Demand Forecasting and Inventory Management for Spare Parts

Capstone Presentation

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Agenda

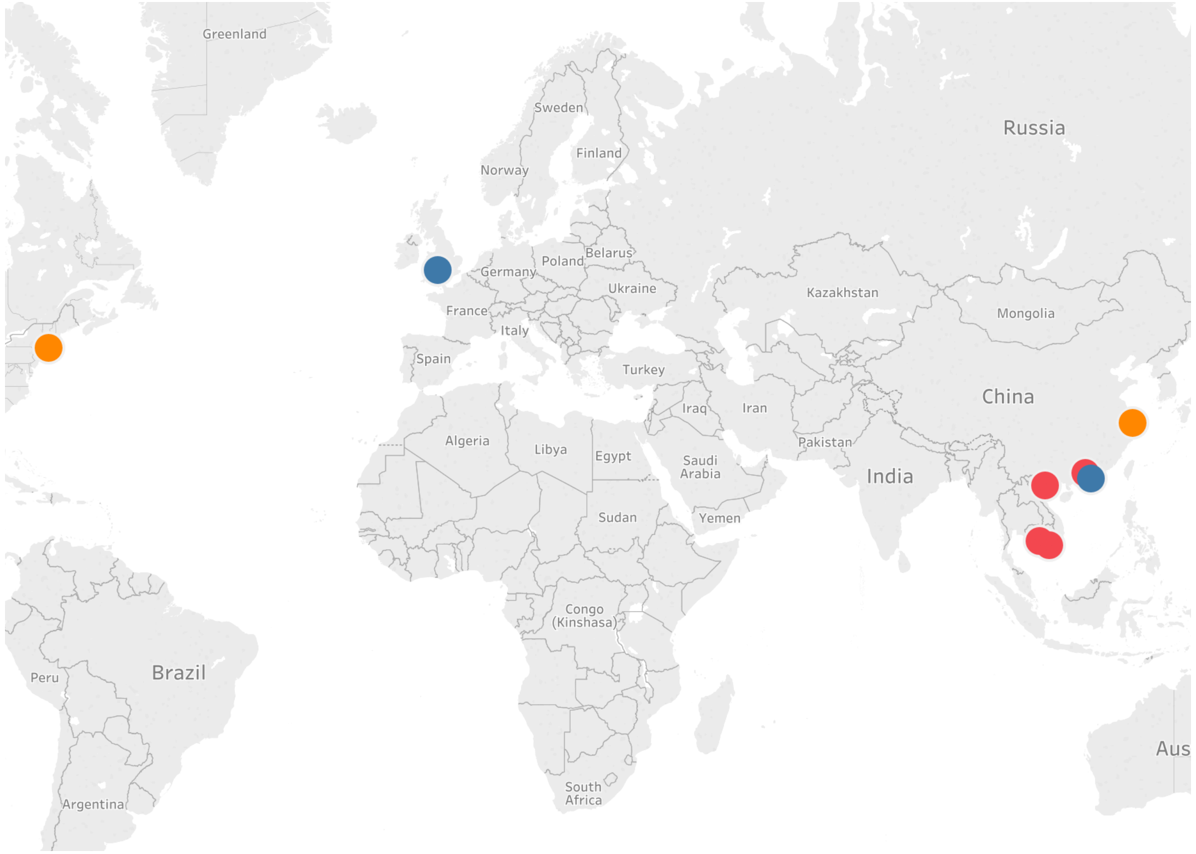
1. Company Setting
2. Problem
3. Methodology
4. Data
5. Results
6. Recommendations

Company Setting

Gerber Technology is a manufacturing company that provides integrated software and hardware solution to more than 78,000 customers in 134 countries.

- The company also provide support to its products with the Aftermarket division
- More than 3,700 SKUs are served to customers to fulfill their spare parts need

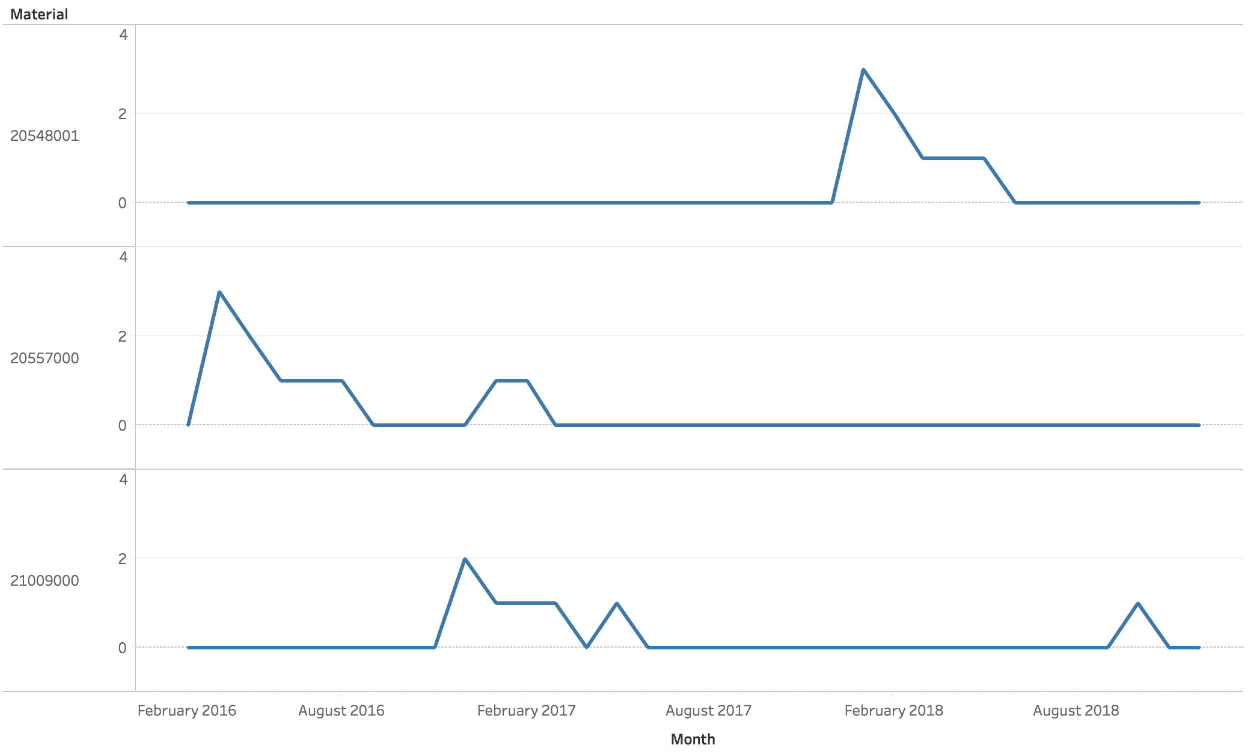
- Two plants, one in Connecticut (US) and other in Shanghai (CN), are used to manufacture its products



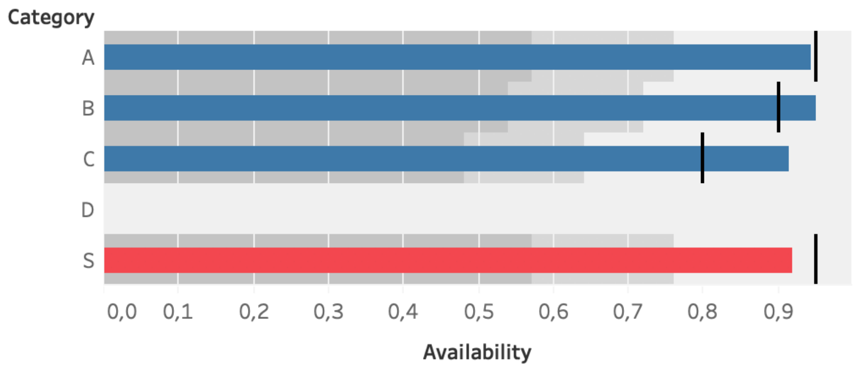
- Distribution and service centers across the globe are used to provide support to its customers

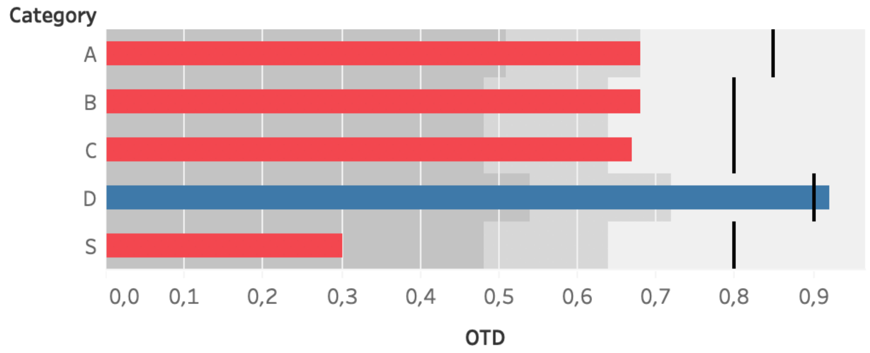
Problem

Spare parts items are characterized by an irregular and intermittent demand pattern.



This irregular pattern is driving the company to hold higher inventory levels than what is targeted and affecting the service level metrics.





- Current product classification only takes into account the revenue brought by each item and special segments defined by marketing.
- This could be leading the excessive inventory of non critical items.

Key Questions

I. How can we better forecast the demand in the Spare Parts contexts?

II. How can we better categorize products for inventory management to capture business needs?

Methodology

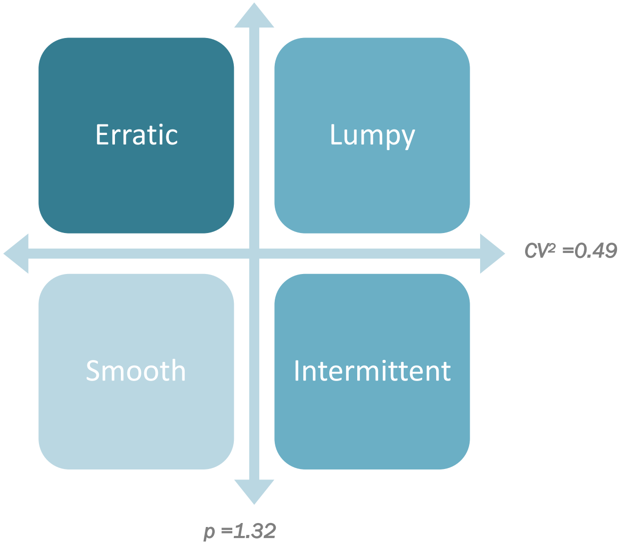
- Compare the changes between the current and proposed process in terms of:
  - Forecast Accuracy (RMSE, GRMSE, MASE)
  - Service Level
  - Inventory Level
  - Inventory Holding Cost

	Demand Planning	Supply Planning
Current	Multiple forecasting models (Regression, Winter's, Croston's, Seasonal, etc.) based on minimum MAPE	SKU classification (A|B|C|D|S) based on revenue and marketing inputs
Proposed	Croston's + Syntethos & Boylan's methods based on SKU classification	Multi-criteria inventory classification using normalized weighted average method.
Impact	Impact on forecast accuracy measured by RMSE[1], GRMSE[2] and MASE[3]	Impact on inventory measured by service levels, inventory levels and inventory holding costs.

[1]RMSE = Root Mean Squared Error; [2]GRMSE = Geometric Root Mean Squared Error; [3]MASE = Mean Absolute Scaled Error

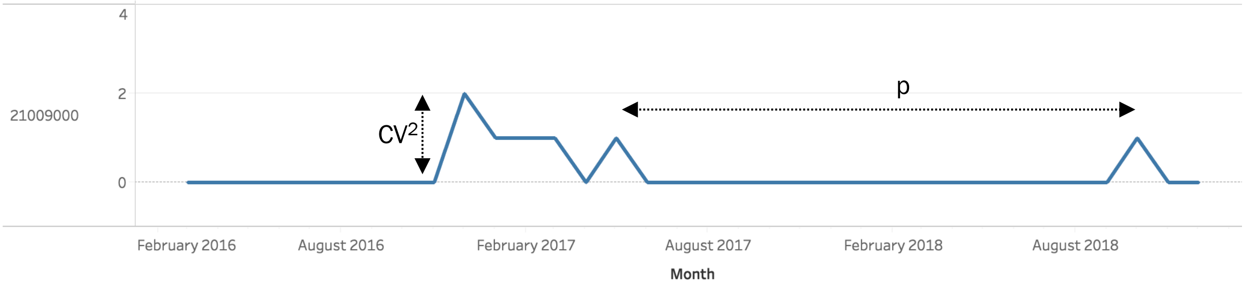
Methodology – Demand Planning

SKU Classification



Demand Patterns Classification

Source: Adapted from (Syntetos, Boylan, & Croston, 2005)



Demand Forecasting

- Smooth Demand – Croston's Method:

$$(1)\ Y'_t = \frac{z'_t}{p'_t}$$

Equation 1 – Croston's Method

Source: Croston (1972)

- Erratic, Lumpy, and Intermittent Demand – SBA's Method:

$$(2)\ Y'_t = \left(1 - \frac{\propto}{2}\right)\frac{z'_t}{p'_t}$$

Equation 2 – Syntetos and Boylan's Method

Source: Syntetos & Boylan (2001)

$Y'_t = estimated\ demand$

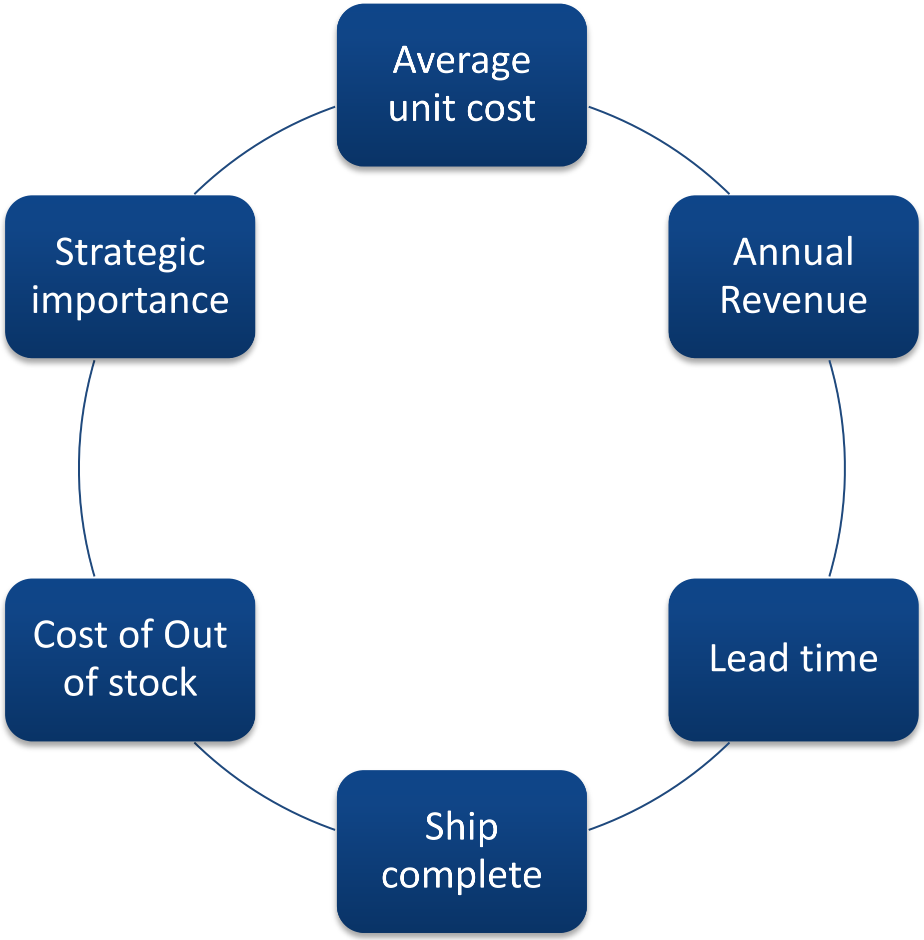
$z'_t = exponentially\ smoothed\ demand\ size$

$p'_t = exponentially\ smoothed\ inter-demand\ interval$

$\propto = smoothing\ constant$

Methodology – Supply Planning

I. Business Parameters



II. Modelling

$$Direct\ Index = \left(\frac{AC}{Avg(AC)}\right) * W(AC) + \left(\frac{AR}{Avg(AR)}\right) * W(AR) + \left(\frac{LT}{Avg(LT)}\right) * W(LT)$$

$$Indirect\ Index = \left(\frac{SC}{Avg(SC)}\right) * W(SC) + \left(\frac{CO}{Avg(CO)}\right) * W(CO) + \left(\frac{SI}{Avg(SI)}\right) * W(SI)$$

III. New Classification

Grouping matrix			
	2	3	4
G1	80%	80%	60%
G2	20%	15%	20%
G3		5%	15%
G4			5%

Service Level Matrix		
New grouping	Old grouping	SL target
G1	A	90%
G2	B	80%
G3	C	80%
G4	S	70%
Overall Service		89%

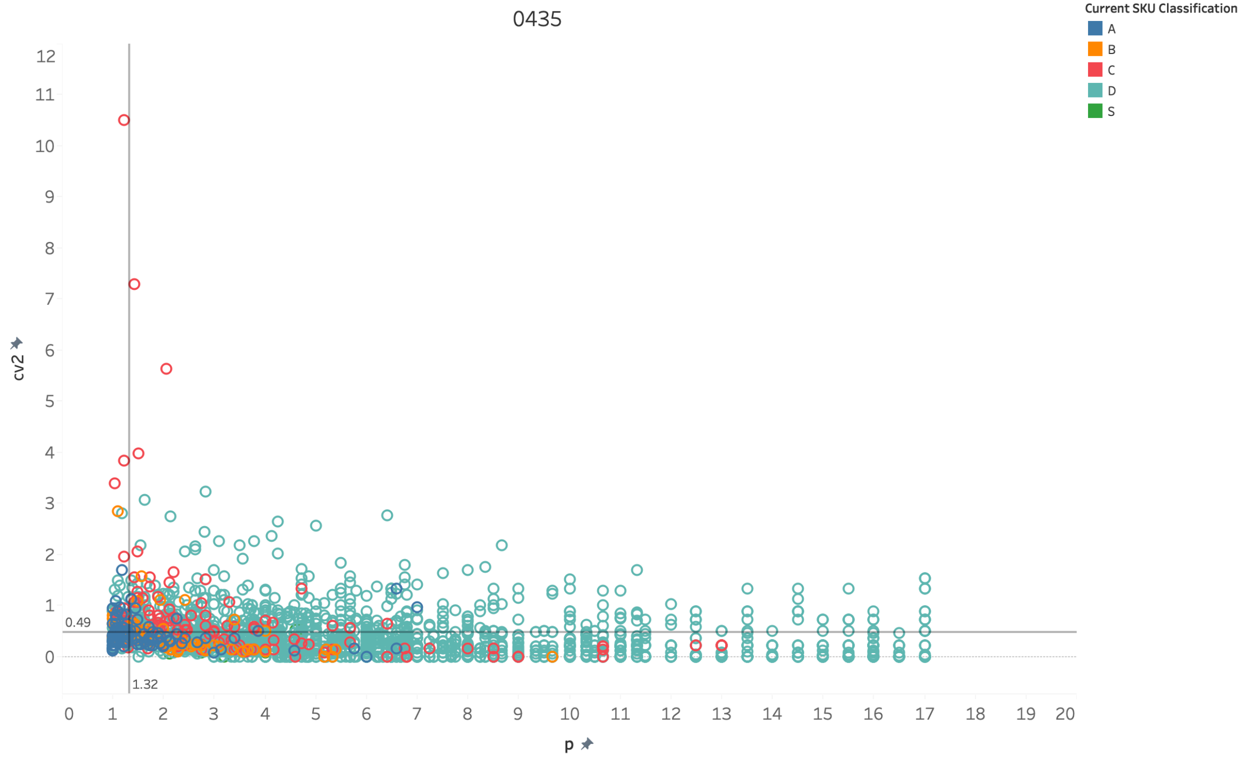
IV. Impact on KPI's

Inventory level, Service Level, Revenue

Results – Demand Planning

SKU Classification

- We analyzed all SKU's in every Gerber plant that serves as a warehouse facility and calculated their squared coefficient of variation and average demand interval



SKU Classification – Plant 0435

- Consolidated Classification:

Plant	Erratic	Intermittent	Lumpy	Smooth
435	83	1,603	539	80
445	132	1,344	489	172
446	4	312	23	18
471	19	612	186	22
480	3	371	87	5

Table – SKU Classification per Plant

- Many SKU's were not classified due to lack of enough demand signals in the past 3 years

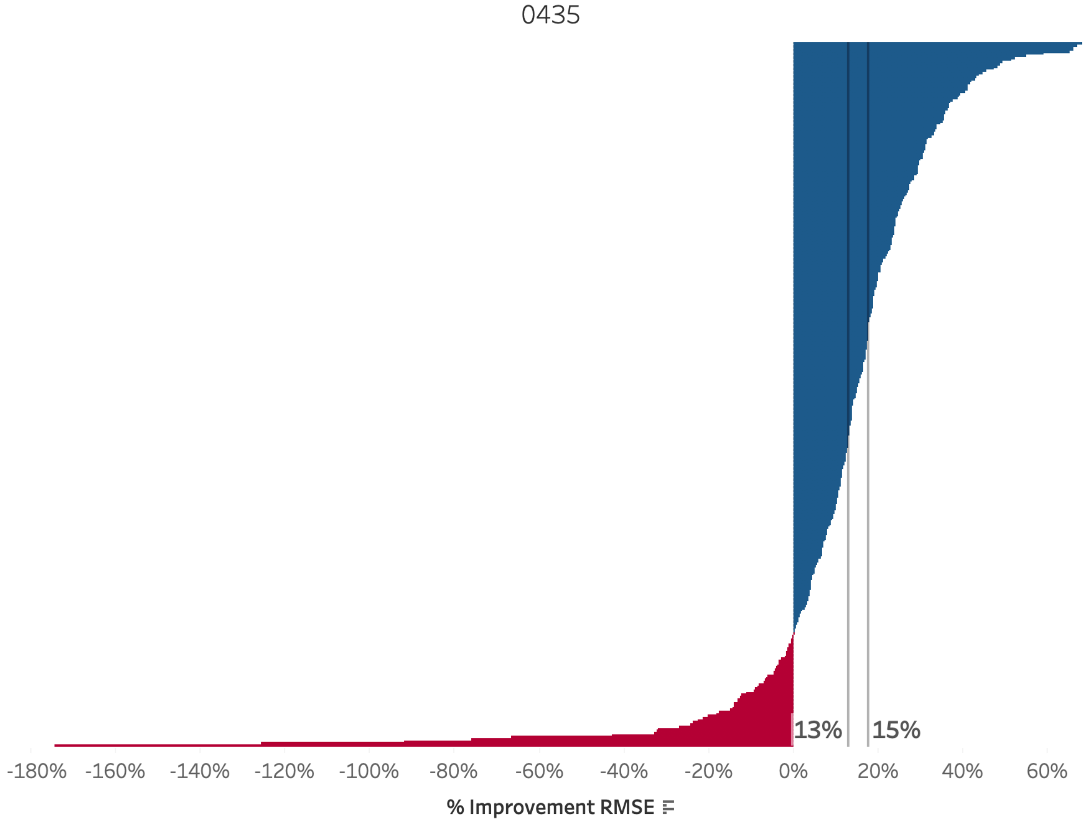
Plant	
435	23.70
445	18.10
446	35.60
471	36.50
480	42.00

Table – Proportion of Non-Classified SKU's per Plant

Results – Demand Planning

Demand Forecasting

- With the classification done, we then allocated the recommended forecasting technique and compared the results to the current practice in terms of RMSE



Demand Forecast Comparison – Plant 0435

- Current Forecasting Techniques:

	Forecast procedures								
Plant	1st Order Exp. Smoothing	2nd Order Exp. Smoothing	Croston	Linear Regression	Seasonal	Seasonal Factors	Winters Additive	Winters Multiplicative	Winters Trend
0435	2	1	871	22	1,647	11	30	789	6
0445	1		712	81	1,621	31	37	547	7
0446			164	8	729	148	5	123	
0471	1		534	6	799	32	24	341	
0480	1		274		526		12	221	

Table – Current Forecasting Techniques

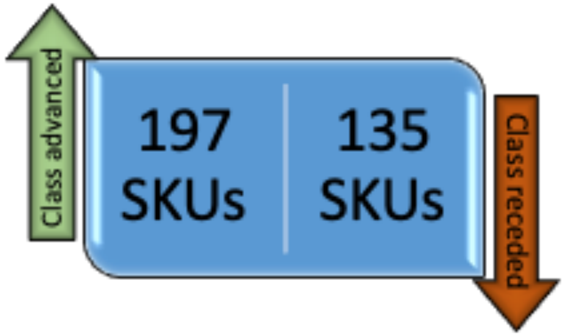
- Aggregated Improvement in RMSE:

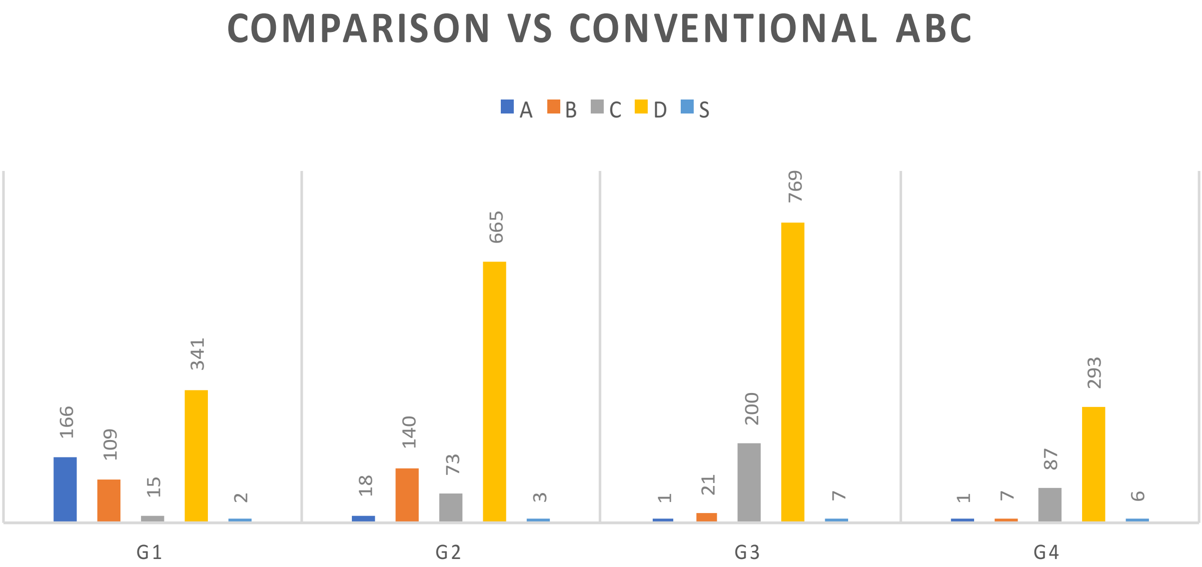
Plant	Median Improvement RMSE - All Cases	Median Improvement RMSE - Positive Cases
0435	13%	15%
0445	10%	13%
0446	14%	17%
0471	7%	14%
0480	11%	17%

Table – Improvement in RMSE per Plant

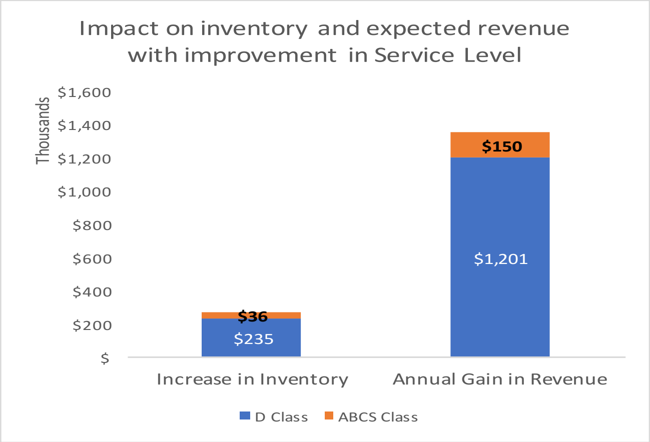
Results –Supply Planning

- The new classification validated the conventional classification while further improving it by allocating appropriate class for each SKUs based on new parameters

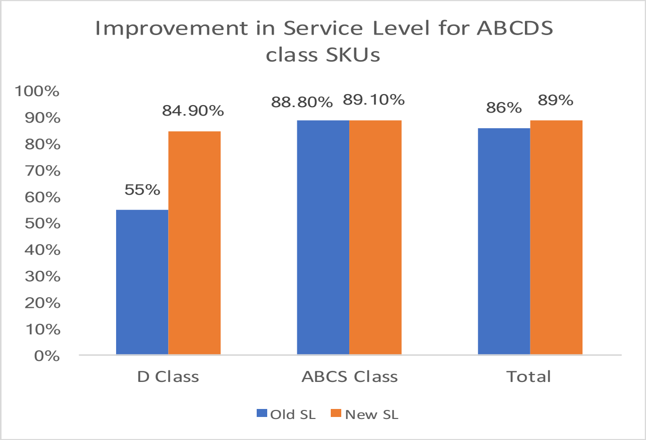




- $1.3M additional revenue opportunity with slight increase in inventory on D class SKUs



- 3% improvement in service level



Recommendations

I. Allocate forecasting techniques based on the CV^2 and p, instead of minimizing for MAPE

II. Pilot study with the new forecasting method on lower value SKU's to see improvement in demand accuracy

III. Revise the inventory classification of key SKUs

IV. Use the inventory optimization tool with different business situations in future

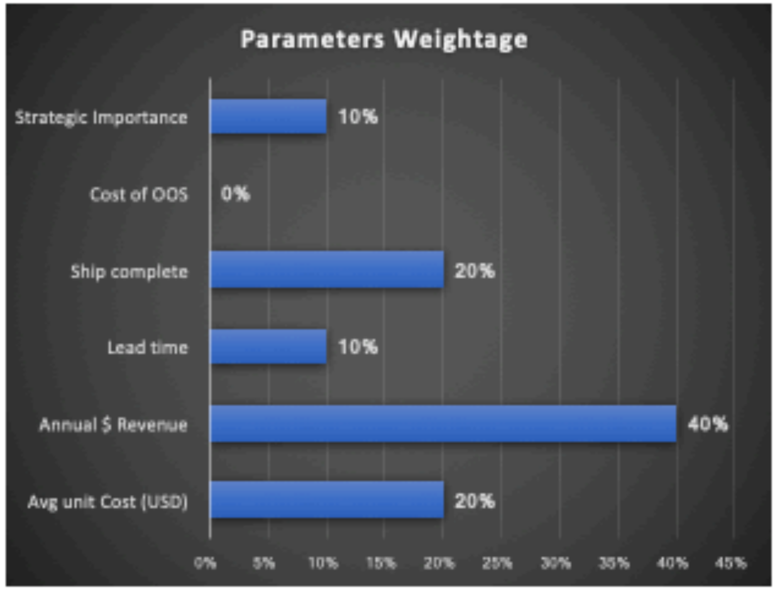
Thank You

Dashboard of Inventory classification tool

Gerber Inventory Optimization tool - Input Dashboard

Parameters Weightage	100%
Avg unit Cost (USD)	20%
Annual $ Revenue	40%
Lead time	10%
Ship complete	20%
Cost of OOS	0%
Strategic Importance	10%

Great! Parameters correctly weighted.



No. of Groups	4

Grouping matrix

	2	3	4
G1	80%	80%	60%
G2	20%	15%	20%
G3		5%	15%
G4			5%

Service Level Matrix

New grouping	Old grouping	SL target
G1	A	90%
G2	B	80%
G3	C	80%
G4	S	70%
Overall Service		89%

Index Weightage

Index Weightage	
Direct Index	70%
Indirect Index	30%

Run Classification