INDUSTRIAL & SYSTEMS ENGINEERING

TEXAS A&M UNIVERSITY

ISEN 615

Production and Inventory Control Course Project Report

# Arconic Fastening Systems and Rings

# VTI of Texas


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Through this medium we would also like to acknowledge the fact that this complied project report and the work we are submitting is our original work. We hold the ideals of our school Texas A&M in high regards and we abide by the code of honor.

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# 1 Arconic Fastening Systems and Rings

### *1.1 Data*

- The input data provides year-to-demand information for each of its customer base for the various Group-Product Family (109) and individual Items (1788) within each group. The data comprises of Three Markets – 1, 2 and 3.
- Out of the 12 variables provided constituting of order date, delivery date, quantity, etc. order date is taken as a time measure, segregated for year/months/quarters/weeks as per the need for the long-term or the short-term model and Quantity (PCS) is taken as a measure to forecast for. Further filters are incorporated to calculate demand forecast for grouped (aggregated) items and/or individual items.

### *1.2 Target*

- Forecast the demand for the various product types (Items)/Product family produced by Arconic, present them in an easy to interpret and a future ready format by automating the model or tool used
- Provide two models for short-term (Month time scale) forecasting and two models for long-term (Year time scale) forecasting
- Provide justification for models chosen (pros/cons)

### *1.3 General Process Outline*

- Filter out the raw data received based on Year and any category of interest (Product family/ Item) to easily sieve through the data for any demand patterns, check for trends or seasonality (if any)
- Execute Internal forecast generation, relying on forecasting methods like:
  1. Moving Average (MA)
  2. Exponential Smoothing (ES)
  3. Double Exponential Smoothing (Holt's Method)
  4. Holt – Winter's Method
  5. Croston's Method
  6. ARIMA Model
- Further compare the results from each of the above methods based on forecast error for the year 2018 and choose the one giving the most accurate forecast. Accuracy of forecast to be measured comparing the Calculated Aggregate Forecast of the year 2018 with the sum Demand available from Historical Data and Open Order Data for the year 2018. Calculations in this report is done on Market A data, and can similarly be followed for Market B and C.

The demand pattern of all the items from year 2014-2018 (monthly) projects a trend and a seasonal pattern can be seen with a period of twelve months (per year).

Since different items may have different seasonality and trend patterns, it is difficult to develop a separate model for each one of them. Hence, some assumptions are to be made.

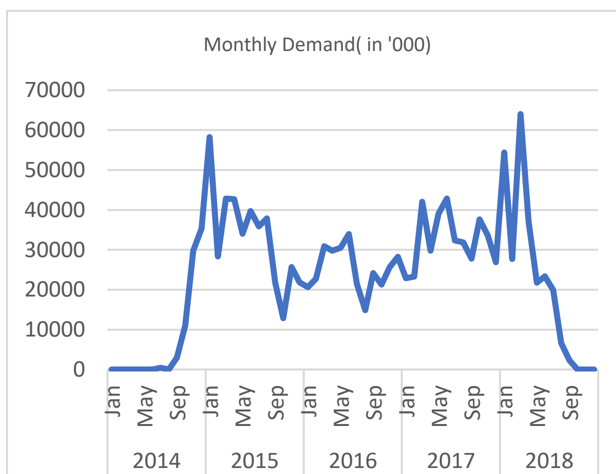


*Figure 1: Demand seasonality and trend pattern*

### 1.4 Underlying principle of the models considered

1. **Moving Average (MA(n))** gives forecast of the data for a period by taking the average of the last 'n' preceding terms, giving equal weight to each term. Since a simple average of terms is taken, trend and seasonality patterns are both well accommodated. It is extremely useful for long-term trend forecasting.

   $F_t = (1/N) * (D_{t-1} + D_{t-2} + \ldots\ldots + D_{t-N})$

2. **Exponential Smoothing (ES (α))** gives forecast by taking a weighted average of the last periods' demands, where α is the weight given/smoothing factor. Depending on value of smoothing constant it assigns priority to new and old data points, and forecast is calculated as an exponentially decreasing function.

   $F_t = \alpha D_{t-1} + (1-\alpha)\ Ft_{-1}$

3. **Double Exponential Smoothing (Holt's)** gives forecast for data with trends but no seasonality and gives good results for short term forecasts. It calculates dynamic estimates using two factors level (intercept, $S_t$) and trend (slope, $G_t$).
   $S_t = \alpha D_t + (1-\alpha)\ (S_{t-1} + G_{t-1})$
   $G_t = \beta\ (S_{t\ -}\ S_{t-1}) + (1-\ \beta)\ G_{t-1}$
   $F_{t,t+T} = S_t +\ _TG_t$

4. **Holt's Winter Method (α, β, γ)** is an extended Holt's method to capture seasonality pattern for forecasting. It gives good results for short-term forecasts using exponential smoothing to encode values from past to predict "typical" values for present and future. The three aspects included are value/average, trend/slope and seasonality/pattern using the parameters α, β and γ. *(Appendix 1)*

5. **Croston's Method (α)** is a standard approach to deal with intermittent demands. It detects the seasonal pattern in demands and divides the period in two different time series: 1. Zero demand values, 2. Non-zero demand values. Smoothing is used in both time-series separately and demand is forecasted. *(Appendix 2)*

   If $Forecast_{t-1} = 0$, then $Forecast_t$ = Average ($Forecast_1$: $Forecast_{t-2}$)

   If $Forecast_{t-1} \neq 0$, then $Forecast_t = Forecast_{t-1} + \alpha*(Demand_{t-1} - Forecast_{t-1})$

6. **ARIMA model (p, d, q)** allows both Auto Regressive (*AR*) (trend) as well as Moving Average (*MA*) components (trend and seasonality). AR component is used to model "change since last time". MA component capture "smooth trends of data". Differencing component (*I*) determines the level of "differencing" to use to help make data stationary (seasonality). It generally requires a minimum of 45-50 data point to give good accuracy of forecasts. *(Appendix 3)*

### 1.5 Modus Operandi

- To present time-scale data of a selected item, a pivot table is used to extract and arrange the data, such that on selection of an item, its demand from 2014 to 2018 is displayed in form of a table, subdivided into quarters/months (*refer Table 1*).
- To adapt our model to inconsistent demands, a dummy variable is introduced such that, if a demand is absent replace the cell with a 0 value.
- Forecasts is done for two terms, Short-term and Long-term, using the afore mentioned methods. The data used is for different Markets i.e. A, B and C and the same models are run to get the forecasts.

*Table 1: Pivot table for monthly demands*

| Item # | (All) | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sum of Quantity (PCS)-Scaled | Column Labels | | | | | | | | | | | |
| Row Labels | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
| 2014 | 0 | 0 | 0 | 5.04 | 0 | 26.75 | 445.85 | 27.291 | 2989.742 | 10972.028 | 29753.663 | 35285.16 |
| 2015 | 58254.101 | 28320.522 | 42852.242 | 42668.964 | 34056.35 | 39705.78 | 35867.694 | 37861.709 | 21748.205 | 12863.522 | 25707.915 | 21846.71 |
| 2016 | 20634.805 | 22715.494 | 30884.95 | 29776.065 | 30535.736 | 33909.67 | 21403.425 | 14843.667 | 24132.902 | 21236.447 | 25604.357 | 28212.769 |
| 2017 | 22859.284 | 23248.852 | 42008.321 | 29749.535 | 39108.163 | 42819.101 | 32328.459 | 31885.287 | 27749.02 | 37609.441 | 33557.227 | 26917.212 |
| 2018 | 54399.858 | 27714.858 | 64010.328 | 37156.037 | 21739.052 | 23387.362 | 19933.613 | 6588.731 | 2282.362 | 0 | 0 | 0 |
| Grand Total | 156148.048 | 101999.726 | 179755.841 | 139355.641 | 125439.301 | 139848.663 | 109979.041 | 91206.685 | 78902.231 | 82681.438 | 114623.162 | 112261.851 |

## 1.6 SHORT TERM FORECASTING MODELS

### 1.6.1. Holt – Winter's Method

- Since different items have different demand patterns, we have produced two results by using m=5 and m=12 respectively. User can opt to select the suitable model according to the performance of model during the training period. The user is also advised to select three best years for the training of model (*Appendix 3*).
- The values of smoothing parameters (α, β and γ) are calculated by minimizing the root mean square error of the forecast during training period.
  **(Assumptions:** $\alpha$=0.01, $\beta$=0.01 and $\gamma$=0.9, initial trend=1, $m_1$=5 and $m_2$=12)
- Short Term forecast were obtained (for six and twelve months).
- An error rate of 22.10% is obtained for the year 2018 using m=12.

*Table 2: Aggregated results for year 2018, Holt-Winter's*

| | |
|---|---|
| **Total demand in 2018** | 494513.596 |
| **Forecast for 2018 using m=12** | 385211.1 |
| **Error (%)** | 22.10 |

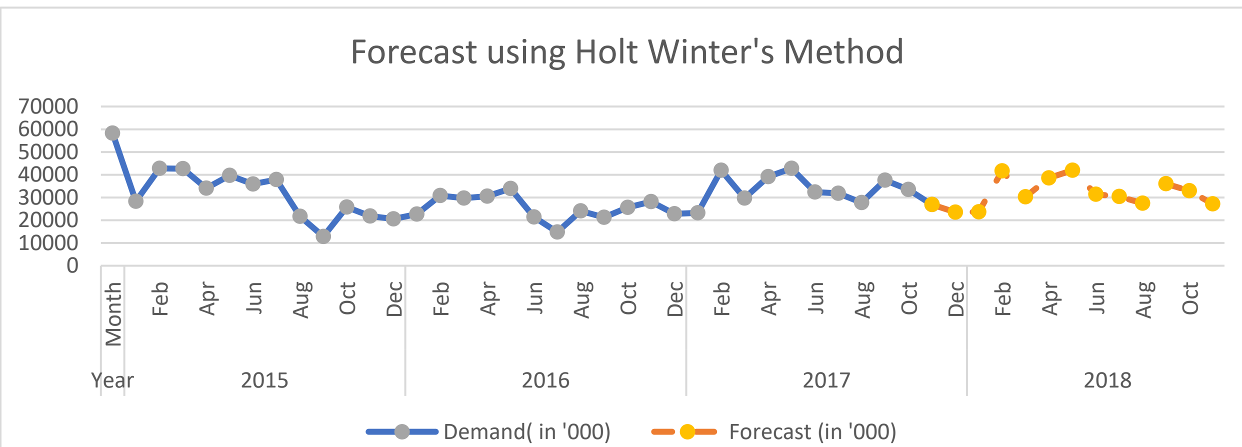


*Figure 2: Monthly forecast using Holt-Winter's Method*

### 1.6.2. ARIMA Model

- ARIMA model for forecasting is created using R, as it is more flexible for creating advanced statistical models and can be automated for getting accurate results from large dataset.
- R model development:
  (i) Number of periods in a season i.e. m=12.
  (ii) d=1 is set as default value for auto.arima(), as seasonality of data reduces considerably at time lagged by 1 period (t-1).
  (iii) ARIMA model trained/fitted on data (2015-2017) to improve its accuracy. The fitted model is tested on data of 2018.
- ARIMA forecast calculated over 80% and 95% confidence interval.
- The blue line in the graph shows forecast for next 12 periods and black line is our demand.This is the forecast of all the items in market 1.

```
         Point Forecast    Lo 80    Hi 80      Lo 95    Hi 95
Jan 2018       28362.49 15105.49 41619.49   8087.665 48637.32
Feb 2018       28752.06 14430.40 43073.72   6848.975 50655.14
Mar 2018       47511.53 32199.06 62824.00  24093.124 70929.93
Apr 2018       35252.74 19009.78 51495.70  10411.282 60094.20
May 2018       44611.37 27488.41 61734.33  18424.070 70798.67
Jun 2018       48322.31 30362.42 66282.19  20855.033 75789.58
Jul 2018       37831.67 19072.15 56591.18   9141.463 66521.87
Aug 2018       37388.49 17862.07 56914.92   7525.402 67251.59
Sep 2018       33252.23 12987.89 53516.56   2260.602 64243.85
Oct 2018       43112.65 22136.35 64088.95  11032.166 75193.13
Nov 2018       39060.43 17395.55 60725.32   5926.858 72194.01
Dec 2018       32420.42 10088.18 54752.66  -1733.796 66574.63
>
```

*Figure 3: Forecast values from ARIMA*

*Table 3: Aggregated forecast for year 2018, ARIMA*

| | |
|---|---|
| **Total demand in 2018** | 494513.596 |
| **Forecast for 2018 using m=12** | 455878.39 |
| **Error (%)** | 7.81 |

- Here we see auto arima gives the best forecast using parameters, (p, d, q) as (0,1,1) and (0,1,0) for different items

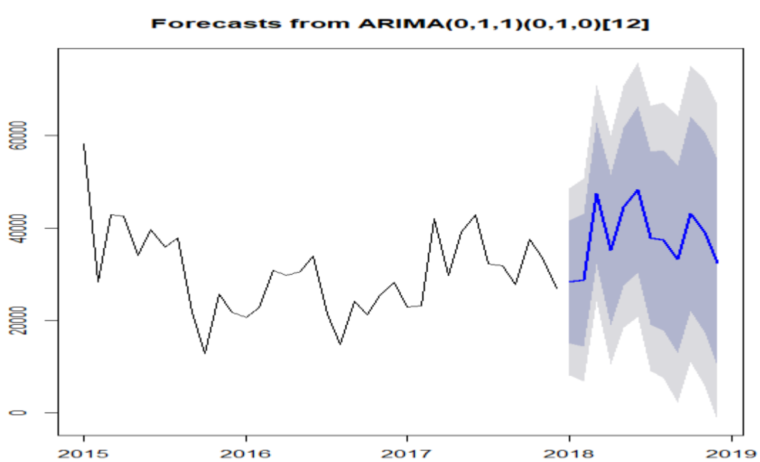


*Figure 4: Demand forecast using ARIMA*

### 1.7 LONG TERM FORECASTING MODELS

#### 1.7.1. MOVING AVERAGE, MA (4)

- Forecast using MA is done on Yearly aggregated data for the last five years (2014-2018) and then scaled based on the truck market rates (YoY%) provided, to adjust the forecasts **(Assumptions:** (i) The forecast for year 2019 is considered as the demand for 2020 and so on. (ii) YoY % forecasted for truck market is also considered same for every item.)
- Forecast without YoY (2019) = AVG [demand (2015:2018)]
- Forecast with YoY (2019) = Forecast (2019) + YoY% * Demand (2018)
- Long term Forecast data obtained for the future five years (2019-2023)
- Error rate of 20.89% is obtained for the year 2018.

*Table 4: Yearly forecast using MA (4)*

| All Values in 1000s | | | | | |
|---|---|---|---|---|---|
| **Year** | **Demand** | **Regular Forecast** | **YoY%** | **Scaled Forecast** | **Open order demand** |
| **2014** | **79505.52** | | | | |
| **2015** | **401753.7** | | | | |
| **2016** | **303890.3** | | **-29%** | | |
| **2017** | **389839.9** | | **12%** | | |
| **2018** | **257212.2** | **293747.357** | **25%** | **391207.332** | **237300.395** |
| **2019** | | **347307.815** | **-3%** | **335571.595** | |
| **2020** | | **333696.340** | **-26%** | **246447.725** | |
| **2021** | | **341147.853** | **15%** | **378115.012** | |
| **2022** | | **328974.841** | **6%** | **351661.742** | |
| **2023** | | **337781.712** | **13%** | **383497.739** | |

*Table 5: Aggregated forecast for year 2018, MA*

| | |
|---|---|
| **Total demand in 2018** | 494513.596 |
| **Forecast for 2018 using m=12** | 391207.332 |
| **Error (%)** | 20.89 |

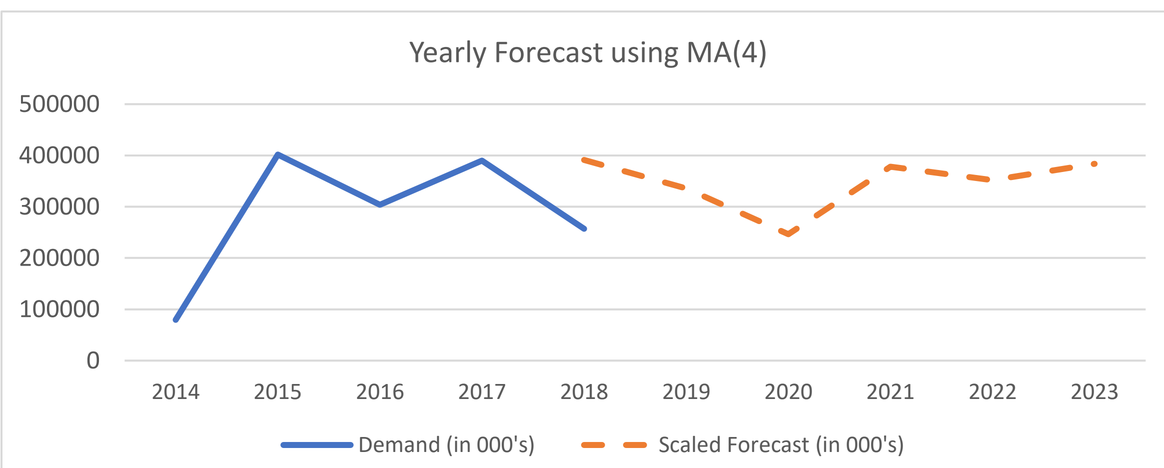


*Figure 5: Demand forecast using MA*

### 1.7.2. CROSTON'S Method

- Forecast using Croston done on monthly aggregated data for the last 60 months of the five years (2014-2018)
- The data is then summed up for calculating data for each year and likewise scaled to adjust for the truck market rates (YoY %).
  **(Assumptions**: (i) Intermittent demand for sixty periods can be combined in group of 12 to forecast for each year.
  (ii) YoY % forecasted for truck market is also considered true for all the items.)
- Error rate of 27.72% is obtained for the year 2018.

*Table 6: Yearly forecast for data using Croston's method*

| Year | Demand (000's) | YoY % | Forecast w/o YoY % | Open Order | Scaled Forecast (in 000's) |
|---|---|---|---|---|---|
| 2015 | 401753.714 | | | | |
| 2016 | 303890.287 | -29% | | | |
| 2017 | 389839.902 | 12% | | | |
| 2018 | 257212.201 | 25% | 259963.5776 | 237300.973 | 357423.5531 |
| 2019 | | -3% | 132887.7754 | | 122165.0688 |
| 2020 | | -26% | 159465.3305 | | 127702.4126 |
| 2021 | | 15% | 159465.3305 | | 178620.6923 |
| 2022 | | 6% | 159465.3305 | | 170182.572 |
| 2023 | | 13% | 159465.3305 | | 181589.0648 |

*Table 7: Aggregated forecast for year 2018, Croston's*

| | |
|---|---|
| **Total demand in 2018** | 494513.173 |
| **Forecast for 2018 using m=12** | 37423.5531 |
| **Error (%)** | 27.72 |

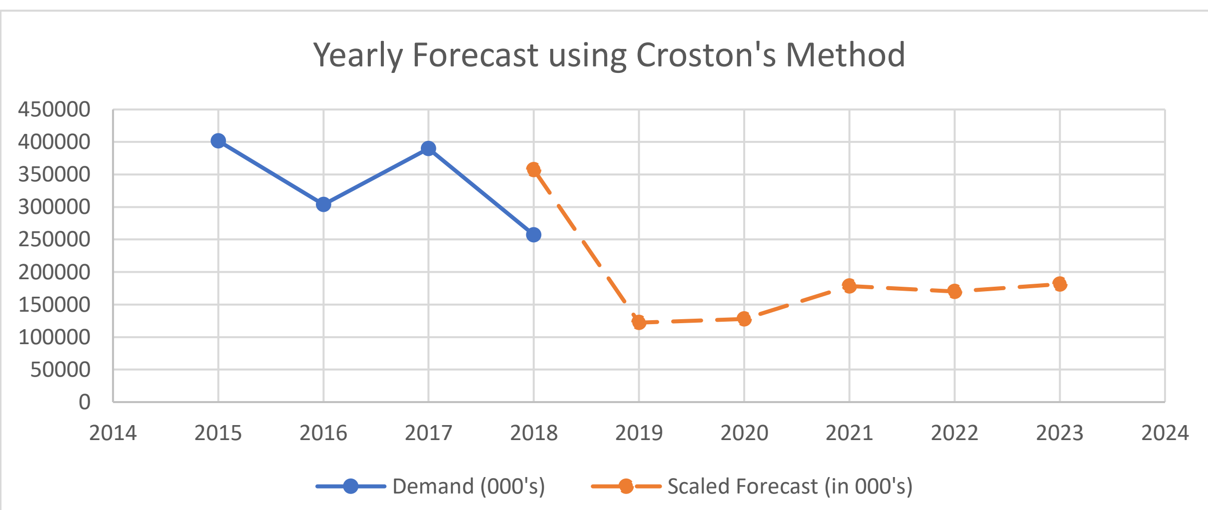


*Figure 6: Demand forecast using Croston's*

# 2 VTI of Texas

### *2.1 Data*

- The input data provides periodic inventory information for each of its product from various suppliers.
- There are 27 items from 4 suppliers., the dimensions as well as weekly demand for each item is provided.
- Three states of inventory items are available, i.e., in storage, on order and new order.

### *2.2 Target*

Inventory Control problem- need to calculate when to order and how much to order, followed by optimizing the truck load storage.

### *2.3 General Process Outline*

- Assuming production rate to be infinite (external production), calculate the demand rate for the 27 product-types made.
- Sort the data with Optimum Order Quantity as $Q^* = \sqrt{2k\lambda}/h$ -using the Economic Order Quantity model
- Applying the Set-up cost and holding cost constraint - calculate optimal order quantity, reorder point and safety stock
- Optimize the truck load based on the given data using linear optimization method

### *2.4 Modus Operandi*

#### *2.4.1. Using Data Log to extract Weekly Demand*

The values in the *Data Log* sheet provides information about *In Storage*, *On Order* and *New Order* quantities per week. For calculation of Order Quantity, it is important to calculate the weekly demand, assuming weekly use to be the weekly demand, we calculate weekly demand by the formula:

*Weekly Demand* = $(\textit{In Storage})_i - (\textit{In Storage})_{i+1} + (\textit{On Order})_i + (\textit{New Order})_i$
where, i stands for the week number

#### *2.4.2. Input*

- Update values of In Storage, On Order and New Order in Data log.
- The values of *Weekly Use* calculated are stored in the sheet *Average Weekly Use* and is automated using Visual Basic Programming.
- The code performs iterative operations, calculating the Demand per week. The values entered in the sheet provides: *Average Weekly Use*, Standard *Deviation* and *Maximum Weekly Use* for weeks of which values in *Data Log* has been entered. As the iterations performed are large in number, executing this takes a bit of time. For this purpose, only *Average Weekly Use* is calculated in another module of VBA as it is an important term in calculating Order Quantity.

#### *2.4.3. Calculating Reorder Point, Reorder to Point, Safety Stock and Order Quantity*

After calculating *Average Weekly Use*, the next step is to calculate Q&R based on Q,R Model. Here, *Service Level II* is assumed. As the company uses Periodic Review System, we will be calculating Reorder Point and Reorder to Point as follows:

From the values Obtained in Q, R Model:
Reorder Point(s) = R
Reorder To (S) = Q+R
Safety Stock = R - $\lambda * \tau$
Order Quantity = 0 (If Current Inventory Level > s)
= S – Current Inventory Level (If Current Inventory Level < s)

### *2.4.4. Inputs*

The values of Holding Cost and Setup costs are assumed for the purpose of calculations. Excel has an option to input these values which are automatically updated in the calculations. The values of Current Inventory Level of each product is required in order to determine the order quantity and number of trucks.

### 2.4.5. Calculating Q, R in VBA

- As Service Level II is assumed, iterations must be performed to obtain the values of Q and R. For each of the 27 products, there are two loops which have been declared, the outer loop tracks the columns (Products) and the inner loop performs iterations for their respective column.
- The value of these columns is incremented after the inner loop completes its iterations and the final values of Q and R for that product are obtained. These values are stored in sheet *Constants*, in rows 28 and 29 respectively. Hence, Reorder Point, Reorder to Point, Safety Stock and Order Quantity are calculated using the formulae mentioned above.

*Table 8: Dashboard for calculating (S, s)*

| Input Values | Units ($) |
|---|---|
| Holding Cost(h) | 4 |
| Setup Cost(k) | 10 |

Calculate

| INPUT | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Product Number** | **40202** | **40201** | **40200** | **40211** | **40210** | **40209** | **40109** | **40108** |
| **Current Inventory Level** | 7690 | 8749 | 9869 | 340 | 363 | 763 | 280 | 243 |

| OUTPUT | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Product Number** | **40202** | **40201** | **40200** | **40211** | **40210** | **40209** | **40109** | **40108** |
| **Vendor** | **Georgia-Pacific** | | | | | | | |
| **Average Weekly Use** | 2633 | 3088 | 3183 | 81 | 81 | 201 | 33 | 25 |
| **Maximum Use** | 11391 | 11678 | 12376 | 414 | 430 | 633 | 200 | 217 |
| **Standard Deviation** | 2080.475 | 2311.9556 | 2753.056 | 76.85409 | 81.65731 | 144.0284 | 58.57316 | 52.71141 |

### 2.4.6. Truck Load Optimization

- One of the objectives of the VTI is to optimize the truck load and maximize the truck usage such that the number of trucks employed are minimum and hence, the cost occurred by leasing/renting the trucks is minimum.
- Earlier calculated optimal quantity and reorder quantity using (Q, R) are used to calculate the cycle time for each item. Next, we use the optimal quantities of each item and their weight and volume per item to find the total weight and volume of total items needed to get delivered/shipped.

- We also assume the maximum limits of each truck, weight and volume wise. Using this, we calculate the number of trucks using weight and volume individually. Finally, we decide the number of trucks based on the maximum value calculated using the weight and volume criteria.

One thing we assume here while using the volume constraint, physically we can't use the total volume of truck, so a factor **α** which defines the ratio of volume is used. Here we take **α= 0.75**.

**Max. volume usage = α * Max. truck volume**

*Considering,*
*Truck type = **53' Air ride Dry Vans***
*Truck payload limit = 20.5 tons = **20500kgs***
*Truck max volume = 52.5 * 8.5 * 8.5* $ft^3$ *= 3800 cubic feet =* **108** $m^3$
*Max. volume usage = 108*0.75 =* **81** $m^3$
*Density =* **700** $kg/m^3$ *(Georgia),* **710** $kg/m^3$ *(Arauco),* **574** $kg/m^3$ *(Pacific Wood),* **700** $kg/m^3$ *(Roseburg)*

*Formulae,*
*Total weight = Summation of (Quantity of each unit * Weight per unit) for all item*
*Total volume = Summation of (Quantity of each item * Volume per unit) for all item*
*Number of Trucks (by weight) = Total weight / Payload limit of one Truck*
*Number of Trucks (by volume) = Total volume / Max. limit of volume usage of one truck*

Then take the maximum number of trucks out of two above mentioned quantities.

*Table 9: Truck load optimization for Georgia-Pacific*

| | 40202 | 40201 | 40200 | 40211 | 40210 | 40209 |
|---|---|---|---|---|---|---|
| | Georgia-P | Georgia-P | Georgia-P | Georgia-P | Georgia-P | Georgia-P |
| Order Quantity(Q) | 2443 | 2688 | 3025 | 260 | 263 | 425 |
| Breadth | 30.25 | 30.25 | 30.25 | 49.25 | 49.25 | 49.25 |
| Length | 97 | 121 | 145 | 97 | 121 | 145 |
| Breadth(m) | 0.76835 | 0.76835 | 0.76835 | 1.25095 | 1.25095 | 1.25095 |
| Length(m) | 2.4638 | 3.0734 | 3.683 | 2.4638 | 3.0734 | 3.683 |
| Thickness(m) | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 |
| Volume(cubic m) | 0.04 | 0.05 | 0.06 | 0.06 | 0.08 | 0.09 |
| Density | 700 | 700 | 700 | 700 | 700 | 700 |
| Mass(w) | 26.5 | 33.06 | 39.62 | 43.15 | 53.83 | 64.5 |
| | | | | | | |
| Total weight | 64740 | 88866 | 119851 | 11219 | 14158 | 27413 |
| Total volume | 92.49495 | 126.9514 | 171.2049 | 16.02687 | 20.22296 | 39.16162 |
| No. of Trucks (By Volume) | 6 | | | | | |
| No. of Trucks (By Weight) | 16 | | | | | |
| No. Of Trucks | 16 | | | | | |

**The user can change values of holding and ordering cost as required. Also, the user can specify the truck dimensions on the truck load optimization sheet. The detailed instructions on how to use and modify the tool can be found at the end of the report (Appendix 4).*

# CONCLUSION

**1. Arconic**

Project demanded two models for each, short-term and long-term forecasting. As given, demand is intermittent, and it exhibits seasonality, so we narrowed down our analysis to following methods respectively-

- Short term forecasting (1 Year) - We were getting high error using methods like MA, ES, so we chose Holt's Winter (error 22.10 %) and ARIMA (error 7.81 %) models.
- Long term forecasting (5 Years)- As there are very few data points from which model can learn to forecast for 5 years so error is bit on higher side as compared to Short term forecasting. The best two models that could accommodate this demand are Croston's (error 27.72%) and Moving Average (error 20.89 %).

**2. VTI**

- Using service level II criterion with 99% fill rate, the S and s model has been developed. This method is considered more efficient as it considers the number of items by which stock-out occurs and thus avoids excess inventory accumulation.
- Truck load optimization is performed based on weight and volume. The total number of trucks required are thus considered as the maximum of the two conditions.

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*Appendix 1*

## HOLT-WINTER'S METHOD

The Holt-Winters seasonal method comprises the forecast ($y_t$) equation and three smoothing equations — one for the level $l_t$, one for the trend $b_t$, and one for the seasonal component $s_t$, with corresponding smoothing parameters α, β and γ. We use *m* to denote the frequency of the seasonality, i.e., the number of seasons in a year. For example, for quarterly data m=5, and for monthly data m=12.

The model is given as follows-

$y_{t+h|t}=l_t+hb_t+s_{t+h-m(k+1)}$

$l_t=\alpha(y_t-s_{t-m}) + (1-\alpha)\,(l_{t-1}+b_{t-1})$

$b_t=\beta\,(l_t-l_{t-1}) + (1-\beta)\,b_{t-1}$

$s_t=\gamma(y_t-l_{t-1}-b_{t-1}) + (1-\gamma)s_{t-m},$

- The method is used for the multiperiod forecasts when there is a presence of both trend and seasonality. However, it can also be used when the correct form of demand is not known, or the demand varies for different items.
- The selection of m is an important factor in using the Holt Winter's method. As the m decides the season frequency, the best values give out the best results.
- The value of α, β and γ is calculated by minimizing the root mean square error in the forecasts during the training period. However, usually it is observed that the values of α and β are low and γ is high.
- The models developed in our project have two separate values of m. for first model, m= 5 and for second m=12.
- In addition, we have taken values of smoothing parameters as given below α= 0.01 β = 0.01 and, γ=0.9. The high value of γ allows the model to better fit (in terms of seasonality) for changing demands.

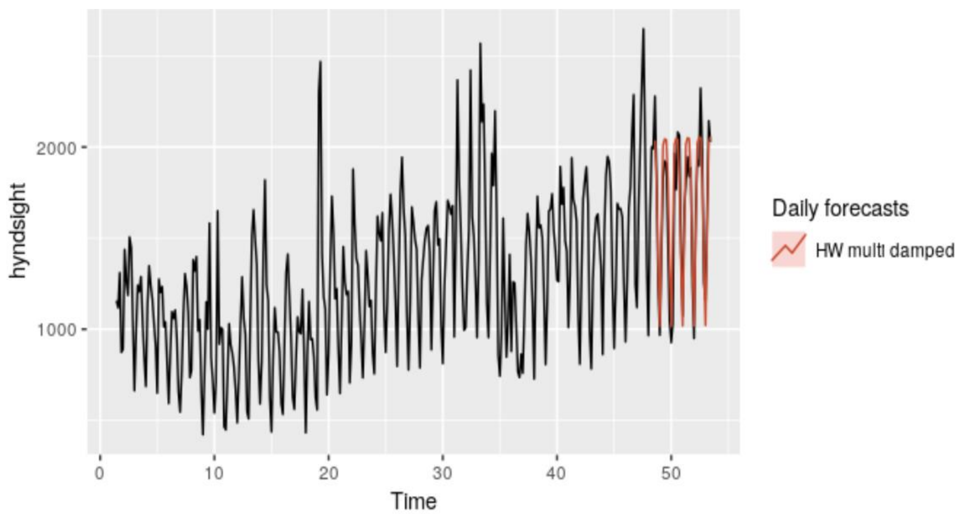


*Figure 7: Forecast of demands using Holt-Winter's*

*Appendix 2*

## ARIMA- Auto Regressive Integrated Moving Average Model

**Basic concept**

- The first step in applying ARIMA methodology is to check for stationarity. *Stationarity* implies that the series remains at a constant level over time.
- If a trend exists, as in most economic or business applications, then your data is NOT stationary. The data should also show a constant variance in its fluctuations over time. This is easily seen with a series that is heavily seasonal and growing at a faster rate. In such a case, the ups and downs in the seasonality will become more dramatic over time.
- Without these stationarity conditions being met, many of the calculations associated with the process cannot be computed.

**Assumptions of ARIMA model**

i. Data should be stationary – by stationary it means that the properties of the series don't depend on the time when it is captured. A white noise series and series with cyclic behavior can also be considered as stationary series.
ii. Data should be univariate – ARIMA works on a single variable. Auto-regression is all about regression with the past values.

**Procedure to forecast using ARIMA in R**

- R contains a predefined function named auto.arima() in the forecast package. So first of all install the forecast package along with some other packages such as "tseries" and "readxl" to convert the data in time series form and import the data from excel file.
- Import demand data by reading excel file for the year 2015 to 2017.Convert it into timeseries form and plot the data.
- Now to get better understanding of our data check various components such as trend, seasonality & irregularities in data by using decompose() function. It gives four plot one for each original data, seasonality, trend and irregularities present in our data.
- Use autocorrelation function acf() and partial autocorrelation function pacf() to check the stationarity of the demand series. If there is sudden drop in the spikes observed in the plot and not much spikes are out of significant limit, then it is concluded the series is stationary. If not, differencing is done to remove the stationarity. auto.arima() in R does this for us and gives the best fit by comparing values of parameters of p,d,q and returning the one with lowest ACF
- Use auto.arima() to fit the data and forecast() to predict the forecast based on the fit. Specify the number of periods in forecast function for which the forecast is needed and plot the graph to have a better understanding of the forecasted values.
- Now to check if the fit is accurate, plot ACF & PACF of the residuals on the fit. If they are within significant limit, then the fit is correct and can be used for forecasting purpose.

*Appendix 3*

## CROSTON'S METHOD

The Croston's method is a forecasting approach that was developed to provide a more accurate estimate for products with intermittent demand. The Croston's method consists of two main steps. First, Croston's method calculates the mean demand per period by separately applying exponential smoothing. Second, the mean interval between demands is calculated. This is then used in a form of the model to predict the future demand.

Let X(t) be the Demand in period t, Y(t) be the estimate of the mean size of a nonzero demand, let P(t) be the estimate of the mean interval between nonzero demands, and let Q be the time interval since the last nonzero demand. $\alpha$ is the smoothing parameter.

The algorithm for the Croston's method is given below-

If X (t) = 0
then Y(t) = Y(t-1)
P(t) = P(t-1)
Q = Q + 1
Else
Y (t) = $\alpha$X(t) + (1-$\alpha$) Y(t-1)
P(t)= $\alpha$Q + (1-$\alpha$) P(t-1)
Q = 1
The estimate of mean demand per period
M(t) = Y(t)/P(t)

Then we can go ahead and do forecasting for t periods ahead using the condition
If t=(n*$Q_{avg}$) +1
Forecast= M(t)
Else
Forecast=0
Where n is any integer >=1

*Appendix 4*

## VISUAL BASIC APPLICATION

### Dashboard

The dashboard provides an overall view of the entire procedure. After values have been entered in sheet Data Log, and values of Holding Cost and Setup Cost are entered, the Calculate button performs all the steps mentioned above and provides the final required values. The calculation of Average Weekly Use and Q, R are combined in a single module, which is shown below:

### Truck Load Optimization

(General) All

```
Sub All()
Dim AvgWeeklyU As Double
Dim AVG, temp, r As Double
Dim Count, t, i, e As Integer
Dim k, h, u, SD, L, EQ, nr, Lz, n As Double
r = 4
i = 3
t = 2
For i = 3 To 29
AVG = 0
temp = 0
Count = 0
r = 4
t = 2
AvgWeeklyU = 0
Worksheets("Data log").Activate
Do While Cells(r, 1) <> ""
If Cells(r + 2, 2).Value = "New Order" Then
AvgWeeklyU = Cells(r, i).Value - Cells(r + 3, i).Value + Cells(r + 1, i).Value + Cells(r + 2, i).Value
r = r + 3
Else
AvgWeeklyU = Cells(r, i).Value - Cells(r + 2, i).Value + Cells(r + 1, i).Value
r = r + 2
End If
Count = Count + 1
temp = AvgWeeklyU + temp
Loop
AVG = temp / Count
Cells(477, i).Value = Application.WorksheetFunction.Round(AVG, 0)
Next i

Worksheets("Constants").Activate
t = 1
i = 3
For i = 3 To 29
k = Cells(22, i).Value
h = Cells(23, i).Value
u = Cells(25, i).Value
SD = Cells(26, i).Value
L = Cells(24, i).Value
EQ = (2 * k * L / h) ^ 0.5
nr = EQ * (1 - 0.99)
Lz = nr / SD
z = 4.85 - (Lz ^ 1.3) * 0.3924 - (Lz ^ 0.135) * 5.359
r = u + SD * z
For t = 1 To 6
n = Application.WorksheetFunction.NormDist(z, 0, 1, 1)
m = 1 - n
EQ = nr / m + (2 * k * L / h + (nr / m) ^ 2) ^ 0.5
nr = EQ * (1 - 0.99)
Lz = nr / SD
z = 4.85 - (Lz ^ 1.3) * 0.3924 - (Lz ^ 0.135) * 5.359
r = u + SD * z
Next t
Cells(28, i).Value = Application.WorksheetFunction.RoundUp(EQ, 0)
Cells(29, i).Value = Application.WorksheetFunction.Round(r, 0)
Next i

e = 3
Worksheets("Constants").Select
For e = 3 To 29
If Cells(32, e).Value < Cells(30, e).Value Then
Cells(33, e).Value = Cells(31, e).Value - Cells(32, e).Value
Else
Cells(33, e).Value = 0
End If
Next e
Worksheets("Dashboard").Activate
```

**Customers**

1) **Georgia Pacific**

| Name of Item | Optimal Quantity(Q) | Weight per unit(kg) | Total weight(kg) | Volume per unit($m^3$) | Total volume() |
|---|---|---|---|---|---|
| **40202** | 2443 | 26.50 | 64739.50 | 0.04 | 97.72 |
| **40201** | 2688 | 33.06 | 88865.28 | 0.05 | 134.4 |
| **40200** | 3025 | 39.62 | 119850.5 | 0.06 | 181.5 |
| **40211** | 260 | 43.15 | 11219 | 0.06 | 15.6 |
| **40210** | 263 | 53.83 | 14158 | 0.08 | 21.04 |
| **40209** | 425 | 64.50 | 27413 | 0.09 | 38.25 |

Number of trucks (by weight) = 16 | Number of trucks (by volume) = 6 | Number of trucks rented =16

2) **Arauco**

| Name of Item | Optimal Quantity(Q) | Weight per unit(kg) | Total weight(kg) | Volume per unit($m^3$) | Total volume() |
|---|---|---|---|---|---|
| **40109** | 183 | 26.88 | 4920 | 0.04 | 6.92 |
| **40108** | 161 | 33.53 | 5399 | 0.05 | 7.60 |
| **40107** | 223 | 40.18 | 8961 | 0.06 | 12.62 |
| **40102** | 99 | 43.54 | 4311 | 0.06 | 6.07 |
| **40304** | 108 | 54.32 | 5867 | 0.08 | 8.26 |
| **40305** | 106 | 65.09 | 6900 | 0.09 | 9.71 |

Number of trucks (by weight) = 2 | Number of trucks (by volume) = 1 | Number of trucks rented = 2

3**) Pacific Wood**

| Name of Item | Optimal Quantity(Q) | Weight per unit(kg) | Total weight(kg) | Volume per unit($m^3$) | Total volume() |
|---|---|---|---|---|---|
| **40008** | 367 | 21.77 | 7990 | 0.04 | 13.89 |
| **40009** | 476 | 27.16 | 12929 | 0.05 | 22.48 |
| **40010** | 634 | 32.54 | 20631 | 0.06 | 35.88 |
| **40011** | 354 | 35.44 | 12546 | 0.06 | 21.82 |
| **40012** | 233 | 44.21 | 10301 | 0.08 | 17.92 |
| **40013** | 428 | 52.98 | 22676 | 0.09 | 39.44 |

Number of trucks (by weight) = 5 | Number of trucks (by volume) = 2 | Number of trucks rented = 5

4) **Roseburg**

| Name of Item | Optimal Quantity(Q) | Weight per unit(kg) | Total weight(kg) | Volume per unit($m^3$) | Total volume() |
|---|---|---|---|---|---|
| **41202** | 178 | 26.28 | 4678 | 0.04 | 6.68 |
| **41201** | 106 | 32.79 | 3476 | 0.05 | 4.96 |
| **41200** | 211 | 39.02 | 8234 | 0.06 | 11.76 |
| **41211** | 446 | 42.93 | 19147 | 0.06 | 27.35 |
| **41210** | 342 | 53.55 | 18315 | 0.08 | 26.16 |
| **41209** | 560 | 64.17 | 35936 | 0.09 | 51.34 |
| **49004** | 143 | 26.5 | 3790 | 0.04 | 5.41 |
| **49005** | 137 | 26.5 | 3631 | 0.04 | 5.19 |
| **49006** | 113 | 39.62 | 4478 | 0.06 | 6.40 |

Number of trucks (by weight) = 5 | Number of trucks (by volume) = 2 | Number of trucks rented =5