September

2018

OPEN IIT DATA ANALYTICS

Team Parsefulness

- *Captained by Yuvraj Khanna*

Understanding the problem:-

Medicine is the backbone of Healthcare Services. Also it is also one of the (major)part comprise in Healthcare services which is quite dependent on the factors like time and space (in term of storage).If we look at consumption of medicine, is quite large and thus for its storage pretty large space is occupied, which might be a problem in case of hospitals and medical centres in metropolitan cities. Also, time is one of the biggest culprit while deciding the backup storage for medicine, as medicines expire after particular duration which might be a big problem in case of medicines for particular disease or with short band i.e., specified for particular disease as their demand is occasional and (like water borne diseases are likely to happen in area of more waterfall and in monsoon.) Also lead time is also major deciding factor in case of emergency.

So basic questions are: -

1)How we going to predict medicine consumption for the hospitals or medical centres precisely?

2)And how are we going to decrease money wasted on medicines that gets expired or somehow are no more usable?

And certainly, to get this answer we are approaching conventional forecast methods in data analytics.

→Q.1)

- # Maintaining a Constant Stock?

Safety stock is simply extra inventory beyond expected demand.

Entrepreneurs and Operations Managers carry safety stock to prevent stock outs, caused by:

Changes in customer demand

Incorrect forecast

Variability in lead times for raw materials

$$SS = z(s_d)\sqrt{LT}$$

(s_d) Standard Deviation of dataset

Z = service factor based on standard deviation of demand

$\sqrt{LT}$ Root of Lead Time

As seen from the plots of medicine A the dataset has seasonal period and trend

Since the lower values as well as the upper bounds are increasing and we can not determine a constant safety stock for all our observations.

This is seen to be true as the demand of the medicines for a given year is dependent upon the previous consumptions moreover the

Results we have obtained are based upon the average rate of, the real values has a probability being close to the actual value.

Maintaining a safety stock maximising the values will cause a the inventory cost to increase as well as taking the average value of safety stock will not be able to meet the demands in peak seasons.

Data description:

Plot of the given data of A medicine results in the observation of seasonal trend of a year.

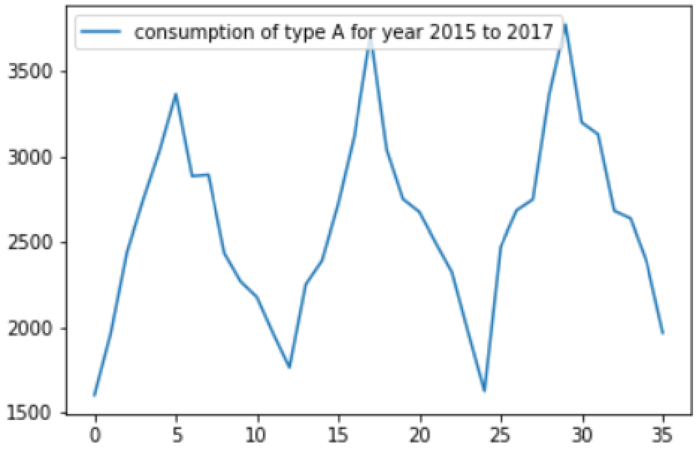


Fig1

Aggregate Plot

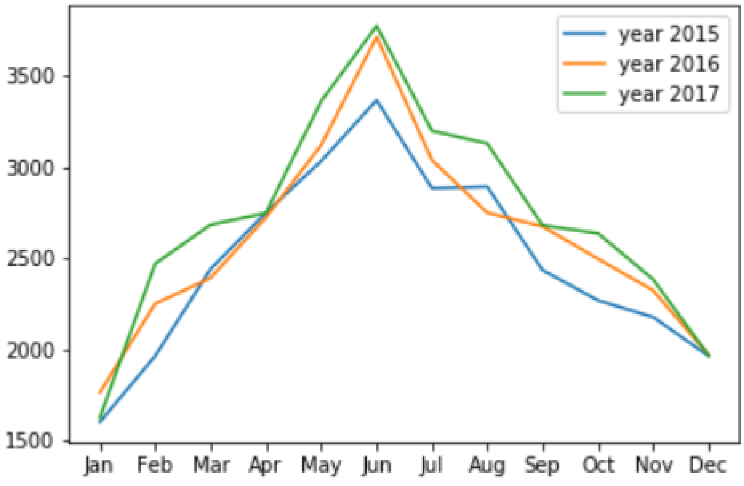
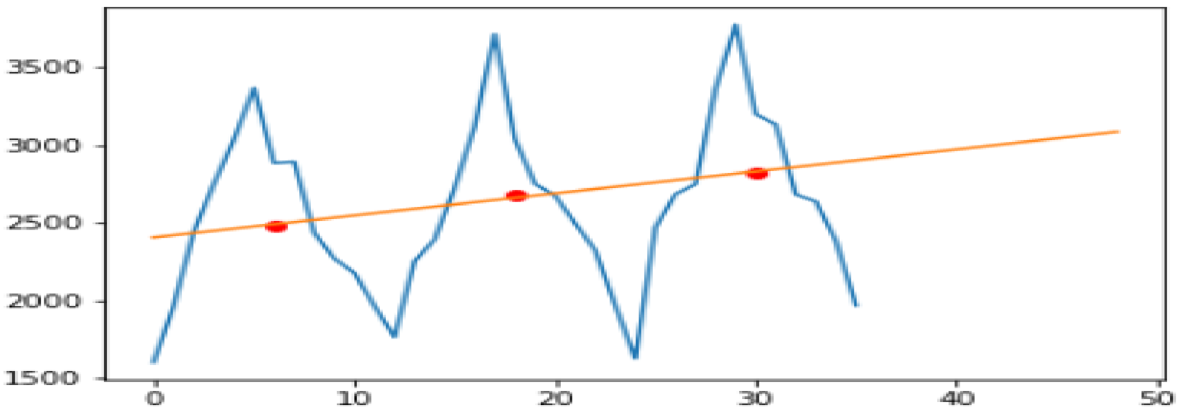


Fig 2

Yearly Plot

Simple Linear Regression Model on the average points of different years

results in a line having a positive slope explicitly shows the increasing trend.



Similarly applying linear regression (shown in Fig4) on the top and bottom points of the data gives a bound of the data as well as the fact that the data is bounded by nonlinear trend showing bottom points

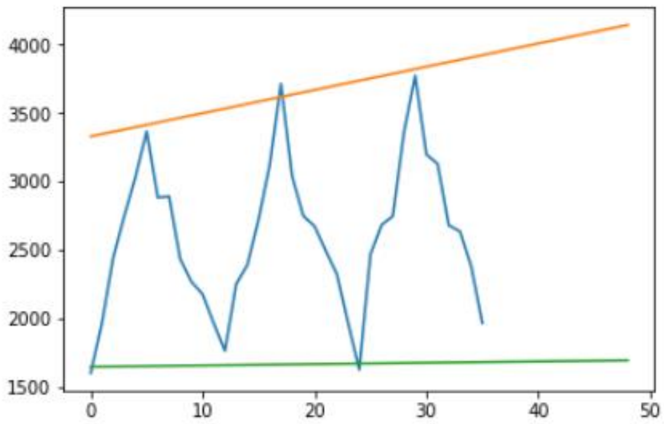


Fig4

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Forecasting Models:

The results obtained from above narrows down our set of forecasting methods to three widely used models

1) Exponential Smoothing

2) Holt-Winter's Method:-

a) Additive Seasonality b) Multiplicative Seasonality.

3) ARIMA

We will briefly explain our approach using each of these models and how we arrived at the conclusion of picking out the best model applicable on this dataset.

Exponential Smoothing

Exponential smoothing is a rule of thumb technique for smoothing time series data using the exponential window function. Whereas in the simple moving average the past observations are weighted equally, exponential functions are used to assign exponentially decreasing weights over time. It is an easily learned and easily applied procedure for making some determination based on prior assumptions by the user, such as seasonality. Exponential smoothing is often used for analysis of time-series data.

Our model for exponential smoothing had the RMSE value of 340.48

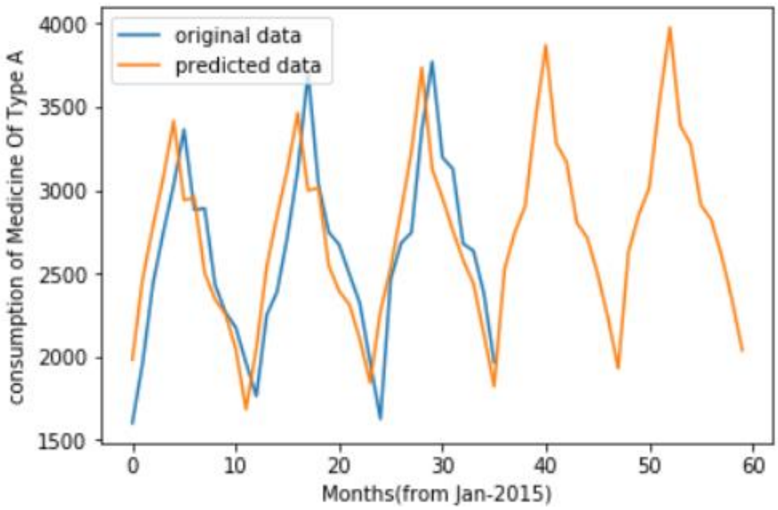


Fig5

From the results obtained above we gave different arguments to the smoothing functions

- Seasonal periods=12
- Seasonal = add
- Trend = add

Main function for exponential smoothing

```
In [6]: model = ExponentialSmoothing(values,seasonal='add',trend='add', seasonal_periods=12).fit()
```

s

We *rejected* this model as the following models showed greater likeness and less rmse for more accurate forecasting and the graph.

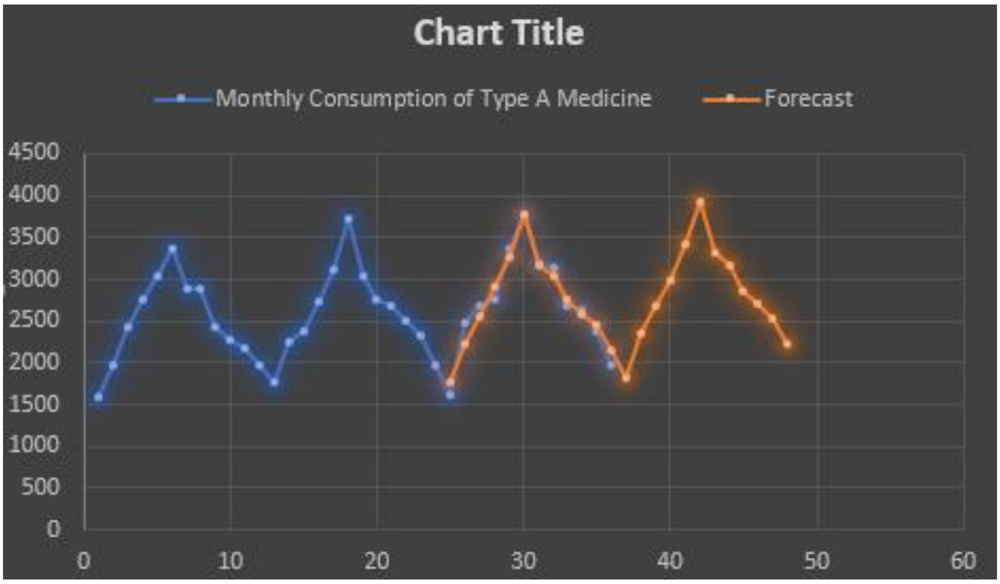
Holt-Winter's Method

There are two variations to this method that differ in the nature of the seasonal component. The additive method is preferred when the seasonal variations are roughly constant through the series, while the multiplicative method is preferred when the seasonal variations are changing proportional to the level of the series.

Both of the variations were implemented in Excel as it showed much better results.

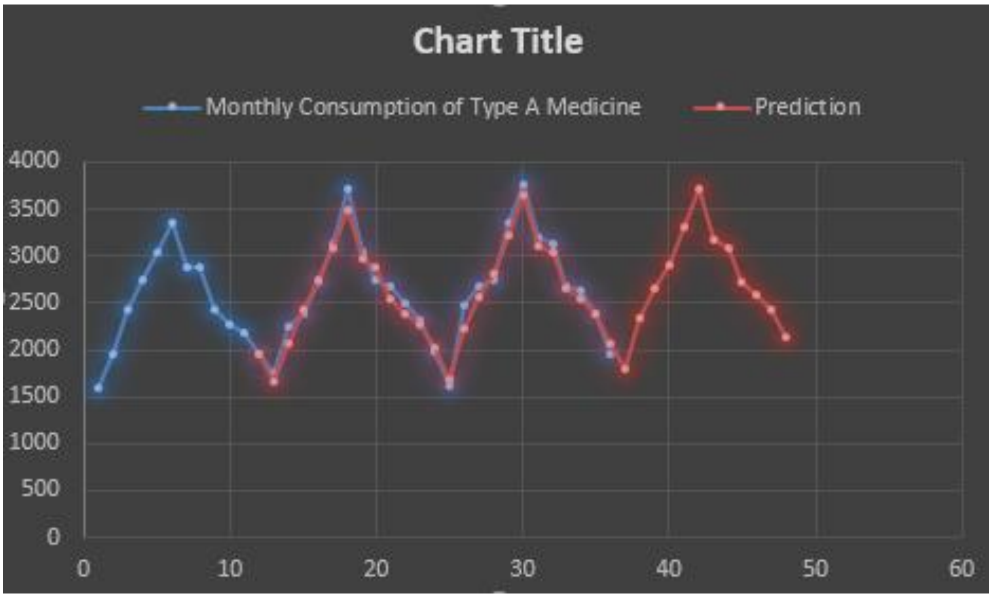
Multiplicative Seasonality

In this method the multiplicative seasonality of Holt-Winter is applied



The RMSE obtained was 124.4 indeed a better improvement as compared to smoothing.

Additive Seasonality :



The RMSE error for additive seasonality was obtained to be 110.2

This was best compared to the above models as the graph likeness was highly increased and the lag in the exponential smoothing model graph was omitted.

- ***ARIMA (AutoRegressive Integrated Moving Average):***

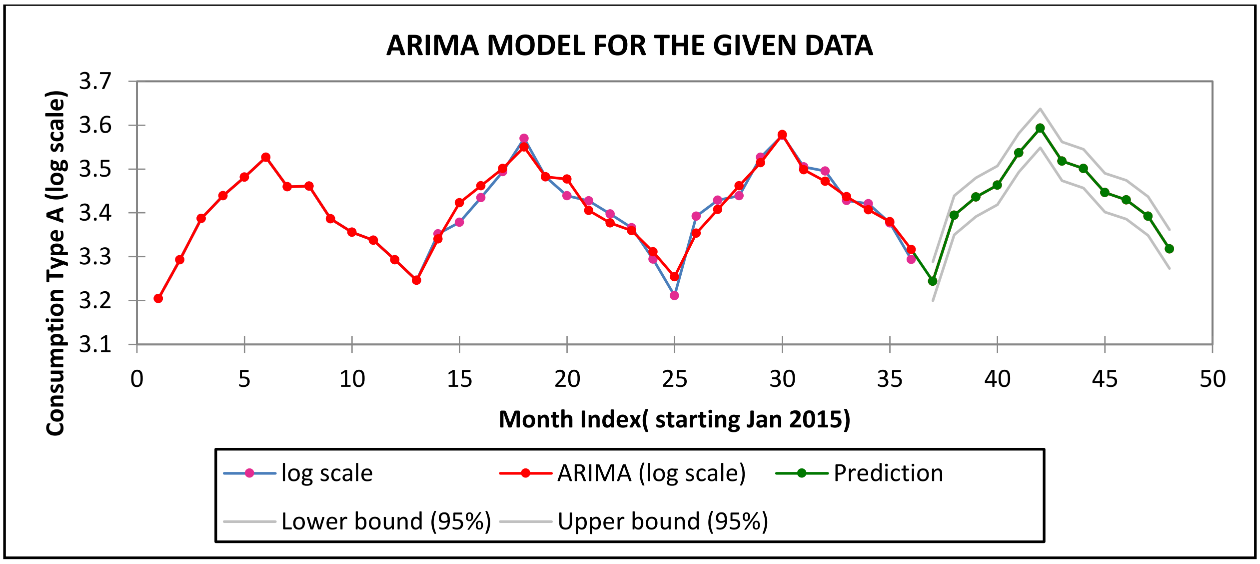
Auto Regressive Integrated Moving Average or ARIMA model is a class of model that captures a suite of different standard temporal structures in time series data.

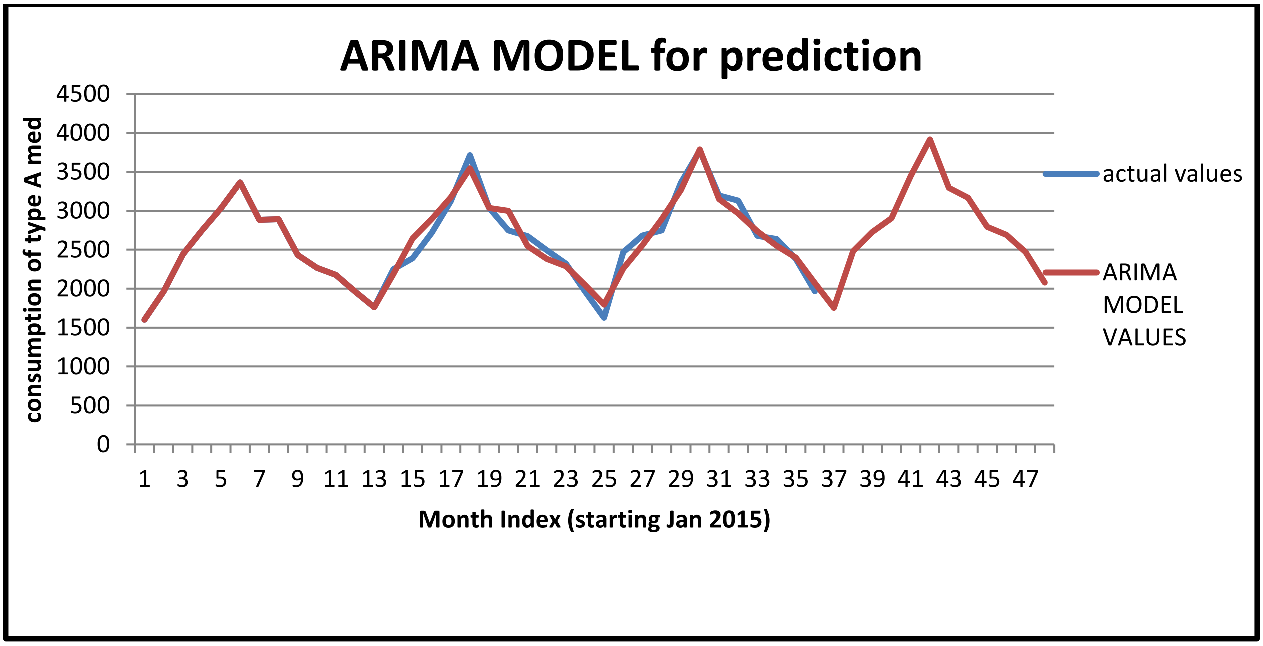
We noticed a global upward trend in the chart and that every year the cycle repeats, variability within a year seems to increase over time.

Before we fit the ARIMA model, we need to stabilize the variability.

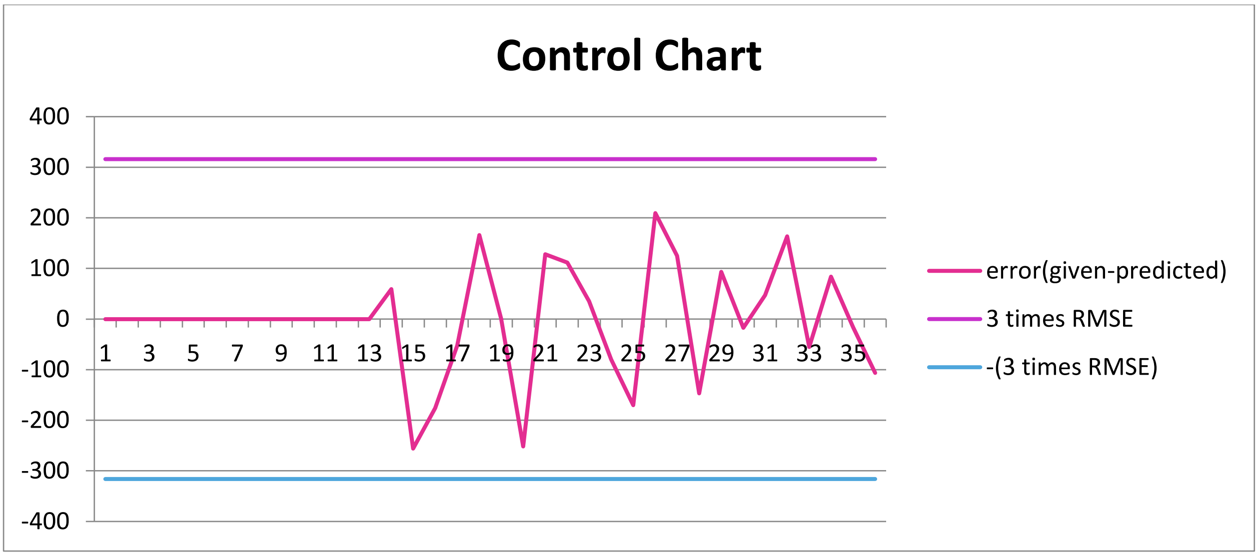
In order to accomplish that, we transform the series using a log transformation and then apply ARIMA model

The results of ARIMA are detailed and as follows:





Year	Month	actual values	log scale	ARIMA (log)	ARIMA(Values)	Errors
2015	Jan	1601	3.204391	3.204	1601	0
2015	Feb	1963	3.29292	3.293	1963	0
2015	Mar	2439	3.387212	3.387	2439	0
2015	Apr	2747	3.438859	3.439	2747	0
2015	May	3032	3.481729	3.482	3032	0
2015	Jun	3365	3.526985	3.527	3365	0
2015	Jul	2882	3.459694	3.460	2882	0
2015	Aug	2891	3.461048	3.461	2891	0
2015	Sep	2433	3.386142	3.386	2433	0
2015	Oct	2268	3.355643	3.356	2268	0
2015	Nov	2176	3.337659	3.338	2176	0
2015	Dec	1963	3.29292	3.293	1963	0
2016	Jan	1763	3.246252	3.246	1763	0
2016	Feb	2250	3.352183	3.341	2190.881	59.11949
2016	Mar	2390	3.378398	3.423	2646.016	-256.016
2016	Apr	2721	3.434729	3.462	2897.017	-176.017
2016	May	3120	3.494155	3.501	3171.83	-51.83
2016	Jun	3712	3.569608	3.550	3546.272	165.7279
2016	Jul	3037	3.482445	3.482	3035.952	1.047583
2016	Aug	2748	3.439017	3.477	2999.963	-251.963
2016	Sep	2673	3.426999	3.406	2545.171	127.8294
2016	Oct	2495	3.397071	3.377	2383.492	111.5075
2016	Nov	2322	3.365862	3.359	2286.541	35.45941
2016	Dec	1969	3.294246	3.311	2048.797	-79.797
2017	Jan	1625	3.210853	3.254	1795.412	-170.412
2017	Feb	2468	3.392345	3.354	2258.627	209.3727
2017	Mar	2682	3.428459	3.408	2557.41	124.5903
2017	Apr	2746	3.438701	3.461	2892.705	-146.705
2017	May	3360	3.526339	3.514	3266.983	93.01702
2017	Jun	3772	3.576572	3.579	3789.037	-17.0375
2017	Jul	3197	3.504743	3.498	3150.079	46.92068
2017	Aug	3128	3.495267	3.472	2964.371	163.6294
2017	Sep	2679	3.427973	3.437	2734.479	-55.4785
2017	Oct	2635	3.420781	3.407	2551.044	83.95561
2017	Nov	2382	3.376942	3.380	2398.299	-16.2993
2017	Dec	1966	3.293584	3.316	2072.115	-106.115
2018	***Jan***	****predicted****		***3.244***	***1754.053***	
2018	***Feb***	****predicted****		***3.394***	***2479.548***	
2018	***Mar***	****predicted****		***3.436***	***2727.634***	
2018	***Apr***	****predicted****		***3.463***	***2903.648***	



*The RMSE value of the dataset obtained is **105.35** which is the best among all applied models hence we will follow the results obtained =p..0from ARIMA model from now on and from the control chart we can clearly see that the error is bounded.*

The values for next 4 months of medicine A after rounding off to the nearest integer are

JAN-2018	**1754**
FEB-2018	2480
MAR-2018	2728
APR-2018	2904

Questions and Answers:

3. For "Type A" medicine, calculate i) EOQ ii) The number of orders per year iii) Reorder level iv) The total annual ordering and carrying costs v) Maximum Inventory level for "Type A" medicine to help Thomson and Cook hospital manage its inventory optimally.

i) EOQ = Economic Order Quantity

A = Annual demand = 31200 units

O = Ordering cost per order = 200 Rs.

C = Holding cost per unit per annum = 10% of per unit order per year

= 20 Rs.

EOQ = sqrt(2AO/C)

= 790 units

ii) the number of orders = (avg annual demand)/ EOQ

= 31200/790

= 39.49367 = 40 (nearly)

iii) Reorder level = d*L + z*σL

d = Average daily demand = (31200)/365 = 85.5

L = Lead time in days (time between placing an order and receiving the items) = 10 days

z = Number of standard deviations for a specified service probability = 1.65

σL = Standard deviation of usage during lead time = 300

R = 85.5*10 + 1.65*390 = 1350

iv) Total carrying cost = (carrying cost per unit per year/ 2)* (avg annual demand)

= 10*31200 = 312000 Rs.

Total Annual ordering cost = (cost per unit)* (avg annual demand)

= 204.2 * 31200 = 6371040 Rs.

Total ordering and carrying cost = 6371040+312000

= 6683040 Rs.

v) Maximum Inventory level = q*(1-d/p)

where, q= EOQ,

p = daily rate at which the order is received over time, also known as the production rate = 135

d = the daily rate at which inventory is demanded = 85.5

Maximum Inventory Level = 290