Time Series Analysis of different data.

Analysis done by: Sairam Chandavale

The following Case Study explores the analysis of different types of time series including

ARIMA, moving average method, SARIMA , Holt-Winters Exponential Smoothing, GARCH and Transfer Function Models.

1] **ARIMA model** is fitted on daily NACH Debit Transactions and check the assumptions by residual analysis and forecasting.

2] Fitting a **SARIMA Model**, residual analysis on monthly rainfall from 2002 to 2022.

3] Fitting a **SARIMA Model** and **Holt Winters Exponential Smoothing** method on monthly closing values of IBM COMPANY. Decide which model is best among them.

4] **Transfer Function Model** is fitted on the yearly GDP Growth rate of India with

the exogenous variable as Inflation rate.

5**] GARCH model** on return data of HDFC from NSE.

Time Series Analysis on daily NACH Debit Transactions

Introduction :

National Automated Clearing House (NACH) is a system developed by the National Payments Corporation of India (NPCI) for banks. This system can be used to make bulk transactions towards distribution of subsidies, dividends, salaries, pension, etc. We take number of daily NACH Debit transactions for 291 days from January 1, 2023 to October 18, 2023. Number of payment transactions are in lakhs per day.

1] Exploratory data analysis by using time- series plot.

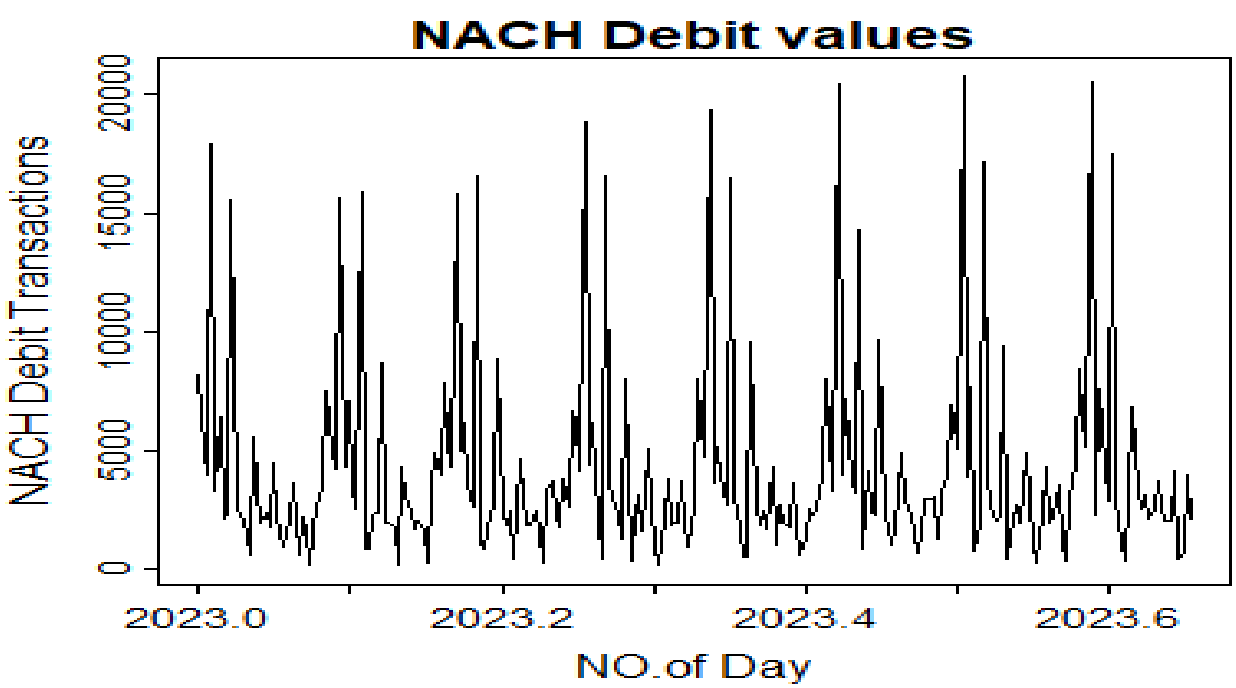
```
library(readxl)

d=read_excel("C:\\Users\\admin\\Desktop\\time series.xlsx")

d=data.frame(d[,1:2])

View(d)

ts.plot(d[,2],main="NACH Debit values", xlab="NO.of Day",ylab="NACH Debit Transactions")
```



From the above time series plot , we observed that

1) The data does not have any trend .

3) No irregularities are seen in the plot.

To check the stationarity of the data we perform ADF test.

```
library(tseries)

adf.test(d[,2])

        Augmented Dickey-Fuller  Test

data:  d[, 2]

Dickey-Fuller = -5.5025,                Lag order = 6,   p-value =0.01

alternative hypothesis: stationary

Warning message:

In adf.test(d[, 2]) : p-value smaller than printed p-value
```

Conclusion :

Null hypothesis has been rejected hence we conclude that the given time series is stationary.

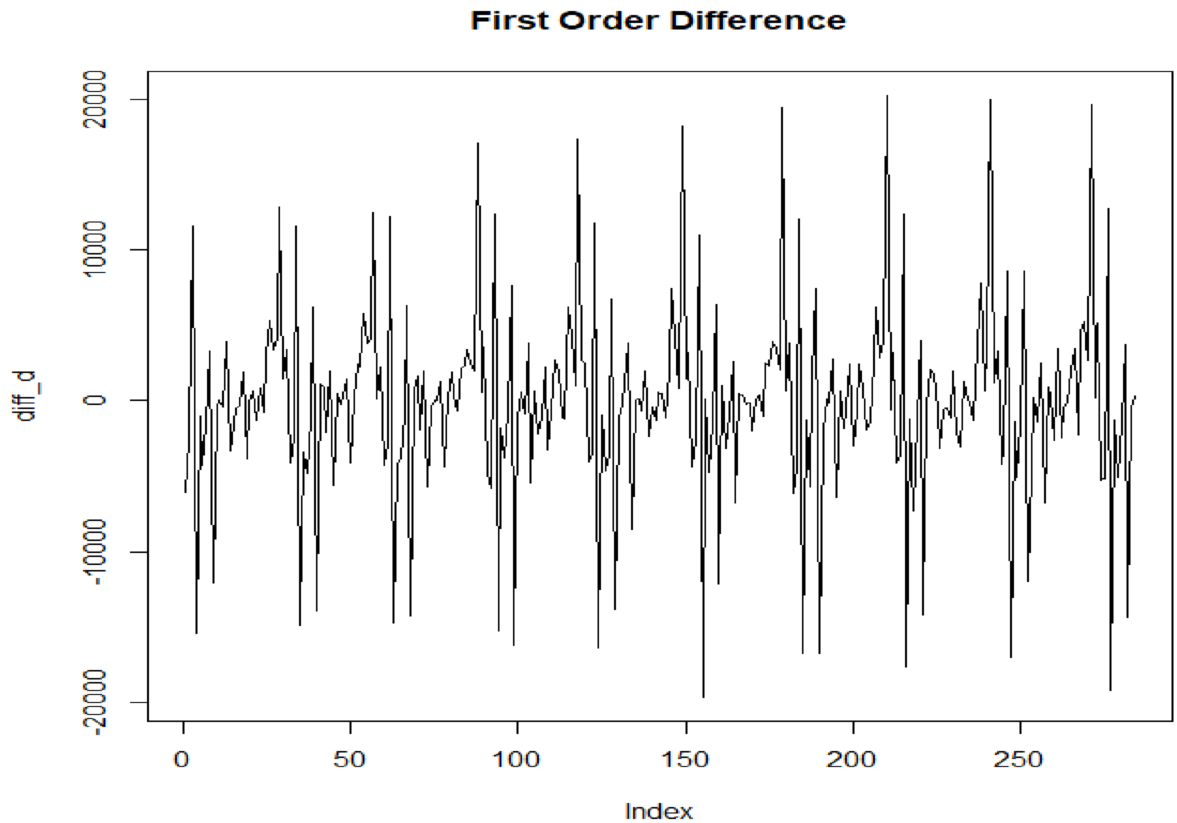
Due to observed seasonality ,to make the time series more stabilize and seasonality present Differencing of order 1 is done and the new time series is plotted.

```
Take the first order difference of the time series

diff_d <- diff(d[, 2],lag=6)

# Plot the differenced time series

plot(diff_d, type = "l", main = "First Order Difference")
```



To check the stationarity after differencing the time series

```
adf.test(diff_d)

      Augmented Dickey-Fuller Test

data:  diff_d

Dickey-Fuller = -7.6254,          Lag order = 6,          p-value =0.01

alternative hypothesis: stationary

Warning message:

In adf.test(diff_d) : p-value smaller than printed p-value
```

Conclusion :

Null hypothesis has been rejected hence we conclude that the given time series is stationary.

mean(diff_d)

[1] -88.79197

var(diff_d)

[1] 40232874   #Here variance has been decreased after differencing

sd(diff_d)

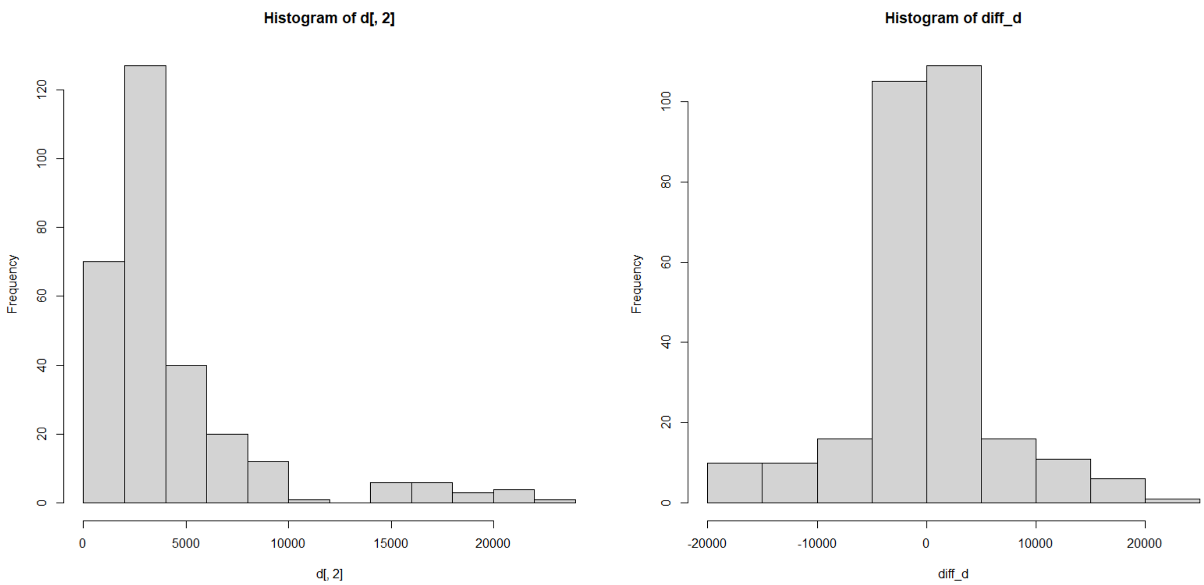
[1] 6342.939

###################

par(mfrow=c(1,2))

hist(d[,2])

hist(diff_d)



After comparing the histograms before and after differencing the time series data , we can observe that after differencing the data has approximately centered around mean zero .

Decompose the time series

#stl <- stl(d[, 2], s.window = "periodic")

Plot the trend, seasonal, and residual components

#plot(stl$time, stl$trend, type = "l", col = "blue", main = "Trend Component")

#plot(stl$time, stl$seasonal, type = "l", col = "green", main = "Seasonal Component")

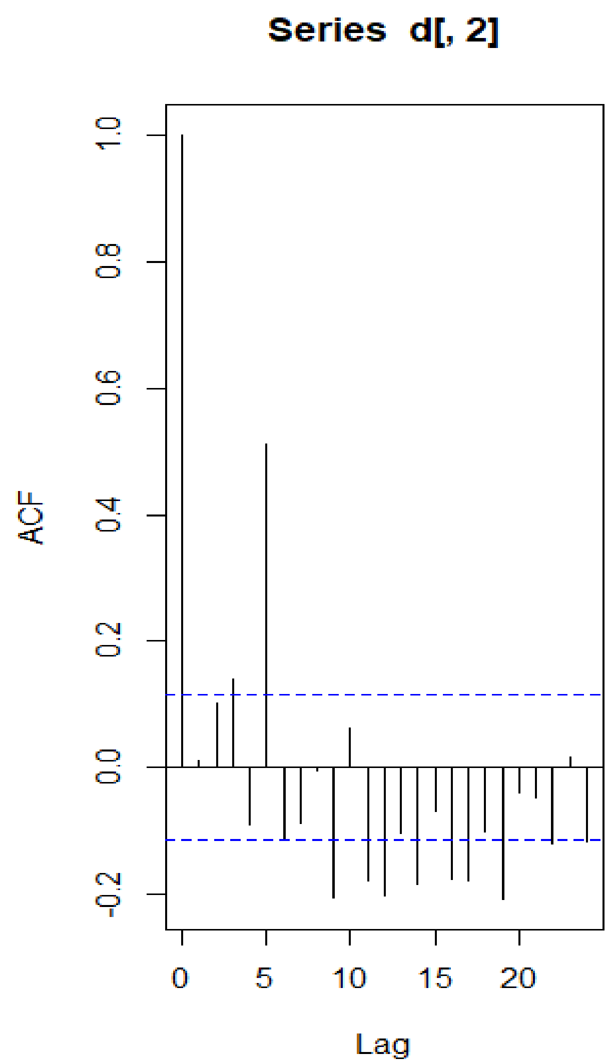
#plot(stl$time, stl$random, type = "l", col = "red", main = "Residual Component")

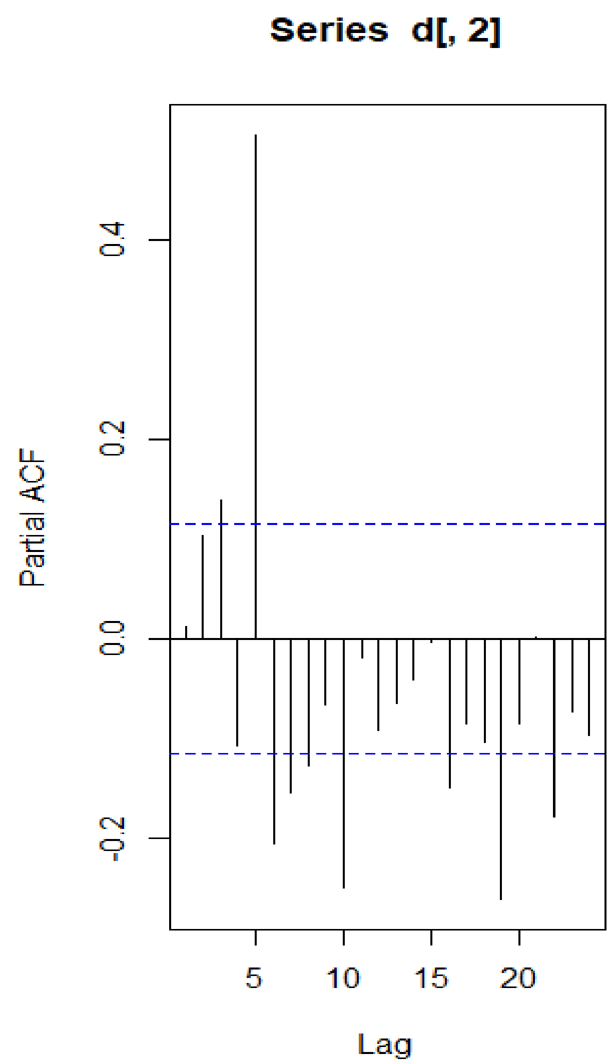
Now,

par(mfrow=c(1,2))

acf(d[,2])

pacf(d[,2])





Conclusion:

The ACF and PACF plots should be considered together to define a process . From the above fig we observe that lags which are multiple of 6 show strong positive correlation.

To check the normality

shapiro.test(diff_d)

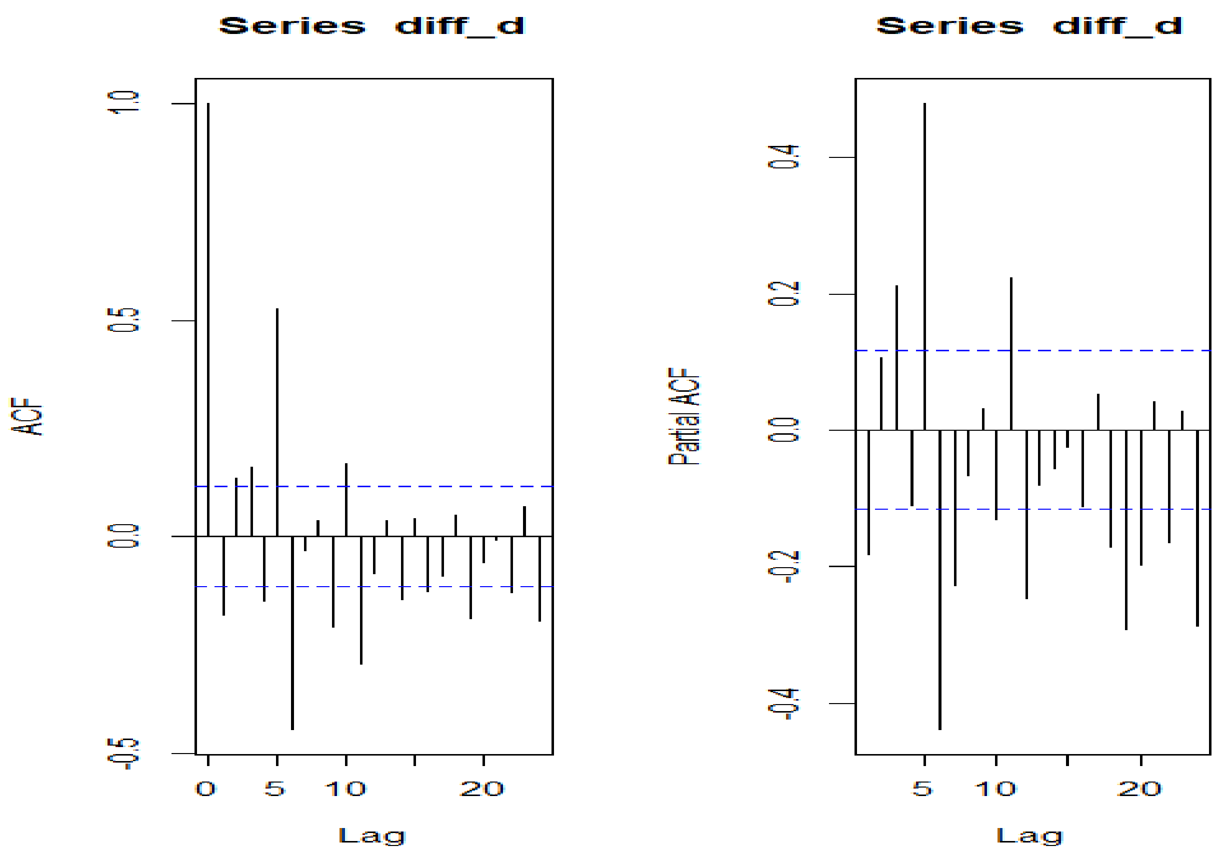
Shapiro-Wilk normality test

data: diff_d

W = 0.91486, p-value = 1.269e-11

Here, p-value is less than los, hence we reject H0.

```
###################
par(mfrow=c(1,2))
acf(diff_d)
pacf(diff_d)
```

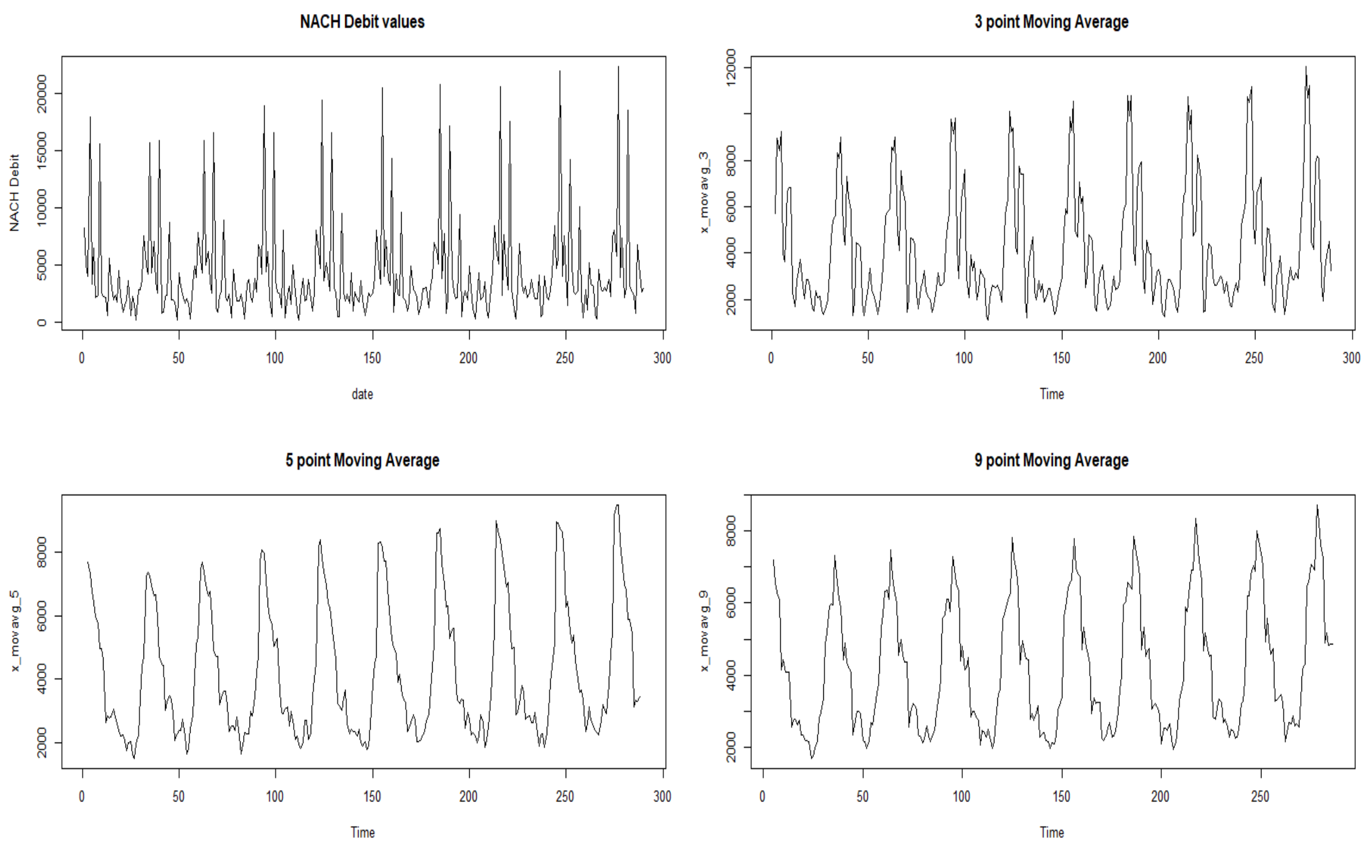


Comclusion:

The ACF and PACF plots should be considered together to define a process . From the above figure we observed that , both the graphs show geometrical decreasing pattern hence mixed ARIMA model is considered for modelling.

```
#############
par(mfrow=c(2,2))
ts.plot(d[,2],main="NACH Debit values", xlab="date",ylab=" NACH Debit ")
# 3 point MA
x_movavg_3=filter(d[,2],sides=2,rep(1,3)/3)
ts.plot(x_movavg_3,main="3 point Moving Average")
#5 point MA
```

```
x_movavg_5=filter(d[,2],sides=2,rep(1,5)/5)
ts.plot(x_movavg_5,main="5 point Moving Average")
#9 point MA
x_movavg_9=filter(d[,2],sides=2,rep(1,9)/9)
x_movavg_9=na.omit(x_movavg_9)
ts.plot(x_movavg_9,main="9 point Moving Average")
```




```
adf.test(x_movavg_9)
```

Augmented Dickey-Fuller Test

data: x_movavg_9

Dickey-Fuller = -8.7225, Lag order = 6, p-value = 0.01

alternative hypothesis: stationary

Warning message:

In adf.test(x_movavg_9) : p-value smaller than printed p-value.

z=auto.arima(d[,2],seasonal=TRUE)   #we fit ARIMA model with seasonality TRUE

z   #it will choose the model which has min AIC and BIC.

Series: d[, 2]

Best model

ARIMA(5,0,3) with non-zero mean

Coefficients:

```
        ar1      ar2     ar3     ma1     ma2       mean
     -1.1152  -0.2265  0.3146  1.2861  0.4510  4251.6943
s.e.   0.0979   0.1161  0.0635  0.0926  0.0899   300.2008
```

sigma^2 = 14686656: log likelihood = -2801.86

AIC=5617.72   AICc=5618.12   BIC=5643.41

z1=auto.arima(d[,2],ic='aic',trace=TRUE)

Fitting models using approximations to speed things up...

```
ARIMA(2,0,2) with non-zero mean : 5657.396
ARIMA(0,0,0) with non-zero mean : 5672.198
ARIMA(1,0,0) with non-zero mean : 5674.301
ARIMA(0,0,1) with non-zero mean : 5674.163
ARIMA(0,0,0) with zero mean     : 5872.059
ARIMA(1,0,2) with non-zero mean : 5674.559
ARIMA(2,0,1) with non-zero mean : 5670.167
ARIMA(3,0,2) with non-zero mean : 5620.07
ARIMA(3,0,1) with non-zero mean : 5629.898
ARIMA(4,0,2) with non-zero mean : 5629.524
ARIMA(3,0,3) with non-zero mean : 5621.428
```

Now re-fitting the best model(s) without approximations...

ARIMA(5,0,3) with non-zero mean : 5570.84

Best model: ARIMA(5,0,3) with non-zero mean

> #To forecast no of transactions for next 80 days :

```
> m=arima(d[,2],order=c(5,0,3))

> m

Call:

arima(x = d[, 2], order = c(5, 0, 3))


Coefficients:

        ar1      ar2      ar3      ar4     ar5     ma1

     -0.1973  -0.1474  -0.0183  -0.0542  0.5420  0.3513

s.e.   0.1060   0.1002   0.0917   0.0517  0.0538  0.1252

        ma2     ma3  intercept

     0.2539  0.1854  4286.1893

s.e.  0.1310  0.1131   411.2132

sigma^2 estimated as 11945422:  log likelihood = -2775.42,  aic = 5570.84


>fcast=forecast(m,h=50)

>fcast


   Point Forecast      Lo 80     Hi 80      Lo 95     Hi 95

291      3106.257 -1323.0608  7535.575 -3667.8000  9880.314

292      5943.216  1461.6914 10424.740  -910.6841 12797.115

293      4072.248  -421.9496  8566.445 -2801.0339 10945.529

294      3269.683 -1260.9273  7800.293 -3659.2874 10198.653

295      3846.113  -703.4766  8395.702 -3111.8838 10804.110

296      3797.481 -1325.4595  8920.422 -4037.3804 11632.343

297      5375.705   252.3843 10499.027 -2459.7381 13211.149
```

298	4090.425	-1035.8990	9216.748	-3749.6108	11930.460
299	3646.059	-1491.1312	8783.249	-4210.5954	11502.714
300	4209.365	-942.7157	9361.445	-3670.0622	12088.792
301	4075.388	-1240.8589	9391.634	-4055.1099	12205.885
302	4951.900	-369.3790	10273.179	-3186.2940	13090.094
303	4115.901	-1211.4162	9443.219	-4031.5278	12263.331
304	3882.736	-1451.0383	9216.511	-4274.5681	12040.041
305	4348.491	-993.3413	9690.324	-3821.1366	12518.119
306	4186.168	-1207.6228	9579.959	-4062.9233	12435.260
307	4674.139	-724.1595	10072.438	-3581.8463	12930.125
308	4152.817	-1249.6768	9555.310	-4109.5842	12415.218
309	4035.109	-1371.8190	9442.037	-4234.0738	12304.292
310	4387.473	-1023.4241	9798.369	-3887.7798	12662.725
311	4230.431	-1197.4641	9658.326	-4070.8181	12531.680
312	4504.336	-926.1011	9934.774	-3800.8011	12809.474
313	4190.834	-1241.7845	9623.452	-4117.6389	12499.307
314	4132.300	-1303.1975	9567.797	-4180.5761	12445.176
315	4384.529	-1052.8945	9821.953	-3931.2927	12700.351
316	4249.178	-1193.8495	9692.206	-4075.2142	12573.571
317	4405.206	-1038.9809	9849.393	-3920.9592	12731.371
318	4223.021	-1222.1698	9668.213	-4104.6800	12550.723
319	4193.054	-1253.8454	9639.953	-4137.2596	12523.367
320	4367.001	-1080.8389	9814.841	-3964.7512	12698.753
321	4258.623	-1191.0593	9708.306	-4075.9469	12593.193
322	4349.345	-1100.7964	9799.487	-3985.9271	12684.617
323	4247.124	-1203.4559	9697.705	-4088.8188	12583.068
324	4230.236	-1221.2775	9681.750	-4107.1346	12567.607
325	4347.123	-1104.8530	9799.098	-3990.9546	12685.200
326	4264.768	-1187.8093	9717.346	-4074.2296	12603.767

>

plot(fcast)

checkresiduals(m)

Ljung-Box test

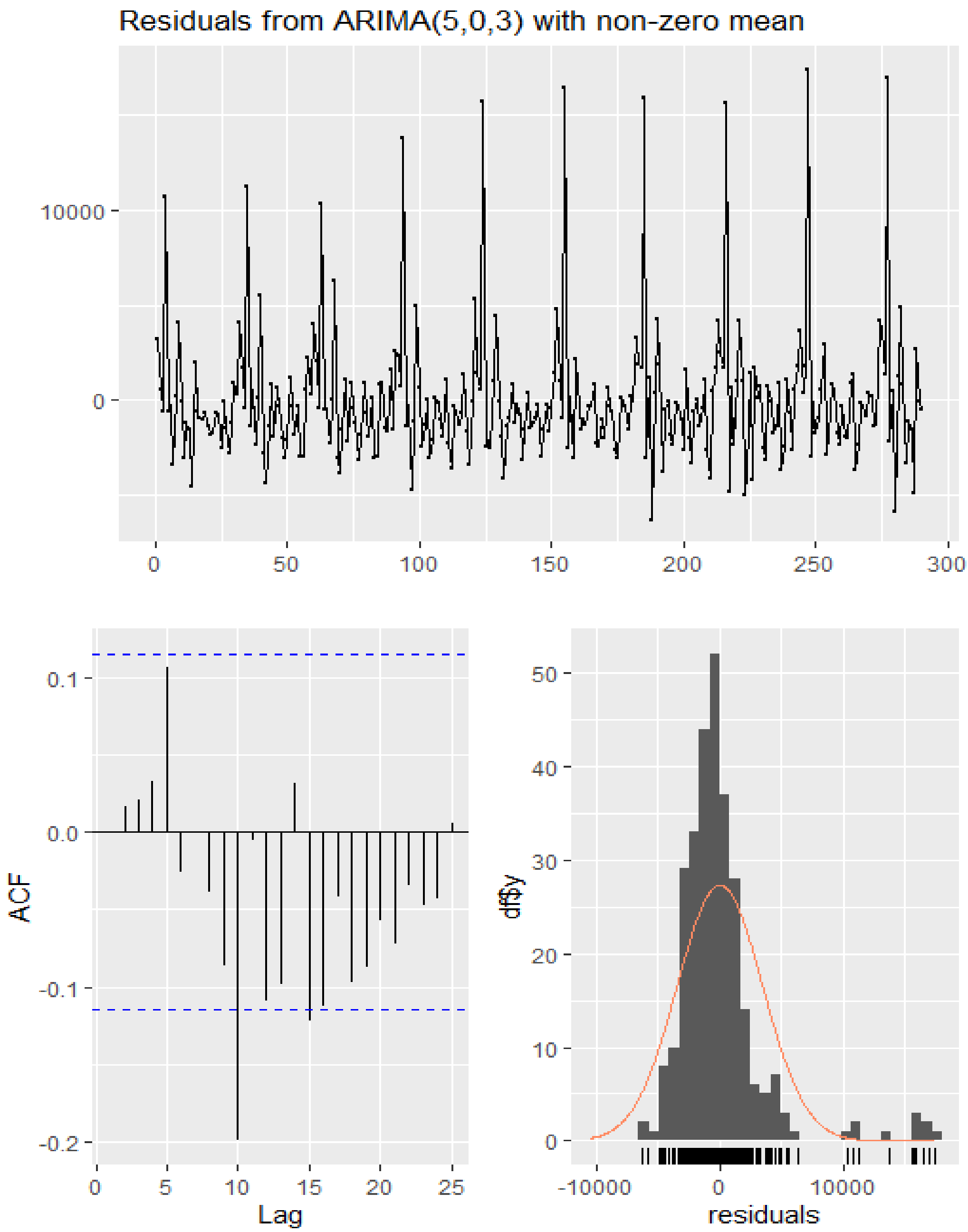
data: Residuals from ARIMA(5,0,3) with non-zero mean

Q* = 18.796, df = 3, p-value = 0.0003013

Model df: 8.   Total lags used: 11

Conclusion:1] there is no serial correlation as based on Ljung-Box test.(p-value<0.5)

2]residuals follow normal distribution.


Residuals from ARIMA(5,0,3) with non-zero mean
10000
0
0
50
100
150
200
250
300
0.1
0.0
-0.1
-0.2
ACF
0
5
10
15
20
25
Lag
50
40
30
20
10
0
df$y
-10000
0
10000
residuals

2] Time Series Analysis on monthly rainfall from 2002 to 2022.

Introduction :
we collect the data of monthly rainfall from 2002 to 2022 from https://data.gov.in/ website.

We have 240 observations from 2002 to 2022. Rainfall measured in mm.

1] Exploratory data analysis by using time- series plot.

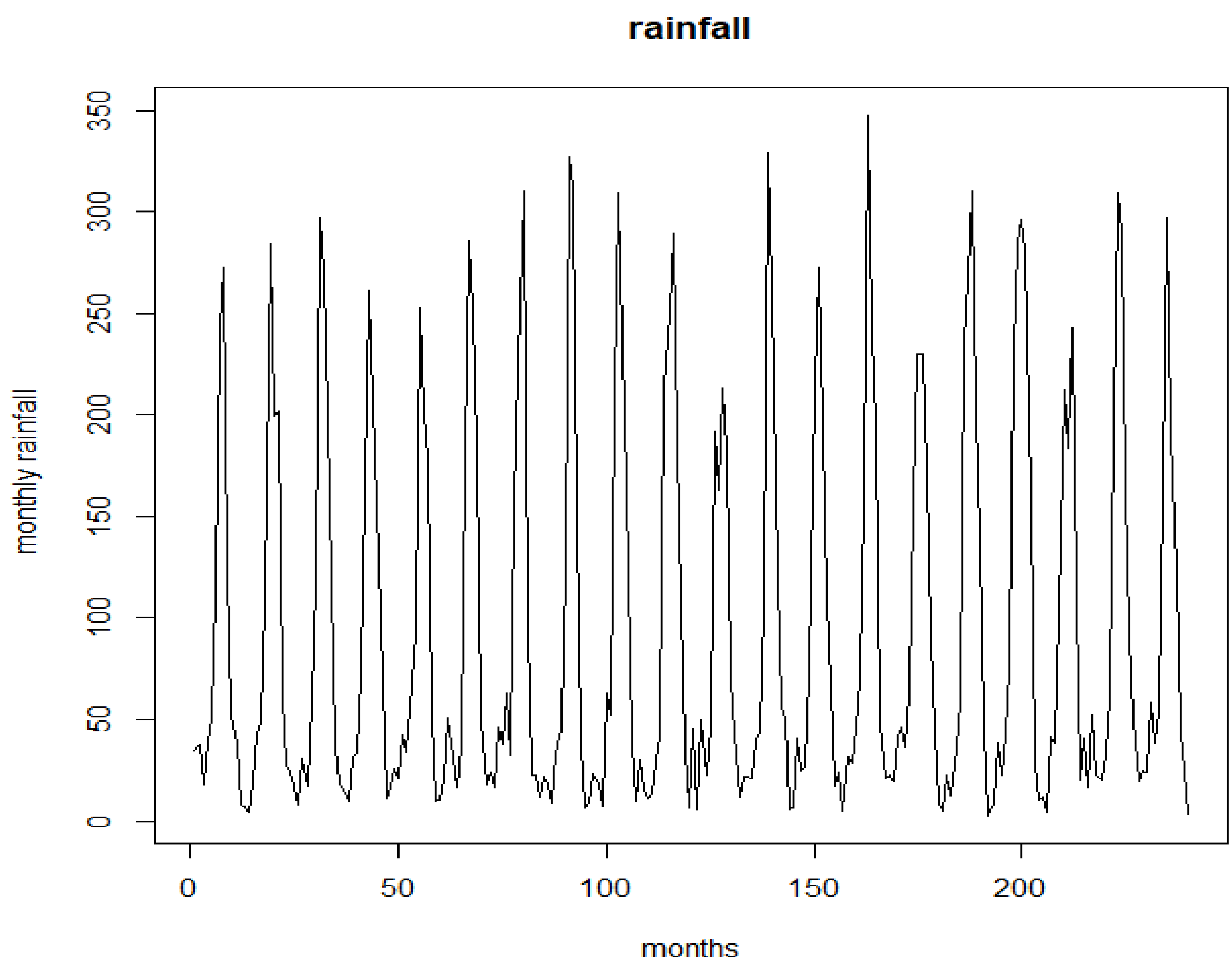
```
library(readxl)

d=read_excel("C:\\Users\\admin\\Desktop\\rainfall.xlsx")

d=data.frame(d)

View(d)

ts.plot(d[,2],main="rainfall", xlab="months",ylab="monthly rainfall  ")
```



From the above time series plot , we observed that

1) The data does not have any trend .

2) Data has seasonality present in it.

3) No irregularities are seen in the plot.

To check the stationarity of the data we perform ADF test.

library(tseries)

adf.test(d[,2])

Augmented Dickey-Fuller Test

data: d[, 2]

Dickey-Fuller = -13.822, Lag order = 6, p-value =0.01

alternative hypothesis: stationary

Warning message:

In adf.test(d[, 2]) : p-value smaller than printed p-value.

Conclusion :

Null hypothesis has been rejected hence we conclude that the given time series is stationary.

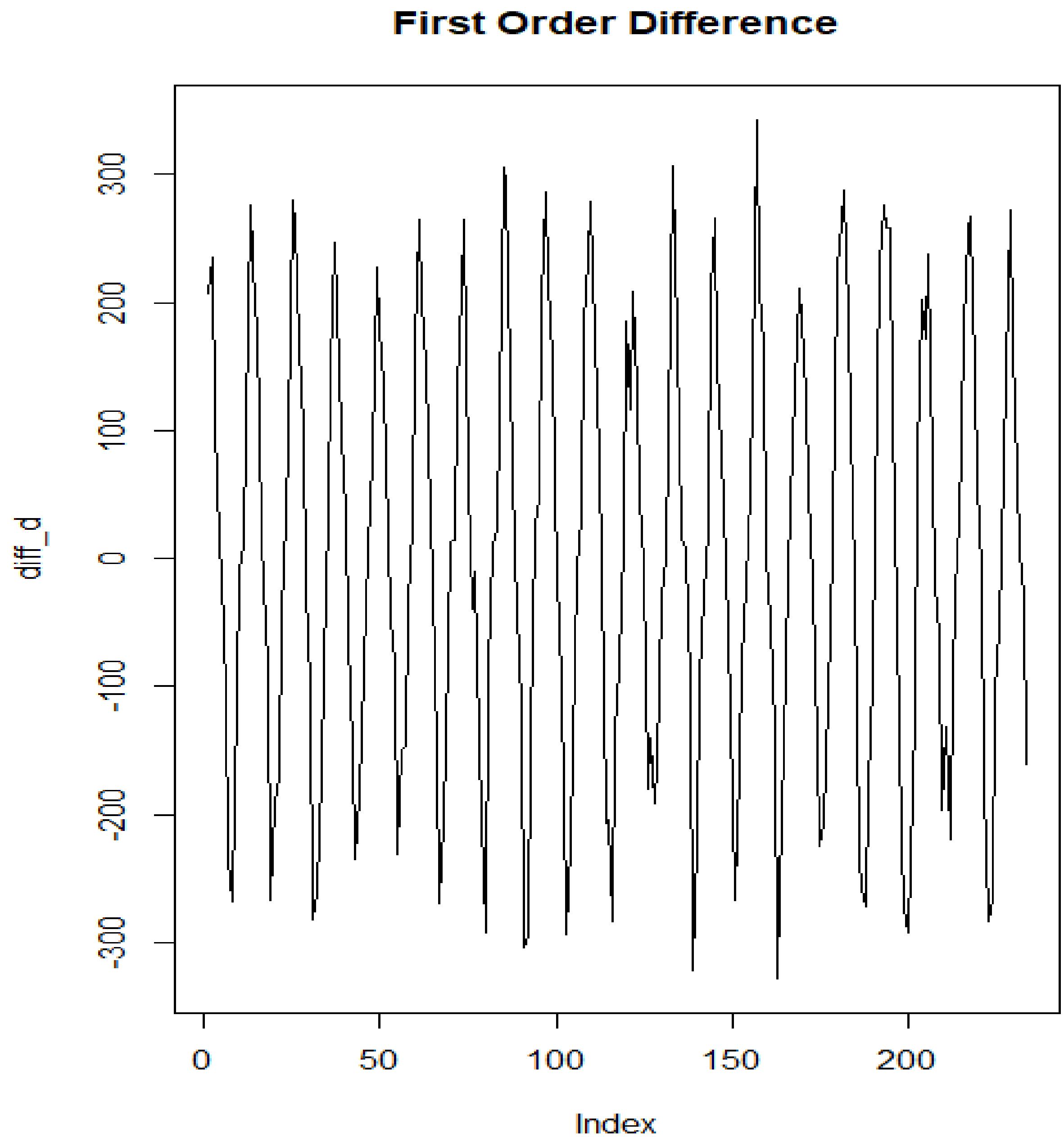
Due to observed seasonality ,to make the time series more stabilize and to eliminate trend and seasonality present Differencing of order 1 is done and the new time series is plotted.

Take the first order difference of the time series

diff_d <- diff(d[, 2],lag=6)

Plot the differenced time series

plot(diff_d, type = "l", main = "First Order Difference")



To check the stationarity after differencing the time series

adf.test(diff_d)

Augmented Dickey-Fuller Test

data: diff_d

Dickey-Fuller = -11.657, Lag order = 6, p-value =0.01

alternative hypothesis: stationary

Warning message:

In adf.test(diff_d) : p-value smaller than printed p-value

Conclusion :

Null hypothesis has been rejected hence we conclude that the given time series is stationary.

> mean(diff_d)

[1] 1.667521

> var(diff_d)

[1] 28416.52 #Here variance has been decreased after differencing

> sd(diff_d)

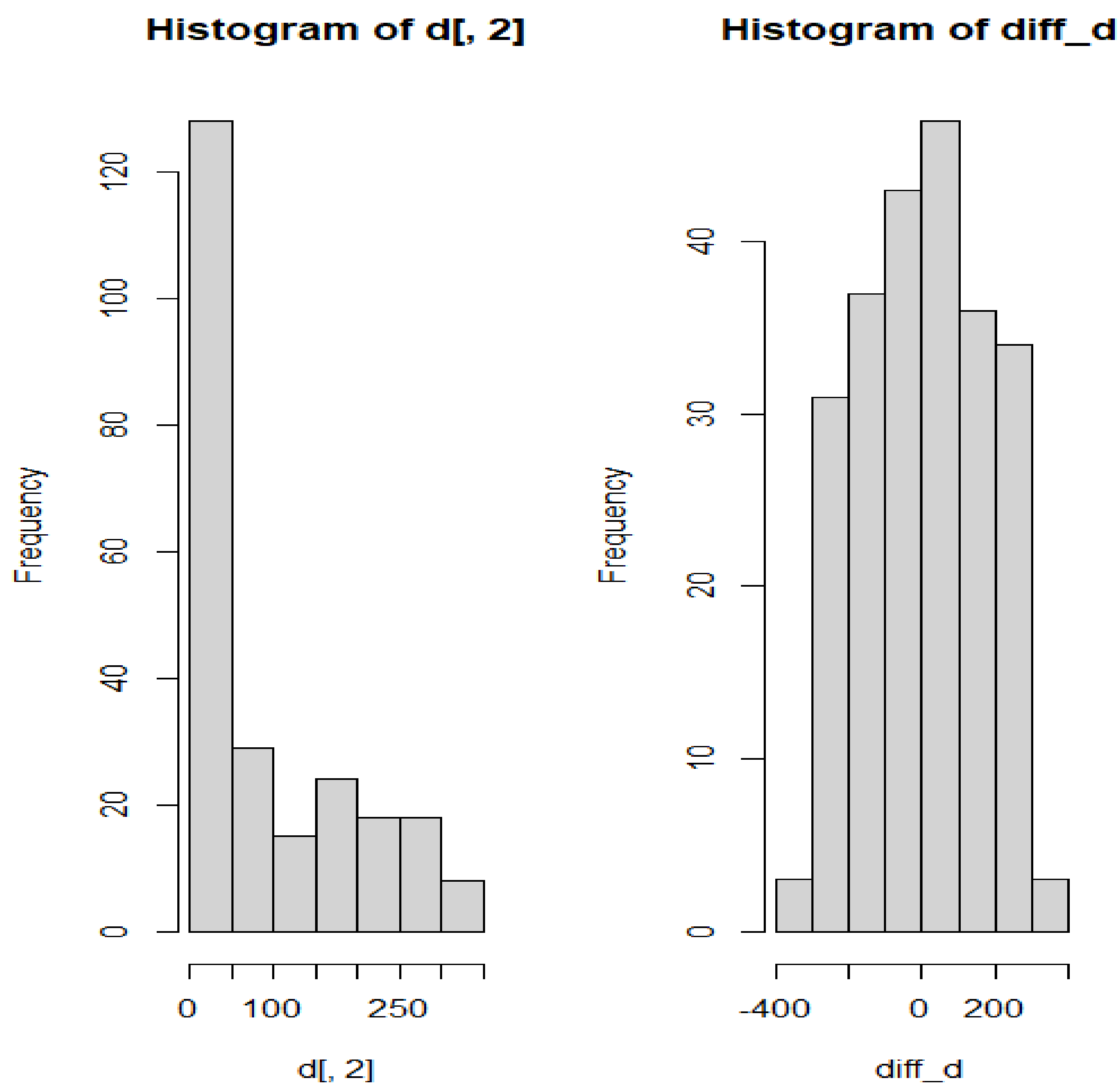
[1] 168.572

####################

par(mfrow=c(1,2))

hist(d[,2])

hist(diff_d)



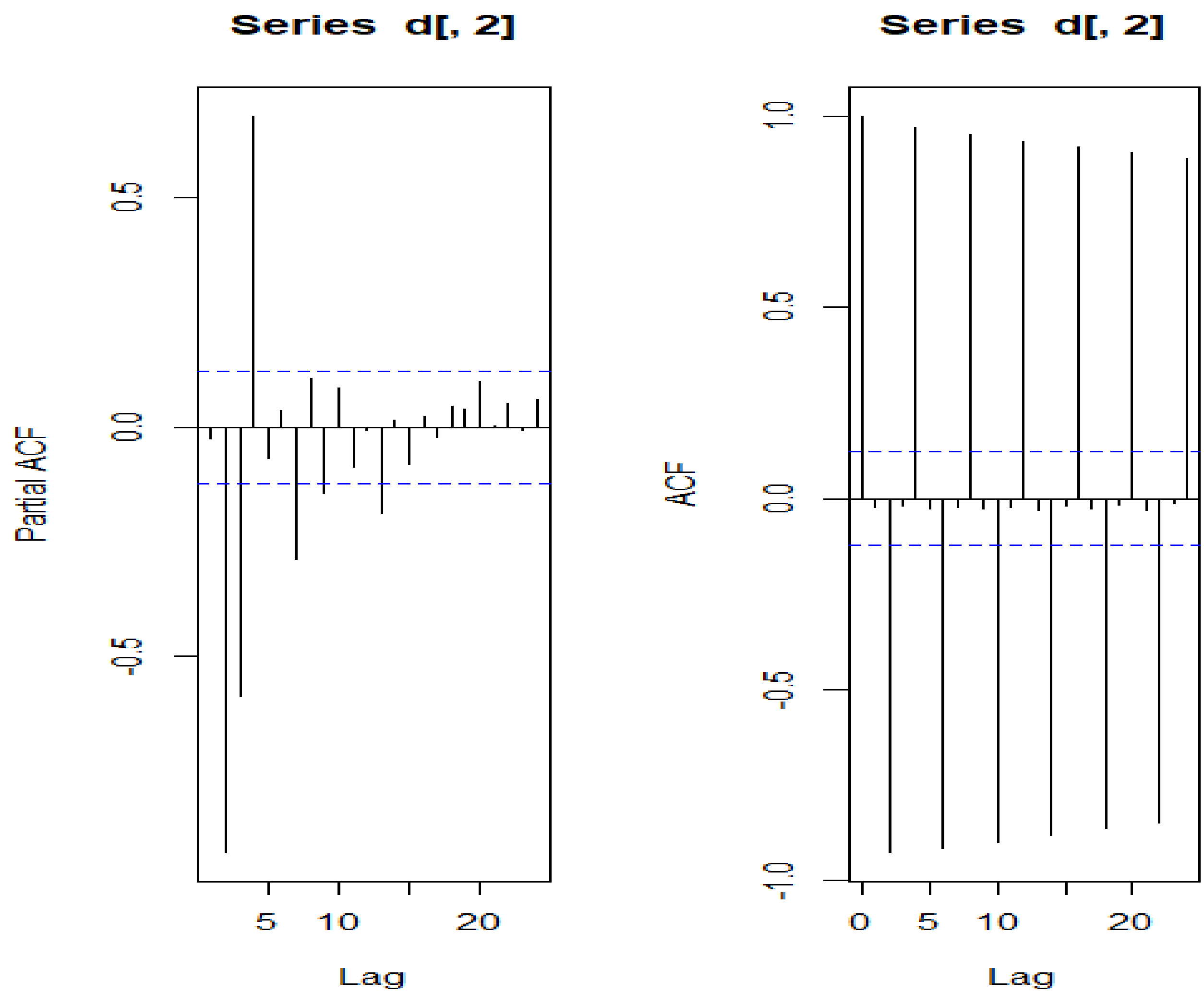
After comparing the histograms before and after differencing the time series data , we can observe that after differencing the data has approximately centered around mean zero .

To check the Collinearity

par(mfrow=c(1,2))

acf(d[,2])

pacf(d[,2])



The ACF and PACF plots should be considered together to define a process . From the above fig we observe that lags which are multiple of 5 show strong positive correlation.

> shapiro.test(diff_d

Shapiro-Wilk normality test

data: diff_d

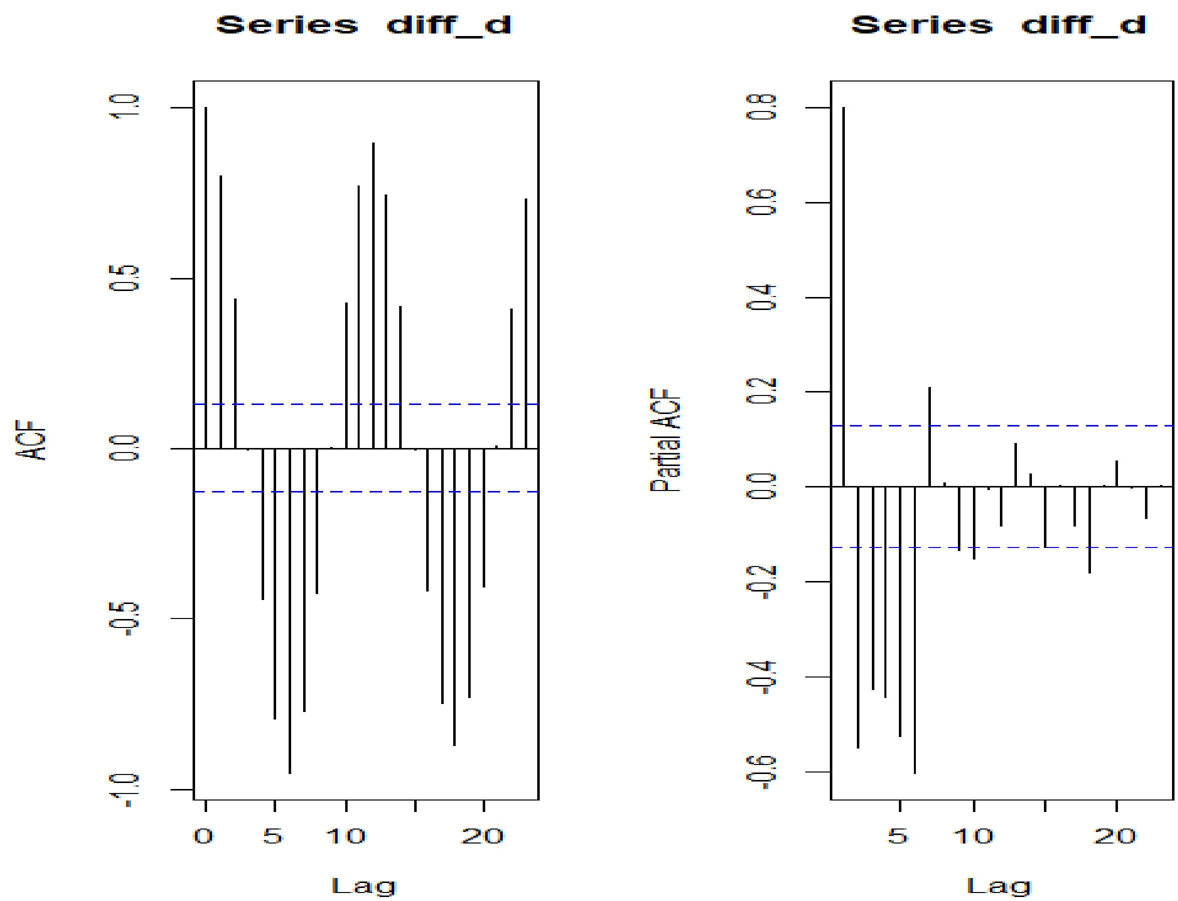
W = 0.9709, p-value = 9.839e-05

###################

par(mfrow=c(1,2))

acf(diff_d)

pacf(diff_d)



Conclusion:

The ACF and PACF plots should be considered together to define a process . From the above figure we observed that , both the graphs show geometrical decreasing pattern hence mixed SARIMA model is considered for modelling.

Here, we consider seasonality is present in the model. Therefore we fit SARIMA model

,we take seasonality is true. We fit the model which has minimum AIC and BIC.

```
library(astsa)

library(tseries)

library(fpp3)

library(forecast)

fit1=sarima(d,2,1,0,1,1,1,12)
```

output:

```
>fit1=sarima(d,2,1,0,1,1,1,12)
```

```
initial  value 3.957064
iter   2 value 3.668401
iter   3 value 3.607178
iter   4 value 3.561301
iter   5 value 3.553501
iter   6 value 3.527395
iter   7 value 3.515419
iter   8 value 3.508994
iter   9 value 3.505019
iter  10 value 3.504226
iter  11 value 3.499883
iter  12 value 3.498903
iter  13 value 3.498752
iter  14 value 3.498617
iter  15 value 3.498614
iter  16 value 3.498611
iter  16 value 3.498611
iter  16 value 3.498611
final  value 3.498611
converged
initial  value 3.488147
iter   2 value 3.477986
iter   3 value 3.466116
iter   4 value 3.464272
iter   5 value 3.463012
iter   6 value 3.462898
iter   7 value 3.462893
iter   8 value 3.462893
iter   8 value 3.462892
```

```
iter   8 value 3.462892
final  value 3.462892
converged
> fit1
$fit

Call:
arima(x = xdata, order = c(p, d, q), seasonal = list(order = c(P, D, Q), period = S),
    include.mean = !no.constant, transform.pars = trans, fixed = fixed, optim.control = list(trace = trc,
        REPORT = 1, reltol = tol))

Coefficients:
         ar1     ar2      ma1    sar1     sma1
      0.1444  0.0729  -1.0000  0.0334  -0.9447
s.e.  0.0665  0.0666   0.0232  0.0788   0.0981

sigma^2 estimated as 879.9:  log likelihood = -1108.18,  aic = 2228.35

$degrees_of_freedom
[1] 222

$ttable
     Estimate     SE  t.value p.value
ar1    0.1444 0.0665   2.1697  0.0311
ar2    0.0729 0.0666   1.0958  0.2743
ma1   -1.0000 0.0232 -43.0446  0.0000
sar1   0.0334 0.0788   0.4239  0.6721
sma1  -0.9447 0.0981  -9.6326  0.0000
```

$AIC

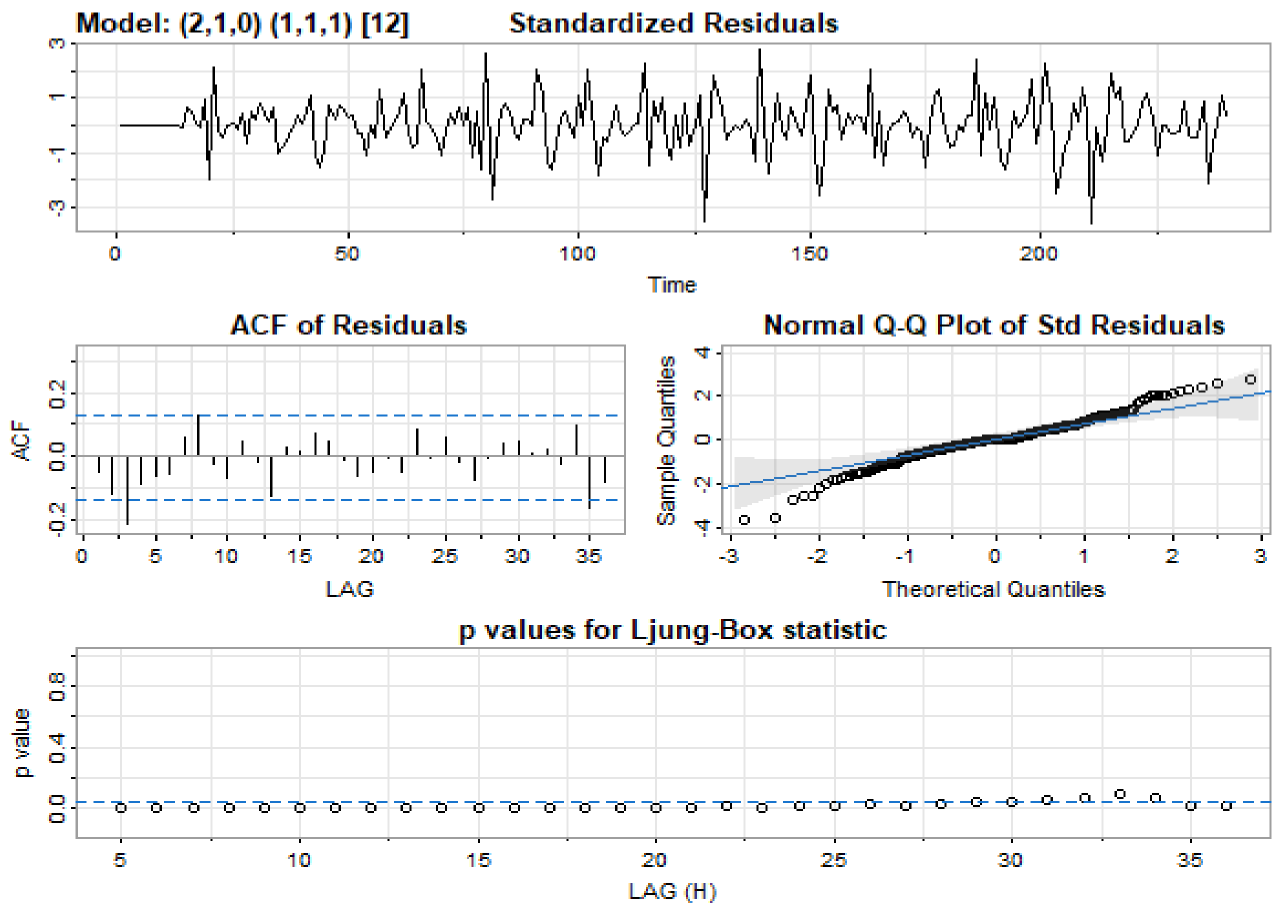
[1] 9.816525

$AICc

[1] 9.817721

$BIC

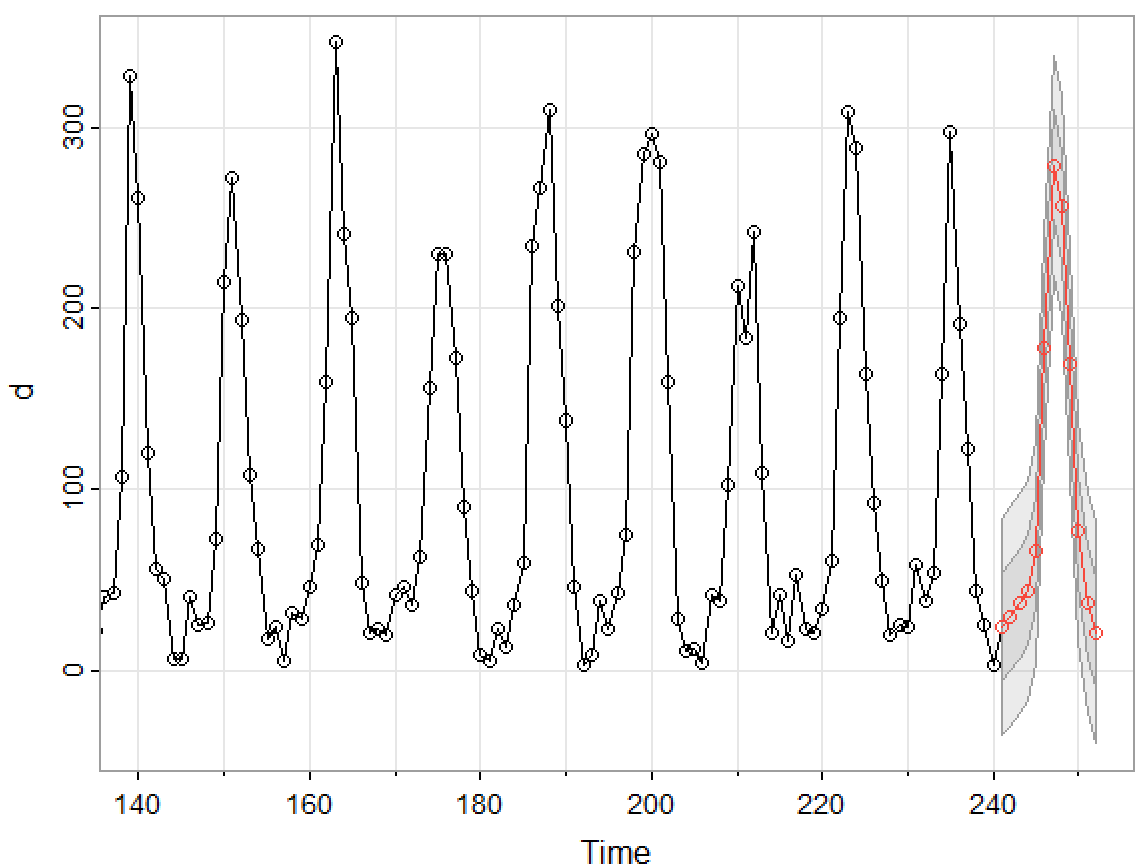
[1] 9.907053




```
> forecast=sarima.for(d,12,2,1,0,1,1,1,12)
>forecast                    #next predicted values of time series.
$pred
Time Series:
Start = 241
End = 252
```

```
Frequency = 1
 [1]  23.93833  29.49204  36.84298  44.00086  65.53913 178.25595 279.39957
 [8] 256.44381 169.55080  77.36384  37.25375  20.99041

$se
Time Series:
Start = 241
End = 252
Frequency = 1
 [1] 30.02499 30.38461 30.55065 30.56917 30.57510 30.57665 30.57721 30.57744
 [9] 30.57767 30.57807 30.57942 30.58133
```



CONCLUSION:

1] There is NO serial auto-correlation between the residuals. This is verified by conducted

the Ljung-Box Test.(i.e. p-value <0.5 for all lag)

2] The residuals of SARIMA MODEL appears to follow Normal Distribution in the histogram.

3] this model has min AIC and BIC

4] from ACF of residuals, we observe that, residuals are uncorrelated.

3] Time Series Analysis on monthly closing values of IBM COMPANY from 2000 to 2023.

The data ,we used in this analysis is '**monthly closing values of stocks of IBM**' which is secondary data available on the https://www.alphavantage.co/documentation/

It has monthly values from jan-2000 to sep 2023. So in this statistical analysis, we tried to figure out, if there could be any trend or seasonality striking out from the data..

Firstly, we did some exploratory data analysis with the help of time series graph.

Then, we used some time series techniques such as differencing, de-trending and de-seasonalizing. Also, for forecasting purpose we used Exponential smoothing technique and SARIMA model and decide which model is best based on AIC and BIC.

Installing the required libraries for the time series analysis.

```
#install.packages("fpp3")

#install.packages("forecast")

library(astsa)

library(tseries)

library(fpp3)

library(forecast)
```

importing the data:

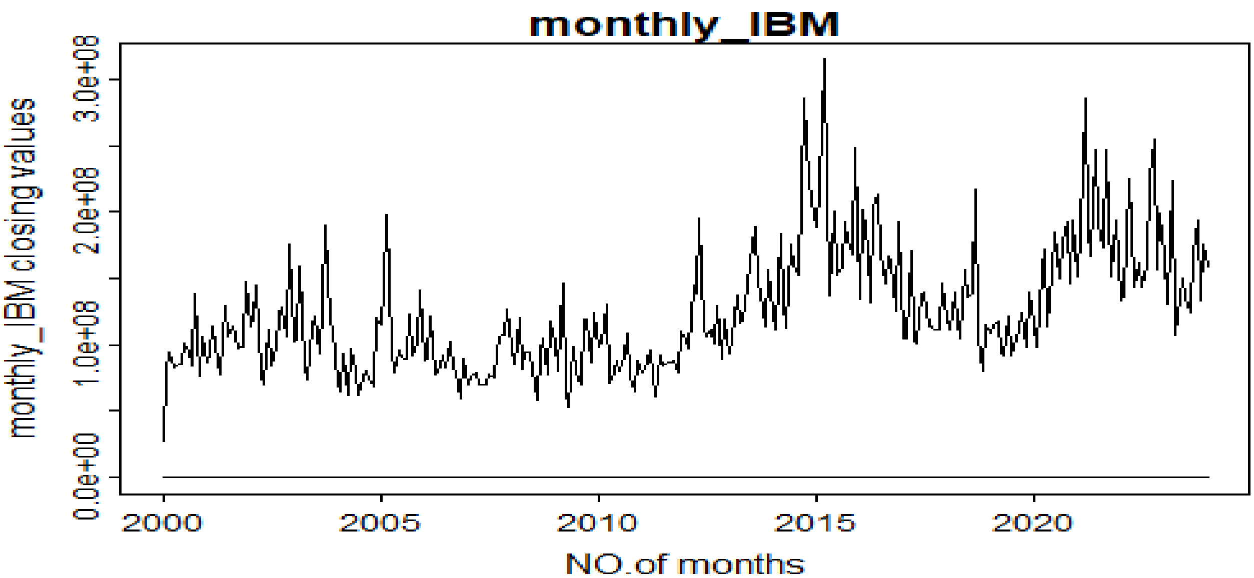
```
data1=read.csv("C:\\Users\\admin\\Downloads\\monthly_IBM.csv")

data1=data.frame(data1[,6])
```

#View(d)

data1=ts((data1), start=2000,freq=12)

ts.plot(data1,main="monthly_IBM", xlab="NO.of months",ylab="monthly_IBM closing values", start=2000,freq=12)



Plotting the components of time series and checking whether trend and seasonality is Present:

decompose(data1)

plot(decompose(data1)) #This implies there is an additive model.

>$figure

 [1] -12994941 -9791951 34584538 -14383950 -19654443   6251427 -7045869 -8732078

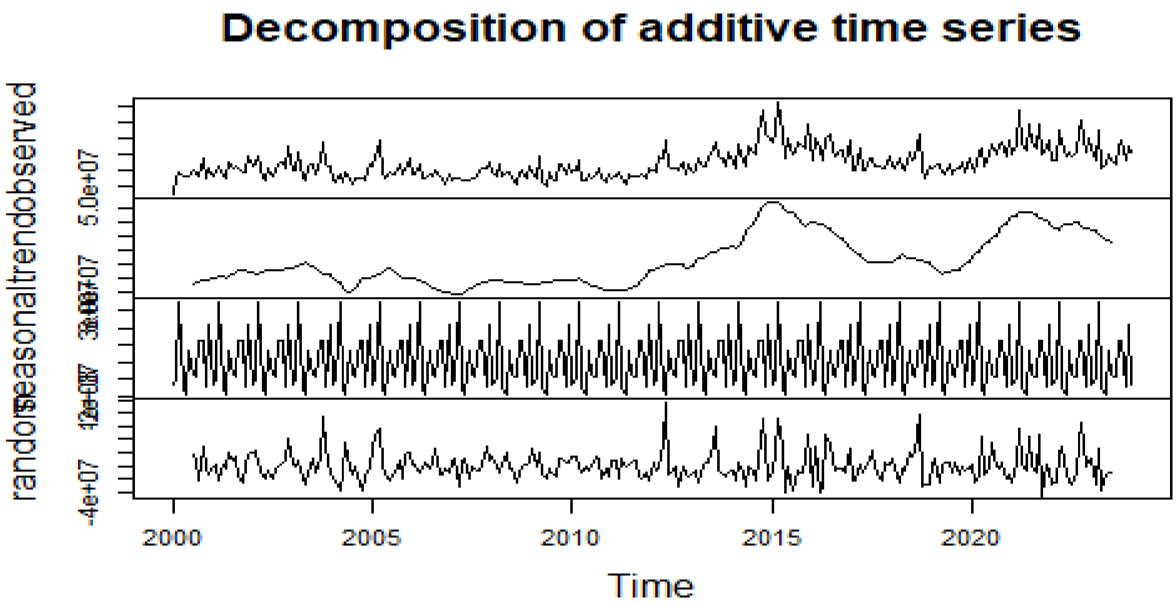
 [9] 12649222 11860277 -14586045 21843813

$type

[1] "additive"

attr(,"class")

[1] "decomposed.ts"



Conclusion: # We can see that trend is present in the above data. Also seasonal effect is present.

Now to check stationarity (i.e. presence of trend)

adf.test(data1)

Augmented Dickey-Fuller Test

data: data1

Dickey-Fuller = -3.2144, Lag order = 6, p-value = 0.08585

alternative hypothesis: stationary

\>

Conclusion: p-value is not less than los , this implies data is non- stationary.

Here , we use first order differencing to make the data stationary.

adf.test(diff(data1,3))

Augmented Dickey-Fuller Test

data: diff(data1, 3)

Dickey-Fuller = -7.2786, Lag order = 6, p-value = 0.01

alternative hypothesis: stationary

Warning message:

In adf.test(diff(data1, 3)) : p-value smaller than printed p-value

Conclusion: p-value is less than los , this implies data is stationary . After first order differencing ,data becomes stationary.

Now we get the stationary data. Now for seasonality we use Forecasting using Holt Winters Exponential Smoothing method. #Double Exp smoothing

data.hw=hw(data1,damped=T,seasonal="additive",h=12)

summary(data.hw)

autoplot(data1)+autolayer(data.hw,PI=T)

output:

>Forecast method: Damped Holt-Winters' additive method

Model Information:

Damped Holt-Winters' additive method

Call:

```
 hw(y = data1, h = 12, seasonal = "additive", damped = T)

  Smoothing parameters:
    alpha = 0.4108
    beta  = 2e-04
    gamma = 2e-04
    phi   = 0.952

  Initial states:
    l = 83328689.0375
    b = 1636563.7625
    s = 21843812 -14586046 11860277 12649221 -8732076 -7045871
           6251427 -19654443 -14383950 34584539 -9791950 -12994941

  sigma:  26280025

     AIC     AICc      BIC
1153.81 1153.35 1159.81
```

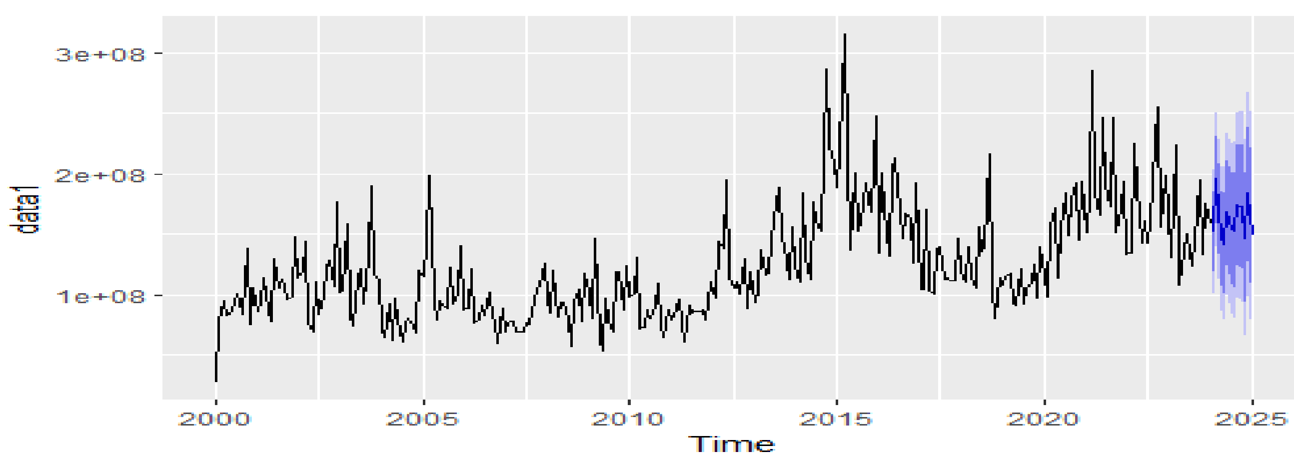
Error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	3837.5	254953	193502	-2.584528	16.28346	0.6029004	0.07618272

Forecasts:

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Feb 2024	151956230	118277023	185635437	100448328	203464132
Mar 2024	196325255	159913018	232737492	140637544	252012966
Apr 2024	147364750	108408909	186320592	87786933	206942568
May 2024	142092780	100747867	183437693	78861192	205324367
Jun 2024	167991920	124387136	211596704	101304158	234679682
Jul 2024	154697171	108942637	200451706	84721649	224672693
Aug 2024	153006965	105198005	200815924	79889471	226124458
Sep 2024	174393953	124614148	224173758	98262311	250525595
Oct 2024	173608492	121931909	225285075	94575978	252641005

……………



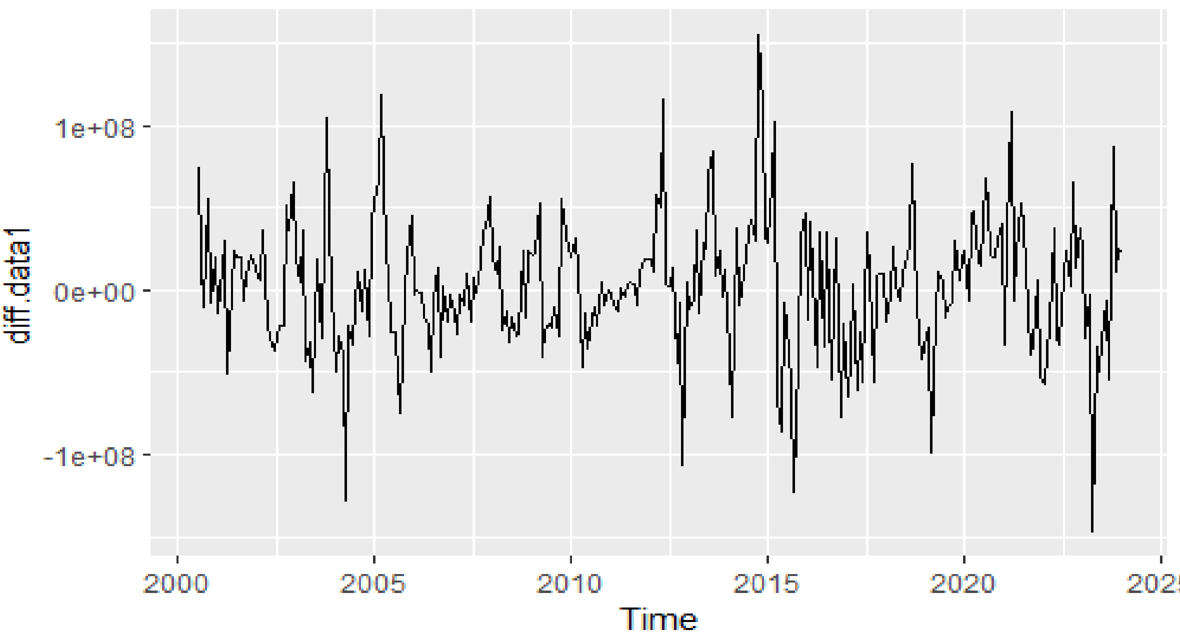
Conclusion: Holt Winters Exponential Smoothing give predictions having high AIC and BIC ,

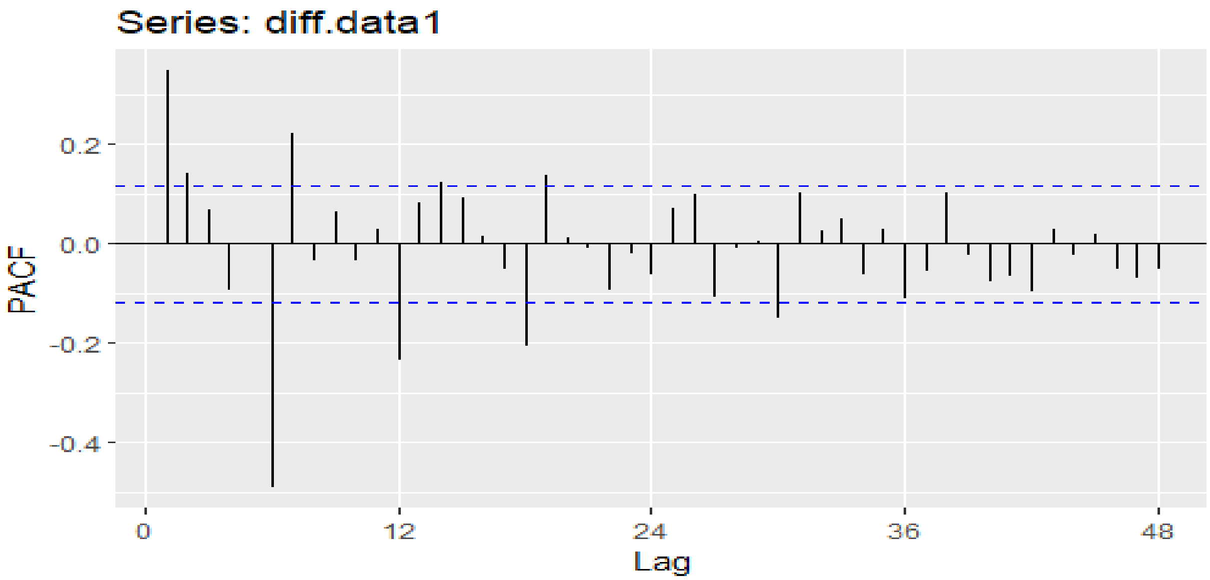
Removing the seasonal effect using differencing. By differencing already we make the data stationaty. Now we remove seasonal effect.

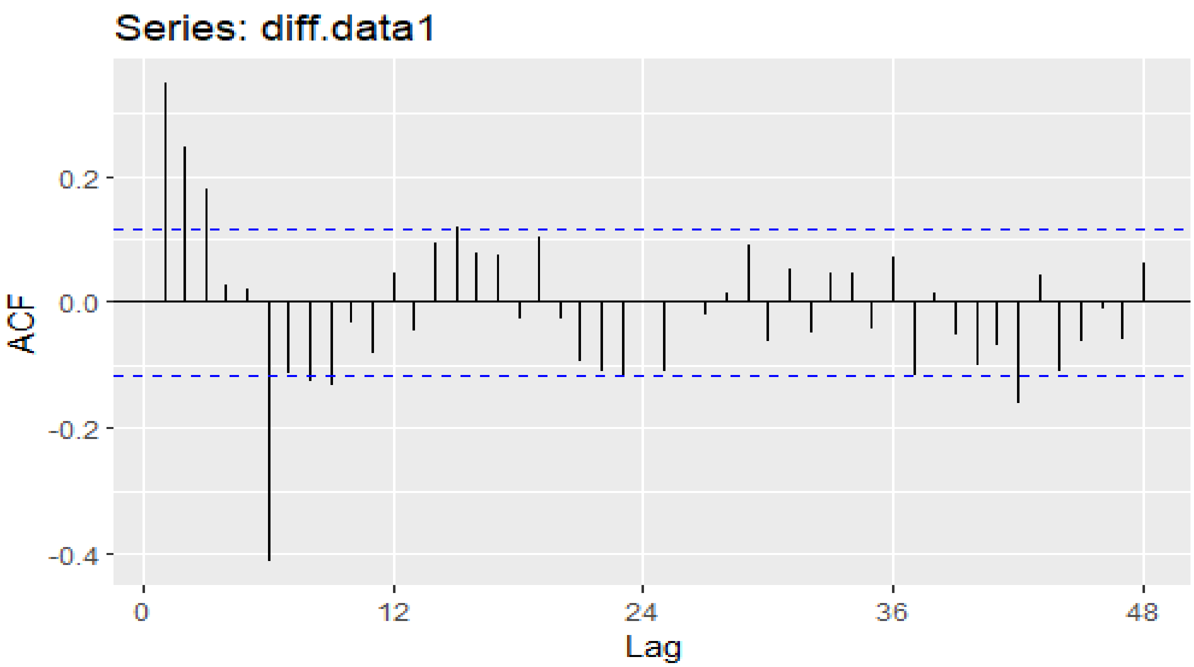
```
diff.data1=diff(data1,lag=6)
autoplot(diff.data1)
```

ggAcf(diff.data1,lag=48)

ggPacf(diff.data1,lag=48)







Conclusion:

As the seasonal effect is present in the dataset and trend is present and after seeing the ACF and PACF of the given data, we can see that SARIMA model is best for the given data (due to seasonal component) as it gives less AIC and BIC than other models.

```
fit1=sarima(data1,2,1,1,1,1,1,12)

fit1

> fit1

$fit

Call:

arima(x = xdata, order = c(p, d, q), seasonal = list(order = c(P, D, Q), period = S),

   include.mean = !no.constant, transform.pars = trans, fixed = fixed, optim.control = list(trace = trc,

      REPORT = 1, reltol = tol))

Coefficients:

        ar1      ar2      ma1     sar1     sma1

     0.1721  -0.0686  -0.6738  -0.0303  -0.9671

s.e.  0.1793   0.1142   0.1753   0.0684   0.1081

sigma^2 estimated as 6.814e+14:  log likelihood = -5120.71,  aic = 10253.42

$degrees_of_freedom

[1] 271

$ttable

    Estimate     SE t.value p.value

ar1    0.1721 0.1793  0.9600  0.3379

ar2   -0.0686 0.1142 -0.6009  0.5484

ma1   -0.6738 0.1753 -3.8429  0.0002

sar1  -0.0303 0.0684 -0.4422  0.6587

sma1  -0.9671 0.1081 -8.9436  0.0000

$AIC
```

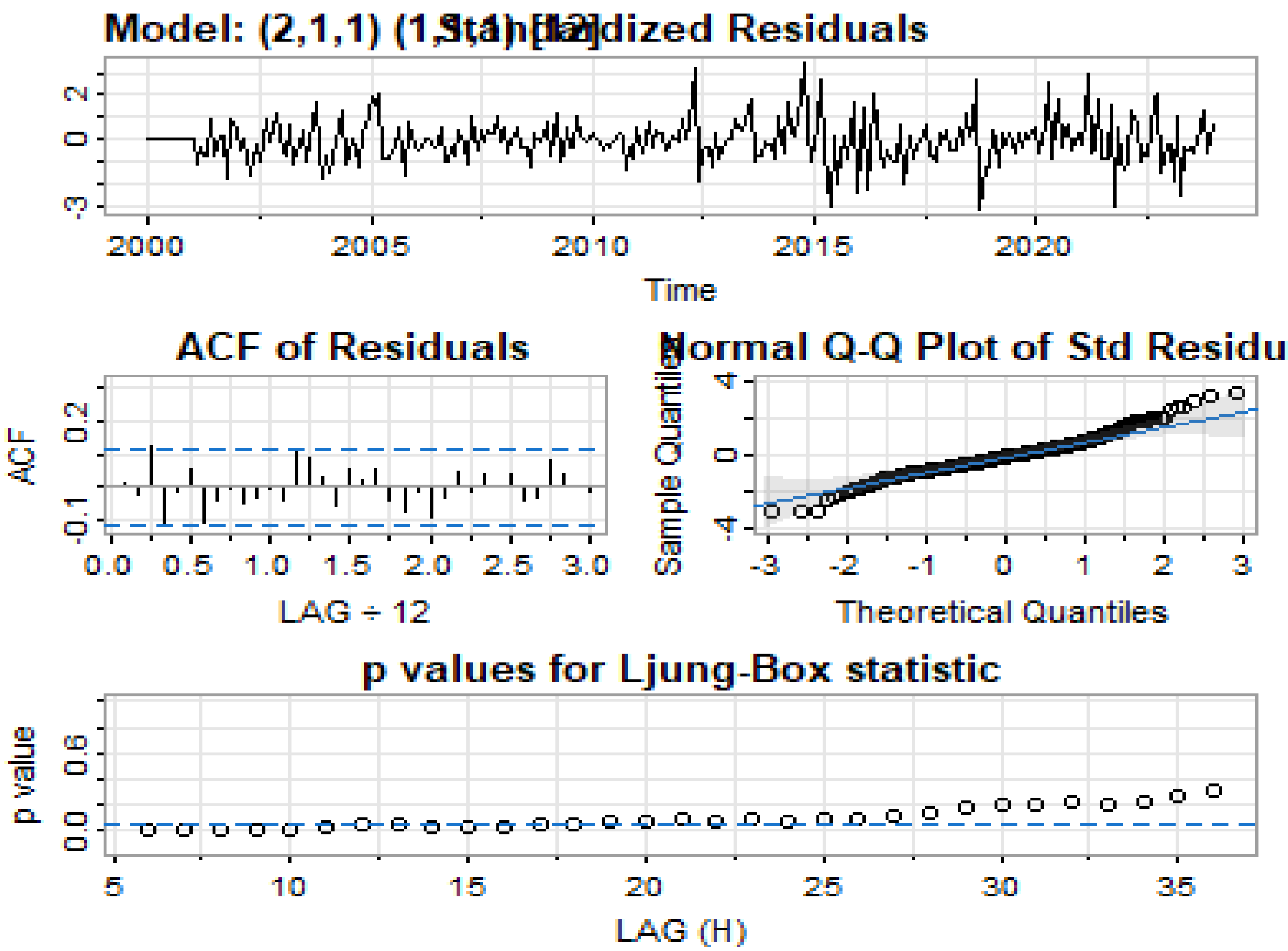
[1] 37.15008

$AICc

[1] 37.15088

$BIC

[1] 37.22878



Conclusion :

all assumptions are hold . 1]residuals are uncorrelated .2] normality assumptions is hold . This SARIMA model is better as compared to Holt Winters Exponential Smoothing as SARIMA has low value of AIC and BIC. SARIMA model performs well on this data.

Now, Forecasting using SARIMA(2,1,1,1,1,1,12) model.

>forecast=sarima.for(data1,12,2,1,1,1,1,1,12)

> forecast

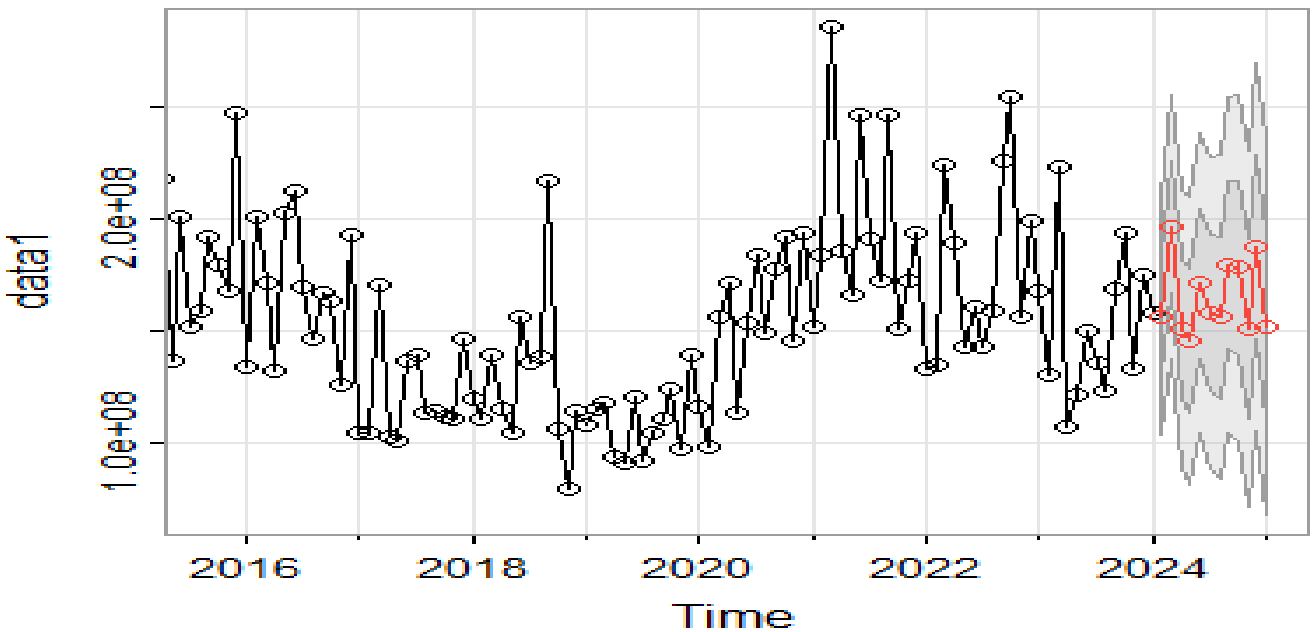
$pred

Jan Feb Mar Apr May Jun Jul Aug

2024 156891898 198798578 152662989 147346716 173035255 160414002 158443854

Sep Oct Nov Dec

2024 181517210 181355653 153992629 190775357



4] **Transfer function model on GDP and Inflation rates of india**

We take data of GDP growth rate and inflation rates of india from 1961 to 2022 from

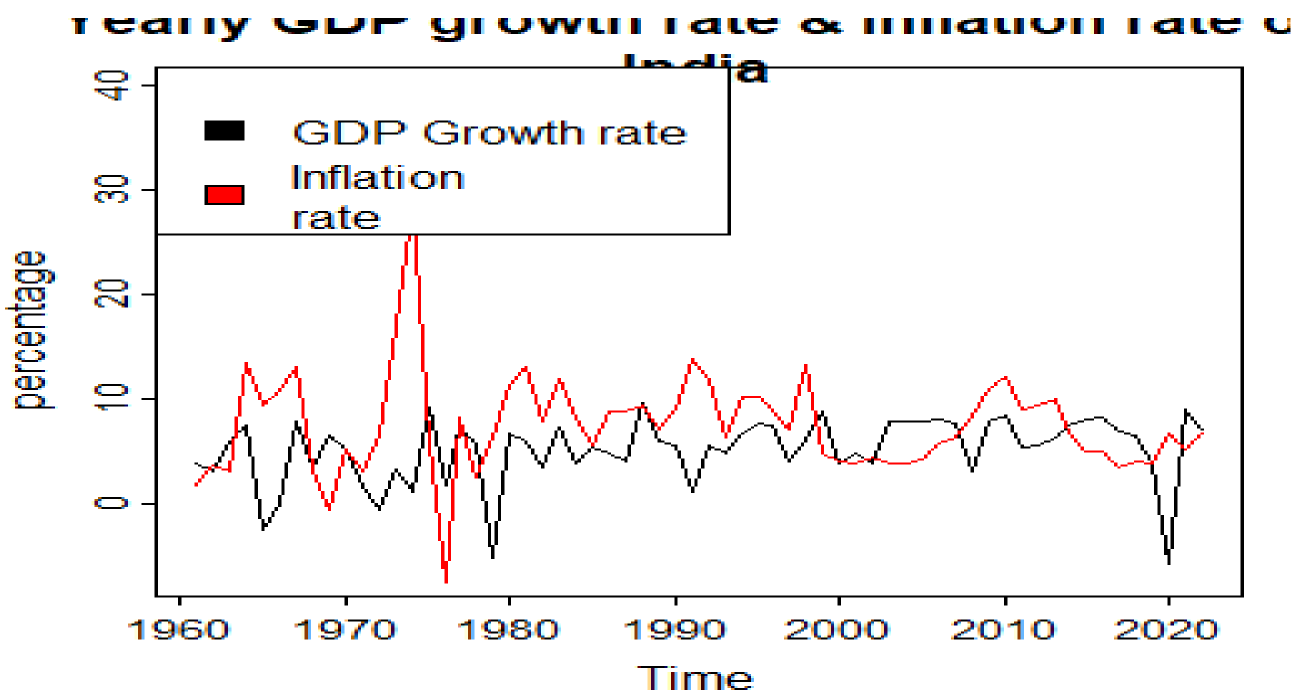
https://www.macrotrends.net/countries/IND/india/gdp-growth-rate .

Transfer Function Model is fitted on the yearly GDP Growth rate of India with the exogenous variable as Inflation rate. We consider the exogenous variable is Yearly inflation rate while GDP growth rate is the response for that.

Importing the data:

```
#install.packages("tfarima")
library(tfarima)
data7=read.csv("C:\\Users\\admin\\Downloads\\india-gdp-growth-rate.csv")
plot(gdp , main="Yearly GDP growth rate & Inflation rate of India",ylab="percentage",ylim=c(7,40))
lines(inflation,col="red")
legend("topleft",legend=c("GDP Growth rate", "Inflation rate"),fill=c("black","red"))
```

Graph of GDP growth rate and inflation rates :



we observe that whenever GDP growth rate decreases, the inflation rate increases.

Model Fitting–

The data is split into train data and validation data. The data till the year 2010 is considered as the train set, and the data after 2010 upto 2022 is considered in the validation set.

The Transfer Function Arima Model is fitted on GDP growth rate, with inflation rate as the response.

Code:

```
gdp1=data7$GDP[1:50]
gdp1=ts(gdp1,start=1961,freq=1)
inflation1=data7$Inflation[1:50]
inflation1=ts(inflation1,start=1961,freq=1)
gdp=data7$GDP
gdp=ts(gdp,start=1961,freq=1)
inflation=data7$Inflation
inflation=ts(inflation,start=1961,freq=1)
#Transfer Function Models
M7 = auto.arima(gdp1,xreg=inflation1)
summary(M7)
```

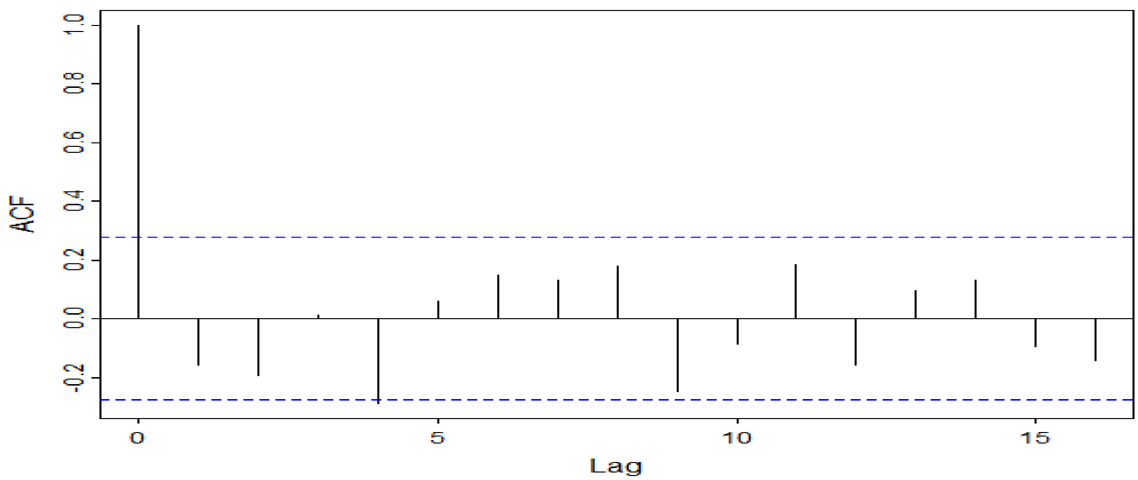
output:

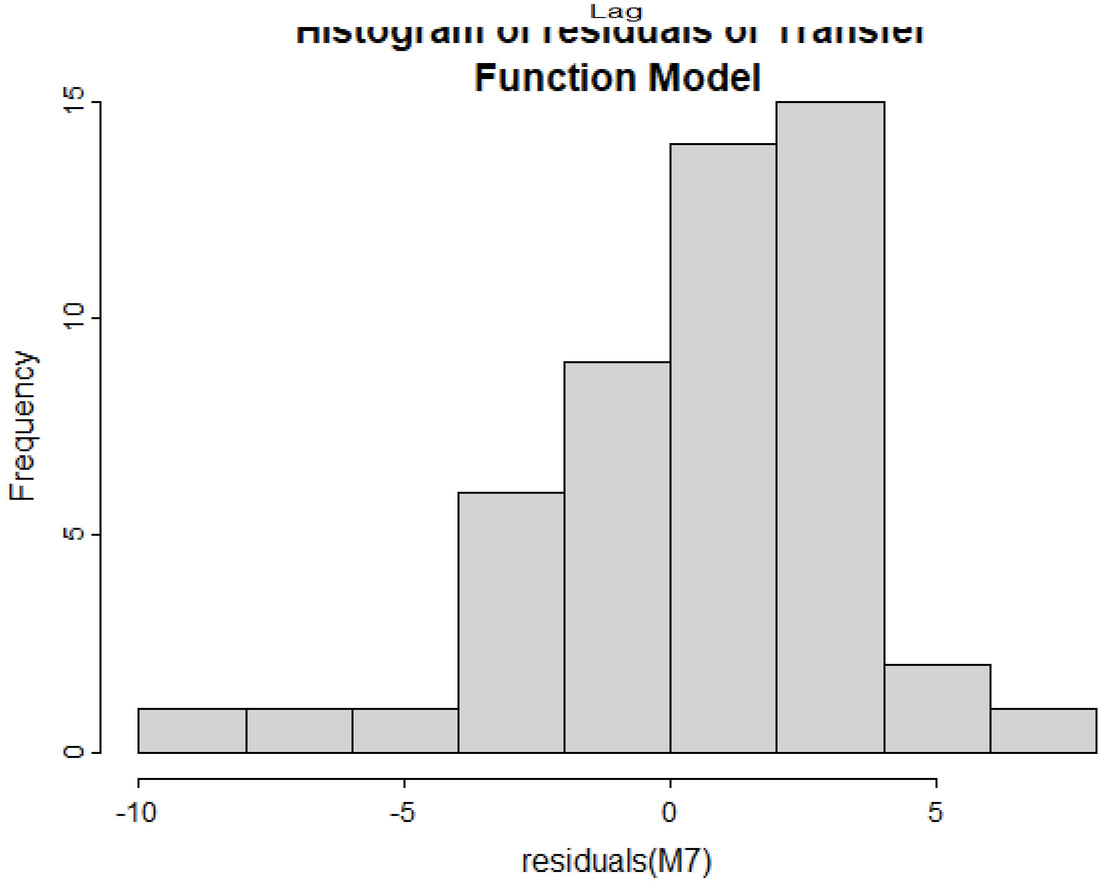
```
>summary(M7)
Series: gdp1
Regression with ARIMA(0,1,1) errors
Coefficients:
        ma1     xreg
     -0.8977  -0.0044
s.e.   0.0520   0.0790
sigma^2 = 9.514:  log likelihood = -124.52
AIC=255.04   AICc=255.57   BIC=260.71
Training set error measures:
              ME    RMSE          MAE          MPE          MAPE          MASE
Training set 0.5297693          2.990442        2.338511        141.2841        185.7994  0.7277008
             ACF1
```

Training set -0.1582956

Residual Analysis

The residuals are analysed of the fitted Model to find the Model adequacy. We will first use exploratory data analysis to check for Normality and serial uncorrelatedness of residuals. We will verify these assumptions by using Shapiro test and Ljung-Box test.





Assumptions checking:

```
>shapiro.test(residuals(M7))

        Shapiro-Wilk normality test

data:  residuals(M7)
W = 0.94352, p-value = 0.0186
```

```
> Box.test(residuals(M7),type="Ljung-Box")

        Box-Ljung test

data:  residuals(M7)
X-squared = 1.3296, df = 1, p-value = 0.2489
```

Conclusion:

1) The Ljung-Box test suggests that the residuals are serially uncorrelated.

2) The Shapiro-Wilik test suggests that at 1% LOS, we can accept the hypothesis that the residuals are normal.

Model Predictions –

The Transfer Function Model has been fitted, and even though the residual analysis is not Very well. We will generate predictions for the test data. We obtain the predictions, and after plotting them on the graph, we note the following things:

code:

```
M7.pred=forecast(M7,h=12,xreg = inflation)$mean[1:12]
M7.pred=ts(M7.pred,start=2011,freq=1)
plot(gdp,main="Yearly GDP growth rate & Inflation rate of
India",ylab="percentage",ylim=c(-7,40))
lines(fitted(M7),col="red",lwd=2)
lines(M7.pred,col="blue",lwd=2)
legend("topleft",legend=c("Predictions on Train
```

Data","Predictions on validation Data", "Actual

data"),fill=c("red","blue","black"))

RMSE.tfm=sum((gdp[51:62]-M7.pred)^2)

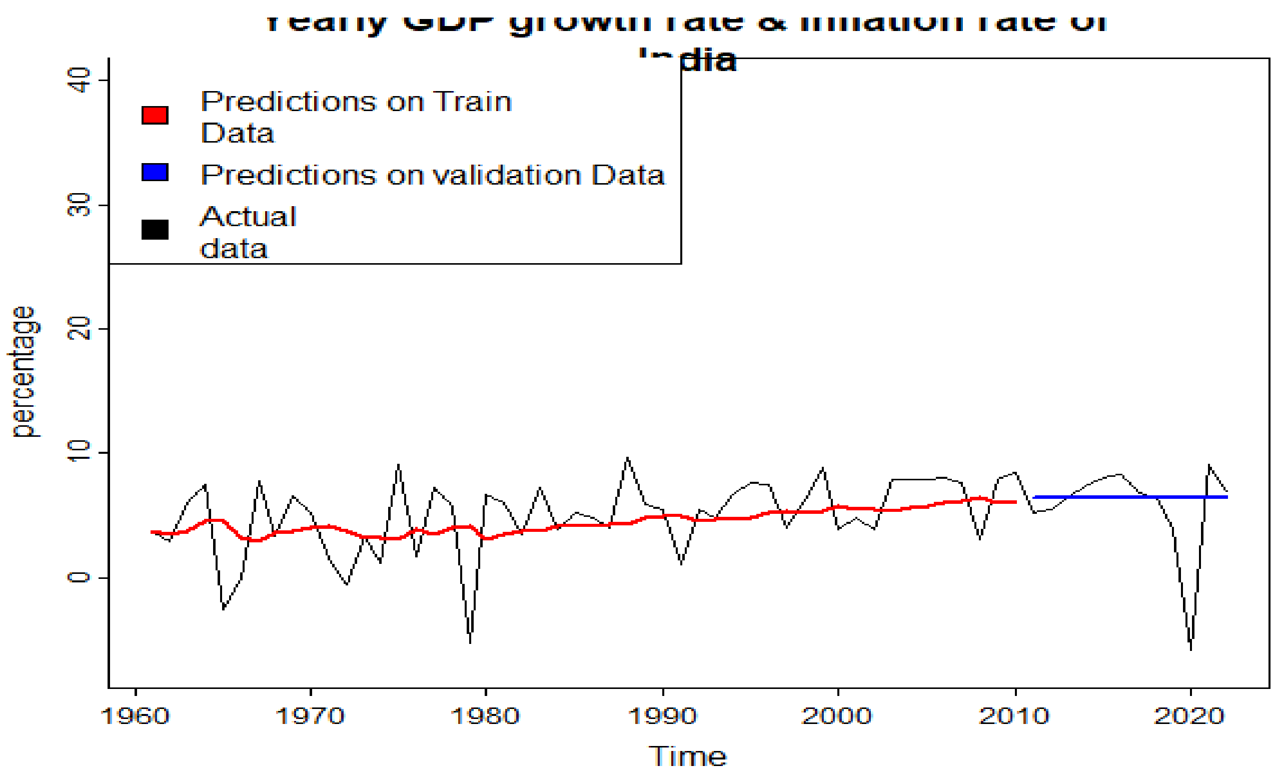
> RMSE.tfm=sum((gdp[51:62]-M7.pred)^2)

> RMSE.tfm

[1] 174.2585

#we get the RMSE value is 174.2585.

Output:



Conclusions :

1) We observe that ARIMA(0,1,1) is used by transfer function with Y=GDP and X=Inflation rate.

2) There is a relationship between the GDP growth rate and Inflation rate.

3) We fit the model and perform residual analysis.

5] GARCH model on return data of HDFC from NSE.

This data is taken as the returns of the NSE. The data is taken from the

https://finance.yahoo.com/quote/HDFC/history?p=HDFC

The data is taken from Jan 2010 to Dec 2023.

Exploratory Data Analysis –

The exploratory data analysis enables us to find the presence of heteroskedasticity in the data. The returns of a stock have drift parameter 0, so there is no need to fit an ARMA Model prior to performing the ARCH-GARCH Model.

We observe the following from the graphs –

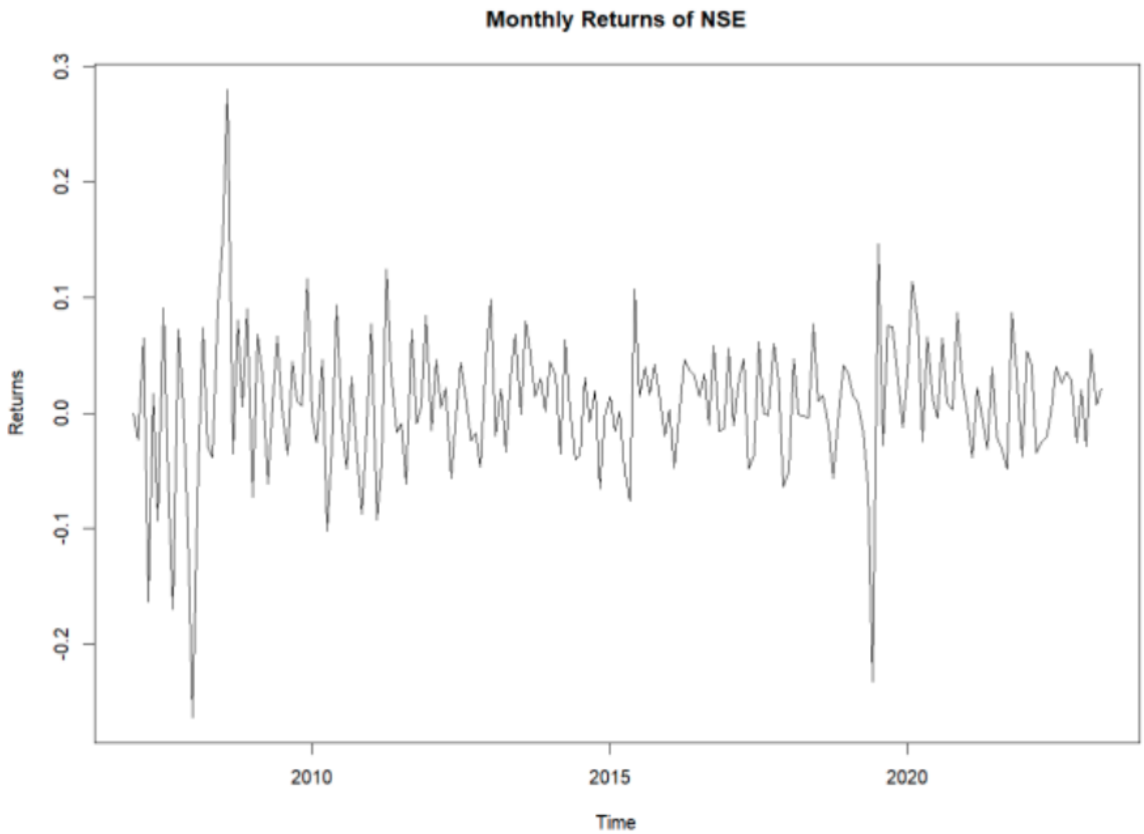
1) The ACF and PACF plots of squared residuals show the presence of GARCH structure.

2) We verify this by using Ljung-Box test, and get the p-value 0.2084

3) The Monthly returns of HDFC has drift parameter 0, so there is no need to fit an ARMA model before conducting the analysis.

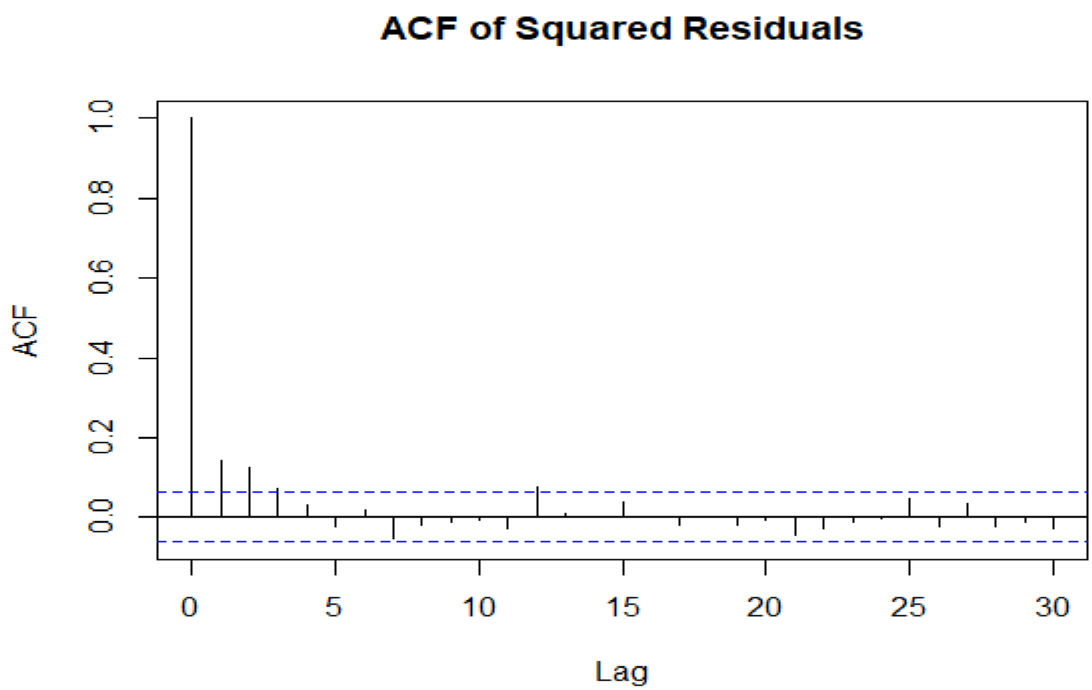
```
data= read.csv("C:\\Users\\admin\\Downloads\\^NSEI.csv")
data=data$returns
data <- ts(data)
```

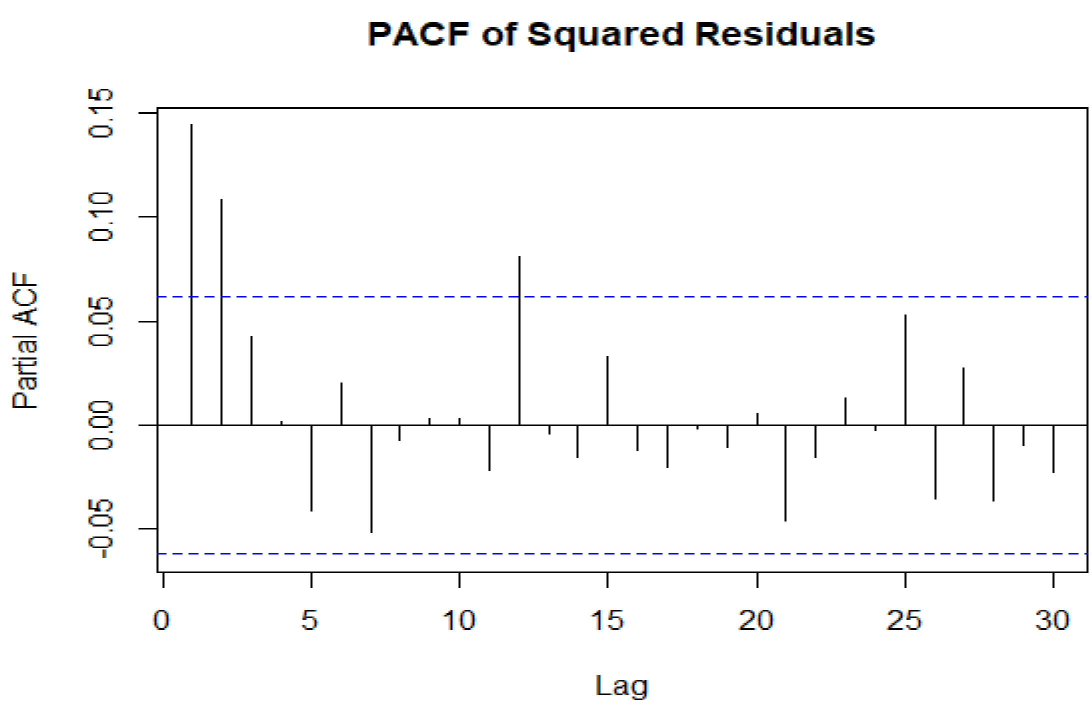
```
plot(data, type = 'l', ylab = 'Returns', main = 'Monthly Returns of NSE' )
```




```
acf_result <- acf(squared_residuals, main = 'ACF of Squared Residuals')
pacf_result <- pacf(squared_residuals, main = 'PACF of Squared Residuals')
```

output:





Model Fitting –

The GARCH(1,1) Model is fitted on this data, and obtain the coefficients of the model. We also obtain the error variance table, which provides the significance of the coefficients.

We choose GARCH(1,1) model since it is the model with the smallest AIC and BIC.

```
>print(garch_model)

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

Optimal Parameters
------------------------------------
       Estimate  Std. Error   t value Pr(>|t|)
omega  0.001046   0.001323 7.9065e-01  0.42915
alpha1 0.000000   0.001342 3.6000e-05  0.99997
beta1  0.999000   0.000040 2.5059e+04  0.00000

Robust Standard Errors:
  Estimate     Std. Error      t value          Pr(>|t|)
omega  0.001046   0.001267 8.2549e-01       0.40910
alpha1 0.000000   0.001249 3.9000e-05       0.99997
beta1  0.999000   0.000042 2.3555e+04       0.00000
LogLikelihood : -1390.893
Information Criteria
------------------------------------
 Akaike     2.7878
```

Bayes 2.8025

Shibata 2.7878

Hannan-Quinn 2.7934

Weighted Ljung-Box Test on Standardized Residuals

----

	statistic	p-value
Lag[1]	1.582	0.2084
Lag[2*(p+q)+(p+q)-1][2]	1.631	0.3320
Lag[4*(p+q)+(p+q)-1][5]	2.453	0.5160

d.o.f=0

H0 : No serial correlation

Weighted Ljung-Box Test on Standardized Squared Residuals

----

	statistic	p-value
Lag[1]	20.63	5.566e-06
Lag[2*(p+q)+(p+q)-1][5]	36.62	4.246e-10
Lag[4*(p+q)+(p+q)-1][9]	40.44	5.444e-10

d.o.f=2

Weighted ARCH LM Tests

	Statistic	Shape	Scale	P-Value
ARCH Lag[3]	5.070	0.500	2.000	0.02434
ARCH Lag[5]	5.967	1.440	1.667	0.06115
ARCH Lag[7]	7.377	2.315	1.543	0.07196

Nyblom stability test

Joint Statistic: 1.996

Individual Statistics:

omega 0.1301

alpha1 0.1212

beta1 0.1273

Asymptotic Critical Values (10% 5% 1%)

Joint Statistic: 0.846 1.01 1.35

Individual Statistic: 0.35 0.47 0.75

Sign Bias Test

----

	t-value	prob	sig
Sign Bias	0.0952	9.242e-01	
Negative Sign Bias	4.0549	5.407e-05	***
Positive Sign Bias	3.1968	1.433e-03	***
Joint Effect	27.2890	5.121e-06	***

Adjusted Pearson Goodness-of-Fit Test:

----

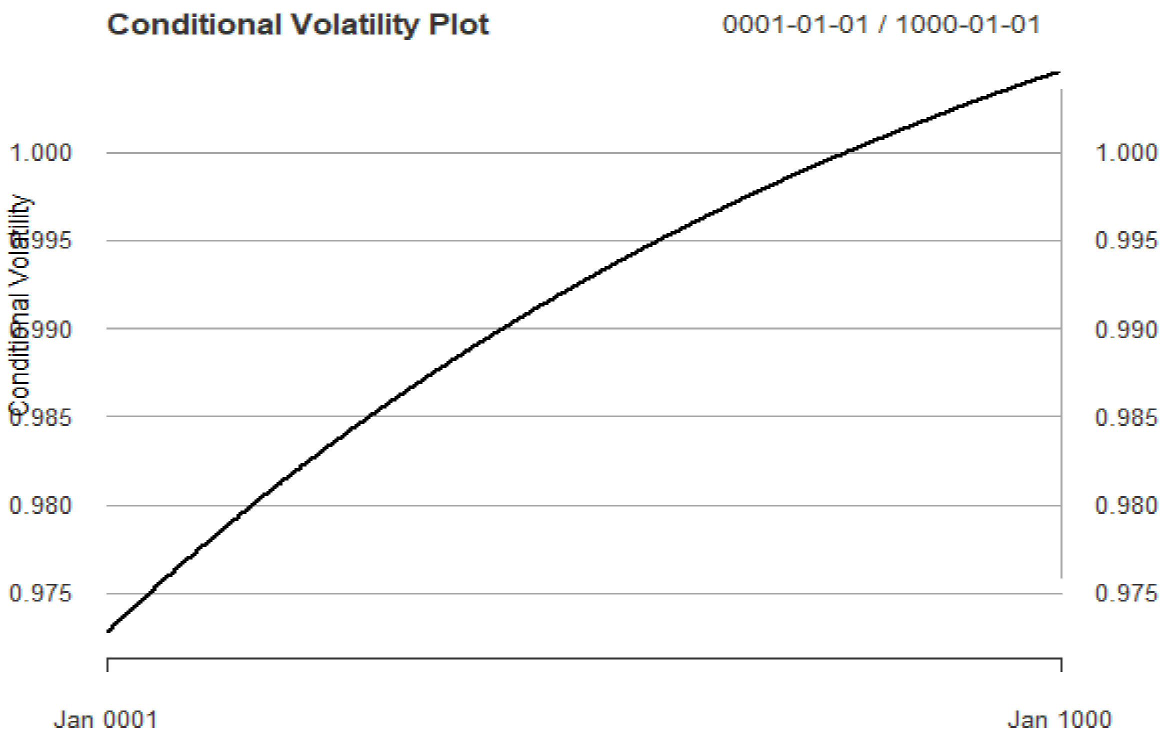
	group	statistic	p-value(g-1)
1	20	18.88	0.4646
2	30	32.24	0.3094
3	40	41.20	0.3746
4	50	51.70	0.3688

Residual Analysis –

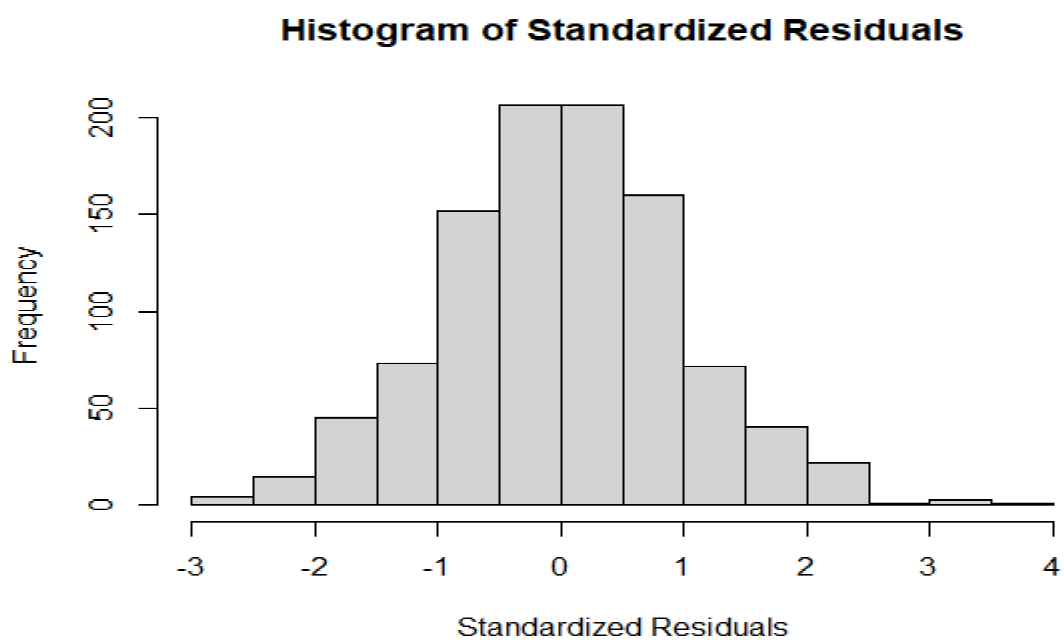
The residuals generated by the ARCH Model are as follows

>plot(conditional_volatility, type = 'l', ylab = 'Conditional Volatility', main = 'Conditional Volatility Plot')

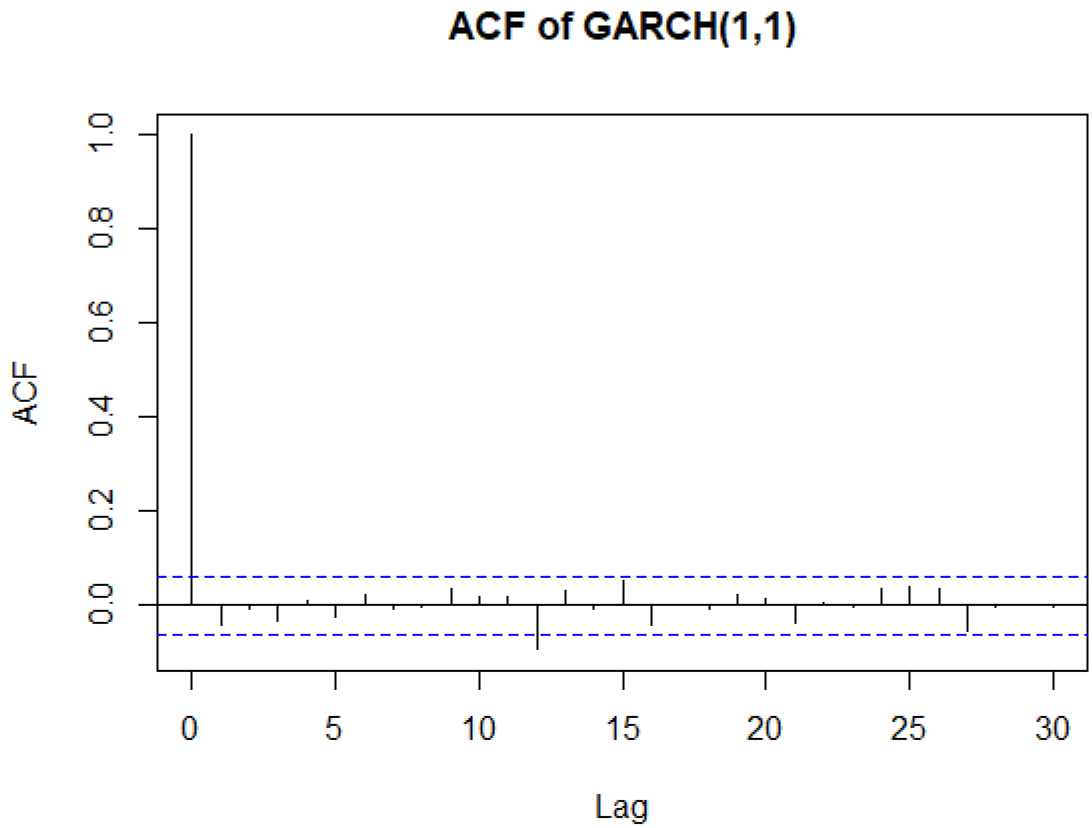
> hist(standardized_residuals, main = 'Histogram of Standardized Residuals', xlab = 'Standardized Residuals')



Conditional Volatility Plot
0001-01-01 / 1000-01-01
Conditional Volatility
1.000
0.995
0.990
0.985
0.980
0.975
Jan 0001
Jan 1000



Histogram of Standardized Residuals
Frequency
0
50
100
150
200
-3
-2
-1
0
1
2
3
4
Standardized Residuals



From the ACF and Histogram of ACFs, we observe that

1) The residuals of GARCH(1,1) appear to follow Normal Distribution in the histogram.

We verify this by conducting Shapiro-Wilik normality test.

2)Serial Correlation: The weighted Ljung-Box tests on both standardized residuals and squared residuals suggest no serial correlation at the specified lags.

3)ARCH Effect: The weighted ARCH LM tests indicate significance for the ARCH effect at lag 3.

4)Nyblom Stability Test: The Nyblom stability test suggests stability in the parameters.

5)Sign Bias Test: The test reveals a significant negative sign bias and a significant positive sign bias.

6)Goodness-of-Fit: The adjusted Pearson goodness-of-fit test provides p-values for assessing the fit of the model at different lag lengths.