

EBTM 881 CAPSTONE PROJECT REPORT

Using Coefficient of Variation Analysis to Improve Inventory Forecasting

STUDENT: Halina Siegel

ADVISOR: Dr. Chaodong Han

TERM: Spring 2020



Table of Contents

Table of Contents	2
1. Introduction & Problem Motivation.....	3
2. Problem Statement.....	3
3. Background & Literature Review.....	3
4. Data	5
5. Model and Analysis.....	5
6. Results and Recommendations	7
7. Conclusions	8
8. Acknowledgements.....	8
9. References.....	9

1. Introduction & Problem Motivation

All supply chains rely on forecasts in order to build the right product, in the right quantity, at the right time, and have it in the right location. It is the responsibility of demand planners to achieve high forecast accuracy across all product lines in order to drive visibility of this imperative information. Poor forecast accuracy can lead to inaccurate production schedules, stock outs, lost sales, and higher inventory holding costs. The motivation of this project is to improve my overall forecast accuracy and the information I drive to the rest of our supply chain at Stanley Black and Decker. The focus of this research is to determine what factors impact poor forecast accuracy, specifically focusing on the volatility of demand history.

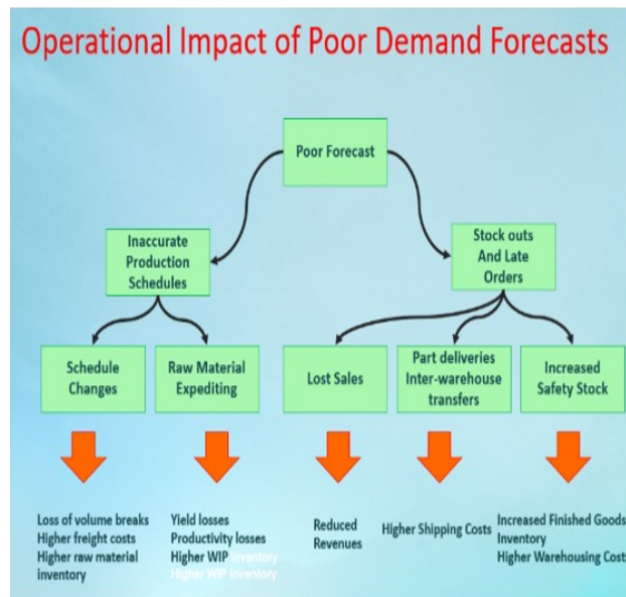


Figure 1: Impacts of Poor Demand Forecasts (Delphus, 2019)

2. Problem Statement

The problem statement for this project is “how does the volatility of demand history impact forecast accuracy and forecastability?” With this problem statement, there are three objectives I am trying to achieve:

- Categorize SKUs based on demand volatility and forecastability
- Create a QlikView dashboard to collect and graphically represent the data
- Determine category-specific strategies for forecasting

3. Background & Literature Review

The idea for this project first stemmed from coursework in Dr. Han’s Logistics and Distribution course at Towson University. Dr. Han’s lesson introduced the impact that the Coefficient of Variation (CoV) of both

demand and supply (lead time) can have on safety stock settings and the overall health of the supply chain. This project and further research focus solely on the coefficient of variation of demand. The coefficient of variation can be used to determine the predictability of a demand pattern, or how easily it can be forecasted. This means that items with a higher coefficient of variation will inherently be harder to forecast. By identifying these items, it is possible to categorize items based on historical behavior. Many companies have adopted use of the coefficient of variation to implement SKU segmentation.

It is important to note two things about the use of coefficient of variation in segmentation. First, seasonal data may have high CoV, but still be very forecastable. By nature, seasonal SKUs will have more variation in not only the timing of demand, but the volume as well. However, seasonality does not mean that it is harder to predict these patterns. Second, CoV ignores the sequence of observations (Singh, 2015). It is solely a measure of variation of the historical demand volume but does not take the sequence of those data points into consideration.

Gilliland (2015) shows one way to graphically represent accuracy vs volatility using a comet chart. A comet chart has volatility (CoV) on the bottom axis and forecast accuracy on the left axis. In the chart lies all SKUs, with a trend line, or forecast value added line, layered on top. Gilliland states that anything above the forecast value-added line represents where the organization produced forecasts more accurate than a moving average, or naïve forecast. Anything below the line shows where the organization's process made the forecast worse.

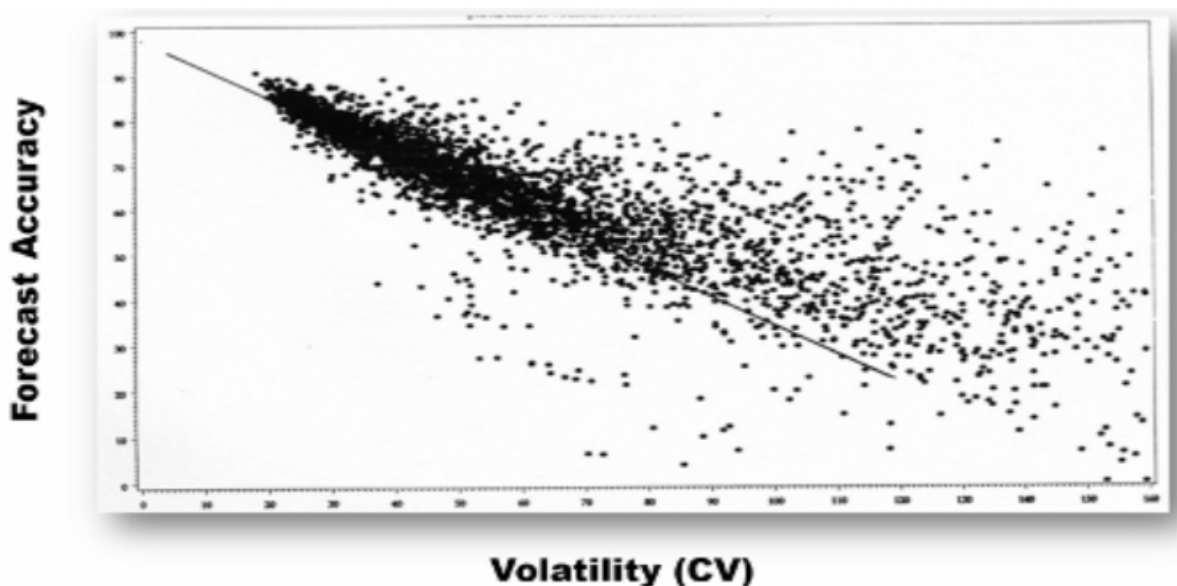


Figure 2: Comet Chart - Accuracy vs. Volatility (Gilliland, 2015)

Frepple (n.d.) brings light to the variability of the demand timing, which is not considered in the coefficient of variation formula. Frepple outlines four categories of items, segmented by their demand volume variability and demand timing variability.

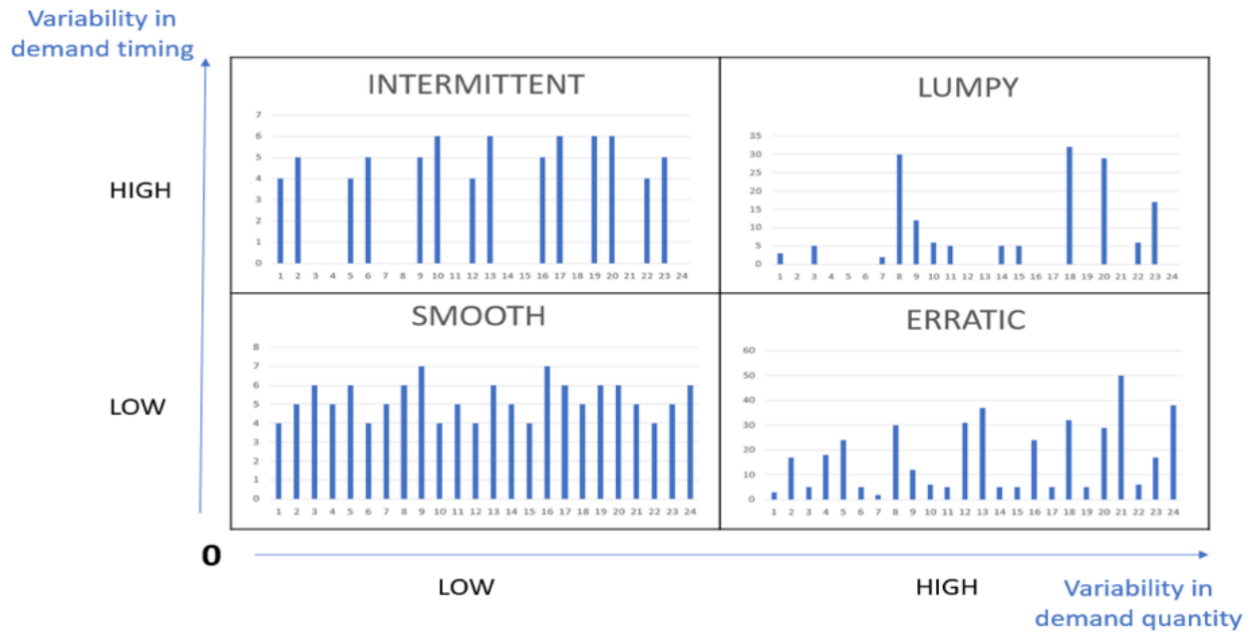


Figure 3: Demand Timing Variability (Frepple, n.d.)

Understanding the variability in timing is important to understand when defining unforecastable SKUs. The higher volume items that are ordered more frequently will be easier to forecast than a low volume item ordered sporadically.

4. Data

Data was collected for all active North America SKUs for all customer groups at Stanley Black and Decker. The data was pulled from January 2018 to January 2020 when this project was started. However, the data will continue to update on a weekly basis in the dashboard going forward. Four pieces of data were collected from existing internal reporting programs – historical demand and forecast, historical forecast accuracy, demand dollars, and historical fill rate.

5. Model and Analysis

The historical demand was used to calculate CoV, which could be analyzed against the historical forecast accuracy to create a comet chart. The demand dollars were used to do an ABC classification, so the team could narrow in the focus on high valued SKUs. Bias and coefficient of correlation calculations were also done using the historical demand and forecast, which allows the team to see if their forecast is trending with the demand. Finally, the frequency of demand history was used to for an XYZ classification.

After researching the use of CoV at existing firms and doing an initial analysis of the data collected, four segmentations were defined. This was done strategically to align with a comet chart, where coefficient of variation is analyzed against historical forecast accuracy.

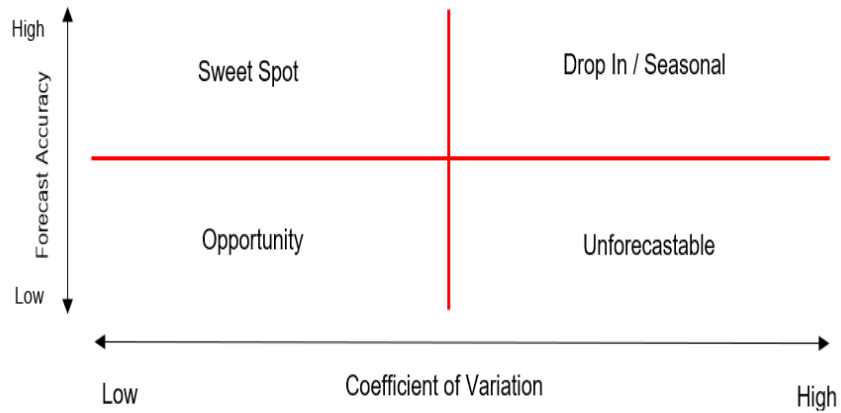


Figure 4: Segmentation Layout

From here, an initial prototype for dashboard was built in Microsoft Excel, focusing only on Power Tools items for the Home Depot channel. This prototype was done to build a case to leadership on the importance of looking at the coefficient of variation and how it could be utilized by the demand planning organization. It also assisted in requesting funding for the QlikView dashboard to begin production.

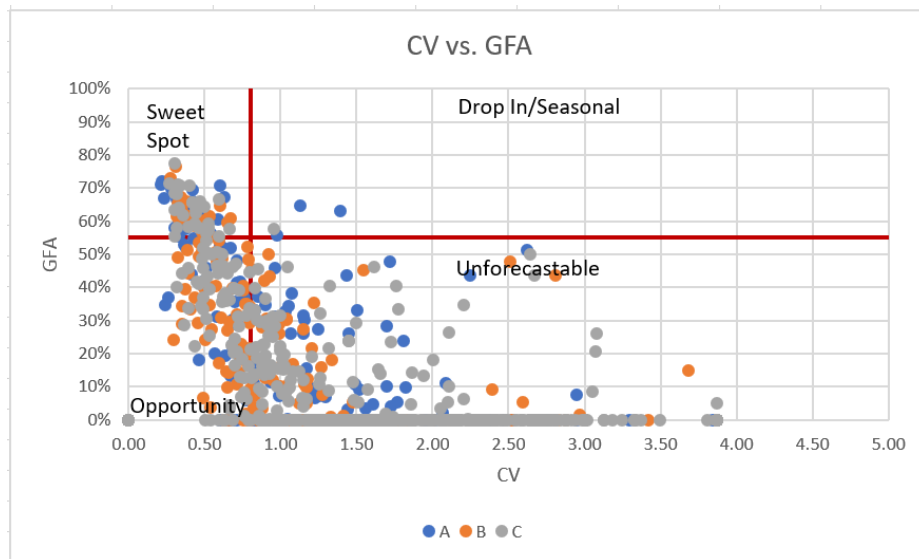


Figure 5: Dashboard Prototype

After getting support from leadership to continue with the project and receiving the necessary funding, the dashboard shown in Figure 6 was developed in QlikView. This dashboard automatically refreshes the data on a daily basis, and allows the entire demand planning organization to look at the data without individually pulling reports. The dashboard can be filtered for any combination of SKUs, time periods, customer groups, etc. The graph on the left side is similar to a comet chart, without the forecast value added line visible. This graph is color coded based on the ABC classification, where green is an A SKU, yellow is a B SKU, and red is a C SKU. The same graph is shown on the right, but the color coding here is based on historical fill rate. Green represents any item filling to our customers at greater than 95%, yellow is greater than 90%, and red is less than 90% for the time period selected. This graph helps draw the connection between the demand planning and supply planning teams, so conversations can be had surrounding unforecastable items and their corresponding safety stock strategies.

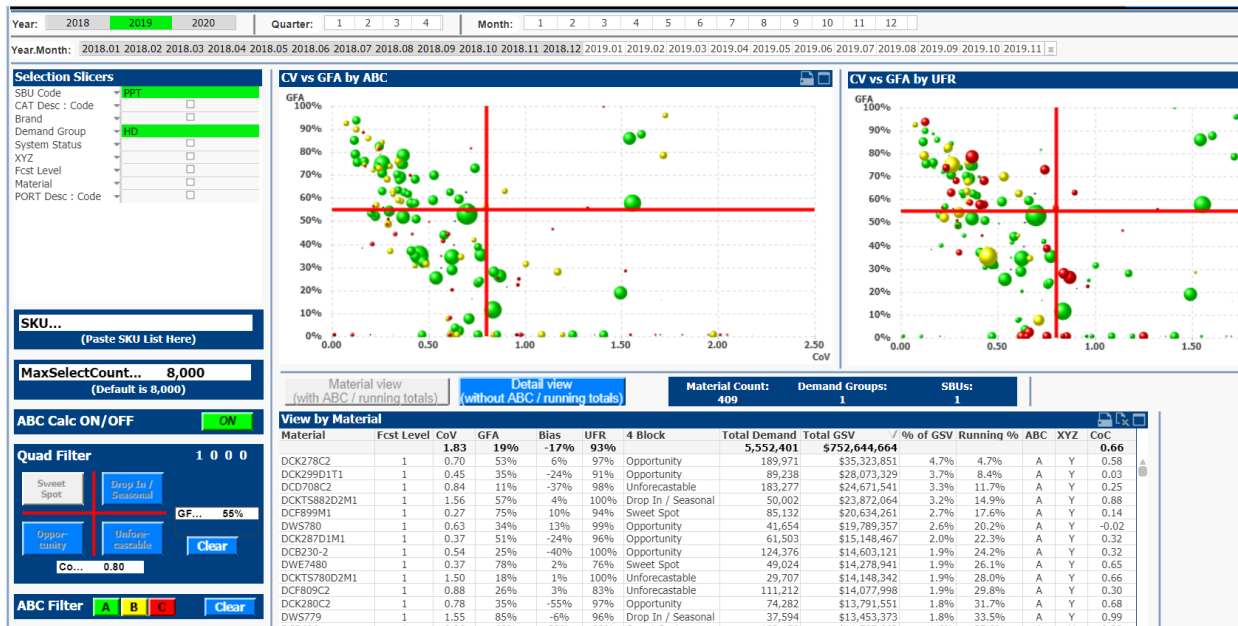


Figure 6: Final QlikView Dashboard

6. Results and Recommendations

This dashboard was rolled out to the entire North America demand planning organization as soon as it was built. Comparing Stanley Black and Decker’s top three customers performance in FY 2019 to the first four months of 2020 enabled the team to track preliminary progress and improvement from using the tool. In 2019, the coefficient of variation for the top three customers was 3.68, with an overall forecast accuracy of 17%. Forecast bias and unit fill rate were 1% and 90%, respectively. In the first four months of 2020, the CoV was 3.39, with a forecast accuracy of 20% (+3%). Bias and fill rate are still aligned to 2019 figures.

Recommendations regarding next steps include training the supply organization, adding global demand groups, and regularly meeting with leadership to discuss strategies for B/C SKUs. Training the supply organization will allow the teams to work collectively towards improving service to our customers.

Understanding which items are unforecastable will enable the supply teams to reevaluate safety stock strategies to be less reliant on a forecast. Adding global demand groups increases the scope of this project beyond our North America channels, which is important to align with our global supply chain strategies. B and C unforecastable SKUs need to be revisited with leadership to discuss best forecasting practices. These SKUs make up only 20% of the company revenue but have the lowest accuracy and highest CoV. Simplistic or naïve models should be evaluated in conjunction with minimum safety stock strategies to maintain service to the customer without inundating the demand planners with items to review.

7. Conclusions

In conclusion, the coefficient of variation is a measure of demand volatility and an indicator of forecastability of an item. The variation in both the volume and timing of demand have a heavy impact on forecast accuracy, and therefore the signals being sent to the supply planning teams. The QlikView dashboard that was developed through this project provides an easy compilation of data and visuals that enhance a planner's ability to dial in on focus areas and problematic SKUs. Since rolling this out at Stanley Black and Decker, the company has seen a 3% increase in forecast accuracy across the top three customers in North America.

8. Acknowledgements

I would like to acknowledge Dr. Chaodong Han for his assistance with this project, as well as introducing me to the concept of Coefficient of Variation in his Logistics and Distribution course at Towson University.

9. References

- Anon, Coefficient of Variation (COV). IBF. Available at: <https://ibf.org/knowledge/glossary/cov-52> [Accessed April 30, 2020]
- Anon, WHY Demand Forecasting Is So Important to Supply Chain Professionals and Managers. Delphus, Inc. Available at: <http://delphus.com/why-demand-forecasting-is-so-important-to-supply-chain-professionals-and-managers/> [Accessed April 30, 2020]
- Gilliland, M., 2016. Changing the Paradigm for Business Forecasting (Part 10 of 12). The Business Forecasting Deal. Available at: <https://blogs.sas.com/content/forecasting/2016/10/25/changing-the-paradigm-for-business-forecasting-part-10/> [Accessed April 30, 2020]

Singh, S., 2019. Do You Use Coefficient Of Variation To Determine Forecastability? - Supply Chain Link Blog. Arkieva. Available at: <https://blog.arkieva.com/do-you-use-coefficient-of-variation-to-determine-forecastability/> [Accessed April 30, 2020]