



Time Series Forecasting-Rose

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Jun_B_21

Date: 16:feb:2022

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Problem Statement - 1

For this particular assignment, the data of different types of wine sales in the 20th century is to be analysed. Both of these data are from the same company but of different wines. As an analyst in the ABC Estate Wines, you are tasked to analyse and forecast Wine Sales in the 20th century.

Data set for the Problem: Sparkling.csv and Rose.csv

1.1 Read the data as an appropriate Time Series data and plot the data.

Sample of the dataset :

Head datasets :

| | YearMonth | Rose |
|---|-----------|-------|
| 0 | 1980-01 | 112.0 |
| 1 | 1980-02 | 118.0 |
| 2 | 1980-03 | 129.0 |
| 3 | 1980-04 | 99.0 |
| 4 | 1980-05 | 116.0 |

Table-01

Tail Datasets :

| | YearMonth | Rose |
|-----|-----------|------|
| 182 | 1995-03 | 45.0 |
| 183 | 1995-04 | 52.0 |
| 184 | 1995-05 | 28.0 |
| 185 | 1995-06 | 40.0 |
| 186 | 1995-07 | 62.0 |

Table-02

Types of variables and missing values in the dataset :

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 187 entries, 0 to 186
Data columns (total 2 columns):
#   Column      Non-Null Count  Dtype
---  -
0   YearMonth   187 non-null    object
1   Rose        185 non-null    float64
dtypes: float64(1), object(1)
memory usage: 3.0+ KB
```

- From the above results we can see that there is some missing value present in the dataset.
- There are a total of 187 rows .

Note: We can see in the datasets. YearMonth variable does not format properly so first we use manual add date column.

```
DatetimeIndex(['1980-01-31', '1980-02-29', '1980-03-31', '1980-04-30',
               '1980-05-31', '1980-06-30', '1980-07-31', '1980-08-31',
               '1980-09-30', '1980-10-31',
               ...,
               '1994-10-31', '1994-11-30', '1994-12-31', '1995-01-31',
               '1995-02-28', '1995-03-31', '1995-04-30', '1995-05-31',
               '1995-06-30', '1995-07-31'],
              dtype='datetime64[ns]', length=187, freq='M')
```

Final datasets :

| Rose | |
|------------|-----|
| Time_Stamp | |
| 1980-01-31 | 112 |
| 1980-02-29 | 118 |
| 1980-03-31 | 129 |
| 1980-04-30 | 99 |
| 1980-05-31 | 116 |

Table-03

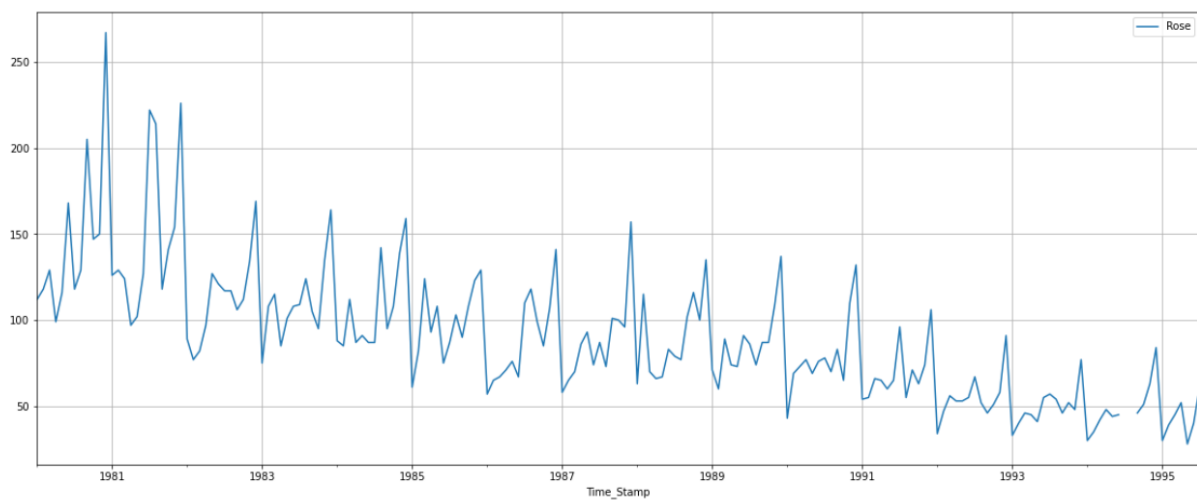


Figure - 01

1.2 Perform appropriate Exploratory Data Analysis to understand the data and also perform decomposition.

Decompose the datasets :

Model = additive :

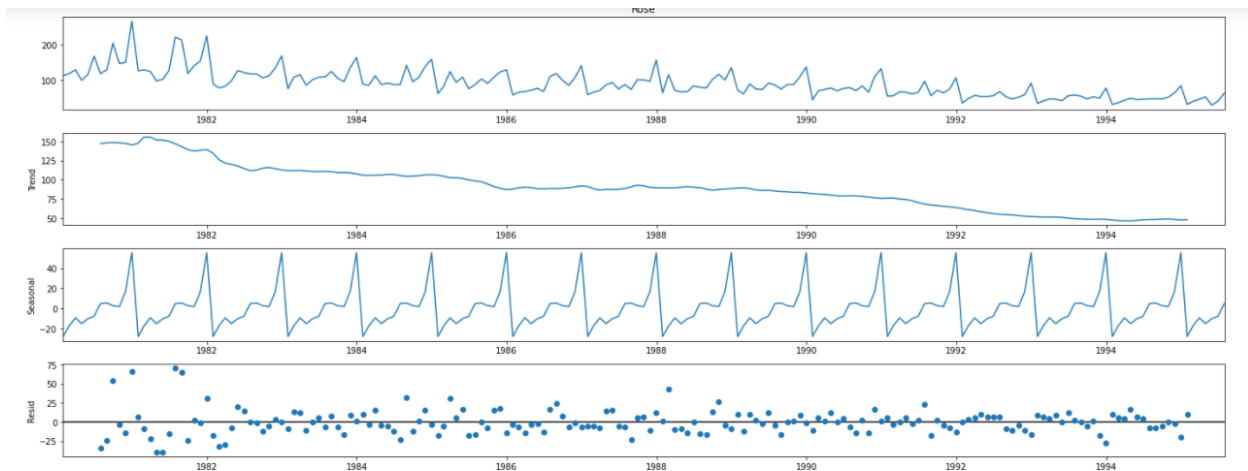


Figure-02

Model= multiplicative :

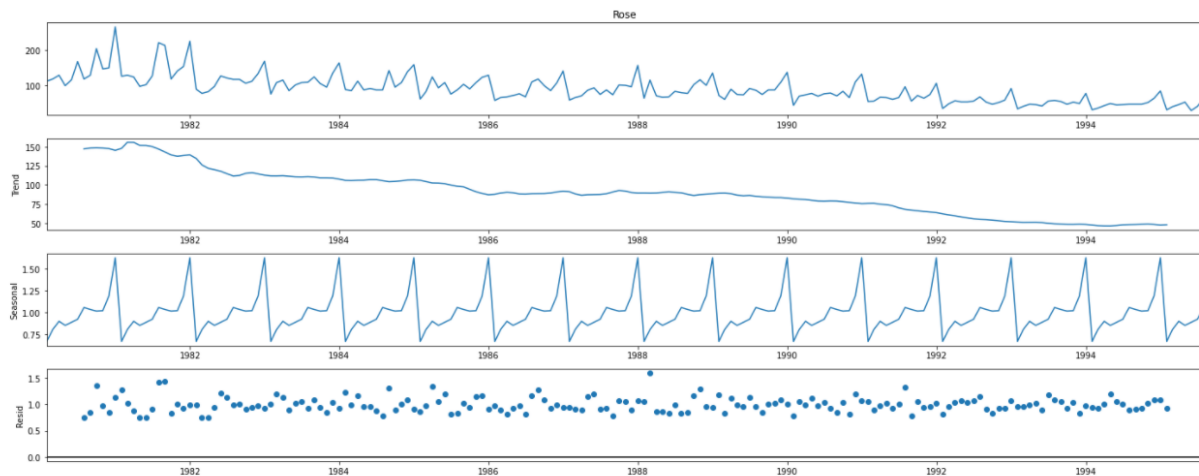


Figure-03

Remarks :

- We can see that the trend is downward.
- For the seasonality, not sure if there is multiplicative or additive seasonality we will see in other graphs.

Pivot Table :

| Time_Stamp | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|------------|-------|-------|-------|------|-------|-------|-------|-------|-------|-------|-------|-------|
| Time_Stamp | | | | | | | | | | | | |
| 1980 | 112.0 | 118.0 | 129.0 | 99.0 | 116.0 | 168.0 | 118.0 | 129.0 | 205.0 | 147.0 | 150.0 | 267.0 |
| 1981 | 126.0 | 129.0 | 124.0 | 97.0 | 102.0 | 127.0 | 222.0 | 214.0 | 118.0 | 141.0 | 154.0 | 226.0 |
| 1982 | 89.0 | 77.0 | 82.0 | 97.0 | 127.0 | 121.0 | 117.0 | 117.0 | 106.0 | 112.0 | 134.0 | 169.0 |
| 1983 | 75.0 | 108.0 | 115.0 | 85.0 | 101.0 | 108.0 | 109.0 | 124.0 | 105.0 | 95.0 | 135.0 | 164.0 |
| 1984 | 88.0 | 85.0 | 112.0 | 87.0 | 91.0 | 87.0 | 87.0 | 142.0 | 95.0 | 108.0 | 139.0 | 159.0 |
| 1985 | 61.0 | 82.0 | 124.0 | 93.0 | 108.0 | 75.0 | 87.0 | 103.0 | 90.0 | 108.0 | 123.0 | 129.0 |
| 1986 | 57.0 | 65.0 | 67.0 | 71.0 | 76.0 | 67.0 | 110.0 | 118.0 | 99.0 | 85.0 | 107.0 | 141.0 |
| 1987 | 58.0 | 65.0 | 70.0 | 86.0 | 93.0 | 74.0 | 87.0 | 73.0 | 101.0 | 100.0 | 96.0 | 157.0 |
| 1988 | 63.0 | 115.0 | 70.0 | 66.0 | 67.0 | 83.0 | 79.0 | 77.0 | 102.0 | 116.0 | 100.0 | 135.0 |
| 1989 | 71.0 | 60.0 | 89.0 | 74.0 | 73.0 | 91.0 | 86.0 | 74.0 | 87.0 | 87.0 | 109.0 | 137.0 |
| 1990 | 43.0 | 69.0 | 73.0 | 77.0 | 69.0 | 76.0 | 78.0 | 70.0 | 83.0 | 65.0 | 110.0 | 132.0 |
| 1991 | 54.0 | 55.0 | 66.0 | 65.0 | 60.0 | 65.0 | 96.0 | 55.0 | 71.0 | 63.0 | 74.0 | 106.0 |
| 1992 | 34.0 | 47.0 | 56.0 | 53.0 | 53.0 | 55.0 | 67.0 | 52.0 | 46.0 | 51.0 | 58.0 | 91.0 |
| 1993 | 33.0 | 40.0 | 46.0 | 45.0 | 41.0 | 55.0 | 57.0 | 54.0 | 46.0 | 52.0 | 48.0 | 77.0 |
| 1994 | 30.0 | 35.0 | 42.0 | 48.0 | 44.0 | 45.0 | 46.0 | 46.0 | 46.0 | 51.0 | 63.0 | 84.0 |
| 1995 | 30.0 | 39.0 | 45.0 | 52.0 | 28.0 | 40.0 | 62.0 | NaN | NaN | NaN | NaN | NaN |

Table- 4

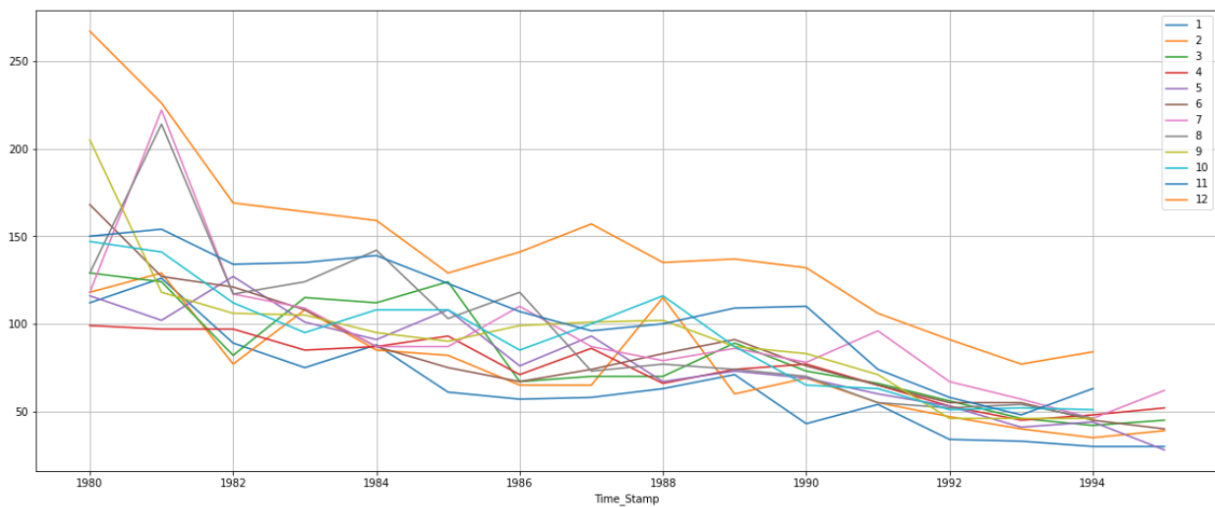


Figure-04

Note: By seeing the above graph we can see that some lines are crossing each other so we can say there is no additive seasonality.

Note : There are some missing values so we imputed using backfill.

Check the residual and normality:

For the multiplicative :

Residual = 0.9994553586957378

```
ShapiroResult(statistic=0.9488479495048523, pvalue=5.949785190750845e-06)
```

C:\Users\Pradeep Mishra\anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
warnings.warn(msg, FutureWarning)

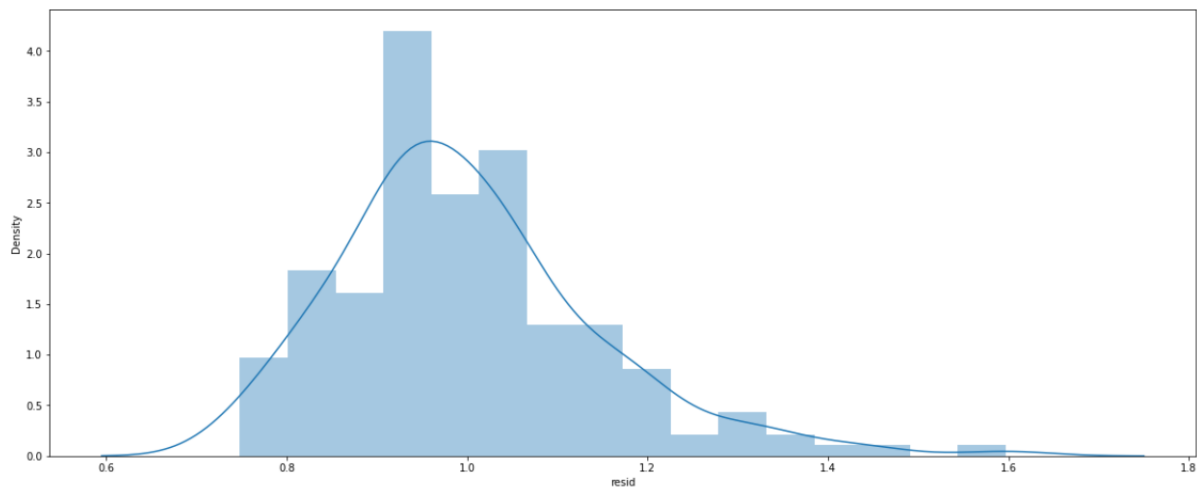


Figure-05

Remarks : for the multiplicative seasonality error mean = 1 and data should be normally distributed.

Note :

- P value is less than 0.05 so null hypothesis is rejected. Residual not normally distributed.
- Residual mean =1 both conditions are not valid so we can say that **seasonality is not multiplicative.**

Bxplot for yearly : To check trends :

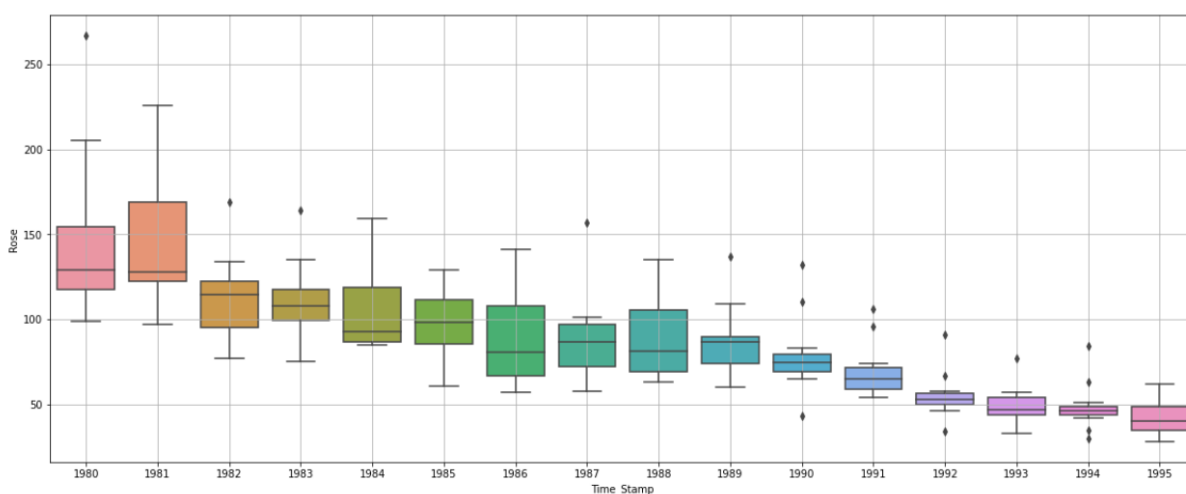


Figure-06

Note :

looks downward trends.

Boxplot for Month : To check seasonality

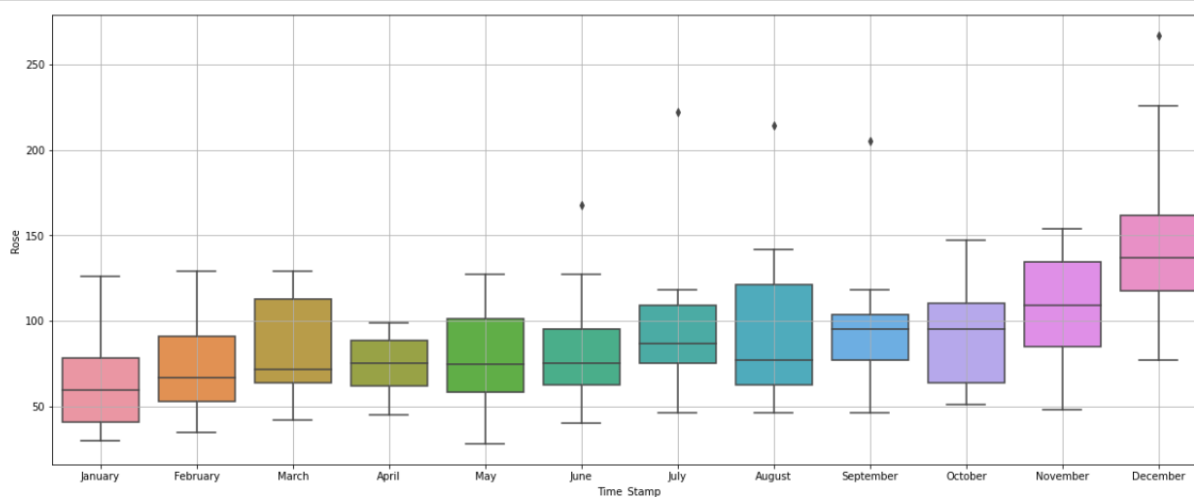


Figure- 07

Note: datasets have no seasonality.

Month plot :

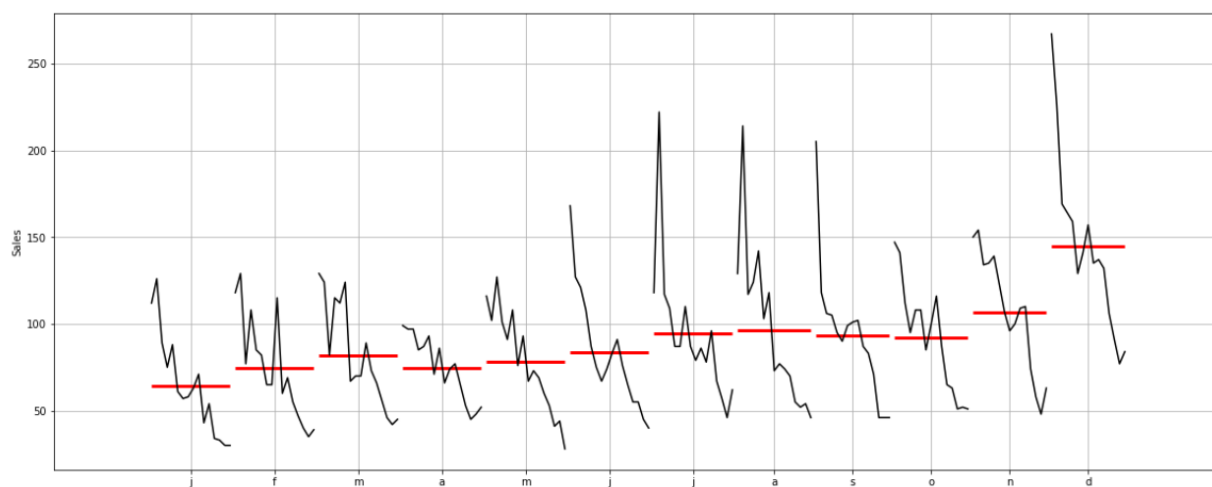


Figure-08

Note : Some month patterns look similar and some of the patterns look different.

So by this pattern we can not justify that data have seasonality.

1.3 Split the data into training and test. The test data should start in 1999.

First few rows of Training Data

| Rose | |
|------------|-----|
| Time_Stamp | |
| 1980-01-31 | 112 |
| 1980-02-29 | 118 |
| 1980-03-31 | 129 |
| 1980-04-30 | 99 |
| 1980-05-31 | 116 |

Last few rows of Training Data

| Rose | |
|------------|-----|
| Time_Stamp | |
| 1990-08-31 | 70 |
| 1990-09-30 | 83 |
| 1990-10-31 | 65 |
| 1990-11-30 | 110 |
| 1990-12-31 | 132 |

First few rows of Test Data

First few rows of Test Data

| Rose | |
|------------|----|
| Time_Stamp | |
| 1991-01-31 | 54 |
| 1991-02-28 | 55 |
| 1991-03-31 | 66 |
| 1991-04-30 | 65 |
| 1991-05-31 | 60 |

Last few rows of Test Data

| Rose | |
|------------|----|
| Time_Stamp | |
| 1995-03-31 | 45 |
| 1995-04-30 | 52 |
| 1995-05-31 | 28 |
| 1995-06-30 | 40 |
| 1995-07-31 | 62 |

Table-06

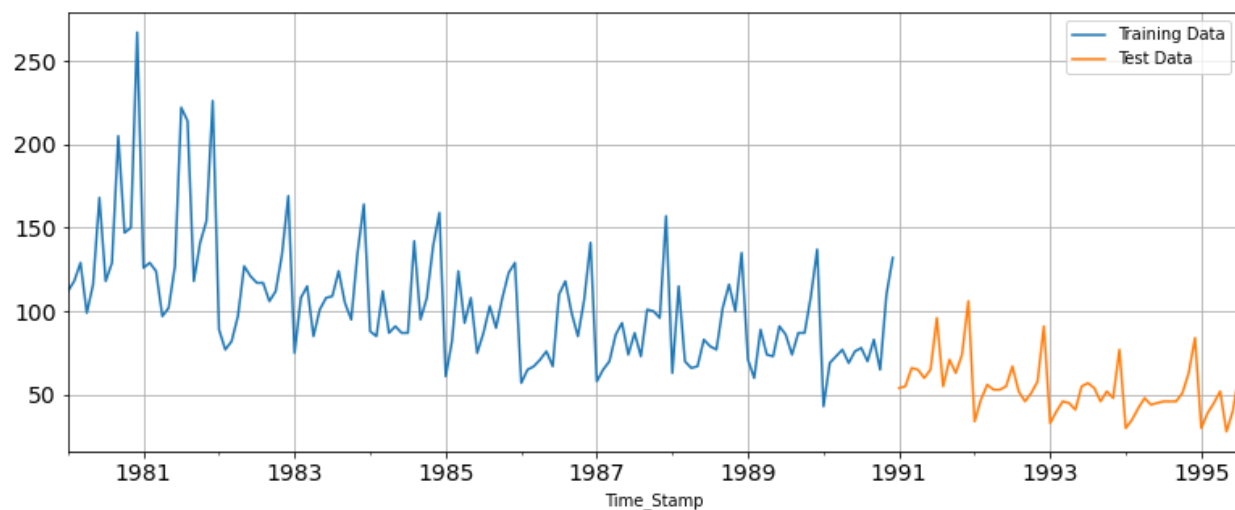


Figure-09

1.4 Build all the exponential smoothing models on the training data and evaluate the model using RMSE on the test data. Other additional models such as regression, naïve forecast models, simple average models, moving average models should also be built on the training data and check the performance on the test data using RMSE.

Linear Regression

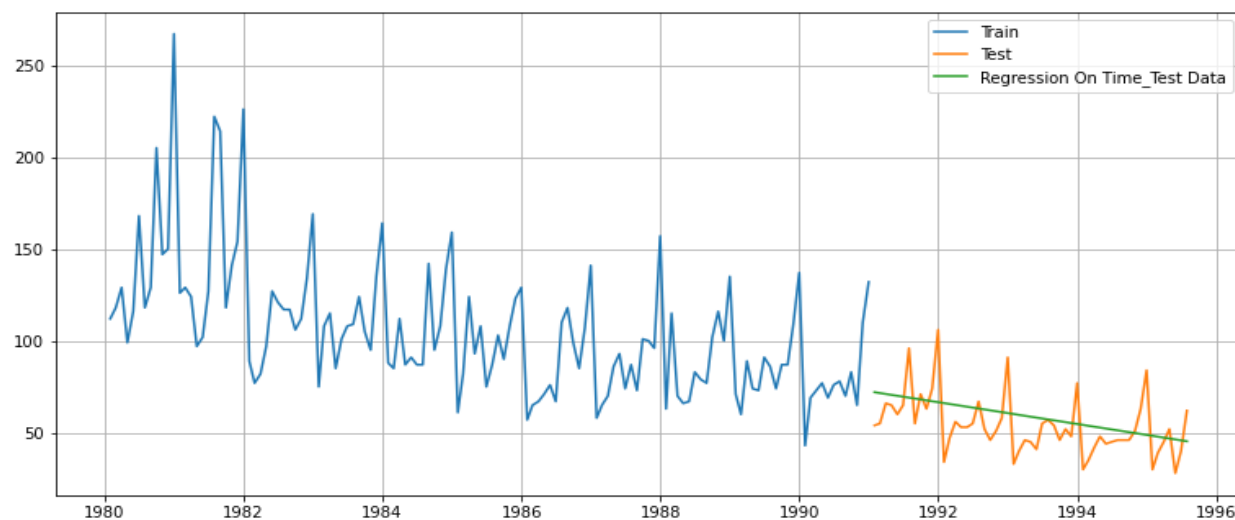


Figure-10

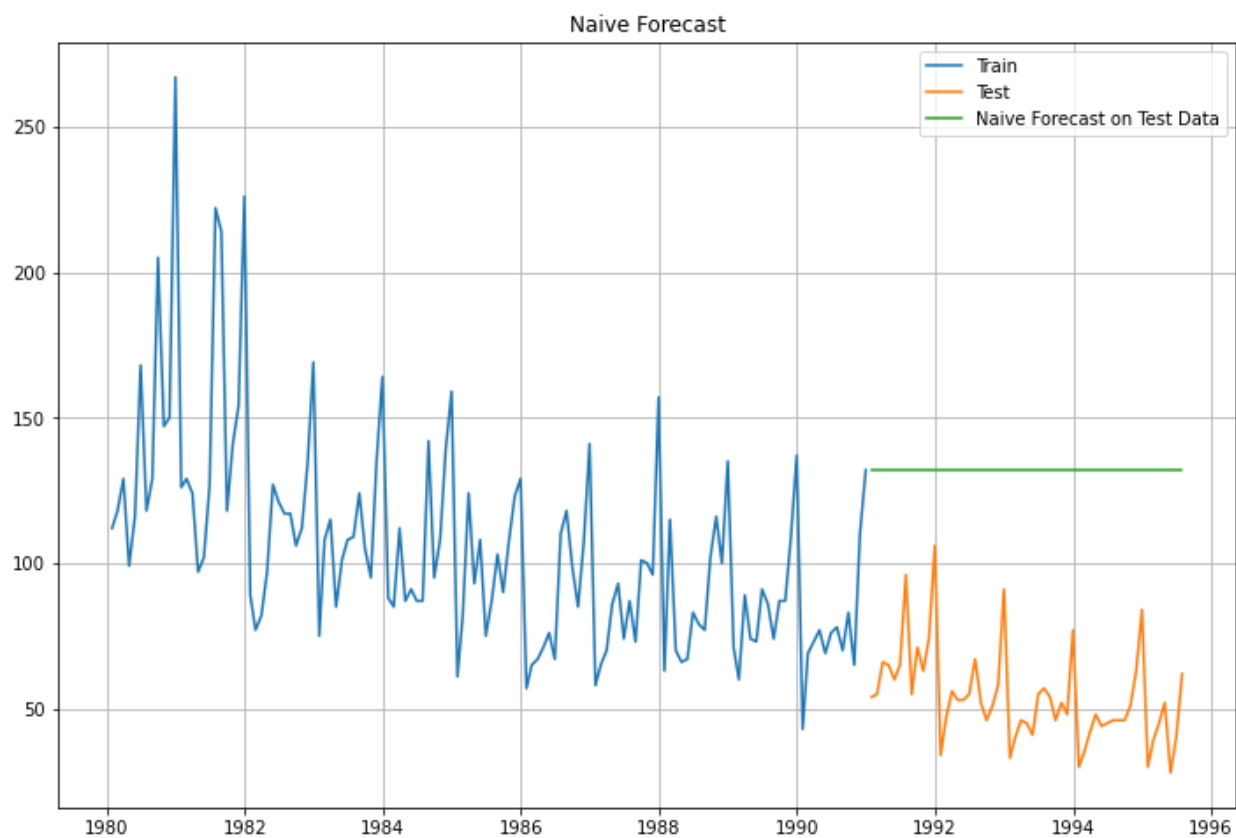
Test RMSE**RegressionOnTime** 15.262509**naïve forecast models :**

Figure-11

For Naive forecast on the Test Data, RMSE is 79.699

simple average models :

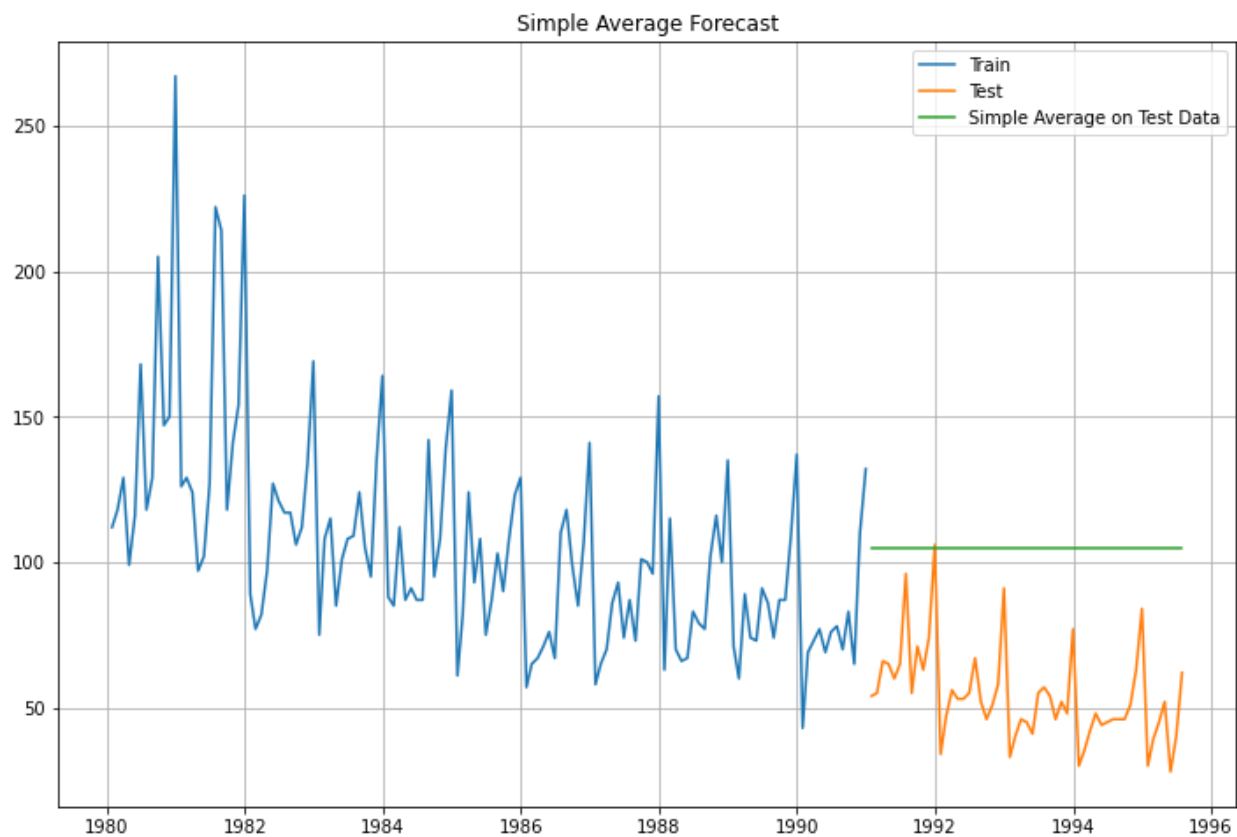


Figure-12

For Simple Average forecast on the Test Data, RMSE is 53.440

Moving Average :

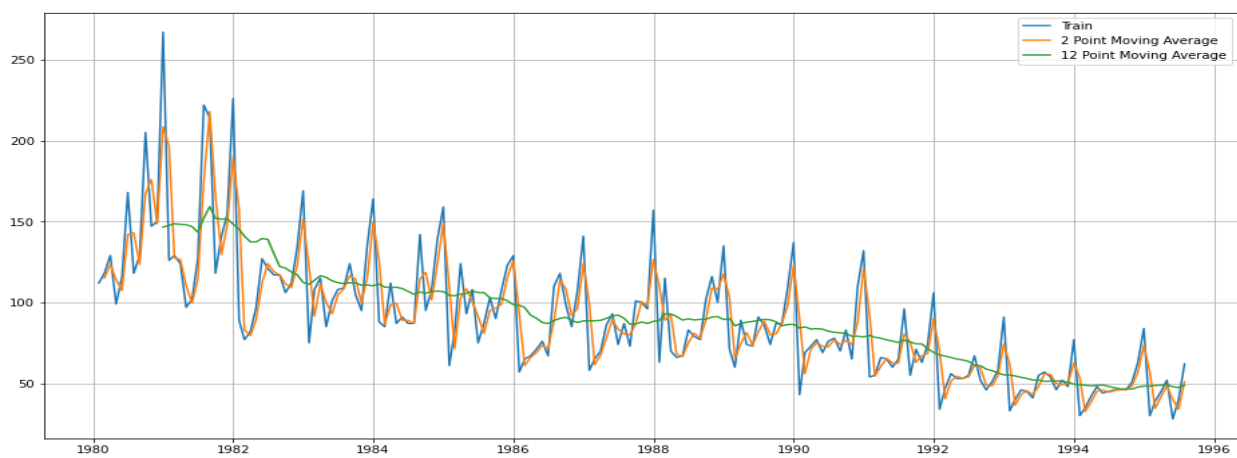


Figure-13

For 2 point Moving Average Model forecast on the Training Data, RMSE is 11.529
For 4 point Moving Average Model forecast on the Training Data, RMSE is 14.449
For 6 point Moving Average Model forecast on the Training Data, RMSE is 14.560
For 9 point Moving Average Model forecast on the Training Data, RMSE is 14.725
For 12 point Moving Average Model forecast on the Training Data, RMSE is 15.234

Simple exponential smoothing :

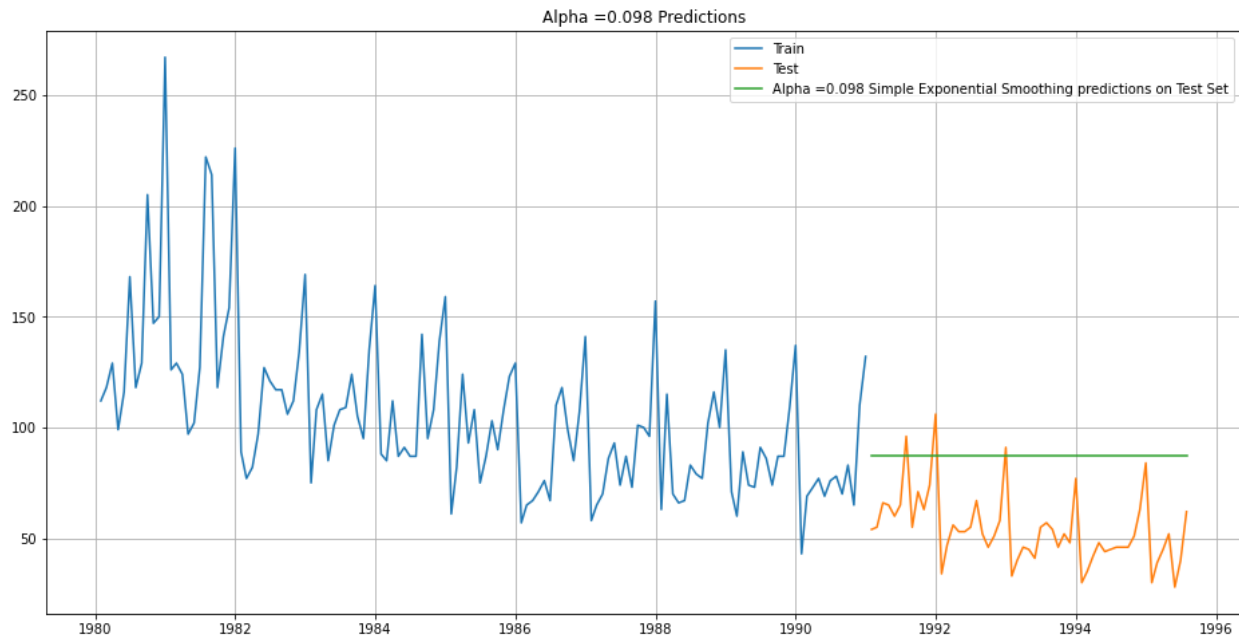


Figure-14

For Alpha =0.098 Simple Exponential Smoothing Model forecast on the Test Data, RMSE is 36.776

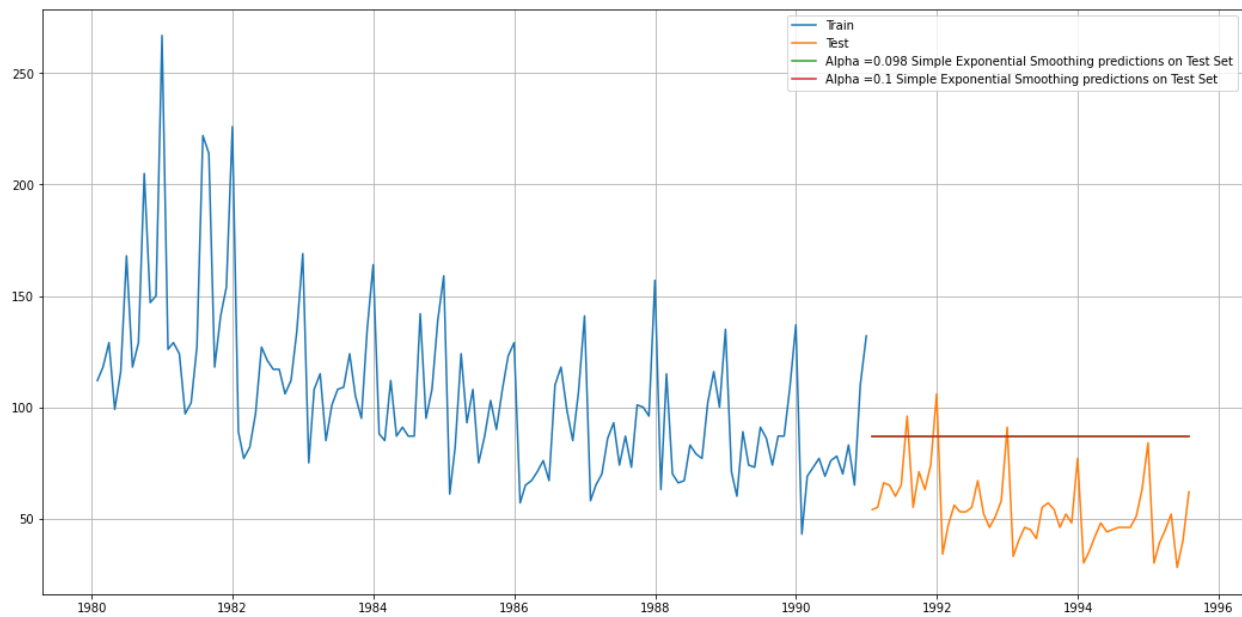


Figure-15

Alpha=0.1,SimpleExponentialSmoothing RMSE = 36.807579

Double exponential smoothing :

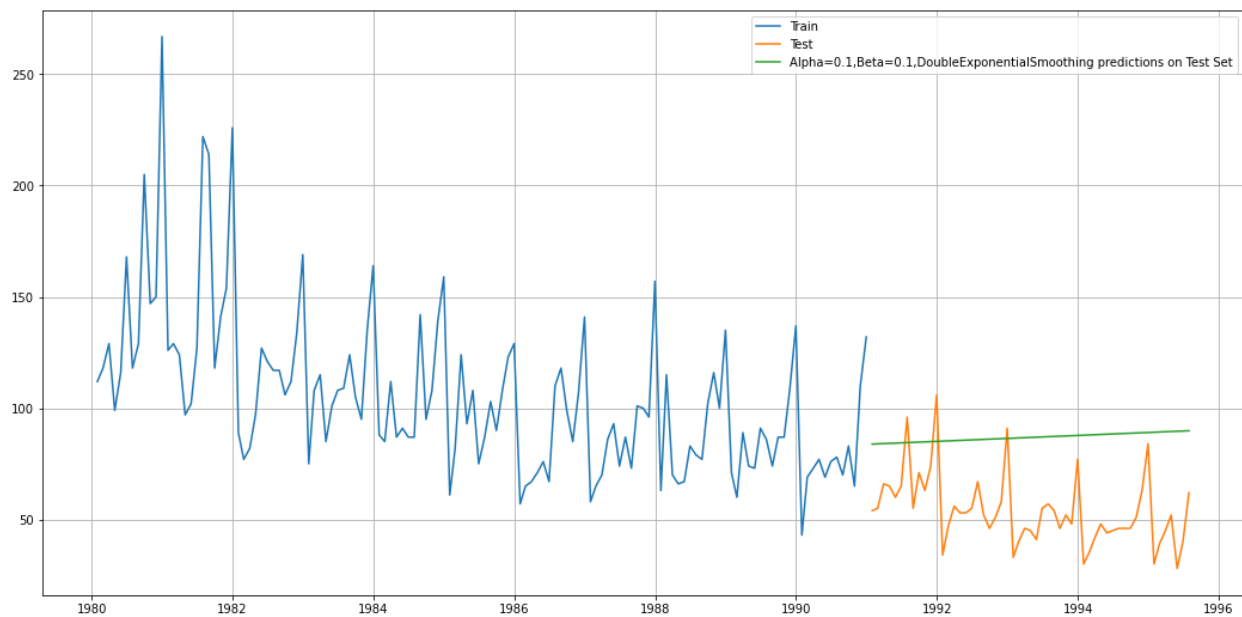


Figure - 16

Alpha=0.1,Beta=0.1,DoubleExponentialSmoothing 36.902316

Triple exponential smoothing :

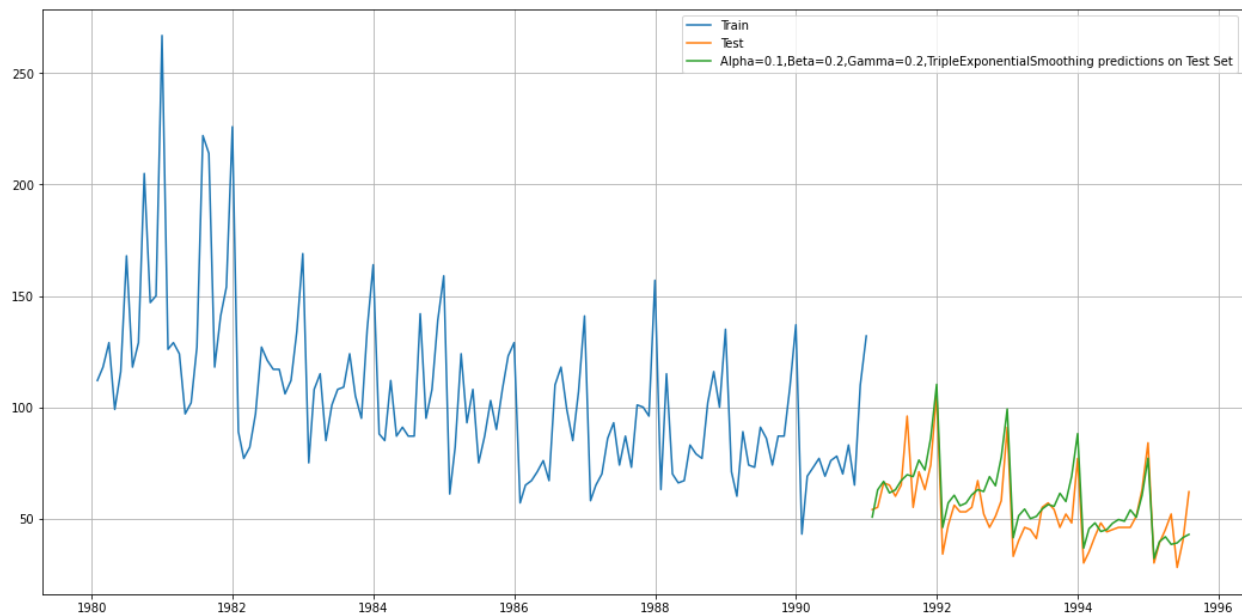


Figure - 17

Alpha=0.1, Beta=0.2, Gamma=0.2, TripleExponentialSmoothing 9.633969

1.5 Check for the stationarity of the data on which the model is being built on using appropriate statistical tests and also mention the hypothesis for the statistical test. If the data is found to be non-stationary, take appropriate steps to make it stationary. Check the new data for stationarity and comment.

Note: Stationarity should be checked at alpha = 0.05.

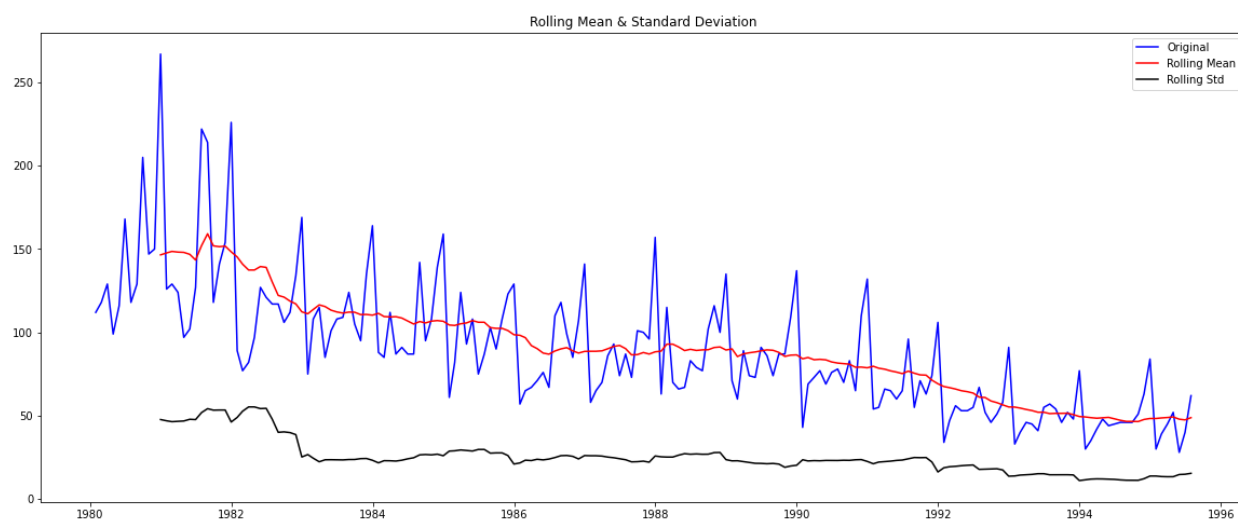


Figure - 18

Results of Dickey-Fuller Test:

| | |
|-----------------------------|------------|
| Test Statistic | -1.877440 |
| p-value | 0.342747 |
| #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 |

Note :

We see that at a 5% significant level the Time Series is non-stationary.

Let us take a difference of order 1 and check whether the Time Series is stationary or not.

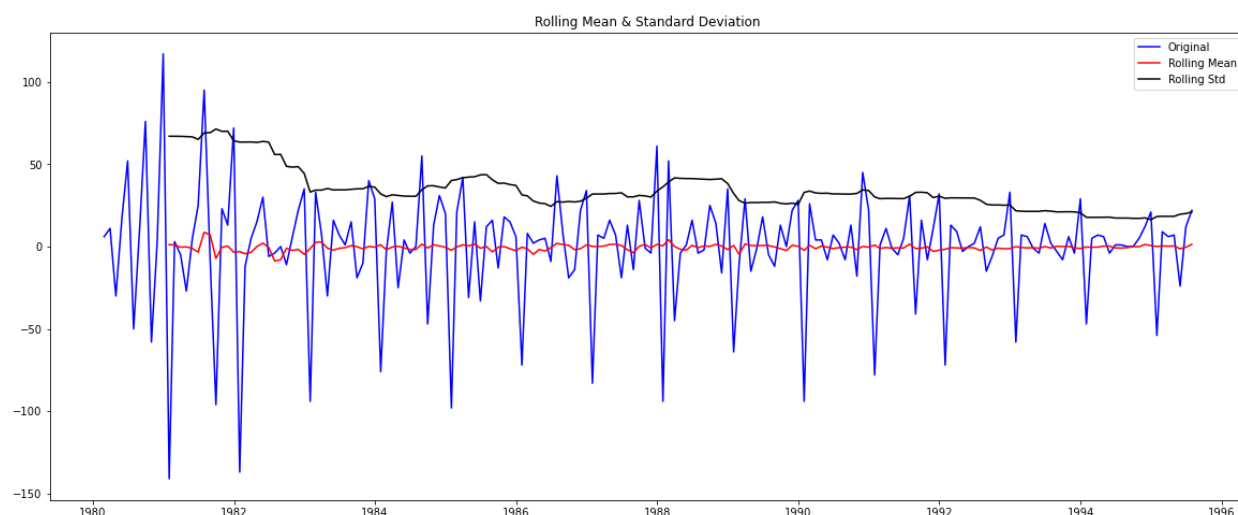


Figure - 19

Results of Dickey-Fuller Test:

| | |
|-----------------------------|---------------|
| Test Statistic | -8.044614e+00 |
| p-value | 1.808550e-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 |

Note :

After differencing We see that at $\alpha = 0.05$ the Time Series is indeed stationary.

1.6 Build an automated version of the ARIMA/SARIMA model in which the parameters are selected using the lowest Akaike Information Criteria (AIC) on the training data and evaluate this model on the test data using RMSE.

AIC Values : In Ascending order

Table-07

| | | | | | | |
|-------------------------|------------------|-------------------|----------|-------|----------|----------|
| Dep. Variable: | Rose | No. Observations: | 132 | | | |
| Model: | ARIMA(2, 1, 3) | Log Likelihood | -631.347 | | | |
| Date: | Wed, 16 Feb 2022 | AIC | 1274.695 | | | |
| Time: | 11:35:56 | BIC | 1291.946 | | | |
| Sample: | 01-31-1980 | HQIC | 1281.705 | | | |
| | - 12-31-1990 | | | | | |
| Covariance Type: | opg | | | | | |
| | coef | std err | z | P> z | [0.025 | 0.975] |
| ar.L1 | -1.6781 | 0.084 | -20.035 | 0.000 | -1.842 | -1.514 |
| ar.L2 | -0.7289 | 0.084 | -8.703 | 0.000 | -0.893 | -0.565 |
| ma.L1 | 1.0450 | 0.685 | 1.527 | 0.127 | -0.297 | 2.387 |
| ma.L2 | -0.7716 | 0.137 | -5.636 | 0.000 | -1.040 | -0.503 |
| ma.L3 | -0.9046 | 0.622 | -1.455 | 0.146 | -2.123 | 0.314 |
| sigma2 | 858.3595 | 576.845 | 1.488 | 0.137 | -272.237 | 1988.956 |
| Ljung-Box (L1) (Q): | 0.02 | Jarque-Bera (JB): | 24.45 | | | |
| Prob(Q): | 0.88 | Prob(JB): | 0.00 | | | |
| Heteroskedasticity (H): | 0.40 | Skew: | 0.71 | | | |
| Prob(H) (two-sided): | 0.00 | Kurtosis: | 4.57 | | | |

Note : All lags are not significant. We can expect the result not to be good.

RMSE of Test data : ARIMA(2,1,3) 36.79705233275287

SARIMA :

AIC Values : In Ascending order

| | param | seasonal | AIC |
|-----|-----------|--------------|-------------|
| 606 | (4, 1, 4) | (1, 1, 1, 6) | 1300.083427 |
| 32 | (0, 1, 1) | (1, 1, 2, 6) | 1303.285643 |
| 157 | (1, 1, 1) | (1, 1, 2, 6) | 1303.900592 |
| 115 | (0, 1, 4) | (3, 1, 0, 6) | 1307.399805 |
| 457 | (3, 1, 3) | (1, 1, 2, 6) | 1307.807674 |

Table-08

| SARIMAX Results | | | | | | |
|-------------------------|---------------------------------|----------|-------------------|-------------------|-----------|----------|
| Dep. Variable: | y | | | No. Observations: | 132 | |
| Model: | SARIMAX(4, 1, 4)x(1, 1, [1], 6) | | | Log Likelihood | -520.116 | |
| Date: | Tue, 15 Feb 2022 | | | AIC | 1062.232 | |
| Time: | 23:35:00 | | | BIC | 1092.330 | |
| Sample: | 0 | | | HQIC | 1074.447 | |
| | - 132 | | | | | |
| Covariance Type: | opg | | | | | |
| | coef | std err | z | P> z | [0.025 | 0.975] |
| ar.L1 | -0.7041 | 0.121 | -5.821 | 0.000 | -0.941 | -0.467 |
| ar.L2 | -0.8000 | 0.102 | -7.849 | 0.000 | -1.000 | -0.600 |
| ar.L3 | -0.6397 | 0.100 | -6.421 | 0.000 | -0.835 | -0.444 |
| ar.L4 | -0.0555 | 0.087 | -0.639 | 0.523 | -0.226 | 0.115 |
| ma.L1 | 0.0217 | 199.186 | 0.000 | 1.000 | -390.377 | 390.420 |
| ma.L2 | 8.261e-08 | 997.038 | 8.29e-11 | 1.000 | -1954.159 | 1954.159 |
| ma.L3 | -0.0217 | 190.887 | -0.000 | 1.000 | -374.153 | 374.110 |
| ma.L4 | -1.0000 | 1027.440 | -0.001 | 0.999 | -2014.744 | 2012.744 |
| ar.S.L6 | -0.9062 | 0.025 | -36.972 | 0.000 | -0.954 | -0.858 |
| ma.S.L6 | 0.3741 | 0.099 | 3.766 | 0.000 | 0.179 | 0.569 |
| sigma2 | 477.7764 | 4.91e+05 | 0.001 | 0.999 | -9.62e+05 | 9.63e+05 |
| Ljung-Box (L1) (Q): | 0.30 | | Jarque-Bera (JB): | 8.48 | | |
| Prob(Q): | 0.58 | | Prob(JB): | 0.01 | | |
| Heteroskedasticity (H): | 0.39 | | Skew: | 0.23 | | |
| Prob(H) (two-sided): | 0.00 | | Kurtosis: | 4.26 | | |

RMSE of test data :

SARIMA(4,1,4)(1,1,1,6) 17.145498

| | param | seasonal | AIC |
|----|-----------|---------------|------------|
| 26 | (0, 1, 2) | (2, 0, 2, 12) | 887.937509 |
| 53 | (1, 1, 2) | (2, 0, 2, 12) | 889.903048 |
| 80 | (2, 1, 2) | (2, 0, 2, 12) | 890.668798 |
| 69 | (2, 1, 1) | (2, 0, 0, 12) | 896.518161 |
| 78 | (2, 1, 2) | (2, 0, 0, 12) | 897.346444 |

Table-09

| SARIMAX Results | | | | | | |
|-------------------------|--------------------------------|-------------------|----------|-------|-----------|----------|
| ===== | | | | | | |
| Dep. Variable: | y | No. Observations: | 132 | | | |
| Model: | SARIMAX(0, 1, 2)x(2, 0, 2, 12) | Log Likelihood | -436.969 | | | |
| Date: | Tue, 15 Feb 2022 | AIC | 887.938 | | | |
| Time: | 23:40:22 | BIC | 906.448 | | | |
| Sample: | 0 | HQIC | 895.437 | | | |
| | - 132 | | | | | |
| Covariance Type: | opg | | | | | |
| ===== | | | | | | |
| | coef | std err | z | P> z | [0.025 | 0.975] |
| ----- | | | | | | |
| ma.L1 | -0.8427 | 189.943 | -0.004 | 0.996 | -373.124 | 371.439 |
| ma.L2 | -0.1573 | 29.841 | -0.005 | 0.996 | -58.645 | 58.330 |
| ar.S.L12 | 0.3467 | 0.079 | 4.375 | 0.000 | 0.191 | 0.502 |
| ar.S.L24 | 0.3023 | 0.076 | 3.996 | 0.000 | 0.154 | 0.451 |
| ma.S.L12 | 0.0767 | 0.133 | 0.577 | 0.564 | -0.184 | 0.337 |
| ma.S.L24 | -0.0726 | 0.146 | -0.498 | 0.618 | -0.358 | 0.213 |
| sigma2 | 251.3137 | 4.77e+04 | 0.005 | 0.996 | -9.33e+04 | 9.38e+04 |
| ===== | | | | | | |
| Ljung-Box (L1) (Q): | 0.10 | Jarque-Bera (JB): | 2.33 | | | |
| Prob(Q): | 0.75 | Prob(JB): | 0.31 | | | |
| Heteroskedasticity (H): | 0.88 | Skew: | 0.37 | | | |
| Prob(H) (two-sided): | 0.70 | Kurtosis: | 3.03 | | | |
| ===== | | | | | | |

RMSE of test data :

SARIMA(0,1,2)(2,0,2,12) 26.907439

1.7 Build ARIMA/SARIMA models based on the cut-off points of ACF and PACF on the training data and evaluate this model on the test data using RMSE.

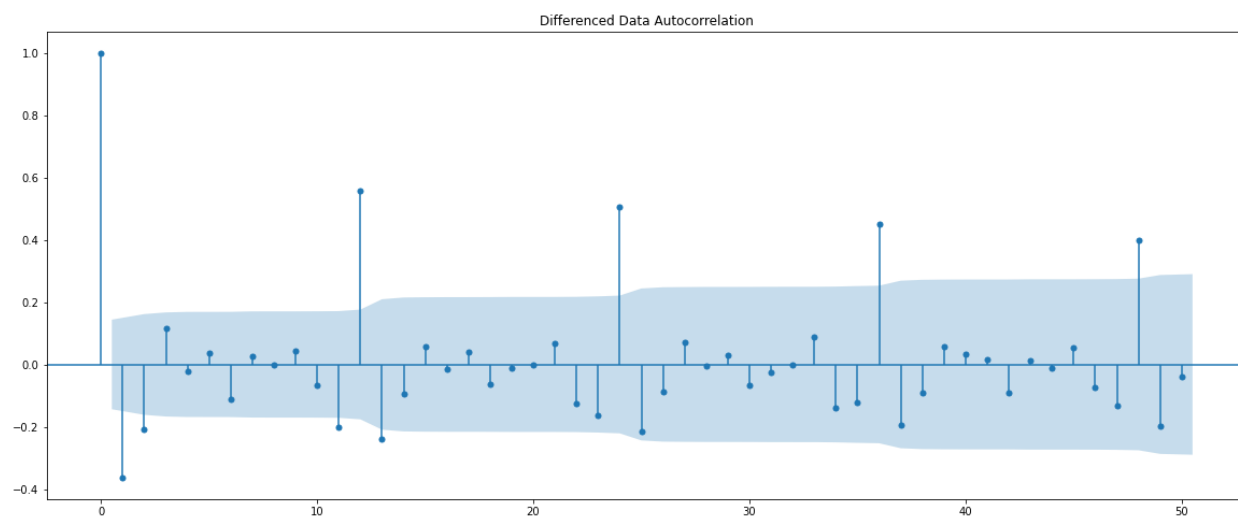


Figure - 20

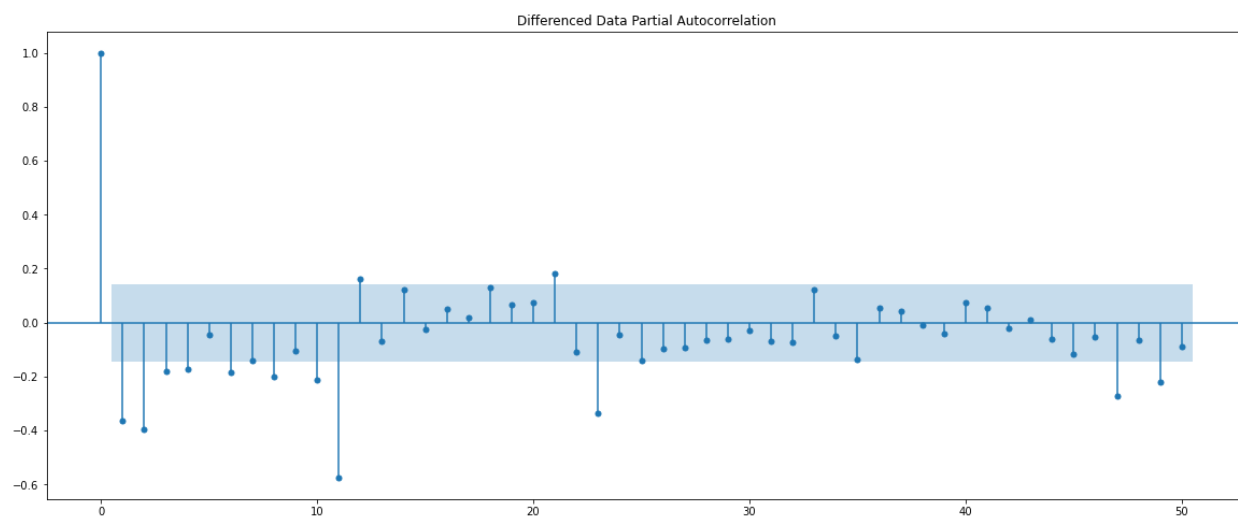


Figure-21

```

=====
SARIMAX Results
=====
Dep. Variable:          Rose      No. Observations:          132
Model:                 ARIMA(1, 1, 0)  Log Likelihood          -656.675
Date:                 Tue, 15 Feb 2022  AIC              1317.350
Time:                 23:48:33    BIC              1323.101
Sample:              01-31-1980    HQIC             1319.687
                   - 12-31-1990
Covariance Type:      opg
=====
              coef      std err          z      P>|z|      [0.025      0.975]
-----
ar.L1         -0.3555      0.067     -5.274      0.000     -0.488     -0.223
sigma2        1321.6677    125.729     10.512      0.000    1075.243    1568.092
=====
Ljung-Box (L1) (Q):          2.56   Jarque-Bera (JB):          19.96
Prob(Q):                    0.11   Prob(JB):              0.00
Heteroskedasticity (H):      0.32   Skew:                 -0.34
Prob(H) (two-sided):        0.00   Kurtosis:             4.79
=====

```

RMSE of test data :

ARIMA(1,1,0) 74.025930

```

=====
SARIMAX Results
=====
Dep. Variable:          y      No. Observations:          132
Model:                 SARIMAX(1, 1, 0)x(0, 1, 0, 6)  Log Likelihood          -672.458
Date:                 Tue, 15 Feb 2022  AIC              1348.917
Time:                 23:54:52    BIC              1354.557
Sample:              0      HQIC             1351.208
                   - 132
Covariance Type:      opg
=====
              coef      std err          z      P>|z|      [0.025      0.975]
-----
ar.L1         -0.3453      0.083     -4.175      0.000     -0.507     -0.183
sigma2        3005.5811    308.165      9.753      0.000    2401.590    3609.573
=====
Ljung-Box (L1) (Q):          1.53   Jarque-Bera (JB):          20.71
Prob(Q):          0.22   Prob(JB):              0.00
Heteroskedasticity (H):      0.30   Skew:                 -0.07
Prob(H) (two-sided):        0.00   Kurtosis:             5.00
=====

```

RMSE of test data :

SARIMA(1,1,0)(0,1,0,6) 334.497445

1.8 Build a table with all the models built along with their corresponding parameters and the respective RMSE values on the test data.

| | Test RMSE |
|--|------------|
| Alpha=0.1,Beta=0.2,Gamma=0.2, TripleExponential Smoothing | 9.633969 |
| 2pointTrailingMovingAverage | 11.529409 |
| 4pointTrailingMovingAverage | 14.448930 |
| 6pointTrailingMovingAverage | 14.560046 |
| 9pointTrailingMovingAverage | 14.724503 |
| 12pointTrailingMovingAverage | 15.234402 |
| RegressionOnTime | 15.262509 |
| SARIMA(4,1,4)(1,1,1,6) | 17.145498 |
| Alpha=0.065,Beta=0.0519,Gamma=3.879136202038614e-06, TripleExponential Smoothing | 20.995338 |
| SARIMA(0,1,2)(2,0,2,12) | 26.907439 |
| Alpha=0.098, SimpleExponential Smoothing | 36.775774 |
| ARIMA(2,1,3) | 36.797052 |
| Alpha=0.1, SimpleExponential Smoothing | 36.807579 |
| Alpha=0.1,Beta=0.1, DoubleExponential Smoothing | 36.902316 |
| SimpleAverageModel | 53.440426 |
| ARIMA(1,1,0) | 74.025930 |
| NaiveModel | 79.699093 |
| SARIMA(1,1,0)(0,1,0,6) | 334.497445 |

Table - 10

Note : We can say that the triple exponential(alpha=0.1, Beta=0.2, gamma=0.2) gives least RMSE.

1.9 Based on the model-building exercise, build the most optimum model(s) on the complete data and predict 12 months into the future with appropriate confidence intervals/bands.

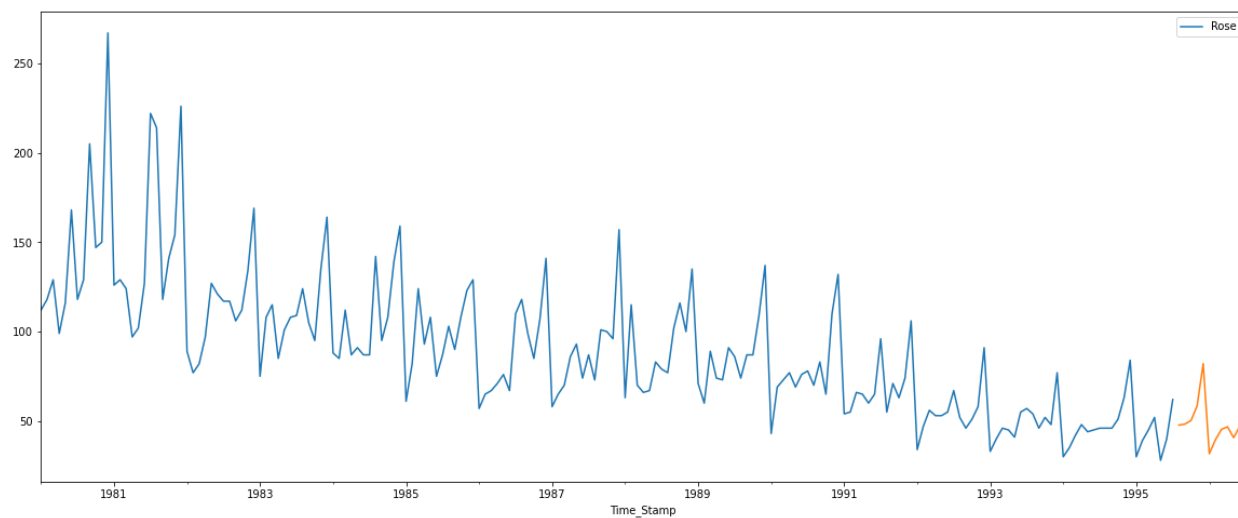


Figure - 22

RMSE of the Full Model 17.40194318433039

| | lower_CI | prediction | upper_ci |
|-------------------|-----------|------------|------------|
| 1995-08-31 | 13.514598 | 47.695360 | 81.876121 |
| 1995-09-30 | 14.103116 | 48.283878 | 82.464639 |
| 1995-10-31 | 16.087505 | 50.268267 | 84.449028 |
| 1995-11-30 | 24.256156 | 58.436918 | 92.617679 |
| 1995-12-31 | 47.893523 | 82.074285 | 116.255046 |

Table-10

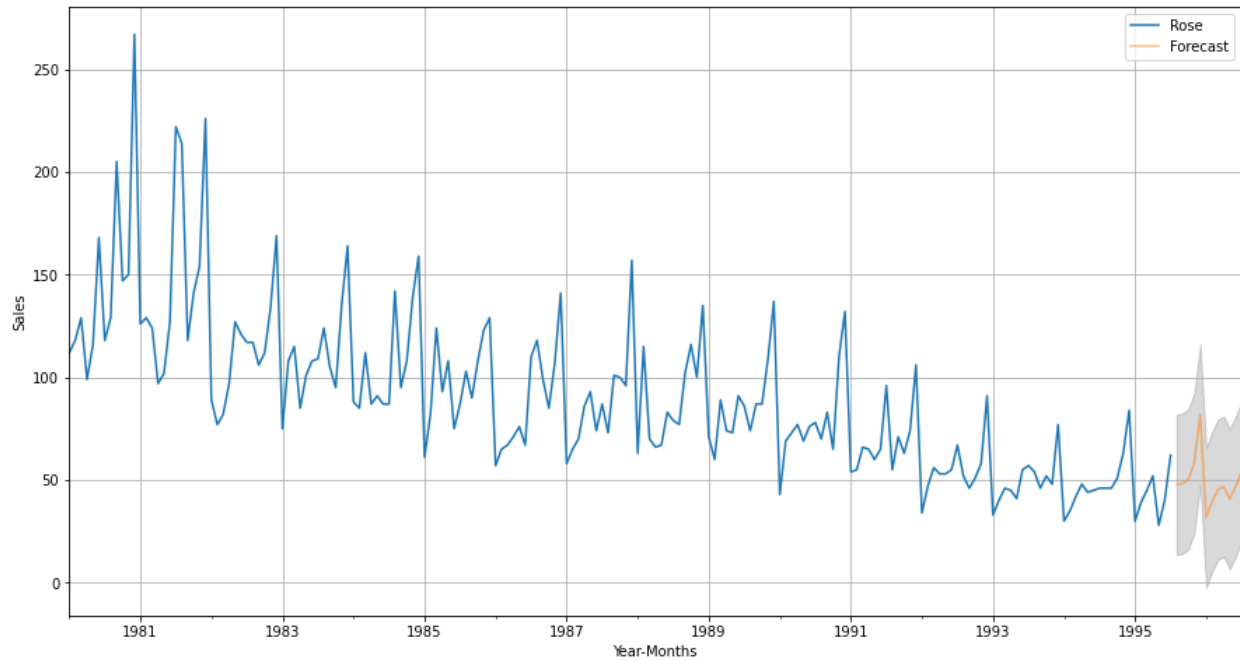


Figure - 23

1.10 Comment on the model thus built and report your findings and suggest the measures that the company should be taking for future sales.

- As we see in the decomposing the datasets trend is going downward so we need to look up seriously why this is happening and try to make sales in an upward trend.
- In December, sales are high.
- need to run promotional marketing campaigns or evaluate if we need to tie up with an alternate agency. It will increase sales.