TIME SERIES PROJECT
by Gabriel Paolo Dino

INTRODUCTION

In a business setting, we want to maximize our resources, to cut out cost but not in the expense of the quality of service we offer to the customers and as well as the well-fare of the workers. To be able to meet the minimum requirement of this scenario, we have to have a little bit of knowledge about WORK FORCE OPTIMIZATION.

The main idea in Work force optimization is all about Business Forecasting. Business Forecasting is the ability to predict the future as accurately as possible, given all the information available including historical data and forecasts (Hyndman, 2013). We try to do this for us to be able to organize future activities trying to incorporate rooms for uncertainties, to be prepared on the possible situation of the business in the future and for effective management.

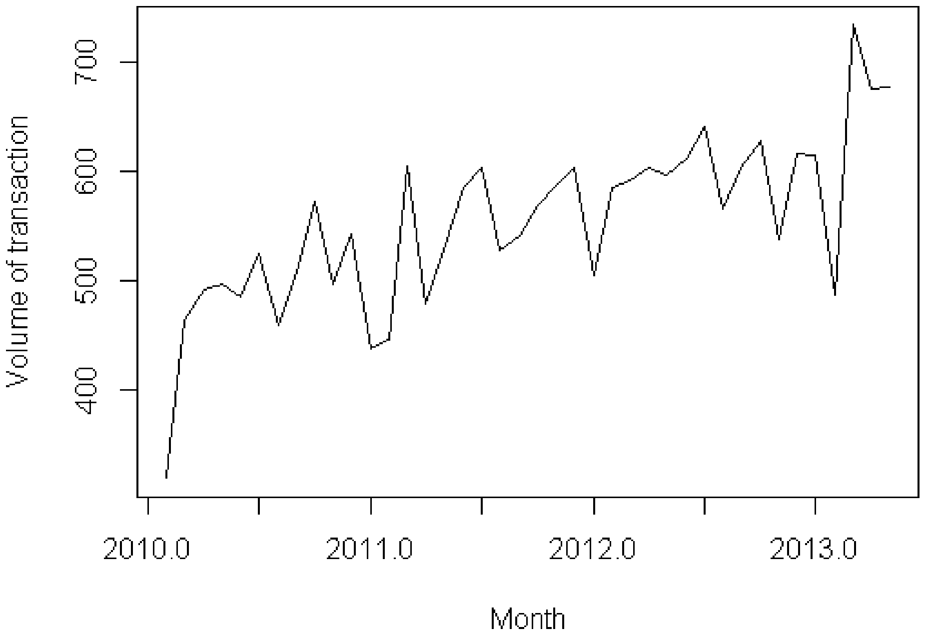
Now, we will look at the health insurance claims data of LoveYourSelf Insurance Company. A certain team in the company handles these medical insurance claims. They review all the transaction requests from the hospital and send a feedback whether the request is approved or denied.

- Transactions in claiming insurance benefits
  - Additional Guarantee Letter (AGL) — request for admission
  - Top Up — request to upgrade the approved medical claim
  - Final Guarantee Letter (FGL) — final transaction for discharge

- Here is the Health Services Historical Claims Data categorized based on their transaction type.

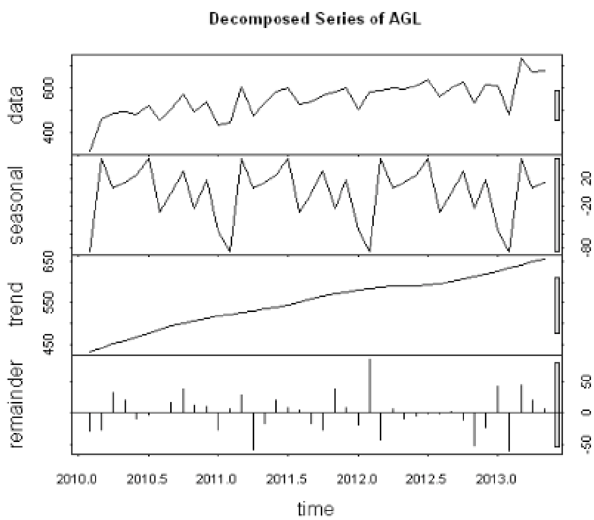
	Month	AGL	TopUp	FGL
1	2010 02	319	42	290
2	2010 03	463	34	388
3	2010 04	491	25	388
4	2010 05	496	51	381
5	2010 06	485	39	380
6	2010 07	524	41	392
7	2010 08	458	29	366
8	2010 09	508	35	354
9	2010 10	571	69	450
10	2010 11	497	47	392
11	2010 12	542	45	452
12	2011 01	437	41	393
13	2011 02	445	44	323
14	2011 03	604	30	452
15	2011 04	479	39	367
16	2011 05	533	40	383
17	2011 06	585	62	407
18	2011 07	603	61	458
19	2011 08	528	76	395
20	2011 09	540	47	395
21	2011 10	569	42	422
22	2011 11	587	56	446
23	2011 12	602	50	451
24	2012 01	505	47	366
25	2012 02	585	52	446
26	2012 03	592	45	483
27	2012 04	602	56	437
28	2012 05	596	63	421
29	2012 06	611	62	432
30	2012 07	640	78	463
31	2012 08	565	41	452
32	2012 09	602	39	432
33	2012 10	627	70	449
34	2012 11	537	46	388
35	2012 12	616	58	457
36	2013 01	614	71	472
37	2013 02	487	62	373
38	2013 03	733	69	570
39	2013 04	675	74	520
40	2013 05	677	66	490

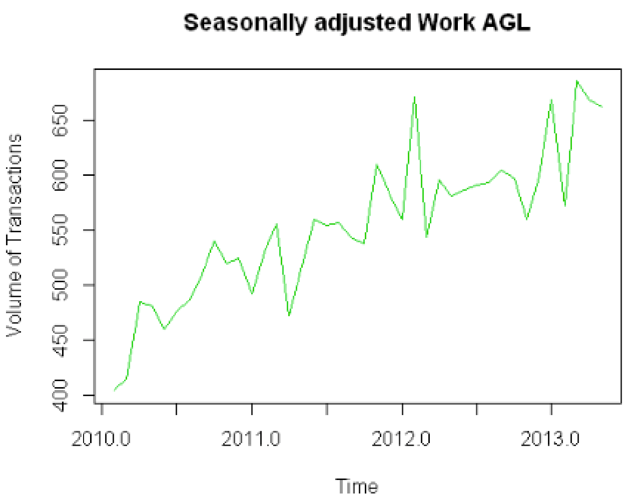
TIME SERIES PLOT
For time series data, the obvious graph to start with is a time plot. That is, the observations are plotted against the time of observation, with consecutive observations joined by straight lines.As we can see; the time series has an increasing pattern.



Now we graph the monthly seasonal plots of each claim per transaction type. We will first proceed with AGL

TREND AND SEASONALITY (AGL)



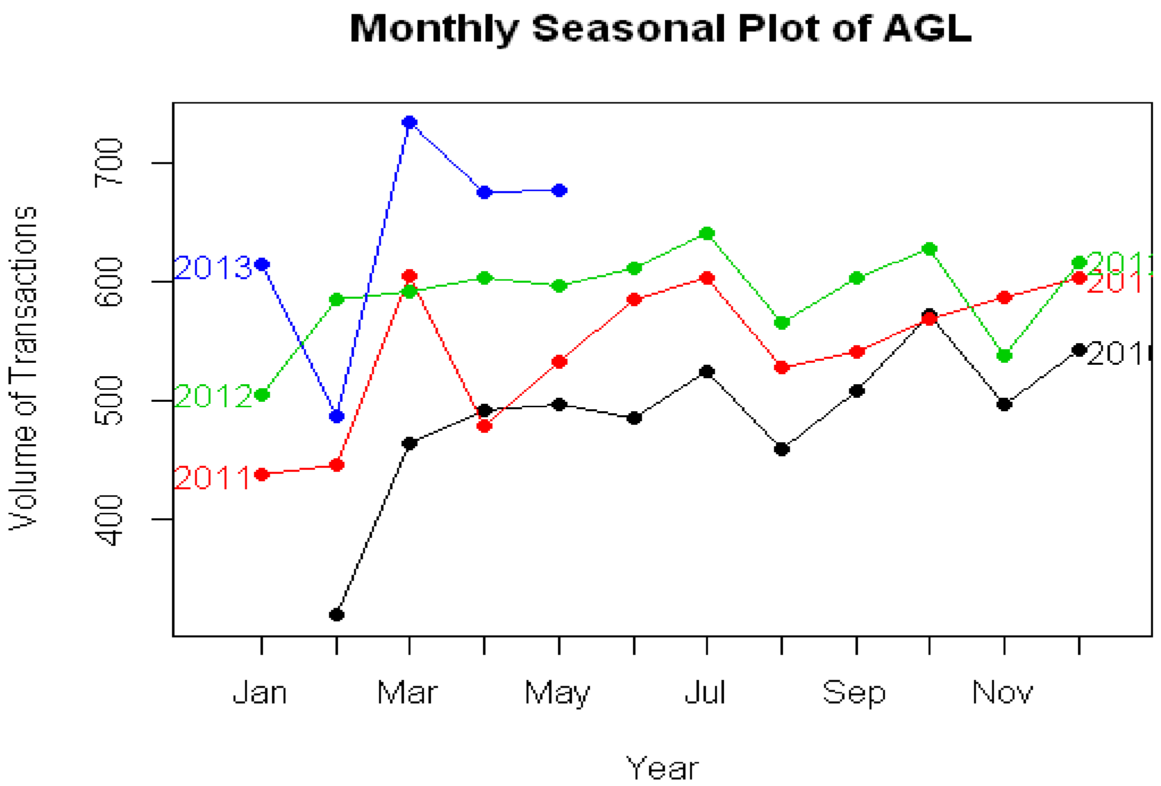


The time series plot can be decomposed to clearly see the seasonality component, trend component and the remainder component. All three components are shown in the bottom three panels. These three components can be added together to reconstruct the data shown in the top panel. The remainder component shown in the bottom panel is what is left over when the seasonal and trend-cycle components have been subtracted from the data.

Clearly from the decomposed series, we can see that there is an increasing trend and a uniform seasonality pattern.

The Seasonally adjusted work for AGL is the resulting plot when we remove the seasonal component from the original data. This can be useful if the variation due to seasonality is not of primary interest. In our case, we will neglect this since we want to see the work load variation including the seasonality component.

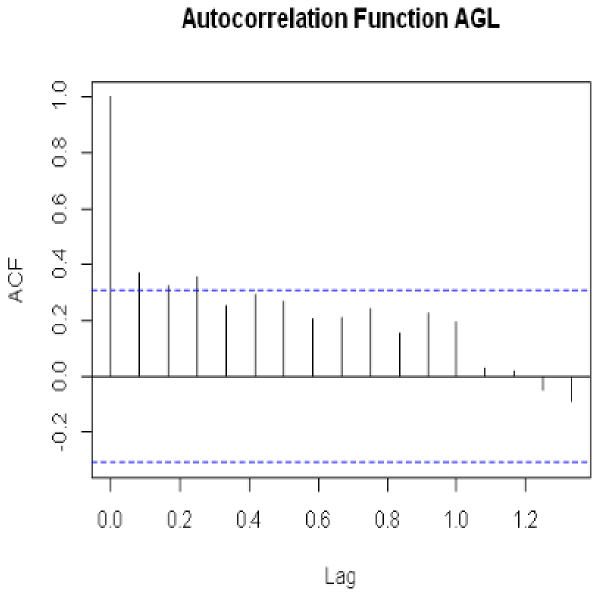
MONTHLY SEASONAL PLOT (AGF)

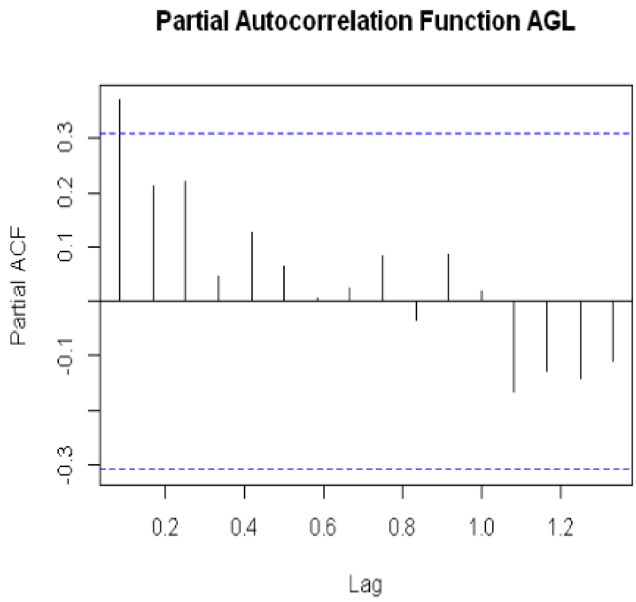


A seasonal plot is similar to time series plot except that the data are plotted against the individual months in which the data were observed. This allows us to understand more clearly the seasonal pattern and to identify any pattern changes.

In our diagram, throughout the years, we can see that there is an increasing pattern from Feb to March, and also there is an annually pattern that can be drawn from May – December. In this case, we would like to examine and investigate on the relationship of data points from Jan-Feb and March-April-May. There might be an unusual event or scenario happened during these times, if this scenario is uncontrollable then we will leave these data points, else, if we know that those events were just special and isolated cases, then we can proceed on correcting our data points to reflected value during that time. In our case, we will not correct any data point.

GENERATE ACF AND PACF PLOTS (AGF)





The autocorrelation function measures the relationship between variables for different values. The partial autocorrelation function plot is useful for identifying non-stationary time series. For a stationary time series, the PACF will drop to zero relatively quickly while the PACF of non-stationary data decreases slowly. Also this is useful in selecting the appropriate parameters for ARIMA method.

In out example, we can see that we don't have a stationary time series data.

The next part of our project discusses about the different forecast models and the process how to choose the best model to represent our time series data.

The best model to use depends on, but not limited to the ff: availability of historical data, strength of relationships of parameters used, existence of trends, seasonality and noises. It is common to compare two or three potential models, and the best model should have the lowest absolute percentage error.

Since the current time series that we have is a non-stationary, we will proceed with different non-stationary forecast models.

FORECAST MODEL: SIMPLE EXPONENTIAL SMOOTHING

Simple Exponential Smoothing is the simplest of all the exponential smoothing methods. This is also known as the Single Exponential Smoothing. This method uses a smoothing constant ∝. This smoothing constant is chosen close to 0 if we want to smoothen out unwanted irregular components and close to 1 if we want to use this method for forecasting. In our case, we will use $\propto = 0.9$

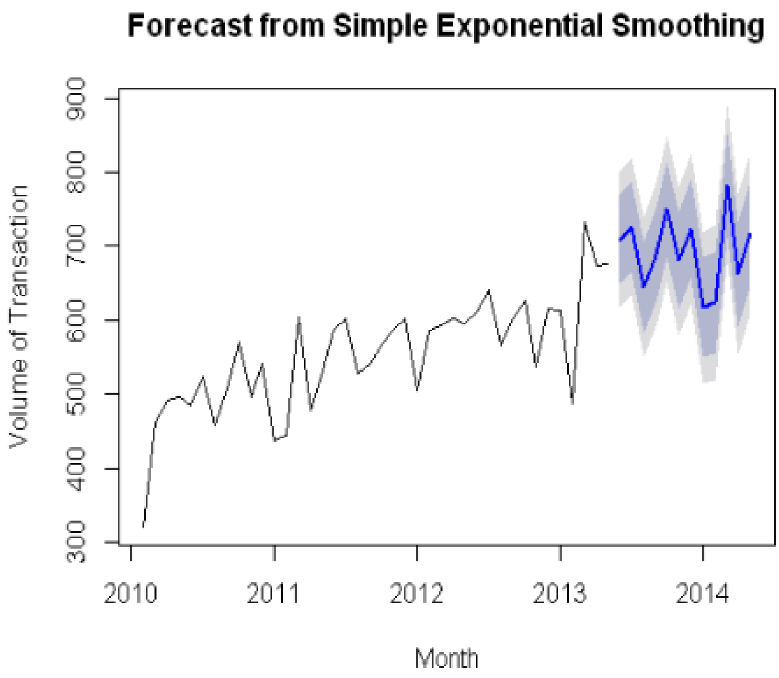
This method is suited for data with no trend and seasonal patterns (stationary data).

We will use R studio program to generate the results of this forecast model.

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Jun 2013	708.9631	649.1459	768.7804	617.4806	800.4457
Jul 2013	726.5131	665.5113	787.5150	633.2188	819.8074
Aug 2013	644.0631	581.8992	706.2270	548.9916	739.1345
Sep 2013	687.8214	624.5168	751.1260	591.0054	784.6374
Oct 2013	750.3297	685.9046	814.7548	651.8000	848.8594
Nov 2013	680.1713	614.6448	745.6978	579.9572	780.3854
Dec 2013	724.3463	657.7367	790.9559	622.4756	826.2170
Jan 2014	616.7713	549.0958	684.4467	513.2706	720.2720
Feb 2014	623.4462	554.7215	692.1710	518.3408	728.5517
Mar 2014	783.0795	713.3213	852.8378	676.3935	889.7656

➢ accuracy(fcast2)

ME	RMSE	MAE	MPE	MAPE	MASE
- 6.7507279	46.3290317	37.4377380	1.0199311	**6.3993757**	**0.6697577**



FORECAST MODEL: HOLT'S EXPONENTIAL SMOOTHING

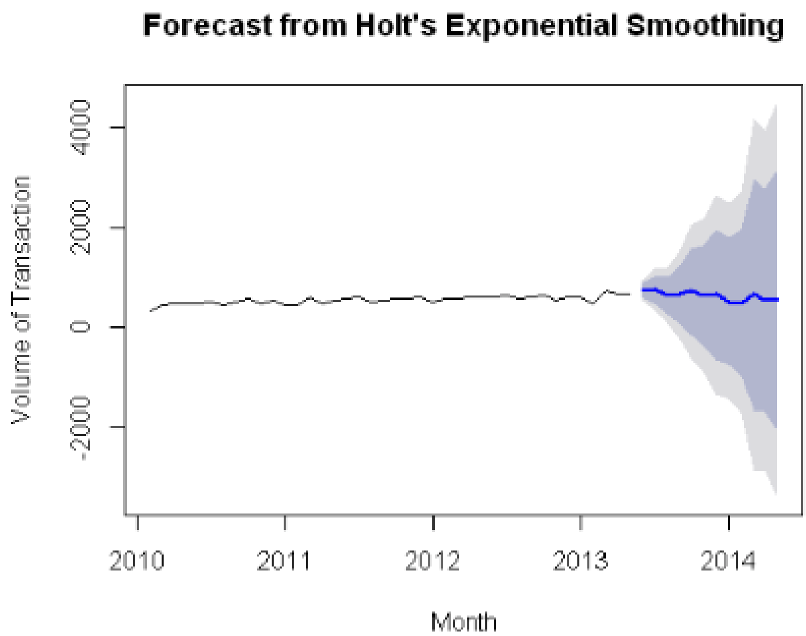
Holt (1957) extended simple exponential smoothing to allow forecasting data with a trend. This method involves a forecast equation and two smoothing equations. The two smoothing parameters will take values close to 1.

We will use R studio program to generate the results of this forecast model.

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Jun 2013	745.4155	612.89996	877.9309	542.75049	948.0804
Jul 2013	758.1817	488.92758	1027.4358	346.39306	1169.9703
Aug 2013	631.3442	257.33688	1005.3516	59.34935	1203.3391
Sep 2013	660.9685	81.64673	1240.2902	-225.02769	1546.9647
Oct 2013	724.3122	-147.44763	1596.0720	-608.92939	2057.5537
Nov 2013	639.1843	-366.37457	1644.7432	-898.68529	2177.0539
Dec 2013	661.4297	-650.15268	1973.0120	-1344.46243	2667.3218
Jan 2014	526.3848	-757.04634	1809.8160	-1436.45377	2489.2235
Feb 2014	495.4514	-962.07594	1952.9788	-1733.64433	2724.5472
Mar 2014	660.9423	-1647.68155	2969.5661	-2869.79319	4191.6778
Apr 2014	543.4222	-1681.38343	2768.2278	-2859.12438	3945.9687

➢ accuracy(fit3)

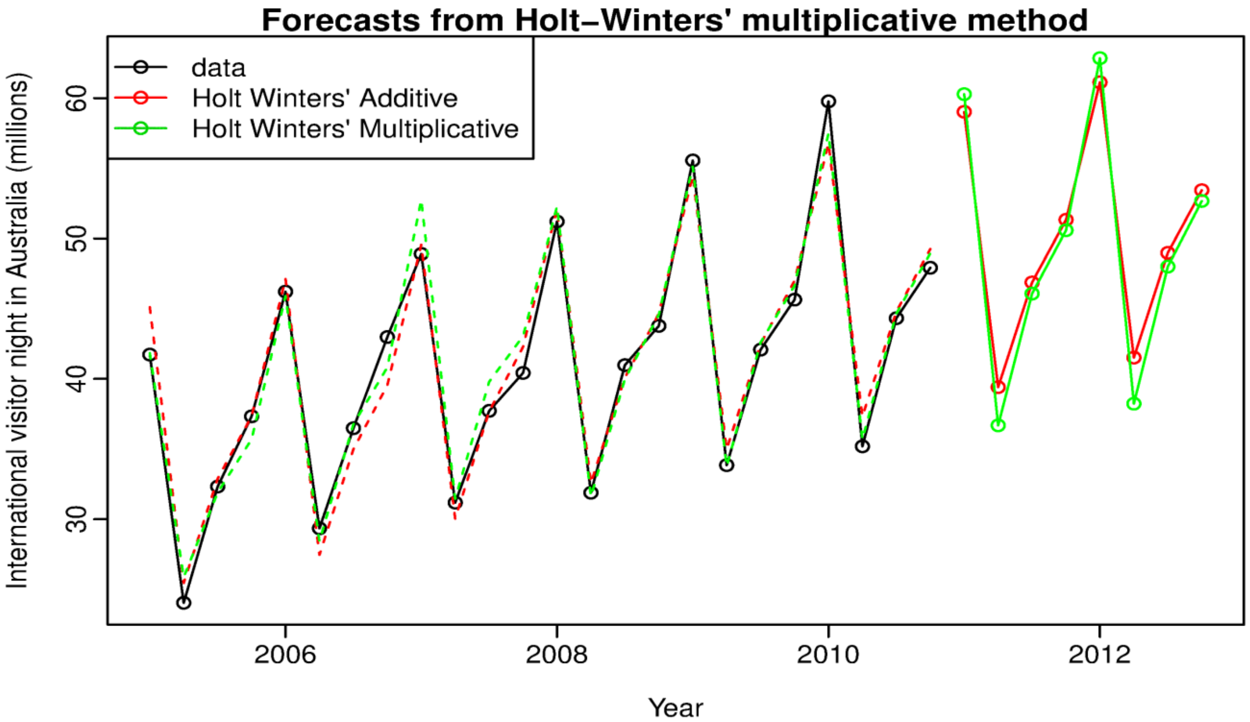
ME	RMSE	MAE	MPE	**MAPE**	**MASE**
-2.4118928	101.6402275	69.7403940	-0.8705765	**11.8087420**	**1.2476493**



FORECAST MODEL: HOLT-WINTERS EXPONENTIAL SMOOTHING

Winter (1960) extended Holt's method to capture seasonality. This method involves a forecast equation and 3 smoothing equations (one for the level, trend and seasonality). All the smoothing parameters should be close to 1.

Since this method now covers seasonality, we must also input the type of seasonality, whether additive or multiplicative seasonality must be used. Luckily according to Rob Hyndman, that the Holt-Winters' additive method and multiplicative method generate almost the same forecast values.

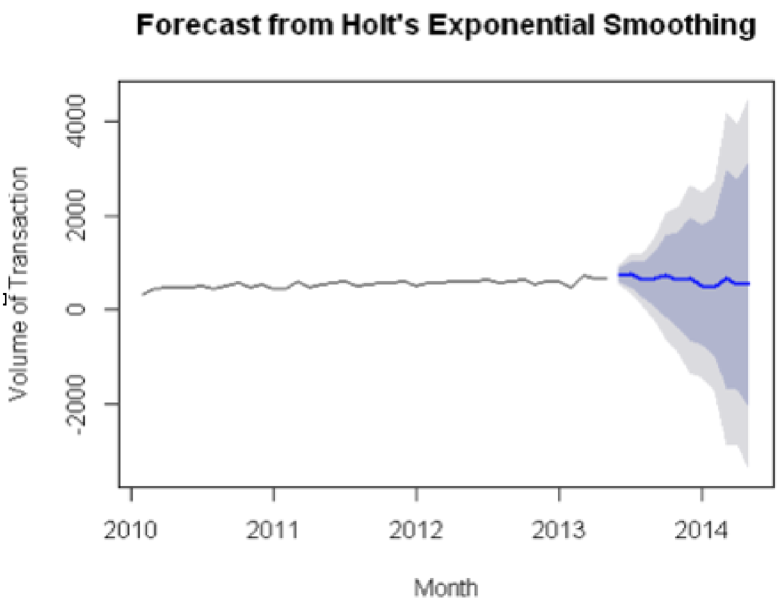


We will use R studio program to generate the results of this forecast model.

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Jun 2013	743.0111	611.70520	874.3170	542.19607	943.8261
Jul 2013	752.9691	484.51540	1021.4228	342.40459	1163.5336
Aug 2013	625.6112	252.13055	999.0918	54.42186	1196.8005
Sep 2013	654.2817	74.43782	1234.1256	-232.51299	1541.0764
Oct 2013	715.0115	-157.75416	1587.7771	-619.76837	2049.7913
Nov 2013	627.2691	-376.45869	1630.9969	-907.80009	2162.3383
Dec 2013	648.2254	-663.19328	1959.6440	-1357.41637	2653.8671
Jan 2014	513.6928	-768.13481	1795.5204	-1446.69334	2474.0789
Feb 2014	484.1526	-978.23736	1946.5426	-1752.37984	2720.6850
Mar 2014	642.6077	-1669.84315	2955.0585	-2893.98067	4179.1960

➢ accuracy(fit4)

ME	RMSE	MAE	MPE	**MAPE**	**MASE**
-2.5042946	101.6594075	70.0914768	-0.8804078	**11.8632796**	**1.2539301**


Forecast from Holt's Exponential Smoothing
Volume of Transaction
4000
2000
0
-2000
2010
2011
2012
2013
2014
Month

FORECAST MODEL: Exponential Smoothing (ETS)

We have seen that adding the seasonal component makes 2 variations of model – additive and multiplicative. In general, a time series data can have 5 variations of trend component (None, additive, additive damped, multiplicative and multiplicative damped) and 3 variations of seasonal component (none, additive and multiplicative) and 2 variations for error component.
Hence we have a total of 30 smoothing methods.

Using R programming, we can call out the ETS function to give us the optimized smoothing method to forecast our given time series data.
Here is the algorithm followed by R studio. It will apply the data in each of 30 models (given that the model is appropriate to the data). It will optimize the parameters and initial values It will then select the best method using AIC

AIC = -2 (log)likelihood + p; where p is the number of parameters.
After selecting the method, it produces the forecast values and obtain the prediction intervals using underlying state space model.

We will use R studio program to generate the results of this forecast model.

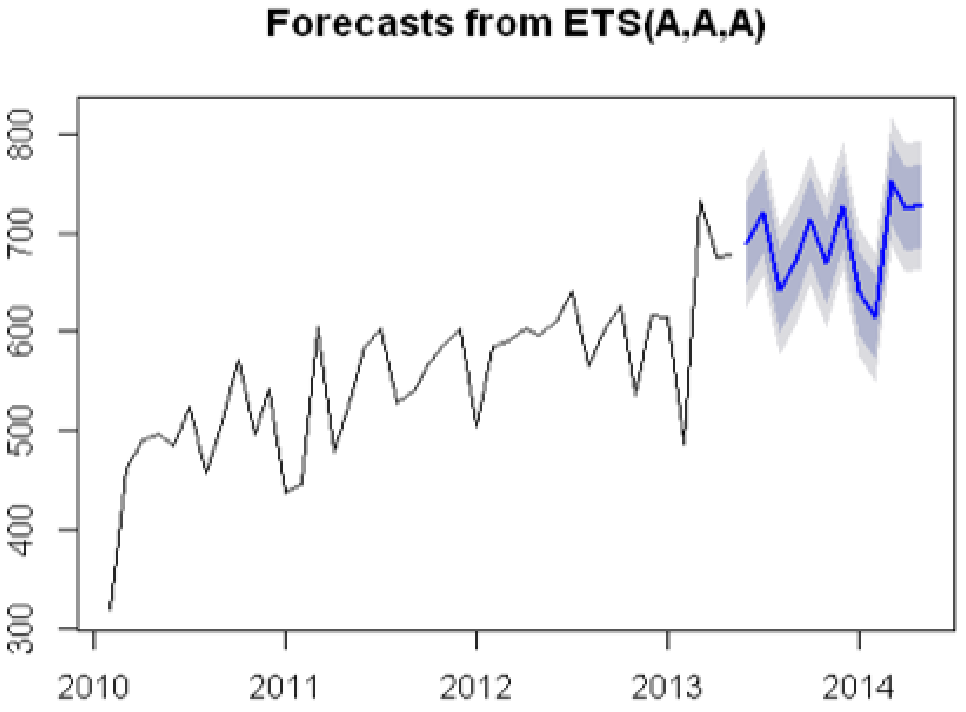
	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Jun 2013	690.0441	647.6325	732.4557	625.1811	754.9070
Jul 2013	721.6861	679.2729	764.0994	656.8206	786.5516
Aug 2013	641.8264	599.4114	684.2413	576.9582	706.6945
Sep 2013	672.1621	629.7454	714.5788	607.2913	737.0329
Oct 2013	713.3185	670.9000	755.7370	648.4449	778.1921
Nov 2013	670.0287	627.6084	712.4491	605.1524	734.9051
Dec 2013	725.8046	683.3823	768.2269	660.9253	790.6839
Jan 2014	639.7104	597.2862	682.1346	574.8282	704.5927
Feb 2014	615.3594	572.9332	657.7856	550.4741	680.2447
Mar 2014	751.4605	709.0323	793.8888	686.5721	816.3490
Apr 2014	724.0100	681.5796	766.4403	659.1183	788.9016

➢ accuracy(fcast7)

ME	RMSE	MAE	MPE	**MAPE**	**MASE**
2.1604522	33.0939541	25.6076269	0.1185396	**4.7472992**	**0.4581181**

```
➢ > fit7
➢
ETS(A,A,A)

Call:
    ets(y = MHS1.ts)

    Smoothing parameters:
                        alpha = 0.0086
                        beta = 1e-04
                        gamma = 0.0018

    Initial states:
                        l = 441.2912
                        b = 5.3451
                        s=-59.4758 32.071 -18.3994 30.217 -5.5958 -30.5621 54.6952
                             28.3929 7.4718 8.8081 41.5511 -89.174

AIC= 459.5032
AICc= 483.1554
BIC=486.5253
```

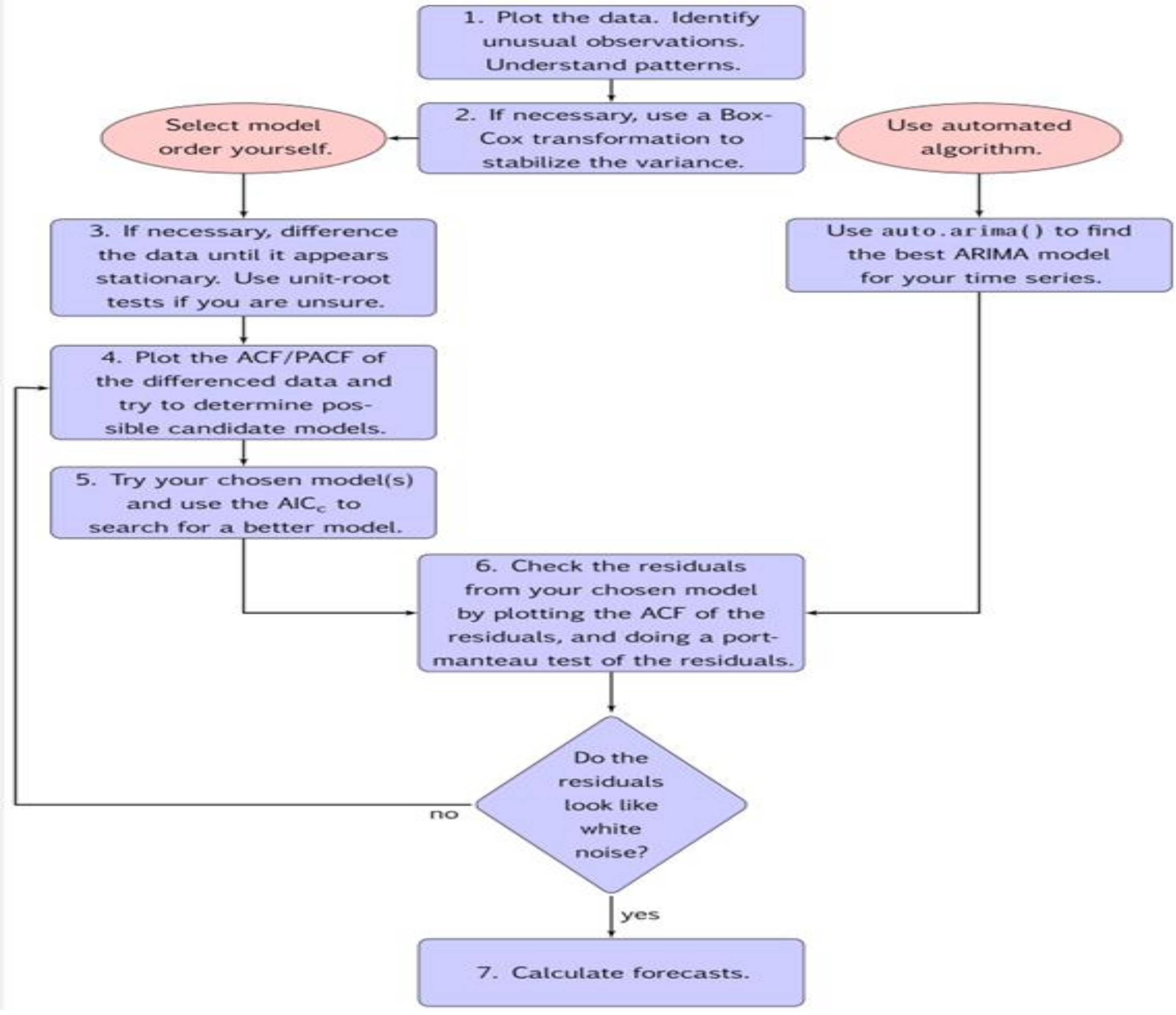
Looking at the forecast detail, R studio categorized our data having additive trend, additive seasonality and additive error component. Hence we have used in particular the Additive Holt-Winter's method with additive errors.



FORECAST MODEL: ARIMA

While exponential smoothing models were based on trend and seasonality in the data, ARIMA models aim to describe the autocorrelations. This method is also known as Box – Jenkins method.

ARIMA method involves solving 3 parameters – number of autocorrelation parameters, number of moving average parameters and number of differencing. But since we are using R studio, we will opt to go the automated algorithm.

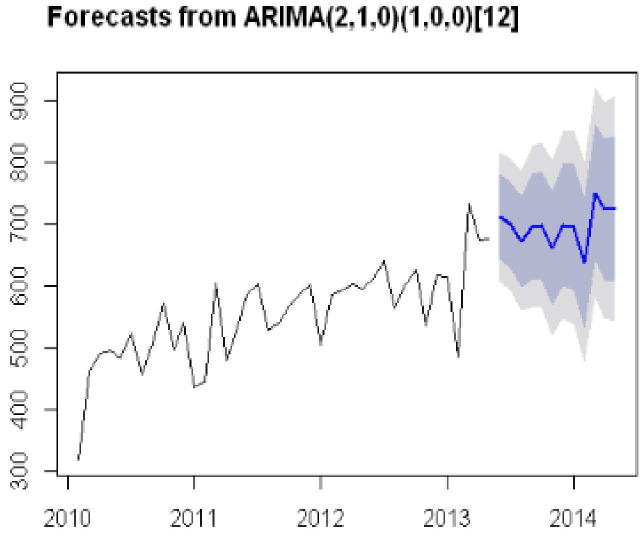


	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Jun 2013	711.4179	642.6772	780.1585	606.2881	816.5477
Jul 2013	699.4662	629.6566	769.2758	592.7016	806.2308
Aug 2013	672.2008	598.3484	746.0532	559.2534	785.1482
Sep 2013	696.0723	610.7254	781.4192	565.5455	826.5991
Oct 2013	698.1753	610.1871	786.1635	563.6090	832.7416
Nov 2013	661.3858	568.5573	754.2143	519.4169	803.3548
Dec 2013	698.5517	599.8239	797.2795	547.5605	849.5428
Jan 2014	694.5153	592.3769	796.6537	538.3081	850.7225
Feb 2014	638.8185	532.2898	745.3472	475.8969	801.7401
Mar 2014	750.3988	639.5492	861.2484	580.8690	919.9287
Apr 2014	723.1267	608.7284	837.5251	548.1696	898.0839

```
➢ > fit5
➢
Series: MHS1.ts
ARIMA(2,1,0)(1,0,0)[12]

Coefficients:
          ar1       ar2       sar1
      -0.8230   -0.5037    0.4535
s.e.   0.1506    0.1433    0.1754

sigma^2 estimated as 2877: log likelihood=-212.51

AIC=433.01   AICc=434.19   BIC=439.67
```

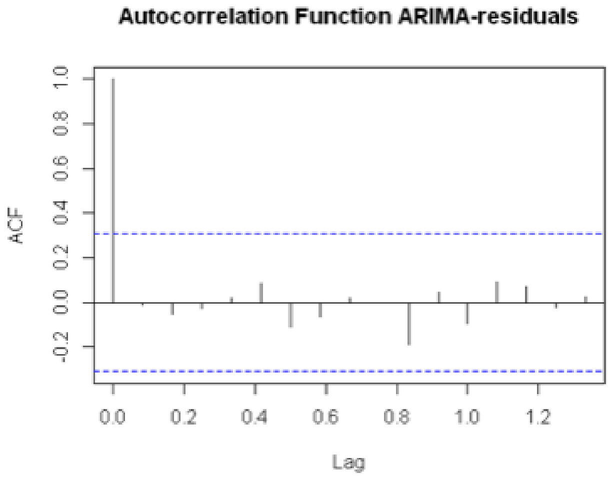
In this case, we have used ARIMA (2,1,0)

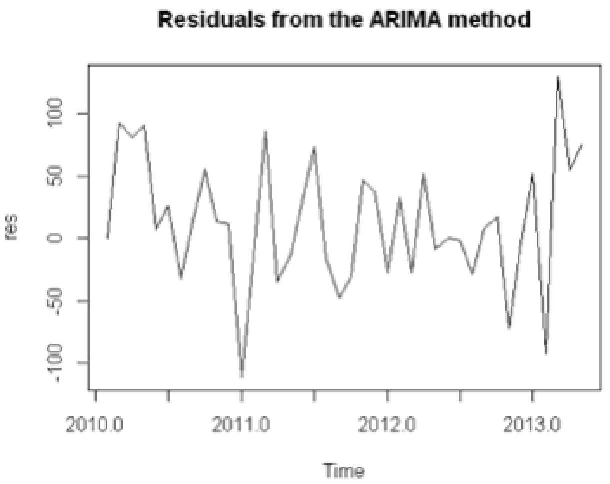
```
➢ accuracy(fcast5)

        ME       RMSE        MAE       MPE      MAPE      MASE
13.1529699 52.9639372 41.2837304 1.8896506 7.5237535 0.7385621
```

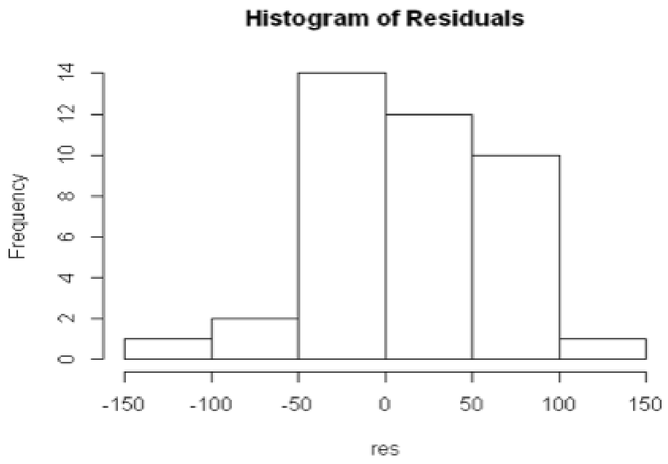


In time series modelling, residuals should follow a white noise process, especially for ARIMA method.

CHECKING FOR WHITE NOISE PROPERTY OF THE RESIUALS







PERFORMANCE BOX TEST

> Box.test(res,lag=10,fitdf=0, type="Lj") Box-Ljung test

data: res
X-squared = 3.3076, df = 10, p-value = 0.9732

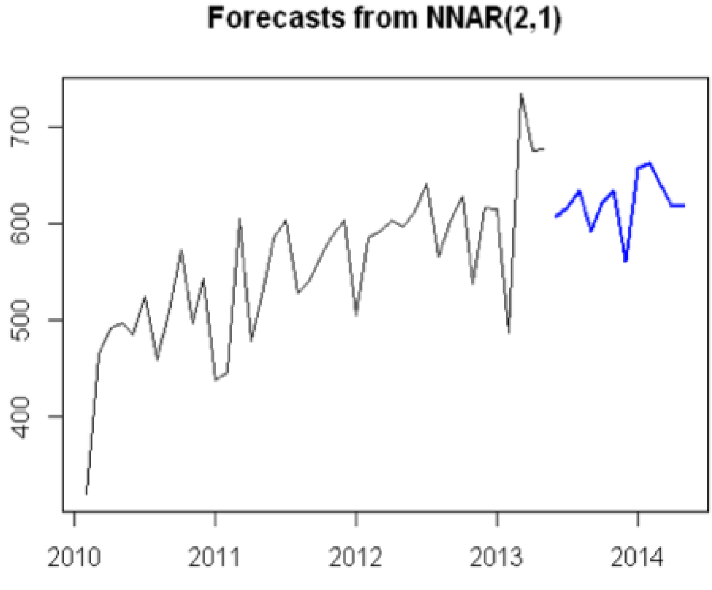
- **Probability value of Box test is 0.9871 which is greater than alpha (0.05), we do not Reject Ho. The ARIMA model does not exhibit lack of fit.**

FORECAST MODEL: NNA

Artificial neural networks are forecasting methods that are based on simple mathematical models of the brain. They allow complex nonlinear relationships between the response variable and its predictors.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2013	605.2074	615.3558	634.3437	591.9618	621.3834	633.5292	560.0005					

```
➢ accuracy(fcast6)
          ME        RMSE         MAE          MPE        MAPE        MASE
-0.07409826 47.94258609 36.95738750  -0.69328923  6.42031736  0.66116427
```



SUMMARY

Forecast Model	MAPE	MASE	AIC	BIC	AICc
Simple Exponential Smoothing	*6.3993757*	*0.6697577*	-	-	-
Holt Exponential	*11.8087420*	*1.2476493*	-	-	-
Holt-Winters	*11.8632796*	*1.2539301*	-	-	-
ARIMA	*7.5237535*	*0.7385621*	*433.01*	*439.67*	*434.19*
Neural Network	*6.42031736*	*0.66116427*	-	-	-
ETS	*4.7472992*	*0.4581181*	*459.5032*	*483.1554*	*486.5253*

Based on different accuracy criteria, we will use ETS as our forecast model.