
```
#simple Average table
SimpleAverage_train = train.copy()
SimpleAverage_test = test.copy()
SimpleAverage_test['mean_forecast'] = train['Rose'].mean()
SimpleAverage_test.head()
```

Out[187]:

	Rose	mean_forecast
YearMonth		
1990-11-01	110.0	104.692308
1990-12-01	132.0	104.692308
1991-01-01	54.0	104.692308
1991-02-01	55.0	104.692308
1991-03-01	66.0	104.692308

In [188]:

```
#Simple Average plot
plt.plot(SimpleAverage_train['Rose'], label='Train')
plt.plot(SimpleAverage_test["Rose"], label='Test')

plt.plot(SimpleAverage_test['mean_forecast'], label='Simple Average on Test Data')

plt.legend(loc='best')
plt.title("Simple Average Forecast")
plt.grid();
```



In [189]:

```
rmse_simple_avg_test = metrics.mean_squared_error(test['Rose'],SimpleAverage_test['mean_forecast'],squared=False)
print("For Simple Average forecast on the Test Data,  RMSE is %3.3f" %(rmse_simple_avg_test))
```

For Simple Average forecast on the Test Data, RMSE is 52.471

In [190]:

```
#rmse table
resultsDf_2=pd.DataFrame({"Test_RMSE":[rmse_simple_avg_test]},index=["simple_average"])
resultsDf = pd.concat([resultsDf, resultsDf_2])
resultsDf
```

Out[190]:

	Test_RMSE
Linear_Regression	17.361118
simple_average	52.471053

Method 3: Moving Average(MA)

For the moving average model, we are going to calculate rolling means (or moving averages) for different intervals. The best interval can be determined by the maximum accuracy (or the minimum error) over here. For Moving Average, we are going to average over the entire data.

In [191]:

```
Moving_avg=df_2.copy()
Moving_avg.head()
```

Out[191]:

	Rose
YearMonth	
1980-01-01	112.0
1980-02-01	118.0
1980-03-01	129.0
1980-04-01	99.0
1980-05-01	116.0

In [192]:

```
Moving_avg['Trailing_2'] = Moving_avg['Rose'].rolling(2).mean()
Moving_avg['Trailing_4'] = Moving_avg['Rose'].rolling(4).mean()
```

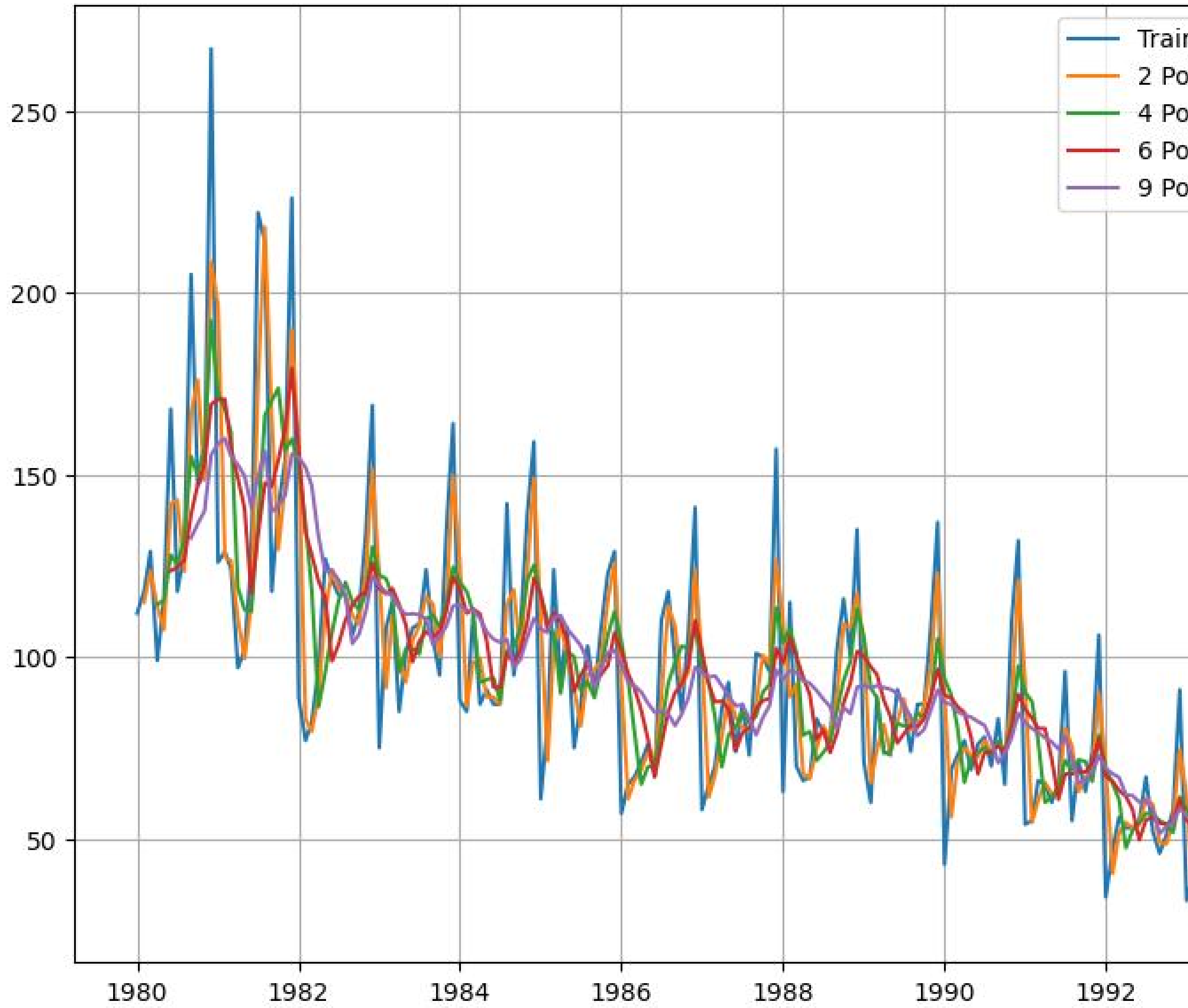
```
Moving_avg['Trailing_6'] = Moving_avg['Rose'].rolling(6).mean()
Moving_avg['Trailing_9'] =Moving_avg['Rose'].rolling(9).mean()

Moving_avg.head()
#moving avg table
```

Out[192]:

	Rose	Trailing_2	Trailing_4	Trailing_6	Trailing_9
YearMonth					
1980-01-01	112.0	NaN	NaN	NaN	NaN
1980-02-01	118.0	115.0	NaN	NaN	NaN
1980-03-01	129.0	123.5	NaN	NaN	NaN
1980-04-01	99.0	114.0	114.5	NaN	NaN
1980-05-01	116.0	107.5	115.5	NaN	NaN

In [193]:

```
## Plotting on the whole data
plt.figure(figsize=(10,7))
plt.plot(Moving_avg['Rose'], label='Train')
plt.plot(Moving_avg['Trailing_2'], label='2 Point Moving Average')
plt.plot(Moving_avg['Trailing_4'], label='4 Point Moving Average')
plt.plot(Moving_avg['Trailing_6'],label = '6 Point Moving Average')
plt.plot(Moving_avg['Trailing_9'],label = '9 Point Moving Average')

plt.legend(loc = 'best')
plt.grid();
```



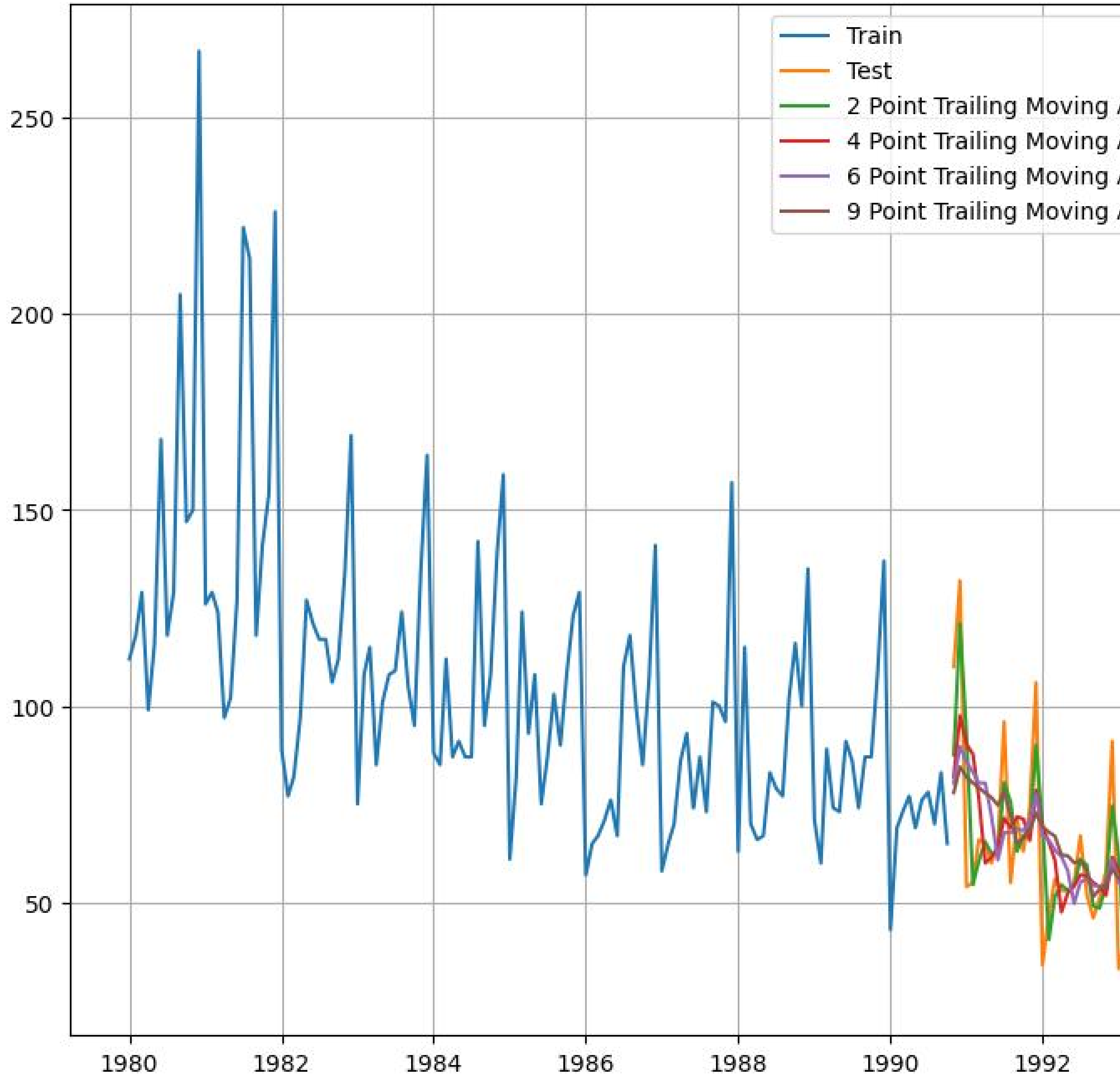
In [194]:

```
#Creating train and test set
trailing_Moving_avg_train=Moving_avg[0:int(len(Moving_avg)*0.7)]
trailing_Moving_avg_test=Moving_avg[int(len(Moving_avg)*0.7):]
```

In [195]:

```
## Plotting on both the Training and Test data

plt.figure(figsize=(10,8))
plt.plot(trailing_Moving_avg_train['Rose'], label='Train')
```

```
plt.plot(trailing_Moving_avg_test['Rose'], label='Test')


plt.plot(trailing_Moving_avg_test['Trailing_2'], label='2 Point Trailing Moving Average on Test Set')
plt.plot(trailing_Moving_avg_test['Trailing_4'], label='4 Point Trailing Moving Average on Test Set')
plt.plot(trailing_Moving_avg_test['Trailing_6'],label = '6 Point Trailing Moving Average on Test Set')
plt.plot(trailing_Moving_avg_test['Trailing_9'],label = '9 Point Trailing Moving Average on Test Set')

plt.legend(loc = 'best')
plt.grid();
```



Model Evaluation

Done only on the test data.

In [196]:

```
## Test Data - RMSE  --> 2 point Trailing MA
rmse_mvg_avg_test_2= metrics.mean_squared_error(test['Rose'],trailing_Moving_avg_test['Trailing_2'],squared=False)
print("For 2 point Moving Average Model forecast on the Training Data,  RMSE is %3.3f" %(rmse_mvg_avg_test_2))

## Test Data - RMSE --> 4 point Trailing MA

rmse_mvg_avg_test_4 = metrics.mean_squared_error(test['Rose'],trailing_Moving_avg_test['Trailing_4'],squared=False)
print("For 4 point Moving Average Model forecast on the Training Data,  RMSE is %3.3f" %(rmse_mvg_avg_test_4))

## Test Data - RMSE --> 6 point Trailing MA

rmse_mvg_avg_test_6 = metrics.mean_squared_error(test['Rose'],trailing_Moving_avg_test['Trailing_6'],squared=False)
print("For 6 point Moving Average Model forecast on the Training Data,  RMSE is %3.3f" %(rmse_mvg_avg_test_6))

## Test Data - RMSE --> 9 point Trailing MA

rmse_mvg_avg_test_9= metrics.mean_squared_error(test['Rose'],trailing_Moving_avg_test['Trailing_9'],squared=False)
print("For 9 point Moving Average Model forecast on the Training Data,  RMSE is %3.3f" %(rmse_mvg_avg_test_9))
```

```
For 2 point Moving Average Model forecast on the Training Data,  RMSE is 11.802
For 4 point Moving Average Model forecast on the Training Data,  RMSE is 15.377
For 6 point Moving Average Model forecast on the Training Data,  RMSE is 15.881
For 9 point Moving Average Model forecast on the Training Data,  RMSE is 16.353
```

In [197]:

```
#rmse Table
resultsDf_3= pd.DataFrame({'Test_RMSE': [rmse_mvg_avg_test_2,rmse_mvg_avg_test_4,rmse_mvg_avg_test_6,rmse_mvg_avg_test_9]}
                         ,index=['2pointTrailingMovingAverage','4pointTrailingMovingAverage'
                                ,'6pointTrailingMovingAverage','9pointTrailingMovingAverage'])

resultsDf = pd.concat([resultsDf, resultsDf_3])
resultsDf
```

Out[197]:

	Test_RMSE
Linear_Regression	17.361118
simple_average	52.471053
2pointTrailingMovingAverage	11.801894
4pointTrailingMovingAverage	15.376848
6pointTrailingMovingAverage	15.880520
9pointTrailingMovingAverage	16.352639

Exponential Models (Single, Double, Triple)

Single Exponential Smoothing Model¶

In [198]:

```
from statsmodels.tsa.api import ExponentialSmoothing,SimpleExpSmoothing,Holt
SES_train=train.copy()
SES_test=test.copy()
```

In [199]:

```
#build model
model_SES=SimpleExpSmoothing(SES_train["Rose"])
```

```
c:\Users\SABIR\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: Valu
eWarning: No frequency information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
```

In [200]:

```
model_SES_autofit=model_SES.fit(optimized=True)
```

In [201]:

```
#SES summary
model_SES_autofit.params
```

Out[201]:

```
{'smoothing_level': 0.10272107174707402,
 'smoothing_trend': nan,
 'smoothing_seasonal': nan,
 'damping_trend': nan,
 'initial_level': 134.26277263347498,
 'initial_trend': nan,
 'initial_seasons': array([], dtype=float64),
 'use_boxcox': False,
 'lamda': None,
 'remove_bias': False}
```

In [202]:

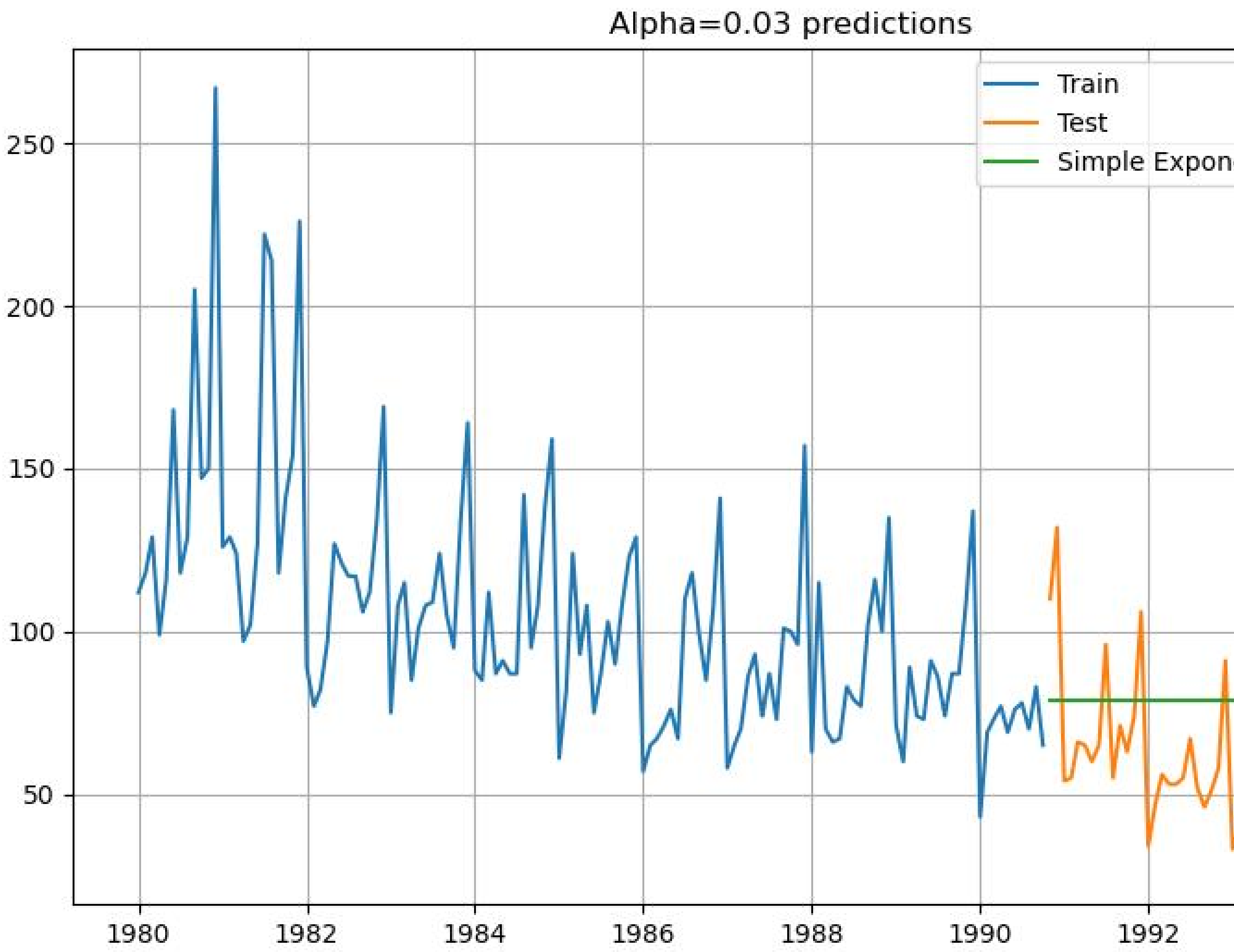
```python
SES_test["predict"]=model_SES_autofit.forecast(steps=len(test))
SES_test.head()
#SES table
```

Out[202]:

	Rose	predict
YearMonth		
1990-11-01	110.0	78.899521
1990-12-01	132.0	78.899521
1991-01-01	54.0	78.899521
1991-02-01	55.0	78.899521
1991-03-01	66.0	78.899521

In [203]:

```python
#SES plot
plt.figure(figsize=(10,6))
plt.plot(train,label="Train")
plt.plot(test,label="Test")
plt.plot(SES_test["predict"],label="Simple Exponentional Smoothing")
plt.legend(loc="best")
plt.grid()
plt.title("Alpha=0.03 predictions");
```



In [204]:

```
rmse_SES_test=metrics.mean_squared_error(SES_test["Rose"],SES_test["predict"],squared=False)
print("For Alpha =0.10 Simple Exponential Smoothing Model forecast on the Test Data, RMSE is %3.3f" %(rmse_SES_test))
```

For Alpha =0.10 Simple Exponential Smoothing Model forecast on the Test Data, RMSE is 30.247

In [205]:

```
#rmse Table
resultsDf_4= pd.DataFrame({'Test_RMSE': [rmse_SES_test]},index=['Alpha=0.10,SimpleExponentialSmoothing'])

resultsDf = pd.concat([resultsDf, resultsDf_4])
```

```
resultsDf
```

Out[205]:

	Test_RMSE
Linear_Regression	17.361118
simple_average	52.471053
2pointTrailingMovingAverage	11.801894
4pointTrailingMovingAverage	15.376848
6pointTrailingMovingAverage	15.880520
9pointTrailingMovingAverage	16.352639
Alpha=0.10,SimpleExponentialSmoothing	30.246633

Setting different alpha values. Remember, the higher the alpha value more weightage is given to the more recent observation. That means, what happened recently will happen again. We will run a loop with different alpha values to understand which particular value works best for alpha on the test set.¶

In [206]:

```
#setting diiferent values
resultsDf_6 = pd.DataFrame({'Alpha Values':[],'Train RMSE':[],'Test RMSE': []})
resultsDf_6
```

Out[206]:

Alpha Values	Train RMSE	Test RMSE

In [207]:

```
for i in np.arange(0.3,1,0.1):
    model_SES_alpha_i = model_SES.fit(smoothing_level=i,optimized=False,use_brute=True)
    SES_train['predict',i] = model_SES_alpha_i.fittedvalues
    SES_test['predict',i] = model_SES_alpha_i.forecast(steps=57)
    
    rmse_model5_train_i = metrics.mean_squared_error(SES_train['Rose'],SES_train['predict',i],squar
ed=False)
    
    rmse_model5_test_i = metrics.mean_squared_error(SES_test['Rose'],SES_test['predict',i],squared=
False)
    
    resultsDf_6 = resultsDf_6.append({'Alpha Values':i,'Train RMSE':rmse_model5_train_i
                                      ,'Test RMSE':rmse_model5_test_i}, ignore_index=True)
```

```
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\2116753667.py:10: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
  resultsDf_6 = resultsDf_6.append({'Alpha Values':i,'Train RMSE':rmse_model5_train_i
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\2116753667.py:10: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
  resultsDf_6 = resultsDf_6.append({'Alpha Values':i,'Train RMSE':rmse_model5_train_i
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\2116753667.py:10: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
  resultsDf_6 = resultsDf_6.append({'Alpha Values':i,'Train RMSE':rmse_model5_train_i
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\2116753667.py:10: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
  resultsDf_6 = resultsDf_6.append({'Alpha Values':i,'Train RMSE':rmse_model5_train_i
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\2116753667.py:10: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
  resultsDf_6 = resultsDf_6.append({'Alpha Values':i,'Train RMSE':rmse_model5_train_i
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\2116753667.py:10: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
  resultsDf_6 = resultsDf_6.append({'Alpha Values':i,'Train RMSE':rmse_model5_train_i
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\2116753667.py:10: FutureWarning:
The frame.append method is deprecated and will be removed from pandas in a future versio
n. Use pandas.concat instead.
  resultsDf_6 = resultsDf_6.append({'Alpha Values':i,'Train RMSE':rmse_model5_train_i
```

In [208]:

```
resultsDf_6
```

Out[208]:

	Alpha Values	Train RMSE	Test RMSE
0	0.3	32.292266	26.366492
1	0.4	32.893017	25.713296
2	0.5	33.578304	25.164534
3	0.6	34.372651	24.583998
4	0.7	35.288467	23.948148
5	0.8	36.330954	23.264723
6	0.9	37.507371	22.547073

In [209]:

```
#Model Evaluation
resultsDf_6.sort_values(by=["Test RMSE"],ascending=True)
```

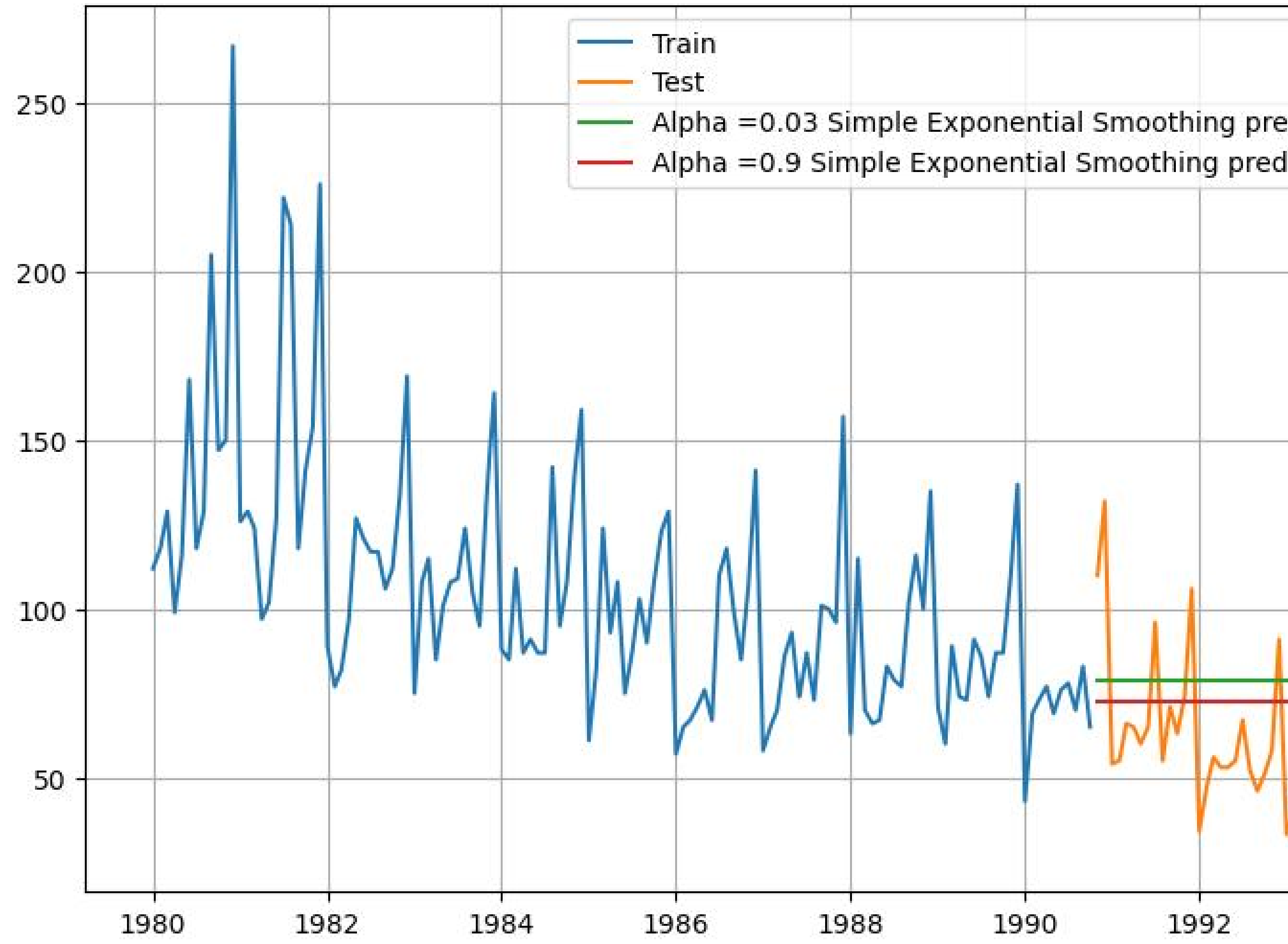
Out[209]:

	Alpha Values	Train RMSE	Test RMSE
6	0.9	37.507371	22.547073
5	0.8	36.330954	23.264723
4	0.7	35.288467	23.948148
3	0.6	34.372651	24.583998
2	0.5	33.578304	25.164534
1	0.4	32.893017	25.713296
0	0.3	32.292266	26.366492

alpha=0.4 model has low test rmse

In [210]:

```
## Plotting on both the Training and Test data

plt.figure(figsize=(10,6))
plt.plot(SES_train['Rose'], label='Train')
plt.plot(SES_test['Rose'], label='Test')

plt.plot(SES_test['predict'], label='Alpha =0.03 Simple Exponential Smoothing predictions on Test Set')

plt.plot(SES_test['predict', 0.4], label='Alpha =0.9 Simple Exponential Smoothing predictions on Test Set')



plt.legend(loc='best')
plt.grid();
```



In [211]:

```
#rmse table
resultsDf_6_1 = pd.DataFrame({'Test_RMSE': [resultsDf_6.sort_values(by=['Test RMSE'],ascending=True).values[0][2]]}
                              ,index=['Alpha=0.9,SimpleExponentialSmoothing'])

resultsDf = pd.concat([resultsDf, resultsDf_6_1])
resultsDf
```

Out[211]:

	Test_RMSE
Linear_Regression	17.361118
simple_average	52.471053
2pointTrailingMovingAverage	11.801894
4pointTrailingMovingAverage	15.376848

	Test_RMSE
6pointTrailingMovingAverage	15.880520
9pointTrailingMovingAverage	16.352639
Alpha=0.10,SimpleExponentialSmoothing	30.246633
Alpha=0.9,SimpleExponentialSmoothing	22.547073

Double Exponential Smoothing (Holt's Model)

Two parameters and are estimated in this model. Level and Trend are accounted for in this model

In [212]:

```
#build model
DES_train = train.copy()
DES_test = test.copy()
model_DES = Holt(DES_train['Rose'])
```

```
c:\Users\SABIR\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
```

In [213]:

```
#setting different values
resultsDf_7 = pd.DataFrame({'Alpha Values':[],'Beta Values':[],'Train RMSE':[],'Test RMSE': []})
resultsDf_7
```

Out[213]:

Alpha Values	Beta Values	Train RMSE	Test RMSE

In [214]:

```
for i in np.arange(0.3,1.1,0.1):
  for j in np.arange(0.3,1.1,0.1):
    model_DES_alpha_i_j = model_DES.fit(smoothing_level=i,smoothing_trend=j,optimized=False,use_brute=True)
    DES_train['predict',i,j] = model_DES_alpha_i_j.fittedvalues
    DES_test['predict',i,j] = model_DES_alpha_i_j.forecast(steps=57)
```

```
    rmse_model6_train = metrics.mean_squared_error(DES_train['Rose'],DES_train['predict',i,j],squ
ared=False)

    rmse_model6_test = metrics.mean_squared_error(DES_test['Rose'],DES_test['predict',i,j],square
d=False)

    resultsDf_7 = resultsDf_7.append({'Alpha Values':i,'Beta Values':j,'Train RMSE':rmse_model6_tra
in
                                      ,'Test RMSE':rmse_model6_test}, ignore_index=True)

#sort values by Test Rmse
resultsDf_7 .sort_values(by="Test RMSE").head()
```

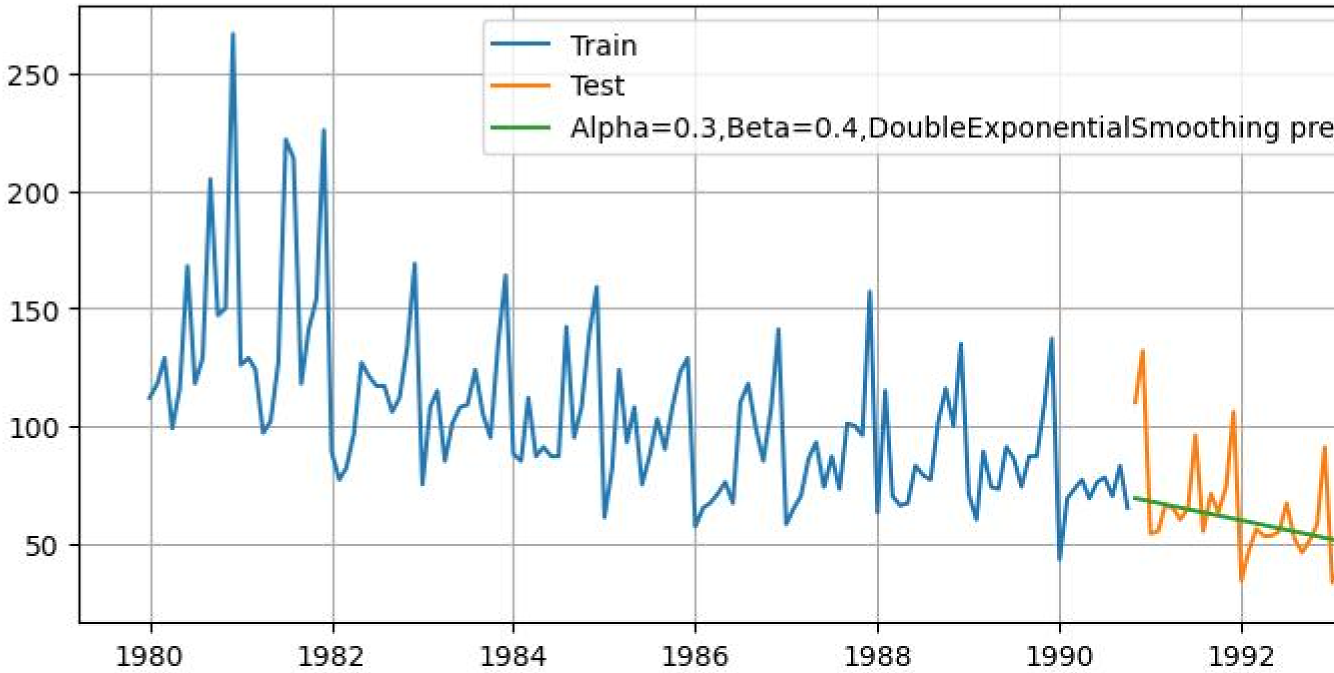
Out[215]:

	Alpha Values	Beta Values	Train RMSE	Test RMSE
1	0.3	0.4	37.287813	18.327400
12	0.4	0.7	40.744796	19.006943
9	0.4	0.4	37.990913	19.168311
17	0.5	0.4	38.598226	19.171709
8	0.4	0.3	36.682435	19.741417

Alpha=0.3,beta=0.4 have low test RMSE

In [216]:

```
## Plotting on both the Training and Test data

plt.figure(figsize=(10,4))
plt.plot(DES_train['Rose'], label='Train')
plt.plot(DES_test['Rose'], label='Test')

plt.plot(DES_test['predict', 0.3, 0.4], label='Alpha=0.3,Beta=0.4,DoubleExponentialSmoothing predicti
ons on Test Set')

plt.legend(loc='best')
plt.grid();
```



In [217]:

```
#rmse table
resultsDf_7_1 = pd.DataFrame({'Test_RMSE': [resultsDf_7.sort_values(by=['Test RMSE']).values[0]
[3]]}
                        ,index=['Alpha=0.3,Beta=0.4,DoubleExponentialSmoothing'])

resultsDf = pd.concat([resultsDf, resultsDf_7_1])
resultsDf
```

Out[217]:

	Test_RMSE
Linear_Regression	17.361118
simple_average	52.471053
2pointTrailingMovingAverage	11.801894
4pointTrailingMovingAverage	15.376848
6pointTrailingMovingAverage	15.880520
9pointTrailingMovingAverage	16.352639
Alpha=0.10,SimpleExponentialSmoothing	30.246633
Alpha=0.9,SimpleExponentialSmoothing	22.547073
Alpha=0.3,Beta=0.4,DoubleExponentialSmoothing	18.327400

Triple Exponential Smoothing (Holt - Winter's Model)

Three parameters , and are estimated in this model. Level, Trend and Seasonality are accounted for in this model.¶

In [218]:

```
TES_train = train.copy()
TES_test = test.copy()
```

In [219]:

```
#build model
model_TES=ExponentialSmoothing(TES_train["Rose"],trend="additive",seasonal="multiplicative")
```

```
c:\Users\SABIR\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: Valu
eWarning: No frequency information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
```

In [220]:

```
model_TES_autofit=model_TES.fit()
```

In [221]:

```
## Prediction on the test data
TES_test['auto_predict'] = model_TES_autofit.forecast(steps=len(test))
TES_test.head()
```

Out[221]:

	Rose	auto_predict
YearMonth		
1990-11-01	110.0	86.307069
1990-12-01	132.0	118.002257
1991-01-01	54.0	51.939718
1991-02-01	55.0	58.202028

	Rose	auto_predict
YearMonth		
1991-03-01	66.0	63.090227

In [222]:

```
## Prediction on the test data

TES_test['auto_predict'] = model_TES_autofit.forecast(steps=len(test))
TES_test.head()
```

Out[222]:

	Rose	auto_predict
YearMonth		
1990-11-01	110.0	86.307069
1990-12-01	132.0	118.002257
1991-01-01	54.0	51.939718
1991-02-01	55.0	58.202028
1991-03-01	66.0	63.090227

In [223]:

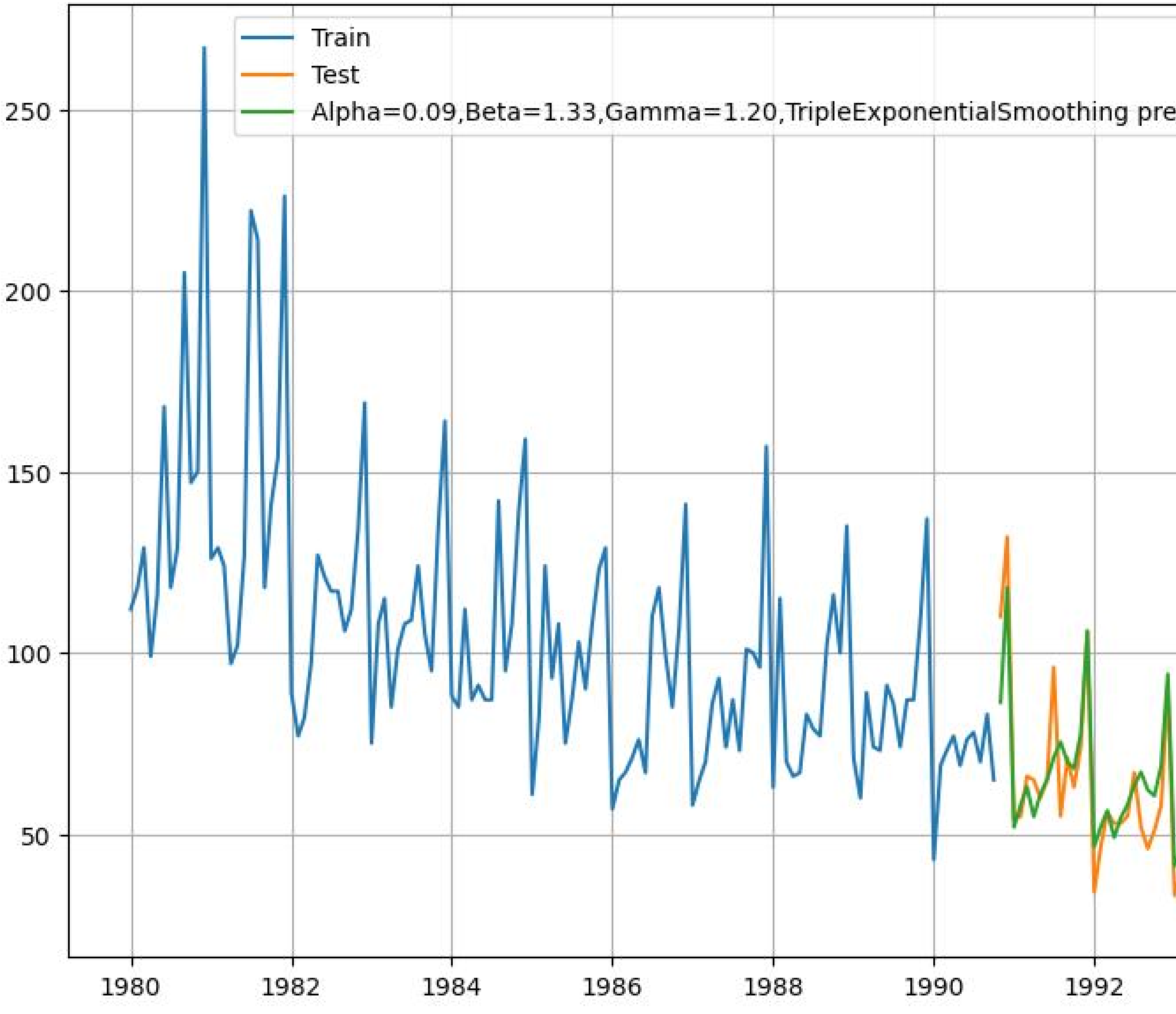
```
#model_TES summary
model_TES_autofit.params
```

Out[223]:

```
{'smoothing_level': 0.09954161352526007,
 'smoothing_trend': 1.3336303508710234e-09,
 'smoothing_seasonal': 1.2069328449342624e-07,
 'damping_trend': nan,
 'initial_level': 158.17849976224244,
 'initial_trend': -0.6388610685846876,
 'initial_seasons': array([0.69310878, 0.78335434, 0.8565105 , 0.75118137, 0.84323397,
        0.90831655, 0.99998662, 1.06934491, 1.00122429, 0.98484092,
        1.13241501, 1.56136821]),
 'use_boxcox': False,
 'lamda': None,
 'remove_bias': False}
```

In [224]:

```
#TripleExponentialSmoothing
plt.figure(figsize=(10,7))
plt.plot(TES_train['Rose'], label='Train')
plt.plot(TES_test['Rose'], label='Test')

plt.plot(TES_test['auto_predict'], label='Alpha=0.09,Beta=1.33,Gamma=1.20,TripleExponentialSmoothing predictions on Test Set')


plt.legend(loc='best')
plt.grid();
```



In [225]:

```
rmse_TES_test_1 = metrics.mean_squared_error(TES_test['Rose'],TES_test['auto_predict'],squared=False)
print("For Alpha=0.09,Beta=1.33,Gamma=1.20, Triple Exponential Smoothing Model forecast on the Test Data,  RMSE is %3.3f" %(rmse_TES_test_1))
```

For Alpha=0.09,Beta=1.33,Gamma=1.20, Triple Exponential Smoothing Model forecast on the Test Data, RMSE is 9.350

In [226]:

```
#rmse table
resultsDf_8= pd.DataFrame({'Test_RMSE': [rmse_TES_test_1]}
                          ,index=['Alpha=0.09,Beta=1.33,Gamma=1.20,TripleExponentialSmoothing'])

resultsDf = pd.concat([resultsDf, resultsDf_8])
resultsDf
```

Out[226]:

	Test_RMSE
Linear_Regression	17.361118
simple_average	52.471053
2pointTrailingMovingAverage	11.801894
4pointTrailingMovingAverage	15.376848
6pointTrailingMovingAverage	15.880520
9pointTrailingMovingAverage	16.352639
Alpha=0.10,SimpleExponentialSmoothing	30.246633
Alpha=0.9,SimpleExponentialSmoothing	22.547073
Alpha=0.3,Beta=0.4,DoubleExponentialSmoothing	18.327400
Alpha=0.09,Beta=1.33,Gamma=1.20,TripleExponentialSmoothing	9.350380

```
#set different values
resultsDf_8_1 = pd.DataFrame({'Alpha Values':[],'Beta Values':[],'Gamma Values':[],'Train RMSE':[],'Test RMSE': []})
resultsDf_8_1
```

Out[227]:

Alpha Values	Beta Values	Gamma Values	Train RMSE	Test RMSE

In [228]:

```
for i in np.arange(0.3,1.1,0.1):
    for j in np.arange(0.3,1.1,0.1):
        for k in np.arange(0.3,1.1,0.1):
            model_TES_alpha_i_j_k = model_TES.fit(smoothing_level=i,smoothing_trend=j,smoothing_se
asonal=k,optimized=False,use_brute=True)
            TES_train['predict',i,j,k] = model_TES_alpha_i_j_k.fittedvalues
            TES_test['predict',i,j,k] = model_TES_alpha_i_j_k.forecast(steps=57)

            rmse_model8_train = metrics.mean_squared_error(TES_train['Rose'],TES_train['predict',i,j,k],s
quared=False)

            rmse_model8_test = metrics.mean_squared_error(TES_test['Rose'],TES_test['predict',i,j,k],squ
ared=False)

            resultsDf_8_1 = resultsDf_8_1.append({'Alpha Values':i,'Beta Values':j,'Gamma Values':k,
                                                  'Train RMSE':rmse_model8_train,'Test RMSE':rmse_model8_test}
                                                 , ignore_index=True)
```

```
resultsDf_8_1 .head()
```

Out[229]:

	Alpha Values	Beta Values	Gamma Values	Train RMSE	Test RMSE
0	0.3	0.3	0.3	23.385275	77.618054
1	0.3	0.3	0.4	24.663714	85.176663
2	0.3	0.3	0.5	26.315722	99.247663
3	0.3	0.3	0.6	28.443126	116.384370
4	0.3	0.3	0.7	31.169740	132.001484

In [230]:

```
#sort values by test rmse
resultsDf_8_1.sort_values(by="Test RMSE").head()
```

Out[230]:

	Alpha Values	Beta Values	Gamma Values	Train RMSE	Test RMSE
33	0.3	0.7	0.4	29.968505	28.301212
177	0.5	0.9	0.4	41.232290	28.896346
25	0.3	0.6	0.4	27.743621	39.592384
78	0.4	0.4	0.9	43.001123	51.487296
135	0.5	0.3	1.0	47.353331	62.101747

alpha=0.3,beta=0.7,gamma=0.4 model has lowest RMSE value

In [231]:

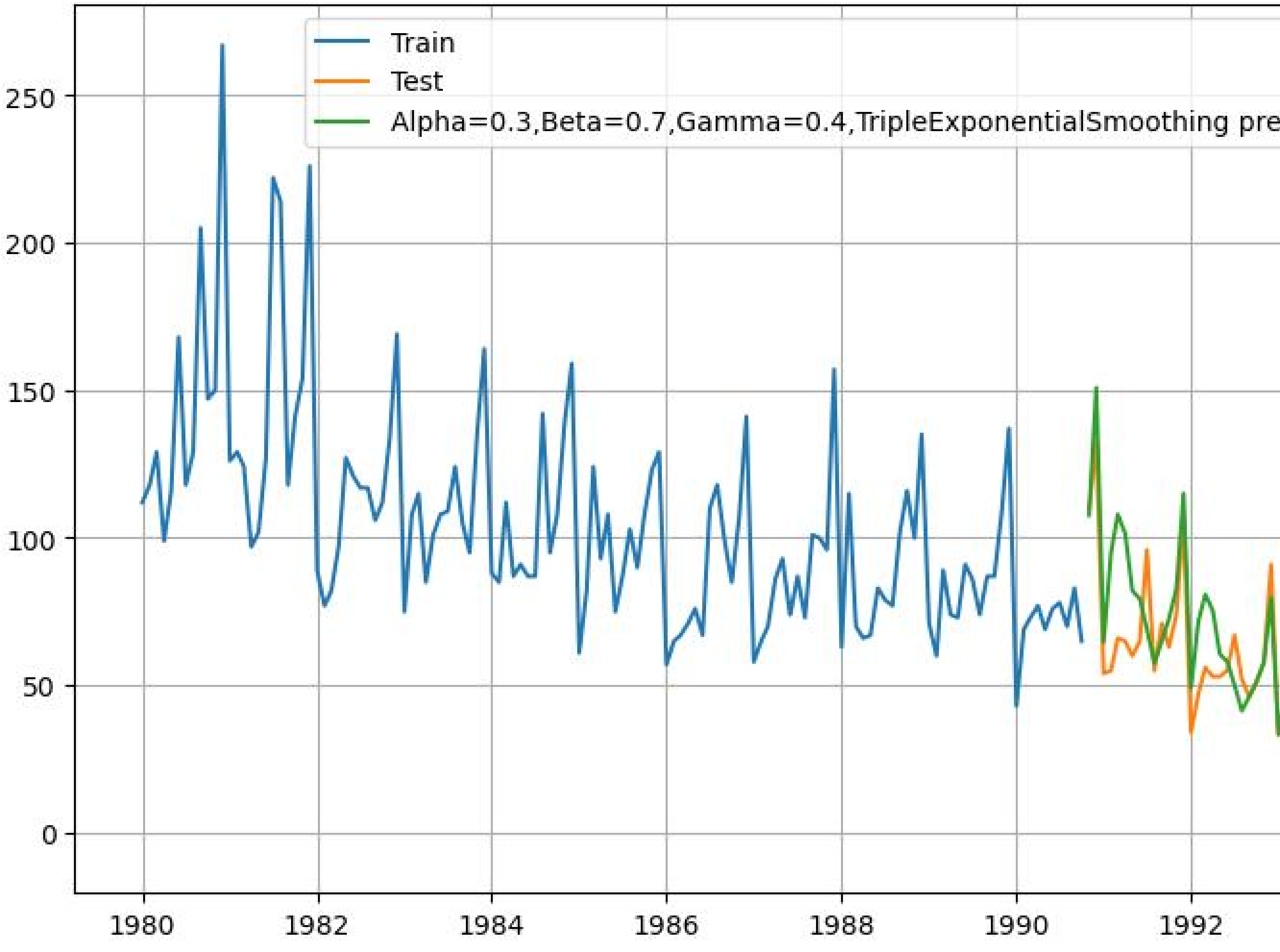
```
#rmse table
resultsDf_8_3 = pd.DataFrame({'Test_RMSE': [resultsDf_8_1.sort_values(by=['Test RMSE']).values[0]
[4]]}
                    ,index=['Alpha=0.7,Beta=0.4,Gamma=0.3,TripleExponentialSmoothing'])

resultsDf = pd.concat([resultsDf, resultsDf_8_3])
resultsDf
```

Out[231]:

	Test_RMSE
Linear_Regression	17.361118
simple_average	52.471053
2pointTrailingMovingAverage	11.801894
4pointTrailingMovingAverage	15.376848
6pointTrailingMovingAverage	15.880520
9pointTrailingMovingAverage	16.352639
Alpha=0.10,SimpleExponentialSmoothing	30.246633
Alpha=0.9,SimpleExponentialSmoothing	22.547073
Alpha=0.3,Beta=0.4,DoubleExponentialSmoothing	18.327400
Alpha=0.09,Beta=1.33,Gamma=1.20,TripleExponentialSmoothing	9.350380
Alpha=0.7,Beta=0.4,Gamma=0.3,TripleExponentialSmoothing	28.301212

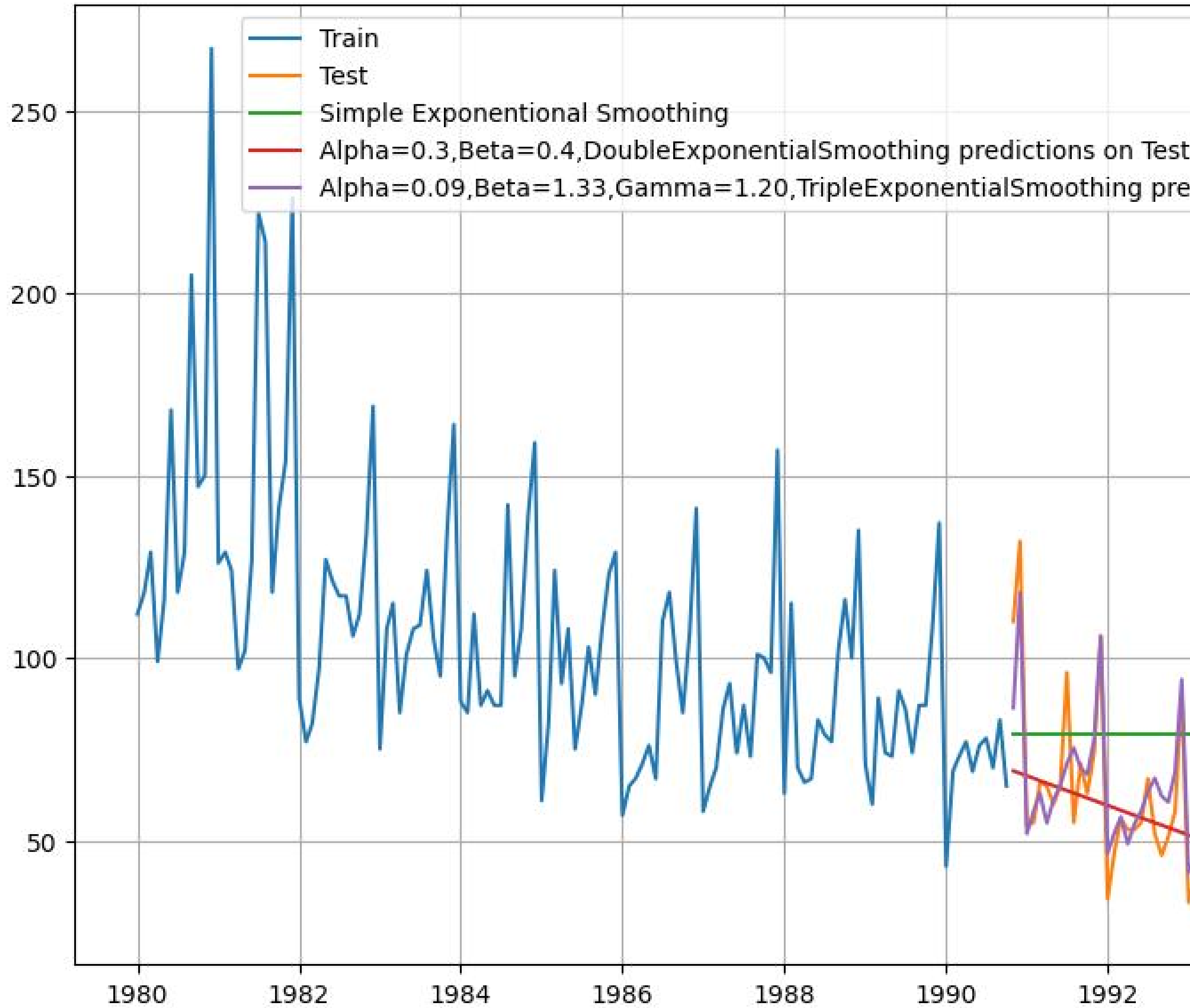
In [232]:

```
#TripleExponentialSmoothing
plt.figure(figsize=(10,6))
plt.plot(TES_train['Rose'], label='Train')
plt.plot(TES_test['Rose'], label='Test')

#The value of alpha and beta is taken like that by python
plt.plot(TES_test['predict',0.3, 0.7000000000000002, 0.4], label='Alpha=0.3,Beta=0.7,Gamma=0.4,TripleExponentialSmoothing predictions on Test Set')


plt.legend(loc='best')
plt.grid();
```



In [233]:

```
#all Exponentional Smoothing
plt.figure(figsize=(10,7))
plt.plot(train,label="Train")
plt.plot(test,label="Test")
plt.plot(SES_test["predict"],label="Simple Exponentional Smoothing")
plt.plot(DES_test['predict', 0.3, 0.4], label='Alpha=0.3,Beta=0.4,DoubleExponentialSmoothing predicti
ons on Test Set')

plt.plot(TES_test['auto_predict'], label='Alpha=0.09,Beta=1.33,Gamma=1.20,TripleExponentialSmoot
hing predictions on Test Set')

plt.legend(loc='best')
plt.grid()
```



QUESTION-4

Check for Stationarity, Check for stationarity - Make the data stationary (if needed)

Dicky Fuller Test

H0:Time series is not stationary

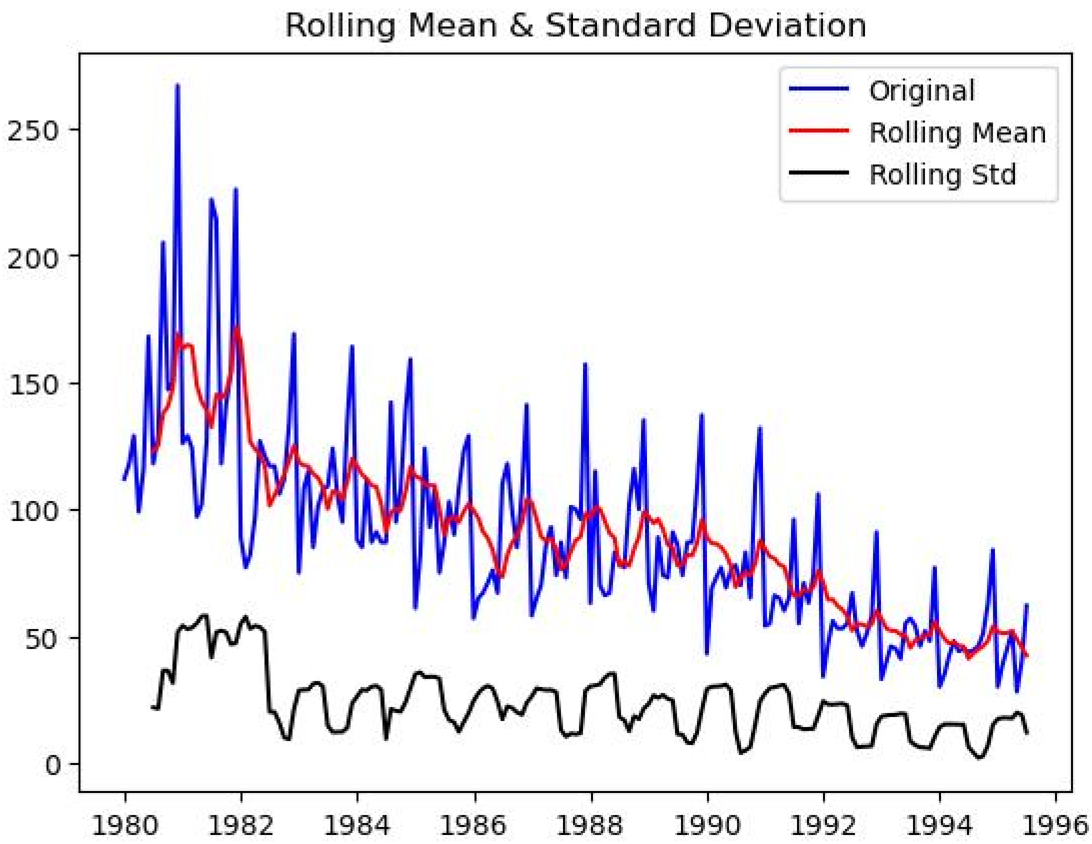
H1:Time series is stationary

In [234]:

```
from statsmodels.tsa.stattools import adfuller
def test_stationarity(time_series):
    #Determing rolling statistics
    rolmean=time_series.rolling(window=7).mean()
    rolstd=time_series.rolling(window=7).std()

    #Plot rolling statistics:
    orig = plt.plot(time_series, color='blue',label='Original')
    mean = plt.plot(rolmean, color='red', label='Rolling Mean')
    std = plt.plot(rolstd, color='black', label = 'Rolling Std')
    plt.legend(loc='best')
    plt.title('Rolling Mean & Standard Deviation')
    plt.show(block=False)

    #Perform Dickey-Fuller test:
    print ('Results of Dickey-Fuller Test:')
    dftest=adfuller(time_series, autolag='AIC')
    dfoutput=pd.Series(dftest[0:4],index=['Test Statistic','p-value','#Lags Used','Number of Observatio
ns Used'])
    for key,value in dftest[4].items():
        dfoutput['Critical Value (%s)'%key] = value
    print (dfoutput,'\n')
```

In [235]:

```
#stationarity plot of orginal series
test_stationarity(df_2['Rose'])
```

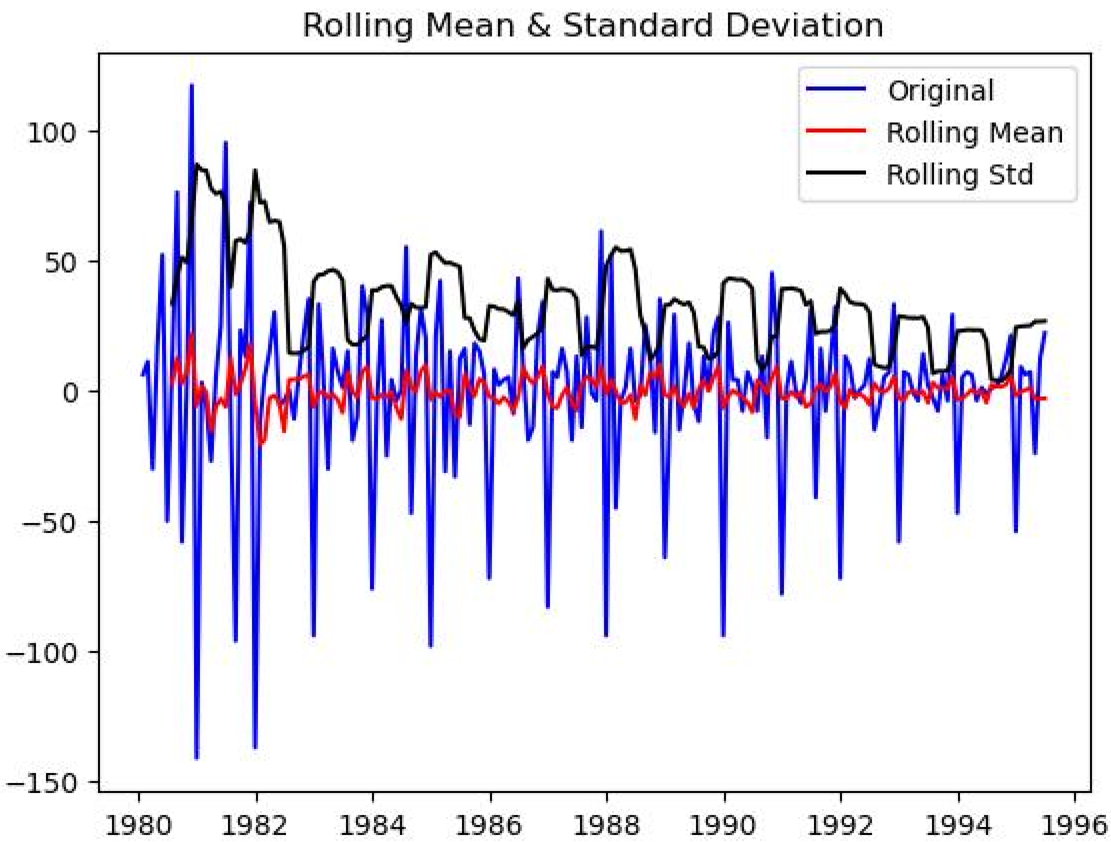


Results of Dickey-Fuller Test:
Test Statistic -1.873514
p-value 0.344622
#Lags Used 13.000000
Number of Observations Used 173.000000
Critical Value (1%) -3.468726
Critical Value (5%) -2.878396
Critical Value (10%) -2.575756
dtype: float64

p-value is greater than 0.05
Let us take a difference of order 1 and check whether the Time Series is stationary or not.

In [236]:

```
#stationarity plot of 1 diff Time series
test_stationarity(df_2['Rose'].diff().dropna())
```



Results of Dickey-Fuller Test:

Test Statistic	-8.043389e+00
p-value	1.821563e-12
#Lags Used	1.200000e+01
Number of Observations Used	1.730000e+02
Critical Value (1%)	-3.468726e+00
Critical Value (5%)	-2.878396e+00
Critical Value (10%)	-2.575756e+00

dtype: float64

p-value less than 0.05 so the 1 difference of the time series is stationary.

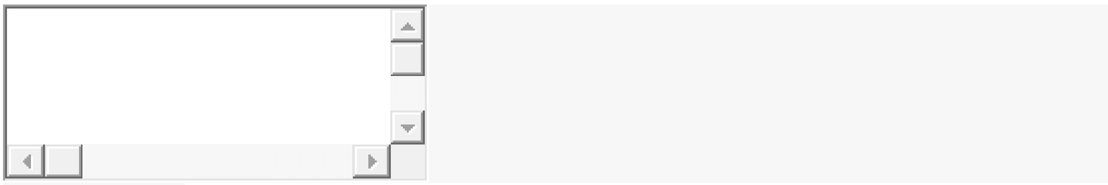
QUESTION-5

Model Building - Stationary Data

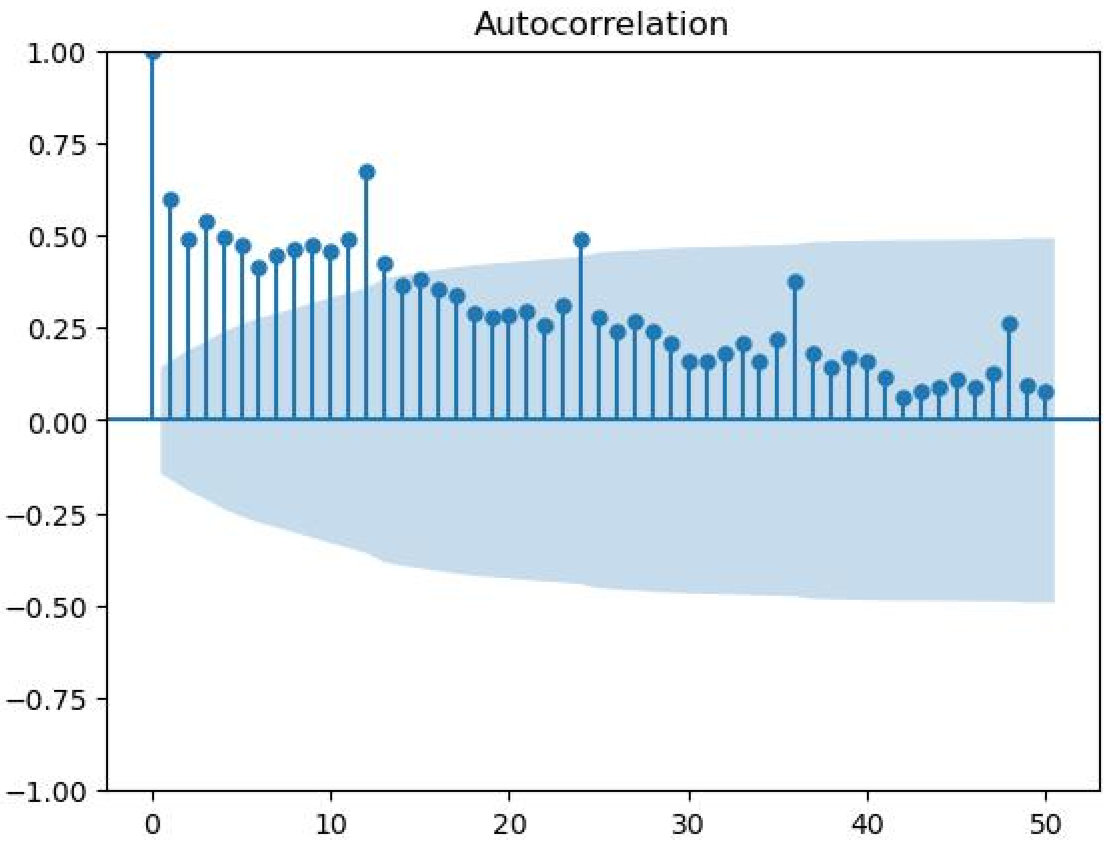
Generate ACF & PACF Plot and find the AR, MA values. - Build different ARIMA models - Auto ARIMA - Manual ARIMA - Build different SARIMA models - Auto SARIMA - Manual SARIMA - Check the performance of the models built

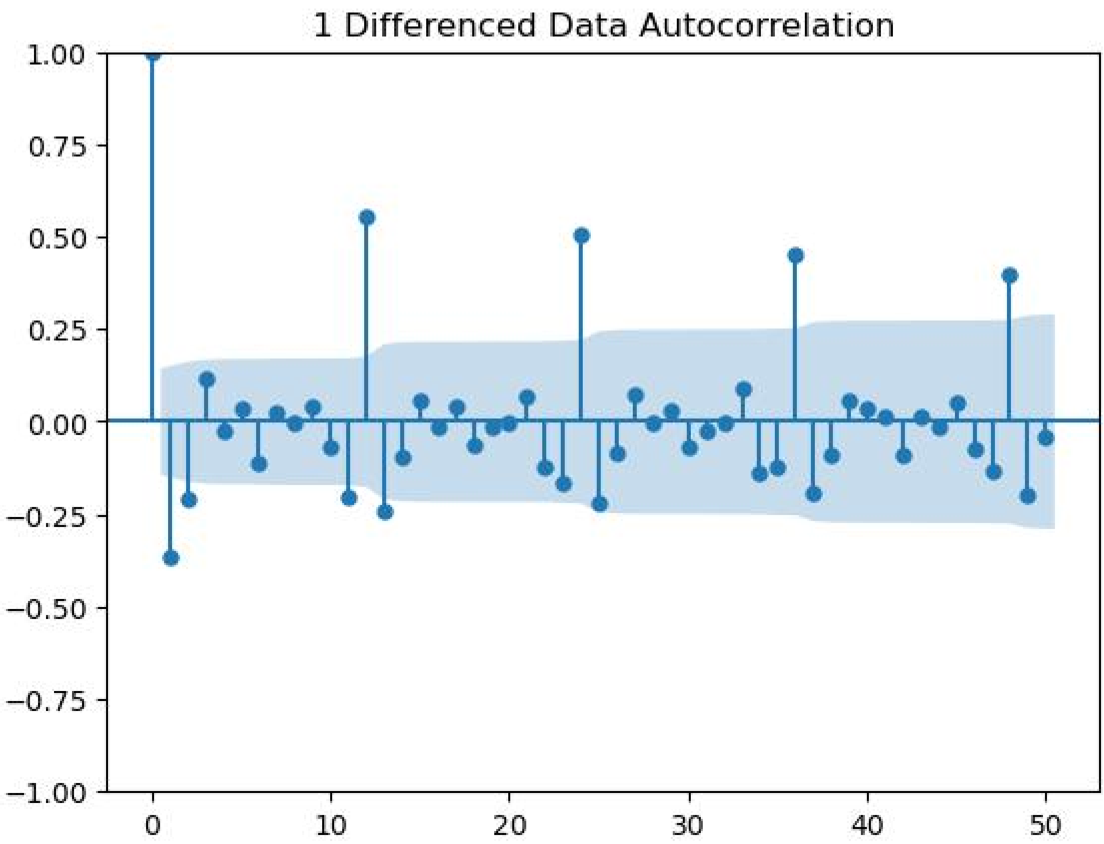
Generate ACF

In [237]:



```
#plot ACF,PACF
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
plot_acf(df_2['Rose'],lags=50)
plot_acf(df_2['Rose'].diff().dropna(),lags=50,title='1 Differenced Data Autocorrelation')
plt.show()
```

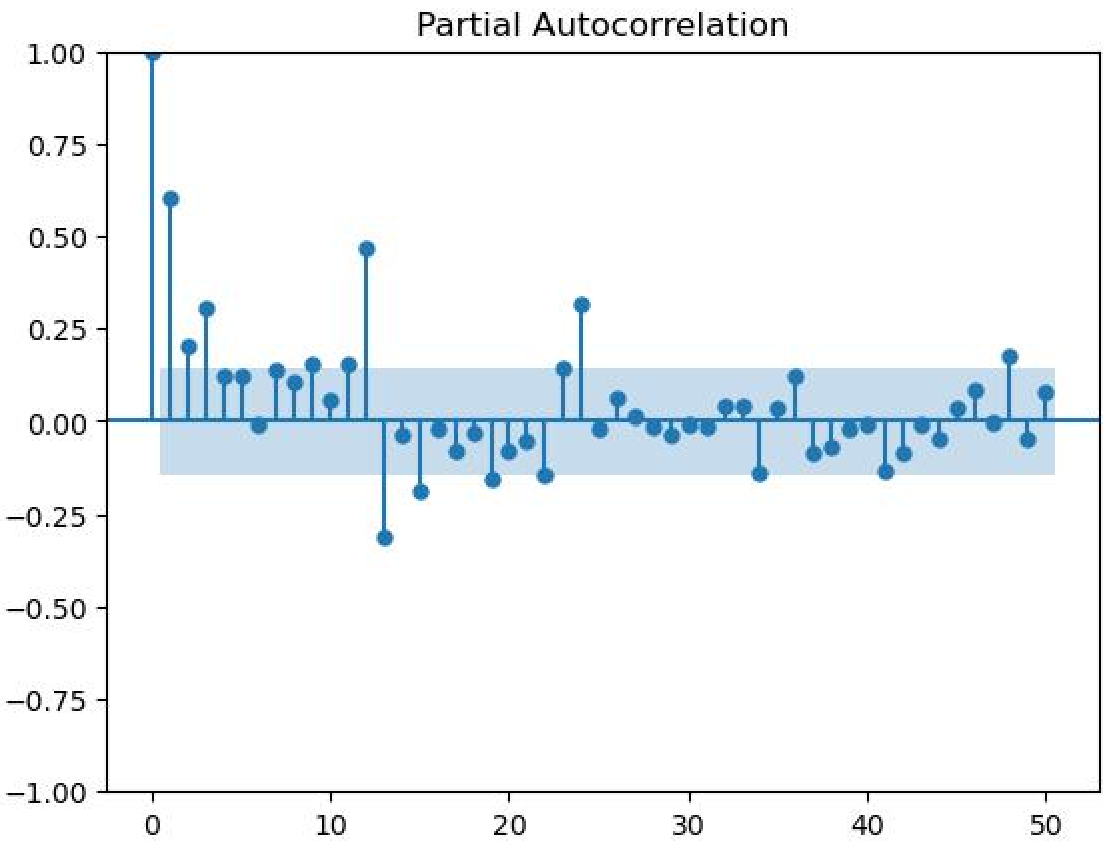


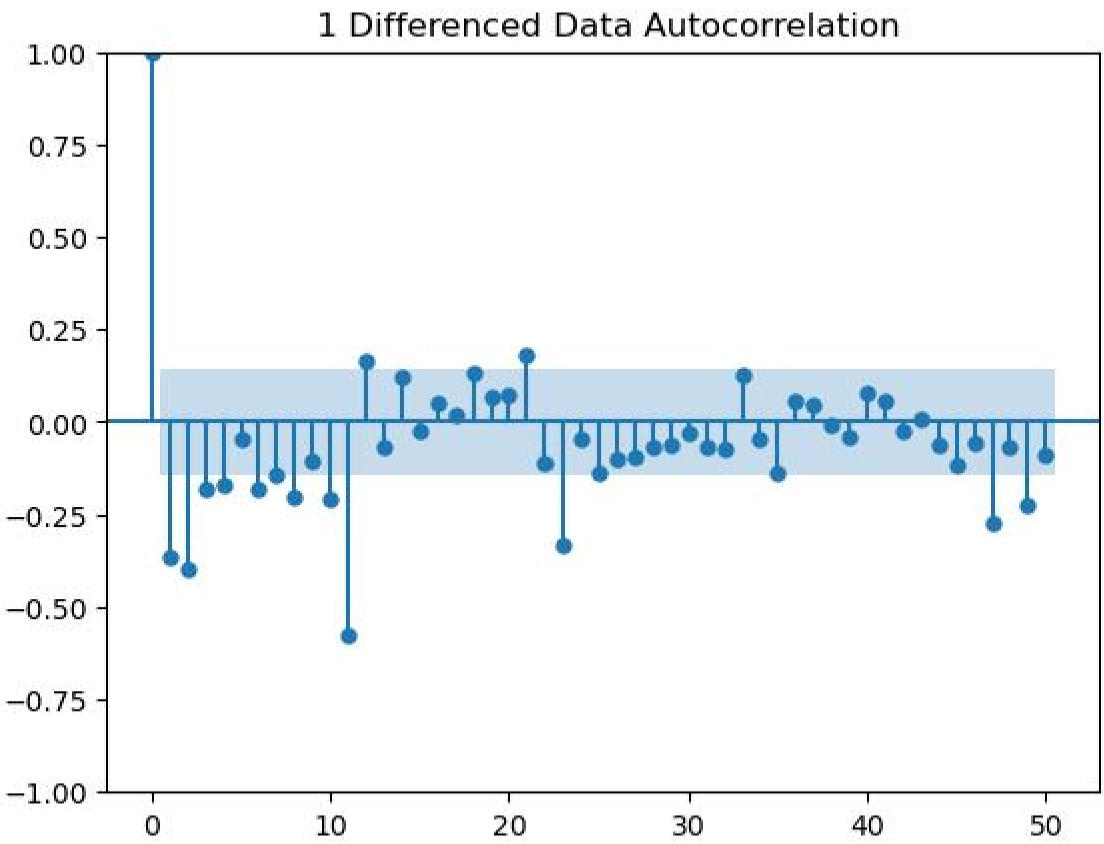


In [238]:

```
plot_pacf(df_2['Rose'],lags=50)
plot_pacf(df_2['Rose'].diff().dropna(),lags=50,title=' 1 Differenced Data Autocorrelation')
plt.show()
```

```
c:\Users\SABIR\anaconda3\Lib\site-packages\statsmodels\graphics\tsaplots.py:348: Future
Warning: The default method 'yw' can produce PACF values outside of the [-1,1] interval. Aft
er 0.13, the default will change tounadjusted Yule-Walker ('ywm'). You can use this method
now by setting method='ywm'.
  warnings.warn(
```





AR=3 (from PACF) ,MA=0 (from ACF)

after for 1 difference time series

AR=5 (FROM PACF), MA=3 (FROM ACF)

Build different ARIMA models - Auto ARIMA - Manual ARIMA -

#Auto ARIMA

In [239]:

```
import itertools
p=q=range(0,3)
d= range(1,2)
pdq=list(itertools.product(p,d,q))
print('Some parameter combinations for the Model...')
for i in range(1,len(pdq)):
    print("model:  {}".format(pdq[i]))
```

```
Some parameter combinations for the Model...
model:  (0, 1, 1)
model:  (0, 1, 2)
model:  (1, 1, 0)
model:  (1, 1, 1)
model:  (1, 1, 2)
model:  (2, 1, 0)
model:  (2, 1, 1)
model:  (2, 1, 2)
```

In [240]:

```
#set different values
ARIMA_AIC=pd.DataFrame(columns=["param","AIC"])
ARIMA_AIC
```

Out[240]:

param	AIC

In [241]:

```
from statsmodels.tsa.arima.model import ARIMA
for param in pdq:
    ARIMA_MODEL=ARIMA(train["Rose"].values,order=param).fit()
    print("ARIMA{}-AIC:{}".format(param, ARIMA_MODEL.aic))
    ARIMA_AIC= ARIMA_AIC.append({"param":param,"AIC":ARIMA_MODEL.aic},ignore_index=True)
```

```
ARIMA(0, 1, 0)-AIC:1313.1758613526429
ARIMA(0, 1, 1)-AIC:1261.3274438405808
```

```
ARIMA(0, 1, 2)-AIC:1259.2477803151237
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\1333580595.py:5: FutureWarning: T
he frame.append method is deprecated and will be removed from pandas in a future version.
 Use pandas.concat instead.
  ARIMA_AIC= ARIMA_AIC.append({"param":param,"AIC":ARIMA_MODEL.aic},ignore_index=
True)
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\1333580595.py:5: FutureWarning: T
he frame.append method is deprecated and will be removed from pandas in a future version.
 Use pandas.concat instead.
  ARIMA_AIC= ARIMA_AIC.append({"param":param,"AIC":ARIMA_MODEL.aic},ignore_index=
True)
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\1333580595.py:5: FutureWarning: T
he frame.append method is deprecated and will be removed from pandas in a future version.
 Use pandas.concat instead.
  ARIMA_AIC= ARIMA_AIC.append({"param":param,"AIC":ARIMA_MODEL.aic},ignore_index=
True)
ARIMA(1, 1, 0)-AIC:1297.0772943848615
ARIMA(1, 1, 1)-AIC:1260.0367627036055
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\1333580595.py:5: FutureWarning: T
he frame.append method is deprecated and will be removed from pandas in a future version.
 Use pandas.concat instead.
  ARIMA_AIC= ARIMA_AIC.append({"param":param,"AIC":ARIMA_MODEL.aic},ignore_index=
True)
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\1333580595.py:5: FutureWarning: T
he frame.append method is deprecated and will be removed from pandas in a future version.
 Use pandas.concat instead.
  ARIMA_AIC= ARIMA_AIC.append({"param":param,"AIC":ARIMA_MODEL.aic},ignore_index=
True)
ARIMA(1, 1, 2)-AIC:1259.4732049501201
ARIMA(2, 1, 0)-AIC:1278.1352807484318
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\1333580595.py:5: FutureWarning: T
he frame.append method is deprecated and will be removed from pandas in a future version.
 Use pandas.concat instead.
  ARIMA_AIC= ARIMA_AIC.append({"param":param,"AIC":ARIMA_MODEL.aic},ignore_index=
True)
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\1333580595.py:5: FutureWarning: T
he frame.append method is deprecated and will be removed from pandas in a future version.
 Use pandas.concat instead.
  ARIMA_AIC= ARIMA_AIC.append({"param":param,"AIC":ARIMA_MODEL.aic},ignore_index=
True)
ARIMA(2, 1, 1)-AIC:1261.0140762916922
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\1333580595.py:5: FutureWarning: T
he frame.append method is deprecated and will be removed from pandas in a future version.
 Use pandas.concat instead.
  ARIMA_AIC= ARIMA_AIC.append({"param":param,"AIC":ARIMA_MODEL.aic},ignore_index=
True)
ARIMA(2, 1, 2)-AIC:1261.4720006569005
C:\Users\SABIR\AppData\Local\Temp\ipykernel_19808\1333580595.py:5: FutureWarning: T
he frame.append method is deprecated and will be removed from pandas in a future version.
 Use pandas.concat instead.
```

```
ARIMA_AIC= ARIMA_AIC.append({"param":param,"AIC":ARIMA_MODEL.aic},ignore_index=True)
```

In [242]:

```
## Sort the above AIC values in the ascending order to get the parameters for the minimum AIC value

ARIMA_AIC.sort_values(by='AIC',ascending=True)
```

Out[242]:

	param	AIC
2	(0, 1, 2)	1259.247780
5	(1, 1, 2)	1259.473205
4	(1, 1, 1)	1260.036763
7	(2, 1, 1)	1261.014076
1	(0, 1, 1)	1261.327444
8	(2, 1, 2)	1261.472001
6	(2, 1, 0)	1278.135281
3	(1, 1, 0)	1297.077294
0	(0, 1, 0)	1313.175861

(0, 1, 2) 1259.247780
p=0,d=1,q=2 have lowest AIC value

In [243]:

```
auto_ARIMA = ARIMA(train['Rose'], order=(0, 1, 2), freq="MS")
```

```
c:\Users\SABIR\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
```

In [244]:

```
results_auto_ARIMA = auto_ARIMA.fit()
```

In [245]:

```
print(results_auto_ARIMA.summary())
                    SARIMAX Results
==============================================================================
===
Dep. Variable:              Rose   No. Observations:            130
Model:            ARIMA(0, 1, 2)   Log Likelihood           -626.624
Date:           Sun, 21 Apr 2024   AIC                      1259.248
Time:                   21:16:19   BIC                      1267.827
Sample:               01-01-1980   HQIC                     1262.734
                    - 10-01-1990
Covariance Type:             opg
==============================================================================
===
              coef    std err        z     P>|z|     [0.025     0.975]
------------------------------------------------------------------------------
ma.L1      -0.7059      0.072    -9.851     0.000     -0.846     -0.565
ma.L2      -0.1915      0.074    -2.574     0.010     -0.337     -0.046
sigma2    958.5998     86.875    11.034     0.000    788.328   1128.872
==============================================================================
========
Ljung-Box (L1) (Q):               0.15   Jarque-Bera (JB):            45.85
Prob(Q):                          0.70   Prob(JB):                     0.00
Heteroskedasticity (H):           0.32   Skew:                         0.88
Prob(H) (two-sided):              0.00   Kurtosis:                     5.34
==============================================================================
========

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

In [246]:

```
predicted_auto_ARIMA = results_auto_ARIMA.forecast(steps=len(test))
```

In [247]:

```
from sklearn.metrics import  mean_squared_error
rmse = mean_squared_error(test['Rose'],predicted_auto_ARIMA,squared=False)
print(rmse)
30.962207900801978
```

In [248]:

```
resultsDf0 = pd.DataFrame({'Test_RMSE': [rmse]}
                          ,index=['ARIMA(0,1,2)'])
resultsDf0
```

Out[248]:

	Test_RMSE
ARIMA(0,1,2)	30.962208

manual_arima_model

In [249]:

```
manual_ARIMA = ARIMA(train['Rose'], order=(1, 1, 2), freq="MS")
```

```
c:\Users\SABIR\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency information was provided, so inferred frequency MS will be used.
  self._init_dates(dates, freq)
```

In [250]:

```
results_manual_ARIMA = manual_ARIMA.fit()
```

In [251]:

```
print(results_manual_ARIMA.summary())
```

```
                               SARIMAX Results
==============================================================================
===
Dep. Variable:                   Rose   No. Observations:                  130
Model:                 ARIMA(1, 1, 2)   Log Likelihood                -625.737
Date:                Sun, 21 Apr 2024   AIC                           1259.473
Time:                        21:16:20   BIC                           1270.912
Sample:                    01-01-1980   HQIC                          1264.121
                         - 10-01-1990
Covariance Type:                  opg
==============================================================================
===
                 coef    std err          z      P>|z|      [0.025      0.975]
```

```
------------------------------------------------------------------------------
ar.L1       -0.4649     0.274    -1.698     0.090    -1.002     0.072
ma.L1       -0.2485     0.253    -0.983     0.326    -0.744     0.247
ma.L2       -0.5971     0.208    -2.874     0.004    -1.004    -0.190
sigma2     945.0250    87.810    10.762     0.000   772.921  1117.129
==============================================================================
========
Ljung-Box (L1) (Q):                   0.03   Jarque-Bera (JB):                40.04
Prob(Q):                              0.86   Prob(JB):                         0.00
Heteroskedasticity (H):               0.33   Skew:                             0.84
Prob(H) (two-sided):                  0.00   Kurtosis:                         5.14
==============================================================================
========

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

In [252]:

```python
predicted_manual_ARIMA = results_manual_ARIMA.forecast(steps=len(test))
```

In [253]:

```python
from sklearn.metrics import  mean_squared_error
rmse = mean_squared_error(test['Rose'],predicted_manual_ARIMA,squared=False)
print(rmse)
```

```
30.52646143714676
```

In [254]:

```python
resultsDf_2 = pd.DataFrame({'Test_RMSE': [rmse]}
                          ,index=[' manual ARIMA(1,1,2)'])
resultsDf0=pd.concat([resultsDf0,resultsDf_2])
resultsDf0
```

Out[254]:

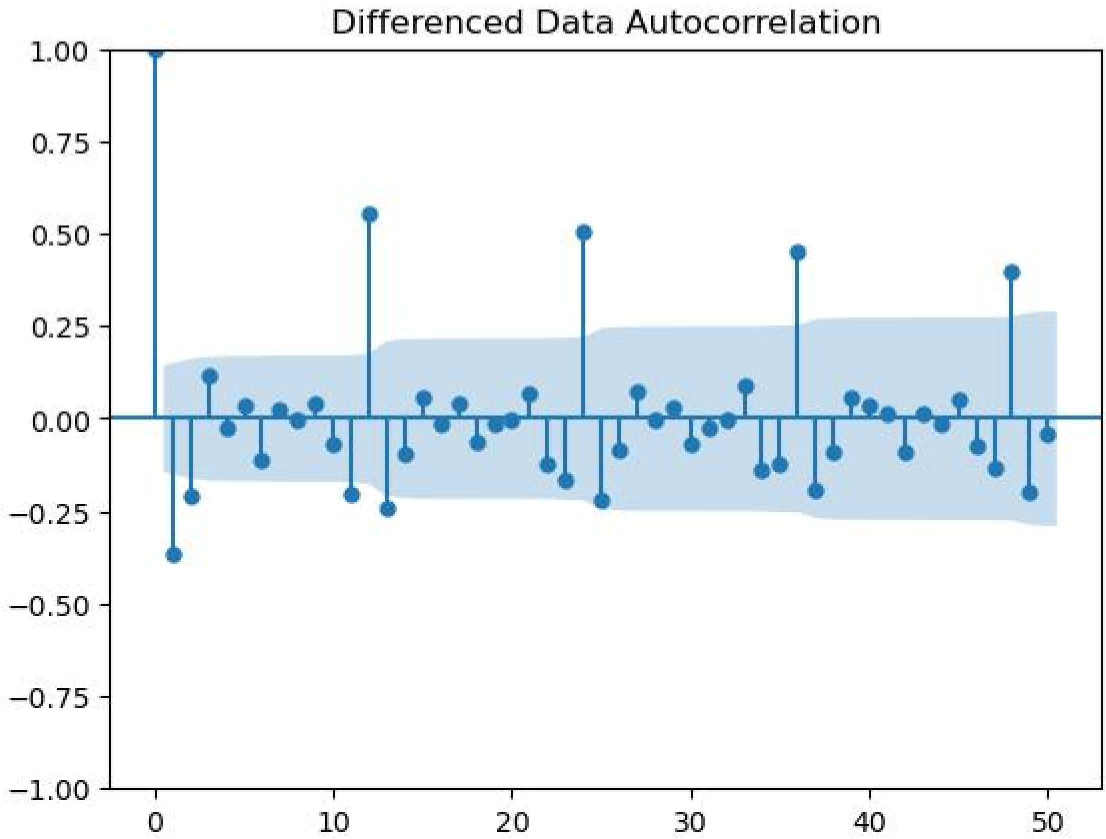
	Test_RMSE
ARIMA(0,1,2)	30.962208
manual ARIMA(1,1,2)	30.526461

Build an Automated version of a SARIMA model for which the best parameters are selected in accordance with the lowest Akaike Information Criteria (AIC).¶¶

In [ ]:

In [255]:

```
plot_acf(df_2['Rose'].diff().dropna(),lags=50,title='Differenced Data Autocorrelation')
plt.show()
```



We see that there can be a seasonality of 6 as well as 12. But from the decompostion at the start we ascertained that visually it looks like the seasonality =12 and thus using the same p-(0 to 2) d-(1) q-(0 to 2) P-(0 to 2) D-(0) Q-(0 to 2) Seasonality-12

In [256]:

In [259]:

```
SARIMA_AIC.sort_values(by="AIC",ascending=True).head()
```

Out[259]:

	param	seasonal	AIC
26	(0, 1, 2)	(2, 0, 2, 12)	871.075238
53	(1, 1, 2)	(2, 0, 2, 12)	873.003875
80	(2, 1, 2)	(2, 0, 2, 12)	874.213961
69	(2, 1, 1)	(2, 0, 0, 12)	879.792363
78	(2, 1, 2)	(2, 0, 0, 12)	880.763857

In [260]:

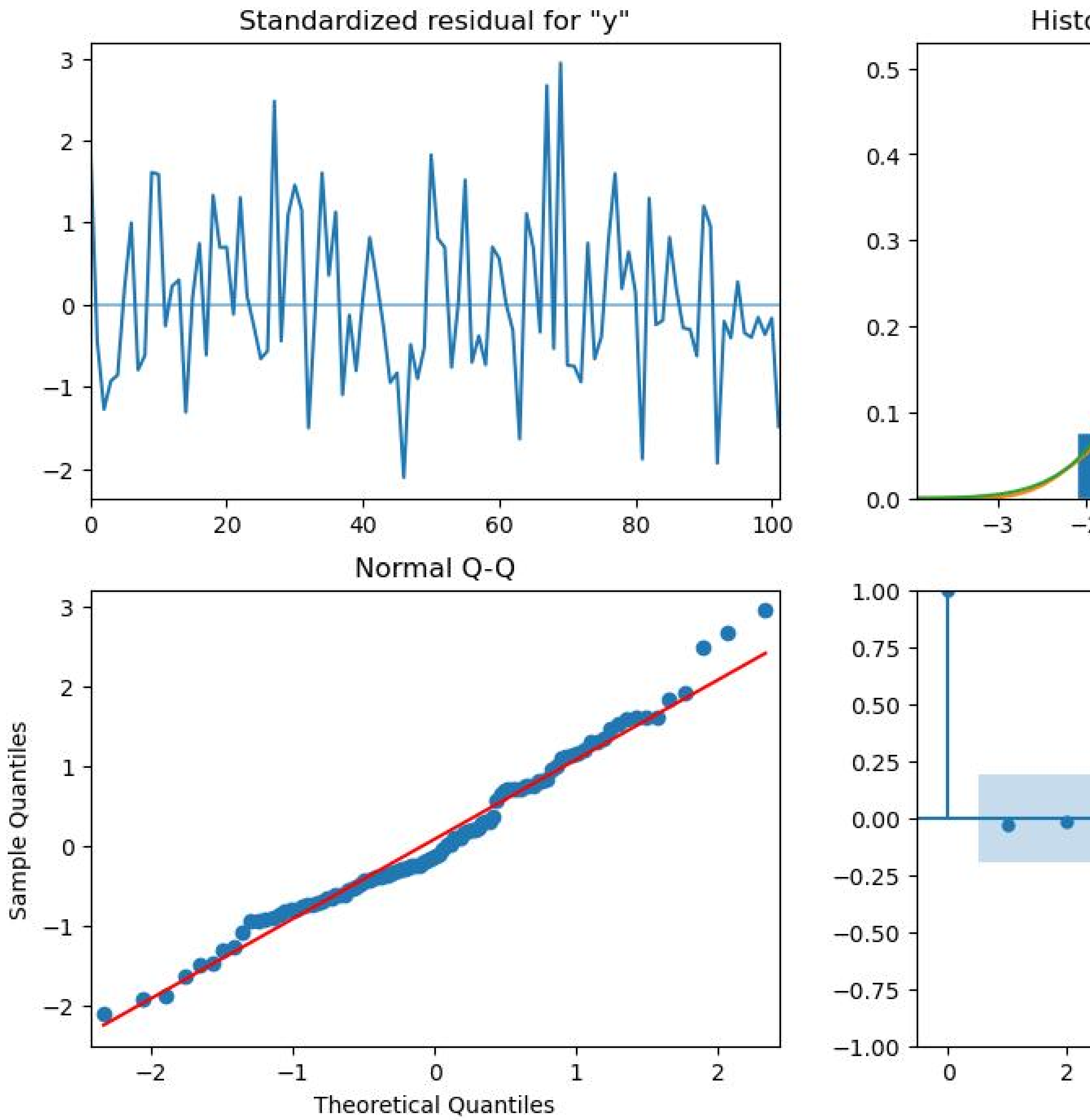
```
#sarima summary
import statsmodels.api as sm

auto_SARIMA_6 = sm.tsa.statespace.SARIMAX(train["Rose"].values,
                order=(0, 1, 2),
                seasonal_order=(2, 0, 2, 12),
                enforce_stationarity=False,
                enforce_invertibility=False)
results_auto_SARIMA_6 = auto_SARIMA_6.fit(maxiter=1000)
print(results_auto_SARIMA_6.summary())
```

```
                                SARIMAX Results
==============================================================================
===============
Dep. Variable:                          y   No. Observations:              130
Model:          SARIMAX(0, 1, 2)x(2, 0, 2, 12)   Log Likelihood            -428.538
Date:                    Sun, 21 Apr 2024   AIC                        871.075
Time:                            21:17:22   BIC                        889.450
Sample:                                 0   HQIC                       878.516
                                    - 130
Covariance Type:                      opg
==============================================================================
===
              coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------
ma.L1      -0.8367    239.114     -0.003      0.997    -469.492     467.819
ma.L2      -0.1633     39.028     -0.004      0.997     -76.656      76.330
ar.S.L12    0.3494      0.079      4.408      0.000       0.194       0.505
ar.S.L24    0.3067      0.075      4.103      0.000       0.160       0.453
```

```
ma.S.L12       0.0454      0.134      0.338      0.735      -0.218       0.309
ma.S.L24      -0.0912      0.145     -0.628      0.530      -0.376       0.193
sigma2       250.7786      6e+04      0.004      0.997   -1.17e+05    1.18e+05
===================================================================================
Ljung-Box (L1) (Q):                   0.09   Jarque-Bera (JB):                 3.10
Prob(Q):                              0.76   Prob(JB):                         0.21
Heteroskedasticity (H):               0.88   Skew:                             0.43
Prob(H) (two-sided):                  0.71   Kurtosis:                         3.05
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

In [261]:

```
#diagnostics plot of SARIMA
results_auto_SARIMA_6.plot_diagnostics(figsize=(12, 8))
plt.show()
```



From the model diagnostics plot, we can see that all the individual diagnostics plots almost follow the theoretical numbers and thus we cannot develop any pattern from these plots.

In [262]:

```
#Predict on the Test Set using this model and evaluate the model.
predicted_auto_SARIMA_6 =results_auto_SARIMA_6.get_forecast(steps=len(test))
predicted_auto_SARIMA_6.summary_frame(alpha=0.05).head()
```

Out[262]:

y	mean	mean_se	mean_ci_lower	mean_ci_upper
0	90.849106	15.914360	59.657533	122.040679
1	114.913416	16.150397	83.259220	146.567612
2	60.936673	16.150397	29.282477	92.590869
3	70.599289	16.150396	38.945094	102.253484
4	76.843515	16.150393	45.189326	108.497704

In [263]:

```
rmse = mean_squared_error(test['Rose'],predicted_auto_SARIMA_6.predicted_mean,squared=False)
print(rmse)
```

25.405804609167674

In [264]:

```
temp_resultsDf = pd.DataFrame({'Test_RMSE': [rmse]}
                          ,index=['SARIMA(0,1,2)(2,0,2,12)'])
```

In [265]:

```
resultsDf0 = pd.concat([resultsDf0,temp_resultsDf])
resultsDf0
```

Out[265]:

	Test_RMSE
ARIMA(0,1,2)	30.962208
manual ARIMA(1,1,2)	30.526461
SARIMA(0,1,2)(2,0,2,12)	25.405805

manual_SARIMA

In [266]:

```
#manual_SARIMA summary
manual_SARIMA_6 = sm.tsa.statespace.SARIMAX(train["Rose"].values,
                        order=(1, 1, 2),
                        seasonal_order=(2, 0, 2, 12),
                        enforce_stationarity=False,
                        enforce_invertibility=False)
results_manual_SARIMA_6 = manual_SARIMA_6.fit(maxiter=1000)
print(results_manual_SARIMA_6.summary())
```

```
                          SARIMAX Results
================================================================================
===============
Dep. Variable:                        y   No. Observations:              130
Model:           SARIMAX(1, 1, 2)x(2, 0, 2, 12)   Log Likelihood            -428.502
Date:                     Sun, 21 Apr 2024   AIC                        873.004
Time:                             21:17:27   BIC                        894.004
Sample:                                  0   HQIC                       881.507
                                     - 130
Covariance Type:                       opg
================================================================================
===
             coef    std err        z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
ar.L1        0.1002    0.350    0.286    0.775    -0.587      0.787
ma.L1       -0.9391   319.747   -0.003    0.998   -627.631    625.753
ma.L2       -0.0609    19.566   -0.003    0.998    -38.409     38.287
ar.S.L12     0.3490    0.077    4.534    0.000     0.198      0.500
ar.S.L24     0.3066    0.073    4.193    0.000     0.163      0.450
ma.S.L12     0.0505    0.133    0.379    0.705    -0.211      0.312
ma.S.L24    -0.0896    0.146   -0.615    0.539    -0.375      0.196
sigma2     250.4580  8.01e+04    0.003    0.998  -1.57e+05   1.57e+05
================================================================================
========
Ljung-Box (L1) (Q):               0.07   Jarque-Bera (JB):             2.89
Prob(Q):                          0.80   Prob(JB):                     0.24
Heteroskedasticity (H):           0.88   Skew:                         0.41
Prob(H) (two-sided):              0.70   Kurtosis:                     3.02
================================================================================
========

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

In [267]:

```
#Predict on the Test Set using this model and evaluate the model.
predicted_manual_SARIMA_6 =results_manual_SARIMA_6.get_forecast(steps=len(test))
predicted_manual_SARIMA_6.summary_frame(alpha=0.05).head()
```

Out[267]:

y	mean	mean_se	mean_ci_lower	mean_ci_upper
0	91.009364	15.904129	59.837844	122.180884
1	114.696368	16.134078	83.074156	146.318579
2	60.836606	16.139005	29.204737	92.468474
3	70.599103	16.139318	38.966620	102.231586
4	76.889886	16.139345	45.257351	108.522420

In [268]:

```
rmse = mean_squared_error(test['Rose'],predicted_manual_SARIMA_6.predicted_mean,squared=False)
print(rmse)
```

25.483993066473502

In [269]:

```
temp_resultsDf = pd.DataFrame({'Test_RMSE': [rmse]}
                   ,index=['manual SARIMA(1,1,2)(2,0,2,12)'])
```

In [270]:

```
#rmse table
resultsDf0=pd.concat([resultsDf0,temp_resultsDf])
resultsDf0
```

Out[270]:

	Test_RMSE
ARIMA(0,1,2)	30.962208
manual ARIMA(1,1,2)	30.526461
SARIMA(0,1,2)(2,0,2,12)	25.405805
manual SARIMA(1,1,2)(2,0,2,12)	25.483993

6- Compare the performance of the models

Compare the performance of all the models built - Choose the best model with proper rationale - Rebuild the best model using the entire data - Make a forecast for the next 12 months

In [271]:

```
resultsDf0
```

Out[271]:

	Test_RMSE
ARIMA(0,1,2)	30.962208
manual ARIMA(1,1,2)	30.526461
SARIMA(0,1,2)(2,0,2,12)	25.405805
manual SARIMA(1,1,2)(2,0,2,12)	25.483993

In [272]:

```
resultsDf=pd.concat([resultsDf,resultsDf0])
resultsDf
```

Out[272]:

	Test_RMSE
Linear_Regression	17.361118
simple_average	52.471053
2pointTrailingMovingAverage	11.801894
4pointTrailingMovingAverage	15.376848
6pointTrailingMovingAverage	15.880520
9pointTrailingMovingAverage	16.352639
Alpha=0.10,SimpleExponentialSmoothing	30.246633
Alpha=0.9,SimpleExponentialSmoothing	22.547073
Alpha=0.3,Beta=0.4,DoubleExponentialSmoothing	18.327400
Alpha=0.09,Beta=1.33,Gamma=1.20,TripleExponentialSmoothing	9.350380
Alpha=0.7,Beta=0.4,Gamma=0.3,TripleExponentialSmoothing	28.301212

	Test_RMSE
ARIMA(0,1,2)	30.962208
manual ARIMA(1,1,2)	30.526461
SARIMA(0,1,2)(2,0,2,12)	25.405805
manual SARIMA(1,1,2)(2,0,2,12)	25.483993

In [273]:

```
#rmse Table sort by test rmse value
resultsDf.sort_values(by="Test_RMSE")
```

Out[273]:

	Test_RMSE
Alpha=0.09,Beta=1.33,Gamma=1.20,TripleExponentialSmoothing	9.350380
2pointTrailingMovingAverage	11.801894
4pointTrailingMovingAverage	15.376848
6pointTrailingMovingAverage	15.880520
9pointTrailingMovingAverage	16.352639
Linear_Regression	17.361118
Alpha=0.3,Beta=0.4,DoubleExponentialSmoothing	18.327400
Alpha=0.9,SimpleExponentialSmoothing	22.547073
SARIMA(0,1,2)(2,0,2,12)	25.405805
manual SARIMA(1,1,2)(2,0,2,12)	25.483993
Alpha=0.7,Beta=0.4,Gamma=0.3,TripleExponentialSmoothing	28.301212
Alpha=0.10,SimpleExponentialSmoothing	30.246633
manual ARIMA(1,1,2)	30.526461
ARIMA(0,1,2)	30.962208
simple_average	52.471053

best model is Alpha=0.09,Beta=1.33,Gamma=1.20,TripleExponentialSmoothing--------
Test_RMSE 9.350380

Rebuild the best model using the entire data - Make a forecast for the next 12 months

In [274]:

```
full_data_model =  sm.tsa.ExponentialSmoothing(df_2['Rose'],trend='additive',seasonal='multiplicative')
results_full_data_model = full_data_model.fit()
print(results_full_data_model.summary())
```

```
c:\Users\SABIR\anaconda3\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:471: ValueWarning: No frequency information was provided, so inferred frequency MS will be used.
 self._init_dates(dates, freq)
```

```
                 ExponentialSmoothing Model Results
==============================================================================
=====
Dep. Variable:                 Rose   No. Observations:              187
Model:           ExponentialSmoothing   SSE                     48488.079
Optimized:                     True   AIC                      1071.339
Trend:                     Additive   BIC                      1123.037
Seasonal:            Multiplicative   AICC                     1075.411
Seasonal Periods:                12   Date:              Sun, 21 Apr 2024
Box-Cox:                      False   Time:                    21:17:29
Box-Cox Coeff.:                None
==============================================================================
======
                 coeff             code          optimized
-----------------------------------------------------------------------------
smoothing_level            0.1071715            alpha             True
smoothing_trend            1.7197e-06            beta             True
smoothing_seasonal         0.0001224            gamma             True
initial_level             127.79908              l.0              True
initial_trend            -0.4858535              b.0              True
initial_seasons.0          0.8442360              s.0              True
initial_seasons.1          0.9587894              s.1              True
initial_seasons.2          1.0576510              s.2              True
initial_seasons.3          0.9451317              s.3              True
initial_seasons.4          1.0331544              s.4              True
initial_seasons.5          1.1189364              s.5              True
initial_seasons.6          1.2548924              s.6              True
initial_seasons.7          1.2932911              s.7              True
initial_seasons.8          1.2214981              s.8              True
initial_seasons.9          1.2072518              s.9              True
initial_seasons.10         1.4013893             s.10              True
initial_seasons.11         1.9318215             s.11              True
-----------------------------------------------------------------------------
```

Evaluate the model on the whole and predict 12 months into the future (till the end of next year).predicted Triple_exponestional

In [275]:

```
# Forecast the next 12 months
forecast_12_months = results_full_data_model.forecast(steps=12)

print("Forecast for the next 12 months:")
print(forecast_12_months)
```

```
Forecast for the next 12 months:
1995-08-01    47.455930
1995-09-01    44.232509
1995-10-01    43.131381
1995-11-01    49.386764
1995-12-01    67.139919
1996-01-01    28.928032
1996-02-01    32.391050
1996-03-01    35.217873
1996-04-01    31.015830
1996-05-01    33.395872
1996-06-01    35.625093
1996-07-01    39.344315
Freq: MS, dtype: float64
```

In [276]:

```
rmse = mean_squared_error(df_2['Rose'],results_full_data_model.fittedvalues,squared=False)
print('RMSE of the Full Model',rmse)
```

```
RMSE of the Full Model 16.10262518586643
```

In [277]:

```
#forcasted Table
forecast_df = pd.DataFrame(forecast_12_months, columns=['Rose'])
forecast_df
```

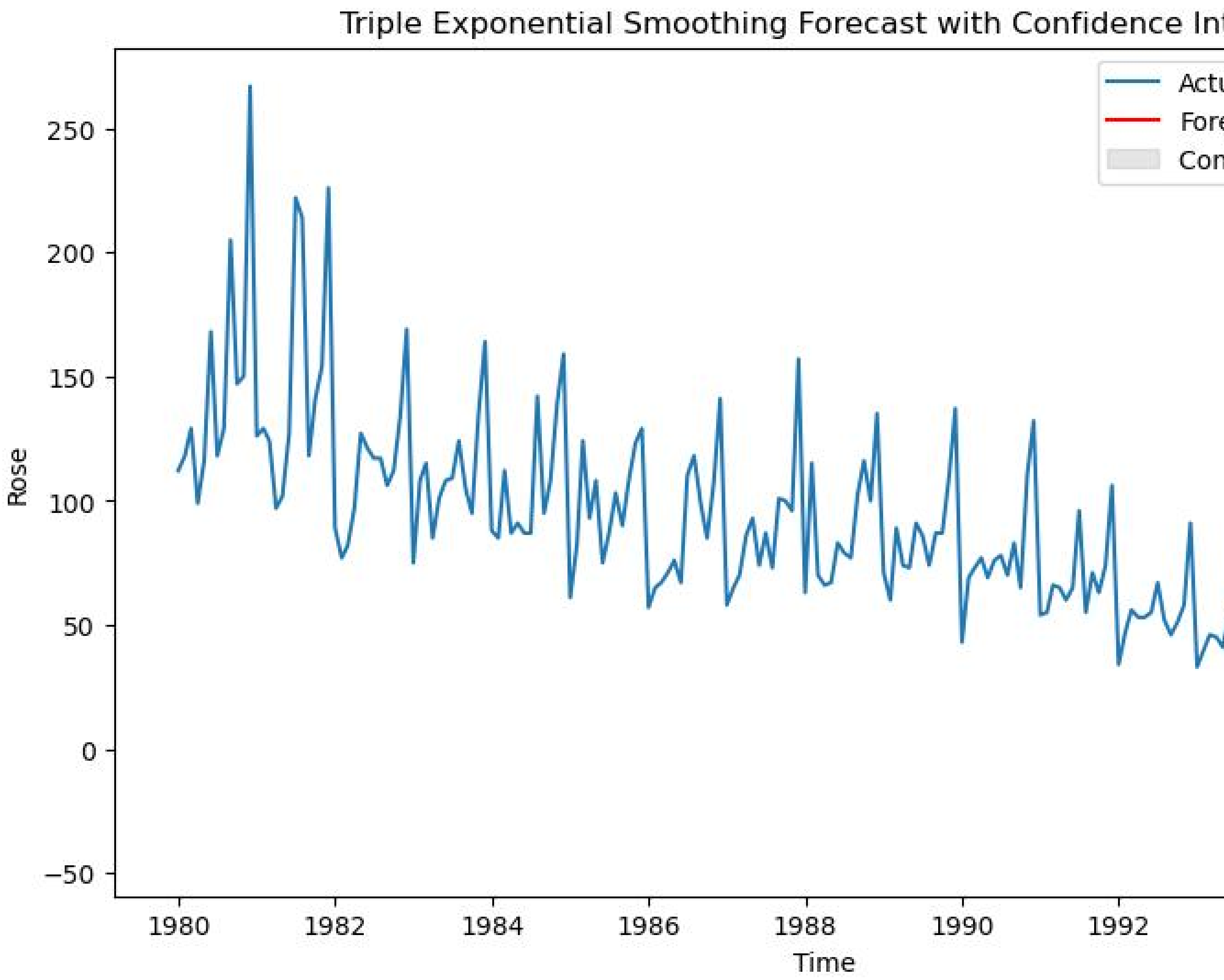
Out[277]:

	Rose
1995-08-01	47.455930
1995-09-01	44.232509
1995-10-01	43.131381

	Rose
1995-11-01	49.386764
1995-12-01	67.139919
1996-01-01	28.928032
1996-02-01	32.391050
1996-03-01	35.217873
1996-04-01	31.015830
1996-05-01	33.395872
1996-06-01	35.625093
1996-07-01	39.344315

In [278]:

```python
# Plot the forecast
plt.figure(figsize=(10, 6))
plt.plot(df_2['Rose'], label='Actual')
plt.plot(forecast_12_months, color='red', label='Forecast')
plt.fill_between(
    forecast_12_months.index,
    forecast_12_months - 1.96 * results_full_data_model.fittedvalues.std(),
    forecast_12_months + 1.96 * results_full_data_model.fittedvalues.std(),
    color='gray', alpha=0.2, label='Confidence Interval (95%)'
)
plt.legend()
plt.title('Triple Exponential Smoothing Forecast with Confidence Interval')
plt.xlabel('Time')
plt.ylabel('Rose')
plt.show()
```



Actionable Insights & Recommendations

Conclude with the key takeaways (actionable insights and recommendations) for the business

Inference

- Rose wine sales shown a decrease in trend on year-on-year basis
- December month has the highest sales in a year.
- Model plot was build based on trend and seasonality.we see the future prediction is inline with the previous year prediction.

Recommendation

- Rose wine sale are seasonal
- we are able to see the Rose wines are sold highly during March/August/October till December.
- Company should plan a head and keep enough stock from september till december to captlize on the demand
- In order to increase the sales company should plan some promotional offers during the low sale period

In [ ]: