

Description :

Source :

"Makridakis, Wheelwright and Hyndman (1998)"

Description :

"Monthly shipment of pollution equipment (in thousands of french francs)"

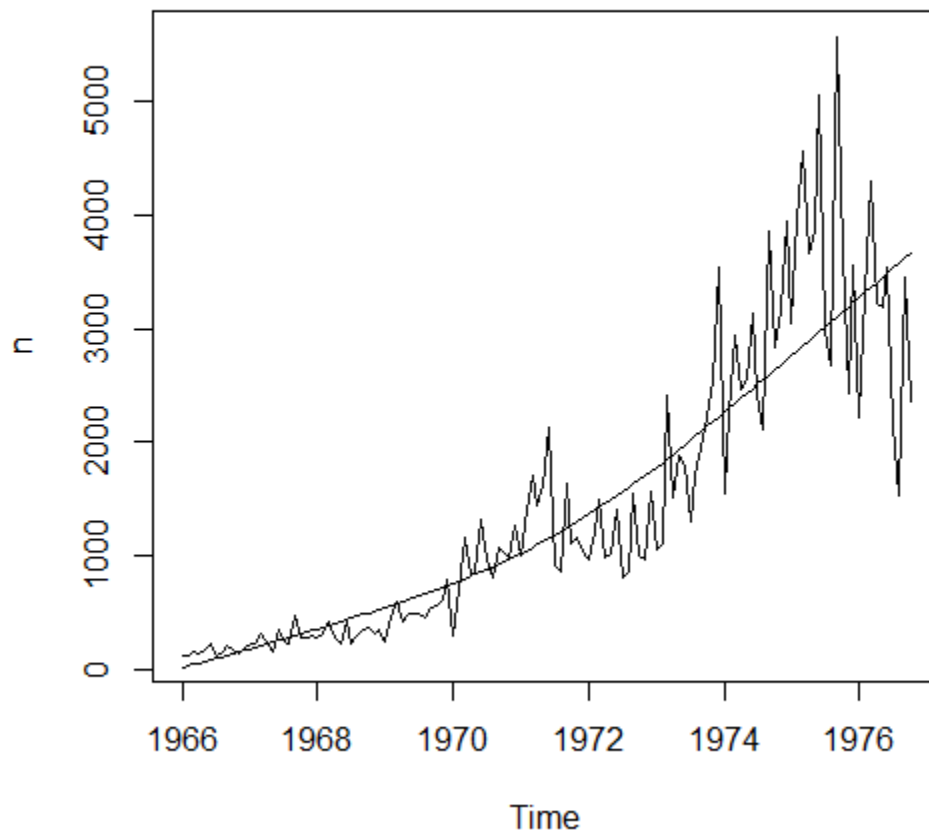
Subject :

"Production"

```
> n = tsdl [[468]]
```

```
> attributes(n)
```

Plot The Time Series :



```
> plot(n)
```

```
> lines(n)
```

```
> lines(lowess(n))
```

- We plot The time series to know is there trend in our data or not and to know the seasonality .

As we see In this data it appear there is seasonal component in the set and not stationarity .

Testing Stationarity:

```
> adf.test(n)
```

Augmented Dickey-Fuller Test

data: n

Dickey-Fuller = -1.6188, Lag order = 5, p-value = 0.735

alternative hypothesis: stationary

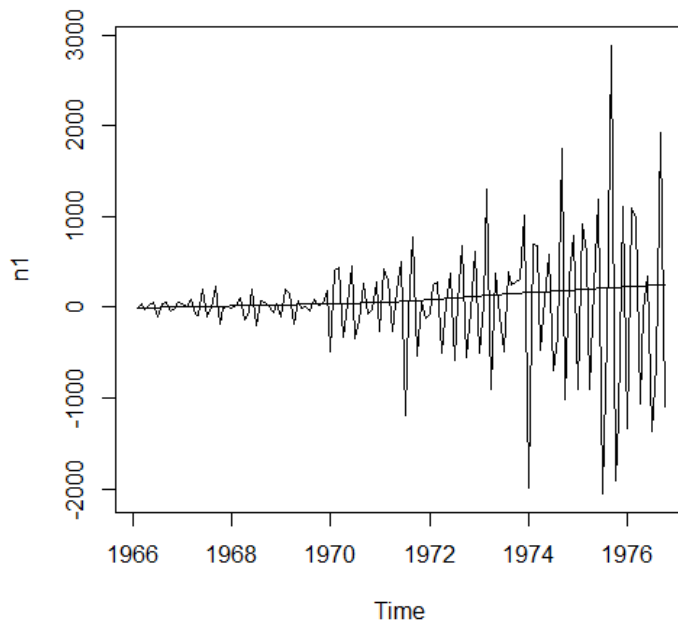
We can test the stationary of the series from this command `> adf.test(n)` and the Hypothesis will be :

H_0 : The series is *not* stationary .

H_1 : The series is stationary .

So since the **P . Value** $> \alpha$, **P . Value** = **0.735** and $\alpha = 0.05$ so we Accept H_0 that's mean the series is not stationary

- Now we should take the difference for series to make it stationary



```
> n1=diff(n,difference=1)
```

```
> plot(n1)
```

```
> lines(n1)
```

```
> lines(lowess(n1))
```

```
> adf.test(n1))
```

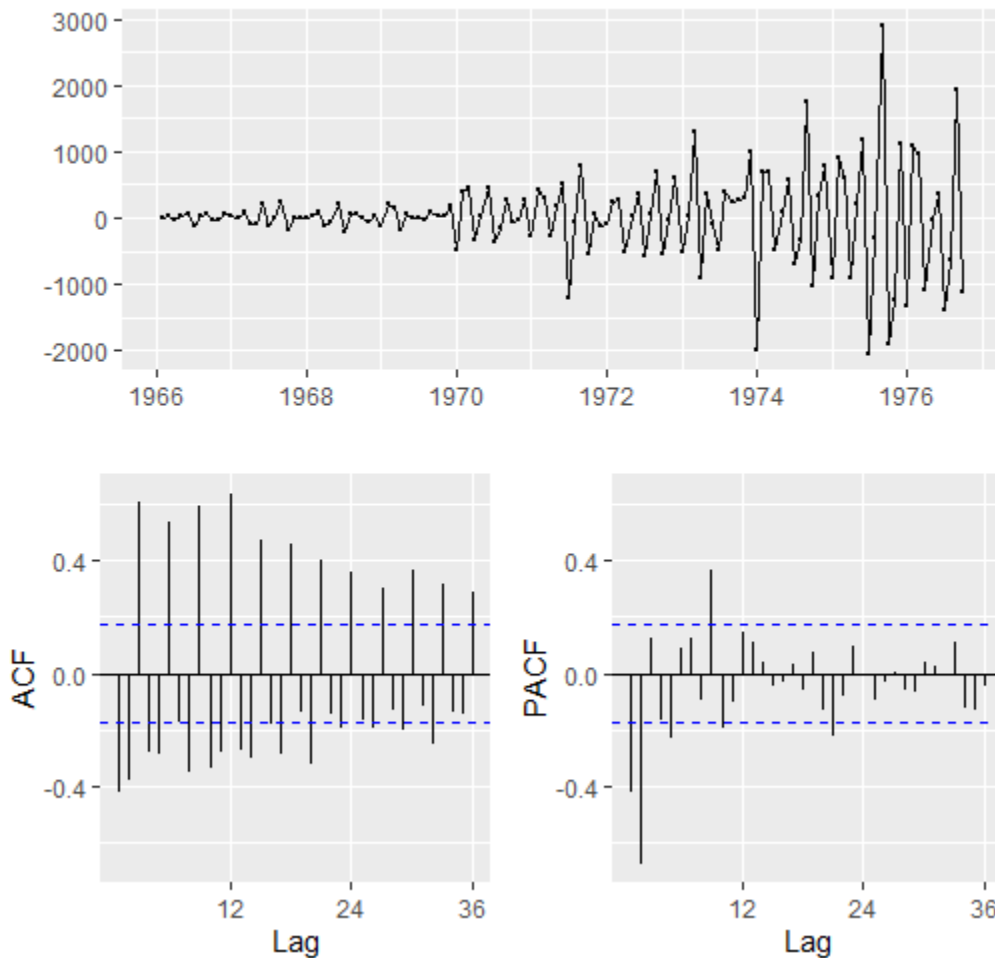
Augmented Dickey-Fuller Test data: n1

Dickey-Fuller = -5.7566, Lag order = 5, p-value = 0.01

alternative hypothesis: stationary

So now we see the series become stationary and since the **P . Value** $< \alpha$, **P . Value** = **0.01** and $\alpha = 0.05$ so we Reject H_0 that's mean the series is stationary

Model Type:



From the AutoCorrelation (ACF) graph and the Partial AutoCorrelation (PACF) graph we can nominate two models are suggested :

SARIMA(0,1,1)(0,0,2)12 , **SARIMA(0,1,1)(0,0,1)** .

Testing Coefficients :

For model **SARIMA(0,1,1)(0,0,2)12** :

```
> fit1 = arima(n,order=c(0,1,1),seasonal=list(order=c(0,0,2),period=12))
```

```
> coeftest(fit1)
```

z test of coefficients:

```
Estimate Std. Error z value Pr(>|z|)
ma1 -0.603531 0.062874 -9.5990 < 2.2e-16 ***
sma1 0.798564 0.098913 8.0734 6.839e-16 ***
sma2 0.338155 0.102954 3.2845 0.001022 **
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The Hypothesis will be :

$$H_0 : \theta_1 = 0 \quad vs \quad H_1 : \theta_1 \neq 0$$

$$H_0 : \theta_2 = 0 \quad vs \quad H_1 : \theta_2 \neq 0$$

$$H_0 : \vartheta_1 = 0 \quad vs \quad H_1 : \vartheta_1 \neq 0$$

Since the ***P.value's in all parameters*** $< \alpha = 0.05$

So we reject H_0 , that's mean the value is significantly different from zero .

For model $\text{SARIMA}(0,1,1)(0,0,1)$

```
> fit2 = arima(n,order=c(0,1,1),seasonal=list(order=c(0,0,1),period=12))
> coeftest(fit2)

z test of coefficients:

      Estimate Std. Error z value Pr(>|z|)
ma1 -0.617118  0.061525 -10.0303 < 2.2e-16 ***
sma1  0.631052  0.073322  8.6066 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The Hypothesis will be :

$$H_0 : \theta_1 = 0 \quad vs \quad H_1 : \theta_1 \neq 0$$

$$H_0 : \vartheta_1 = 0 \quad vs \quad H_1 : \vartheta_1 \neq 0$$

Since the ***P.value's in all parameters*** $< \alpha = 0.05$

So we reject H_0 , that's mean the value is significantly different from zero .

Testing Residuals :

For Model **SARIMA(0,1,1)(0,0,2)12** :

```
> tsdiag(fit1)
Box.test(res1,lag=12,type=c("Ljung-Box"))
Box-Ljung test
data: res1
X-squared = 2.542, df = 12, p-value = 0.5244
```

- We test the residuals are correlated or not :

$$H_0 : \rho_1 = \rho_2 = \dots = \rho_k = 0$$

$$H_1 : \text{at least two } \neq 0$$

From the **graph** and **p.value** for **Ljung-Box statistic** we notice all the **p.value's = 0.5244 > $\alpha = 0.05$** , so we **Accept H_0** , that's mean all the residuals are not correlated .

For Model **SARIMA(0,1,1)(0,0,1)12** :

```
> tsdiag(fit2)
> Box.test(res2,lag=12,type=c("Ljung-Box"))
Box-Ljung test
data: res2
X-squared = 3.232, df = 12, p-value = 0.3302
```

- We test the residuals are correlated or not :

$$H_0 : \rho_1 = \rho_2 = \dots = \rho_k = 0$$

$$H_1 : \text{at least two} \neq 0$$

From the **graph** p.value for Ljung-Box statistic we notice all the **p.value's = 0.3302 > $\alpha = 0.05$** , so we Accept H_0 , that's mean all the residuals are not correlated .

- Now we test are the Residuals random or not :

For model **SARIMA(0,1,1)(0,0,2)12** :

H_0 : *Residuals are random*

H_1 : *Residuals are **not** random*

```
> runs.test(fit1$res)
```

Runs Test

data: fit1\$res

statistic = -0.70438, runs = 62, n1 = 65, n2 = 65, n = 130, p-value =
0.4812

alternative hypothesis: nonrandomness

Since the ***p.value*** = **0.4812** > **α** = **0.05** , so we
Accept H_0 , that's mean the residuals are random .

For model `SARIMA(0,1,1)(0,0,1)12` :

H_0 : Residuals are random

H_1 : Residuals are *not* random

```
> runs.test(fit2$res)
```

Runs Test

data: fit2\$res

statistic = -0.1761, runs = 65, n1 = 65, n2 = 65, n = 130, p-value =
0.8602

Since the ***p. value*** = **0.8602** > α = **0.05** , so we
Accept H_0 , that's mean the residuals are random .

- Now we test the mean of the ε_t equal zero or not :

For model **SARIMA(0,1,1)(0,0,2)12** :

$$H_0 : E(\varepsilon_t) = 0$$

$$H_1 : E(\varepsilon_t) \neq 0$$

```
> t.test(fit1$res)
```

One Sample t-test

data: fit1\$res

t = 0.13093, df = 129, p-value = 0.896

alternative hypothesis: true mean is not equal to 0

95 percent confidence interval:

-65.36488 74.62923

sample estimates:

mean of x

4.632172

Since the ***p.value* = 0.896** > **$\alpha = 0.05$** , so we Accept H_0 , that's mean the expectation of ε_t equal zero .

For model **SARIMA(0,1,1)(0,0,1)12** :

$$H_0 : E(\varepsilon_t) = 0$$

$$H_1 : E(\varepsilon_t) \neq 0$$

```
> t.test(fit2$res)
```

One Sample t-test

data: fit2\$res

t = 0.43557, df = 129, p-value = 0.6639

alternative hypothesis: true mean is not equal to 0

95 percent confidence interval:

-57.37843 89.77344

sample estimates:

mean of x

16.1975

Since the ***p.value* = 0.6639** > **$\alpha = 0.05$** , so we Accept H_0 , that's mean the expectation of ε_t equal zero .

- Now we do invertibility analysis :

$$\theta_1 = -0.6035$$

$$\theta_2 = 0.7986$$

$$\vartheta_1 = 0.3382$$

$$|\theta_2| < 1 \checkmark$$

$$\theta_1 + \theta_2 < 1 \checkmark$$

$$\theta_1 - \theta_2 < 1 \checkmark$$

And the same manner for another model.

- Now we test the Normality of the Residuals :

For model **SARIMA(0,1,1)(0,0,2)12** :

H_0 : the Residuals follow Normal Distribution

H_1 : the Residuals **Don't** follow Normal Distribution

```
> shapiro.test(res1)
```

Shapiro-Wilk normality test

data: res1

W = 0.98315, p-value = 0.1018

Since the ***p.value*** = **0.1018** > **α** = **0.05** , so we Accept H_0 , that's mean the Residual are follow Normal Distribution .

For model **SARIMA(0,1,1)(0,0,1)12** :

H_0 : *the Residuals follow Normal Distribution*

H_1 : *the Residuals **Don't** follow Normal Distribution*

```
> shapiro.test(fit2$res)
```

Shapiro-Wilk normality test

data: fit2\$res

W = 0.87541, p-value = 4.691e-09

Since the ***p.value*** = $4.691e - 09 < \alpha = 0.05$, so we Reject H_0 , that's mean the Residual don't follow Normal Distribution , so we eliminate this model

AIC or BIC for Models:

Now we have Model **SARIMA(0,1,1)(0,0,2)12** :and we calculate AIC :

```
> fit1$aic  
[1] 1930.716  
  
> fit2$aic  
[1] 1939.677
```

We choose the lowest AIC between models , so **SARIMA(0,1,1)(0,0,2)12** more appropriate and just to make sure of that we compare it with AIC of **SARIMA(0,1,1)(0,0,1)12** .

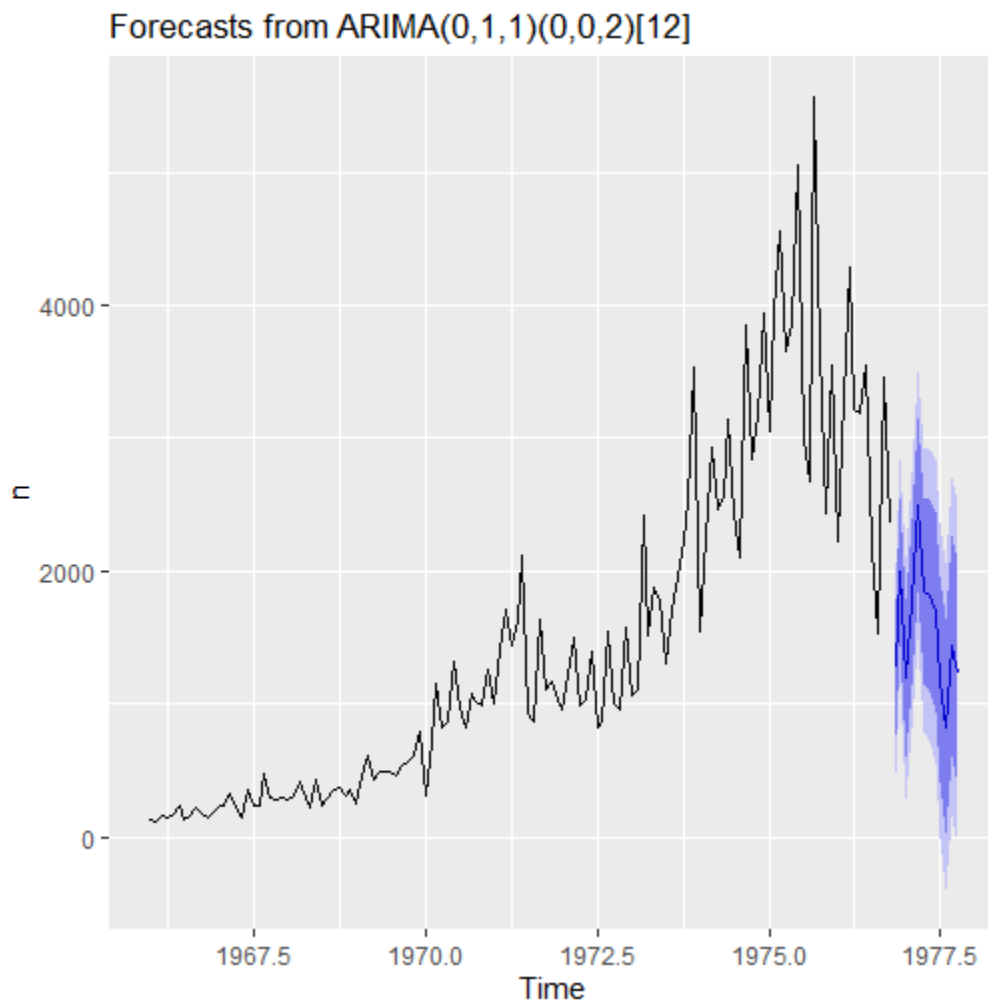
Mathematical form of **SARIMA(0,1,1)(0,0,2)12** :

$$y_t = (1 - \theta_1 B)(1 - \theta_1 B^{12} - \theta_2 B^{24})(1 - B)\varepsilon_t$$

```
> auto.arima(n)  
Series: n  
ARIMA(0,1,1)(0,0,2)[12]  
  
Coefficients:  
      ma1  sma1  sma2  
-0.6035  0.7986  0.3382  
s.e.  0.0629  0.0989  0.1030
```

Forecasting:

We ready now to forecast with our model
 $\text{SARIMA}(0,1,1)(0,0,1)_{12}$:



```
> f=forecast(fit1, h=12)
```

```
> autoplot(f)
```

```
> f
```

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Nov 1976	1272.2026	755.22060	1789.185	481.546871	2062.858
Dec 1976	1993.8976	1437.76631	2550.029	1143.368183	2844.427
Jan 1977	1192.7796	600.07925	1785.480	286.322649	2099.237
Feb 1977	1768.2914	1141.15079	2395.432	809.162603	2727.420
Mar 1977	2498.9638	1839.17825	3158.749	1489.908855	3508.019
Apr 1977	1851.1821	1160.29228	2542.072	794.557327	2907.807
May 1977	1812.2115	1091.55879	2532.864	710.068279	2914.355
Jun 1977	1692.7338	943.49949	2441.968	546.878815	2838.589
Jul 1977	1186.6784	409.91351	1963.443	-1.280979	2374.638
Aug 1977	829.0518	25.69921	1632.404	-399.569954	2057.673
Sep 1977	1433.9166	604.82854	2263.005	165.935834	2701.897
Oct 1977	1221.9339	367.88552	2075.982	-84.220390	2528.088

We Forecast the next 10 values .

Attachments

The Packages and libraries are used :

```
install.packages("zoo")  
install.packages("devtools")  
devtools::install_github("FinYang/tsdl")  
install.packages("nortest")  
install.packages("fBasics")  
install.packages("forecast")  
install.packages("tseries")  
install.packages("randtests")  
install.packages("astsa")  
install.packages("lmtest")  
  
library("zoo")  
library(tsdl)  
library(nortest)  
library(fBasics)  
library(forecast)  
library(tseries)  
library(randtests)  
library(astsa)  
library(lmtest)
```

Codes Are used :

<u>Code</u>	<u>Meaning</u>
<code>>attributes(m)</code>	To describe the data for what
<code>> plot.ts(m)</code>	To plot your series
<code>> adf.test(m)</code>	To test the stationarity of series
<code>>fit1 = arima(m,order=c(0,0,0),include.mean=T)</code>	To identify your model
<code>>coeftest(fit1)</code>	To test the coefficients of model
<code>>Box.test(res,lag=12,type=c("Ljung-Box"))</code>	To test the residuals are correlated or not
<code>> tsdiag(fit)</code>	To show the graph and test residuals are correlated or not
<code>> runs.test(res1)</code>	To test the residuals are random or not
<code>> t.test(res1)</code>	To test the expectation of residuals are zero or not
<code>>Shapiro.test(res1)</code>	To residuals are follow normal distribution
<code>>aic\$fit</code>	To know what model have less AIC
<code>> f=forecast(fit1, h=12) > autoplot(f)</code>	To predict next values To plot the forecast
<code>> n1=diff(n,diffrence=1)</code>	To take difference fot the series

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