Report
By

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a. The assignment is done using R as well as python
b. Dataset used is 100 Yen/INR exchange rate and gathered from RBI website
c. We will analyze daily timeframe data from the period 27-08-1998 to 30-12-2022

Libraries used : library(lubridate), library(tseries) ,library(Metrics)

Part 1

ARMA/ ARIMA and its variation

Step 1: Loading the data

```
No of datapoints 5943
No of columns in the data 2
```

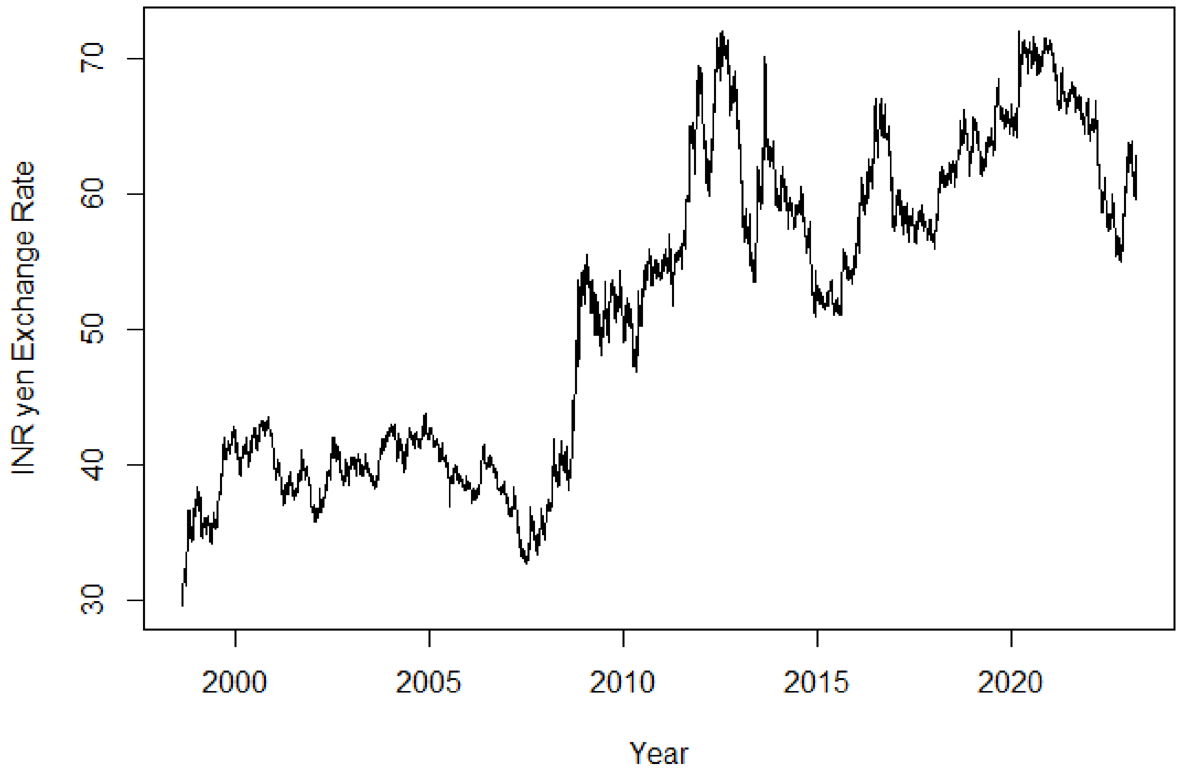
	Date	Yen
1	27-Aug-98	29.6191
2	28-Aug-98	29.8151
3	1-Sep-98	30.5548
4	2-Sep-98	30.8859
5	3-Sep-98	31.1566
6	4-Sep-98	31.4820
7	10-Sep-98	31.3254
8	11-Sep-98	32.2654
9	14-Sep-98	32.1141
10	15-Sep-98	31.9040
11	16-Sep-98	31.6266
12	17-Sep-98	31.5766
13	18-Sep-98	32.1636
14	21-Sep-98	31.7309
15	22-Sep-98	31.5686
16	23-Sep-98	31.3289
17	24-Sep-98	31.1210
18	25-Sep-98	31.3913
19	28-Sep-98	31.3320
20	29-Sep-98	31.4974
21	5-Oct-98	31.4429
22	6-Oct-98	31.9349
23	7-Oct-98	32.7521
24	8-Oct-98	34.4654
25	9-Oct-98	36.3795
26	11-Oct-98	34.5602

Showing 1 to 27 of 5,943 entries, 2 total columns

Console

Step 2: Plotting time series

Note that :
Data is for 100JPY to inr



Step 3: Test for non-stationarity using ADF and PP

ADF Test

The augmented Dickey-Fuller (ADF) test is a formal statistical test for stationary check.
The null hypothesis assumes that the series is non-stationary.
The null-hypothesis for an ADF test is that the data are non-stationary.
So p-value greater than 0.05 indicates non-stationary, and p-values less than 0.05 suggest stationary.

```
Augmented Dickey-Fuller Test

data:  ts(train_set)
Dickey-Fuller = -0.76101, Lag order = 6, p-value = 0.9641
alternative hypothesis: stationary
```

This test is also used to check whether time series is stationary or not.
In the KPSS test, the null-hypothesis is that the data are stationary.
In this case, p-value less than 0.05 indicates non-stationary series and p-value greater than 0.05 indicates stationary series.

```
KPSS Test for Level Stationarity
```

```
data:  ts(train_set)
KPSS Level = 2.7596, Truncation lag parameter = 4, p-value = 0.01
```

ADF and PP statistics and p-value rejects the null hypothesis for stationarity, hence this series is non- stationary

Since the p-value of the KPSS test (`0.01`) is less than 0.05, and p-value of ADF test (`0.9641`) greater than 0.05 it indicates the time series is non-stationary.

Ljung-Box test

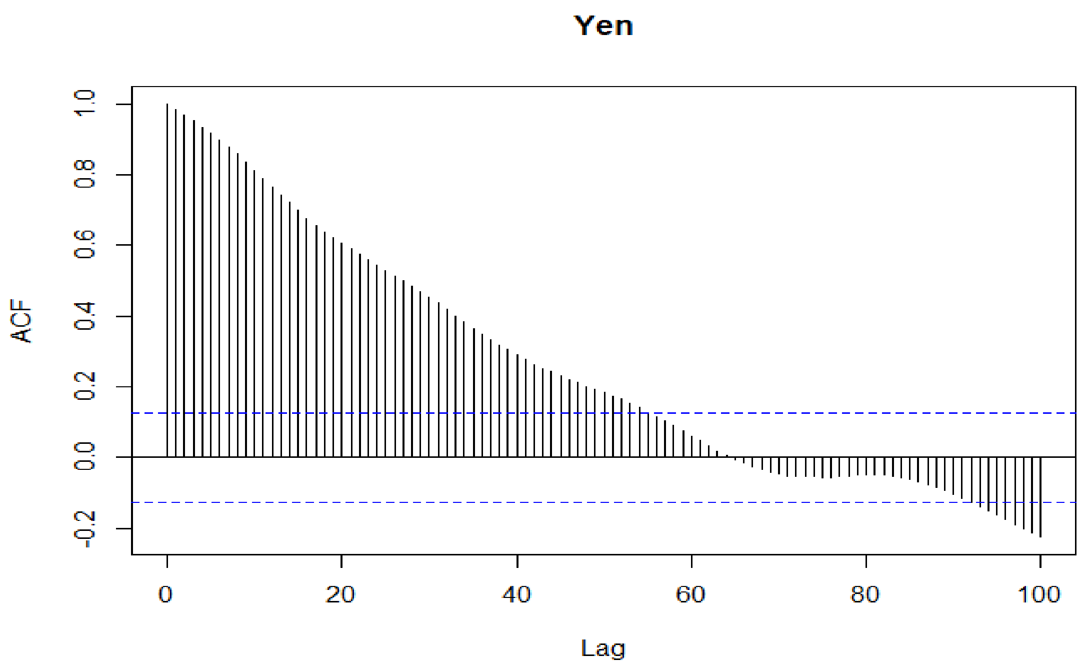
The Ljung-Box test is a classical hypothesis test that is designed to test whether a set of auto-correlations of a fitted time series model differ significantly from zero.

```
Box-Ljung test

data:  train_set
X-squared = 236.63, df = 1, p-value < 2.2e-16
```

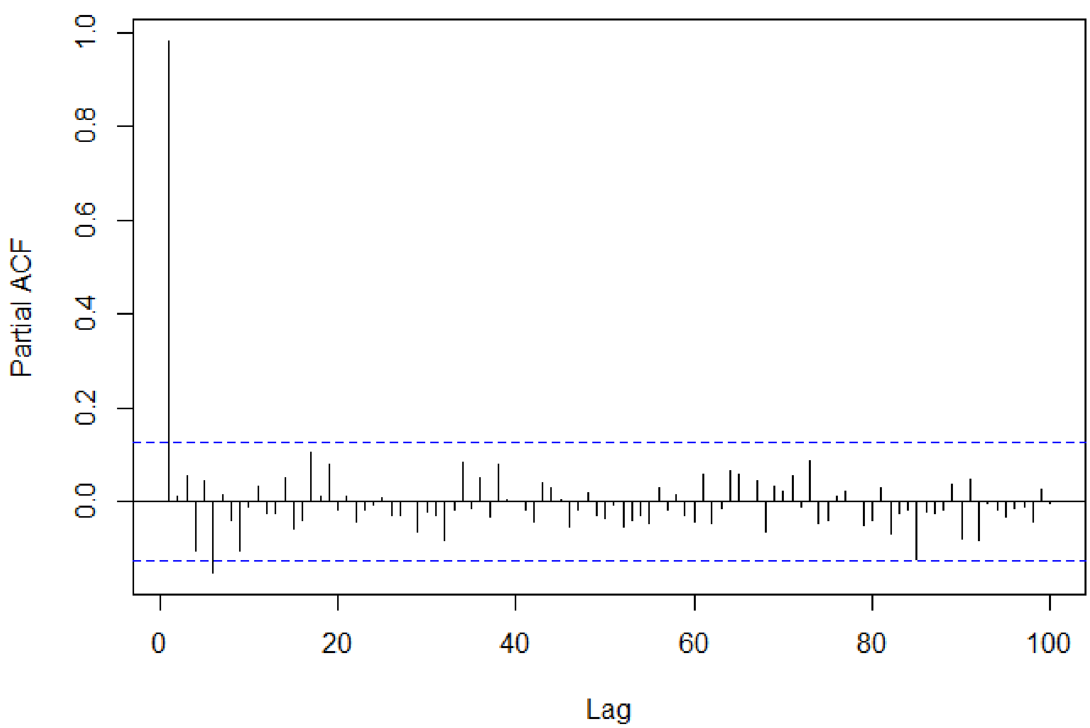
Step 5: Test for non-stationarity at First Difference of the series using Autocorrelation and Partial Autocorrelation

ACF



Since the ACF plot shows that Auto-correlation is dropping immediately after the first lag and we can use the ARIMA model.

PACF



Step 5: Building ARIMA model

ARIMA models and its variation based on ARIMA(p,d,q)

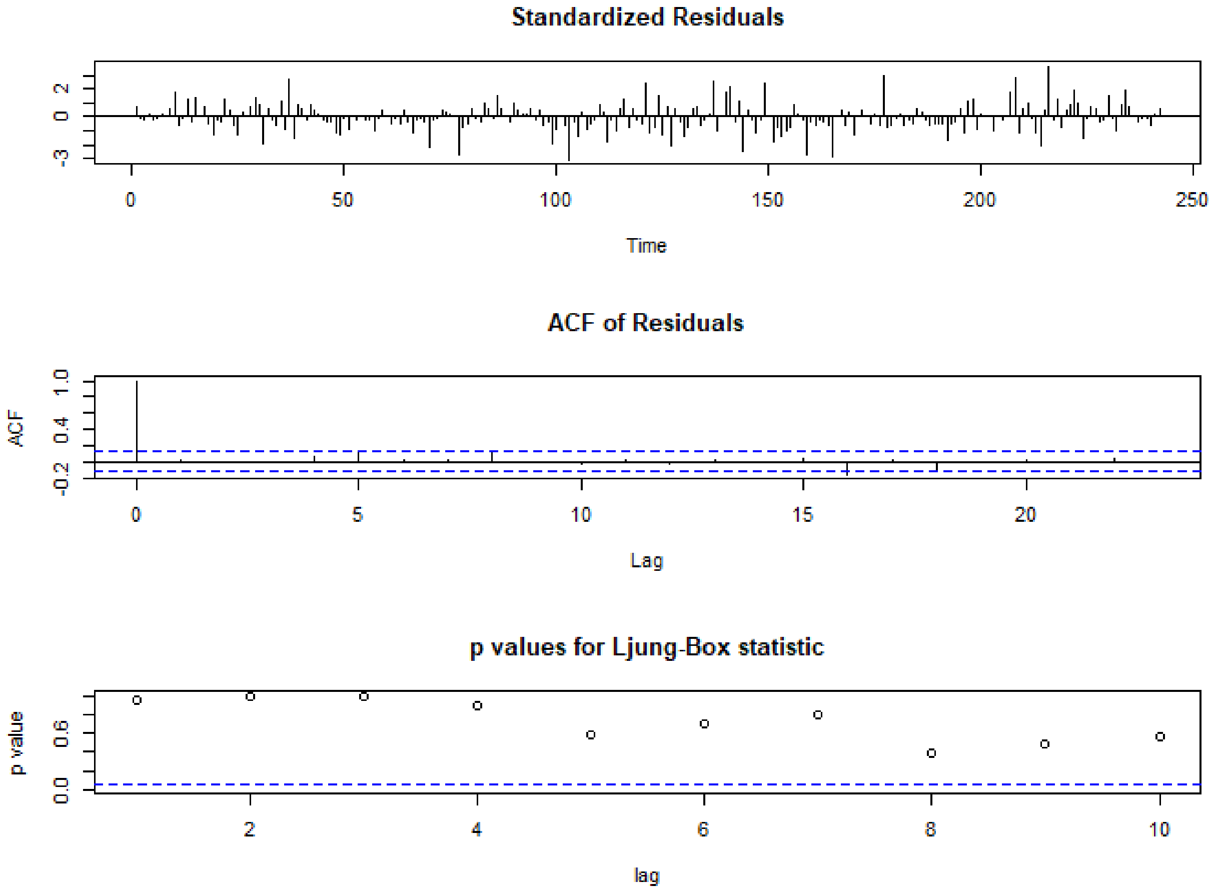
1. ARIMA model [Order (5,0,1)]

```
       ar1          ar2          ar3          ar4          ar5          ma1
intercept
  0.36083566   0.54425914   0.14350579  -0.11337687   0.04388598   0.66131358
125.67301205
```

```
                   ar1          ar2           ar3          ar4          ar5
ma1
ar1         0.0418229563 -0.039239303  0.0008243126 -0.012485313  0.009693083
-0.038125233
ar2        -0.0392393026  0.042374953 -0.0036943080  0.010002613 -0.009980822
0.038156295
ar3         0.0008243126 -0.003694308  0.0059788948 -0.001547030 -0.001506166
-0.003133697
ar4        -0.0124853135  0.010002613 -0.0015470302  0.008246349 -0.004349280
0.011906828
ar5         0.0096930828 -0.009980822 -0.0015061655 -0.004349280  0.006358445
-0.009373762
ma1        -0.0381252331  0.038156295 -0.0031336966  0.011906828 -0.009373762
0.038535615
intercept  0.1055985829 -0.140745994  0.0134920154  0.028952955  0.137072107
-0.124768683
```

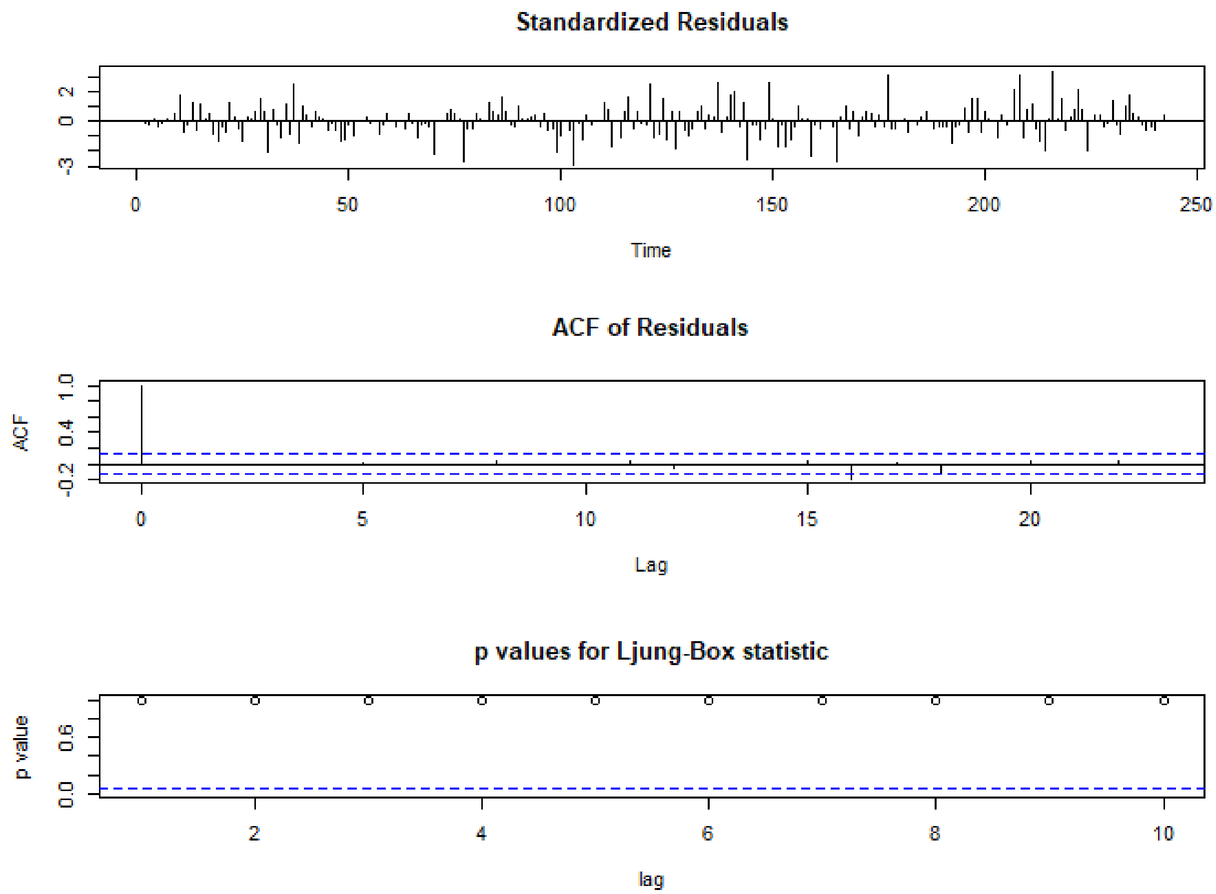
```
              intercept
ar1          0.10559858
ar2         -0.14074599
ar3          0.01349202
ar4          0.02895295
ar5          0.13707211
ma1         -0.12476868
intercept 1488.18075642

> model1[["aic"]]
[1] 1789.788
```



b. ARIMA [Order(10,0,1)]

```
       ar1         ar2         ar3         ar4         ar5         ar6
ar7         ar8
 0.12037479 -0.10593337  0.12402962 -0.08091159  0.18949156 -0.06277169
0.05253006  0.09779418
        ar9        ar10         ma1
-0.02053705 -0.02621571 -0.09164079
```




```
> model2[["aic"]]
[1] 1780.629
```

Step:9 Testing ARIMA models

Model	Order	MSPE
ARIMA model 1	[5,0,1]	0.8161
ARIMA model 2	[10,0,1]	0.8499

Debold Mariano Test

```
        Diebold-Mariano Test

data:  residuals(model1)residuals(model2)
DM = 1.0433, Forecast horizon = 1, Loss function power = 2, p-value = 0.2979
alternative hypothesis: two.sided
```

Since we can reject the null hypothesis of Debold Mariano test at 3% which suggest both forecaster are similar and MSPE show **model 1 is performing better**.

Step 10: Exchange Forecast for next 10 days using ARIMA model 1

We are predicting the first period ahead forecast for 10 points i.e 2nd Jan 2023 till 11th Jan 2023

Predicted Results from ARIMA model1

Date	Predicted value
2-1-2023	61.82643
3-1-2023	61.95222
4-1-2023	61.85266
5-1-2023	61.88815
6-1-2023	61.87390
9-1-2023	61.86109
10-1-2023	61.86307
11-1-2023	61.85056

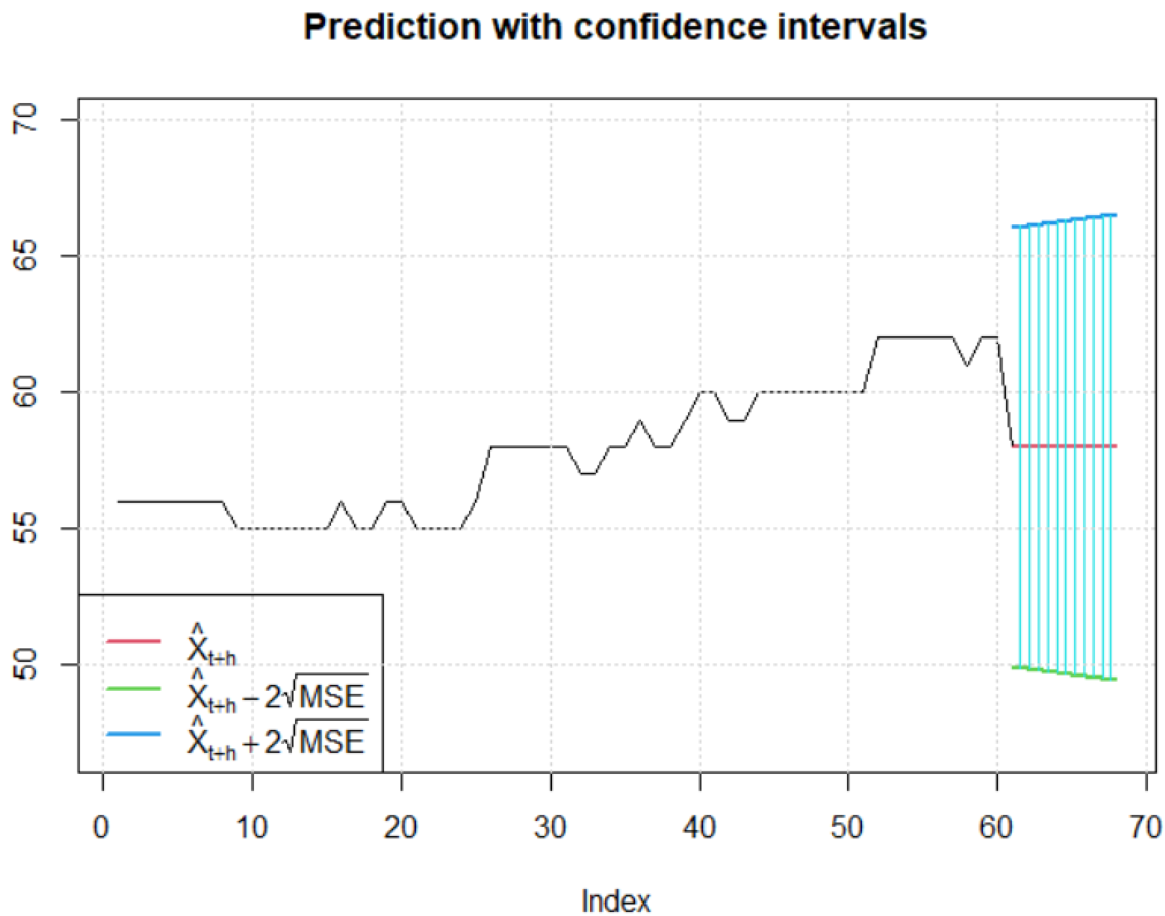


Figure 1 ARIMA model1 forecast value

Part 2

ARCH/ GARCH and its variation

Stationarity of the data is already checked in Step1 till Step4

Step 5: Building 2 different ARCH model

1. ARCH model with lag 5
2. ARCH model with lag 10

```
> ArchTest(ts(train_set))

      ARCH LM-test; Null hypothesis: no ARCH effects

data:  ts(train_set)
Chi-squared = 15980, df = 12, p-value < 2.2e-16
```

Because the p-value is < 0.05, we reject the null hypothesis and conclude the presence of ARCH(1) effects.

Step:6 Fitting ARCH model on train data

```
## Because the p-value is < 0.05, we reject the null hypothesis and conclude the presence of

## Estimating ARCH Models

arch_model <- garchFit(~garch(5,0), data = train_set, trace = F)
summary(arch_model)
plot.zoo(fitted(arch_model))
predict(arch_model, n.ahead = 8, plot=TRUE, crit_val = 2)
```

Arch model summary

```
Title:
 GARCH Modelling

Call:
 garchFit(formula = ~garch(5, 0), data = train_set, trace = F)

Mean and Variance Equation:
 data ~ garch(5, 0)
<environment: 0x000001cc0b3f15e8>
 [data = train_set]

Conditional Distribution:
 norm
```

```
Coefficient(s):
        mu       omega      alpha1      alpha2      alpha3      alpha4      a
lpha5
5.7998e+01  2.7402e-01  1.0000e+00  1.0000e-08  1.0000e-08  1.0000e-08  1.000
0e-08

Std. Errors:
 based on Hessian

Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)
mu     5.800e+01   9.488e-02  611.303  < 2e-16 ***
omega  2.740e-01   7.580e-02    3.615    3e-04 ***
alpha1 1.000e+00   1.262e-01    7.927 2.22e-15 ***
alpha2 1.000e-08   1.672e-01    0.000    1e+00
alpha3 1.000e-08   1.453e-01    0.000    1e+00
alpha4 1.000e-08   4.149e-02    0.000    1e+00
alpha5 1.000e-08         NaN      NaN      NaN
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Log Likelihood:
 -508.3546    normalized:  -2.100639

Description:
 Wed Apr  5 21:48:26 2023 by user: Ajay Kumar GGN


Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test   R    Chi^2  15.73919  0.0003821887
 Shapiro-Wilk Test  R    W      0.9026344 2.013482e-11
 Ljung-Box Test     R    Q(10)  1119.819  0
 Ljung-Box Test     R    Q(15)  1388.308  0
 Ljung-Box Test     R    Q(20)  1540.929  0
 Ljung-Box Test     R^2  Q(10)  14.40654  0.1552424
 Ljung-Box Test     R^2  Q(15)  17.00462  0.3185885
 Ljung-Box Test     R^2  Q(20)  31.95976  0.04372898
 LM Arch Test       R    TR^2   15.59144  0.2106731

Information Criterion Statistics:
     AIC      BIC      SIC     HQIC
4.259129 4.360049 4.257518 4.299783
```

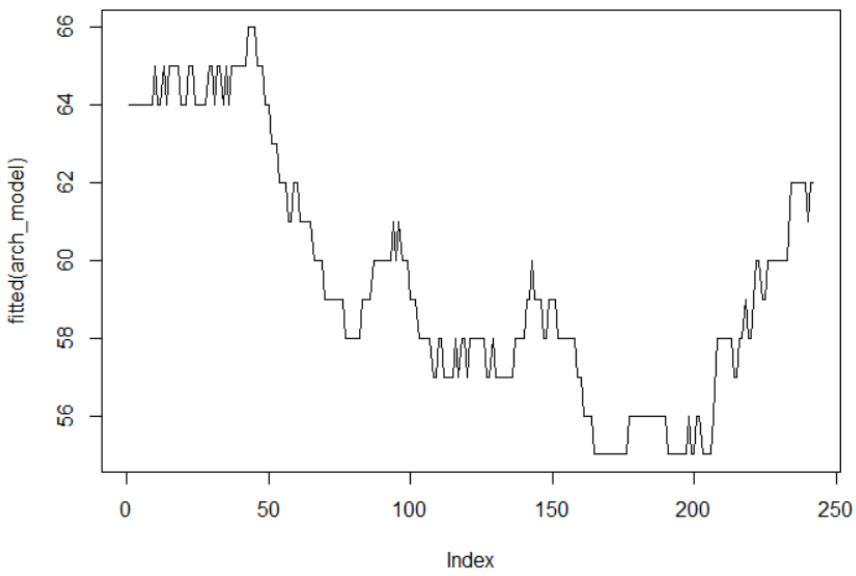
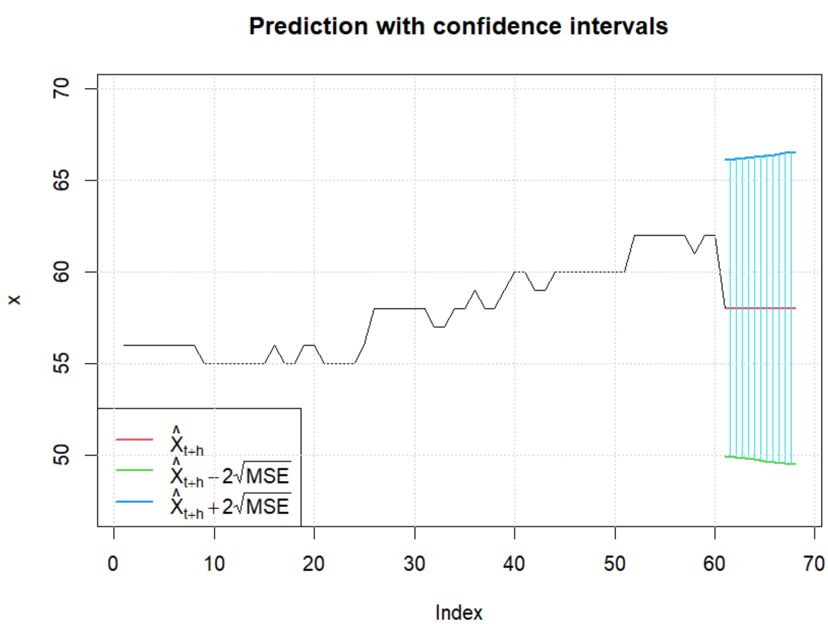


Figure 2 ARCH model fit on the data

Step 7: Exchange Forecast for next 10 days using ARCH model 1



Garch model and its Variations

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model : sGARCH(1,1)
Mean Model  : ARFIMA(0,0,0)
Distribution      : std

Optimal Parameters
------------------------------------
        Estimate  Std. Error    t value Pr(>|t|)
mu     2.0028e+03    2.050901 976.556594  0.00000
omega  4.5630e+04  885.539701  51.527875  0.00000
alpha1 9.9855e-01    0.028376  35.190479  0.00000
beta1  2.0400e-04    0.031605   0.006467  0.99484
shape  9.8404e+01   18.923130   5.200207  0.00000

Robust Standard Errors:
        Estimate  Std. Error    t value Pr(>|t|)
mu     2.0028e+03     1.32317 1.5136e+03  0.00000
omega  4.5630e+04  2742.24045 1.6640e+01  0.00000
alpha1 9.9855e-01     0.16740 5.9650e+00  0.00000
beta1  2.0400e-04     0.16913 1.2080e-03  0.99904
shape  9.8404e+01    16.31738 6.0306e+00  0.00000

LogLikelihood : -139517.8


         mu        omega       alpha1        beta1        shape
2.002820e+03 4.562998e+04 9.985517e-01 2.043745e-04 9.840419e+01


*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model : fGARCH(1,1)
fGARCH Sub-Model  : TGARCH
Mean Model  : ARFIMA(0,0,0)
Distribution      : std
```

```
Optimal Parameters
------------------------------------
          Estimate  Std. Error     t value Pr(>|t|)
mu      6.3421e+03   79.308704   79.967118        0
omega   4.4392e+04  929.878930   47.739958        0
alpha1  5.4130e-03    0.000212   25.565459        0
beta1   0.0000e+00    0.012949    0.000005        1
eta11  -9.9964e-01    0.050013  -19.987583        0
shape   2.1000e+00    0.001571 1337.130518        0

Robust Standard Errors:
          Estimate  Std. Error    t value Pr(>|t|)
mu      6.3421e+03  3.1958e+02  19.845133        0
omega   4.4392e+04  3.9085e+03  11.357895        0
alpha1  5.4130e-03  3.9800e-04  13.586043        0
beta1   0.0000e+00  8.8591e-02   0.000001        1
eta11  -9.9964e-01  1.1792e-01  -8.477529        0
shape   2.1000e+00  4.7140e-03 445.498482        0

LogLikelihood : -168417.6



*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model : fGARCH(1,1)
fGARCH Sub-Model  : APARCH
Mean Model  : ARFIMA(0,0,0)
Distribution      : std

Optimal Parameters
------------------------------------
          Estimate  Std. Error  t value Pr(>|t|)
mu      2.8180e+04          NA       NA       NA
archm  -2.8285e-02          NA       NA       NA
omega   9.5922e+02          NA       NA       NA
alpha1  5.0000e-02          NA       NA       NA
beta1   9.0000e-01          NA       NA       NA
eta11   5.0000e-02          NA       NA       NA
lambda  1.0000e+00          NA       NA       NA
shape   4.0000e+00          NA       NA       NA

Robust Standard Errors:
          Estimate  Std. Error  t value Pr(>|t|)
mu      2.8180e+04          NA       NA       NA
```

```
archm  -2.8285e-02          NA        NA        NA
omega   9.5922e+02          NA        NA        NA
alpha1  5.0000e-02          NA        NA        NA
beta1   9.0000e-01          NA        NA        NA
eta11   5.0000e-02          NA        NA        NA
lambda  1.0000e+00          NA        NA        NA
shape   4.0000e+00          NA        NA        NA

 failed to invert hessian
LogLikelihood : -1.1
```