Time Series Analysis On Exchange Rate of Indian Rupees With Dollar

NAME=SHARAD DESHMUKH

PRN=2012

ABSTRACT:

Through this study, we attempt to understand the dynamics of Indian Rupee fluctuations against US Dollar by using monthly observations over the period of 10 years spanning from January 2010 to December 2021. We also make an attempt to identify the key variables that influence the Indian rupee - US Dollar exchange rate movements. After applying **ARIMA (0,1,0) and EXPONETIAL SMOOTHING and HOLT-WINTER Model** we observe that the Holt-winter Model gives approximately some kind of Proper forecasting factors as compare to other model.

Introduction:

In finance, an exchange rate (also known as conversion rate) between two currencies is the rate at which one currency can be exchanged for another. Exchange rates play a vital role in a country's level of trade, which is critical to almost every free market economy in the world today. Therefore, exchange rates are among the most monitored, analysed and governmentally manipulated economic measures. Exchange rate matters not just on the big macroeconomic scene but also on a smaller one. It impacts the real return of an investor's portfolio, profitability of firms, growth of specific sectors amongst various other determinants of the economy.
The Indian rupee, which was on a par with the American currency at the time of Independence in 1947, has depreciated by a little more than 68 times against the greenback in the past 67 years. On 28th August 2013, the Indian Rupee had gone down to an all-time low of 68.825 against the US dollar. This volatility became severe in the past few years affecting major macro-economic data, including growth, inflation, trade and investment. Through this study, we aim at exploring the dynamics of exchange rate mechanism, the Rupee's journey against dollar since 2010. So we try to used Time Series Forecasting to check the volatility of Exchange rate and also try to forecast the Values. For the accurate forecast We Segmented the Data into two parts which are Training set and Testing Set.

Training Set would be year 2010 to 2020 and Testing set would be year 2021.The Original Data Consist Of 144 month. Original Data Downloaded From above Site.
https://in.investing.com/currencies/usd-inr-historical-data?end_date=1640629800&interval_sec=monthly&st_date=1262284200

Time series is a sequence of numerical data that generally occurs in uniform intervals over a period of time. The main application of time series analysis is forecasting by analyzed historical data (Monfared et al. 2013). Forecasting techniques is usually applied as an aid in controlling past and present operations in planning for future needs. Among the most effective approaches for analyzing time series data we go for multiple
Methods which we have seen in Abstract.

Exploratory Analysis For Original Data:

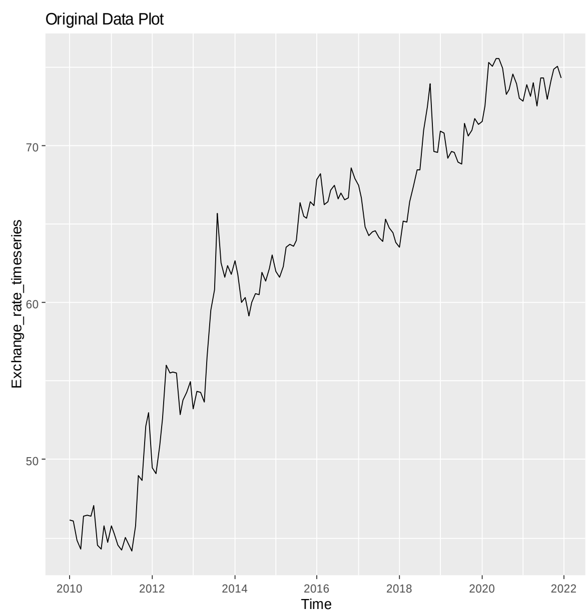

Fig. 1. Plotting of original data.

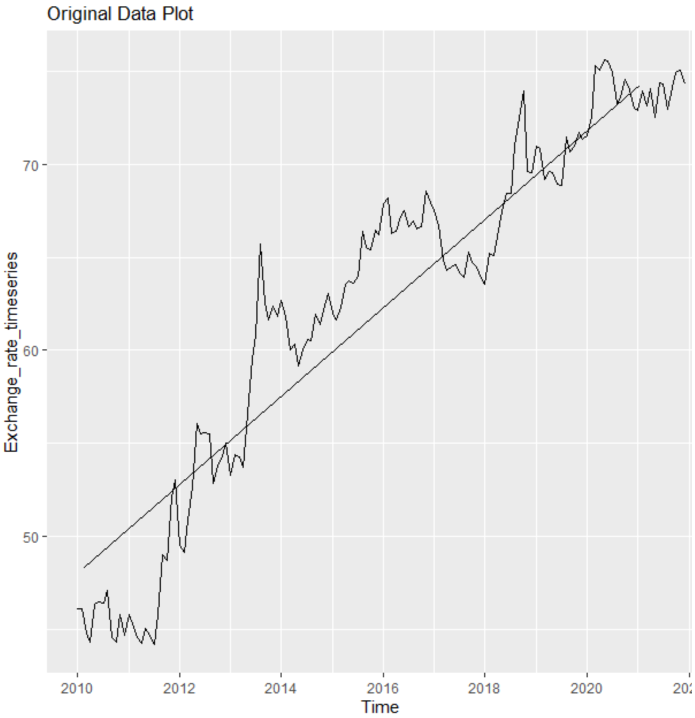

Fig.2

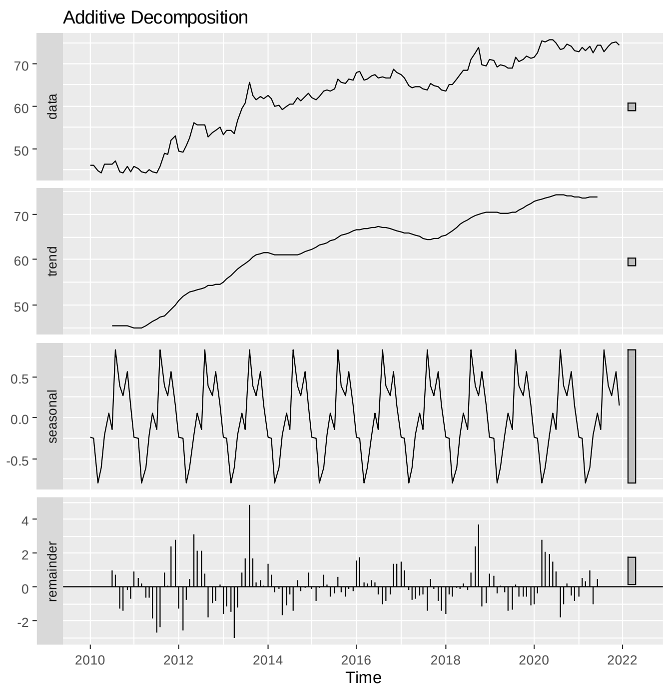

Fig.3

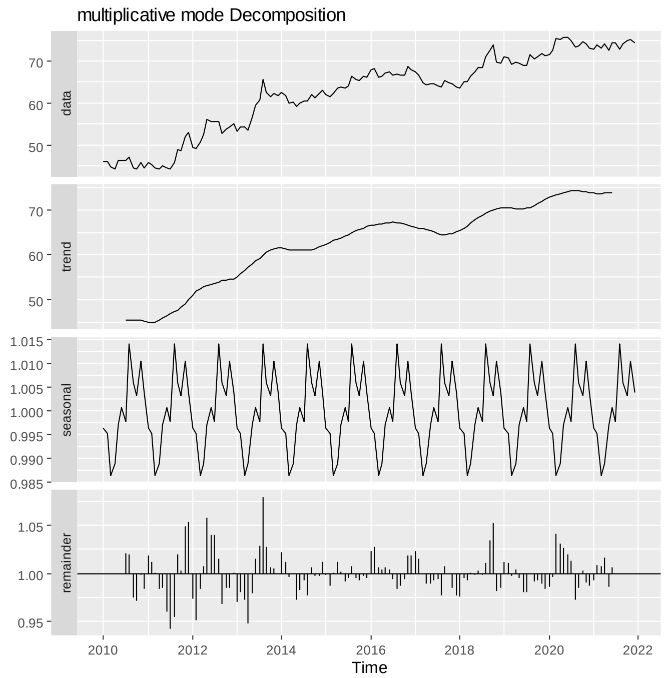

Fig.4 Decomposition Plot.

In **Fig. 2** we draw the linear line into the original plot. The Linear line is nothing but mean , the inference which we can draw from this access as the time increases the mean also increases in other words the mean is function of the time variable but as the mean is the function of time then this time series Data is not Stationary so this the one problem.

Here we get 4 components:

- Observed – the actual data plot
- Trend – the overall upward movement of the data points
- Seasonal – any monthly pattern of the data points
- Random – unexplainable part of the data

. As we plot both Additive and multiplicative plot in **Fig.3** and **Fig.4** we can say that there is not that much difference in both plot so we can used any of the model in forecasting Data.

Methods/Models:

Data consist of 144 month from year 2010 to year 2021, So I want to check how my forecast is correct, so for this I segmented the data into Training And Testing Part. So I can compare my Testing part with forecasted Value from this we can conclude that which model gives best forecasted price Values. Hence I consider the Data from Year 2010 to Year 2020 as Training Set and Testing part will be Year 2021. I have forecast only for 12 month because

The financial Market is changing with time for better forecast it would be better to forecast for 12 month.

Arima Model:

Lets Check first stationarity Of model for this I used augmented Dicky fuller test which conclude that as P value is greater than 0.05 so we accept null Hypothesis so Time series is not Stationary.

Null Hypothesis : Time series is not Stationary

Alternative Hypothesis: Time Series is Stationary

Augmented Dickey-Fuller Test

data: Exchange_rate_timeseries

Dickey-Fuller = -2.0413, Lag order = 5, p-value = 0.5593

alternative hypothesis: stationary

after then we convert train set into Stationary by diff() function we get constant mean, as you can see from Fig.6

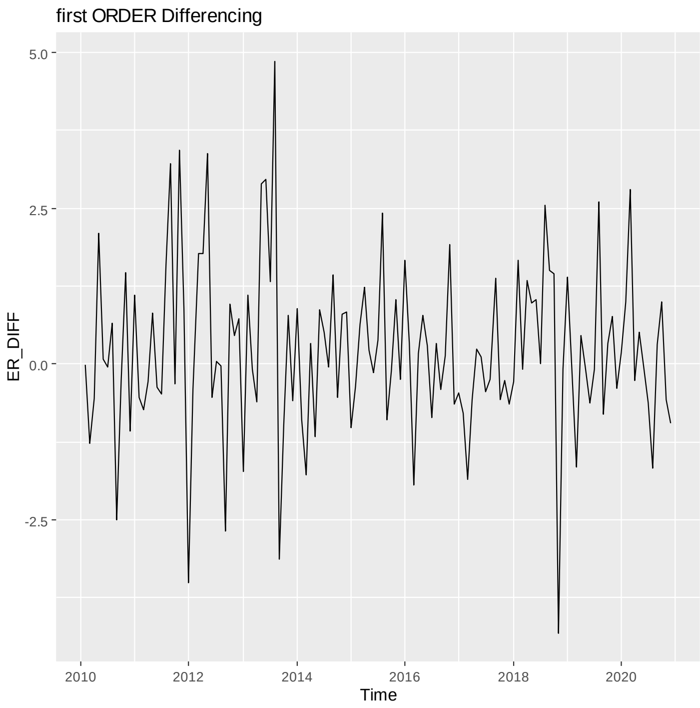

Fig. 5 First Order Differencing

Augmented Dickey-Fuller Test

data: ER_DIFF

Dickey-Fuller = -4.7848, Lag order = 5, p-value = 0.01

alternative hypothesis: stationary

As you can see from Augmented Dickey-Fuller Test from first order differencing that the data is stationary as p value is less than 0.05 so we conclude the first differencing is stationary.

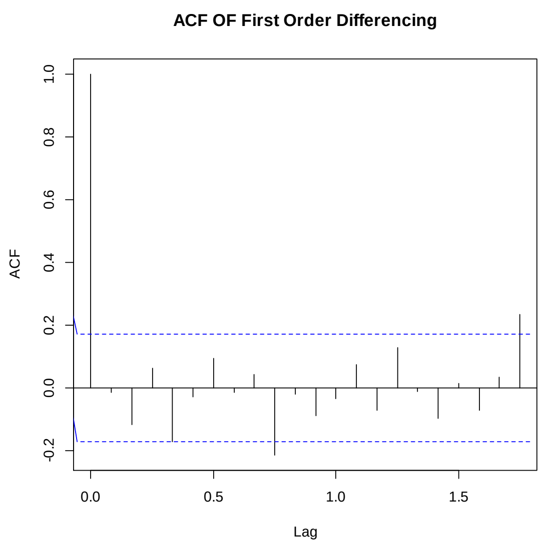

Fig. 6 ACF OF First Order Differencing

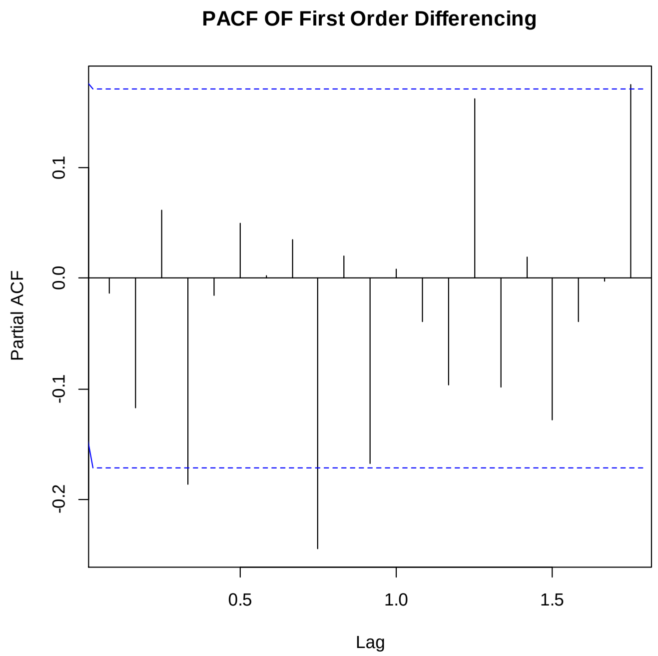

Fig. 7 PACF OF First Order Differencing

Estimating Parameter of Arima (p,d,q) model by Acf and Pacf plot in Fig.7 and Fig.8.

“q” would be that line in Fig.7 from which comes before first inverted line so the numbering start from 0. So the value “q” is 0.

“p” would be that line in Fig.8 from which comes before first inverted line so the numbering start from 0. So the value “p” is 0.

value of “d” can be find number of times we differencing the dataset to make the mean constant we differincing only once hence d=1

so we build Arima (0,1,0)

As we Fit Manually from acf and pacf plot . after than we will see the model on the basis of Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were estimated

As the criteria for the best model to fit for the available data is the model with lowest AIC (**458.1554**) &BIC (**461.0306**) the best model fit for the current data was selected as Arima (0,1,0) (Table 1).

MODEL	**AIC**	**BIC**
ARIMA (0,1,0)	**457.2201**	**462.9705**
ARIMA (1,1,0) (1,0,0) [12]	**461.0522**	**472.553**
ARIMA (0,1,1) (0,0,1) [12]	**461.0511**	**472.5518**
ARIMA (0,1,0)	**458.1554**	**461.0306**
ARIMA (0,1,0) (1,0,0) [12]	**459.0773**	**467.7029**
ARIMA (0,1,0) (0,0,1) [12]	**459.0839**	**472.5755**
ARIMA (0,1,0) (1,0,1) [12]	**461.0747**	**467.8221**
ARIMA (1,1,0)	**459.1965**	**467.815**

Table No.1

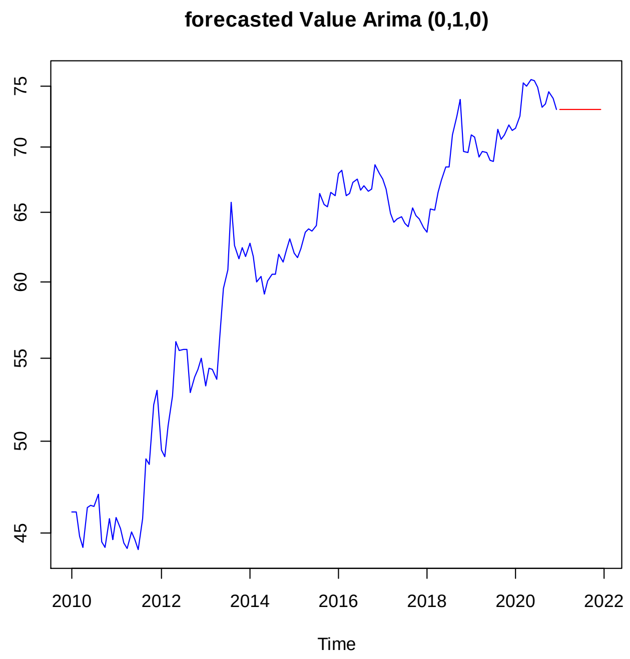

Fig.9 Forecasted Arima (0,1,0) Model

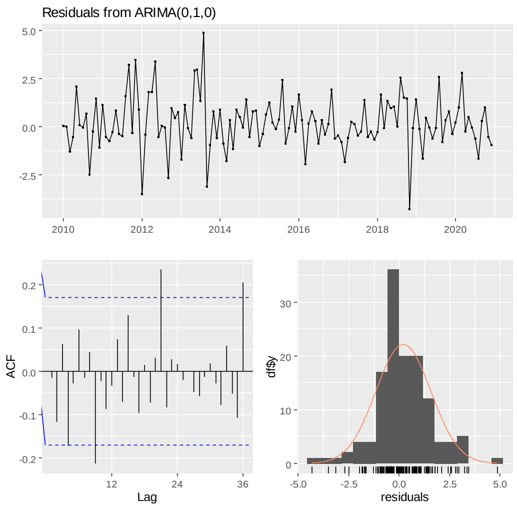

Fig.10 Residual Plot for Arima(0,1,0)

A Ljung-Box test shows the residuals are uncorrelated.

As you can see from Fig.10 we see thar the Residual of arima are normally Distributed so we conclude that our forecasted model is valid.

From Fig.9 we see straight line red in colour which shows the forecasted values of 2021 **,** The *Time Plot* of the ARIMA model shows predictions like that of a random walk with drift forecast.The *Time Plot* is a line graph that plots each observed value against the time of the observation, with a single line connecting each observation across the entire period. When plotting forecast results, it displays the forecasts as well as predication intervals.

Month-yr	Actual Value	Projected Value
Jan-21	72.877	73.036
Feb-21	73.92	73.036
Mar-21	73.137	73.036
Apr-21	74.05	73.036
May-21	72.511	73.036
Jun-21	74.36	73.036
Jul-21	74.337	73.036
Aug-21	72.947	73.036
Sep-21	74.164	73.036
Oct-21	74.914	73.036
Nov-21	75.09	73.036
Dec-21	74.3	73.036

Table No. 2

Ljung-Box test :

data: Residuals from ARIMA(0,1,0)

Q* = 32.675, df = 24, p-value = 0.1111

Model df: 0. Total lags used: 24

say that the recent changes in the data will be leaving a greater impact on the forecasting.

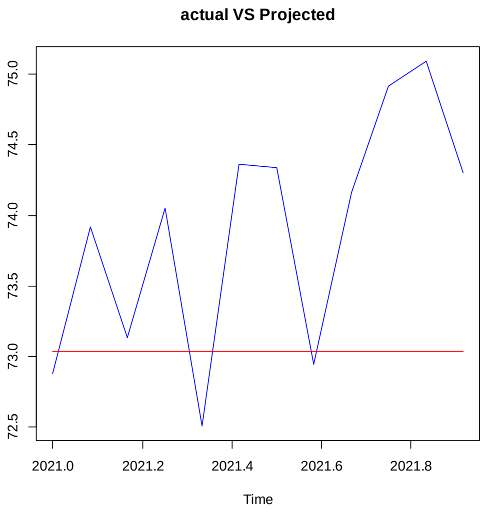

Fig. 11 Actual Vs Projected Plot

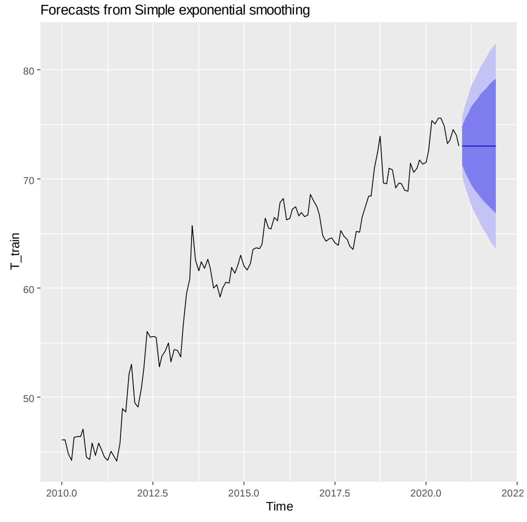

Fig.12 Forecast Simple exponentialSmoothing

As you can see in the Arima Forecasted values are constant and it is represent as red and blue line represent the Actual Values , so for the better prediction I would like to go further Techniques ,which are further :

Simple Exponential Smoothing Technique:

The **Simple Exponential smoothing** technique is used for data that has no trend or seasonal pattern. The SES is the simplest among all the exponential smoothing techniques. We know that in any type of exponential smoothing we weigh the recent values or observations more heavily rather than the old values or observations. The weight of each and every parameter is always determined by a **smoothing parameter** or **alpha**. The value of alpha lies between 0 and 1. In practice, if alpha is between 0.1 and 0.2 then SES will perform quite well. When alpha is closer to 0 then it is considered as slow learning since the algorithm is giving more weight to the historical data. If the value of alpha is closer to 1 then it is referred to as fast learning since the algorithm is giving the recent observations or data more weight. Hence we can

From the above output graph, we can notice that a flatlined estimate is projected towards the future by our forecast model. Hence we can say that from the data it is not capturing the present trend.

Also from table 2 we can see the forecasted Values are Constant but here is the good part is than we can see the forecasted Values lies in 95% Confidence Interval.

Month-Yr	Actual Values	Projected Values	Lowest 95% C.I	Highest 95% C.I
Jan-21	72.877	73.0361	70.3208	75.7513
Feb-21	73.92	73.0361	69.1964	76.8758
Mar-21	73.137	73.0361	68.3335	77.7386
Apr-21	74.05	73.0361	67.6060	78.4661
May-21	72.511	73.0361	66.9651	79.1070
Jun-21	74.36	73.0361	66.3857	79.6864
Jul-21	74.337	73.0361	65.8529	80.2192
Aug-21	72.947	73.0361	65.3569	80.7152
Sep-21	74.164	73.0361	64.8911	81.1810
Oct-21	74.915	73.0361	64.4506	81.6215
Nov-21	75.09	73.0361	64.0315	82.0406
Dec-21	74.3	73.0361	63.631	82.4410

Table No.3 Simple Exponential smoothing Forecast Values.

Double Exponential Smoothing Method:

As mentioned and observed in the previous section, SES does not perform well with data that has a long-term trend. An alternative method to apply exponential smoothing while capturing trend in the data is to use *Holt's Method*.

Holt's Method makes predictions for data with a trend using ***two*** smoothing parameters, α and β, which correspond to the level and trend components, respectively. For Holt's method, the prediction will be a line of some non-zero slope that extends from the time step after the last collected data point onwards.

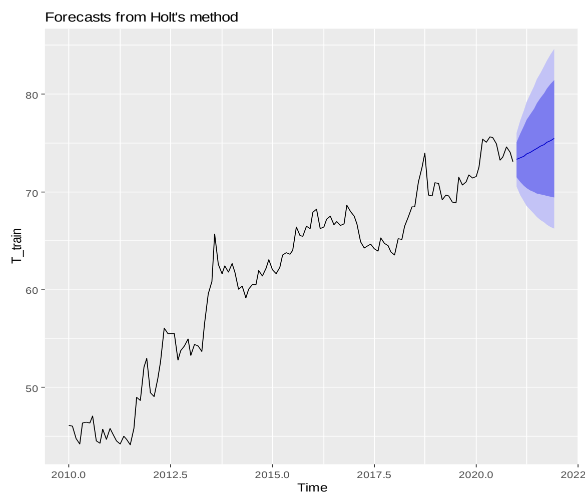

Fig.13 Forecast Double exponential Smoothing

Within **Holt** you can manually set the α and β parameters; however, if you leave those parameters as NULL, the **Holt** function will actually identify the optimal model parameters. It does this by minimizing AIC and BIC values. We can see the model selected by **Holt**. In this case, α=0.9767 meaning fast learning in the day-to-day movements and β=0.0001 which means slow learning for the trend.

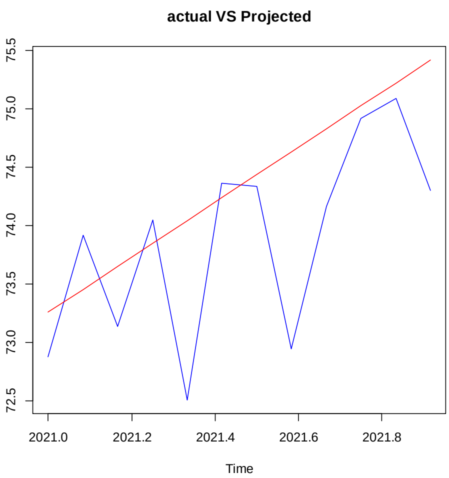

Fig14.Actual Vs Projected Value

Month-Yr	Actual Values	Projected Value	Lowest 95% C.I	Highest 95% C.I
Jan-21	72.877	73.25916	70.55048	75.96783
Feb-21	73.92	73.45507	69.66868	77.24146
Mar-21	73.137	73.65098	69.03167	78.27028
Apr-21	74.05	73.84689	68.52329	79.17048
May-21	72.511	74.0428	68.09765	79.98795
Jun-21	74.36	74.23871	67.73099	80.74642
Jul-21	74.337	74.43462	67.40914	81.46009
Aug-21	72.947	74.63053	67.12281	82.13824
Sep-21	74.164	74.82644	66.86556	82.78731
Oct-21	74.915	75.02235	66.63266	83.41203
Nov-21	75.09	75.21825	66.42055	84.01596
Dec-21	74.3	75.41416	66.22647	84.60186

Table No.4 Double Exponential Smoothing Forecast Values

As you can see from the Fig.14 and Table No.4 the projected values are increasing in constant trend but the actual test data has some fluctuation in September ,October.

The inceasing seasonality trend not observed by the Double exponential Method so we will go for Holt-Winter Seasonal method.

Holt-Winter’s Seasonal Method :

The **Holt-Winter’s Seasonal** method is used for data with both seasonal patterns and trends. This method can be implemented either by using **Additive structure** or by using the **Multiplicative structure** depending on the data set. The Additive structure or model is used when the seasonal pattern of data has the same magnitude or is consistent throughout, while the Multiplicative structure or model is used if the magnitude of the seasonal pattern of the data increases over time. It uses **three smoothing parameters,- alpha, beta, and gamma**.

So from Fig.15 we can see the Holt-winter Additive model is increasing constant with alpha = 0.9694 and RMSE value is 1.271544 in testing set ,and in the other side the Holt-winter Multiplicative model is Increasing With alpha = 0.5021, beta = 0.0311, gamma = 0.0002 And the RMSE Value is 1.249064 . The smoothing parameters and initial estimates for the components have been estimated by minimising RMSE .

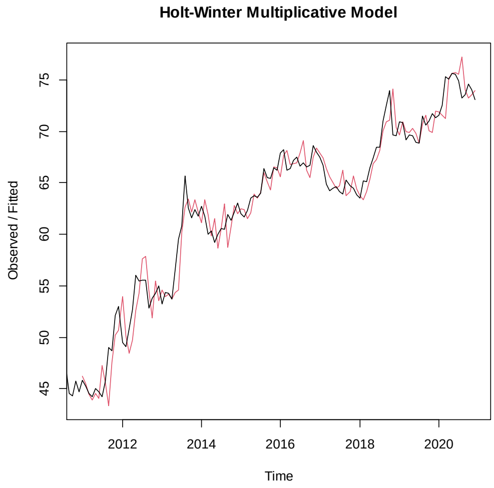

Fig.16 Holt-winter Multiplicative Model

Fig.15 Holt-winter Additive-Multiplicative Model

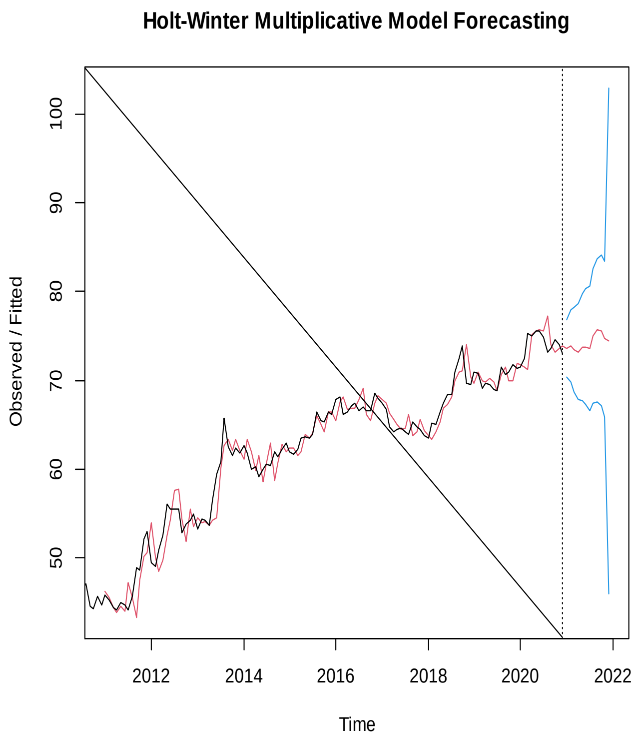

Fig.17 Holt-winter Multiplicative Model Forecasting

The Red Line shows forecasted Result and The Black Line Indicates the Actual Training Data.in **Fig 17**

Month-Yr	Actual Values	Projected Values	Lowest 95% C.I	Highest 95% C.I
Jan-21	72.877	73.67313	70.46107	76.8852
Feb-21	73.92	73.90928	69.81673	78.00183
Mar-21	73.137	73.46384	68.66499	78.26269
Apr-21	74.05	73.25263	67.83081	78.67445
May-21	72.511	73.75701	67.73452	79.77949
Jun-21	74.36	73.80196	67.25394	80.34999
Jul-21	74.337	73.64431	66.62146	80.66715
Aug-21	72.947	75.00464	67.41015	82.59914
Sep-21	74.164	75.67818	67.59357	83.76279
Oct-21	74.915	75.61609	67.12968	84.10251
Nov-21	75.09	74.69857	65.91393	83.48321
Dec-21	74.3	74.45675	46.02229	102.8912

Table No.5 Holt-winter Multiplicative Model Forecasting Values.

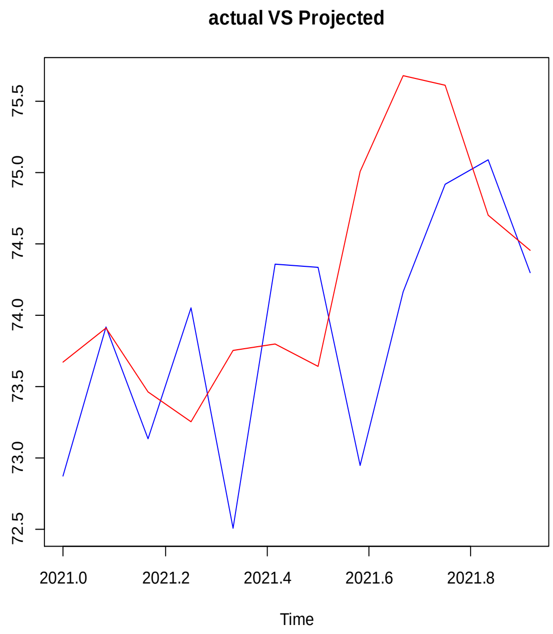

Fig.18 Actual Vs Projected Values of Holt-winter Multiplicative Model

AS in Fig.18 and Table No. 5 we get approximately better result than Any other Model that we Used so far.

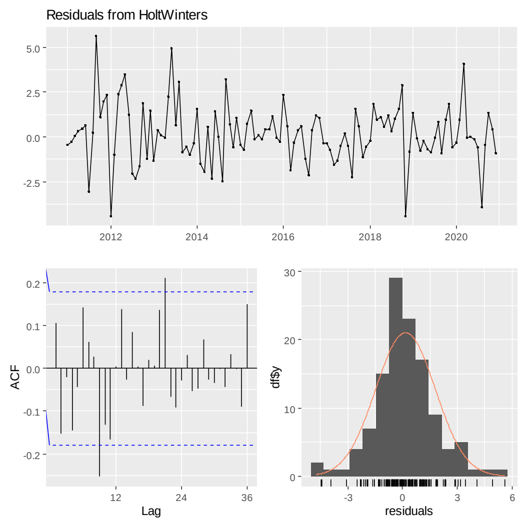

Fig.19 Residuals Of Holt-winter Method

As You can See From above Fig.19 that Residuals Are normally Distributed and independent to each other Also residuals Have constant Variance We can see.

Conclusion=

Model	RMSE	MAPE	MAE
ARIMA Model	1.161676	1.313661	0.976833
Simple Exponetial Smoothing	1.161606	1.313596	0.976785
Double Exponetial Smoothing	0.794811	0.796005	0.584218
Holt-Winter Seasonal Multiplicative Model	1.249064	1.231773	0.903553

Table No.6 Model Checking

Suppose we fit four Different models and find their corresponding RMSE values:

Model 3 has the lowest RMSE, which tells us that it's able to fit the dataset the best out of the Four potential models.

Since the Financial Market are very unpredictable and they bound to have

Several Fluctuation, The fluctuation that we have seen Like the fluctuation Which we have seen During Any Economical Crisis, Coronavirus,import-Export will create Huge Fluctuation in Exchange Rate of Indian Rupees with Dollar.