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UAS ANALISIS RUNTUN WAKTU

PENYELESAIAN

Untuk melakukan pemodelan dengan metode Box-Jenkin, akan dilakukan dengan 4 tahapan besar, yaitu

1. Identifikasi Model,

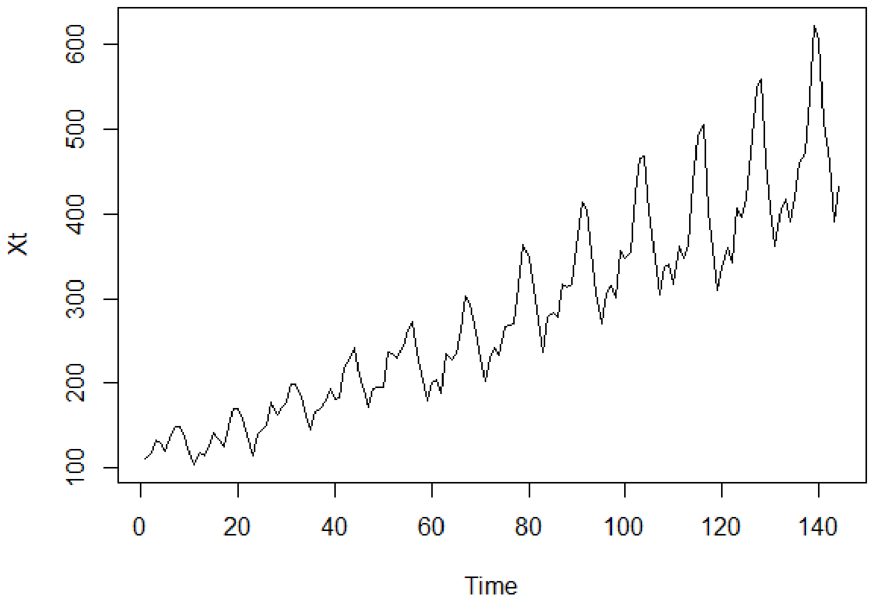
2. Pendugaan Model atau Estimasi Model,

3. Pemeriksaan Diagnostik Model, dan

4. Penggunaan Model Untuk Peramalan (forecasting)

1. Identifikasi model

Untuk tahap awal mengidentifikasi data yang akan di proses untuk mengetahui apakah mengandung tren atau musiman, dan akan ditunjukkan grafik plot data asli, grafik ACF dan PACF dari data asli untuk mengetahui apakah data tersebut merupakan data stasioner atau tidak stasioner. Dan jika data sudah stasioner maka proses bisa dilanjutkan ke tahap berikutnya.



Dari plot di atas, terlihat bahwa pengunjung taman safari memiliki pola naik turun dalam kurun waktu tertentu (musiman) dan terdapat tren naik sehingga ada indikasi data tidak stasioner.

Akan di analisis apakah data set tersebut stasioner menggunakan uji ADF (*augmented dicky fuller*)

1) H_0 : Data Tidak Stasioner

   H_1 : Data Stasioner

2) Tetapkan uji signifikansi α = 0.05
3) Statistik uji

   Menggunakan uji Augmented Dicky-Fuller

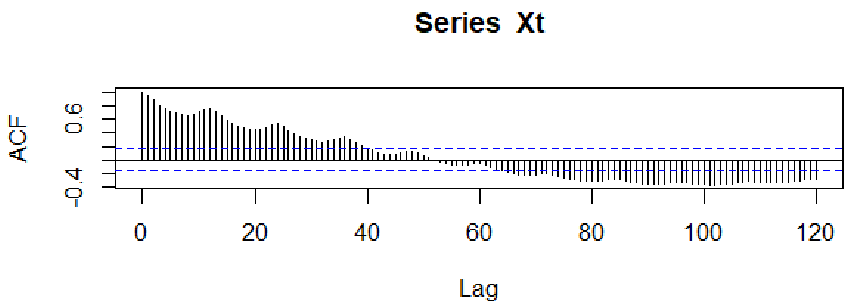
   Dengan daerah penolakannya yaitu $H0$ ditolak jika p-value < α

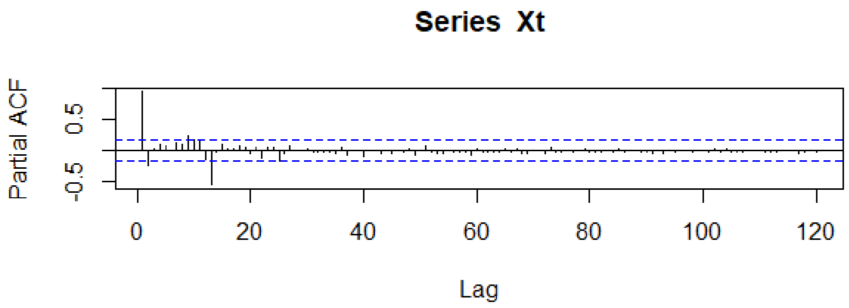
4) Perhitungan

   p-value = 0.01
5) Kesimpulan

   Karena $p - value = 0.01 < \alpha = 0.05$, sehingga H_0 ditolak sehingga menghasilkan Data Stasioner.

   Akan dipastkan hasilnya menggunakan plot grafik acf dan pacf.

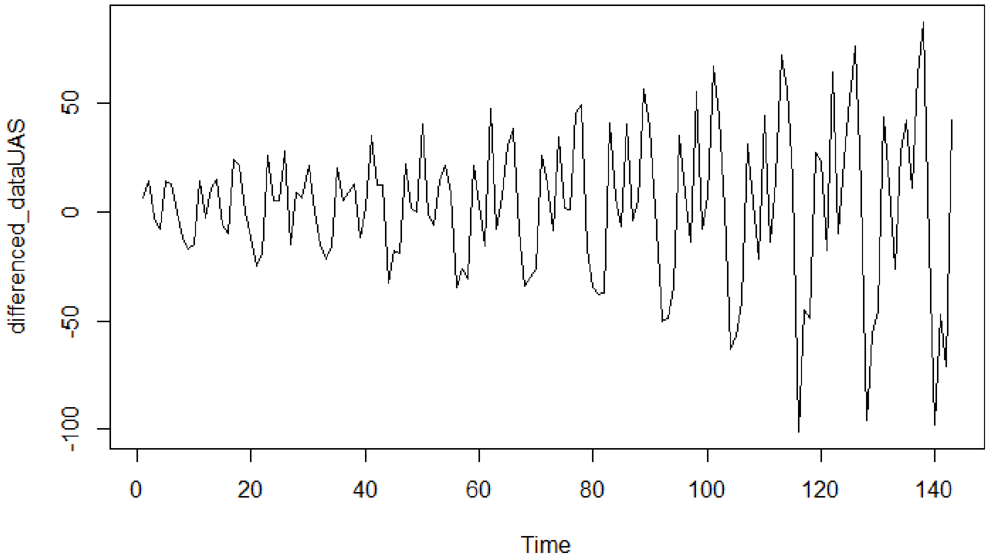




Dari grafik ACF, penurunan nilai lambat sehingga mengindikasikan data tidak stasioner. Begitu juga dengan PACF, mengindikasikan data set tidak stasioner karena merupakan grafik sinus teredam.

Karena data tidak stasioner, maka data akan distasionerkan dengan *differencing*.

Setelah data di-*differencing*, berikut adalah grafiknya



Terlihat bahwa data sudah stasioner secara rata-rata.

Lalu akan diperiksa menggunakan uji adf.

Metode Uji Akar Unit (Uji Augmented Dickey Fuller).

Hipotesis yang di uji adalah:

1) $H0$: Data Tidak Stasioner

   $H1$: Data Stasioner

2) Tetapkan uji signifikansi $\alpha = 0.05$

3) Statistik uji

   Menggunakan uji Augmented Dicky-Fuller

   Dengan daerah penolakannya yaitu $H0$ ditolak jika p-value < α

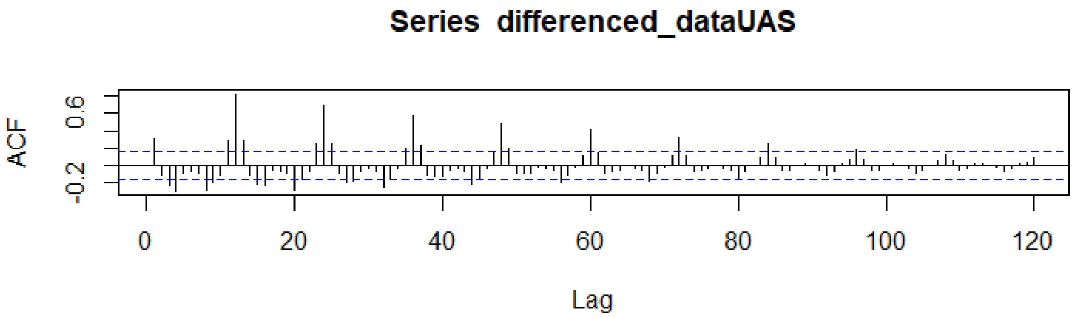
4) Perhitungan

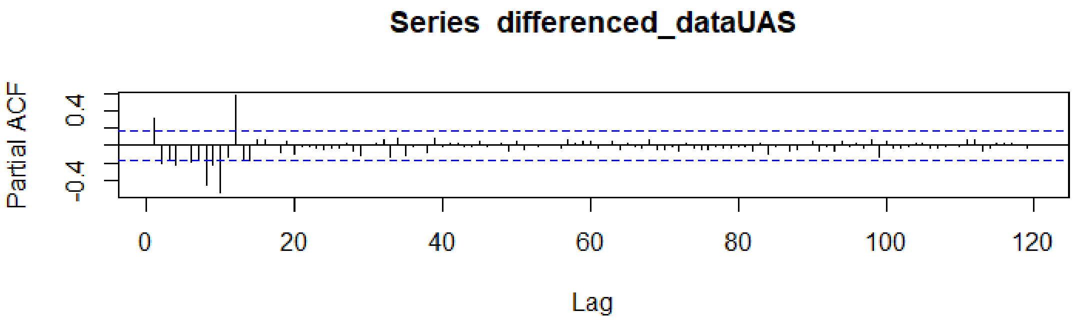
p-value = 0.01

5) Kesimpulan

Karena nilai $p - value$ p-value = 0.01 $< \propto = 0.05$, maka H_0 ditolak sehingga hipotesis alternatif diterima (H_1), data stasioner.

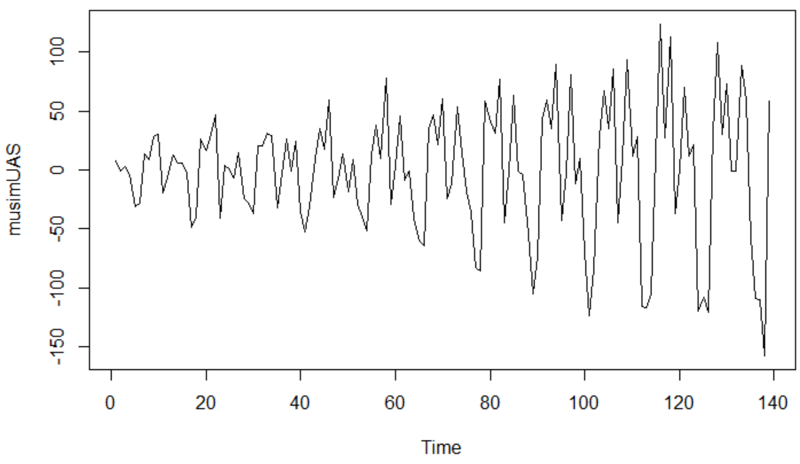
Akan dipastikan bahwa grafik ACF dan PACF juga menunjukkan hasil yang stasioner.





Karena pada musim data tidak stasioner, maka untuk musim akan di*differencing* lagi.

Setelah di*differencing* sebanyak 1 kali, berikut adalah grafiknya.



Lalu akan diperiksa menggunakan uji adf.

Metode Uji Akar Unit (Uji Augmented Dickey Fuller).

Hipotesis yang di uji adalah:

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3) Statistik uji

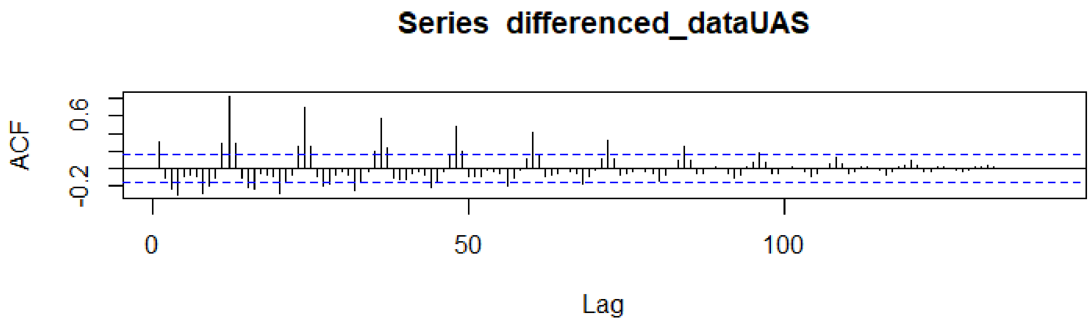
   Menggunakan uji Augmented Dicky-Fuller

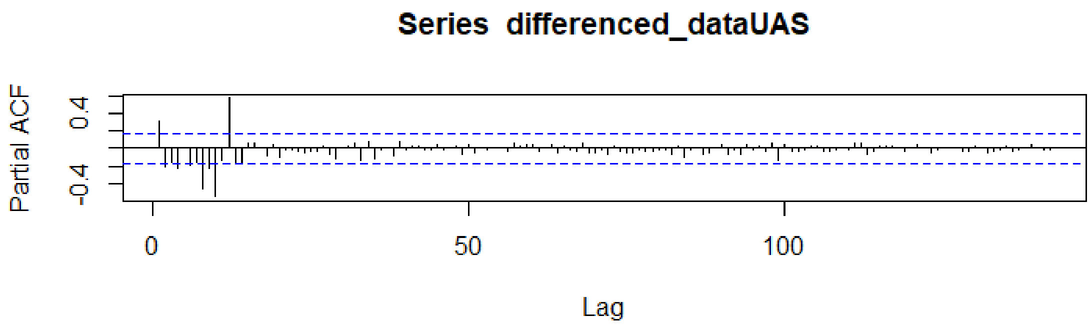
   Dengan daerah penolakannya yaitu $H0$ ditolak jika p-value < α
4) Perhitungan

   p-value = 0.01
5) Kesimpulan

   Karena nilai $p - value$ p-value = 0.01 $<\propto = 0.05$, maka H_0 ditolak sehingga hipotesis alternatif diterima (H_1), data stasioner.

Akan dipastikan bahwa grafik ACF dan PACF juga menunjukkan hasil yang stasioner.





Pada data musiman, grafik ACF menunjukkan penurunan yang sama seperti *differencing* 1 kali pada musiman, maka kita kana menggunakan data yang di-diferencing musiman 1 kali saja.

2. Estimasi Model

Untuk data non-musiman:

Perhatikan bahwa data non-musiman dan non musiman sudah stasioner dan di *differencing* 1 kali pada data non musiman dan 1 kali pada data musiman sebelumnya.

- Pada grafik ACF, model signifikan pada lag 1 (garis pertama berada di luar pita biru) sehingga nilai $q = 1$.
- Pada grafik PACF, model signifikan pada 1 lag pertama (1 garis pertama berada di luar pita biru) sehingga $p = 1$.
- Grafik ACF dan PACF menunjukkan pola naik pada periode ke-6.

Untuk data musiman:

- Pada grafik ACF musiman, model signifikan pada lag 2 (2 garis pertama setelah periode ke-4 melewati pita) sehingga nilai $Q = 2$.
- Pada grafik PACF musiman, model signifikan pada lag 1 (1 garis melewati pita), sehingga nilai $P = 1$.

Karena data sudah stasioner, maka nilai $d = 1$ dan $D = 1$, dan $p = 1, q = 1, P = 1$ dan $Q = 2$. Maka, alternatif model SARIMA yang mungkin adalah sebagai berikut:

1) SARIMA $(0,1,0)(0,1,0)_4$
2) SARIMA $(1,1,0)(0,1,0)_4$
3) SARIMA $(1,1,1)(0,1,0)_4$
4) SARIMA $(1,1,0)(1,1,0)_4$
5) SARIMA $(1,1,0)(0,1,1)_4$
6) SARIMA $(1,1,1)(1,1,0)_4$
7) SARIMA $(1,1,0)(1,1,1)_4$
8) SARIMA $(1,1,1)(0,1,1)_4$
9) SARIMA $(1,1,1)(1,1,1)_4$
10) SARIMA $(0,1,1)(0,1,0)_4$
11) SARIMA $(0,1,1)(1,1,0)_4$
12) SARIMA $(0,1,1)(0,1,1)_4$
13) SARIMA $(0,1,1)(1,1,1)_4$
14) SARIMA $(0,1,0)(1,1,0)_4$
15) SARIMA $(0,1,0)(1,1,1)_4$
16) SARIMA $(0,1,0)(0,1,1)_4$
17) SARIMA $(0,1,0)(0,1,2)_4$
18) SARIMA $(1,1,0)(0,1,2)_4$
19) SARIMA $(0,1,1)(0,1,2)_4$
20) SARIMA $(0,1,0)(1,1,2)_4$
21) SARIMA $(1,1,1)(0,1,2)_4$
22) SARIMA $(1,1,0)(1,1,2)_4$

23) SARIMA $(0,1,1)(1,1,2)_4$ 24) SARIMA $(1,1,1)(1,1,2)_4$

3. Pemeriksaan Diagnostik Model

Pada tahap ini semua alternatif model SARIMA akan diuji untuk mengetahui apakah residual white noise, residual berdistribusi normal dan AIC minimum. Tujuan diuji tersebut untuk mendapatkan salah satu model terbaik dari alternatif SARIMA model yang mungkin, model terbaik jika terdapat nilai AIC minimum, Residual white noise dan Residual berdistribusi normal.

Dengan menggunakan taraf signifikansi α = 0.05, berikut hipotesis untuk menguji residual white noise dan residual berdistribusi normal.

1) Hipotesis untuk menguji residual apakah white atau tidak dengan metode Ljung-Box test:

   Hipotesis yang diuji:

   $H0$: Residual white noise

   $H1$: Residual tidak white noise

   Wilayah kritis: $H0$ ditolak jika $p - value$ < α.

2) Hipotesis untuk menguji residual apakah berdistribusi normal atau tidak dengan metode Shapiro-Wilk normality test:

   Hipotesis yang diuji:

   $H0$: Residual berdistribusi normal

   $H1$: Residual tidak berdistribusi normal

   Wilayah kritis: $H0$ ditolak jika $p - value$ < α.

SARIMA	WHITE NOISE	DISTIRBUSI NORMAL	AIC
1	TIDAK	TIDAK	1503.94
2	TIDAK	YA	1487.61
3	TIDAK	YA	1466.88
4	TIDAK	YA	1453.75
5	TIDAK	YA	1366.9

6	TIDAK	YA	1454.42
7	TIDAK	YA	1344.25
8	TIDAK	YA	1344.93
9	TIDAK	YA	1329.82
10	TIDAK	YA	1485.85
11	TIDAK	YA	1452.61
12	TIDAK	YA	1365.41
13	TIDAK	YA	1343.01
14	TIDAK	YA	1469.99
15	TIDAK	YA	1355.26
16	TIDAK	YA	1381.06
17	TIDAK	YA	1408.91
18	YA	YA	1297.9
19	TIDAK	YA	1297.77
20	TIDAK	TIDAK	1367.23
21	YA	YA	1299.56
22	TIDAK	YA	1353.71
23	TIDAK	YA	1352.42
24	TIDAK	YA	1354.37

Berdasarkan hasil di atas hasil dengan menggunakan fungsi yang terdapat pada R, model SARIMA yang terpilih adalah SARIMA $(1,1,0)(0,1,2)_4$

Dari mode SARIMA $(1,1,1)(0,1,2)_4$ dengan persamaan umum:

$$\phi_P(B)\Phi_P(B^S)(1-B)^D(1-B^S)^D Y_t = \phi_P(B)\Theta_Q(B^s)e_t$$

ϕ_p : koefisien komponen AR dengan orde ke-*p*,

B : operator *backward* non musiman,

Φ_P : koefisien komponen AR musiman dengan orde ke-*P*,

B^s : operator *backward* musiman,

d : pembedaan (*differencing*) orde ke-*d* non musiman,

D : pembedaan (*differencing*) orde ke-*D* non musiman,

Y_t : nilai variabel *Y* pada waktu *t*,

θ_q : koefisien komponen MA dengan orde ke-*q*,

Θ_Q : koefisien komponen MA musiman dengan orde ke-*Q*,

e_t : *residual white noise*.

Maka persamaannya adalah:

Dengan:

ar1	sma1	sma2
0.2274	-1.6797	0.792

$$\phi_1(B)\Phi_1(B^4)(1-B)(1-B^4)Y_t = \phi_1(B)\Theta_1(B^4) + \Theta_2(B^8)\varepsilon_t$$

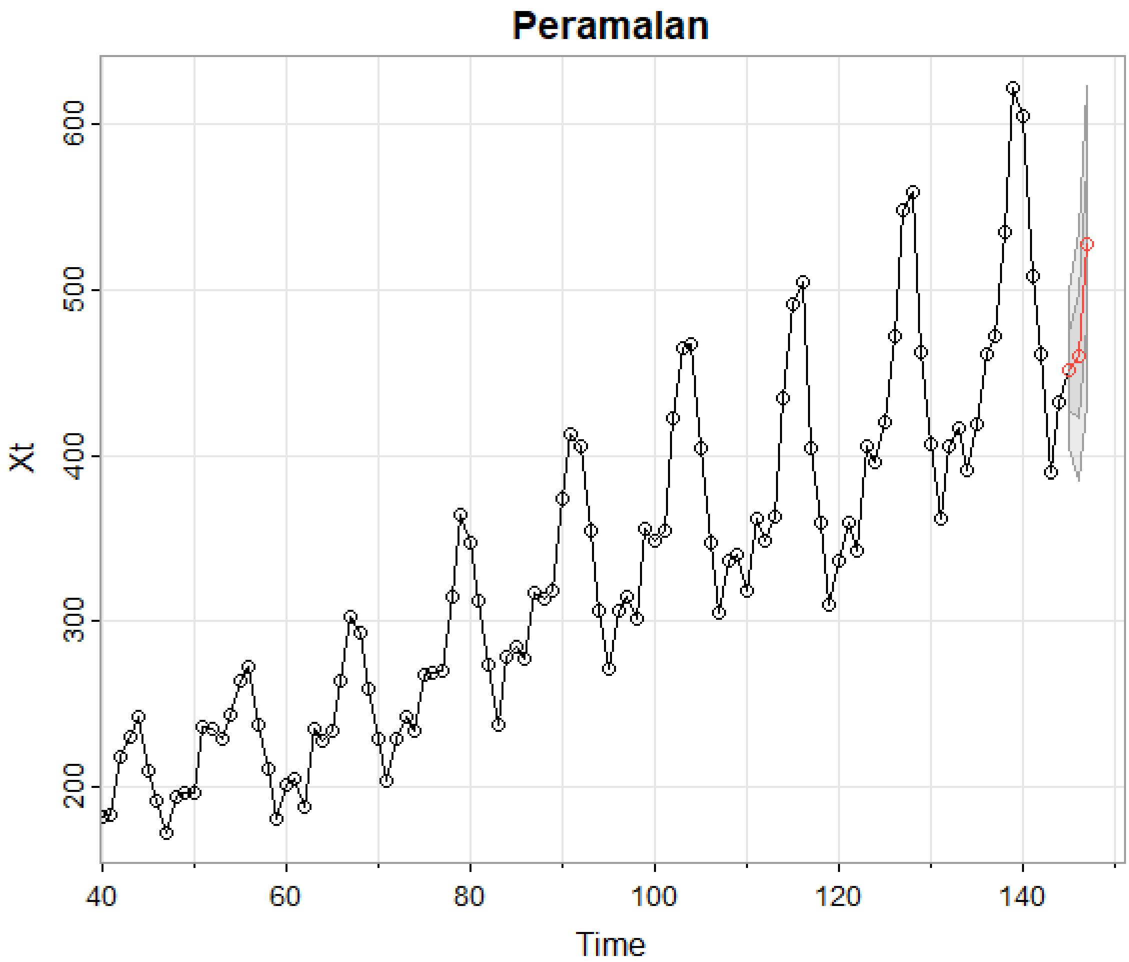
$$(1 - 0.2274B)(1 - B)Xt = (1 + 1.6797B + 0.7920B^2)(1 - B^4)e_t$$

Substitusi nilai ar1, sma1 dan sma2.

Didapat persamaannya adalah:

$$Xt = 0.2274Xt-1 + Xt-1 - 0.2274Xt-2 + et + 0.6797et-4 + 1.4717et - 8 - 0.7920et-12$$

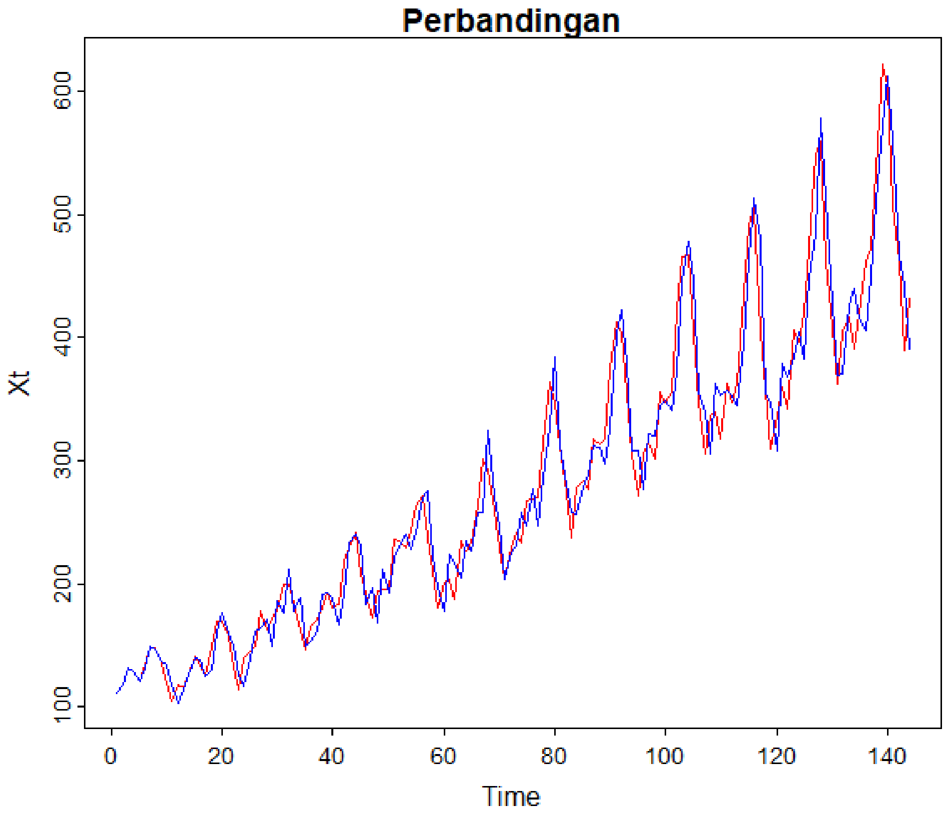
4. Peramalan



Peramalan 3 bulan ke depan menggunakan library forecast.

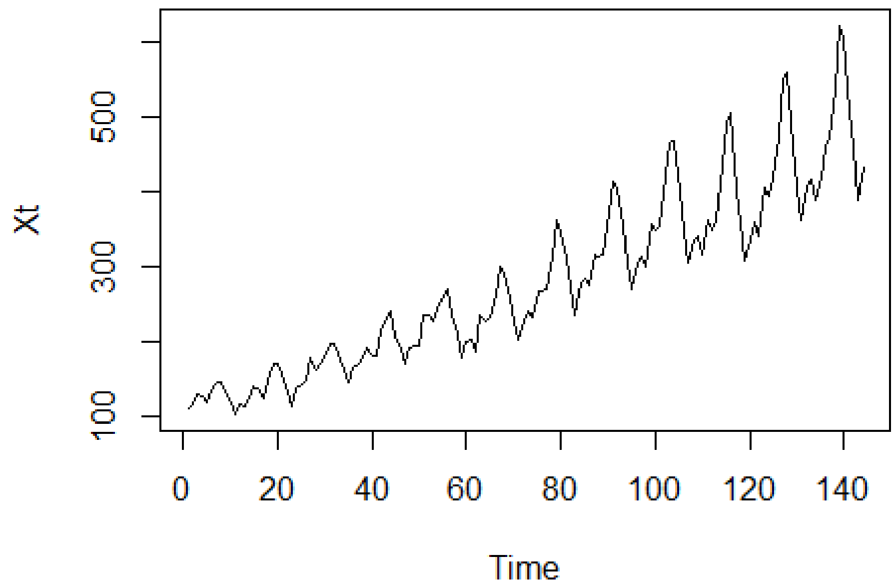
Bulan	Januari	Februari	Maret
Prediksi	451.1692	460.0787	527.4001

5. Perbandingan

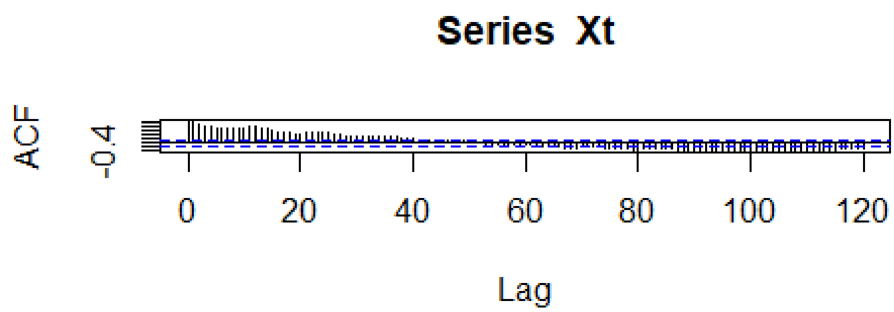


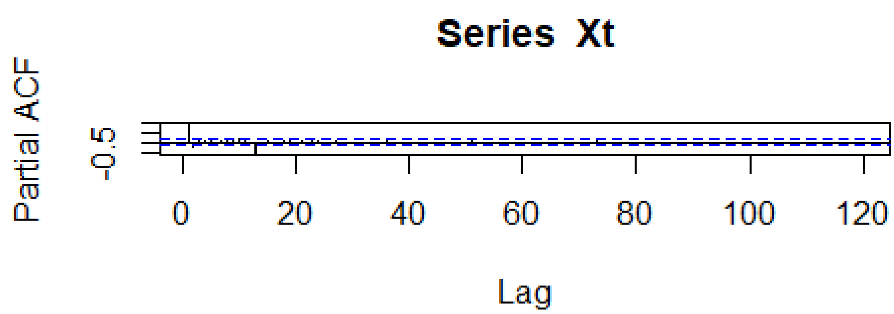
LAMPIRAN

```
library(forecast)

  Warning: package 'forecast' was built under R version 4.2.3

  Registered S3 method overwritten by 'quantmod':
    method            from
    as.zoo.data.frame zoo

library(tseries)

  Warning: package 'tseries' was built under R version 4.2.3

dataUAS = read.csv(file = "D:/Semester VIII/Analisis Runtun Waktu/uts 2/da
taUAS.csv", header = TRUE, sep = ";")
attach(dataUAS)
xT = (dataUAS$Xt)
# Melakukan tes ADF pada data
adf.test(Xt)

  Warning in adf.test(Xt): p-value smaller than printed p-value


   Augmented Dickey-Fuller Test

  data:  Xt
  Dickey-Fuller = -7.3186, Lag order = 5, p-value = 0.01
  alternative hypothesis: stationary

# Menampilkan plot data
par(mfrow=c(1,1))
plot.ts(Xt, lag.max = 200)

  Warning in plot.window(xlim, ylim, log, ...): "lag.max" is not a graphic
al
  parameter

  Warning in title(main = main, xlab = xlab, ylab = ylab, ...): "lag.max"
is not
  a graphical parameter

  Warning in axis(1, ...): "lag.max" is not a graphical parameter

  Warning in axis(2, ...): "lag.max" is not a graphical parameter

  Warning in box(...): "lag.max" is not a graphical parameter
```



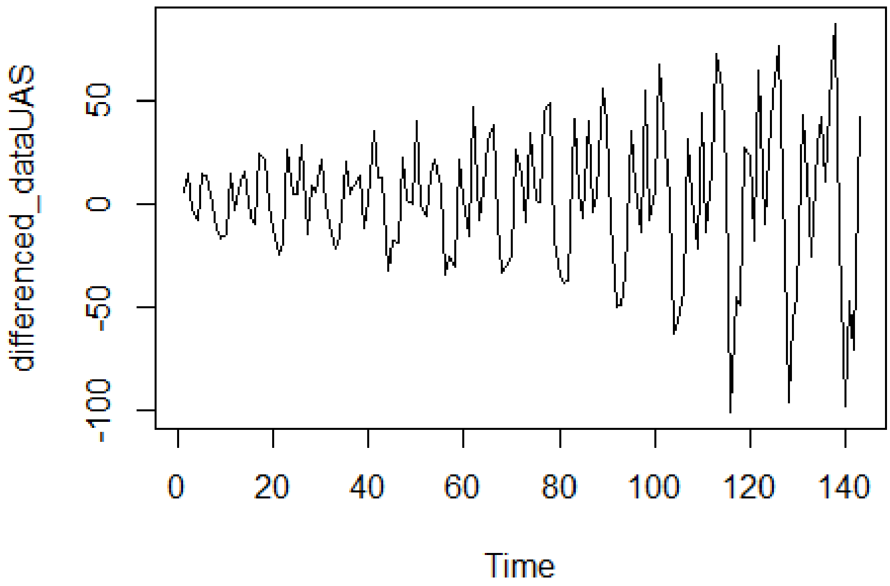

```
# Menampilkan plot ACF dan PACF
par(mfrow=c(2,1))
acf(Xt, lag.max = 120)
pacf(Xt, lag.max = 120)
```



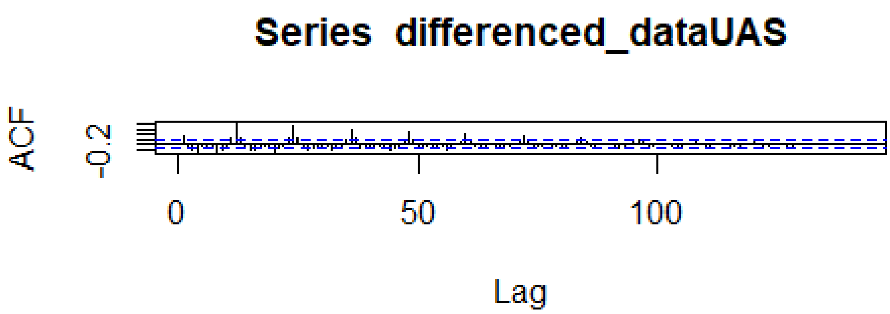


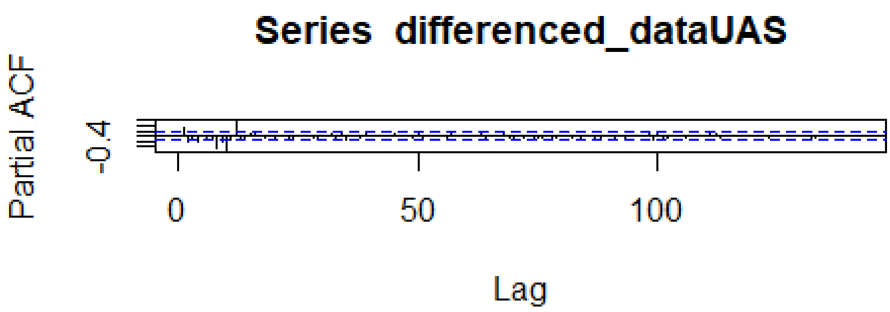

```
# Melakukan diferensiasi pada data untuk membuatnya stasioner
differenced_dataUAS <- diff(Xt)
```

```
# Menampilkan plot data yang sudah didiferensiasi
par(mfrow=c(1,1))
plot.ts(differenced_dataUAS)
```

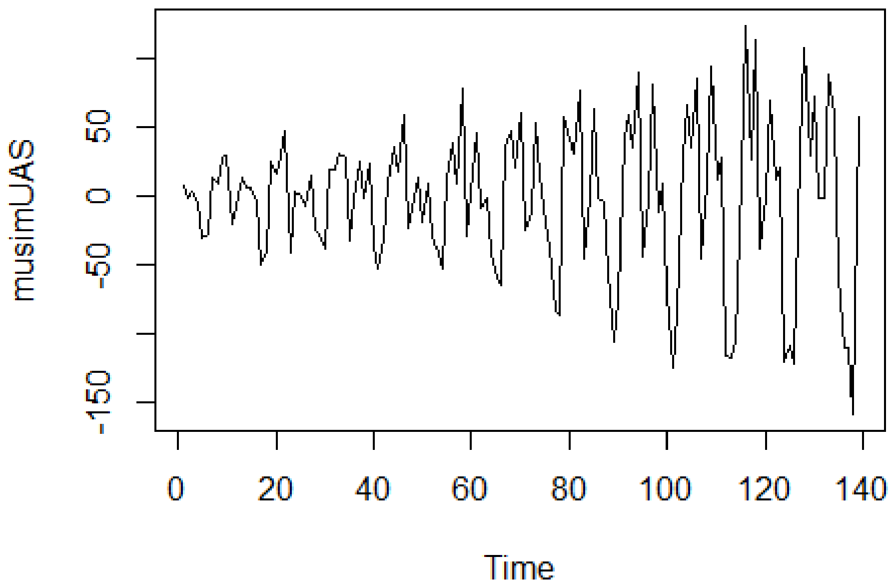



```
# Melakukan tes ADF pada data yang sudah didiferensiasi
adf.test(differenced_dataUAS)

  Warning in adf.test(differenced_dataUAS): p-value smaller than printed p
-value


   Augmented Dickey-Fuller Test

  data:  differenced_dataUAS
  Dickey-Fuller = -7.0177, Lag order = 5, p-value = 0.01
  alternative hypothesis: stationary

# Menampilkan plot ACF dan PACF dari data yang sudah didiferensiasi
par(mfrow=c(2,1))
Acf(differenced_dataUAS, lag.max = 200)
Pacf(differenced_dataUAS, lag.max = 200)
```

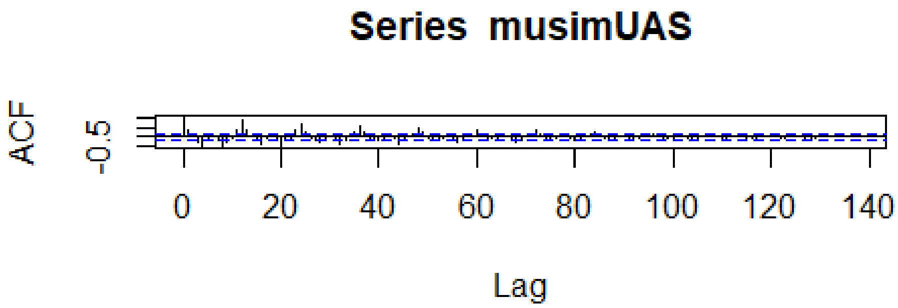


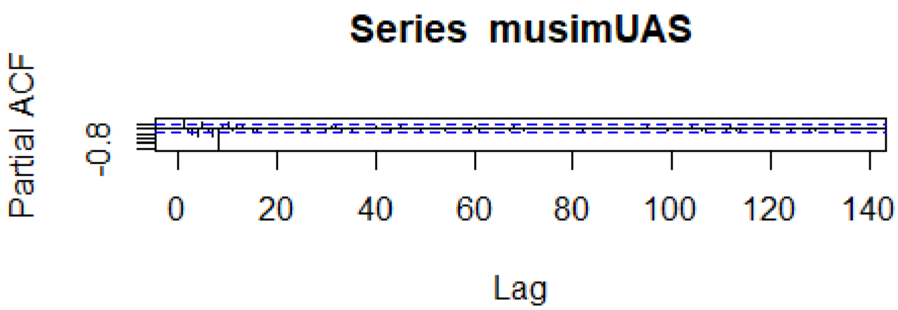



```
# Melakukan diferensiasi musiman pada data yang sudah didiferensiasi
musimUAS = diff(differenced_dataUAS, lag=4)
adf.test(musimUAS)

  Warning in adf.test(musimUAS): p-value smaller than printed p-value


   Augmented Dickey-Fuller Test

  data:  musimUAS
  Dickey-Fuller = -5.6189, Lag order = 5, p-value = 0.01
  alternative hypothesis: stationary

par(mfrow=c(1,1))
plot.ts(musimUAS)
```




```
# Menampilkan plot ACF dan PACF dari data yang sudah didiferensiasi musima
n
par(mfrow=c(2,1))
acf(musimUAS, lag.max = 200)
pacf(musimUAS, lag.max = 200)
```





```
  estimasi
#estimasi1
estimasi1=arima(Xt,order=c(0,1,0),seasonal=list(order=c(0,1,0),period = 4))
estimasi1


  Call:
  arima(x = Xt, order = c(0, 1, 0), seasonal = list(order = c(0, 1, 0), pe
riod = 4))


  sigma^2 estimated as 2885:  log likelihood = -750.97,  aic = 1503.94

residual1=resid(estimasi1)
shapiro.test(residual1)


   Shapiro-Wilk normality test

  data:  residual1
  W = 0.97485, p-value = 0.009384

Box.test(residual1,lag=6,type="Ljung-Box")


   Box-Ljung test

  data:  residual1
  X-squared = 58.076, df = 6, p-value = 1.106e-10

#estimasi2
estimasi2=arima(Xt,order=c(1,1,0),seasonal=list(order=c(0,1,0),period = 4))
estimasi2


  Call:
  arima(x = Xt, order = c(1, 1, 0), seasonal = list(order = c(0, 1, 0), pe
riod = 4))

  Coefficients:
           ar1
        0.3517
  s.e.  0.0793

  sigma^2 estimated as 2527:  log likelihood = -741.8,  aic = 1487.61

residual2=resid(estimasi2)
shapiro.test(residual2)


   Shapiro-Wilk normality test

  data:  residual2
  W = 0.9914, p-value = 0.5307
```

```
Box.test(residual2,lag=6,type="Ljung-Box")


   Box-Ljung test

  data:  residual2
  X-squared = 36.477, df = 6, p-value = 2.226e-06

#estimasi3
estimasi3=arima(Xt,order=c(1,1,1),seasonal=list(order=c(0,1,0),period = 4)
)
estimasi3


  Call:
  arima(x = Xt, order = c(1, 1, 1), seasonal = list(order = c(0, 1, 0), pe
riod = 4))

  Coefficients:
            ar1     ma1
        -0.4163  1.0000
  s.e.   0.0814  0.0254

  sigma^2 estimated as 2086:  log likelihood = -730.44,  aic = 1466.88

residual3=resid(estimasi3)
shapiro.test(residual3)


   Shapiro-Wilk normality test

  data:  residual3
  W = 0.98332, p-value = 0.07763

Box.test(residual3,lag=6,type="Ljung-Box")


   Box-Ljung test

  data:  residual3
  X-squared = 32.795, df = 6, p-value = 1.148e-05

#estimasi4
estimasi4=arima(Xt,order=c(1,1,0),seasonal=list(order=c(1,1,0),period = 4)
)
estimasi4


  Call:
  arima(x = Xt, order = c(1, 1, 0), seasonal = list(order = c(1, 1, 0), pe
riod = 4))

  Coefficients:
           ar1      sar1
        0.3503  -0.4976
  s.e.  0.0793   0.0769
```

```
  sigma^2 estimated as 1936:  log likelihood = -723.87,  aic = 1453.75

residual4=resid(estimasi4)
shapiro.test(residual4)


   Shapiro-Wilk normality test

  data:  residual4
  W = 0.99017, p-value = 0.4113

Box.test(residual4,lag=6,type="Ljung-Box")


   Box-Ljung test

  data:  residual4
  X-squared = 35.919, df = 6, p-value = 2.858e-06

#estimasi5
estimasi5=arima(Xt,order=c(1,1,0),seasonal=list(order=c(0,1,1),period = 4)
)
estimasi5


  Call:
  arima(x = Xt, order = c(1, 1, 0), seasonal = list(order = c(0, 1, 1), pe
riod = 4))

  Coefficients:
           ar1     sma1
        0.3321  -1.0000
  s.e.  0.0803   0.0648

  sigma^2 estimated as 943.1:  log likelihood = -680.45,  aic = 1366.9

residual5=resid(estimasi5)
shapiro.test(residual5)


   Shapiro-Wilk normality test

  data:  residual5
  W = 0.98302, p-value = 0.07194

Box.test(residual5,lag=6,type="Ljung-Box")


   Box-Ljung test

  data:  residual5
  X-squared = 28.772, df = 6, p-value = 6.72e-05

#estimasi6
estimasi6=arima(Xt,order=c(1,1,1),seasonal=list(order=c(1,1,0),period = 4)
```

```
)
estimasi6


  Call:
  arima(x = Xt, order = c(1, 1, 1), seasonal = list(order = c(1, 1, 0), pe
riod = 4))

  Coefficients:
           ar1     ma1     sar1
        0.1498  0.2360  -0.4962
  s.e.  0.2545  0.2572   0.0771

  sigma^2 estimated as 1917:  log likelihood = -723.21,  aic = 1454.42

residual6=resid(estimasi6)
shapiro.test(residual6)


   Shapiro-Wilk normality test

  data:  residual6
  W = 0.98835, p-value = 0.271

Box.test(residual6,lag=6,type="Ljung-Box")


   Box-Ljung test

  data:  residual6
  X-squared = 32.555, df = 6, p-value = 1.277e-05

#estimasi7
estimasi7=arima(Xt,order=c(1,1,0),seasonal=list(order=c(1,1,1),period = 4)
)
estimasi7


  Call:
  arima(x = Xt, order = c(1, 1, 0), seasonal = list(order = c(1, 1, 1), pe
riod = 4))

  Coefficients:
           ar1      sar1     sma1
        0.3013  -0.4351  -0.9404
  s.e.  0.0816   0.0815   0.0467

  sigma^2 estimated as 802.3:  log likelihood = -668.12,  aic = 1344.25

residual7=resid(estimasi7)
shapiro.test(residual7)


   Shapiro-Wilk normality test
```

```
  data:  residual7
  W = 0.98839, p-value = 0.2741

Box.test(residual7,lag=6,type="Ljung-Box")


   Box-Ljung test

  data:  residual7
  X-squared = 22.108, df = 6, p-value = 0.001158

#estimasi8
estimasi8=arima(Xt,order=c(1,1,1),seasonal=list(order=c(0,1,1),period = 4)
)
estimasi8


  Call:
  arima(x = Xt, order = c(1, 1, 1), seasonal = list(order = c(0, 1, 1), pe
riod = 4))

  Coefficients:
            ar1     ma1     sma1
        -0.5023  0.8789  -1.0000
  s.e.   0.1151  0.0770   0.0608

  sigma^2 estimated as 900.9:  log likelihood = -678.32,  aic = 1364.65

residual8=resid(estimasi8)
shapiro.test(residual8)


   Shapiro-Wilk normality test

  data:  residual8
  W = 0.98778, p-value = 0.2366

Box.test(residual8,lag=6,type="Ljung-Box")


   Box-Ljung test

  data:  residual8
  X-squared = 28.472, df = 6, p-value = 7.654e-05

#estimasi9
estimasi9=arima(Xt,order=c(1,1,1),seasonal=list(order=c(1,1,1),period = 4)
)
estimasi9


  Call:
  arima(x = Xt, order = c(1, 1, 1), seasonal = list(order = c(1, 1, 1), pe
riod = 4))

  Coefficients:
```

```
          ar1     ma1     sar1     sma1
       0.0776  0.2537  -0.4321  -0.9503
  s.e.  0.2570  0.2506   0.0819   0.0538

  sigma^2 estimated as 790.7:  log likelihood = -667.46,  aic = 1344.93

residual9=resid(estimasi9)
shapiro.test(residual9)


   Shapiro-Wilk normality test

  data:  residual9
  W = 0.98867, p-value = 0.2923

Box.test(residual9,lag=6,type="Ljung-Box")


   Box-Ljung test

  data:  residual9
  X-squared = 19.762, df = 6, p-value = 0.003053

#estimasi10
estimasi10=arima(Xt,order=c(0,1,1),seasonal=list(order=c(0,1,0),period = 4
))
estimasi10


  Call:
  arima(x = Xt, order = c(0, 1, 1), seasonal = list(order = c(0, 1, 0), pe
riod = 4))

  Coefficients:
          ma1
       0.4066
  s.e.  0.0940

  sigma^2 estimated as 2494:  log likelihood = -740.92,  aic = 1485.85

residual10=resid(estimasi10)
shapiro.test(residual10)


   Shapiro-Wilk normality test

  data:  residual10
  W = 0.98941, p-value = 0.3469

Box.test(residual10,lag=6,type="Ljung-Box")


   Box-Ljung test

  data:  residual10
  X-squared = 32.756, df = 6, p-value = 1.168e-05
```

```
#estimasi11
estimasi11=arima(Xt,order=c(0,1,1),seasonal=list(order=c(1,1,0),period = 4
))
estimasi11


  Call:
  arima(x = Xt, order = c(0, 1, 1), seasonal = list(order = c(1, 1, 0), pe
riod = 4))

  Coefficients:
           ma1     sar1
        0.3847  -0.4950
  s.e.  0.0877   0.0773

  sigma^2 estimated as 1920:  log likelihood = -723.3,  aic = 1452.61

residual11=resid(estimasi11)
shapiro.test(residual11)


   Shapiro-Wilk normality test

  data:  residual11
  W = 0.98721, p-value = 0.2061

Box.test(residual11,lag=6,type="Ljung-Box")


   Box-Ljung test

  data:  residual11
  X-squared = 32.746, df = 6, p-value = 1.173e-05

#estimasi12
estimasi12=arima(Xt,order=c(0,1,1),seasonal=list(order=c(0,1,1),period = 4
))
estimasi12


  Call:
  arima(x = Xt, order = c(0, 1, 1), seasonal = list(order = c(0, 1, 1), pe
riod = 4))

  Coefficients:
           ma1     sma1
        0.3680  -1.0000
  s.e.  0.0856   0.0547

  sigma^2 estimated as 932.4:  log likelihood = -679.7,  aic = 1365.41

residual12=resid(estimasi12)
shapiro.test(residual12)


   Shapiro-Wilk normality test
```

```
  data:  residual12
  W = 0.98587, p-value = 0.1478

Box.test(residual12,lag=6,type="Ljung-Box")


   Box-Ljung test

  data:  residual12
  X-squared = 26.446, df = 6, p-value = 0.0001839

#estimasi13
estimasi13=arima(Xt,order=c(0,1,1),seasonal=list(order=c(1,1,1),period = 4
))
estimasi13


  Call:
  arima(x = Xt, order = c(0, 1, 1), seasonal = list(order = c(1, 1, 1), pe
riod = 4))

  Coefficients:
           ma1     sar1     sma1
        0.3250  -0.4319  -0.9538
  s.e.  0.0818   0.0820   0.0553

  sigma^2 estimated as 789.6:  log likelihood = -667.5,  aic = 1343.01

residual13=resid(estimasi13)
shapiro.test(residual13)


   Shapiro-Wilk normality test

  data:  residual13
  W = 0.98853, p-value = 0.2827

Box.test(residual13,lag=6,type="Ljung-Box")


   Box-Ljung test

  data:  residual13
  X-squared = 20.088, df = 6, p-value = 0.002671

#estimasi14
estimasi14=arima(Xt,order=c(0,1,0),seasonal=list(order=c(1,1,0),period = 4
))
estimasi14


  Call:
  arima(x = Xt, order = c(0, 1, 0), seasonal = list(order = c(1, 1, 0), pe
riod = 4))
```

```
  Coefficients:
           sar1
        -0.5024
  s.e.   0.0775

  sigma^2 estimated as 2209:  log likelihood = -733,  aic = 1469.99

residual14=resid(estimasi14)
shapiro.test(residual14)


   Shapiro-Wilk normality test

  data:  residual14
  W = 0.9822, p-value = 0.05851

Box.test(residual14,lag=6,type="Ljung-Box")


   Box-Ljung test

  data:  residual14
  X-squared = 61.458, df = 6, p-value = 2.275e-11

#estimasi15
estimasi15=arima(Xt,order=c(0,1,0),seasonal=list(order=c(1,1,1),period = 4
))
estimasi15


  Call:
  arima(x = Xt, order = c(0, 1, 0), seasonal = list(order = c(1, 1, 1), pe
riod = 4))

  Coefficients:
           sar1     sma1
        -0.4560  -0.9548
  s.e.   0.0805   0.0543

  sigma^2 estimated as 873.8:  log likelihood = -674.63,  aic = 1355.26

residual15=resid(estimasi15)
shapiro.test(residual15)


   Shapiro-Wilk normality test

  data:  residual15
  W = 0.98848, p-value = 0.2795

Box.test(residual15,lag=6,type="Ljung-Box")


   Box-Ljung test
```

```
  data:  residual15
  X-squared = 45.062, df = 6, p-value = 4.549e-08

#estimasi16
estimasi16=arima(Xt,order=c(0,1,0),seasonal=list(order=c(0,1,1),period = 4
))
estimasi16


  Call:
  arima(x = Xt, order = c(0, 1, 0), seasonal = list(order = c(0, 1, 1), pe
riod = 4))

  Coefficients:
           sma1
        -1.0000
  s.e.   0.0537

  sigma^2 estimated as 1060:  log likelihood = -688.53,  aic = 1381.06

residual16=resid(estimasi16)
shapiro.test(residual16)


   Shapiro-Wilk normality test

  data:  residual16
  W = 0.98178, p-value = 0.05251

Box.test(residual16,lag=6,type="Ljung-Box")


   Box-Ljung test

  data:  residual16
  X-squared = 53.816, df = 6, p-value = 8.036e-10

#estimasi17
estimasi17=arima(Xt,order=c(0,1,0),seasonal=list(order=c(0,1,2),period = 4
))
estimasi17


  Call:
  arima(x = Xt, order = c(0, 1, 0), seasonal = list(order = c(0, 1, 2), pe
riod = 4))

  Coefficients:
           sma1     sma2
        -0.1371  -0.8629
  s.e.   0.0652   0.0619

  sigma^2 estimated as 1271:  log likelihood = -701.45,  aic = 1408.91

residual17=resid(estimasi17)
shapiro.test(residual17)
```

```
  Shapiro-Wilk normality test

 data:  residual17
 W = 0.99113, p-value = 0.5031

Box.test(residual17,lag=6,type="Ljung-Box")


  Box-Ljung test

 data:  residual17
 X-squared = 51.496, df = 6, p-value = 2.355e-09

#estimasi18
estimasi18=arima(Xt,order=c(1,1,0),seasonal=list(order=c(0,1,2),period = 4
))
estimasi18


 Call:
 arima(x = Xt, order = c(1, 1, 0), seasonal = list(order = c(0, 1, 2), pe
riod = 4))

 Coefficients:
          ar1     sma1    sma2
       0.2274  -1.6797  0.7920
 s.e.  0.0846   0.0619  0.0585

 sigma^2 estimated as 557.9:  log likelihood = -644.95,  aic = 1297.9

residual18=resid(estimasi18)
shapiro.test(residual18)


  Shapiro-Wilk normality test

 data:  residual18
 W = 0.99221, p-value = 0.6185

Box.test(residual18,lag=6,type="Ljung-Box")


  Box-Ljung test

 data:  residual18
 X-squared = 12.424, df = 6, p-value = 0.05315

#estimasi19
estimasi19=arima(Xt,order=c(0,1,1),seasonal=list(order=c(0,1,2),period = 4
))
estimasi19


 Call:
 arima(x = Xt, order = c(0, 1, 1), seasonal = list(order = c(0, 1, 2), pe
```

```
riod = 4))

  Coefficients:
           ma1     sma1    sma2
        0.2242  -1.6852  0.7928
  s.e.  0.0790   0.0616  0.0587

  sigma^2 estimated as 556.5:  log likelihood = -644.88,  aic = 1297.77

residual19=resid(estimasi19)
shapiro.test(residual19)


   Shapiro-Wilk normality test

  data:  residual19
  W = 0.99284, p-value = 0.6882

Box.test(residual19,lag=6,type="Ljung-Box")


   Box-Ljung test

  data:  residual19
  X-squared = 12.605, df = 6, p-value = 0.04975

#estimasi20
estimasi20=arima(Xt,order=c(0,1,0),seasonal=list(order=c(1,1,2),period = 4
))
estimasi20


  Call:
  arima(x = Xt, order = c(0, 1, 0), seasonal = list(order = c(1, 1, 2), pe
riod = 4))

  Coefficients:
           sar1     sma1     sma2
        -0.6033  -0.0406  -0.9594
  s.e.   0.0887   0.0797   0.0784

  sigma^2 estimated as 910.6:  log likelihood = -679.61,  aic = 1367.23

residual20=resid(estimasi20)
shapiro.test(residual20)


   Shapiro-Wilk normality test

  data:  residual20
  W = 0.97242, p-value = 0.005256

Box.test(residual20,lag=6,type="Ljung-Box")


   Box-Ljung test
```

```
  data:  residual20
  X-squared = 52.72, df = 6, p-value = 1.336e-09

#estimasi21
estimasi21=arima(Xt,order=c(1,1,1),seasonal=list(order=c(0,1,2),period = 4
))
estimasi21


  Call:
  arima(x = Xt, order = c(1, 1, 1), seasonal = list(order = c(0, 1, 2), pe
riod = 4))

  Coefficients:
           ar1     ma1      sma1    sma2
        0.1098  0.1285   -1.6815  0.7909
  s.e.  0.2324  0.2233    0.0622  0.0588

  sigma^2 estimated as 556.3:  log likelihood = -644.78,  aic = 1299.56

residual21=resid(estimasi21)
shapiro.test(residual21)


   Shapiro-Wilk normality test

  data:  residual21
  W = 0.99294, p-value = 0.7001

Box.test(residual21,lag=6,type="Ljung-Box")


   Box-Ljung test

  data:  residual21
  X-squared = 12.006, df = 6, p-value = 0.06183

#estimasi22
estimasi22=arima(Xt,order=c(1,1,0),seasonal=list(order=c(1,1,2),period = 4
))
estimasi22


  Call:
  arima(x = Xt, order = c(1, 1, 0), seasonal = list(order = c(1, 1, 2), pe
riod = 4))

  Coefficients:
           ar1     sar1     sma1     sma2
        0.3276  -0.6269  -0.0244  -0.9756
  s.e.  0.0808   0.0893   0.1131   0.1124

  sigma^2 estimated as 807.2:  log likelihood = -671.86,  aic = 1353.71
```

```
residual22=resid(estimasi22)
shapiro.test(residual22)


   Shapiro-Wilk normality test

  data:  residual22
  W = 0.98689, p-value = 0.1905

Box.test(residual22,lag=6,type="Ljung-Box")


   Box-Ljung test

  data:  residual22
  X-squared = 30.605, df = 6, p-value = 3.015e-05

#estimasi23
estimasi23=arima(Xt,order=c(0,1,1),seasonal=list(order=c(1,1,2),period = 4
))
estimasi23


  Call:
  arima(x = Xt, order = c(0, 1, 1), seasonal = list(order = c(1, 1, 2), pe
riod = 4))

  Coefficients:
           ma1      sar1      sma1      sma2
        0.3645   -0.6275   -0.0283   -0.9717
  s.e.  0.0885    0.0897    0.1009    0.1002

  sigma^2 estimated as 801.4:  log likelihood = -671.21,  aic = 1352.42

residual23=resid(estimasi23)
shapiro.test(residual23)


   Shapiro-Wilk normality test

  data:  residual23
  W = 0.98511, p-value = 0.1222

Box.test(residual23,lag=6,type="Ljung-Box")


   Box-Ljung test

  data:  residual23
  X-squared = 28.399, df = 6, p-value = 7.904e-05

#estimasi24
estimasi24=arima(Xt,order=c(1,1,1),seasonal=list(order=c(1,1,2),period = 4
))
estimasi24
```

```
  Call:
  arima(x = Xt, order = c(1, 1, 1), seasonal = list(order = c(1, 1, 2), pe
riod = 4))

  Coefficients:
           ar1     ma1     sar1     sma1     sma2
        0.0926  0.2722  -0.6297  -0.0259  -0.9741
  s.e.  0.3227  0.3274   0.0898   0.1074   0.1068

  sigma^2 estimated as 800.1:  log likelihood = -671.19,  aic = 1354.37
```

```
residual24=resid(estimasi24)
shapiro.test(residual24)
```

```

   Shapiro-Wilk normality test

  data:  residual24
  W = 0.98566, p-value = 0.1402
```

```
Box.test(residual24,lag=6,type="Ljung-Box")
```

```

   Box-Ljung test

  data:  residual24
  X-squared = 28.256, df = 6, p-value = 8.408e-05
```

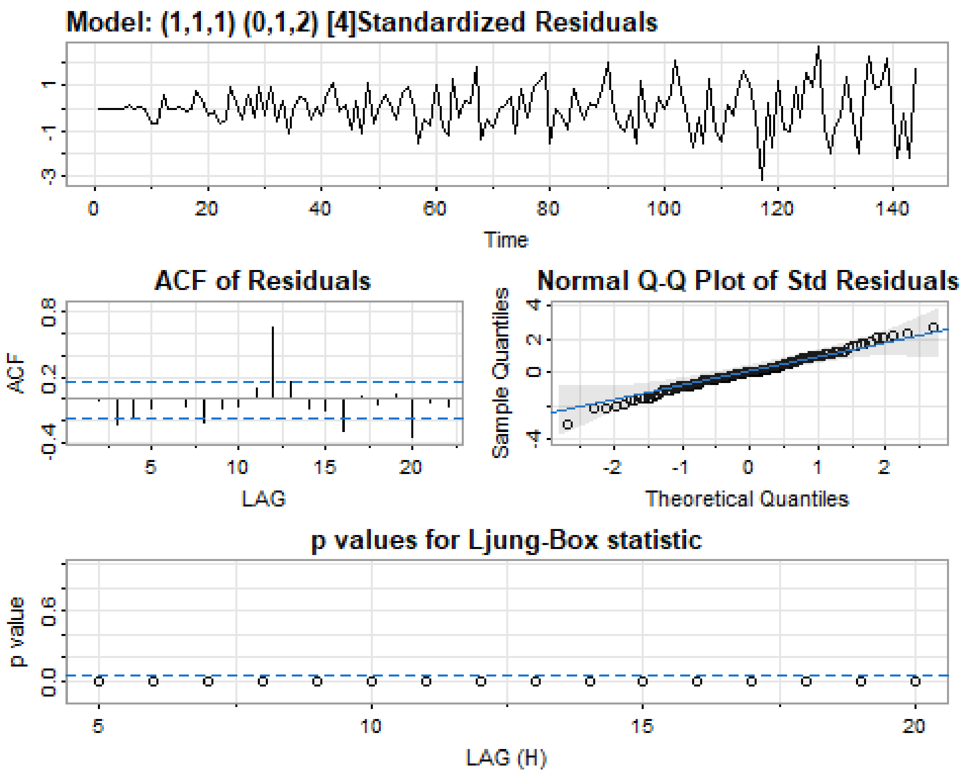
```
# SAIMA (1,1,1,0,1,2)
library(astsa)
```

```
  Warning: package 'astsa' was built under R version 4.3.0


  Attaching package: 'astsa'

  The following object is masked from 'package:forecast':

      gas
```

```
Xt5<-sarima(Xt,1,1,1,0,1,2,4)
```

```
  initial  value 3.987248 
  iter   2 value 3.619139
  iter   3 value 3.609560
  iter   4 value 3.573574
  iter   5 value 3.569111
  iter   6 value 3.566032
  iter   7 value 3.564273
  iter   8 value 3.561425
  iter   9 value 3.560810
  iter  10 value 3.543078
  iter  11 value 3.539794
  iter  12 value 3.460655
  iter  13 value 3.447574
```

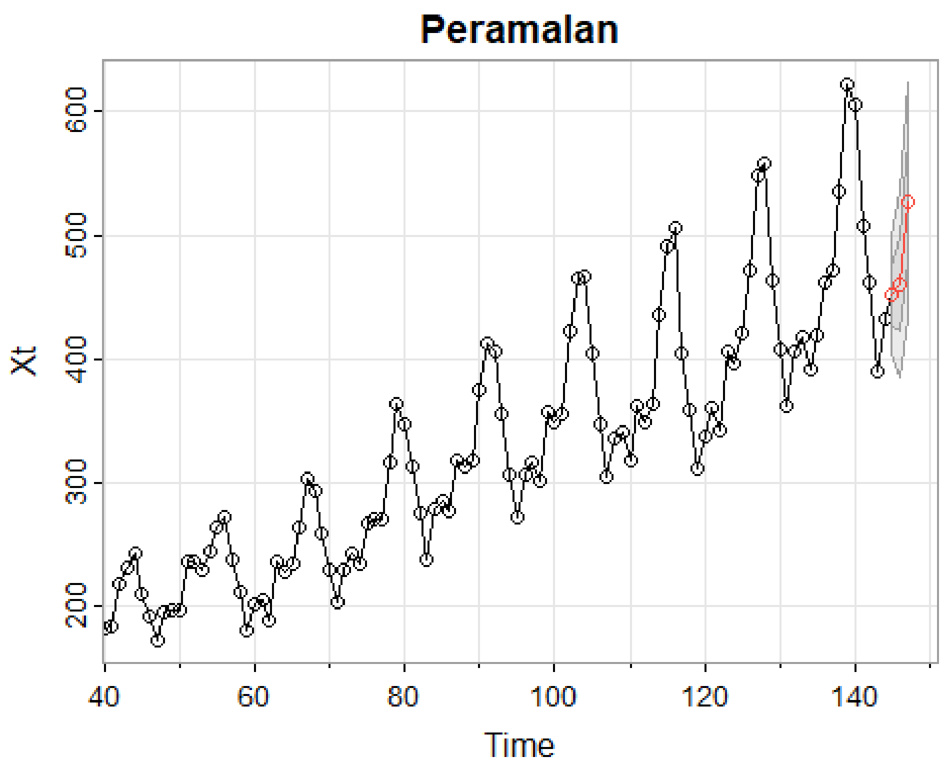
```
iter  14 value 3.311735
iter  15 value 3.269198
iter  16 value 3.201161
iter  17 value 3.200046
iter  18 value 3.199488
iter  19 value 3.199310
iter  20 value 3.199023
iter  21 value 3.198579
iter  22 value 3.198556
iter  23 value 3.198478
iter  24 value 3.198418
iter  25 value 3.198396
iter  26 value 3.198353
iter  27 value 3.198275
iter  28 value 3.198266
iter  29 value 3.198266
iter  29 value 3.198266
iter  29 value 3.198266
final  value 3.198266 
converged
initial  value 3.222760 
iter   2 value 3.222300
iter   3 value 3.221881
iter   4 value 3.221383
iter   5 value 3.220489
iter   6 value 3.219957
iter   7 value 3.219816
iter   8 value 3.219785
iter   9 value 3.219783
iter   9 value 3.219783
iter   9 value 3.219783
final  value 3.219783 
converged
```




```
Xt5$ttable

       Estimate     SE  t.value p.value
  ar1    0.1098 0.2324   0.4725  0.6374
  ma1    0.1285 0.2233   0.5755  0.5659
  sma1  -1.6815 0.0622 -27.0304  0.0000
  sma2   0.7909 0.0588  13.4550  0.0000
```

Peramalan

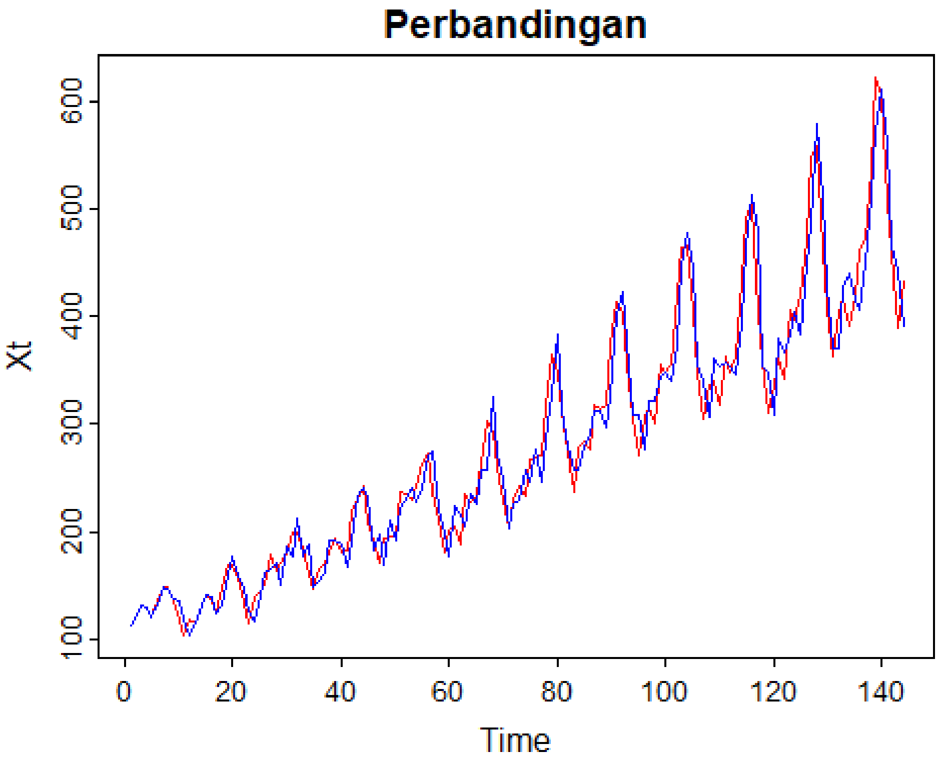
```
library(astsa)
par(mfrow = c(1, 1))
sarima.for(Xt, n.ahead = 3, 1, 1, 0, 0, 1, 2, 4, main = "Peramalan")
```




```
$pred
Time Series:
Start = 145
End = 147
Frequency = 1
[1] 451.1692 460.0787 527.4001

$se
Time Series:
Start = 145
End = 147
Frequency = 1
[1] 23.62114 37.39658 48.07671
```

Perbandingan

```
library(forecast)
fit <- Arima(Xt, order = c(1, 1, 0), seasonal = list(order = c(0, 1, 2), period = 4))
plot.ts(Xt, col = "red", main = "Perbandingan")
lines(fitted(fit), col = "blue")
```


Perbandingan
Xt
100
200
300
400
500
600
0
20
40
60
80
100
120
140
Time