Manpower Planning

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Preparation

```
library(scales)
library(rlang)
library(lazyeval)
```

```
##
## Attaching package: 'lazyeval'

## The following objects are masked from 'package:rlang':
##
##     as_name, call_modify, call_standardise, expr_label, expr_text,
##     f_env, f_env<-, f_label, f_lhs, f_lhs<-, f_rhs, f_rhs<-, f_text,
##     is_atomic, is_call, is_formula, is_lang, is_pairlist, missing_arg
```

```
library(ggplot2)
library(fpp2)
```

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

## -- Attaching packages ---------------------------------------------- fpp2 2.4 --

## v forecast  8.15     v expsmooth 2.3
## v fma       2.4

##
```

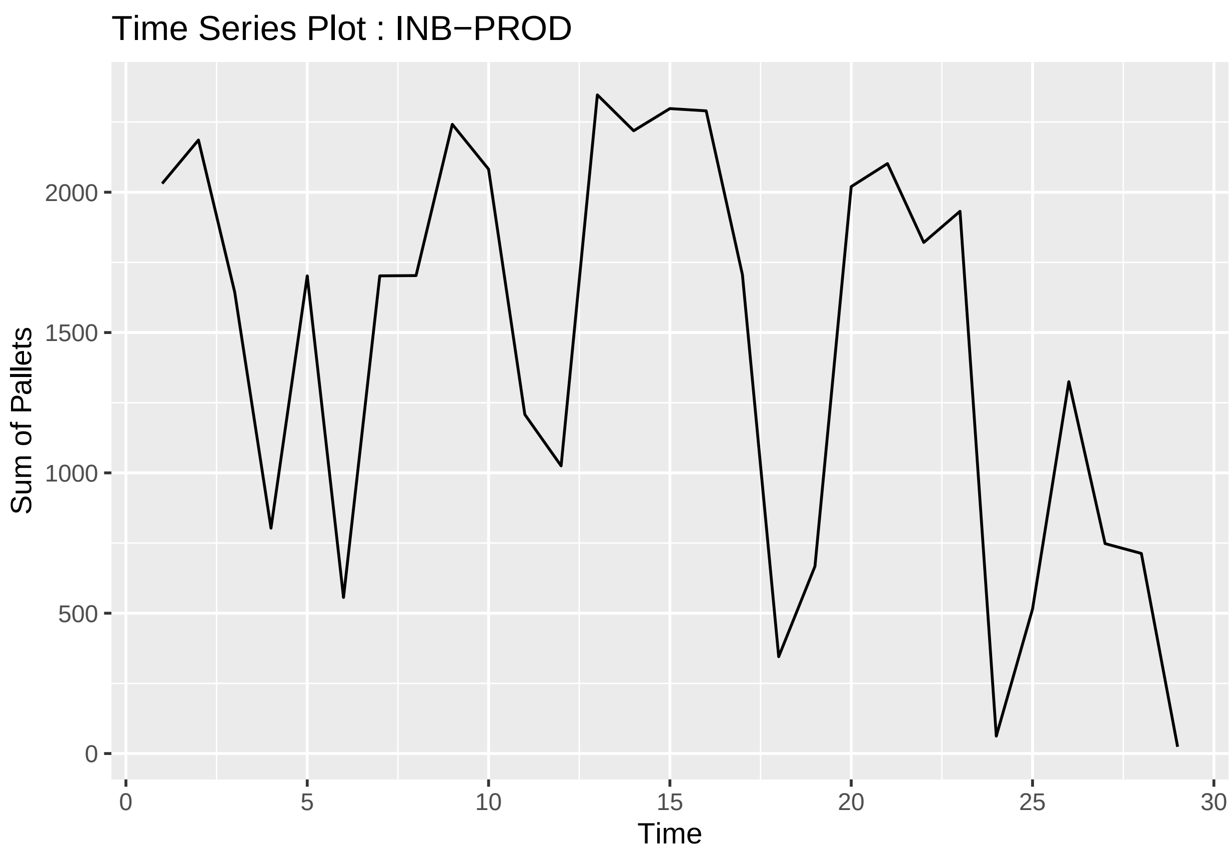
```
library(readxl)

df_prod <- read.csv("https://raw.githubusercontent.com/dhykac/manpower_planning/main/df_productivity.cs
summary(df_prod)
```

```
##      DATE              INB.PROD        INBOUND        INTERNAL
##  Length:29          Min.   :  24   Min.   : 151   Min.   :  48.0
##  Class :character   1st Qu.: 748   1st Qu.:2441   1st Qu.: 303.0
##  Mode  :character   Median :1702   Median :3062   Median : 434.0
##                     Mean   :1449   Mean   :2908   Mean   : 426.5
##                     3rd Qu.:2082   3rd Qu.:3517   3rd Qu.: 531.0
##                     Max.   :2347   Max.   :4492   Max.   :1004.0
##      NARROW        NARROW.OUT      NARROW.RPL      O.PND.OUT
##  Min.   :  4.0   Min.   : 41.0   Min.   : 3.00   Min.   :  7.0
##  1st Qu.:196.0   1st Qu.:201.0   1st Qu.:12.00   1st Qu.:172.0
##  Median :299.0   Median :304.0   Median :16.00   Median :208.0
##  Mean   :269.3   Mean   :275.8   Mean   :17.69   Mean   :218.9
##  3rd Qu.:330.0   3rd Qu.:355.0   3rd Qu.:23.00   3rd Qu.:265.0
##  Max.   :550.0   Max.   :458.0   Max.   :45.00   Max.   :512.0
##     OUT.CONT         OUTBOUND
##  Min.   :  10.0   Min.   : 361
##  1st Qu.: 742.0   1st Qu.:1608
##  Median : 836.0   Median :2018
##  Mean   : 855.6   Mean   :1841
##  3rd Qu.:1049.0   3rd Qu.:2133
##  Max.   :1474.0   Max.   :2572
```

```
View(df_prod)
```

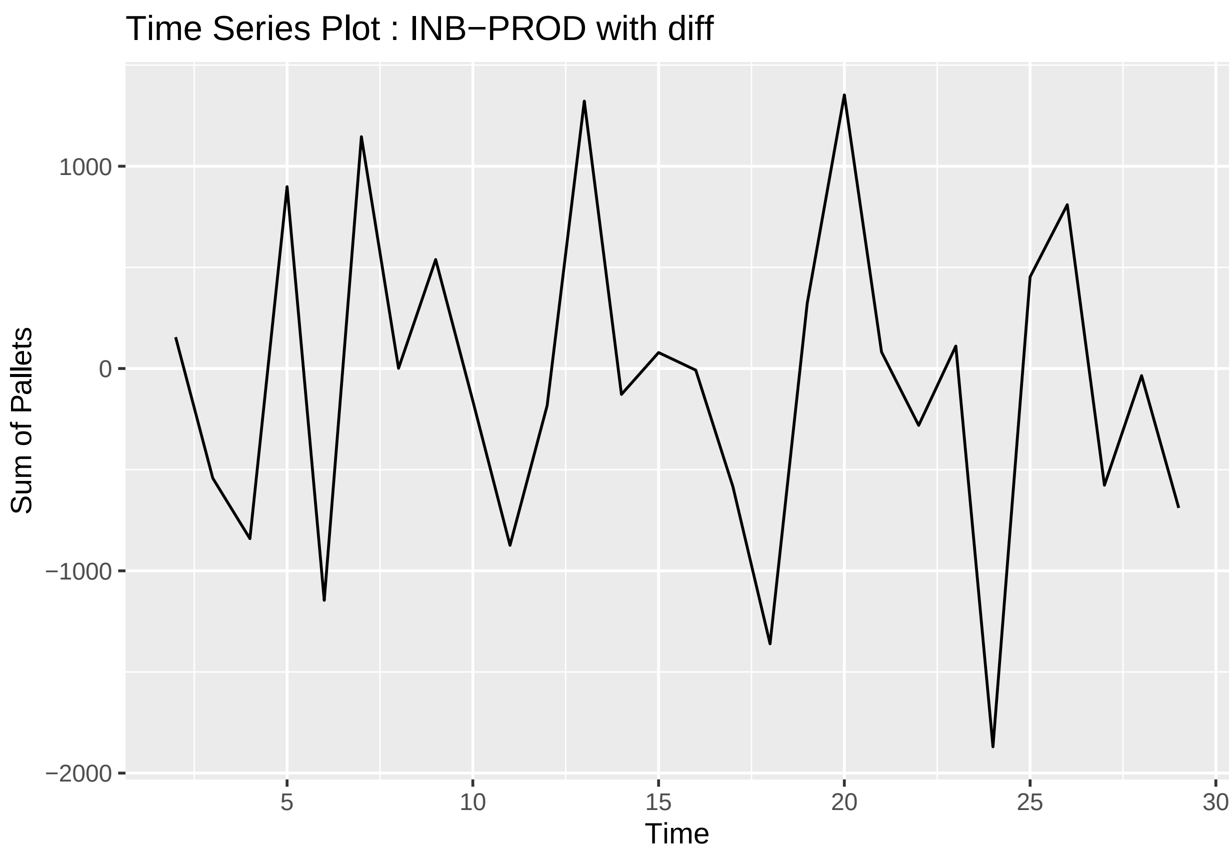
INB-PROD

```
Yinp <- ts(df_prod[,2])
autoplot(Yinp) + ggtitle("Time Series Plot : INB-PROD") + ylab("Sum of Pallets")
```



As we can see, the data had a trend so we will made new data with added differencing method.

```
DYinp <- diff(Yinp)
autoplot(DYinp) + ggtitle("Time Series Plot : INB-PROD with diff") + ylab("Sum of Pallets")
```



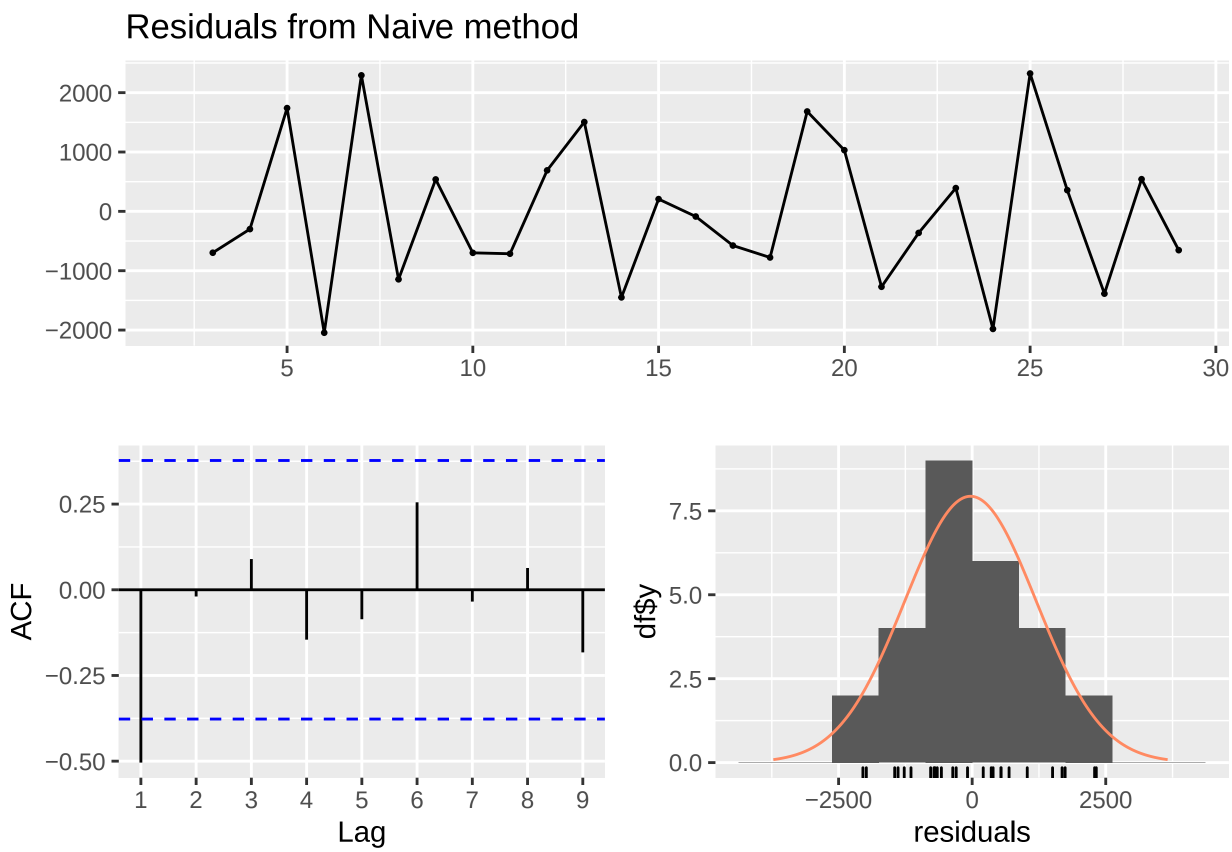
The data didn't have seasonal. So we could go to next step for determine best model.

```
fit <- naive(DYinp)
print(summary(fit))
```

```
##
## Forecast method: Naive method
##
## Model Information:
## Call: naive(y = DYinp)
##
## Residual sd: 1207.348
##
## Error measures:
##                     ME     RMSE      MAE       MPE    MAPE MASE       ACF1
## Training set -31.25926 1207.348 1016.519 -4140.386 4598.59    1 -0.5041858
##
## Forecasts:
##    Point Forecast     Lo 80     Hi 80     Lo 95    Hi 95
## 30           -689 -2236.279  858.2787 -3055.359 1677.359
## 31           -689 -2877.182 1499.1825 -4035.536 2657.536
## 32           -689 -3368.965 1990.9653 -4787.653 3409.653
## 33           -689 -3783.557 2405.5574 -5421.717 4043.717
## 34           -689 -4148.820 2770.8203 -5980.339 4602.339
## 35           -689 -4479.043 3101.0432 -6485.371 5107.371
## 36           -689 -4782.715 3404.7146 -6949.796 5571.796
```

```
## 37            -689 -5065.365 3687.3650 -7382.073 6004.073
## 38            -689 -5330.836 3952.8360 -7788.076 6410.076
## 39            -689 -5581.925 4203.9248 -8172.083 6794.083
```

```
checkresiduals(fit)
```



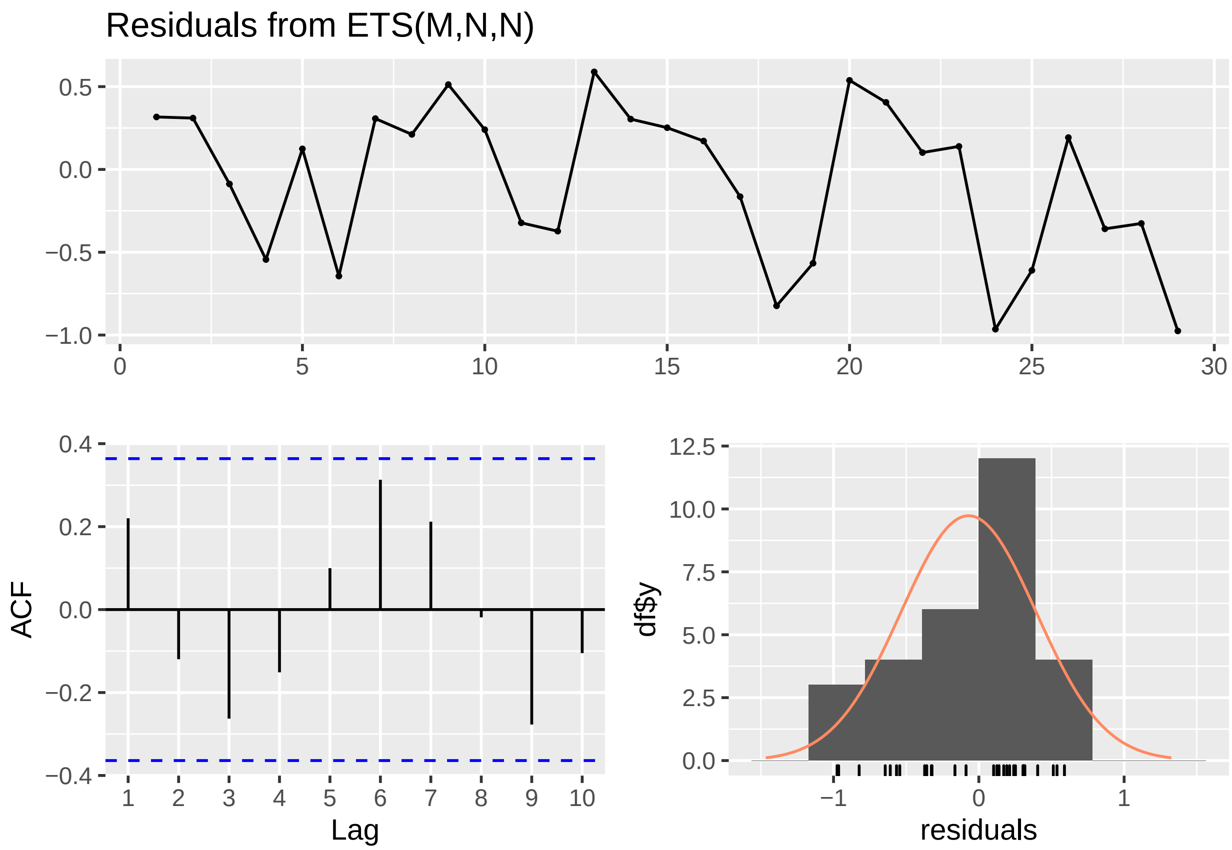

```
##
##  Ljung-Box test
##
## data:  Residuals from Naive method
## Q* = 11.343, df = 6, p-value = 0.07832
##
## Model df: 0.   Total lags used: 6
```

```
## Residuals = 1208

fit_ets <- ets(Yinp)
print(summary(fit_ets))
```

```
## ETS(M,N,N)
##
## Call:
##  ets(y = Yinp)
##
```

```
##   Smoothing parameters:
##     alpha = 0.2585
##
##   Initial states:
##     l = 1542.3899
##
##   sigma:  0.4792
##
##      AIC     AICc      BIC
## 484.3477 485.3077 488.4496
##
## Training set error measures:
##                     ME     RMSE      MAE       MPE     MAPE     MASE     ACF1
## Training set -109.0727 712.1233 603.5252 -262.6421 286.7469 1.021008 0.228689
```

```
checkresiduals(fit_ets)
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ETS(M,N,N)
## Q* = 9.4489, df = 4, p-value = 0.05081
##
## Model df: 2.   Total lags used: 6
```

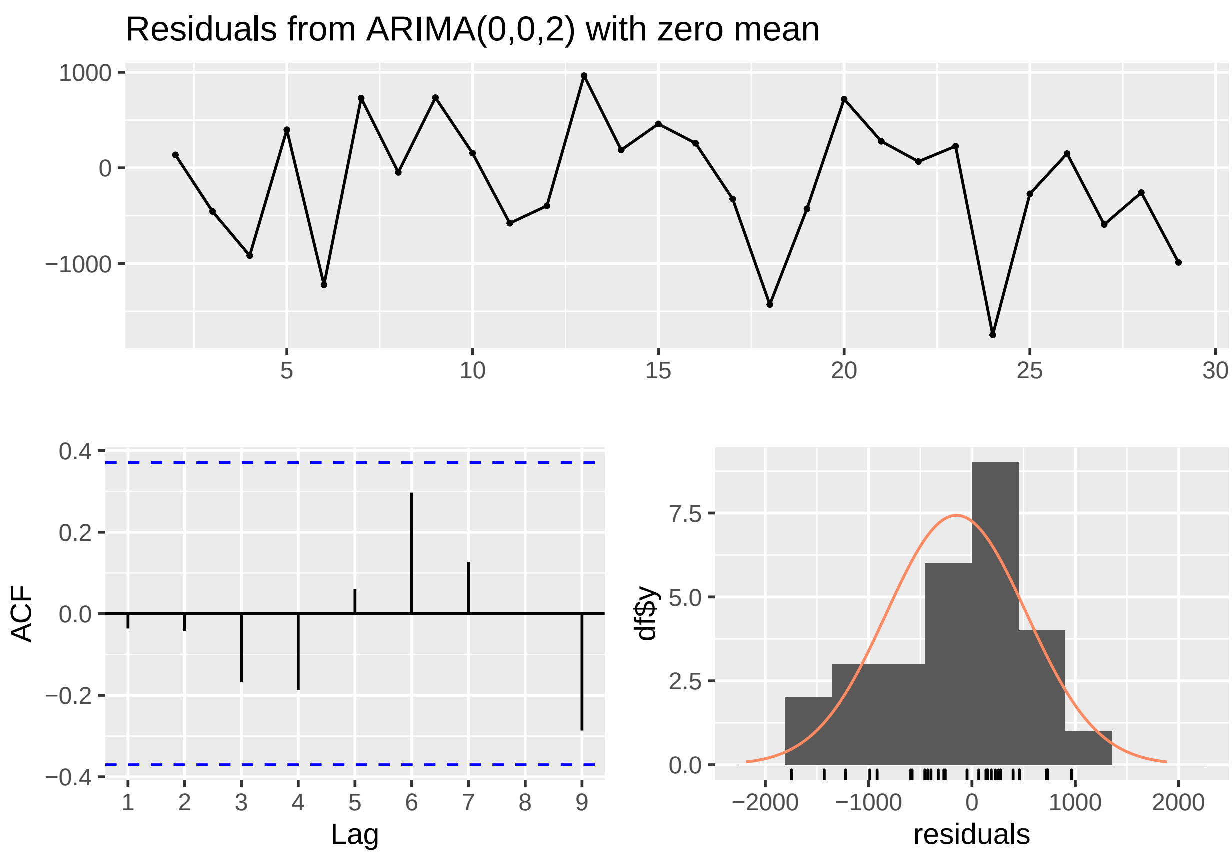
```r
## Residuals = 713
fit_arima <- auto.arima(DYinp, d=0, D=0, stepwise = FALSE, approximation = FALSE, trace = TRUE)
```

```
##
##  ARIMA(0,0,0) with zero mean     : 454.0396
##  ARIMA(0,0,0) with non-zero mean : 456.124
##  ARIMA(0,0,1) with zero mean     : 453.3351
##  ARIMA(0,0,1) with non-zero mean : 454.519
##  ARIMA(0,0,2) with zero mean     : 452.7407
##  ARIMA(0,0,2) with non-zero mean : Inf
##  ARIMA(0,0,3) with zero mean     : 455.3701
##  ARIMA(0,0,3) with non-zero mean : Inf
##  ARIMA(0,0,4) with zero mean     : Inf
##  ARIMA(0,0,4) with non-zero mean : Inf
##  ARIMA(0,0,5) with zero mean     : Inf
##  ARIMA(0,0,5) with non-zero mean : Inf
##  ARIMA(1,0,0) with zero mean     : 455.334
##  ARIMA(1,0,0) with non-zero mean : 457.5222
##  ARIMA(1,0,1) with zero mean     : 453.1091
##  ARIMA(1,0,1) with non-zero mean : Inf
##  ARIMA(1,0,2) with zero mean     : 455.4153
##  ARIMA(1,0,2) with non-zero mean : Inf
##  ARIMA(1,0,3) with zero mean     : 458.3514
##  ARIMA(1,0,3) with non-zero mean : Inf
##  ARIMA(1,0,4) with zero mean     : 461.63
##  ARIMA(1,0,4) with non-zero mean : Inf
##  ARIMA(2,0,0) with zero mean     : 456.6571
##  ARIMA(2,0,0) with non-zero mean : 458.9605
##  ARIMA(2,0,1) with zero mean     : 455.0421
##  ARIMA(2,0,1) with non-zero mean : Inf
##  ARIMA(2,0,2) with zero mean     : Inf
##  ARIMA(2,0,2) with non-zero mean : Inf
##  ARIMA(2,0,3) with zero mean     : Inf
##  ARIMA(2,0,3) with non-zero mean : Inf
##  ARIMA(3,0,0) with zero mean     : 458.0465
##  ARIMA(3,0,0) with non-zero mean : 460.5526
##  ARIMA(3,0,1) with zero mean     : 456.9538
##  ARIMA(3,0,1) with non-zero mean : 458.8053
##  ARIMA(3,0,2) with zero mean     : Inf
##  ARIMA(3,0,2) with non-zero mean : Inf
##  ARIMA(4,0,0) with zero mean     : 456.6327
##  ARIMA(4,0,0) with non-zero mean : 458.9529
##  ARIMA(4,0,1) with zero mean     : 458.0754
##  ARIMA(4,0,1) with non-zero mean : 460.1598
##  ARIMA(5,0,0) with zero mean     : 456.5436
##  ARIMA(5,0,0) with non-zero mean : 458.4851
##
##
##
##  Best model: ARIMA(0,0,2) with zero mean
```

```r
print(summary(fit_arima))
```

```
## Series: DYinp
## ARIMA(0,0,2) with zero mean
##
## Coefficients:
##           ma1      ma2
##       -0.4546  -0.3074
## s.e.   0.1855   0.1704
##
## sigma^2 estimated as 502987:  log likelihood=-222.87
## AIC=451.74   AICc=452.74   BIC=455.74
##
## Training set error measures:
##                     ME     RMSE     MAE       MPE     MAPE      MASE
## Training set -150.0653 683.4174 539.912 -178.3821 422.7748 0.5311383
##                     ACF1
## Training set -0.03624902
```

```r
checkresiduals(fit_arima)
```

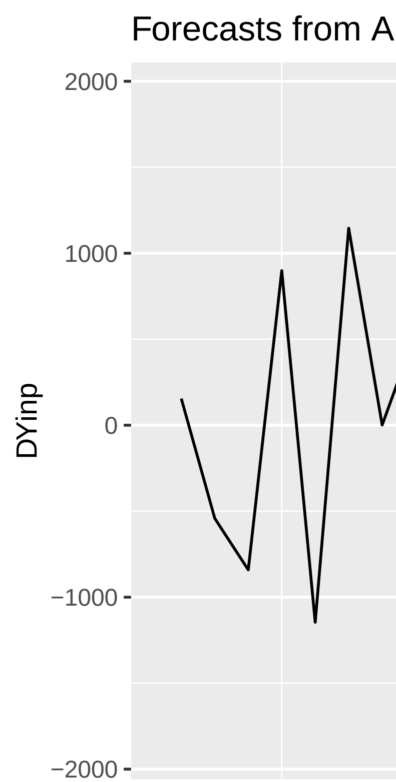



```
##
##  Ljung-Box test
##
```

```
## data:  Residuals from ARIMA(0,0,2) with zero mean
## Q* = 5.783, df = 4, p-value = 0.2159
##
## Model df: 2.   Total lags used: 6
```

```
## Residuals = 710
## Residuals diff 2 = 779
```

```
fcast <- forecast(fit_arima, h=3)
autoplot(fcast)
```



The best model for this one is ARIMA, since the model had smallest residuals.

```
print(summary(fcast))
```

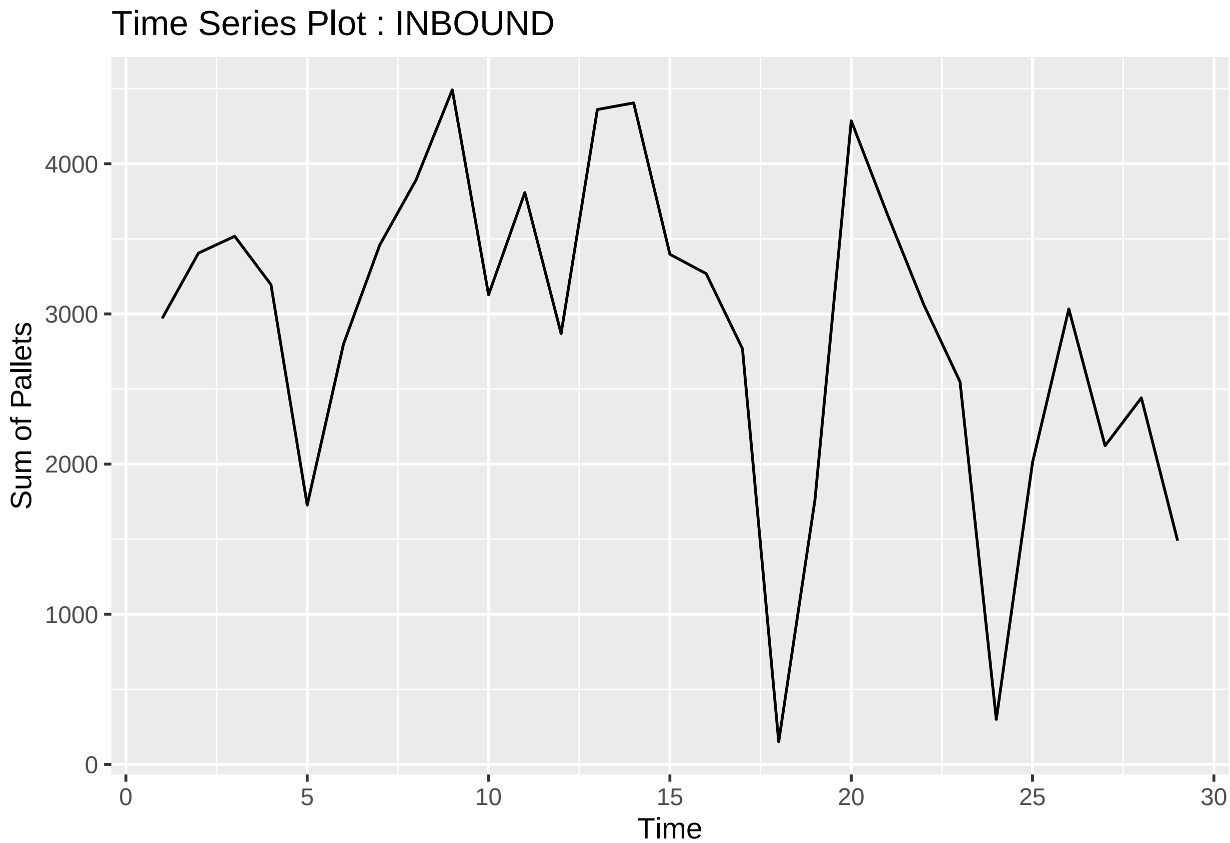
```
##
## Forecast method: ARIMA(0,0,2) with zero mean
##
## Model Information:
## Series: DYinp
## ARIMA(0,0,2) with zero mean
##
## Coefficients:
##           ma1      ma2
```

```
##       -0.4546  -0.3074
## s.e.   0.1855   0.1704
##
## sigma^2 estimated as 502987:  log likelihood=-222.87
## AIC=451.74   AICc=452.74   BIC=455.74
##
## Error measures:
##                     ME     RMSE     MAE       MPE     MAPE      MASE
## Training set -150.0653 683.4174 539.912 -178.3821 422.7748 0.5311383
##                     ACF1
## Training set -0.03624902
##
## Forecasts:
##    Point Forecast       Lo 80    Hi 80       Lo 95    Hi 95
## 30       528.8416  -380.0569 1437.740  -861.1986 1918.882
## 31       303.9202  -694.4938 1302.334 -1223.0222 1830.863
## 32         0.0000 -1036.7782 1036.778 -1585.6154 1585.615
```

Forecast workload for next day with confidence 95% is 1919 pallets.

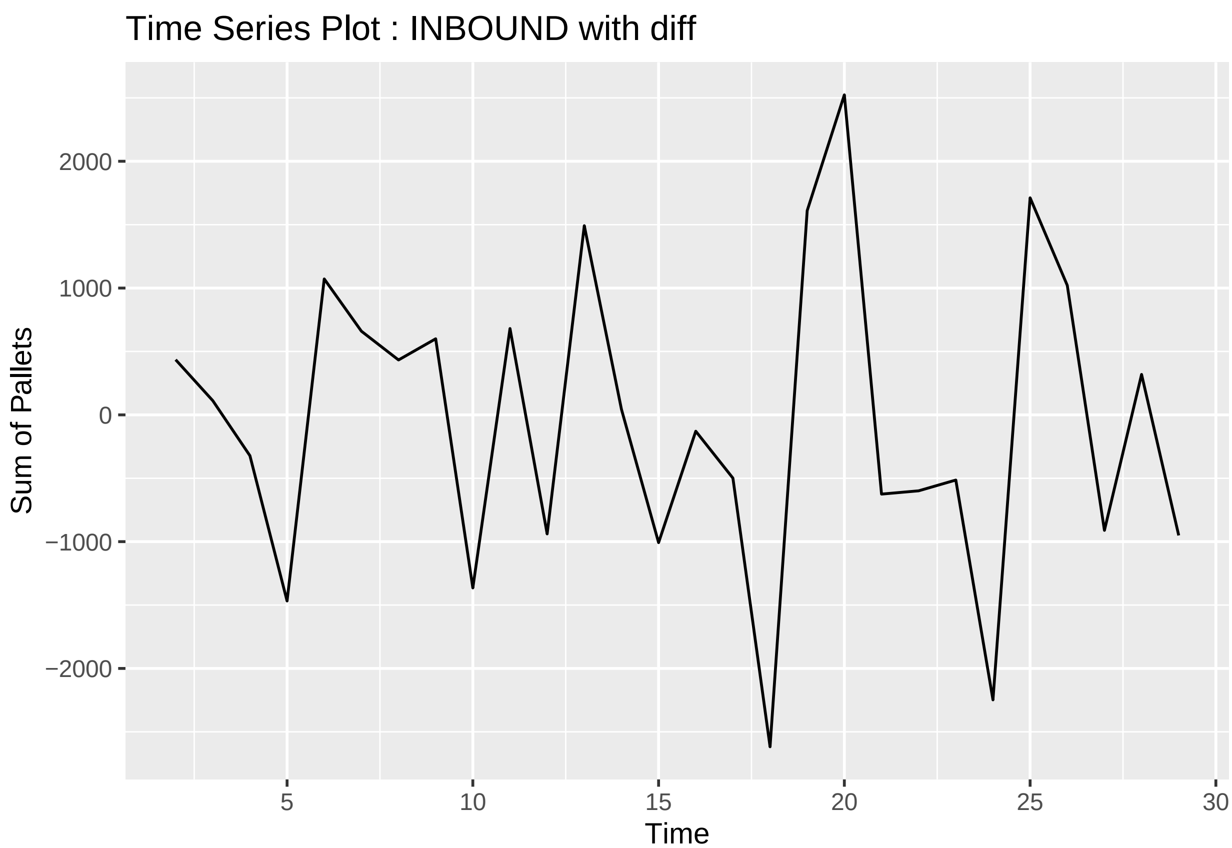
INBOUND

```r
Yinc <- ts(df_prod[,3])
autoplot(Yinc) + ggtitle("Time Series Plot : INBOUND") + ylab("Sum of Pallets")
```



As we can see, the data had a trend so we will made new data with added differencing method.

```
DYinc <- diff(Yinc)
autoplot(DYinc) + ggtitle("Time Series Plot : INBOUND with diff") + ylab("Sum of Pallets")
```



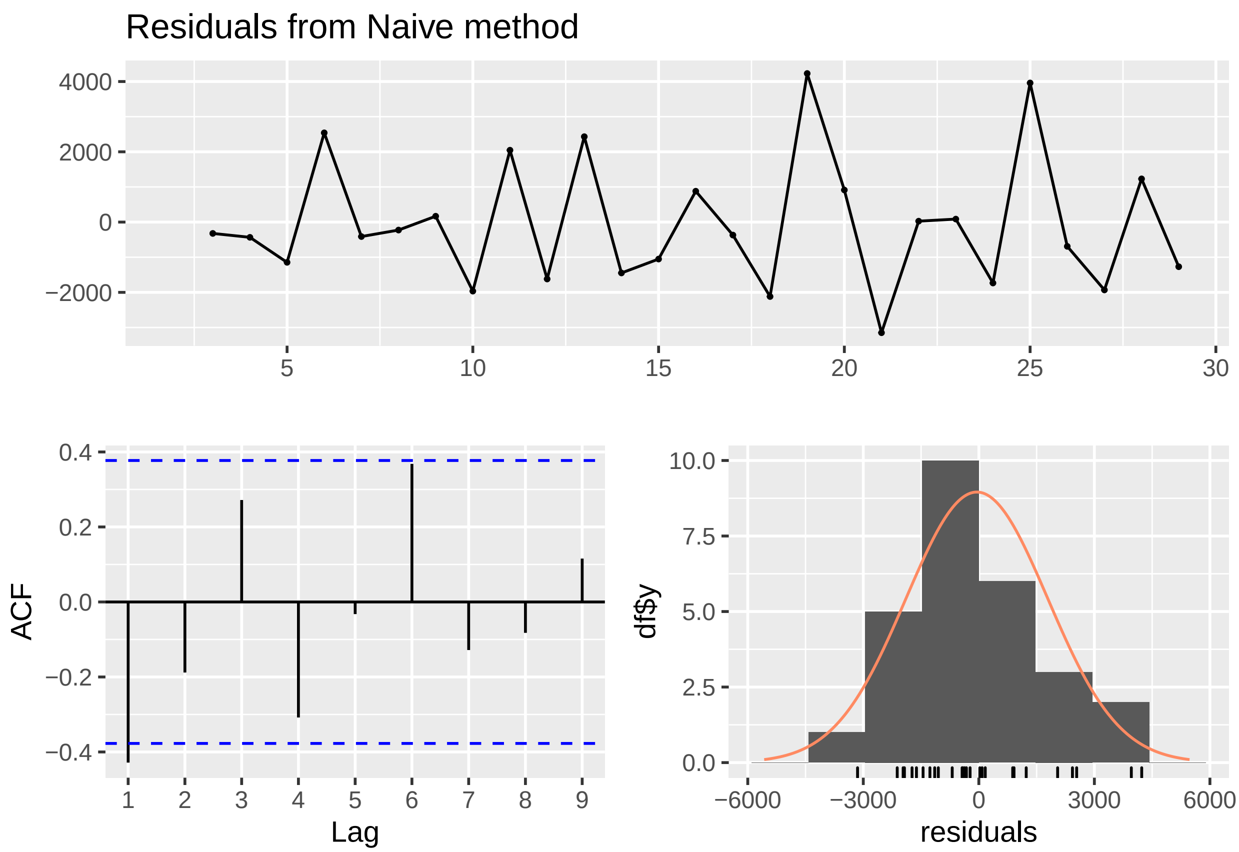
The data didn't have seasonal. So we could go to next step for determine best model.

```
fit <- naive(DYinc)
print(summary(fit))
```

```
##
## Forecast method: Naive method
##
## Model Information:
## Call: naive(y = DYinc)
##
## Residual sd: 1806.9593
##
## Error measures:
##                     ME     RMSE      MAE       MPE    MAPE MASE       ACF1
## Training set -51.33333 1806.959 1422.148 -40.92628 289.748    1 -0.4283156
##
## Forecasts:
##    Point Forecast     Lo 80    Hi 80      Lo 95    Hi 95
## 30           -951 -3266.711 1364.711  -4492.575 2590.575
## 31           -951 -4225.911 2323.911  -5959.544 4057.544
## 32           -951 -4961.930 3059.930  -7085.188 5183.188
## 33           -951 -5582.423 3680.423  -8034.150 6132.150
## 34           -951 -6129.088 4227.088  -8870.203 6968.203
## 35           -951 -6623.311 4721.311  -9626.052 7724.052
## 36           -951 -7077.797 5175.797 -10321.127 8419.127
```

```
## 37            -951 -7500.821 5598.821 -10968.087  9066.087
## 38            -951 -7898.134 5996.134 -11575.725  9673.725
## 39            -951 -8273.923 6371.923 -12150.444 10248.444
```

```r
checkresiduals(fit)
```



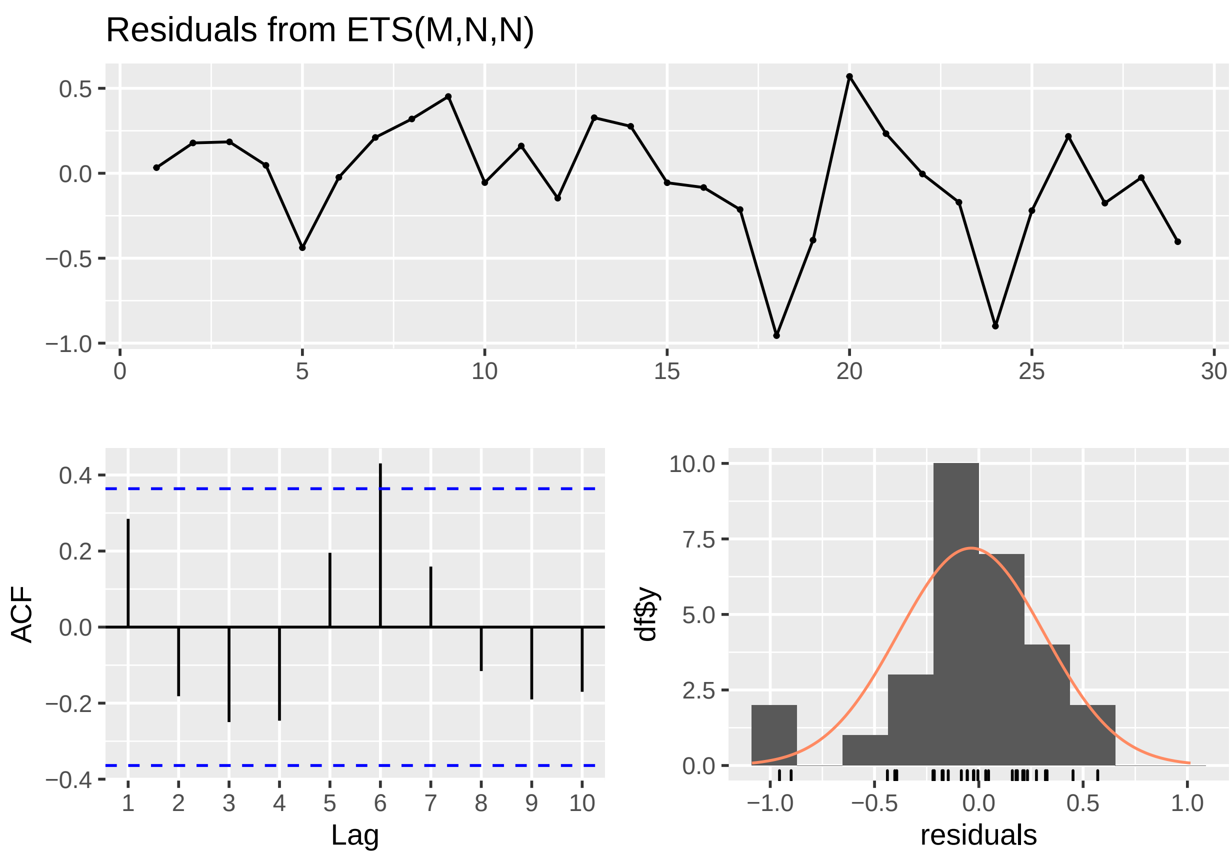

```
##
##  Ljung-Box test
##
## data:  Residuals from Naive method
## Q* = 17.368, df = 6, p-value = 0.008023
##
## Model df: 0.   Total lags used: 6
```

```r
## Residuals = 1806

fit_ets <- ets(Yinc)
print(summary(fit_ets))
```

```
## ETS(M,N,N)
##
## Call:
##  ets(y = Yinc)
##
```

```
##   Smoothing parameters:
##     alpha = 0.1536
##
##   Initial states:
##     l = 2874.8681
##
##   sigma:  0.3589
##
##      AIC     AICc      BIC
## 506.7157 507.6757 510.8176
##
## Training set error measures:
##                     ME     RMSE      MAE       MPE     MAPE      MASE      ACF1
## Training set -119.8268 1068.267 781.0304 -108.9612 125.8087 0.8126059 0.2985748
```

```
checkresiduals(fit_ets)
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ETS(M,N,N)
## Q* = 16.709, df = 4, p-value = 0.002202
##
## Model df: 2.   Total lags used: 6
```

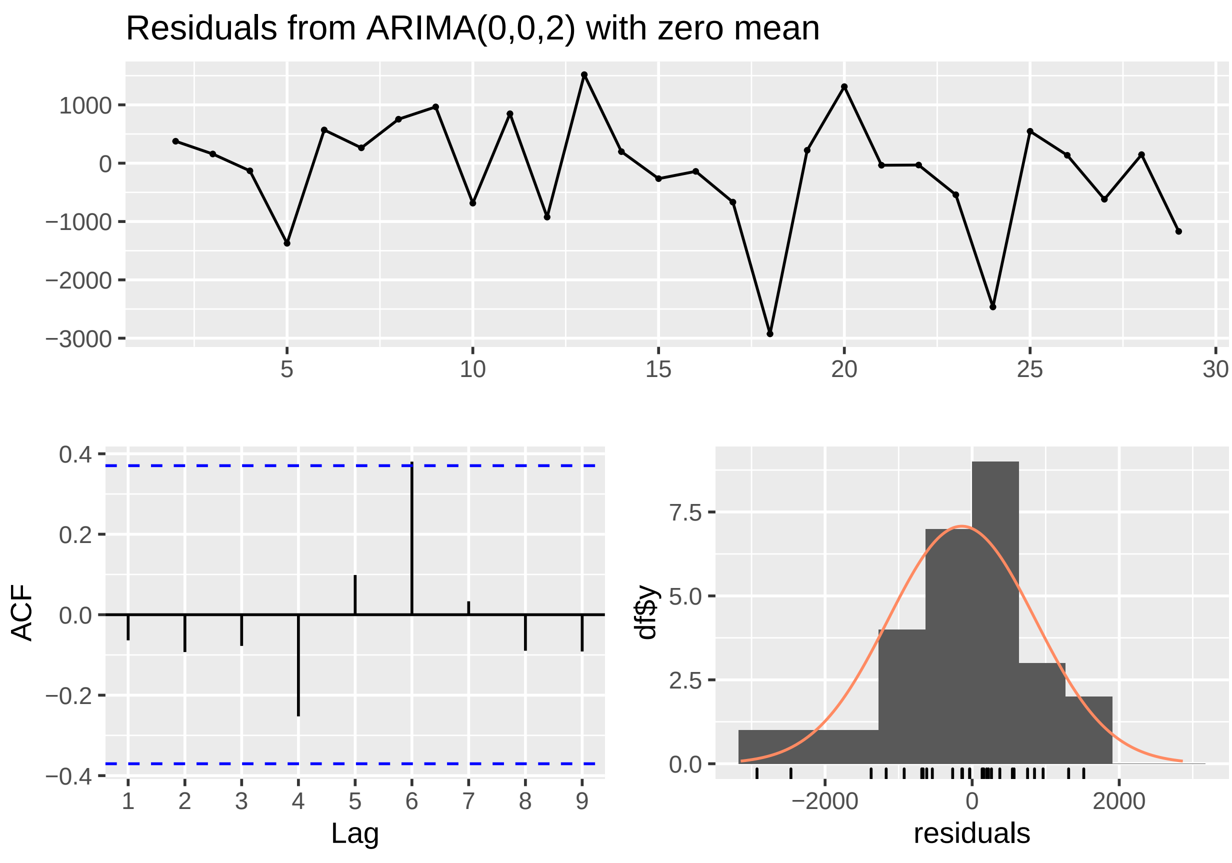
```
## Residuals = 1069

fit_arima <- auto.arima(DYinc, d=0, D=0, stepwise = FALSE, approximation = FALSE, trace = TRUE)
```

```
##
##  ARIMA(0,0,0) with zero mean     : 477.7321
##  ARIMA(0,0,0) with non-zero mean : 480.0021
##  ARIMA(0,0,1) with zero mean     : 476.1677
##  ARIMA(0,0,1) with non-zero mean : Inf
##  ARIMA(0,0,2) with zero mean     : 474.0089
##  ARIMA(0,0,2) with non-zero mean : Inf
##  ARIMA(0,0,3) with zero mean     : 476.556
##  ARIMA(0,0,3) with non-zero mean : Inf
##  ARIMA(0,0,4) with zero mean     : 479.3156
##  ARIMA(0,0,4) with non-zero mean : Inf
##  ARIMA(0,0,5) with zero mean     : 480.7735
##  ARIMA(0,0,5) with non-zero mean : Inf
##  ARIMA(1,0,0) with zero mean     : 479.4757
##  ARIMA(1,0,0) with non-zero mean : 481.9263
##  ARIMA(1,0,1) with zero mean     : 475.6147
##  ARIMA(1,0,1) with non-zero mean : Inf
##  ARIMA(1,0,2) with zero mean     : 476.5792
##  ARIMA(1,0,2) with non-zero mean : Inf
##  ARIMA(1,0,3) with zero mean     : 479.5672
##  ARIMA(1,0,3) with non-zero mean : Inf
##  ARIMA(1,0,4) with zero mean     : 482.7997
##  ARIMA(1,0,4) with non-zero mean : Inf
##  ARIMA(2,0,0) with zero mean     : 479.2171
##  ARIMA(2,0,0) with non-zero mean : 481.8245
##  ARIMA(2,0,1) with zero mean     : 476.5509
##  ARIMA(2,0,1) with non-zero mean : Inf
##  ARIMA(2,0,2) with zero mean     : 479.5668
##  ARIMA(2,0,2) with non-zero mean : Inf
##  ARIMA(2,0,3) with zero mean     : Inf
##  ARIMA(2,0,3) with non-zero mean : Inf
##  ARIMA(3,0,0) with zero mean     : 481.3585
##  ARIMA(3,0,0) with non-zero mean : 484.1942
##  ARIMA(3,0,1) with zero mean     : 479.1898
##  ARIMA(3,0,1) with non-zero mean : Inf
##  ARIMA(3,0,2) with zero mean     : 482.5428
##  ARIMA(3,0,2) with non-zero mean : Inf
##  ARIMA(4,0,0) with zero mean     : 475.1125
##  ARIMA(4,0,0) with non-zero mean : 478.0982
##  ARIMA(4,0,1) with zero mean     : 476.7469
##  ARIMA(4,0,1) with non-zero mean : 479.7254
##  ARIMA(5,0,0) with zero mean     : 475.5013
##  ARIMA(5,0,0) with non-zero mean : 478.3648
##
##
##
##  Best model: ARIMA(0,0,2) with zero mean
```

```r
print(summary(fit_arima))
```

```
## Series: DYinc
## ARIMA(0,0,2) with zero mean
##
## Coefficients:
##           ma1      ma2
##       -0.3758  -0.4427
## s.e.   0.1960   0.1910
##
## sigma^2 estimated as 1064370:  log likelihood=-233.5
## AIC=473.01   AICc=474.01   BIC=477.01
##
## Training set error measures:
##                   ME     RMSE     MAE     MPE    MAPE      MASE        ACF1
## Training set -141.536 994.1548 713.734 91.6835 91.6835 0.5018704 -0.06370472
```

```r
checkresiduals(fit_arima)
```

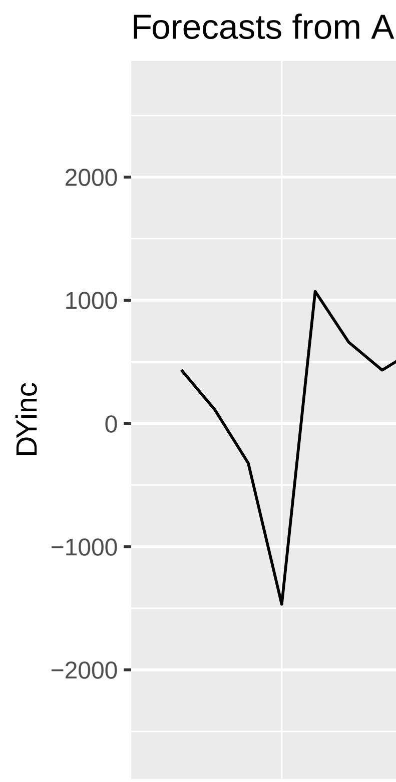



```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,0,2) with zero mean
## Q* = 8.7218, df = 4, p-value = 0.06844
```

```
##
## Model df: 2.   Total lags used: 6
```

```
## Residuals = 1032
## Residuals diff 2 = 1108
```

```
fcast <- forecast(fit_arima, h=3)
autoplot(fcast)
```



The best model for this one is ARIMA, since the model had smallest residuals.

```
print(summary(fcast))
```

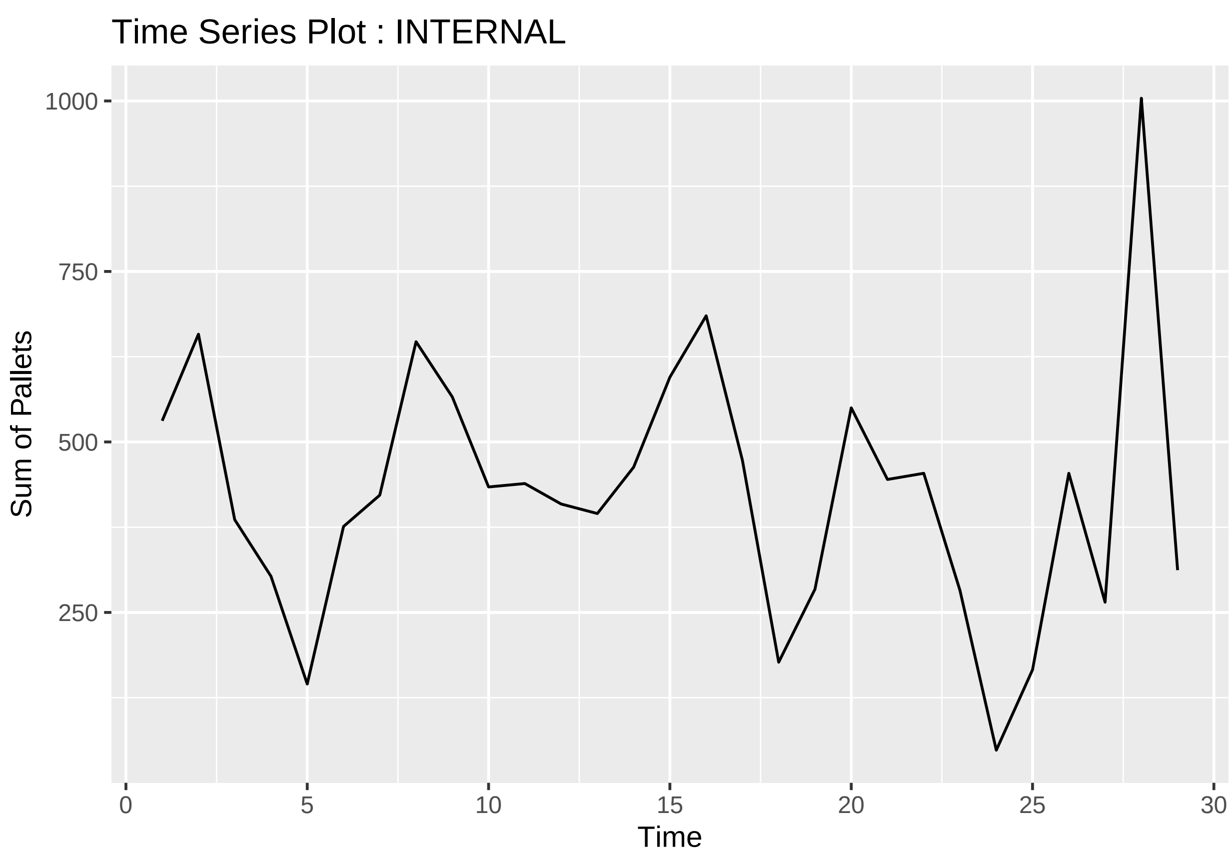
```
##
## Forecast method: ARIMA(0,0,2) with zero mean
##
## Model Information:
## Series: DYinc
## ARIMA(0,0,2) with zero mean
##
## Coefficients:
##           ma1      ma2
##       -0.3758  -0.4427
## s.e.   0.1960   0.1910
```

```
##
## sigma^2 estimated as 1064370:  log likelihood=-233.5
## AIC=473.01   AICc=474.01   BIC=477.01
##
## Error measures:
##                    ME     RMSE     MAE     MPE    MAPE      MASE        ACF1
## Training set -141.536 994.1548 713.734 91.6835 91.6835 0.5018704 -0.06370472
##
## Forecasts:
##    Point Forecast       Lo 80    Hi 80     Lo 95    Hi 95
## 30       374.2757  -947.9521 1696.504 -1647.897 2396.449
## 31       517.6361  -894.8125 1930.085 -1642.518 2677.790
## 32         0.0000 -1528.9227 1528.923 -2338.285 2338.285
```

Forecast workload for next day with confidence 95% is 2397 pallets.

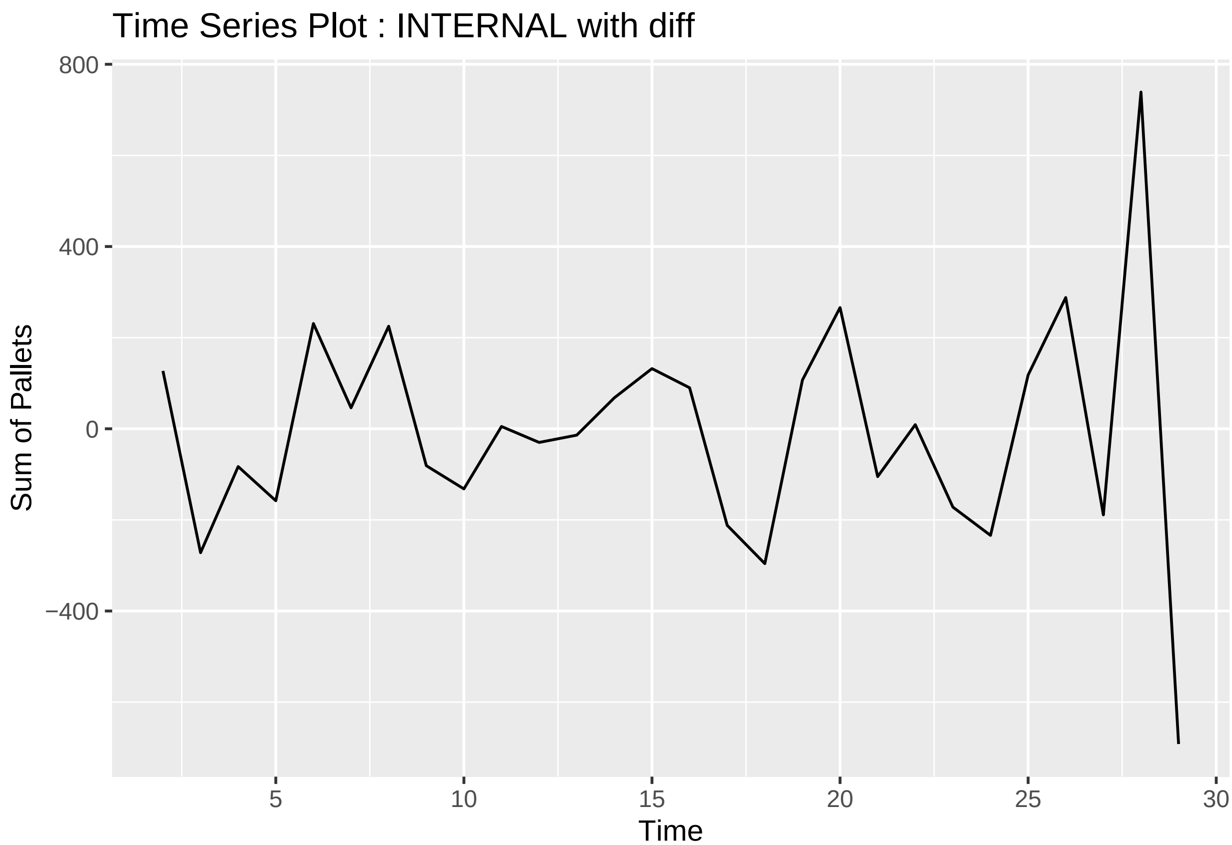
INTERNAL

```
Yint <- ts(df_prod[,4])
autoplot(Yint) + ggtitle("Time Series Plot : INTERNAL") + ylab("Sum of Pallets")
```



As we can see, the data had a trend so we will made new data with added differencing method.

```r
DYint <- diff(Yint)
autoplot(DYint) + ggtitle("Time Series Plot : INTERNAL with diff") + ylab("Sum of Pallets")
```



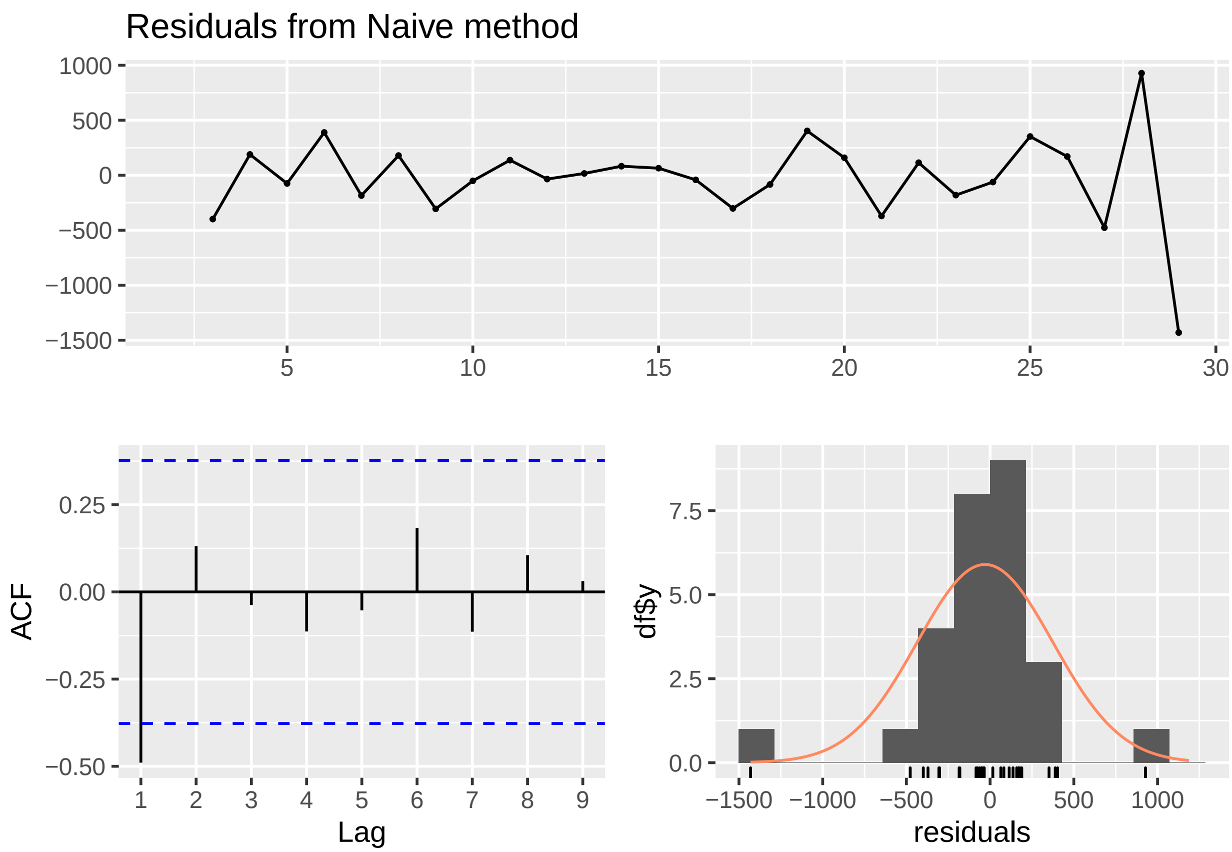
The data didn't have seasonal. So we could go to next step for determine best model.

```r
fit <- naive(DYint)
print(summary(fit))
```

```
##
## Forecast method: Naive method
##
## Model Information:
## Call: naive(y = DYint)
##
## Residual sd: 399.5217
##
## Error measures:
##                     ME     RMSE     MAE      MPE     MAPE MASE       ACF1
## Training set -30.33333 399.5217 266.037 236.8326 295.4131    1 -0.4895987
##
## Forecasts:
##    Point Forecast      Lo 80      Hi 80     Lo 95     Hi 95
## 30           -692 -1204.008 -179.99233 -1475.048  91.04815
## 31           -692 -1416.088   32.08819 -1799.397 415.39732
## 32           -692 -1578.823  194.82329 -2048.279 664.27918
## 33           -692 -1716.015  332.01533 -2258.096 874.09630
```

```
## 34           -692 -1836.884  452.88395 -2442.949 1058.94890
## 35           -692 -1946.158  562.15753 -2610.068 1226.06842
## 36           -692 -2046.645  662.64495 -2763.751 1379.75068
## 37           -692 -2140.176  756.17637 -2906.795 1522.79463
## 38           -692 -2228.023  844.02300 -3041.144 1657.14446
## 39           -692 -2311.110  927.11040 -3168.216 1784.21568
```

```
checkresiduals(fit)
```



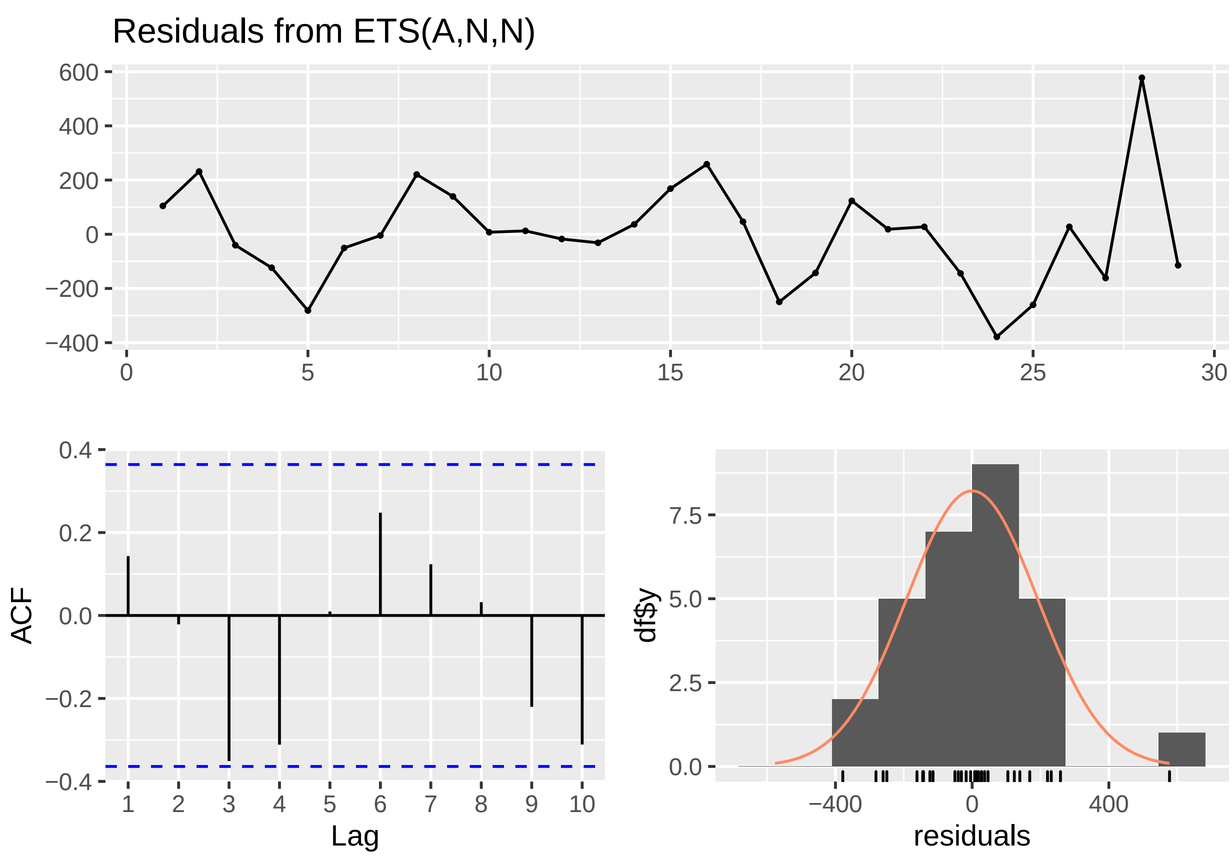

```
##
##  Ljung-Box test
##
## data:  Residuals from Naive method
## Q* = 9.6037, df = 6, p-value = 0.1424
##
## Model df: 0.   Total lags used: 6
```

```
## Residuals = 400

fit_ets <- ets(Yint)
print(summary(fit_ets))
```

```
## ETS(A,N,N)
##
```

```
## Call:
##  ets(y = Yint)
##
##   Smoothing parameters:
##     alpha = 1e-04
##
##   Initial states:
##     l = 426.5376
##
##   sigma:  195.8823
##
##      AIC     AICc      BIC
## 407.6751 408.6351 411.7770
##
## Training set error measures:
##                       ME     RMSE      MAE       MPE     MAPE      MASE
## Training set -0.07084547 189.0071 137.9831 -43.44883 64.00257 0.7544476
##                   ACF1
## Training set 0.1431771
```

```
checkresiduals(fit_ets)
```




```
##
##  Ljung-Box test
##
```

```
## data:  Residuals from ETS(A,N,N)
## Q* = 10.827, df = 4, p-value = 0.02857
##
## Model df: 2.   Total lags used: 6
```

```
## Residuals = 189

fit_arima <- auto.arima(DYint, d=0, D=0, stepwise = FALSE, approximation = FALSE, trace = TRUE)
```

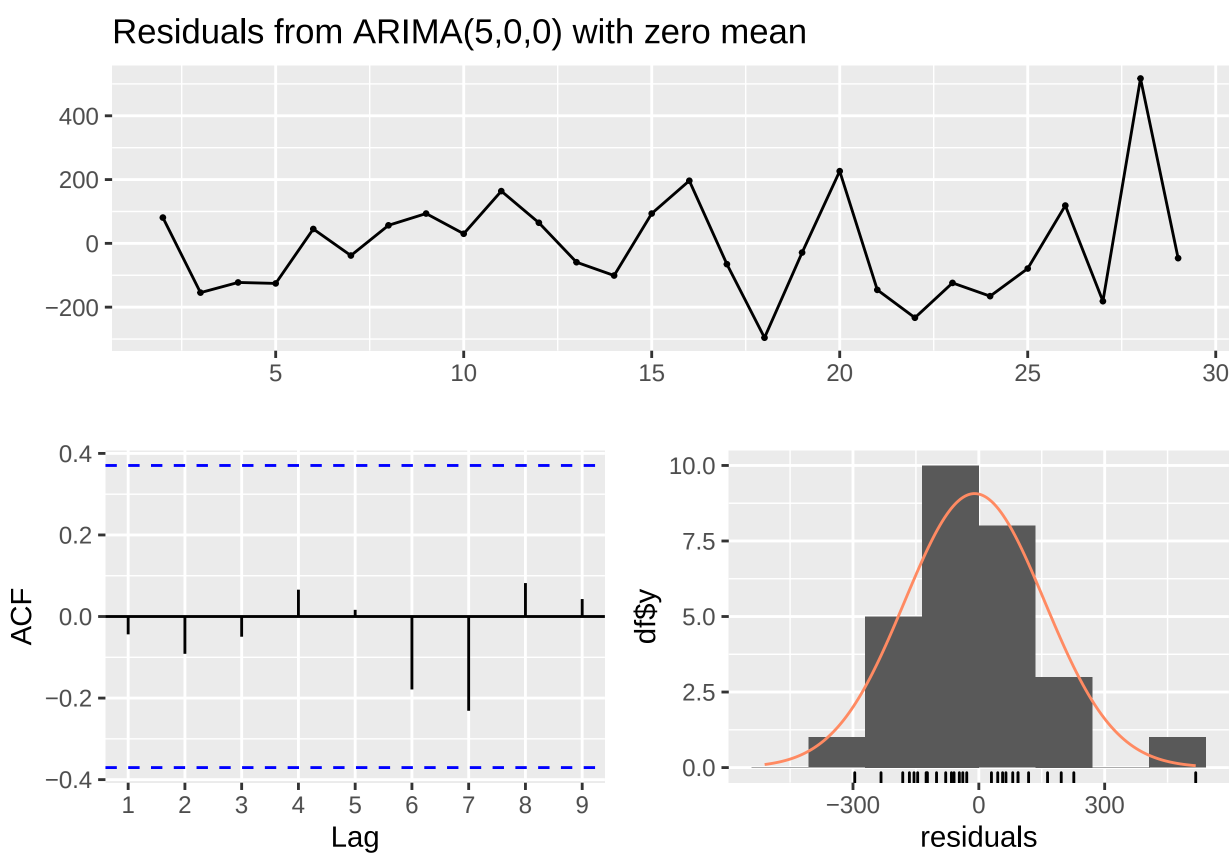
```
##
##  ARIMA(0,0,0) with zero mean     : 390.8339
##  ARIMA(0,0,0) with non-zero mean : 393.1327
##  ARIMA(0,0,1) with zero mean     : Inf
##  ARIMA(0,0,1) with non-zero mean : Inf
##  ARIMA(0,0,2) with zero mean     : Inf
##  ARIMA(0,0,2) with non-zero mean : Inf
##  ARIMA(0,0,3) with zero mean     : Inf
##  ARIMA(0,0,3) with non-zero mean : Inf
##  ARIMA(0,0,4) with zero mean     : Inf
##  ARIMA(0,0,4) with non-zero mean : Inf
##  ARIMA(0,0,5) with zero mean     : Inf
##  ARIMA(0,0,5) with non-zero mean : Inf
##  ARIMA(1,0,0) with zero mean     : 387.4572
##  ARIMA(1,0,0) with non-zero mean : 389.9755
##  ARIMA(1,0,1) with zero mean     : Inf
##  ARIMA(1,0,1) with non-zero mean : Inf
##  ARIMA(1,0,2) with zero mean     : Inf
##  ARIMA(1,0,2) with non-zero mean : Inf
##  ARIMA(1,0,3) with zero mean     : Inf
##  ARIMA(1,0,3) with non-zero mean : Inf
##  ARIMA(1,0,4) with zero mean     : 386.3619
##  ARIMA(1,0,4) with non-zero mean : Inf
##  ARIMA(2,0,0) with zero mean     : 389.9206
##  ARIMA(2,0,0) with non-zero mean : 392.6583
##  ARIMA(2,0,1) with zero mean     : Inf
##  ARIMA(2,0,1) with non-zero mean : Inf
##  ARIMA(2,0,2) with zero mean     : Inf
##  ARIMA(2,0,2) with non-zero mean : Inf
##  ARIMA(2,0,3) with zero mean     : Inf
##  ARIMA(2,0,3) with non-zero mean : Inf
##  ARIMA(3,0,0) with zero mean     : Inf
##  ARIMA(3,0,0) with non-zero mean : Inf
##  ARIMA(3,0,1) with zero mean     : Inf
##  ARIMA(3,0,1) with non-zero mean : Inf
##  ARIMA(3,0,2) with zero mean     : Inf
##  ARIMA(3,0,2) with non-zero mean : Inf
##  ARIMA(4,0,0) with zero mean     : 386.1892
##  ARIMA(4,0,0) with non-zero mean : 389.4585
##  ARIMA(4,0,1) with zero mean     : 385.245
##  ARIMA(4,0,1) with non-zero mean : 388.7446
##  ARIMA(5,0,0) with zero mean     : 384.5303
##  ARIMA(5,0,0) with non-zero mean : 388.1232
##
##
```

```
##
##  Best model: ARIMA(5,0,0) with zero mean
```

```
print(summary(fit_arima))
```

```
## Series: DYint
## ARIMA(5,0,0) with zero mean
##
## Coefficients:
##           ar1      ar2      ar3      ar4      ar5
##       -0.7946  -0.4558  -0.6206  -0.7829  -0.5411
## s.e.   0.1620   0.2278   0.1730   0.1854   0.2125
##
## sigma^2 estimated as 32811:  log likelihood=-184.27
## AIC=380.53   AICc=384.53   BIC=388.52
##
## Training set error measures:
##                     ME     RMSE      MAE     MPE     MAPE     MASE      ACF1
## Training set -9.999187 164.1709 130.4651 65.0792 298.6644 0.490402 -0.043742
```

```
checkresiduals(fit_arima)
```

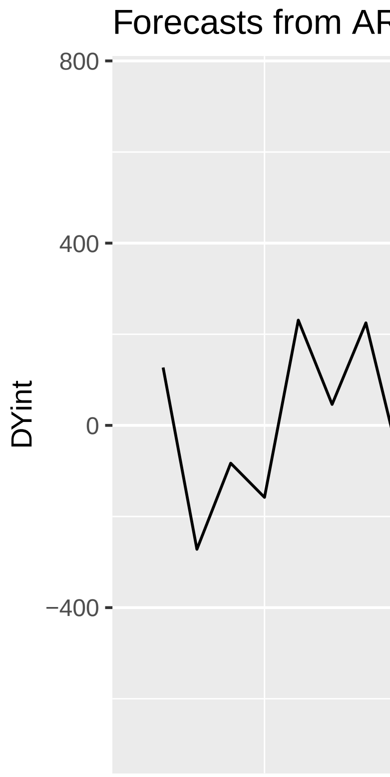



```
##
##  Ljung-Box test
```

```
##
## data:  Residuals from ARIMA(5,0,0) with zero mean
## Q* = 4.2149, df = 3, p-value = 0.2392
##
## Model df: 5.   Total lags used: 8
```

```
## Residuals = 182
## Residuals diff 2 = 290
```

```
fcast <- forecast(fit_arima, h=3)
autoplot(fcast)
```



The best model for this one is ARIMA, since the model had smallest residuals.

```
print(summary(fcast))
```

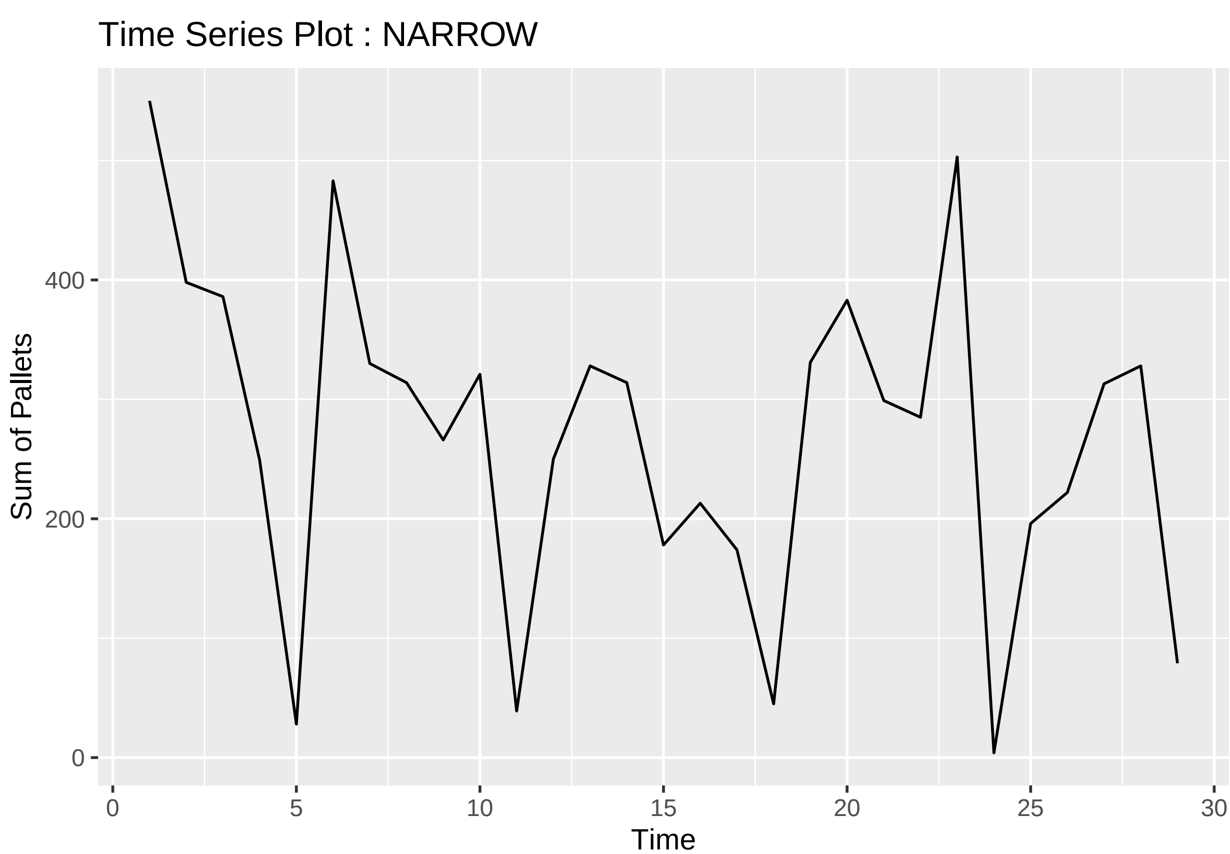
```
##
## Forecast method: ARIMA(5,0,0) with zero mean
##
## Model Information:
## Series: DYint
## ARIMA(5,0,0) with zero mean
##
## Coefficients:
```

```
##           ar1      ar2      ar3      ar4      ar5
##       -0.7946  -0.4558  -0.6206  -0.7829  -0.5411
## s.e.   0.1620   0.2278   0.1730   0.1854   0.2125
##
## sigma^2 estimated as 32811:  log likelihood=-184.27
## AIC=380.53   AICc=384.53   BIC=388.52
##
## Error measures:
##                     ME     RMSE      MAE     MPE     MAPE     MASE      ACF1
## Training set -9.999187 164.1709 130.4651 65.0792 298.6644 0.490402 -0.043742
##
## Forecasts:
##    Point Forecast      Lo 80    Hi 80     Lo 95    Hi 95
## 30       41.00802 -191.1305 273.1466 -314.0173 396.0333
## 31     -183.71492 -480.2114 112.7816 -637.1671 269.7373
## 32       80.49330 -218.7912 379.7778 -377.2228 538.2094
```

Forecast workload for next day with confidence 95% is 397 pallets.

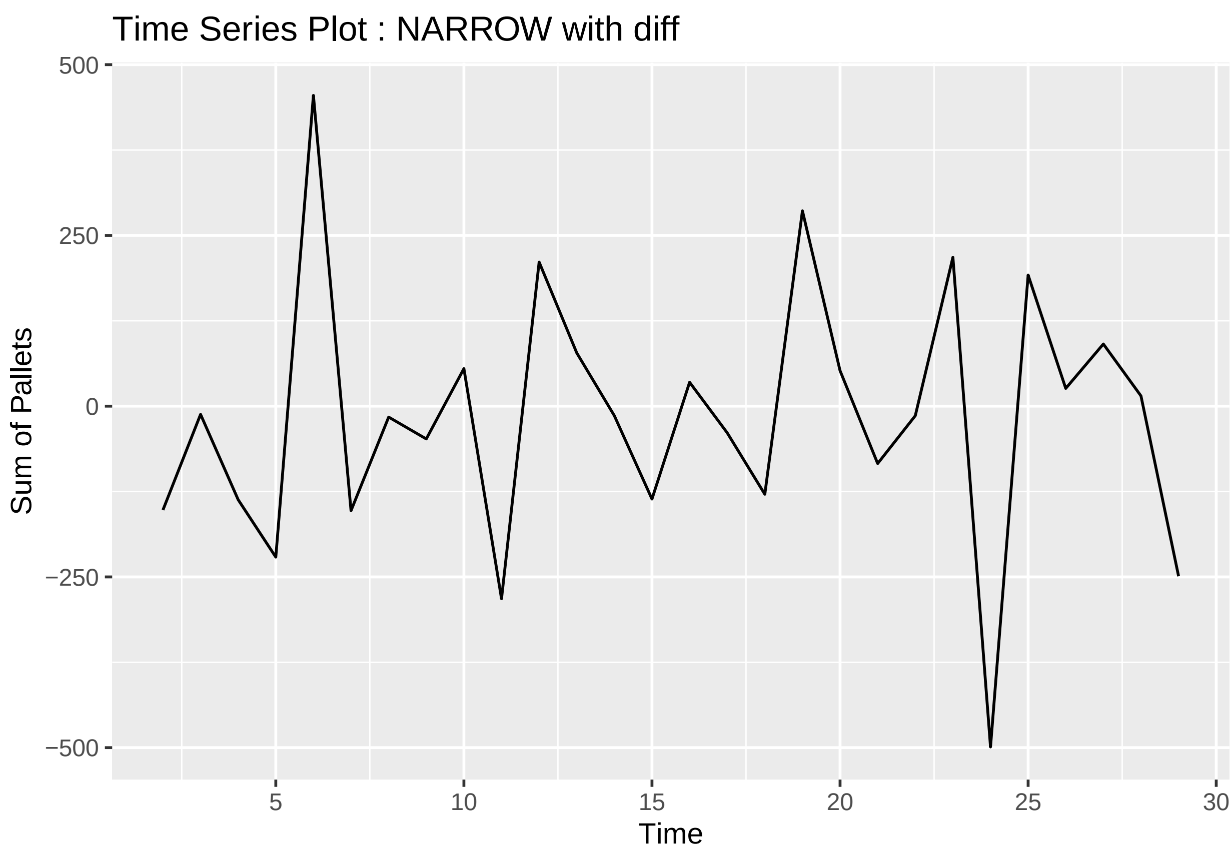
NARROW

```r
Ynar <- ts(df_prod[,5])
autoplot(Ynar) + ggtitle("Time Series Plot : NARROW") + ylab("Sum of Pallets")
```



As we can see, the data had a trend so we will made new data with added differencing method.

```
DYnar <- diff(Ynar)
autoplot(DYnar) + ggtitle("Time Series Plot : NARROW with diff") + ylab("Sum of Pallets")
```



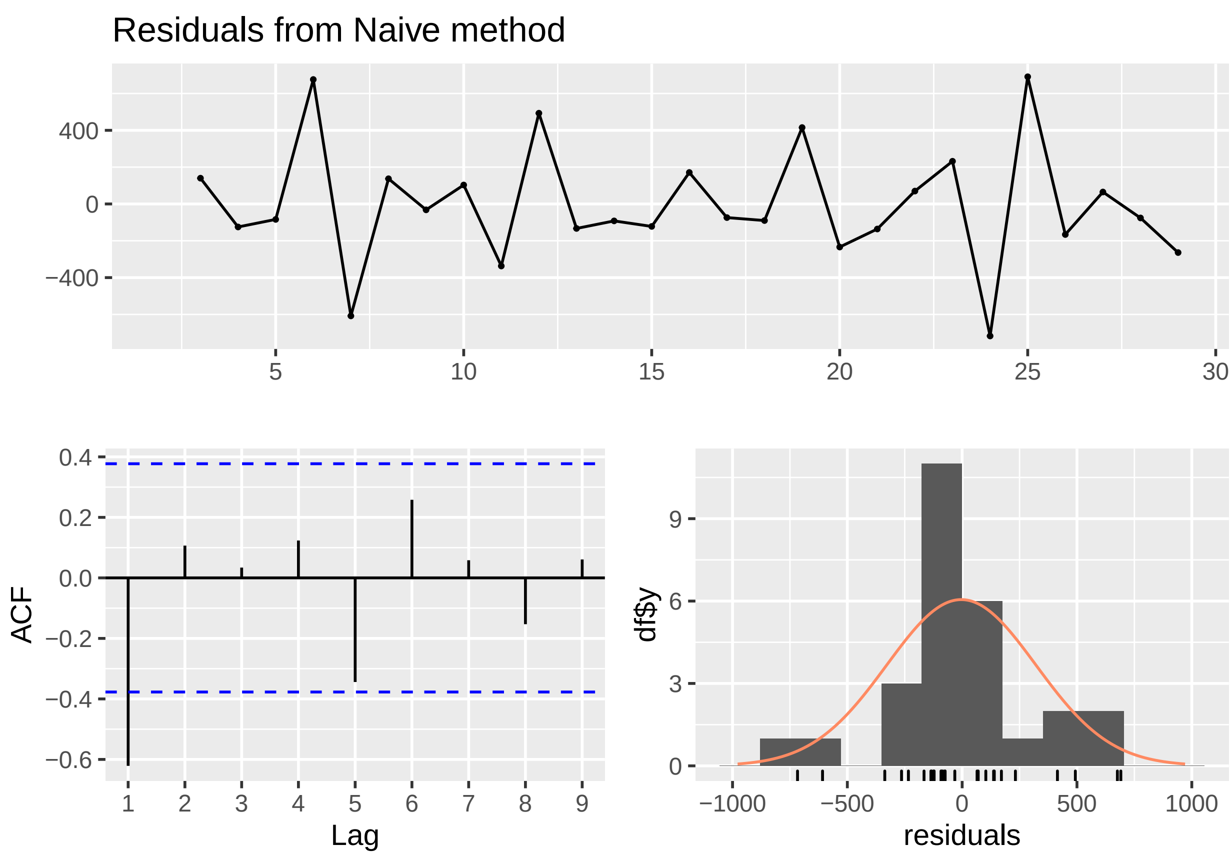
The data didn't have seasonal. So we could go to next step for determine best model.

```
fit <- naive(DYnar)
print(summary(fit))
```

```
##
## Forecast method: Naive method
##
## Model Information:
## Call: naive(y = DYnar)
##
## Residual sd: 318.7254
##
## Error measures:
##                     ME     RMSE      MAE       MPE     MAPE MASE       ACF1
## Training set -3.592593 318.7254 240.1111 -15.43925 302.2317    1 -0.6211844
##
## Forecasts:
##    Point Forecast       Lo 80     Hi 80      Lo 95     Hi 95
## 30           -249  -657.4631  159.4631  -873.6903  375.6903
## 31           -249  -826.6540  328.6540 -1132.4455  634.4455
```

```
## 32           -249  -956.4788  458.4788 -1330.9954  832.9954
## 33           -249 -1065.9261  567.9261 -1498.3807 1000.3807
## 34           -249 -1162.3512  664.3512 -1645.8500 1147.8500
## 35           -249 -1249.5261  751.5261 -1779.1726 1281.1726
## 36           -249 -1329.6917  831.6917 -1901.7753 1403.7753
## 37           -249 -1404.3080  906.3080 -2015.8911 1517.8911
## 38           -249 -1474.3892  976.3892 -2123.0710 1625.0710
## 39           -249 -1540.6736 1042.6736 -2224.4443 1726.4443
```

```
checkresiduals(fit)
```



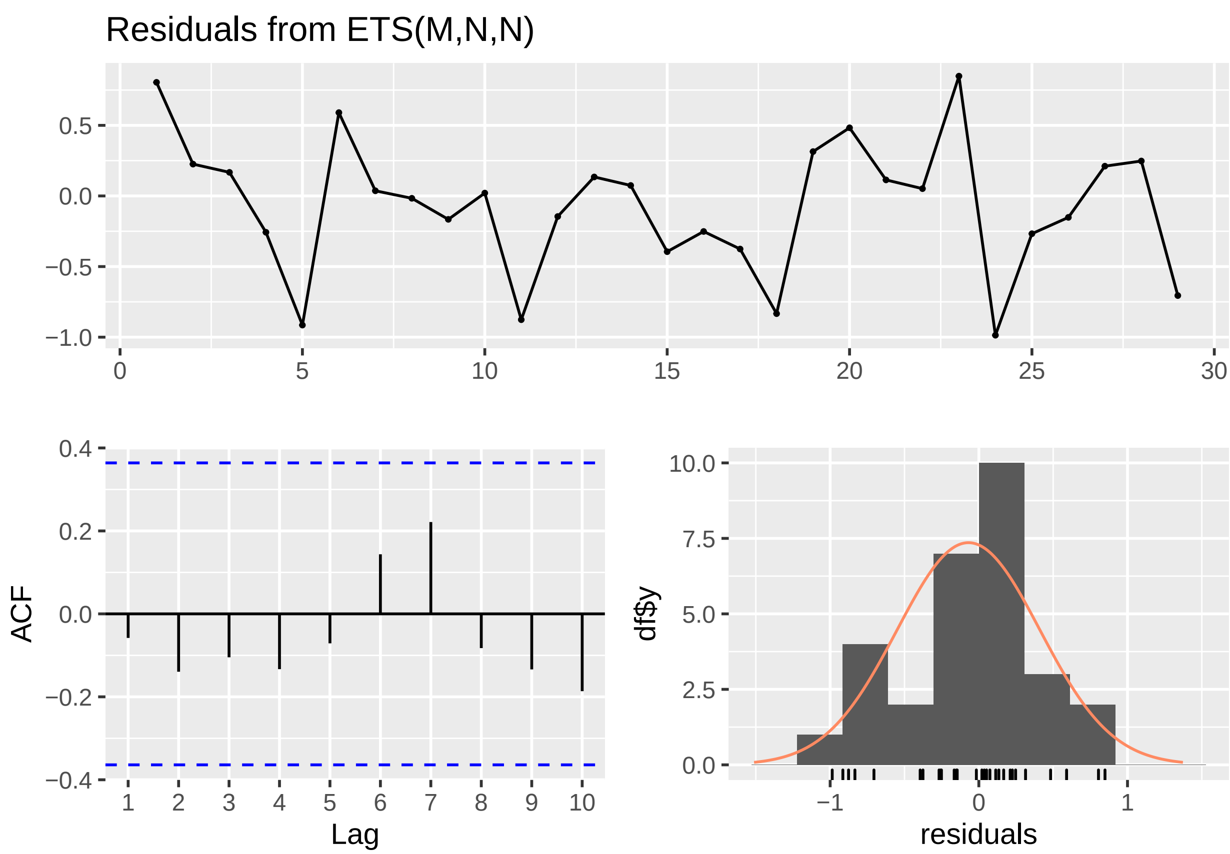

```
##
##  Ljung-Box test
##
## data:  Residuals from Naive method
## Q* = 19.231, df = 6, p-value = 0.00379
##
## Model df: 0.   Total lags used: 6
```

```
## Residuals = 319

fit_ets <- ets(Ynar)
print(summary(fit_ets))
```

```
## ETS(M,N,N)
```

```
##
## Call:
##  ets(y = Ynar)
##
##   Smoothing parameters:
##     alpha = 0.0815
##
##   Initial states:
##     l = 304.7504
##
##   sigma:  0.4949
##
##      AIC     AICc      BIC
## 389.6720 390.6320 393.7739
##
## Training set error measures:
##                     ME     RMSE      MAE       MPE    MAPE      MASE
## Training set -21.98114 140.1774 106.8587 -334.0034 354.247 0.7673871
##                     ACF1
## Training set -0.05882794
```

```
checkresiduals(fit_ets)
```




```
##
##  Ljung-Box test
```

```
##
## data:  Residuals from ETS(M,N,N)
## Q* = 2.769, df = 4, p-value = 0.5972
##
## Model df: 2.   Total lags used: 6
```

```r
## Residuals = 141

fit_arima <- auto.arima(DYnar, d=0, D=0, stepwise = FALSE, approximation = FALSE, trace = TRUE)
```

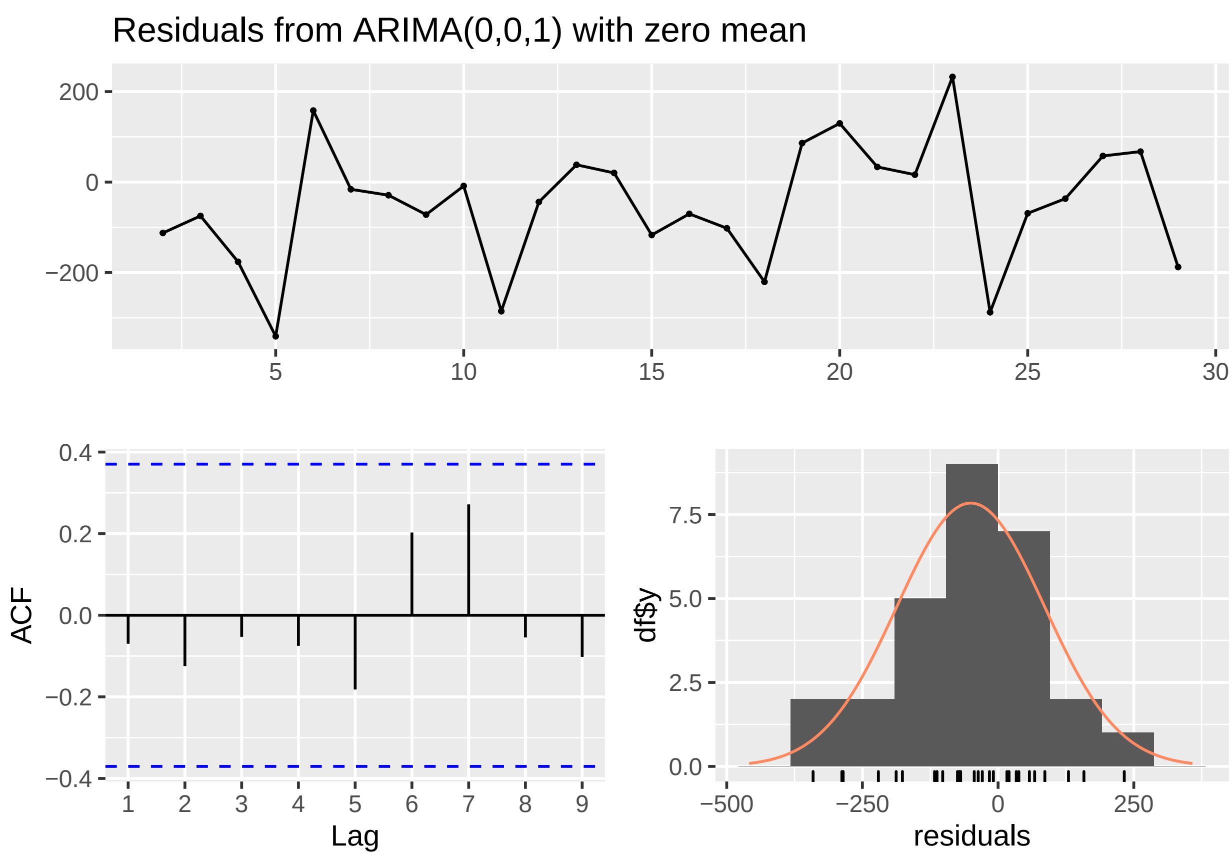
```
##
##  ARIMA(0,0,0) with zero mean     : 374.9054
##  ARIMA(0,0,0) with non-zero mean : 377.0069
##  ARIMA(0,0,1) with zero mean     : 363.5515
##  ARIMA(0,0,1) with non-zero mean : Inf
##  ARIMA(0,0,2) with zero mean     : 366.0704
##  ARIMA(0,0,2) with non-zero mean : Inf
##  ARIMA(0,0,3) with zero mean     : 368.3514
##  ARIMA(0,0,3) with non-zero mean : Inf
##  ARIMA(0,0,4) with zero mean     : 370.9155
##  ARIMA(0,0,4) with non-zero mean : Inf
##  ARIMA(0,0,5) with zero mean     : 374.2351
##  ARIMA(0,0,5) with non-zero mean : Inf
##  ARIMA(1,0,0) with zero mean     : 371.263
##  ARIMA(1,0,0) with non-zero mean : 373.4562
##  ARIMA(1,0,1) with zero mean     : 366.0706
##  ARIMA(1,0,1) with non-zero mean : Inf
##  ARIMA(1,0,2) with zero mean     : Inf
##  ARIMA(1,0,2) with non-zero mean : Inf
##  ARIMA(1,0,3) with zero mean     : 371.0632
##  ARIMA(1,0,3) with non-zero mean : Inf
##  ARIMA(1,0,4) with zero mean     : 374.1296
##  ARIMA(1,0,4) with non-zero mean : Inf
##  ARIMA(2,0,0) with zero mean     : 370.9493
##  ARIMA(2,0,0) with non-zero mean : 373.2621
##  ARIMA(2,0,1) with zero mean     : 368.5785
##  ARIMA(2,0,1) with non-zero mean : Inf
##  ARIMA(2,0,2) with zero mean     : 370.7768
##  ARIMA(2,0,2) with non-zero mean : Inf
##  ARIMA(2,0,3) with zero mean     : Inf
##  ARIMA(2,0,3) with non-zero mean : Inf
##  ARIMA(3,0,0) with zero mean     : 372.652
##  ARIMA(3,0,0) with non-zero mean : 375.1513
##  ARIMA(3,0,1) with zero mean     : 371.2719
##  ARIMA(3,0,1) with non-zero mean : Inf
##  ARIMA(3,0,2) with zero mean     : 373.8208
##  ARIMA(3,0,2) with non-zero mean : Inf
##  ARIMA(4,0,0) with zero mean     : 374.6992
##  ARIMA(4,0,0) with non-zero mean : 377.4779
##  ARIMA(4,0,1) with zero mean     : 373.5868
##  ARIMA(4,0,1) with non-zero mean : Inf
##  ARIMA(5,0,0) with zero mean     : 372.6809
##  ARIMA(5,0,0) with non-zero mean : 375.001
##
```

```
##
##
##  Best model: ARIMA(0,0,1) with zero mean
```

```r
print(summary(fit_arima))
```

```
## Series: DYnar
## ARIMA(0,0,1) with zero mean
##
## Coefficients:
##           ma1
##       -0.9082
## s.e.   0.1331
##
## sigma^2 estimated as 21171:  log likelihood=-179.54
## AIC=363.07   AICc=363.55   BIC=365.74
##
## Training set error measures:
##                     ME     RMSE     MAE      MPE     MAPE      MASE        ACF1
## Training set -50.39227 142.8822 110.373 83.67381 134.7339 0.4596746 -0.06983265
```

```r
checkresiduals(fit_arima)
```



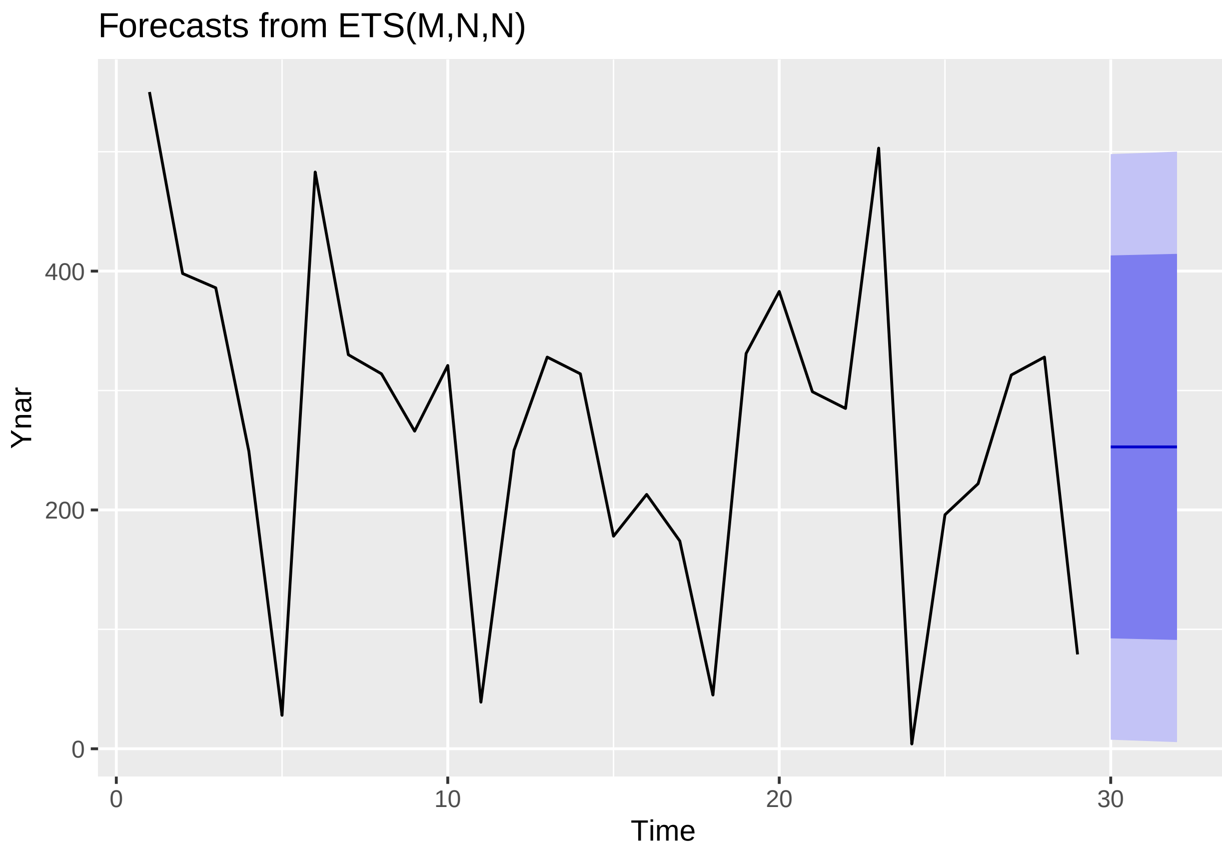

```
##
```

```
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,0,1) with zero mean
## Q* = 3.7225, df = 5, p-value = 0.59
##
## Model df: 1.   Total lags used: 6
```

```
## Residuals = 145
## Residuals diff 2 = 154
```

```
fcast <- forecast(fit_ets, h=3)
autoplot(fcast)
```

The best model for this one is Exponential Smoothing, since the model had smallest residuals.




```
print(summary(fcast))
```

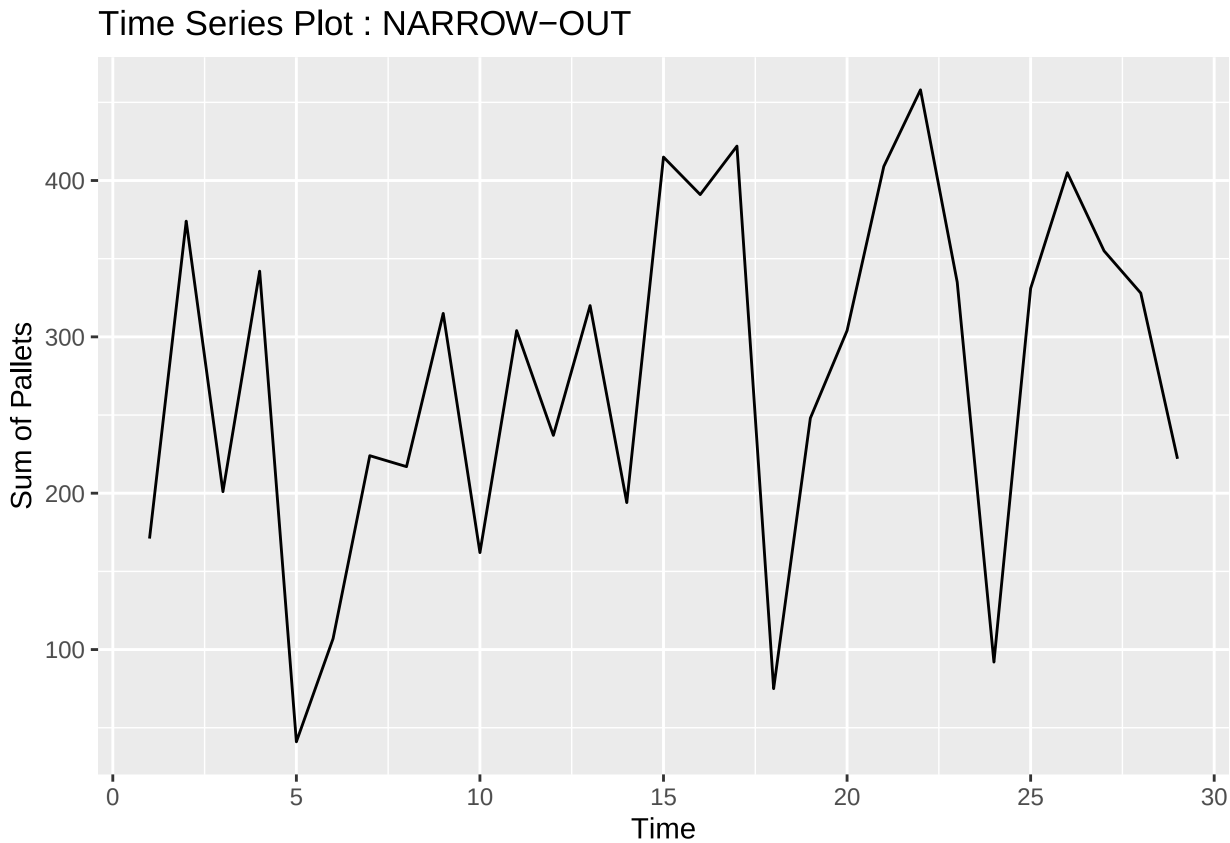
```
##
## Forecast method: ETS(M,N,N)
##
## Model Information:
## ETS(M,N,N)
##
```

```
## Call:
##  ets(y = Ynar)
##
##   Smoothing parameters:
##     alpha = 0.0815
##
##   Initial states:
##     l = 304.7504
##
##   sigma:  0.4949
##
##      AIC     AICc      BIC
## 389.6720 390.6320 393.7739
##
## Error measures:
##                     ME     RMSE      MAE       MPE    MAPE      MASE
## Training set -21.98114 140.1774 106.8587 -334.0034 354.247 0.7673871
##                     ACF1
## Training set -0.05882794
##
## Forecasts:
##    Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## 30       252.7992 92.46699 413.1315 7.592221 498.0062
## 31       252.7992 91.80548 413.7930 6.580543 499.0179
## 32       252.7992 91.14562 414.4528 5.571370 500.0271
```

Forecast workload for next day with confidence 95% is 498 pallets.

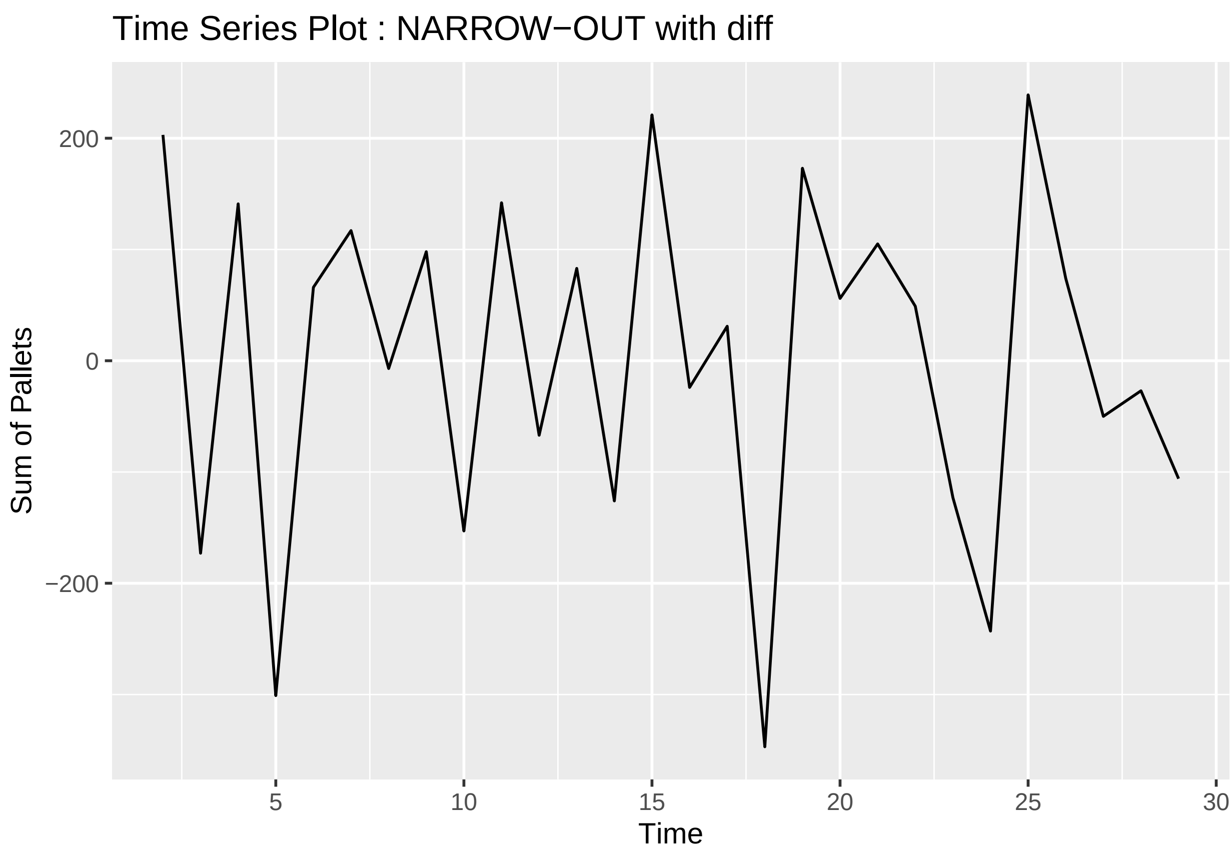
NARROW-OUT

```
Ynao <- ts(df_prod[,6])
autoplot(Ynao) + ggtitle("Time Series Plot : NARROW-OUT") + ylab("Sum of Pallets")
```



As we can see, the data had a trend so we will made new data with added differencing method.

```
DYnao <- diff(Ynao)
autoplot(DYnao) + ggtitle("Time Series Plot : NARROW-OUT with diff") + ylab("Sum of Pallets")
```



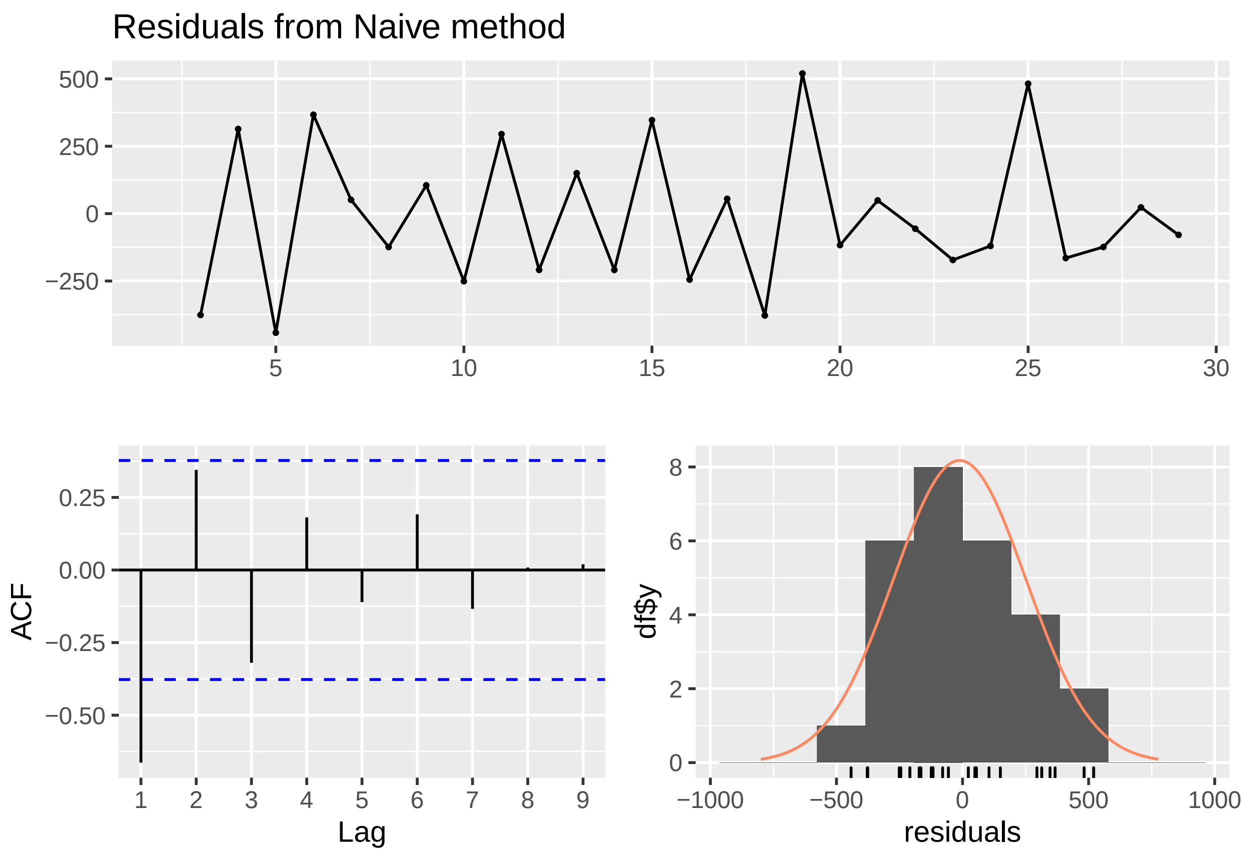
The data didn't have seasonal. So we could go to next step for determine best model.

```r
fit <- naive(DYnao)
print(summary(fit))
```

```
##
## Forecast method: Naive method
##
## Model Information:
## Call: naive(y = DYnao)
##
## Residual sd: 258.2393
##
## Error measures:
##                     ME     RMSE      MAE      MPE     MAPE MASE       ACF1
## Training set -11.44444 258.2393 215.7407 221.8123 268.5806    1 -0.6632595
##
## Forecasts:
##    Point Forecast      Lo 80    Hi 80      Lo 95     Hi 95
## 30           -106  -436.9469 224.9469  -612.1397  400.1397
## 31           -106  -574.0296 362.0296  -821.7896  609.7896
## 32           -106  -679.2169 467.2169  -982.6596  770.6596
## 33           -106  -767.8939 555.8939 -1118.2793  906.2793
## 34           -106  -846.0198 634.0198 -1237.7627 1025.7627
## 35           -106  -916.6511 704.6511 -1345.7839 1133.7839
## 36           -106  -981.6033 769.6033 -1445.1197 1233.1197
```

```
## 37          -106 -1042.0593 830.0593 -1537.5791 1325.5791
## 38          -106 -1098.8408 886.8408 -1624.4190 1412.4190
## 39          -106 -1152.5461 940.5461 -1706.5541 1494.5541
```

```
checkresiduals(fit)
```



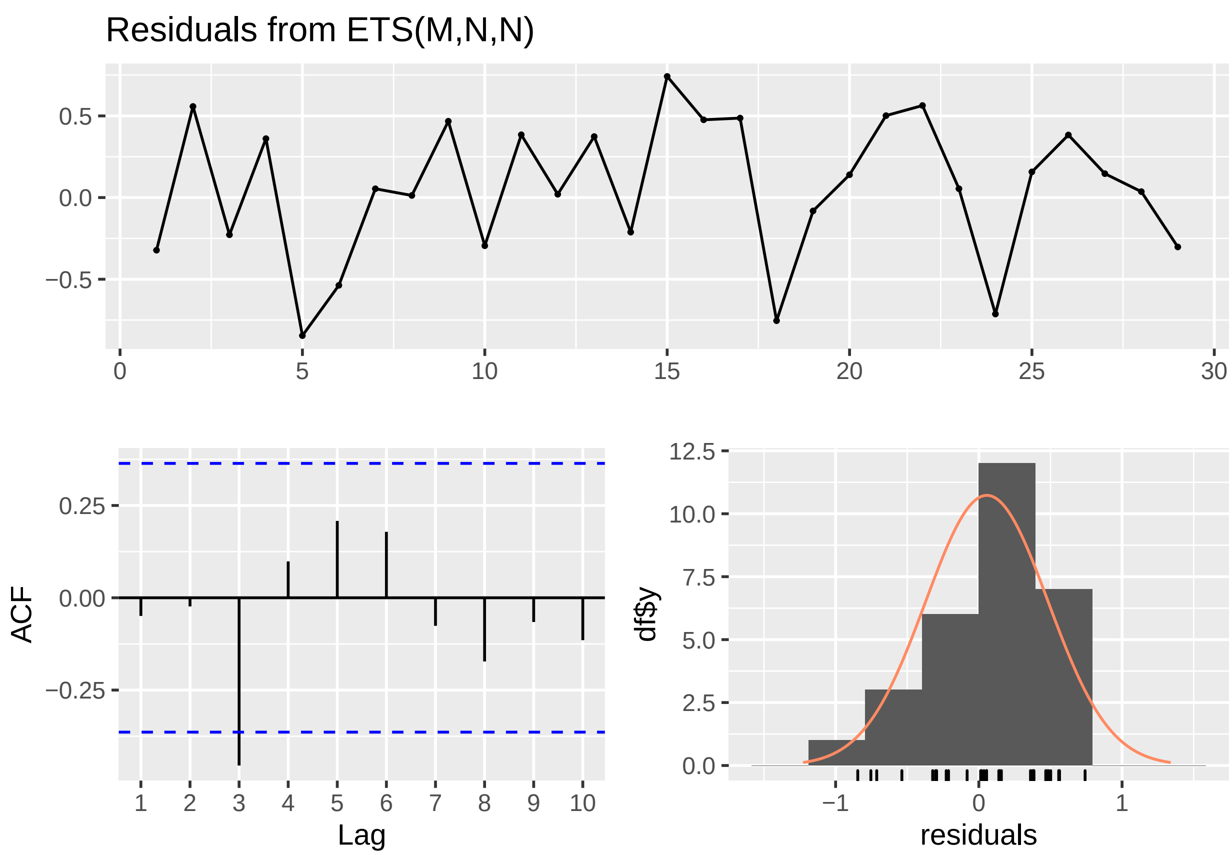

```
##
##  Ljung-Box test
##
## data:  Residuals from Naive method
## Q* = 23.229, df = 6, p-value = 0.0007231
##
## Model df: 0.   Total lags used: 6
```

```
## Residuals = 258

fit_ets <- ets(Ynao)
print(summary(fit_ets))
```

```
## ETS(M,N,N)
##
## Call:
##  ets(y = Ynao)
##
```

```
##   Smoothing parameters:
##     alpha = 0.1506
##
##   Initial states:
##     l = 252.3288
##
##   sigma:  0.4395
##
##      AIC     AICc      BIC
## 376.8314 377.7914 380.9333
##
## Training set error measures:
##                    ME     RMSE      MAE       MPE     MAPE      MASE       ACF1
## Training set 11.77107 114.3812 93.50058 -34.66927 62.90946 0.7385095 -0.0304693
```

```
checkresiduals(fit_ets)
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ETS(M,N,N)
## Q* = 10.451, df = 4, p-value = 0.03348
##
## Model df: 2.   Total lags used: 6
```

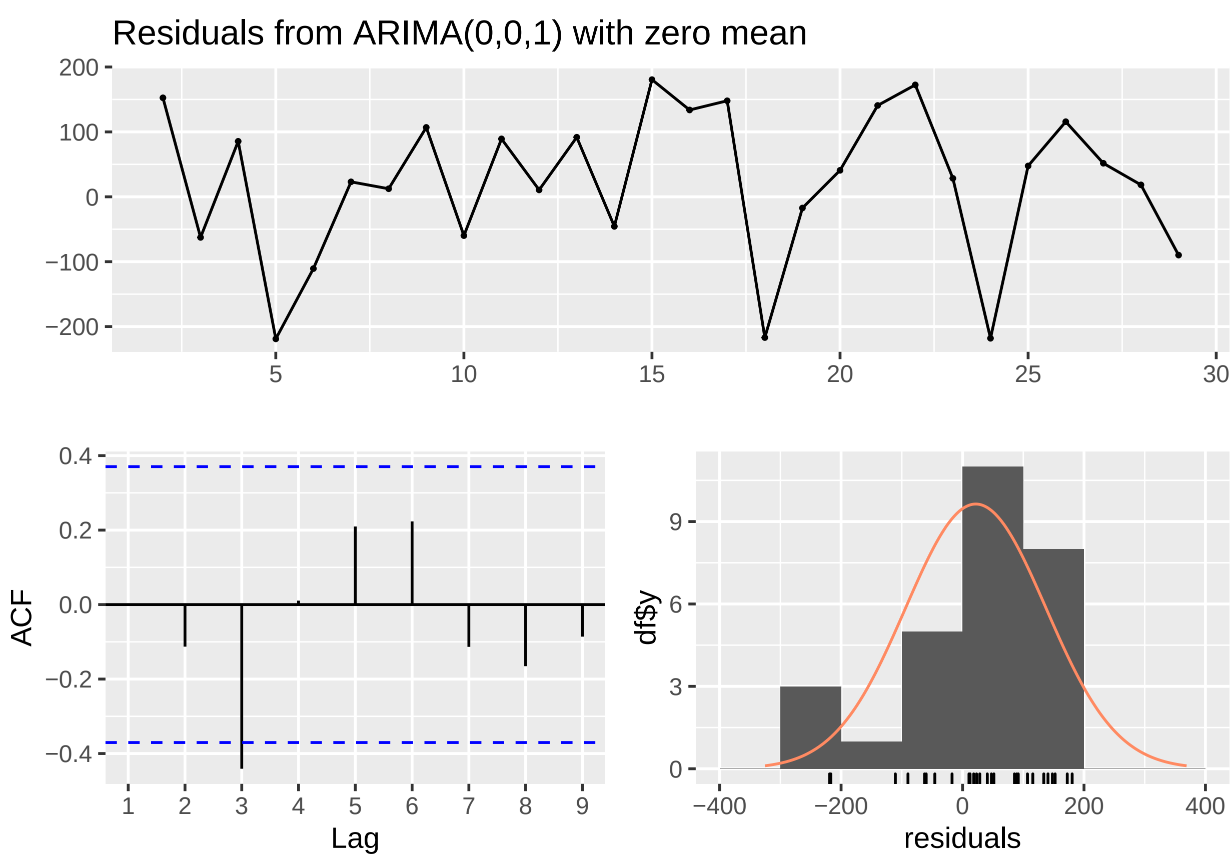
```r
## Residuals = 115

fit_arima <- auto.arima(DYnao, d=0, D=0, stepwise = FALSE, approximation = FALSE, trace = TRUE)
```

```
##
##  ARIMA(0,0,0) with zero mean     : 363.0274
##  ARIMA(0,0,0) with non-zero mean : 365.3495
##  ARIMA(0,0,1) with zero mean     : 351.481
##  ARIMA(0,0,1) with non-zero mean : Inf
##  ARIMA(0,0,2) with zero mean     : 353.9491
##  ARIMA(0,0,2) with non-zero mean : Inf
##  ARIMA(0,0,3) with zero mean     : 356.6401
##  ARIMA(0,0,3) with non-zero mean : Inf
##  ARIMA(0,0,4) with zero mean     : 354.5678
##  ARIMA(0,0,4) with non-zero mean : Inf
##  ARIMA(0,0,5) with zero mean     : 357.6135
##  ARIMA(0,0,5) with non-zero mean : Inf
##  ARIMA(1,0,0) with zero mean     : 359.3538
##  ARIMA(1,0,0) with non-zero mean : 361.872
##  ARIMA(1,0,1) with zero mean     : 353.9517
##  ARIMA(1,0,1) with non-zero mean : Inf
##  ARIMA(1,0,2) with zero mean     : 356.507
##  ARIMA(1,0,2) with non-zero mean : Inf
##  ARIMA(1,0,3) with zero mean     : 357.6112
##  ARIMA(1,0,3) with non-zero mean : Inf
##  ARIMA(1,0,4) with zero mean     : 357.7495
##  ARIMA(1,0,4) with non-zero mean : Inf
##  ARIMA(2,0,0) with zero mean     : 361.6924
##  ARIMA(2,0,0) with non-zero mean : 364.4281
##  ARIMA(2,0,1) with zero mean     : 356.6336
##  ARIMA(2,0,1) with non-zero mean : Inf
##  ARIMA(2,0,2) with zero mean     : 358.8136
##  ARIMA(2,0,2) with non-zero mean : Inf
##  ARIMA(2,0,3) with zero mean     : Inf
##  ARIMA(2,0,3) with non-zero mean : Inf
##  ARIMA(3,0,0) with zero mean     : 355.6691
##  ARIMA(3,0,0) with non-zero mean : 358.6216
##  ARIMA(3,0,1) with zero mean     : 352.4765
##  ARIMA(3,0,1) with non-zero mean : Inf
##  ARIMA(3,0,2) with zero mean     : Inf
##  ARIMA(3,0,2) with non-zero mean : Inf
##  ARIMA(4,0,0) with zero mean     : 353.5541
##  ARIMA(4,0,0) with non-zero mean : 356.555
##  ARIMA(4,0,1) with zero mean     : 354.8143
##  ARIMA(4,0,1) with non-zero mean : Inf
##  ARIMA(5,0,0) with zero mean     : 354.5209
##  ARIMA(5,0,0) with non-zero mean : 357.4728
##
##
##
##  Best model: ARIMA(0,0,1) with zero mean
```

```r
print(summary(fit_arima))
```

```
## Series: DYnao
## ARIMA(0,0,1) with zero mean
##
## Coefficients:
##           ma1
##       -0.8785
## s.e.   0.1008
##
## sigma^2 estimated as 13886:  log likelihood=-173.5
## AIC=351   AICc=351.48   BIC=353.67
##
## Training set error measures:
##                    ME    RMSE      MAE      MPE     MAPE      MASE         ACF1
## Training set 21.78474 115.716 96.05438 36.82666 116.9731 0.4452306 -0.002699795
```

```r
checkresiduals(fit_arima)
```



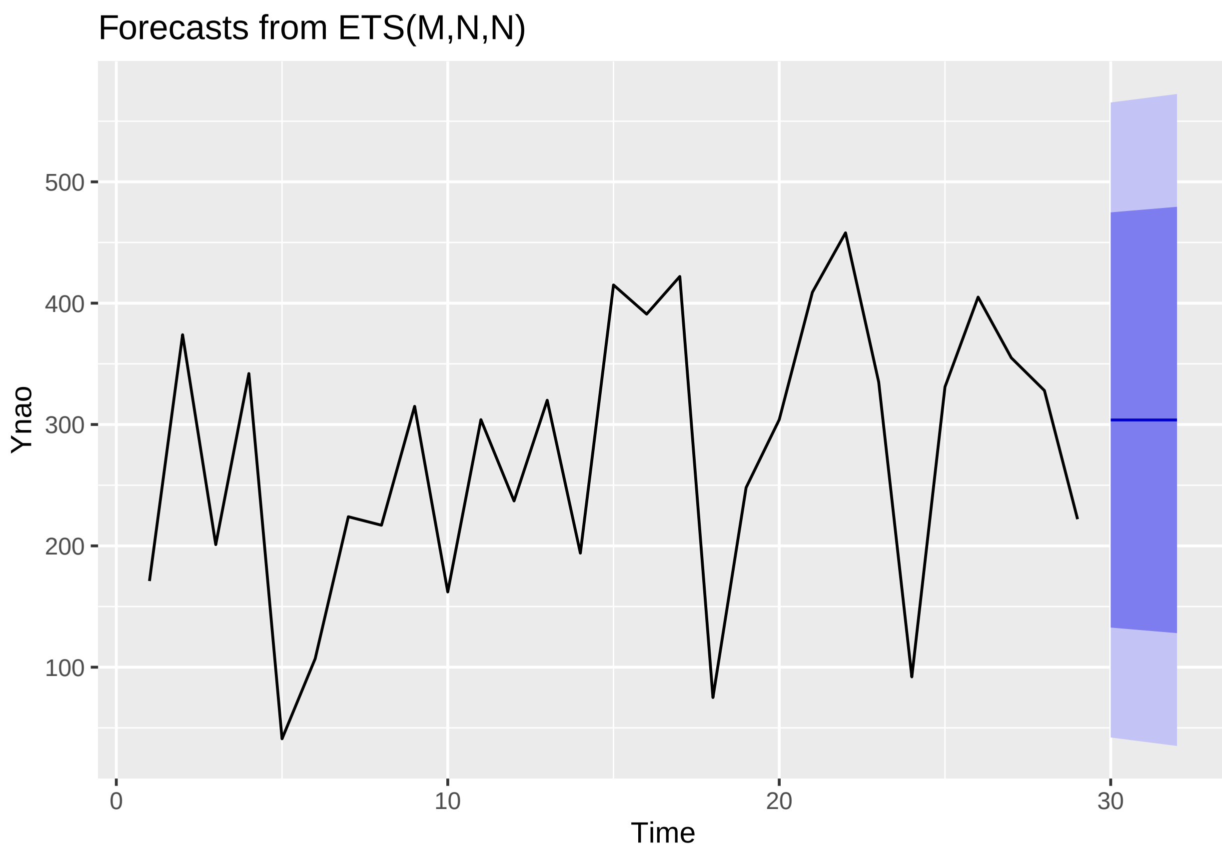

```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,0,1) with zero mean
## Q* = 10.456, df = 5, p-value = 0.0633
```

```
##
## Model df: 1.   Total lags used: 6
```

```
## Residuals = 118
## Residuals diff 2 = 137
```

```
fcast <- forecast(fit_ets, h=3)
autoplot(fcast)
```

The best model for this one is Exponential Smoothing, since the model had smallest residuals.




```
print(summary(fcast))
```

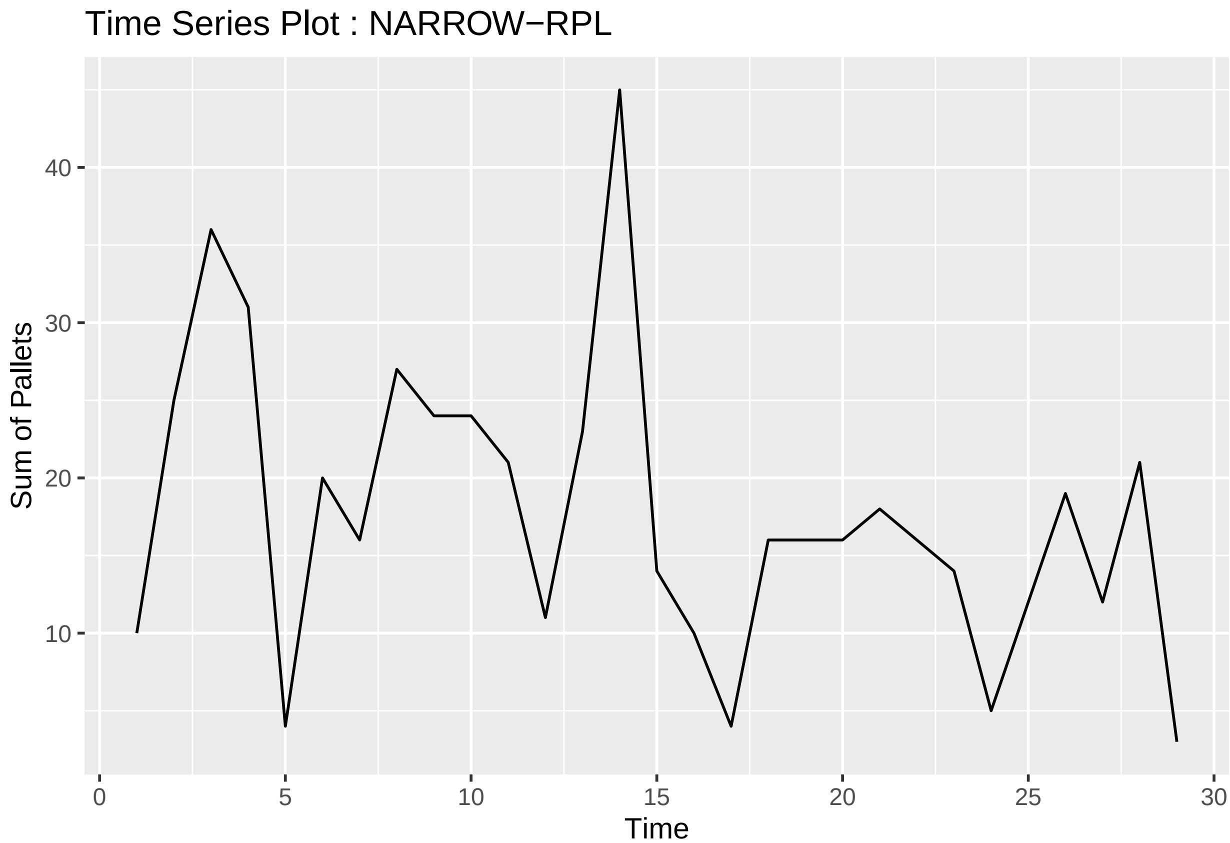
```
##
## Forecast method: ETS(M,N,N)
##
## Model Information:
## ETS(M,N,N)
##
## Call:
##  ets(y = Ynao)
##
##   Smoothing parameters:
```

```
##     alpha = 0.1506
##
##   Initial states:
##     l = 252.3288
##
##   sigma:  0.4395
##
##      AIC     AICc      BIC
## 376.8314 377.7914 380.9333
##
## Error measures:
##                    ME     RMSE      MAE       MPE     MAPE      MASE       ACF1
## Training set 11.77107 114.3812 93.50058 -34.66927 62.90946 0.7385095 -0.0304693
##
## Forecasts:
##    Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## 30       303.7399 132.6573 474.8225 42.09159 565.3881
## 31       303.7399 130.3576 477.1221 38.57465 568.9051
## 32       303.7399 128.0783 479.4014 35.08864 572.3911
```

Forecast workload for next day with confidence 95% is 565 pallets.

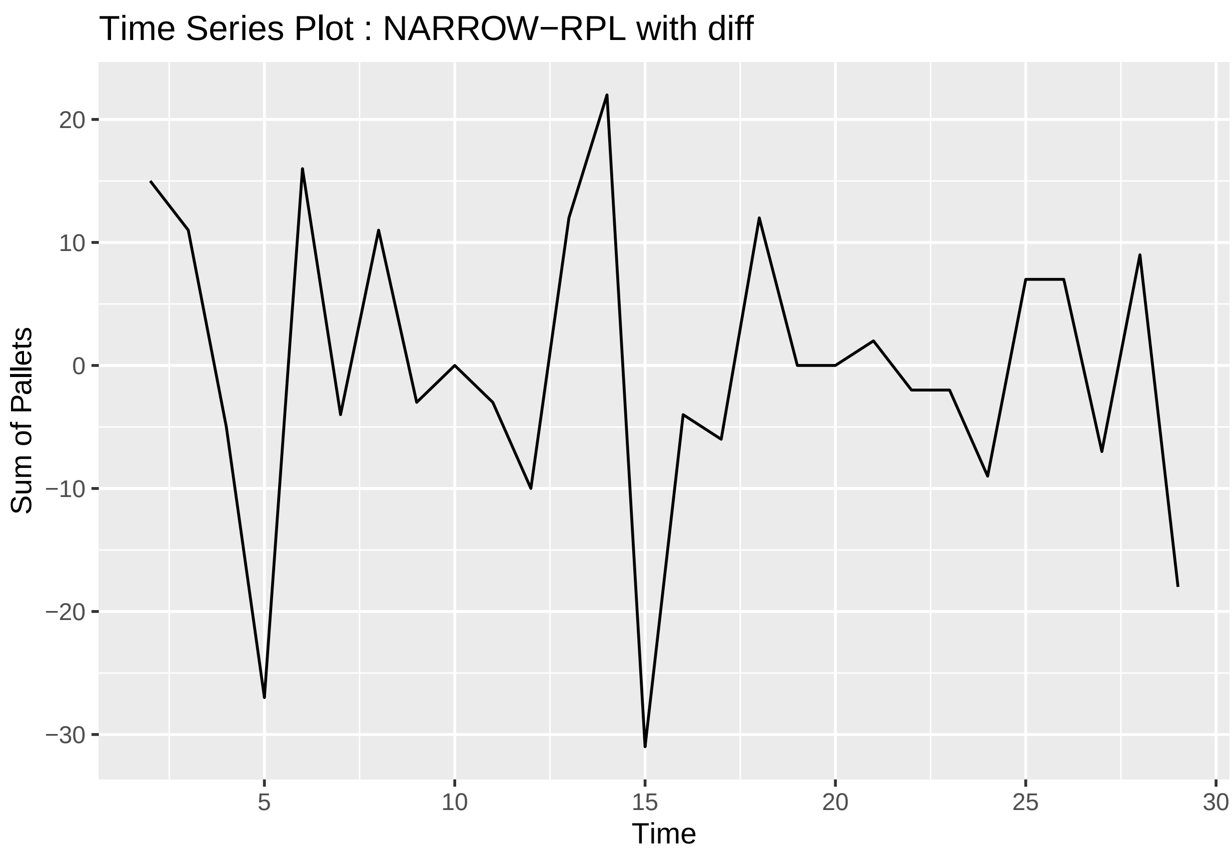
NARROW-RPL

```
Ynarp <- ts(df_prod[,7])
autoplot(Ynarp) + ggtitle("Time Series Plot : NARROW-RPL") + ylab("Sum of Pallets")
```



As we can see, the data had a trend so we will made new data with added differencing method.

```
DYnarp <- diff(Ynarp)
autoplot(DYnarp) + ggtitle("Time Series Plot : NARROW-RPL with diff") + ylab("Sum of Pallets")
```



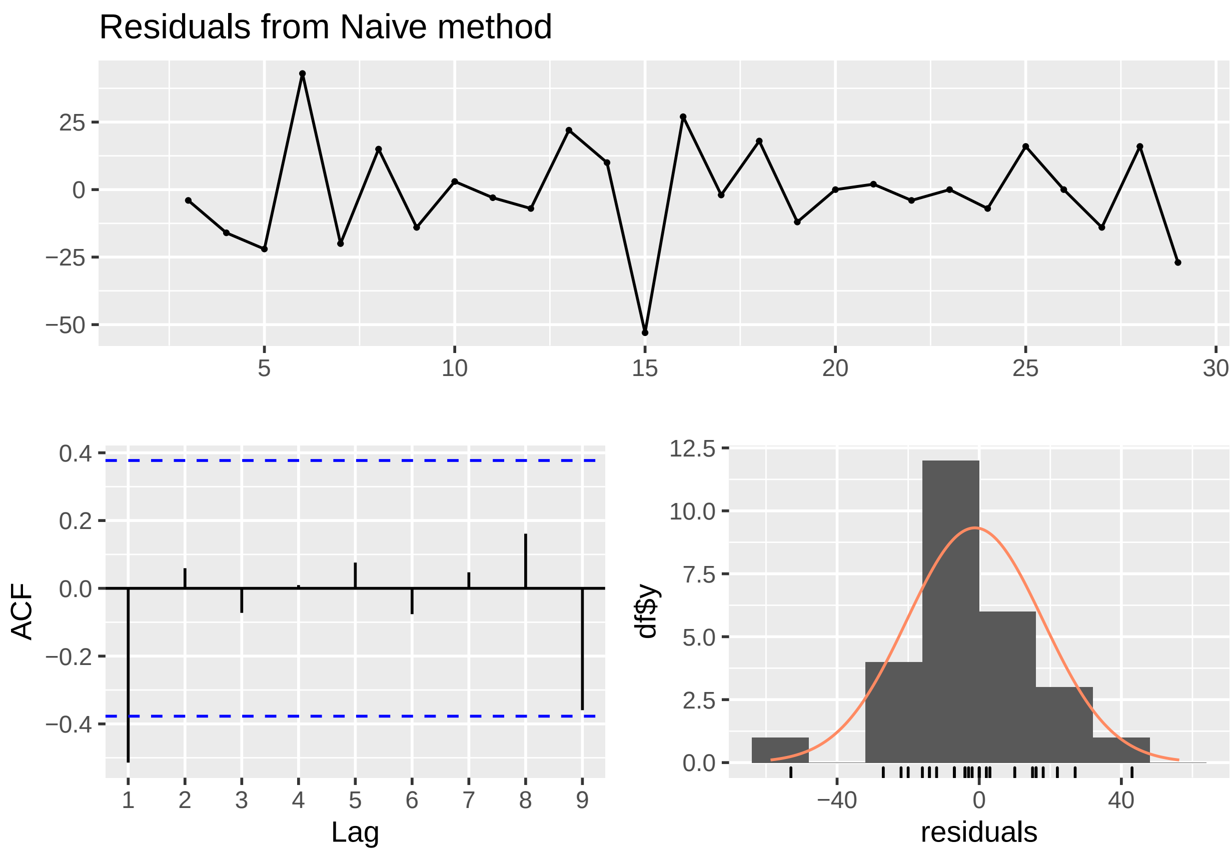
The data didn't have seasonal. So we could go to next step for determine best model.

```r
fit <- naive(DYnarp)
print(summary(fit))
```

```
##
## Forecast method: Naive method
##
## Model Information:
## Call: naive(y = DYnarp)
##
## Residual sd: 18.8493
##
## Error measures:
##                     ME    RMSE      MAE MPE MAPE MASE       ACF1
## Training set -1.222222 18.8493 13.96296 NaN  Inf    1 -0.5140908
##
## Forecasts:
##    Point Forecast      Lo 80     Hi 80      Lo 95    Hi 95
## 30            -18 -42.15636  6.156356  -54.94396 18.94396
## 31            -18 -52.16225 16.162247  -70.24665 34.24665
## 32            -18 -59.84004 23.840036  -81.98881 45.98881
## 33            -18 -66.31271 30.312712  -91.88792 55.88792
## 34            -18 -72.01525 36.015255 -100.60920 64.60920
## 35            -18 -77.17075 41.170747 -108.49385 72.49385
## 36            -18 -81.91171 45.911711 -115.74453 79.74453
```

```
## 37             -18 -86.32449 50.324493 -122.49330 86.49330
## 38             -18 -90.46907 54.469069 -128.83188 92.83188
## 39             -18 -94.38911 58.389106 -134.82706 98.82706
```

```
checkresiduals(fit)
```



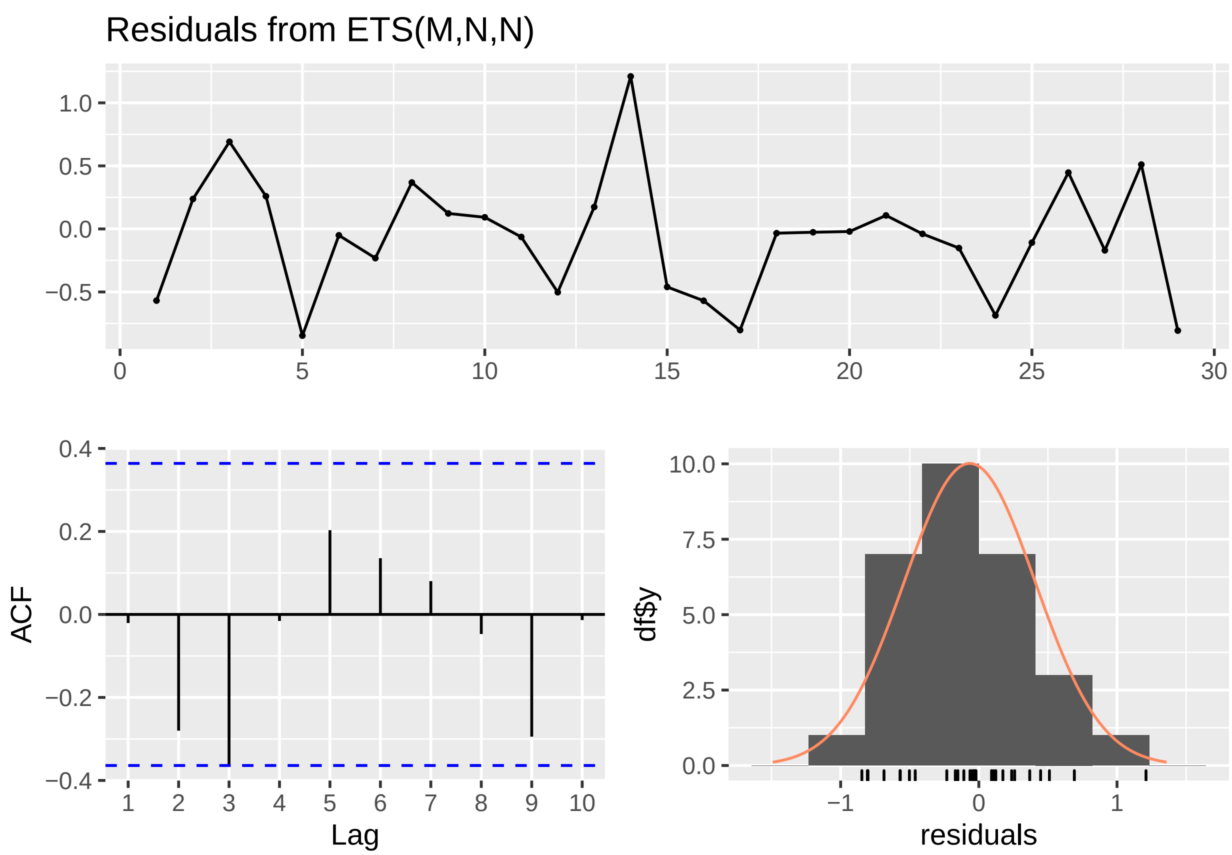

```
##
##  Ljung-Box test
##
## data:  Residuals from Naive method
## Q* = 8.6652, df = 6, p-value = 0.1933
##
## Model df: 0.   Total lags used: 6
```

```
## Residuals = 19

fit_ets <- ets(Ynarp)
print(summary(fit_ets))
```

```
## ETS(M,N,N)
##
## Call:
##  ets(y = Ynarp)
##
```

```
##   Smoothing parameters:
##     alpha = 0.2265
##
##   Initial states:
##     l = 23.1859
##
##   sigma:  0.4887
##
##      AIC     AICc      BIC
## 230.6277 231.5877 234.7296
##
## Training set error measures:
##                     ME    RMSE      MAE       MPE    MAPE      MASE        ACF1
## Training set -1.600123 9.71009 7.156168 -64.77056 83.4509 0.7857754 0.001605747
```

```
checkresiduals(fit_ets)
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ETS(M,N,N)
## Q* = 9.4343, df = 4, p-value = 0.05112
##
## Model df: 2.   Total lags used: 6
```

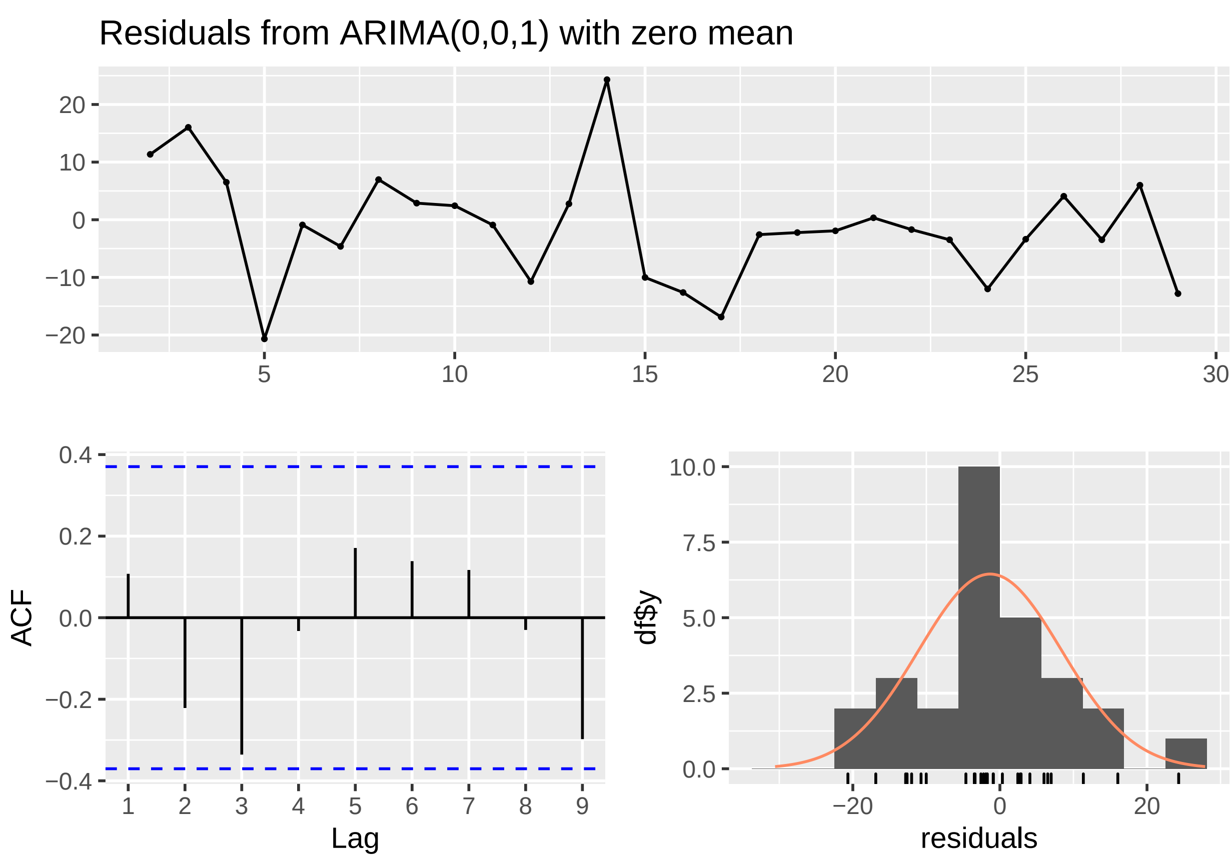
```r
## Residuals = 10

fit_arima <- auto.arima(DYnarp, d=0, D=0, stepwise = FALSE, approximation = FALSE, trace = TRUE)
```

```
##
##  ARIMA(0,0,0) with zero mean     : 220.8316
##  ARIMA(0,0,0) with non-zero mean : 223.1456
##  ARIMA(0,0,1) with zero mean     : 212.3392
##  ARIMA(0,0,1) with non-zero mean : Inf
##  ARIMA(0,0,2) with zero mean     : 214.2699
##  ARIMA(0,0,2) with non-zero mean : Inf
##  ARIMA(0,0,3) with zero mean     : 215.1882
##  ARIMA(0,0,3) with non-zero mean : Inf
##  ARIMA(0,0,4) with zero mean     : 215.244
##  ARIMA(0,0,4) with non-zero mean : Inf
##  ARIMA(0,0,5) with zero mean     : 218.4894
##  ARIMA(0,0,5) with non-zero mean : Inf
##  ARIMA(1,0,0) with zero mean     : 221.0566
##  ARIMA(1,0,0) with non-zero mean : 223.5586
##  ARIMA(1,0,1) with zero mean     : 214.5161
##  ARIMA(1,0,1) with non-zero mean : Inf
##  ARIMA(1,0,2) with zero mean     : 216.9186
##  ARIMA(1,0,2) with non-zero mean : Inf
##  ARIMA(1,0,3) with zero mean     : Inf
##  ARIMA(1,0,3) with non-zero mean : Inf
##  ARIMA(1,0,4) with zero mean     : 218.506
##  ARIMA(1,0,4) with non-zero mean : Inf
##  ARIMA(2,0,0) with zero mean     : 221.398
##  ARIMA(2,0,0) with non-zero mean : 224.0633
##  ARIMA(2,0,1) with zero mean     : 215.3222
##  ARIMA(2,0,1) with non-zero mean : Inf
##  ARIMA(2,0,2) with zero mean     : 215.2461
##  ARIMA(2,0,2) with non-zero mean : Inf
##  ARIMA(2,0,3) with zero mean     : Inf
##  ARIMA(2,0,3) with non-zero mean : Inf
##  ARIMA(3,0,0) with zero mean     : 217.6902
##  ARIMA(3,0,0) with non-zero mean : 220.3838
##  ARIMA(3,0,1) with zero mean     : 214.9358
##  ARIMA(3,0,1) with non-zero mean : Inf
##  ARIMA(3,0,2) with zero mean     : 217.4868
##  ARIMA(3,0,2) with non-zero mean : Inf
##  ARIMA(4,0,0) with zero mean     : 217.0408
##  ARIMA(4,0,0) with non-zero mean : 219.8487
##  ARIMA(4,0,1) with zero mean     : 217.7064
##  ARIMA(4,0,1) with non-zero mean : Inf
##  ARIMA(5,0,0) with zero mean     : 218.8104
##  ARIMA(5,0,0) with non-zero mean : 221.5541
##
##
##
##  Best model: ARIMA(0,0,1) with zero mean
```

```r
print(summary(fit_arima))
```

```
## Series: DYnarp
## ARIMA(0,0,1) with zero mean
##
## Coefficients:
##           ma1
##       -0.8649
## s.e.   0.0962
##
## sigma^2 estimated as 96.82:  log likelihood=-103.93
## AIC=211.86   AICc=212.34   BIC=214.52
##
## Training set error measures:
##                     ME     RMSE      MAE MPE MAPE      MASE      ACF1
## Training set -1.331623 9.662178 7.306235 NaN  Inf 0.5232582 0.1075793
```

```r
checkresiduals(fit_arima)
```



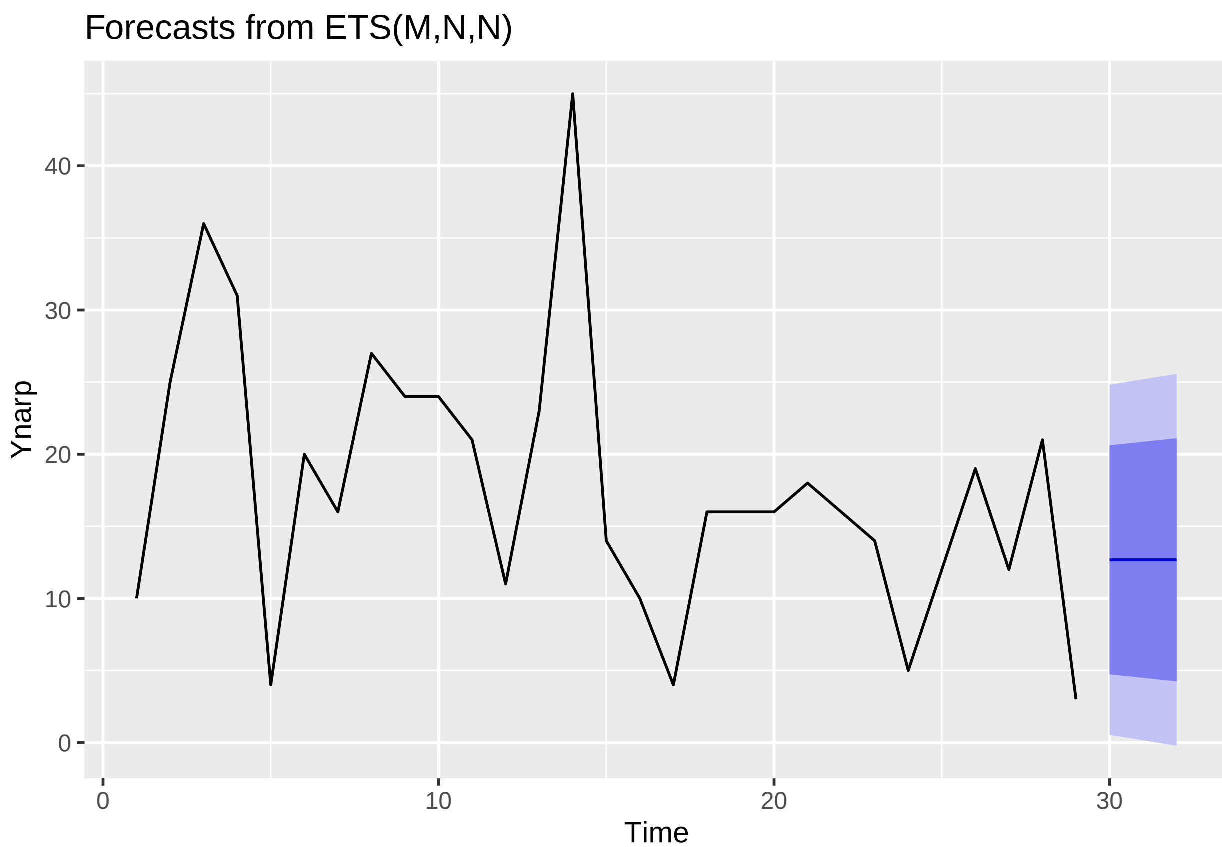

```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,0,1) with zero mean
## Q* = 7.571, df = 5, p-value = 0.1815
```

```
##
## Model df: 1.   Total lags used: 6
```

```
## Residuals = 10
## Residuals diff 2 = 14
```

```
fcast <- forecast(fit_ets, h=3)
autoplot(fcast)
```

The best model for this one is Exponential Smoothing, since the model had smallest residuals.




```
print(summary(fcast))
```

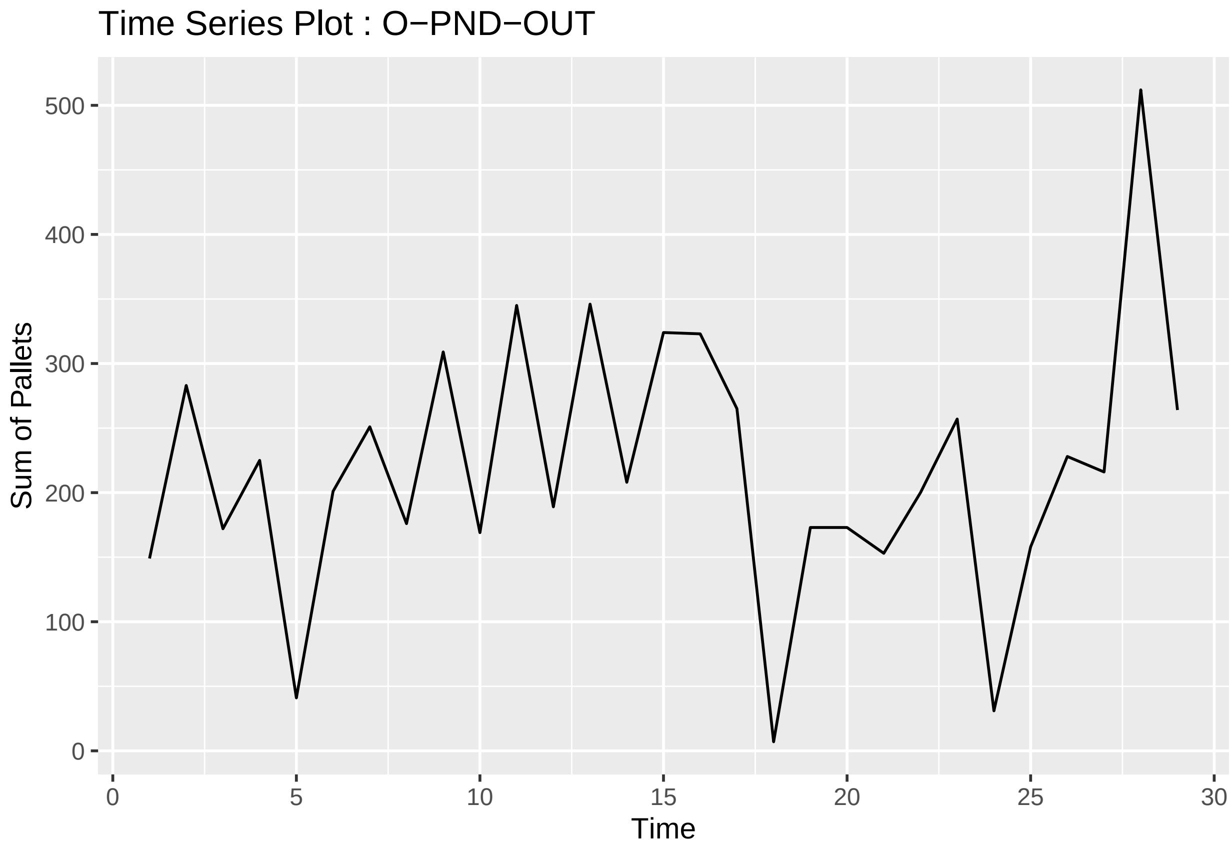
```
##
## Forecast method: ETS(M,N,N)
##
## Model Information:
## ETS(M,N,N)
##
## Call:
##  ets(y = Ynarp)
##
##   Smoothing parameters:
```

```
##     alpha = 0.2265
##
##   Initial states:
##     l = 23.1859
##
##   sigma:  0.4887
##
##      AIC     AICc      BIC
## 230.6277 231.5877 234.7296
##
## Error measures:
##                     ME    RMSE      MAE       MPE    MAPE      MASE        ACF1
## Training set -1.600123 9.71009 7.156168 -64.77056 83.4509 0.7857754 0.001605747
##
## Forecasts:
##    Point Forecast    Lo 80    Hi 80      Lo 95    Hi 95
## 30        12.6768 4.737214 20.61640  0.5342484 24.81936
## 31        12.6768 4.488860 20.86475  0.1544231 25.19919
## 32        12.6768 4.244910 21.10870 -0.2186663 25.57228
```

Forecast workload for next day with confidence 95% is 25 pallets.

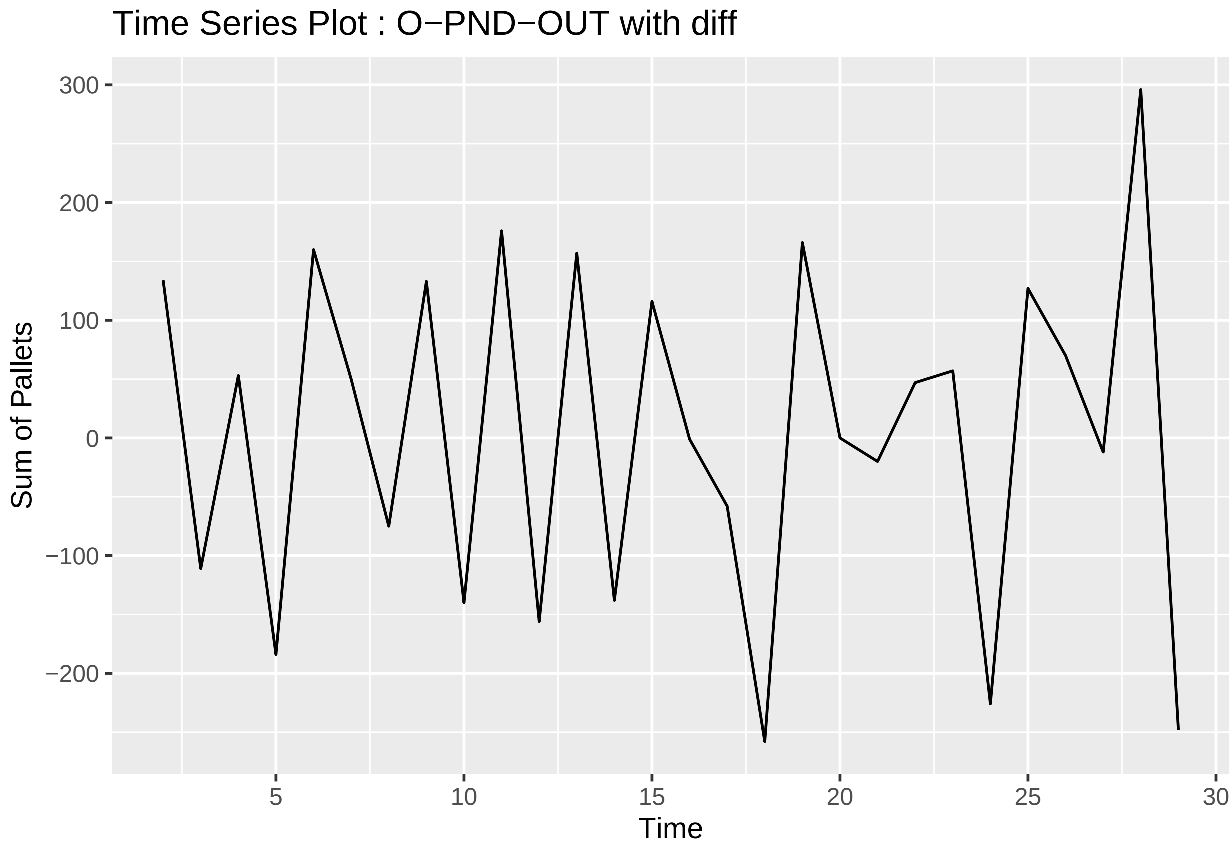
O-PND-OUT

```r
Ypnd <- ts(df_prod[,8])
autoplot(Ypnd) + ggtitle("Time Series Plot : O-PND-OUT") + ylab("Sum of Pallets")
```



As we can see, the data had a trend so we will made new data with added differencing method.

```
DYpnd <- diff(Ypnd)
autoplot(DYpnd) + ggtitle("Time Series Plot : O-PND-OUT with diff") + ylab("Sum of Pallets")
```



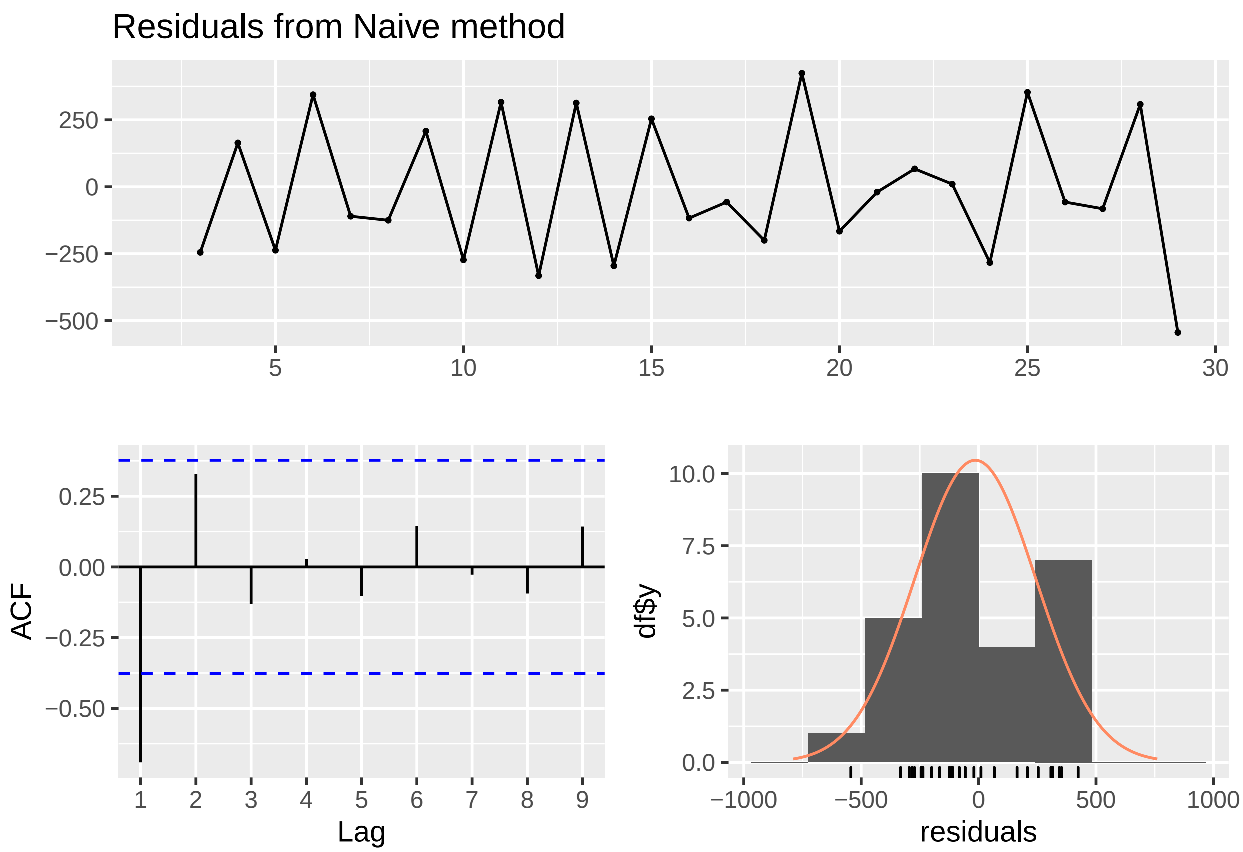
The data didn’t have seasonal. So we could go to next step for determine best model.

```
fit <- naive(DYpnd)
print(summary(fit))
```

```
##
## Forecast method: Naive method
##
## Model Information:
## Call: naive(y = DYpnd)
##
## Residual sd: 253.9513
##
## Error measures:
##                     ME     RMSE      MAE  MPE MAPE MASE      ACF1
## Training set -14.14815 253.9513 218.6667 -Inf  Inf    1 -0.690966
##
## Forecasts:
##    Point Forecast       Lo 80     Hi 80      Lo 95     Hi 95
## 30           -248  -573.4517  77.45168  -745.7354  249.7354
## 31           -248  -708.2582 212.25818  -951.9041  455.9041
## 32           -248  -811.6988 315.69884 -1110.1030  614.1030
## 33           -248  -898.9034 402.90335 -1243.4708  747.4708
## 34           -248  -975.7321 479.73207 -1360.9702  864.9702
## 35           -248 -1045.1905 549.19055 -1467.1977  971.1977
## 36           -248 -1109.0642 613.06420 -1564.8841 1068.8841
```

```
## 37             -248 -1168.5164 672.51635 -1655.8083 1159.8083
## 38             -248 -1224.3550 728.35503 -1741.2062 1245.2062
## 39             -248 -1277.1686 781.16857 -1821.9775 1325.9775
```

```
checkresiduals(fit)
```



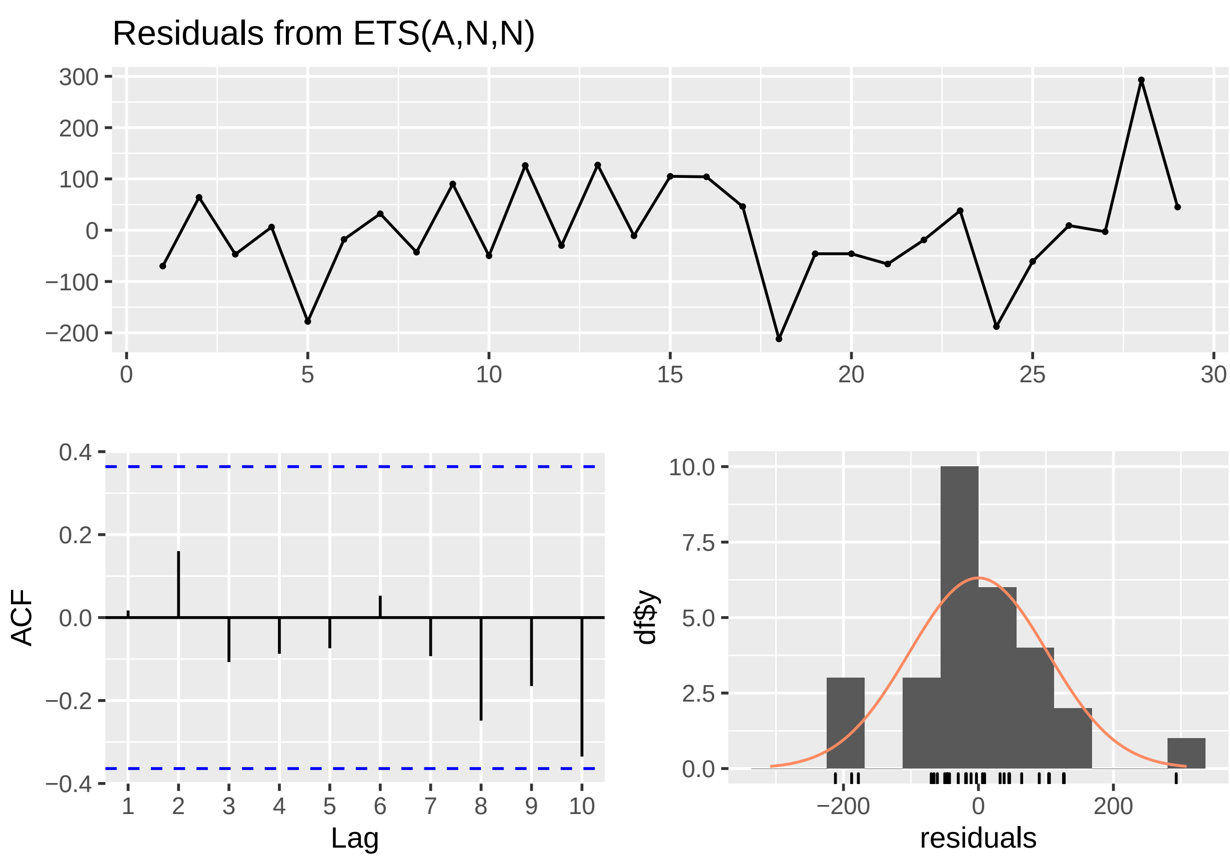

```
##
##  Ljung-Box test
##
## data:  Residuals from Naive method
## Q* = 19.524, df = 6, p-value = 0.003364
##
## Model df: 0.   Total lags used: 6
```

```
## Residuals = 254

fit_ets <- ets(Ypnd)
print(summary(fit_ets))
```

```
## ETS(A,N,N)
##
## Call:
##  ets(y = Ypnd)
##
```

```
##   Smoothing parameters:
##     alpha = 1e-04
##
##   Initial states:
##     l = 218.9088
##
##   sigma:  104.7219
##
##      AIC     AICc      BIC
## 371.3552 372.3152 375.4570
##
## Training set error measures:
##                        ME     RMSE      MAE       MPE     MAPE      MASE
## Training set -0.002563295 101.0463 74.92224 -139.8402 161.6204 0.6226841
##                   ACF1
## Training set 0.0170433
```

```
checkresiduals(fit_ets)
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ETS(A,N,N)
## Q* = 1.8482, df = 4, p-value = 0.7637
##
## Model df: 2.   Total lags used: 6
```

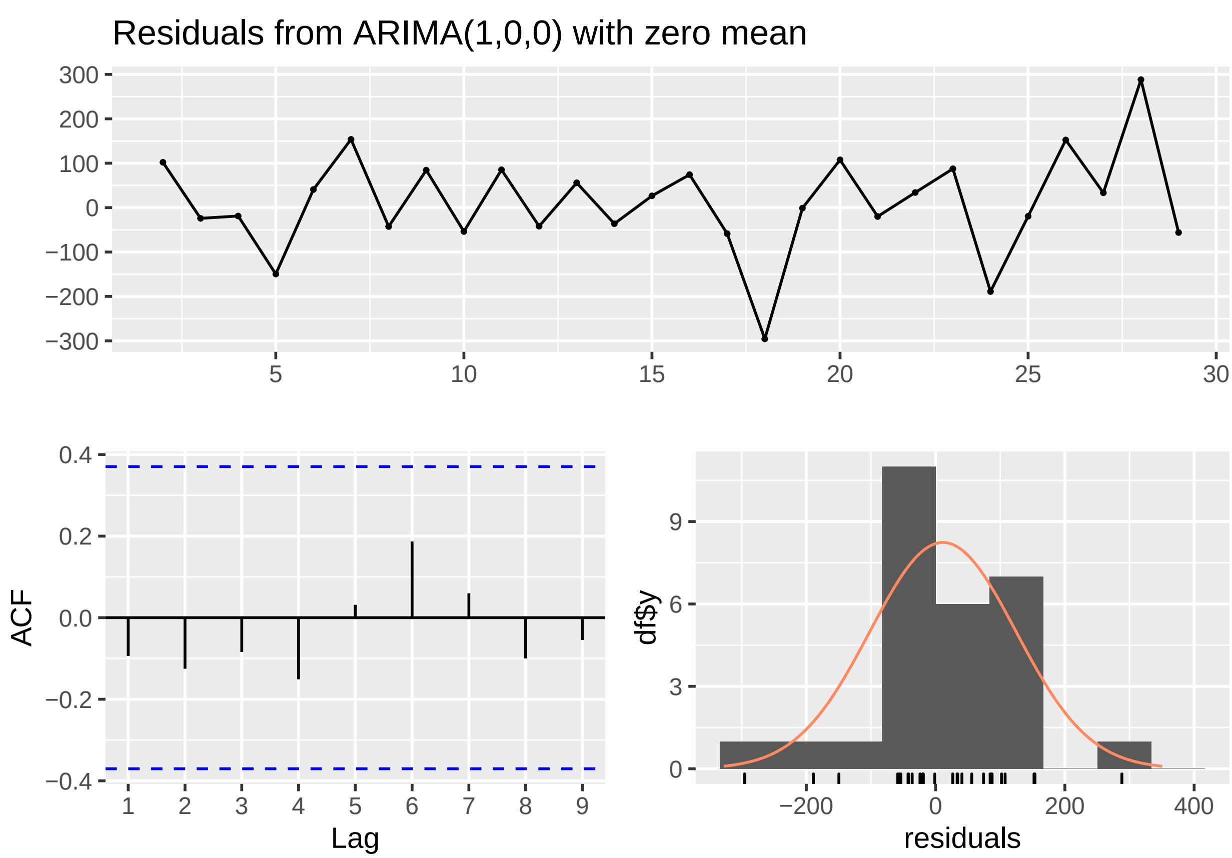
```r
## Residuals = 101

fit_arima <- auto.arima(DYpnd, d=0, D=0, stepwise = FALSE, approximation = FALSE, trace = TRUE)
```

```
##
##  ARIMA(0,0,0) with zero mean     : 359.6585
##  ARIMA(0,0,0) with non-zero mean : 361.9616
##  ARIMA(0,0,1) with zero mean     : Inf
##  ARIMA(0,0,1) with non-zero mean : Inf
##  ARIMA(0,0,2) with zero mean     : Inf
##  ARIMA(0,0,2) with non-zero mean : Inf
##  ARIMA(0,0,3) with zero mean     : Inf
##  ARIMA(0,0,3) with non-zero mean : Inf
##  ARIMA(0,0,4) with zero mean     : Inf
##  ARIMA(0,0,4) with non-zero mean : Inf
##  ARIMA(0,0,5) with zero mean     : Inf
##  ARIMA(0,0,5) with non-zero mean : Inf
##  ARIMA(1,0,0) with zero mean     : 348.5265
##  ARIMA(1,0,0) with non-zero mean : 350.8402
##  ARIMA(1,0,1) with zero mean     : 350.1401
##  ARIMA(1,0,1) with non-zero mean : 352.5409
##  ARIMA(1,0,2) with zero mean     : Inf
##  ARIMA(1,0,2) with non-zero mean : Inf
##  ARIMA(1,0,3) with zero mean     : Inf
##  ARIMA(1,0,3) with non-zero mean : Inf
##  ARIMA(1,0,4) with zero mean     : Inf
##  ARIMA(1,0,4) with non-zero mean : Inf
##  ARIMA(2,0,0) with zero mean     : 350.5736
##  ARIMA(2,0,0) with non-zero mean : 353.0604
##  ARIMA(2,0,1) with zero mean     : Inf
##  ARIMA(2,0,1) with non-zero mean : Inf
##  ARIMA(2,0,2) with zero mean     : Inf
##  ARIMA(2,0,2) with non-zero mean : Inf
##  ARIMA(2,0,3) with zero mean     : Inf
##  ARIMA(2,0,3) with non-zero mean : Inf
##  ARIMA(3,0,0) with zero mean     : 353.0668
##  ARIMA(3,0,0) with non-zero mean : 355.7859
##  ARIMA(3,0,1) with zero mean     : Inf
##  ARIMA(3,0,1) with non-zero mean : Inf
##  ARIMA(3,0,2) with zero mean     : Inf
##  ARIMA(3,0,2) with non-zero mean : Inf
##  ARIMA(4,0,0) with zero mean     : 355.284
##  ARIMA(4,0,0) with non-zero mean : 358.2113
##  ARIMA(4,0,1) with zero mean     : Inf
##  ARIMA(4,0,1) with non-zero mean : Inf
##  ARIMA(5,0,0) with zero mean     : 357.093
##  ARIMA(5,0,0) with non-zero mean : 360.314
##
##
##
##  Best model: ARIMA(1,0,0) with zero mean
```

```r
print(summary(fit_arima))
```

```
## Series: DYpnd
## ARIMA(1,0,0) with zero mean
##
## Coefficients:
##           ar1
##       -0.6482
## s.e.   0.1510
##
## sigma^2 estimated as 12918:  log likelihood=-172.02
## AIC=348.05   AICc=348.53   BIC=350.71
##
## Training set error measures:
##                   ME     RMSE      MAE MPE MAPE      MASE        ACF1
## Training set 11.3693 111.6106 83.32734 Inf  Inf 0.3810702 -0.09373473
```

```r
checkresiduals(fit_arima)
```



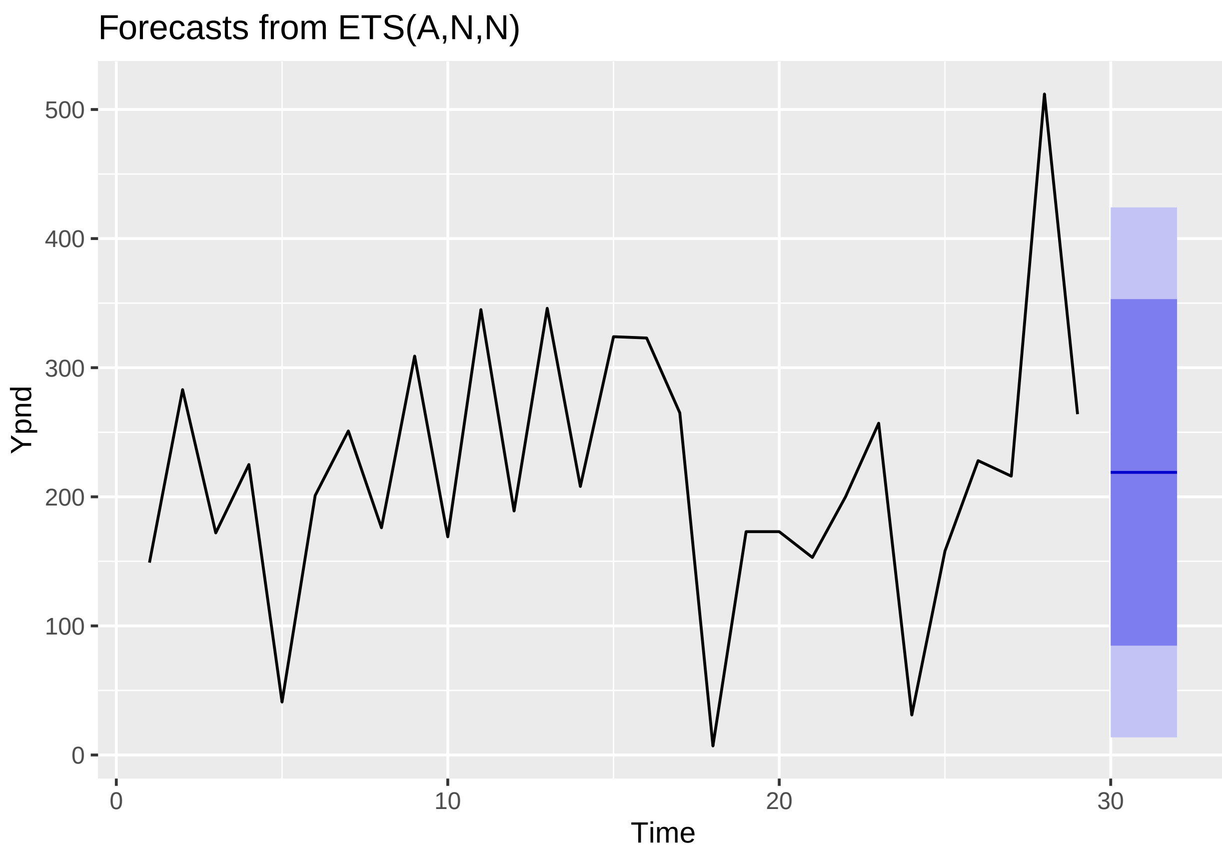

```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(1,0,0) with zero mean
## Q* = 3.1879, df = 5, p-value = 0.671
```

```
##
## Model df: 1.   Total lags used: 6
```

```
## Residuals = 114
## Residuals diff 2 = 147
```

```r
fcast <- forecast(fit_ets, h=3)
autoplot(fcast)
```

The best model for this one is Exponential Smoothing, since the model had smallest residuals.




```r
print(summary(fcast))
```

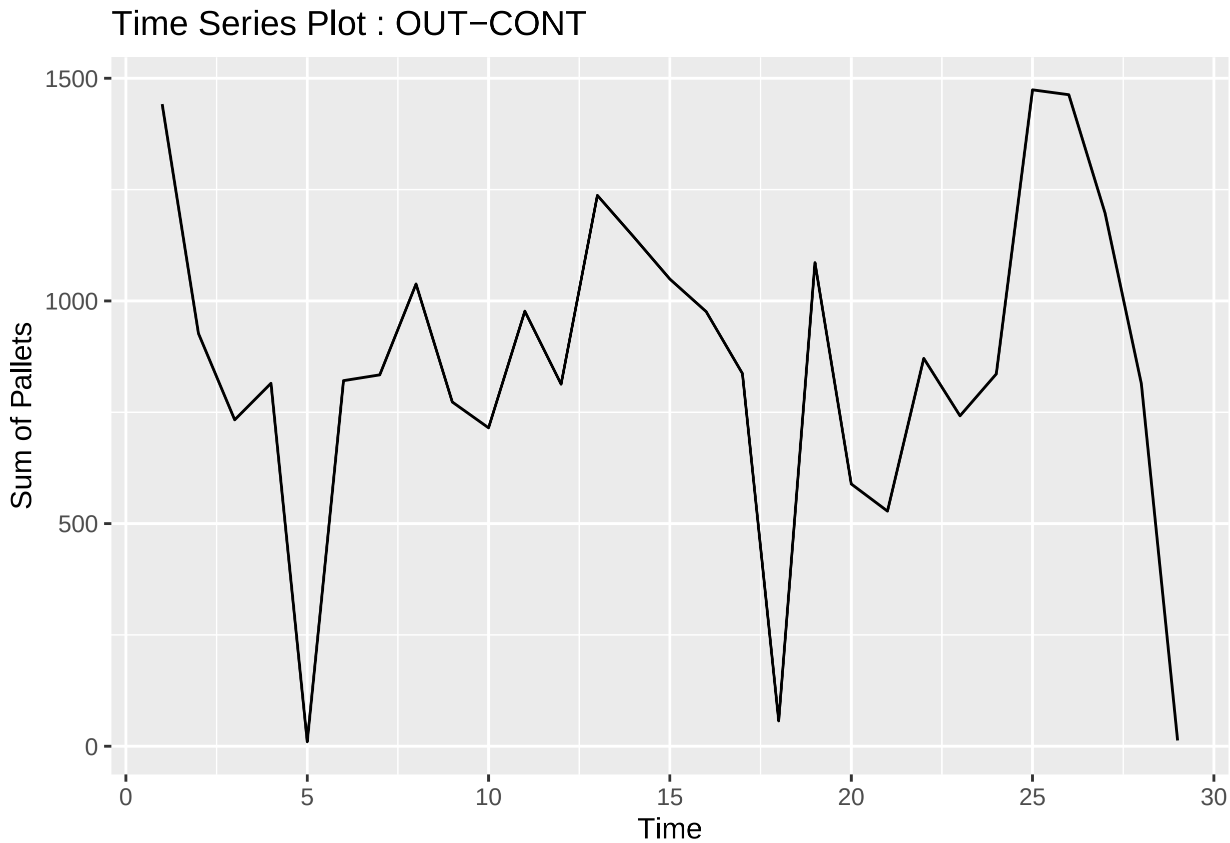
```
##
## Forecast method: ETS(A,N,N)
##
## Model Information:
## ETS(A,N,N)
##
## Call:
##  ets(y = Ypnd)
##
##   Smoothing parameters:
```

```
##     alpha = 1e-04
##
##   Initial states:
##     l = 218.9088
##
##   sigma:  104.7219
##
##      AIC     AICc      BIC
## 371.3552 372.3152 375.4570
##
## Error measures:
##                        ME     RMSE      MAE       MPE     MAPE      MASE
## Training set -0.002563295 101.0463 74.92224 -139.8402 161.6204 0.6226841
##                   ACF1
## Training set 0.0170433
##
## Forecasts:
##    Point Forecast    Lo 80    Hi 80    Lo 95  Hi 95
## 30       218.9088 84.70227 353.1153 13.65763 424.16
## 31       218.9088 84.70227 353.1153 13.65763 424.16
## 32       218.9088 84.70227 353.1153 13.65763 424.16
```

Forecast workload for next day with confidence 95% is 425 pallets.

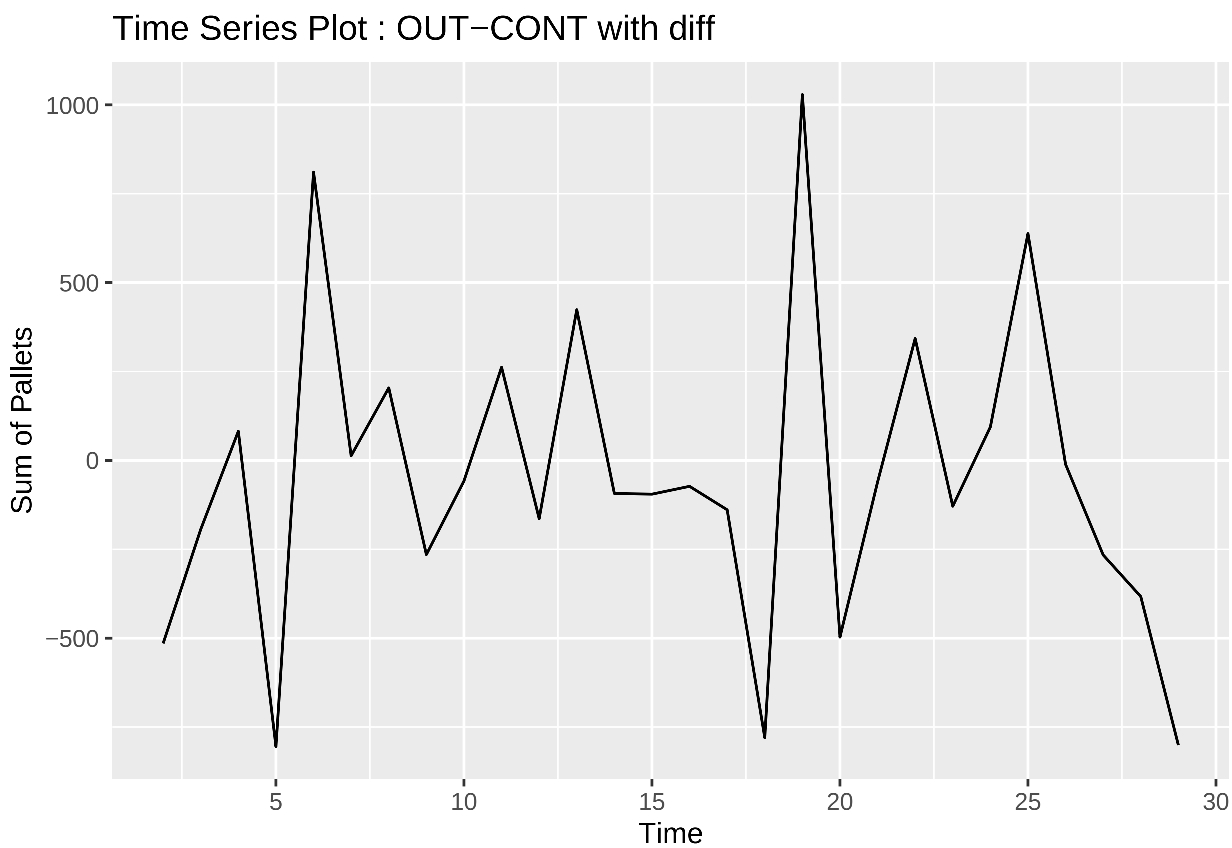
OUT-CONT

```
Youc <- ts(df_prod[,9])
autoplot(Youc) + ggtitle("Time Series Plot : OUT-CONT") + ylab("Sum of Pallets")
```



As we can see, the data had a trend so we will made new data with added differencing method.

```
DYouc <- diff(Youc)
autoplot(DYouc) + ggtitle("Time Series Plot : OUT-CONT with diff") + ylab("Sum of Pallets")
```



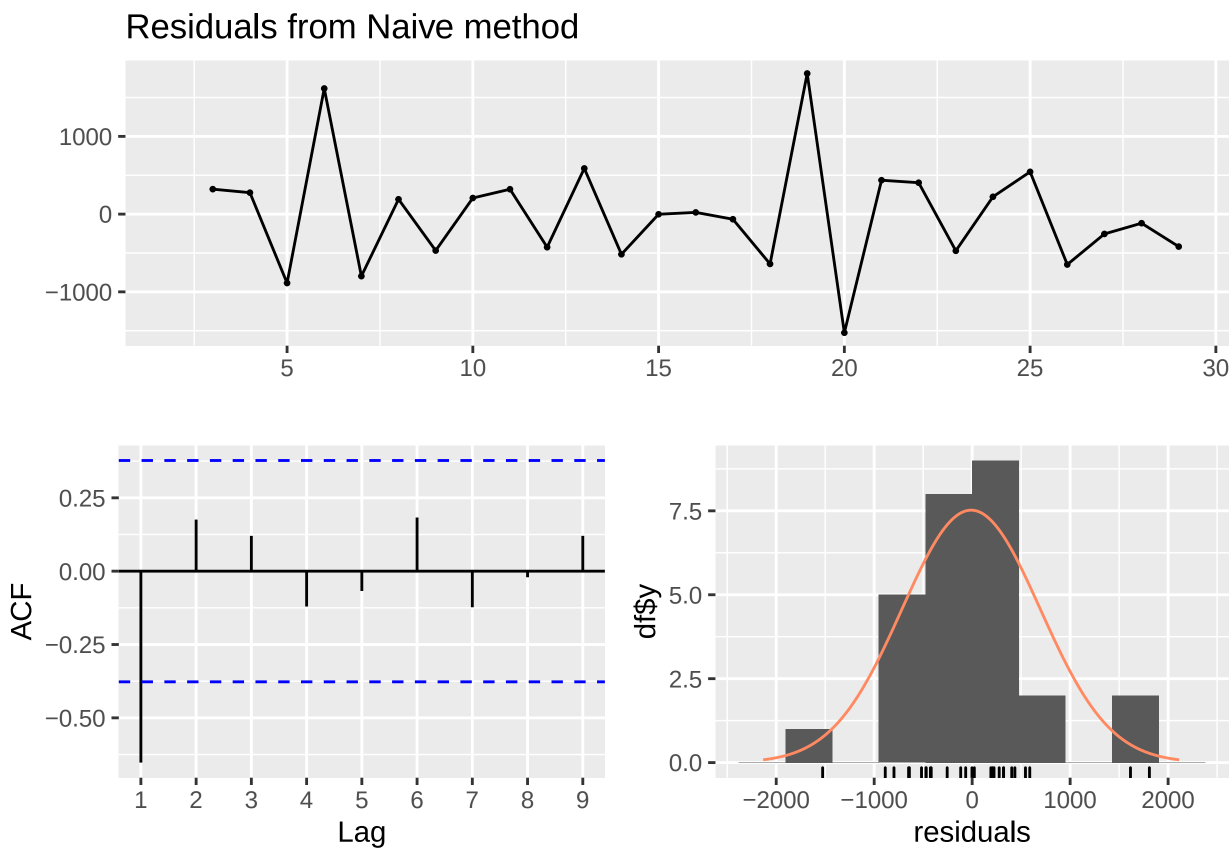
The data didn't have seasonal. So we could go to next step for determine best model.

```
fit <- naive(DYouc)
print(summary(fit))
```

```
##
## Forecast method: Naive method
##
## Model Information:
## Call: naive(y = DYouc)
##
## Residual sd: 694.5216
##
## Error measures:
##                      ME     RMSE      MAE      MPE     MAPE MASE       ACF1
## Training set -10.59259 694.5216 525.9259 77.28885 625.8602    1 -0.6524871
##
## Forecasts:
##    Point Forecast     Lo 80      Hi 80     Lo 95     Hi 95
## 30           -801 -1691.065   89.06528 -2162.237  560.2374
## 31           -801 -2059.742  457.74240 -2726.080 1124.0804
## 32           -801 -2342.638  740.63829 -3158.732 1556.7323
## 33           -801 -2581.131  979.13057 -3523.475 1921.4748
## 34           -801 -2791.246 1189.24648 -3844.819 2242.8193
## 35           -801 -2981.206 1379.20578 -4135.337 2533.3370
## 36           -801 -3155.891 1553.89139 -4402.496 2800.4956
```

```
## 37           -801 -3318.485 1716.48479 -4651.161 3049.1607
## 38           -801 -3471.196 1869.19585 -4884.712 3282.7122
## 39           -801 -3615.634 2013.63356 -5105.611 3503.6106
```

```
checkresiduals(fit)
```



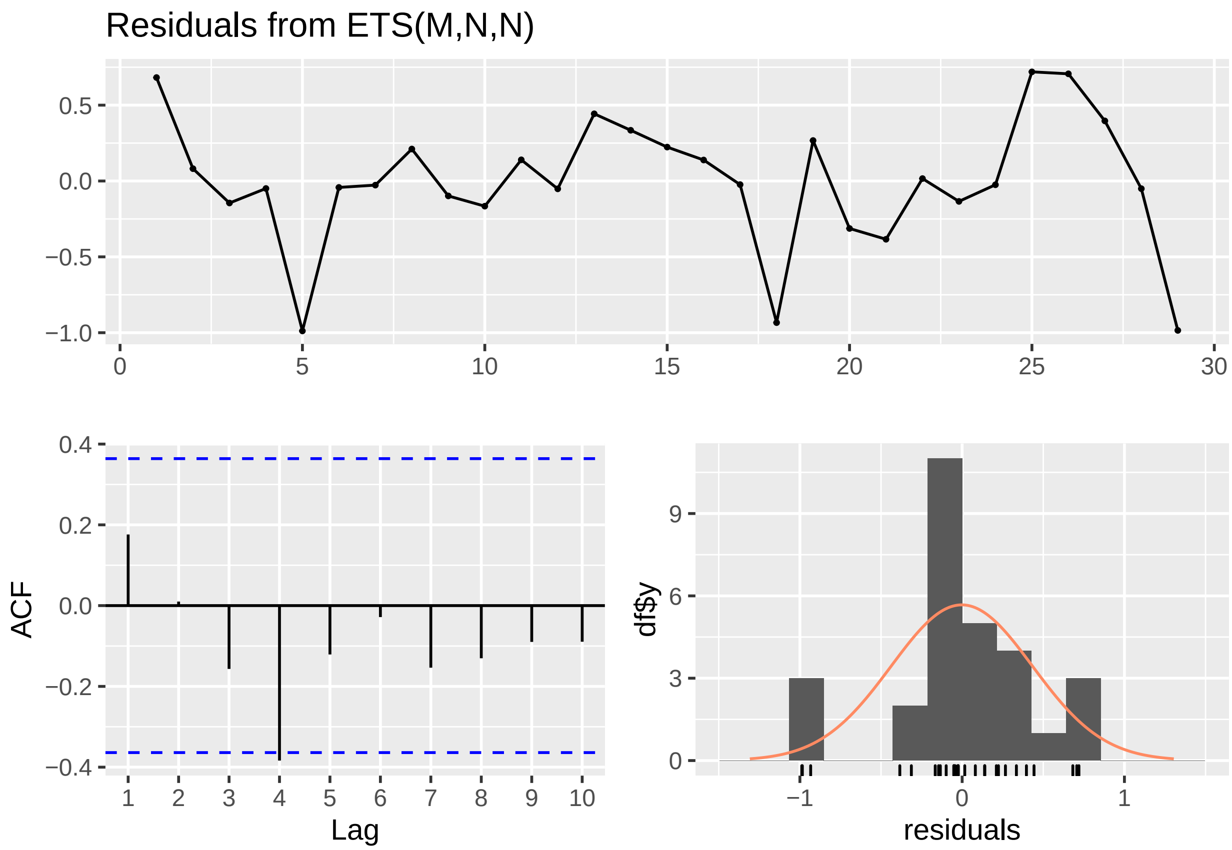

```
##
##  Ljung-Box test
##
## data:  Residuals from Naive method
## Q* = 16.166, df = 6, p-value = 0.01289
##
## Model df: 0.   Total lags used: 6
```

```
## Residuals = 695

fit_ets <- ets(Youc)
print(summary(fit_ets))
```

```
## ETS(M,N,N)
##
## Call:
##  ets(y = Youc)
##
```

```
##   Smoothing parameters:
##     alpha = 1e-04
##
##   Initial states:
##     l = 857.3272
##
##   sigma:  0.4434
##
##      AIC     AICc      BIC
## 446.1352 447.0952 450.2371
##
## Training set error measures:
##                    ME     RMSE      MAE       MPE     MAPE     MASE      ACF1
## Training set -1.77574 366.8369 259.4213 -561.1944 581.7563 0.787062 0.1761386
```

```
checkresiduals(fit_ets)
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ETS(M,N,N)
## Q* = 7.7206, df = 4, p-value = 0.1024
##
## Model df: 2.   Total lags used: 6
```

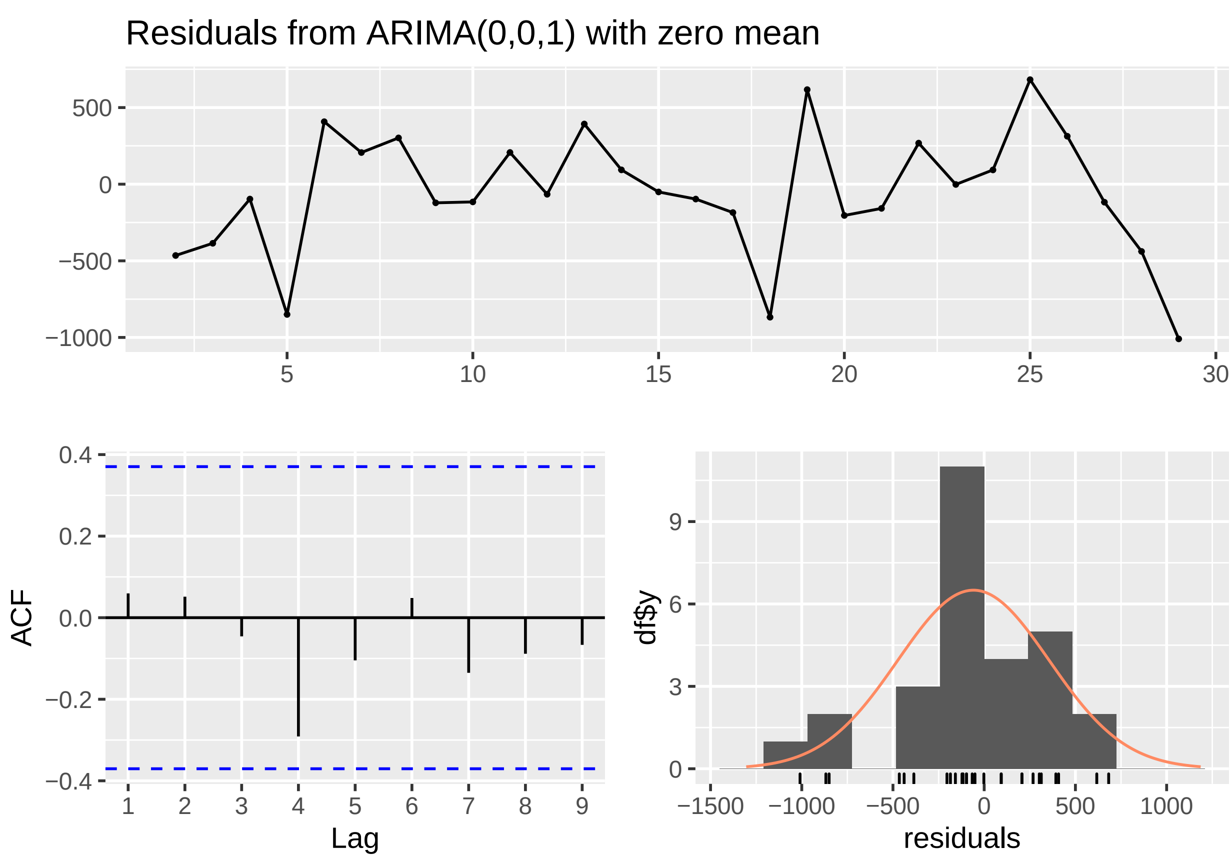
```r
## Residuals = 367

fit_arima <- auto.arima(DYouc, d=0, D=0, stepwise = FALSE, approximation = FALSE, trace = TRUE)
```

```
##
##  ARIMA(0,0,0) with zero mean     : 422.2396
##  ARIMA(0,0,0) with non-zero mean : 424.1833
##  ARIMA(0,0,1) with zero mean     : 421.3631
##  ARIMA(0,0,1) with non-zero mean : 423.5213
##  ARIMA(0,0,2) with zero mean     : Inf
##  ARIMA(0,0,2) with non-zero mean : Inf
##  ARIMA(0,0,3) with zero mean     : Inf
##  ARIMA(0,0,3) with non-zero mean : Inf
##  ARIMA(0,0,4) with zero mean     : Inf
##  ARIMA(0,0,4) with non-zero mean : Inf
##  ARIMA(0,0,5) with zero mean     : Inf
##  ARIMA(0,0,5) with non-zero mean : Inf
##  ARIMA(1,0,0) with zero mean     : 421.5831
##  ARIMA(1,0,0) with non-zero mean : 423.6433
##  ARIMA(1,0,1) with zero mean     : Inf
##  ARIMA(1,0,1) with non-zero mean : 426.309
##  ARIMA(1,0,2) with zero mean     : Inf
##  ARIMA(1,0,2) with non-zero mean : Inf
##  ARIMA(1,0,3) with zero mean     : Inf
##  ARIMA(1,0,3) with non-zero mean : Inf
##  ARIMA(1,0,4) with zero mean     : Inf
##  ARIMA(1,0,4) with non-zero mean : Inf
##  ARIMA(2,0,0) with zero mean     : 423.9938
##  ARIMA(2,0,0) with non-zero mean : 426.2856
##  ARIMA(2,0,1) with zero mean     : Inf
##  ARIMA(2,0,1) with non-zero mean : Inf
##  ARIMA(2,0,2) with zero mean     : Inf
##  ARIMA(2,0,2) with non-zero mean : Inf
##  ARIMA(2,0,3) with zero mean     : Inf
##  ARIMA(2,0,3) with non-zero mean : Inf
##  ARIMA(3,0,0) with zero mean     : 426.5219
##  ARIMA(3,0,0) with non-zero mean : 429.0087
##  ARIMA(3,0,1) with zero mean     : Inf
##  ARIMA(3,0,1) with non-zero mean : Inf
##  ARIMA(3,0,2) with zero mean     : Inf
##  ARIMA(3,0,2) with non-zero mean : Inf
##  ARIMA(4,0,0) with zero mean     : 426.4768
##  ARIMA(4,0,0) with non-zero mean : 429.6014
##  ARIMA(4,0,1) with zero mean     : Inf
##  ARIMA(4,0,1) with non-zero mean : Inf
##  ARIMA(5,0,0) with zero mean     : 426.2693
##  ARIMA(5,0,0) with non-zero mean : 429.8154
##
##
##
##  Best model: ARIMA(0,0,1) with zero mean
```

```
print(summary(fit_arima))
```

```
## Series: DYouc
## ARIMA(0,0,1) with zero mean
##
## Coefficients:
##           ma1
##       -0.4747
## s.e.   0.4903
##
## sigma^2 estimated as 175967:  log likelihood=-208.44
## AIC=420.88   AICc=421.36   BIC=423.55
##
## Training set error measures:
##                     ME     RMSE      MAE      MPE     MAPE      MASE       ACF1
## Training set -58.84209 411.9257 314.7755 33.45541 252.2418 0.5985169 0.05961721
```

```
checkresiduals(fit_arima)
```



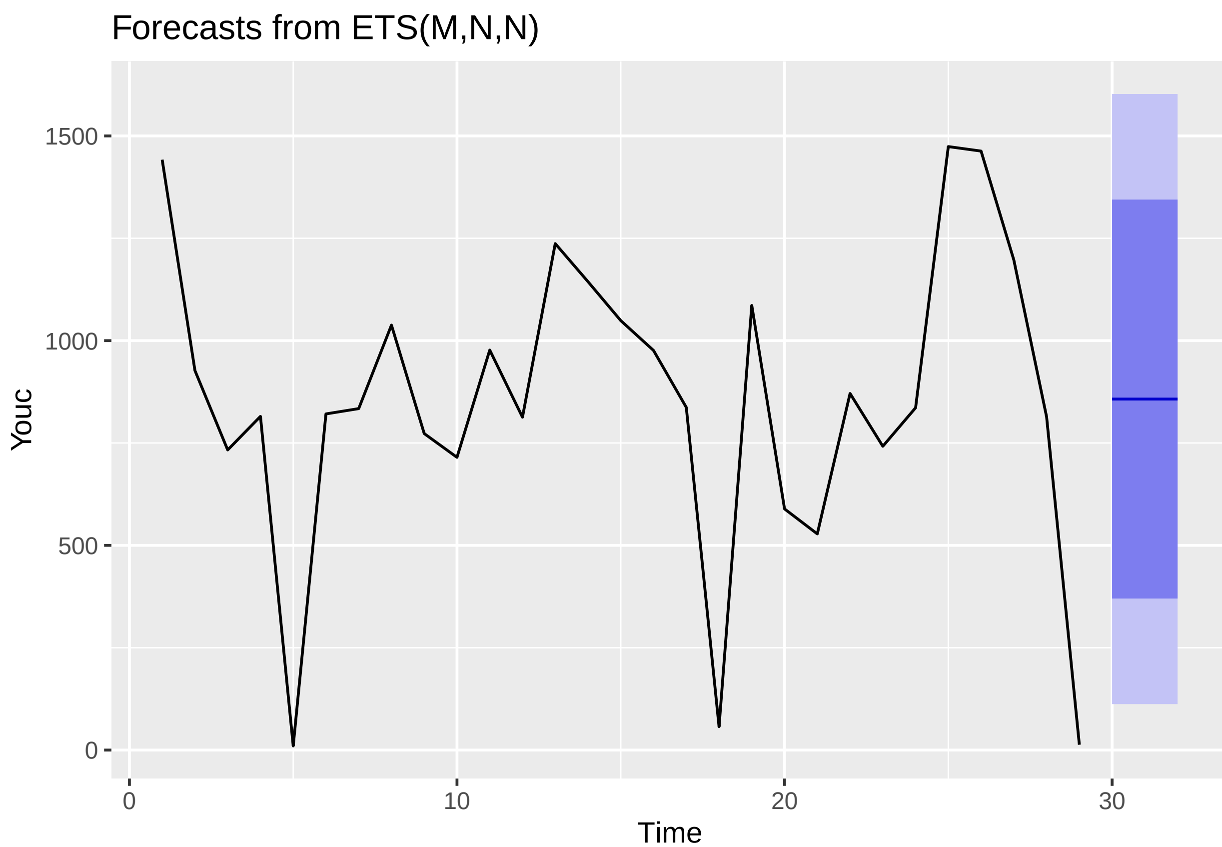

```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,0,1) with zero mean
## Q* = 3.7237, df = 5, p-value = 0.5898
```

```
##
## Model df: 1.   Total lags used: 6
```

```
## Residuals = 420
## Residuals diff 2 = 475
```

```r
fcast <- forecast(fit_ets, h=3)
autoplot(fcast)
```

The best model for this one is Exponential Smoothing, since the model had smallest residuals.




```r
print(summary(fcast))
```

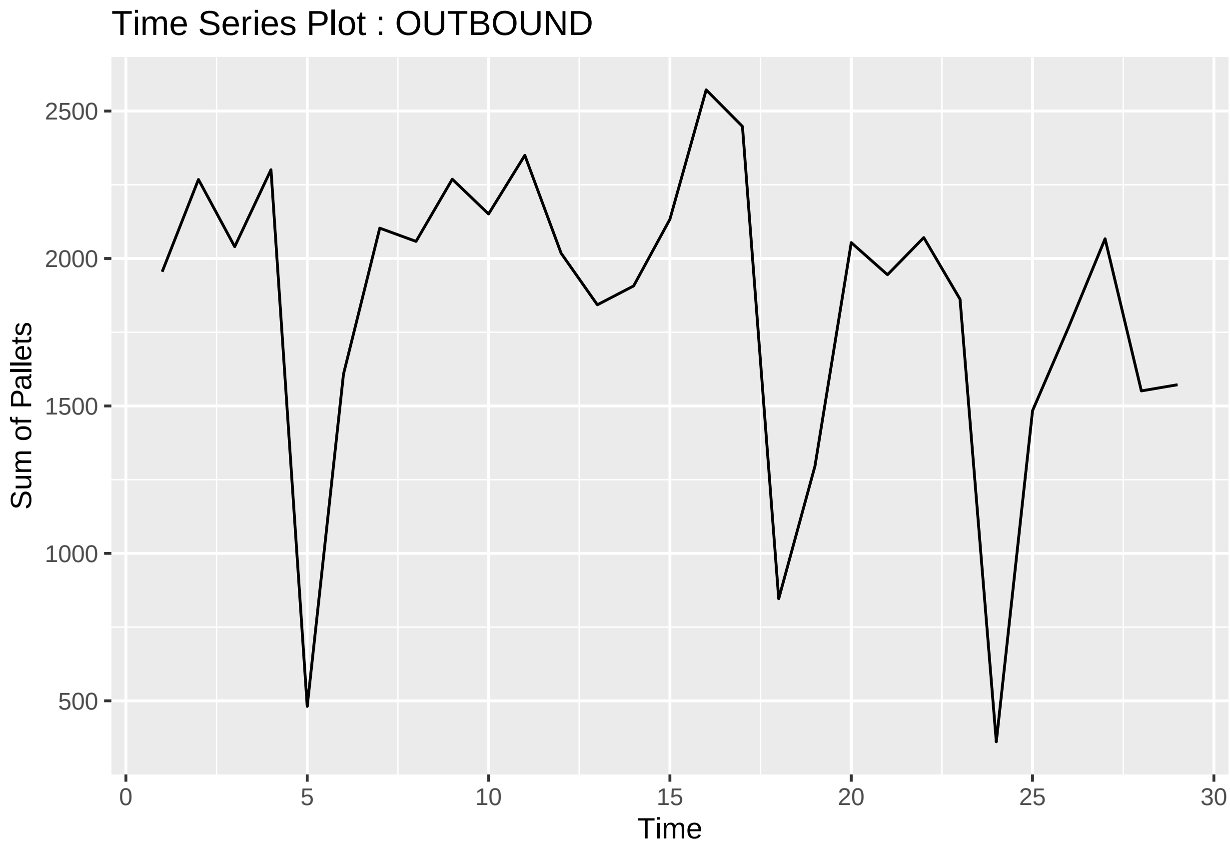
```
##
## Forecast method: ETS(M,N,N)
##
## Model Information:
## ETS(M,N,N)
##
## Call:
##  ets(y = Youc)
##
##   Smoothing parameters:
```

```
##     alpha = 1e-04
##
##   Initial states:
##     l = 857.3272
##
##   sigma:  0.4434
##
##      AIC     AICc      BIC
## 446.1352 447.0952 450.2371
##
## Error measures:
##                    ME     RMSE      MAE       MPE     MAPE     MASE      ACF1
## Training set -1.77574 366.8369 259.4213 -561.1944 581.7563 0.787062 0.1761386
##
## Forecasts:
##    Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## 30        857.322 370.1171 1344.527 112.2064 1602.438
## 31        857.322 370.1171 1344.527 112.2064 1602.438
## 32        857.322 370.1171 1344.527 112.2064 1602.438
```

Forecast workload for next day with confidence 95% is 1602 pallets.

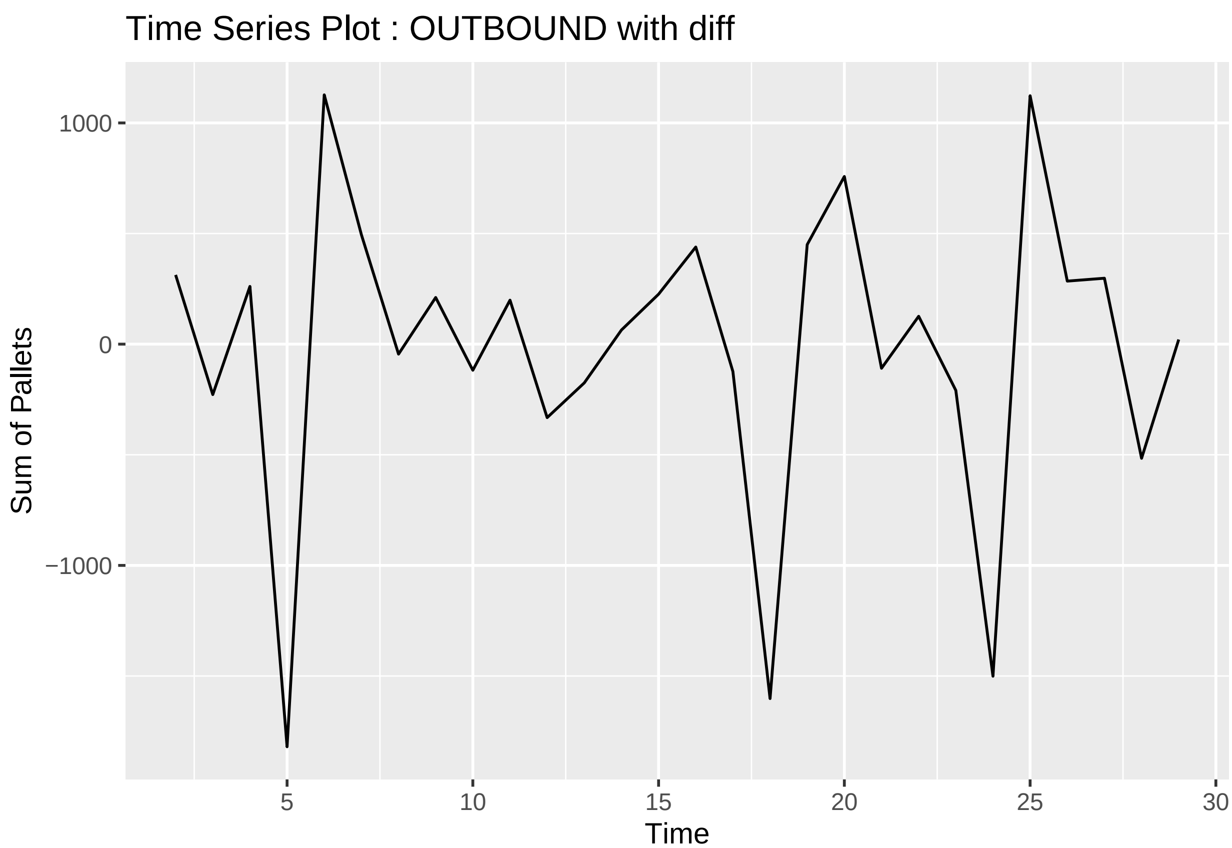
OUTBOUND

```
Youb <- ts(df_prod[,10])
autoplot(Youb) + ggtitle("Time Series Plot : OUTBOUND") + ylab("Sum of Pallets")
```



As we can see, the data had a trend so we will made new data with added differencing method.

```
DYoub <- diff(Youb)
autoplot(DYoub) + ggtitle("Time Series Plot : OUTBOUND with diff") + ylab("Sum of Pallets")
```



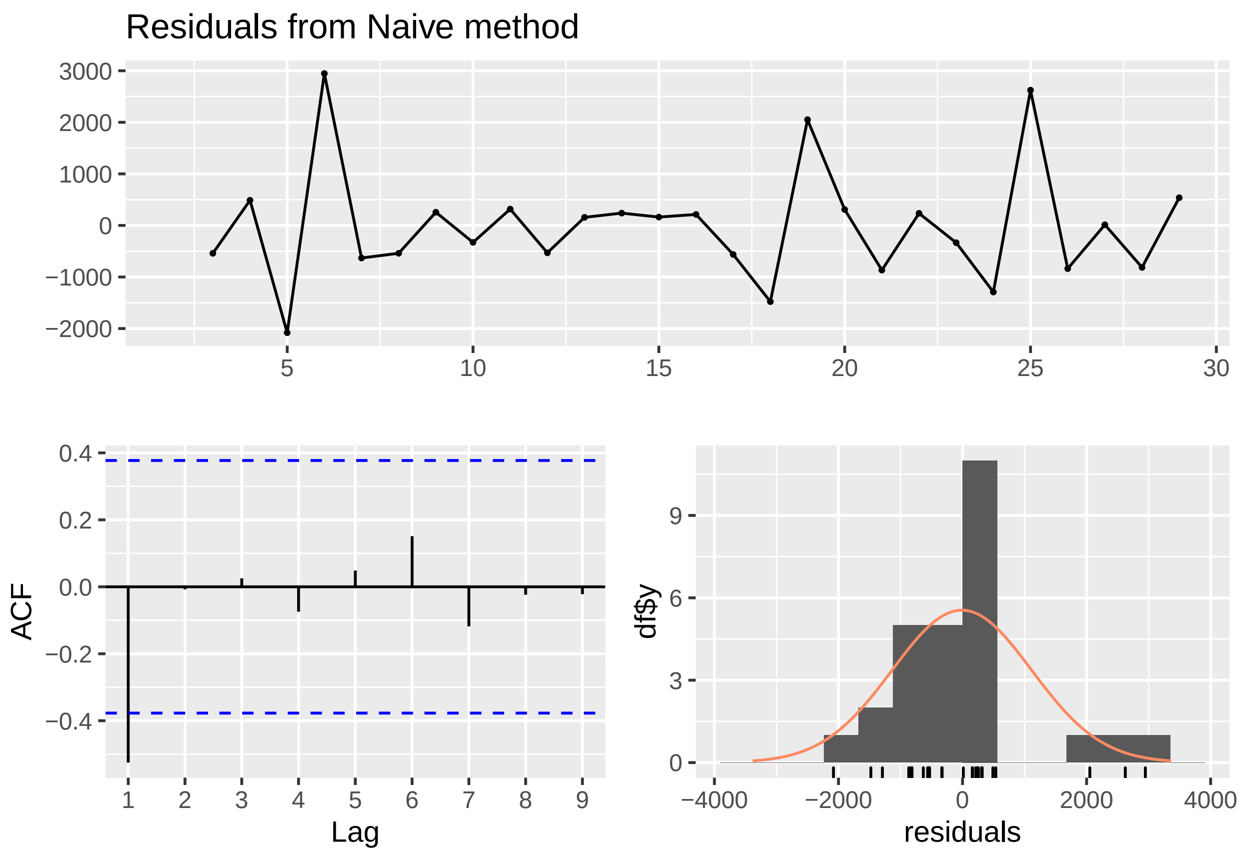
The data didn't have seasonal. So we could go to next step for determine best model.

```
fit <- naive(DYoub)
print(summary(fit))
```

```
##
## Forecast method: Naive method
##
## Model Information:
## Call: naive(y = DYoub)
##
## Residual sd: 1103.563
##
## Error measures:
##                     ME     RMSE      MAE      MPE     MAPE MASE     ACF1
## Training set -10.81481 1103.563 792.2222 293.5623 331.4458    1 -0.52496
##
## Forecasts:
##    Point Forecast     Lo 80    Hi 80     Lo 95    Hi 95
## 30             21 -1393.273 1435.273 -2141.944 2183.944
## 31             21 -1979.084 2021.084 -3037.864 3079.864
## 32             21 -2428.592 2470.592 -3725.328 3767.328
## 33             21 -2807.546 2849.546 -4304.887 4346.887
## 34             21 -3141.410 3183.410 -4815.489 4857.489
## 35             21 -3443.247 3485.247 -5277.108 5319.108
## 36             21 -3720.814 3762.814 -5701.611 5743.611
```

```
## 37              21 -3979.168 4021.168 -6096.729 6138.729
## 38              21 -4221.819 4263.819 -6467.831 6509.831
## 39              21 -4451.324 4493.324 -6818.829 6860.829
```

```
checkresiduals(fit)
```



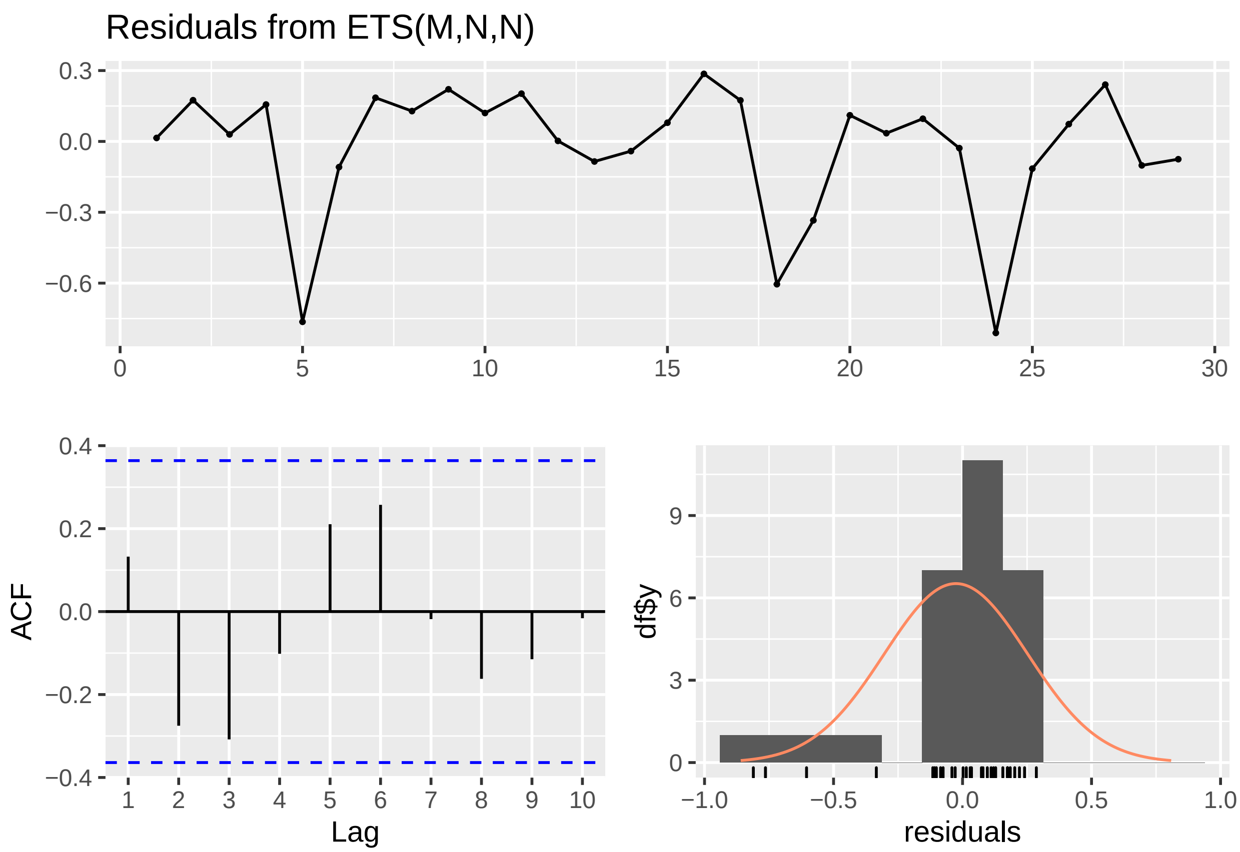

```
##
##  Ljung-Box test
##
## data:  Residuals from Naive method
## Q* = 9.4454, df = 6, p-value = 0.15
##
## Model df: 0.   Total lags used: 6
```

```
## Residuals = 1104

fit_ets <- ets(Youb)
print(summary(fit_ets))
```

```
## ETS(M,N,N)
##
## Call:
##  ets(y = Youb)
##
```

```
##   Smoothing parameters:
##     alpha = 0.1494
##
##   Initial states:
##     l = 1926.8547
##
##   sigma:  0.2844
##
##      AIC     AICc      BIC
## 466.3225 467.2825 470.4244
##
## Training set error measures:
##                     ME     RMSE      MAE       MPE     MAPE      MASE      ACF1
## Training set -56.75984 543.4486 360.3025 -28.21217 41.87983 0.7657282 0.1164747
```

```
checkresiduals(fit_ets)
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ETS(M,N,N)
## Q* = 10.992, df = 4, p-value = 0.02665
##
## Model df: 2.   Total lags used: 6
```

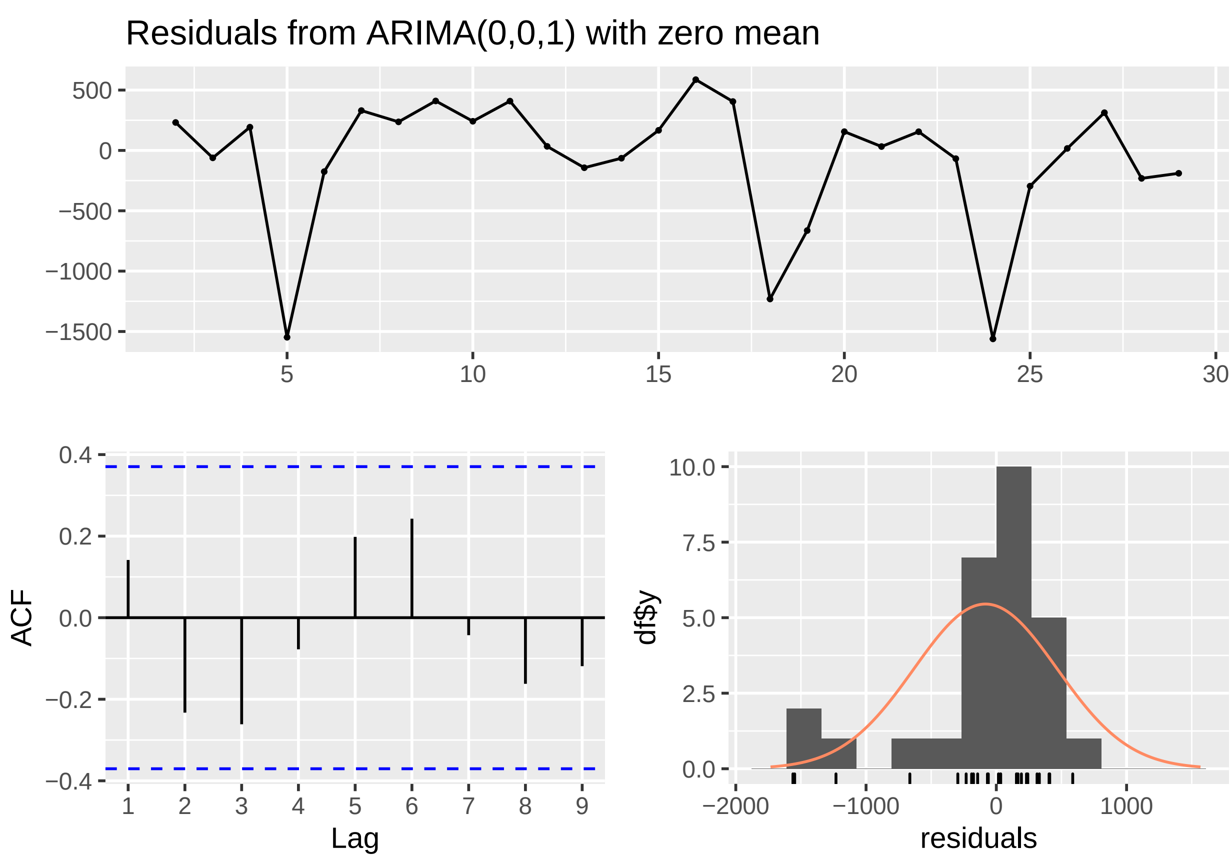
```r
## Residuals = 544

fit_arima <- auto.arima(DYoub, d=0, D=0, stepwise = FALSE, approximation = FALSE, trace = TRUE)
```

```
##
##  ARIMA(0,0,0) with zero mean     : 446.7831
##  ARIMA(0,0,0) with non-zero mean : 449.0979
##  ARIMA(0,0,1) with zero mean     : 438.6939
##  ARIMA(0,0,1) with non-zero mean : Inf
##  ARIMA(0,0,2) with zero mean     : Inf
##  ARIMA(0,0,2) with non-zero mean : Inf
##  ARIMA(0,0,3) with zero mean     : 442.0891
##  ARIMA(0,0,3) with non-zero mean : Inf
##  ARIMA(0,0,4) with zero mean     : 444.425
##  ARIMA(0,0,4) with non-zero mean : Inf
##  ARIMA(0,0,5) with zero mean     : 447.5224
##  ARIMA(0,0,5) with non-zero mean : Inf
##  ARIMA(1,0,0) with zero mean     : 446.9381
##  ARIMA(1,0,0) with non-zero mean : 449.4298
##  ARIMA(1,0,1) with zero mean     : 440.0723
##  ARIMA(1,0,1) with non-zero mean : Inf
##  ARIMA(1,0,2) with zero mean     : 442.2603
##  ARIMA(1,0,2) with non-zero mean : Inf
##  ARIMA(1,0,3) with zero mean     : Inf
##  ARIMA(1,0,3) with non-zero mean : Inf
##  ARIMA(1,0,4) with zero mean     : 447.9643
##  ARIMA(1,0,4) with non-zero mean : Inf
##  ARIMA(2,0,0) with zero mean     : 446.8771
##  ARIMA(2,0,0) with non-zero mean : 449.5782
##  ARIMA(2,0,1) with zero mean     : 441.5508
##  ARIMA(2,0,1) with non-zero mean : Inf
##  ARIMA(2,0,2) with zero mean     : 442.7163
##  ARIMA(2,0,2) with non-zero mean : Inf
##  ARIMA(2,0,3) with zero mean     : Inf
##  ARIMA(2,0,3) with non-zero mean : Inf
##  ARIMA(3,0,0) with zero mean     : 446.4911
##  ARIMA(3,0,0) with non-zero mean : 449.3944
##  ARIMA(3,0,1) with zero mean     : 443.5517
##  ARIMA(3,0,1) with non-zero mean : Inf
##  ARIMA(3,0,2) with zero mean     : 444.6272
##  ARIMA(3,0,2) with non-zero mean : Inf
##  ARIMA(4,0,0) with zero mean     : 444.0707
##  ARIMA(4,0,0) with non-zero mean : 447.2888
##  ARIMA(4,0,1) with zero mean     : 444.9508
##  ARIMA(4,0,1) with non-zero mean : 448.3129
##  ARIMA(5,0,0) with zero mean     : 443.8636
##  ARIMA(5,0,0) with non-zero mean : 447.2046
##
##
##
##  Best model: ARIMA(0,0,1) with zero mean
```

```r
print(summary(fit_arima))
```

```
## Series: DYoub
## ARIMA(0,0,1) with zero mean
##
## Coefficients:
##           ma1
##       -0.9098
## s.e.   0.1291
##
## sigma^2 estimated as 309737:  log likelihood=-217.11
## AIC=438.21   AICc=438.69   BIC=440.88
##
## Training set error measures:
##                    ME     RMSE      MAE       MPE     MAPE      MASE    ACF1
## Training set -82.8432 546.5117 362.4153 -27.19084 136.3173 0.4574667 0.14157
```

```r
checkresiduals(fit_arima)
```



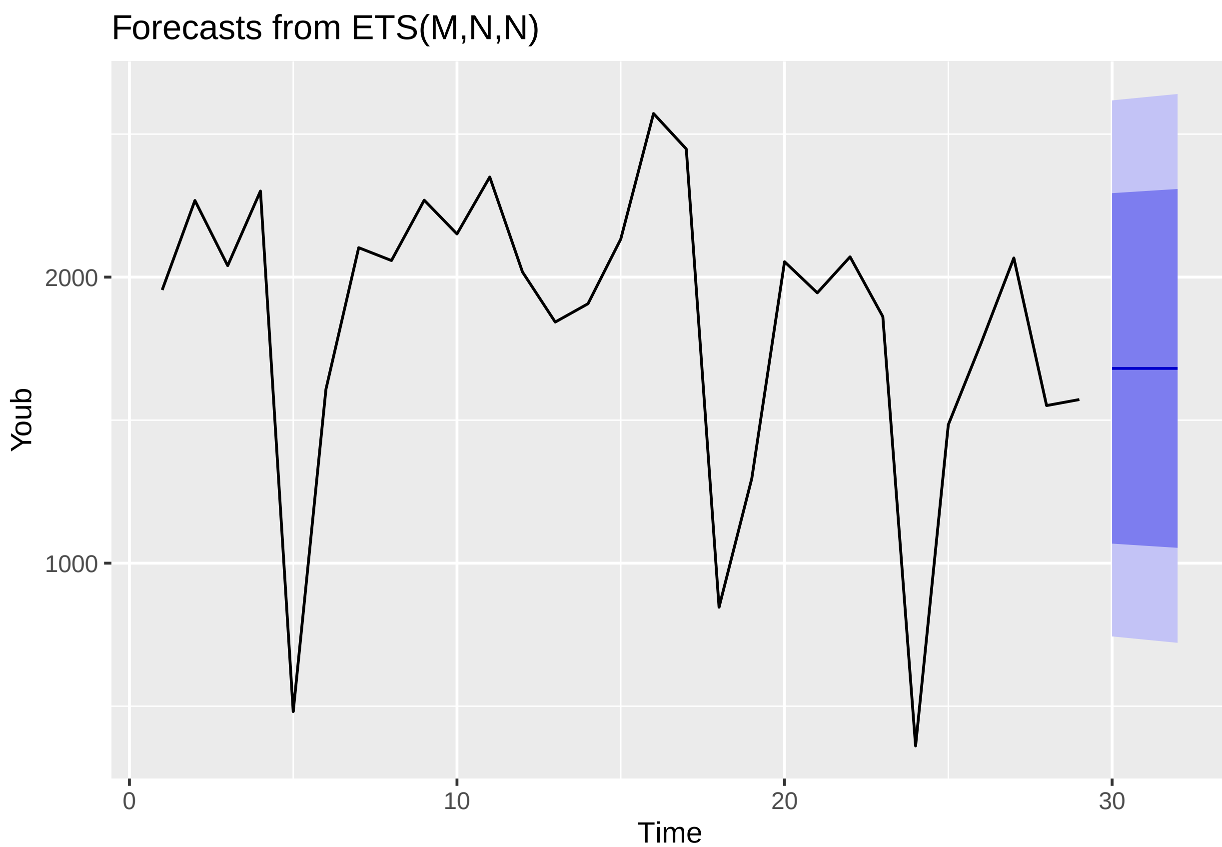

```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(0,0,1) with zero mean
## Q* = 8.5661, df = 5, p-value = 0.1277
```

```
##
## Model df: 1.   Total lags used: 6
```

```
## Residuals = 557
## Residuals diff 2 = 661
```

```
fcast <- forecast(fit_ets, h=3)
autoplot(fcast)
```

The best model for this one is Exponential Smoothing, since the model had smallest residuals.




```
print(summary(fcast))
```

```
##
## Forecast method: ETS(M,N,N)
##
## Model Information:
## ETS(M,N,N)
##
## Call:
##  ets(y = Youb)
##
##   Smoothing parameters:
```

```
##     alpha = 0.1494
##
##   Initial states:
##     l = 1926.8547
##
##   sigma:  0.2844
##
##      AIC     AICc      BIC
## 466.3225 467.2825 470.4244
##
## Error measures:
##                     ME     RMSE      MAE       MPE     MAPE      MASE      ACF1
## Training set -56.75984 543.4486 360.3025 -28.21217 41.87983 0.7657282 0.1164747
##
## Forecasts:
##    Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## 30       1680.943 1068.308 2293.579 743.9984 2617.888
## 31       1680.943 1060.962 2300.924 732.7642 2629.123
## 32       1680.943 1053.690 2308.197 721.6416 2640.245
```

Forecast workload for next day with confidence 95% is 2617 pallets.

So the total workload is :

- INB-PROD 1919 pallets
- INBOUND 2397 pallets
- INTERNAL 397 pallets
- NARROW 498 pallets
- NARROW-OUT 565 pallets
- NARROW-RPL 25 pallets
- O-PND-OUT 425 pallets
- OUT-CONT 1602 pallets #### OUTBOUND 2617 pallets