Solving inventory optimization and distribution management issues for a low-volume high-mix auto-parts business using data analytics and business intelligence

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ABSTRACT:

This paper highlights how supply chain concepts, Data Analytics and Statistics was leveraged to evaluate as well as solve critical challenges an automotive parts business faced during supply chain planning and distribution phases. The primary challenges this auto-parts Manufacturer and Supplier was facing was inefficient classification of SKUs. As a result, the client faced high cross-docking costs, and inefficient Inventory Management. Solving these supply chain bottlenecks would lead to significant reduction in Operating Expenses for the client, resulting in significant improvement in bottom line. For this purpose, multiple datasets relating to Sales, Transportation, and Inventory was collected for a length of time appropriate to carry out this study. The data records were analyzed and validated through Exploratory Data Analysis (EDA). EDA helped with problem solving as the rationale behind the issues were brought to light at this stage. Many of the supply chain concepts and techniques were then leveraged along with analytics to solve these issues on logical basis and an improved classification strategy was formulated to reduce OPEX along with a Business Intelligence (BI) solution for improved performance tracking.

Keywords: Data Science, Analytics, K-means clustering, model, Inventory Optimization, Cross Docking, Supply Chain Distribution, ABC-XYZ analysis, KPI tracking, Demand Planning, Exploratory Data Analysis

INTRODUCTION:

The client's business model is to sell different auto parts, mainly wheelbase, to the auto enthusiasts for vehicle enhancements. The product portfolio consists of low volume, high mix SKUs. Therefore, the supply chain for procuring, storage and distribution is quite complex, creating lots of unique challenges with respect to planning, order fulfillment and inventory management. The firm has grown at an accelerated rate over the past few years, therefore with growing product portfolio and new acquisitions, the supply chain distribution is only getting more complicated and inefficient, facing issues like being inventory heavy in certain DCs leading to higher drop shipping charges when one location is facing stock-outs and requires SKUs to be transferred from another location. The situation will only get worse as the company continues to grow and scale unless a feasible and sustainable solution is applied.

The auto parts manufacturer has more than 30 distribution centers (DCs) across the USA, with few of them operating at international level. However, the primary market is still the USA. These distribution centers are supported and supplied to by 3 major Logical Centers (LCs). Keeping up with the contemporary way of selling, the business has an ecommerce site that serves the end consumers to view, order and purchase the products they desire.

The company has already invested in an enterprise software solution that provides the capability to generate demand forecasts for the SKUs. However, inefficient distribution model is still causing certain locations to become inventory heavy while others do not receive sufficient inventory. The classification is done based on sales velocity (Exhibit 1) and the distribution to LCs and DCs are based on this model.

Another important issue for the firm is not being able to track the performance of different functions effectively and accurately such as Planning and Inventory. There are no standard measurements in place for a planner to gauge the performance of demand forecast generated by the system, or whether the system is under or over-forecasting. In addition to this, from inventory management perspective, the company would want to track how efficient and effective the inventory management has been with respect to different classification categories. This would help the business monitor its cross-docking and control drop shipping.

LITERATURE REVIEW:

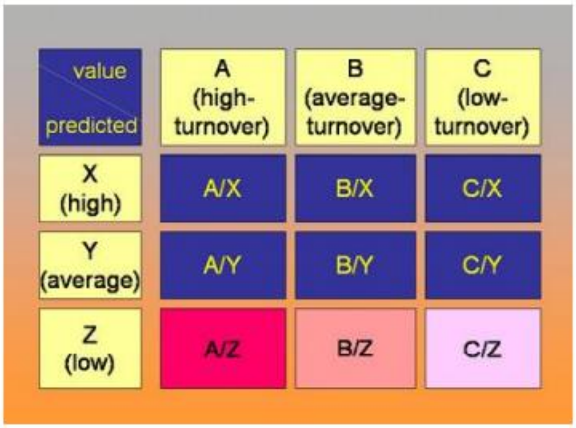
Drop shipping is a method of product fulfillment where the online merchant (retailer) does not keep any goods in stock but instead passes on the customer order and shipment details to a wholesaler, who then ships the goods directly to the customer. This eliminates the need for the retailer to carry inventory, handle, or ship goods. Zack Rutherford provides a good explanation regarding it. However, drop shipping can create issues with low volume high mix inventory. This is because of the need for a higher level of stock keeping and order processing, as well as the possibility of goods being out of stock. Since each item has a low volume, it is difficult to maintain the stock levels of all the items, and hence, order fulfillment could be delayed. Moreover, due to the low volume, it is difficult to predict the demand for each item, resulting in a higher chance of an incorrect order being shipped.

The major issue that our project was facing is drop shipping. To mitigate this, better inventory management was needed which required improving the classification of inventory.

Milan Stojanović, Dušan Regodić (2017) provide a good reference regarding the classification of inventory. The analysis of inventories by means of the ABC classification is an approach that is used widely in the industry. The traditional ABC classification was developed at General Electric in the 1950s. The ABC ranking of products is usually done based on only one criterion (for e.g., sales frequency or sales revenue). The importance of the ABC analysis is demonstrated by the fact that it makes it possible to monitor inventories as well as identify those that may be useful in achieving goals and those that are simply costs and burdens for the company. Inventory management is made possible by the ABC classification at various levels according to importance. The ABC technique is renowned for its ease of use, but it is also criticized for using just one criterion for classification.).

One sales enterprise's product inventory should be stocked to the level of demand. XYZ is employed in sales companies where demand for specific products can change significantly from one to the next. The elements are divided into three categories by the XYZ analysis based on the characteristics of consumption. The products sold continuously in Group X are those with very slight oscillations, making it possible to forecast demand for this group of products with great accuracy; the products sold intermittently in Group Y are those with fluctuations in demand, and forecasts for this group of products are of middle accuracy; Since Group Z includes products that are occasionally supplied and whose volume of demand varies greatly, it is highly challenging to predict demand with any degree of accuracy.

In a paired comparison matrix, the activities for each of the specified groups of articles are determined using the integrated ABC-XYZ technique.



The Combined ABC and XYZ Analysis

The elements in Group A/X have a significant percentage of the total value, are continuously used, and the demand forecast is extremely accurate. There is no need to maintain significant safety stock levels because of these goods' ability to enable exact planning and ordering. The products in Group A/Y have a significant part of the total value, but their consumption is irregular, and their forecasting accuracy is lower. In order to reach purchase prices at the lowest cost, this group of products should receive enough planning attention. Products in Group A/Z have a substantial share of the total value but are only sometimes purchased, making it difficult to predict their demand. The management of inventories is the most difficult of these. Products in Group B/X are those with a middle share of the overall value, constant consumption, and highly accurate demand forecasts. When it comes to this particular set of products, the dynamics of buying should be identified together with the lowest inventory levels. Products in Group B/Y have a middle share of the total value, discontinuous consumption, and a middling level of forecasting demand accuracy. Products in Group C/X are those with a modest percentage of the overall value, constant consumption, and excellent demand forecasting. Ordering for these goods ought to be done in compliance with requirements. The items from the groupings B/Z, C/Y, and C/Z have minimal effects on an enterprise's business operations; as a result, they are rarely purchased, and their planning is typically overlooked or delegated to suppliers in conjunction with another product. In general, it can be claimed that the categories AX, BX, and AY are candidates for just-in-time techniques, whereas efforts for the low-value items with unpredictable demand, which fall under the CZ category, must be reduced. The investigation of each of the remaining material groups is necessary.

In our project, we used concepts from this ABC-XYZ classification to reduce the instances of drop shipping and reduce the logistics cost for the company.

DATA:

All data that was provided by our client was in form of excel sheets and CSV files. Of all the data, the data that was useful for project was:

Data	Description
Sales data by zip code	Sales data included things like Material Id, Plant code, Profit Center code, Billing Quantity, Net value, Date of order, etc. The range of data is from September 2019 to June 2022.
Inventory data stock report	It includes the data for every material like Material Id, Material Description, ABC Class, Stock On Hand, Safety Stock, Reorder Point etc.
Transportation data (Land-to-Land)	It has the shipment data like Tracking Number, shipping date, shipper name, shipper city, Recipient Name, Recipient City, number of units, shipment weight, etc.
LC-DC zip code mapping	DC details like DC code, City, Division 10 LC code (For all categories of shipment), and Division 20 LC code (For only sports category) are included here.
Warehouse mapping	It has the name, code and location of the warehouse and zip code to which it is mapped.
Cost Per Unit	It contains the average cost for each material.
Receipts	It contains the inventory receipts data at each location.

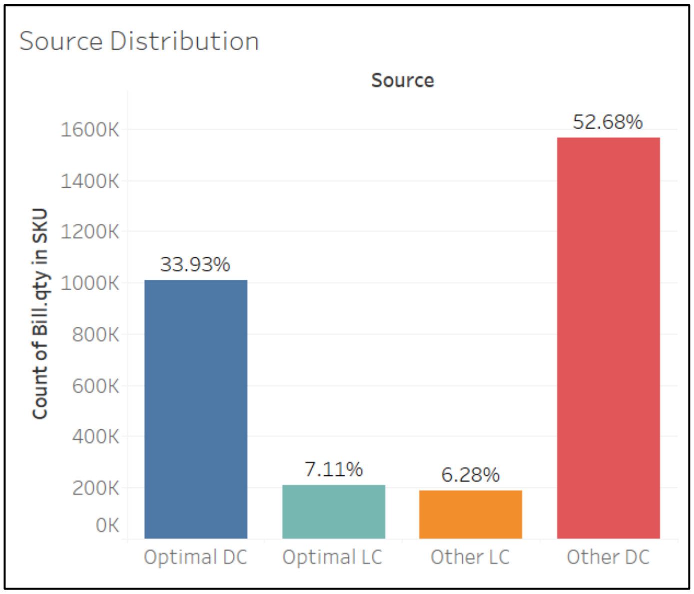
METHODOLOGY:

Sales data was used analyze the performance of over 50,000 SKUs enlisted under the current inventory report. Inaccuracies in the current state of inventory shipments were calculated by comparing the point of sale to the source of the material sold. Based on where the material was shipped from, the sales were divided into four categories:

Optimal DC	If the material item sold is available at the Distribution Center assigned to serve a given zip code.
Optimal LC	By the standards defined by the company, in case of stock-outs at DC, the sale must be fulfilled by their designated Logistic Center.

Other DC	If a material item is sourced from another Distribution Center. Since every Distribution Center operates individually, this is identified as Drop-Shipping.
Other LC	If a material item is sourced from another Logistic Center. This is also identified as Drop-Shipping.

Based on the initial strategy established by the clients, if an item is received from a non-optimal source, it is marked as an inaccuracy. Using this standard, over a period of 36 months (2019 to 2022), 52.68% of sales were fulfilled by other DC and 6.28% were fulfilled by other LC aggregating to a net 58.96% inaccuracy.

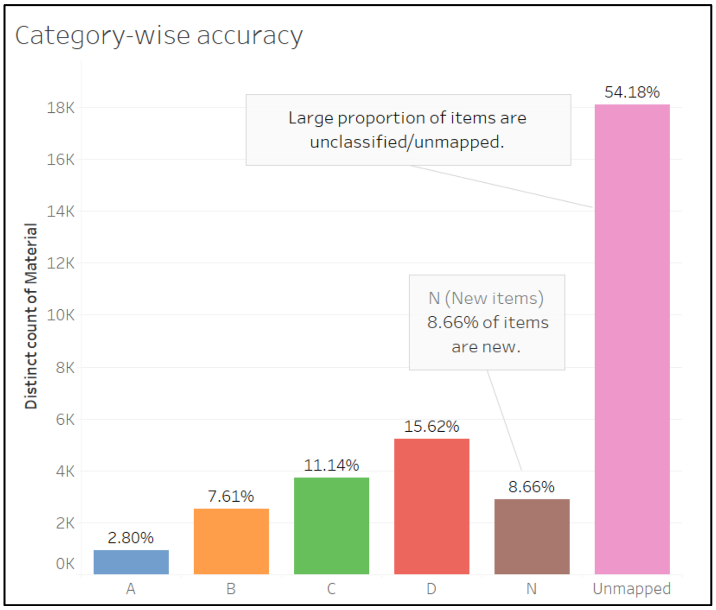


In the past, the company has been managing its inventory by classifying it based on the volume of sale of each SKU. (Exhibit 1)

These category labels are essentially used to define the cross-docking strategy for an item. Cross docking is a logistics process that involves receiving goods from one source, consolidating them, and then sending them to their destination without any storage in between. This helps to improve response times by reducing delays caused by waiting for goods to be stored in warehouses, thus allowing businesses to respond to customer orders more quickly. The cross-docking strategy employed for each category is as follows:

A	Cross-dock inventory to Distribution Center.
B	Cross-dock inventory to Distribution Center.
C	Stock inventory at Logistic Center.
D	Stock inventory at Logistic Center.
N/Unclassified	Stock inventory at Logistic Center.

Since the company has expanded rapidly by acquiring numerous companies and merging their product range. The classification of pre-existing brands was evaluated by the company, whereas the classification of new brands was inspired by the classification assigned to an SKU by the merging brand. As this was not established as a standard, a large portion of the SKU mix was incorrectly classified. The current SKU mix fall into the pre-defined classes in the following proportions:

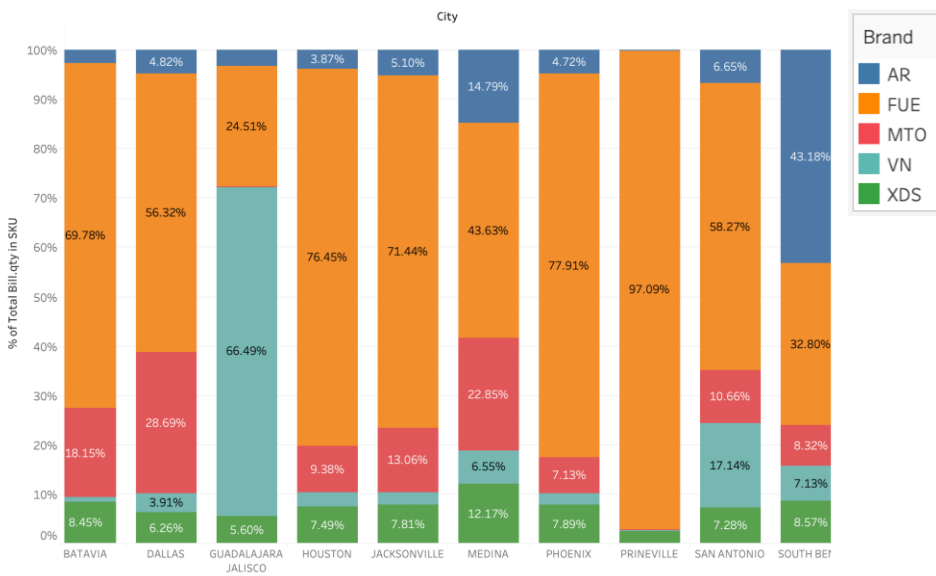


Several drawbacks were realized during the analysis of the existing classification of items:

- Frequency of sale is an important metric in inventory planning because it helps businesses determine how much inventory to keep on hand. Knowing the frequency of sale for each item helps businesses better forecast customer demand and plan for any potential shortages. While observing the frequency of sales of items across different categories, significant amount of overlap in confidence interval which can be easily observed using box plots.

This points out that the current classification does not form mutually exclusive bins in terms of frequency of sales. Since the classes are not mutually exclusive, it is infeasible to categorize an item which is currently unclassified.

- Another issue observed in the current methodology is that the classification of items is performed at a national aggregate level. Every quarter, sales of all SKUs are rolled-up to national aggregate level to evaluate the demand of the product. Based on this the cross-docking strategy is decide for the SKU across US. However, upon examining past sales, it was noticed that the brands did not have the same level of popularity across different geographical locations.



This reveals the need to go more granular to fix a cross-docking strategy for any SKU. Instead of planning inventory at national level, the company needs to perform classification for every profit center (LCs and DCs) individually.

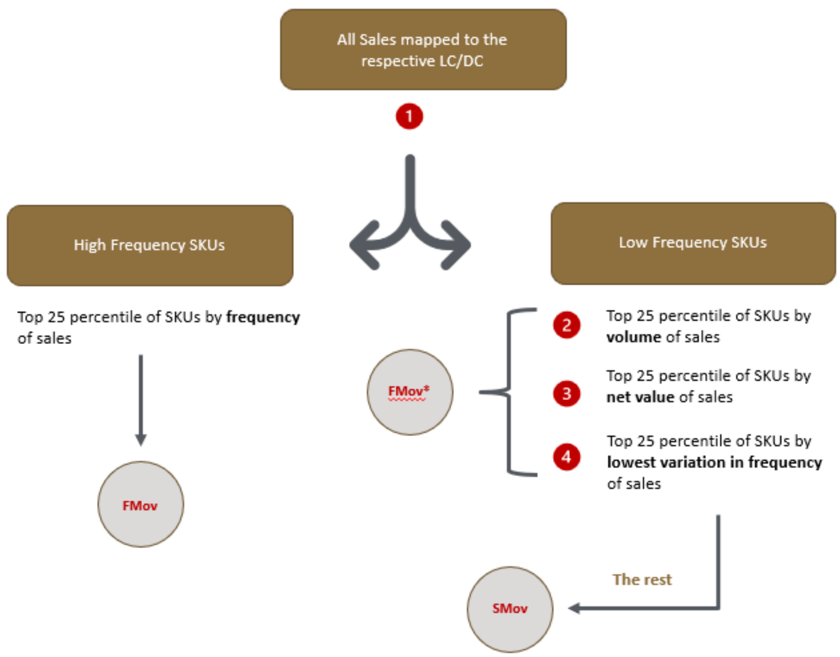
- Current classification system is unidimensional and does not consider other information necessary for deciding the cross-docking strategy. Metrics such as Variation in demand, Frequency and Price of the product were not considered, but should be considered for inventory planning.

Following the above observations, a new classification model was developed to resolve these limitations.

Revised classification model

While the frequency of sale and the volume of sale are both important metrics for low volume, high SKU mix businesses, frequency of sale is more important than the volume of sale because it provides insight into the demand of an item. Volume of sale only indicates how much of an item has been sold, not how often. Knowing the frequency of sale allows a business to better manage their inventory and ensure they have the right amount of product available to meet customer demand.

Using the frequency of sale to split the SKUs, we obtain two groups - fast-moving items and slow-moving items. Further, volume of sale, price, and variation in frequency can be used to identify high-value items even if the frequency of their sales is low. For example, if a product that has a relatively low frequency of sale is selling at a higher unit price and larger volume than other similar items, it may be a good indicator that this item is more desirable and valuable to the clients. Additionally, analyzing the variation of frequency over time can help identify any potential trends in customer buying behavior and provide insight into which specific items are consistently in demand. From the sales data, variance in days between consecutive sales of an item is used as variance in frequency. These metrics can be used to identify high-value items and help inform inventory management decisions.



Revised classification method

From the new classification, products are divided int three categories:

Class	Business Interpretation	Cross-docking strategy to be used
FMov	Fast-moving SKU	Cross-dock to DC.
FMov*	High value, consistently selling SKU (Slower moving than FMov)	Cross-dock to DC but maintain smaller inventory.
SMov	Slow-moving SKU	Store at LC. Do not cross-dock.

Since the above classification tree utilizes percentiles for its calculation, it can be used to compute the classes for an item at different levels of granularity. For example, the same methodology can be applied to any level of granularity - Distribution Center (DC), Logistic Center (LC) or national aggregate level. Also, the cross-docking percentage can be adjusted as per the warehouse storage capacity by tuning the percentile value for splitting from 25 percentile to a different value. The clients had established a standard of 40% cross-docking for its operations which was met by setting the percentile split at 25%.

Essentially, the revised classification methodology is designed to tackle the shortcomings observed previously in the existing ABC classification model.

Comparing the performance of models

Total distance shipped was used to determine the performance of the distribution model. Greater distances shipped would imply inefficiencies in the system because of stock outs of inventory or poor planning of expected inventory.

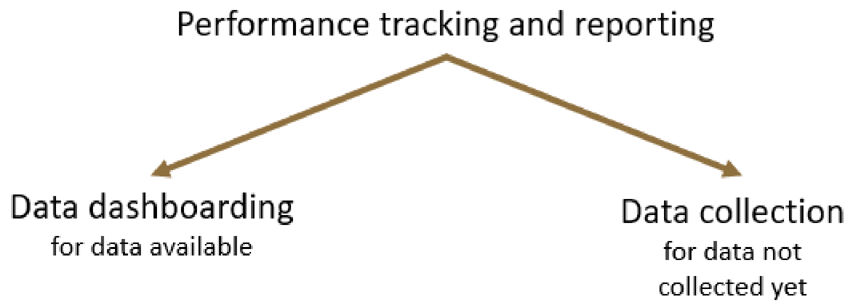
A theoretical "ideal" distance was also calculated based on perfect prediction and application of the model against the expected sales using 2022 data. The "ideal" distance is calculated assuming all Fast Movers and Fast Movers* were sold from the DCs and the Slow Movers were sold from the LCs. This did not consider any stockouts or misplaced inventory in the system. Comparison with the "ideal" distance allows for benchmarking the model to account for the inaccuracy of predicting sales for 2022 based on the classification of the previous year's sales.

To benchmark and compare the existing distribution model's performance, a theoretical strategy was also considered where the complete inventory is sourced from the relevant LCs. The distance observed from application of this strategy set a benchmark for observing the performance of the model with respect to distribution of inventory in the DCs.

Modeling the key performance indicators

Now, when it comes to tracking the performance of inventory planning and management for the business, we soon realized that although the managerial team (particularly the inventory planner and the transportation planner) operated on the SKU-level for their planning and management tasks, they only had visibility at an overall level and not at the location-wise levels (supplier LCs and seller DCs), they utilized very few performance indicators at the granular levels (location-wise SKU-levels), and thus, they faced difficulty in reporting operational and financial performance to the executive team. Realizing the project scope and timelines, we agreed upon a two-prong approach to deal with performance tracking and reporting issues.

First, we analyzed the Key Performance Indicators (KPIs) currently used by the business. Secondly, we carried out an in-depth market research for the KPIs used by competitors, adjacent markets, and other low-volume high-mix businesses to come up with a laundry list of KPIs we should measure. Finally, we cross-validated this list with the data available at the business to segregate it into a list of KPIs we can calculate and create dashboards for and another list of KPIs we recommend the business to begin collecting data on for future consideration.



The KPIs we agreed to work upon are:

1. Demand Forecast Accuracy
2. Percentage Bias
3. Inventory Turnover Rate
4. Stock Days On Hand
5. Sell Through Rate
6. Revenue-, cost-, profit-per-unit
7. Gross Margin
8. Cross Docking %

The KPIs we recommended for future use are:

1. Fill Rate
2. Service Level
3. Back Order Rate
4. Stockouts %
5. Lost Sales Rate

Demand Forecasting helps a business predict future sales. It's a supply chain management process of generating prediction for Sales by studying historical customer behavior, projected trends and market and economic conditions, among other factors, to increase the chances of meeting customer demands while avoiding excess inventory.

Demand Forecasting KPIs gauge the results of demand planning efforts. It tells you how accurate your predictions for sales have been. For demand planners, it's the top-line insight into the quality of their output.

Typical KPIs for demand forecasting are (The highlighted ones are recommended to be used for our study):

1. MAPE (Mean Absolute Percentage Error)
2. **WMAPE (Weighted Mean Absolute Percentage Error)**
3. MAD (Mean Absolute Deviation)
4. Bias
5. **Percentage Bias**

One would ask: *Why is WMAPE a recommended measure here instead of MAPE?*

MAPE is commonly used to measure forecasting errors in case of supervised learning methods used for different applications, such as calculating sales forecast accuracy. But MAPE can be deceiving when sales reach numbers close to zero, i.e., when the SKUs for which demand forecast is being calculated contains a lot of slow movers., or in intermittent sales. WMAPE is a measure that counters this by weighting both errors and actual sales. WMAPE is used when the use case requires to put priority in certain sales. It gives weight on the prioritized item that biases the prediction error towards it.

Therefore, WMAPE should be given priority over MAPE when your product portfolio contains a lot of slow selling items.

Below table will provide a clear comparison between the two measures:

MAPE	WMAPE
Each forecast error is weighted equally, independent of the magnitude of sales.	Better comparable across slices of data.
Not applicable if there are zero values (as MAPE value will become close to infinity).	This weights the errors by volume, so this is more rigorous and reliable.
Should not be used for slow moving products as well (error values will be huge) because large error on a slow mover will unfairly skew the overall error.	

The formulae to calculate each is as follows:

$$\textit{Mean Absolute Percentage Error (MAPE)} = \frac{\textit{Sum of (ABS(Actual Sales – Forecast) / Actual Sales)}}{\textit{Number of Observations}} \times 100$$

$$\textit{Weighted Mean Absolute Percentage Error (WMAPE)} = \frac{\textit{Sum of (ABS(Forecast – Actual Sales))}}{\textit{Sum of (Actual Sales)}} \times 100$$

For further clarification, please see the example below:

Slow moving items

SKUs	Actual Sales	Forecast	Error	Absolute Error	% Error
Product V	1	3	-2	2	200%
Product W	5	10	5	50	100%
Product X	75	25	50	50	67%
Product Y	74	75	-1	1	1%
Product Z	75	100	-25	25	33%
Total =	230	213	27	128	-
Average =	46	42.6	5.4	25.6	**~80% (MAPE)**
					~55% (WMAPE)

MAPE = Average of (200%, 100%, 67%, 1%, and 33%)
= 80% (skewed to a higher value due to Product V & W)

WMAPE = Sum of (Absolute Error) / Sum of Actual Sales = 128 / 230 = **55%**

Therefore, as much of the SKUs at our target company are slow movers, it makes more sense to leverage **WMAPE** instead of MAPE for Demand Forecasting KPI calculation.

Coming to the **Percentage Bias**, it is the tendency for forecast errors to trend in one direction — consistently higher (or over-forecast) or lower (under-forecast) than actual sales results.)

The formula for Percentage Bias is:

Percentage Bias =
(Sum of observed forecast errors over multiple periods / Sum of Actual sales) x 100

Below example will make the usage of Percentage BIAS into perspective:

	Week 1	Week 2	Week 3	Week 4
Actual Sales	12	8	8	7
Forecasted Sales	10	10	10	10
Forecast Error	-2	2	2	3

Therefore, Percentage Bias = ((2-2-2-3) / (12+8+8+7)) * 100 = (5 / 35) * 100 = 14.28%

Here, positive percentage bias represents that we are over-forecasting. For the purpose of this study, we will use Percentage Bias along with WMAPE to calculate demand forecast errors.

The following are some standard inventory and financial management KPIs that help businesses monitor and make decisions about their stock and operations as well as the formulae to calculate each of them. They enable businesses to view progress against benchmarks, check which processes or entities need work, and examine where they find success. We have also summarized why these KPIs particularly have tremendous utility and relevance to the business we're working with.

Inventory Turnover Rate: Also known as inventory turnover ratio or inventory turn, inventory turnover rate is the number of times a company sells and replaces its stock in a period, usually one year. You can use the inventory rate to determine if a business has too much inventory compared to how much of its stock is selling. Inventory rate measures how well a company makes sales from its inventory.

Inventory Turnover Rate = (Cost of goods sold / Average inventory cost) x 100

This KPI is particularly useful for the business we're working with since it allows benchmarking the inventory levels for each classification and/or at each location with the overall inventory levels to monitor which ones are more effective or less effective at making sales from their inventories.

Stock Days On Hand: Also known as the average days to sell inventory (DSI) or average age of inventory, is the rate of inventory turns by day. This daily interval is the most common timeframe used after an annual range.

Stock Days On Hand =
(Average inventory cost for period / Cost of goods sold for period) x 100

This KPI enables the inventory planner to monitor the days of stock usually available overall and for each classification and/or at each location, make specific decisions for each link in the entire supply chain especially before stocks reach critically low levels, and prevent stockout situations.

Sell Through Rate: Sell-through rate is a comparison of the inventory amount sold and the amount of inventory received from a manufacturer. This helps demonstrate the efficiency of a supply chain at different locations.

Sell Through Rate = (# units sold / # units received) x 100

As the business we're working with has tremendous issues with planning DC-wise inventory and needs to drop ship them the stocks they require from their optimal and non-optimal LCs as well as from other DCs, sell through rate monitors this flow and measures how optimally it occurs at each location. For example, any LC having an unusually low sell through rate versus its DCs indicates that the LC and its corresponding DCs have sold more inventory than they received, which is possible only when the DCs were supplied by drop shipping from other non-optimal locations. Other than monitoring this important issue that the business would like to control, it also provides a numerical measure of how relatively less or more efficient any DC is at selling the inventory it receives versus the overall business, its optimal LC, its group's DCs, as well as other DCs.

Revenue per unit: Revenue per unit is how much one unit of product is worth, overall and at each location.

Revenue per unit = (total revenue for a period / average units sold for a period) x 100

Cost per unit: Cost per unit is how much one unit of product costs the company to produce or buy, overall and at each location.

Cost per unit = (total cost of goods sold for a period / average units sold for a period) x 100

Profit per unit: Profit per unit is how much one unit of product generates profits, overall and at each location.

Profit per unit = [(net sales – cost of goods sold) / average units sold for a period] x 100

Gross margin: Gross margin is the amount of money a company keeps per dollar of sales. This metric removes any costs from producing the item.

Gross margin = [(net sales – cost of goods sold) / net sales] x 100

The 4 KPIs mentioned above, although already calculated at an overall level, would be calculated for each classification and/or at each location to provide more accurate measures of actual financial performance. As the business could not track granular information, they had to rely on different high-level assumptions to report these metrics at an overall level. These KPIs, when monitored at such a granular level, allows the business to be more agile and adaptive in making decisions and managing risk based on readily calculable financial metrics.

Cross docking %: Cross docking % is a measure of the inventory amount cross-docked directly to seller DCs from the inventory amount received at supplier LCs.

Cross docking % = (# units cross-docked to DCs / # units received at LCs) x 100

This KPI was very particular to the business we were working with as they had a long-term strategic goal of cross-docking 20% of its SKUs that contribute 80% of its revenues directly to its seller DCs and stocking the rest to ship only on a need-to-sell basis from the supplier LCs.

During market research and competitor analysis, we realized that the industry practices for the market this business operates in are moving towards different lead indicators to plan ahead rather than react later by relying on lag indicators. However, the information required to calculate these KPIs are not being collected by the business. Hence, we recommend them to consider utilizing these KPIs for their day-to-day operations and begin collecting data to measure and monitor them in the future.

Fill Rate: Also called order fulfillment rate, is the percentage of orders that the business can ship from their available stock without any lost sales, backorders, or stockouts. It can be calculated at the order, line, and unit levels. It's a good reflection of any business's ability to meet customer demand and the overall effectiveness of their operations.

Fill Rate = [(# total items - # shipped items) / # total items] x 100

Service Level: Service level is a metric that addresses the percentage of customers who do not experience stock-outs. It can be used to balance excess inventory costs and stockout costs resulting from having too much and not enough inventory to fulfill orders. It also helps companies account for the challenges of the supply chain, customer demand and stock rotation.

Service Level = (# orders delivered - # orders received) x 100

Back Order Rate: Backorder rate is a measurement of the number of orders a company cannot fulfill when a customer places an order. It shows how well a company stocks in-demand products.

Back Order Rate = (# delayed orders due to back orders / total # orders placed) x 100

Stockouts %: Stockouts %, also known as rate of out-of-stock items, is the percentage of items not available in inventory when a customer places an order. This metric shows a company's ability to meet customer demand. Companies hope to keep this percent low.

Stockouts % = (# items out of stock / # items shipped) x 100

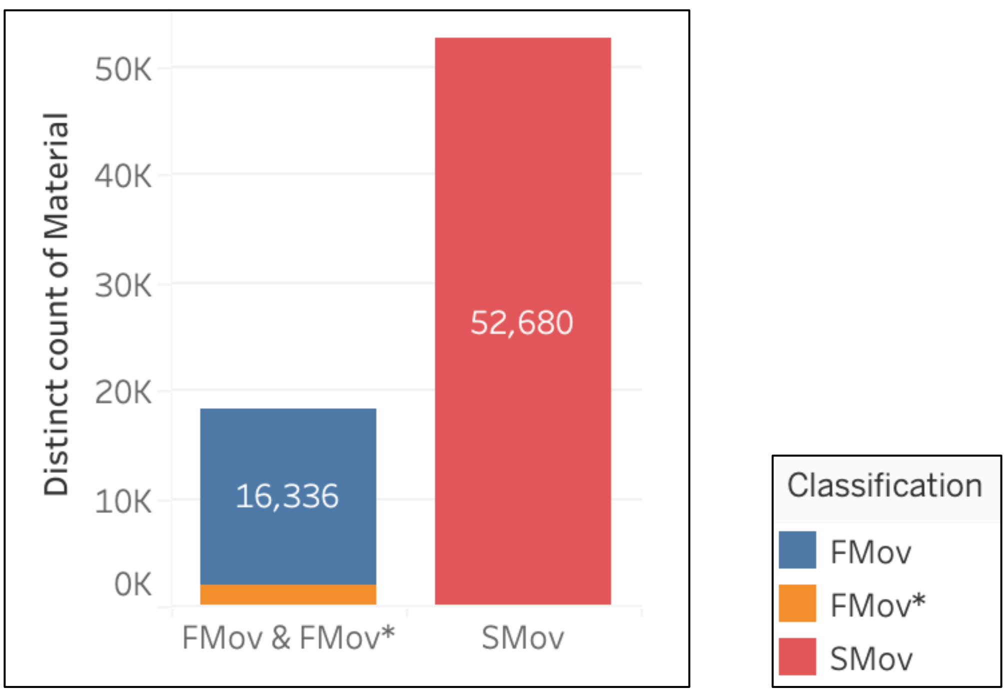
Lost Sales Rate: Also called lost sales ratio, is the number of days a specific product is out of stock compared to the expected rate of sales for that product. It indicates when a company runs too lean on its stock.

Lost Sales Rate = (# days product is out of stock / 365) x 100

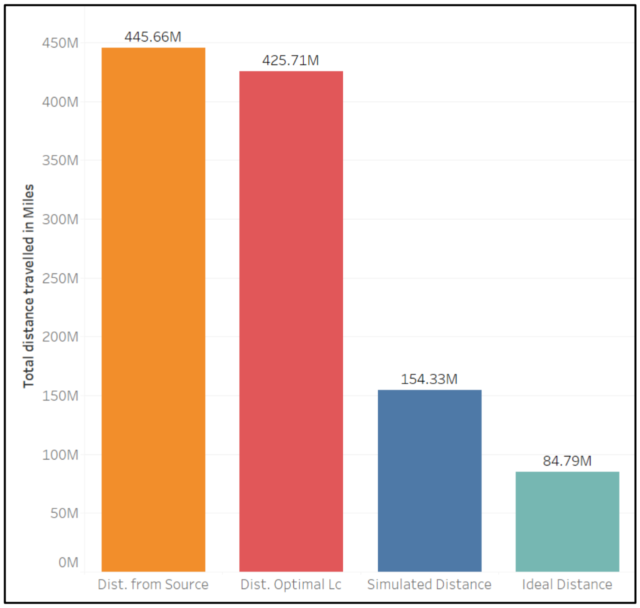
These KPIs will not only shift the existing business processes to be more outcome-based than output-based but also ease scaling up with future inorganic acquisitions as the business plans to strategically continue doing so.

RESULTS:

Application of the new classification system generated using the 2021 data revealed the following classification:



The division of the inventory as per the new classification followed the expected cross-docking percentage of 35%. The new distribution model would thus expect 35% of total inventory to be shipped to the DCs directly. The above classification was used to simulate the expected performance of the distribution model when tested on the existing sales data for 2022.



The existing distribution model gave the distance from source as 445.66 million miles. This was larger than the naïve benchmark of operating just from the LCs of 425.71 million miles. The new classification system applied to 2022 sales gave an improvement of over 65%, operating at only 154.33 million miles. The "ideal" distance was 84.79 million miles, showing further evidence of the improved performance of the new distribution model.

Demand Forecasting

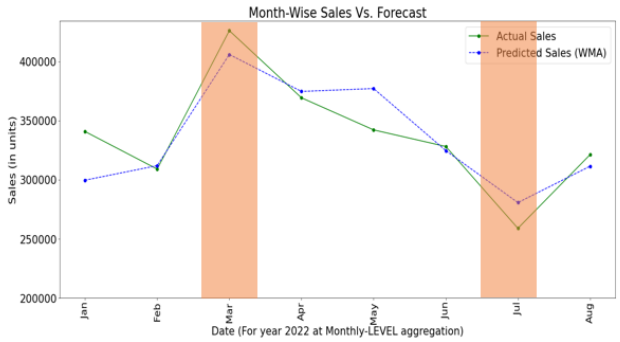
Coming to the performance tracking and reporting: to measure the demand forecast accuracy using WMAPE and Percentage Bias, we cross-plot the calculated forecast against the actual sales at different points in time.

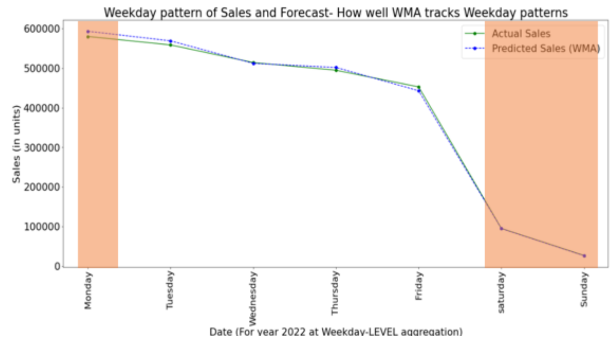
Weighted Moving Average: A baseline algorithm to gauge efficacy of more sophisticated models.

WMA is a naïve time-series method to forecast the demand and is used in industries like Retail. It can help measure the performance of a much more sophisticated models. For the purpose of this study, the auto parts client already has a system in place that generates future sales. WMA algo can be used as a benchmark to see when the model used by the company is under performing or needs to be tuned.

Below are 2 Use Cases created to see how the forecast generated by WMA compares against actual sales. It also highlights how we can leverage the Demand Planning KPIs to calculate forecasting errors and accuracy rates.

Use Case 1: Benchmark closely matches actual monthly sales pattern

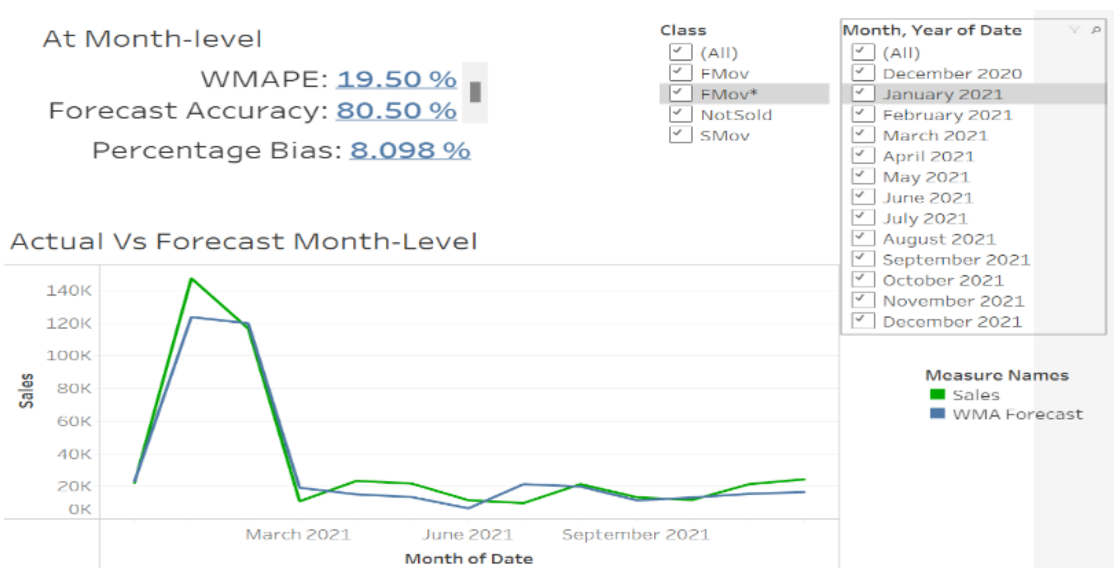




Key highlights and insights from this use case:

- The prediction period is starting from January 1, 2022 and ends on September 6, 2022.
- Weighted Moving Average (WMA, the industry standard benchmarking algo) forecast, highlighted in blue is able to closely mimic the pattern of the actual sales, highlighted in green, and is doing well when aggregated at ALL SKUs – ALL Locations – MONTHLY level granularity.
- Seasonality in sales is quite apparent in client's actual sales data. Peak period is around March and down period is around July of every year (Note: this is true only for the time period between January and August as it is the time period of interest here)
- The WMA time-series model is able to capture the peaks and valleys of monthly seasonality in actual sales quite well.
- The weekday level sales pattern shows that the highest sales happen on Monday, Tuesday and it gradually diminishes.

Use Case 2: How Demand Planning KPIs can help calculate the forecast performance



(Source: snapshot of Tableau Dashboard developed to monitor Demand Planning KPI)

Key highlights and insights from this use case:

- WMAPE and Percentage Bias are key in identifying how we are planning at demand planning stage, especially for Wheel Pros where we have lots of Slow Movers. It is also great for identifying how different categories (Fast sellers, Slow movers)
- These forecast accuracy figures are created at a very high aggregation level (summing up sales for all SKUs at all locations together at Month level). Thus, accuracy will go down considerably when we predict at per SKU level/per Location level/Daily level.
- WMA can be used as a benchmarking algorithm for other sophisticated models such as Machine Learning models, or the sophisticated model currently used by the client, because WMA doesn't consider effect of many other factors such as Price Elasticity, Events, Promotions to name a few.

Now for the inventory management KPIs, we began by measuring the performance based on the existing classification methodology to understand the current state and create a baseline for future improvements in classification.

Class	%volume	%value	Inventory turnover rate	Days inventory	Sell through rate
A	**31%**	**27%**	**4.36**	**84 days**	**81.3%**
B	**22%**	**22%**	**3.50**	**104 days**	**77.8%**
C	14%	15%	3.22	113 days	76%
D	9%	10%	4.83	76 days	83%
E	4%	4%	3.85	95 days	79%
CDE	**27%**	**29%**	**3.84**	**95 days**	**79.3%**
N	**19%**	**21%**	**1.45**	**252 days**	**59.2%**
Removed	1%	1%	-	-	-
Overall	**100%**	**100%**	**3.49**	**105 days**	**77.7%**

Although SKUs contributing 50% of the volume are captured as fast movers (A & B), we see that the classification currently in use is not split evenly based on the sales value. SKUs contributing 29% of the sales value are classified as slow movers (CDE) despite having a better inventory turnover and sell through rate than those classified as B. Also, many SKUs remain unclassified (N) despite contributing volume and value comparable to the classified ones. This indicates that the classification is either not correct or updated recently.

Also, SKUs classified as D and E have significantly high inventory turnover and sell through rates despite contributing low volume and values. This indicates that the classification is not factoring in the high sales frequency for these SKUs.

Once we created the classification based on the methodology mentioned above, we observe a more accurate trend of Inventory Turnover Rates benchmarking how well each location is at making sales from the inventory for each classification.

Inventory Turnover Ratio

Class	Group 1: 1085	1006	1008	1011	1013	1025	1031	1032	Overall
FMov	8.49	10.11	6.56	16.54	7.19	10.09	9.50	8.04	3.58
FMov*	6.29	5.08	4.03	10.22	7.20	14.73	1.62	12.16	1.92
SMov	4.11	5.18	3.46	5.84	3.62	4.31	4.72	4.07	2.40
NotSold	0.53	2.69	1.51	1.94	1.58	1.50	2.11	1.92	
Overall	5.59	6.17	4.09	6.20	4.63	5.52	5.83	4.80	3.19

Class	Group 2: 1086	1001	1002	1003	1004	1007	1009	1015	1019	1028	1035	1036	Overall
FMov	8.31	10.09	8.82	13.52	7.70	9.95	10.38	6.25	6.80	8.33	1.16	6.80	3.58
FMov*	9.30	8.07	4.32	3.03	11.16	1.08	60.29	7.16	7.62	0.44		4.09	1.92
SMov	7.52	4.85	4.94	5.19	5.41	4.13	4.85	4.23	3.93	4.36	0.87	3.59	2.40
NotSold	0.38	2.68	2.39	2.61	3.15	2.80	1.79	1.58	2.20	2.48	0.69	2.31	
Overall	7.57	5.46	6.21	6.83	5.65	5.22	4.62	4.44	4.22	4.92	0.89	3.69	3.19

Class	Group 3: 1088	1005	1014	1016	1018	1020	1021	1022	1024	1026	1029	1030	1034	1042	1043	1421	Overall
FMov	5.81	6.43	8.19	6.06	8.69	7.90	6.40	5.22	5.85	6.63	8.26	8.24	4.97	8.06	6.52	4.13	3.58
FMov*	18.35	3.65	4.89	2.84	11.60	5.37	4.96		5.34		1.34	9.19	12.00		7.49	11.14	1.92
SMov	8.30	2.88	3.33	3.99	3.48	4.16	4.20	3.50	4.13	4.57	3.80	4.02	3.09	3.97	3.62	3.31	2.40
NotSold	0.86	1.97	1.82	3.14	1.52	1.91	2.20	2.72	2.42	3.17	3.14	2.48	2.15	2.65	3.19	1.97	
Overall	6.11	3.63	4.83	4.32	4.39	4.43	3.78	3.46	4.87	3.65	5.05	4.51	3.30	3.56	3.96	2.85	3.19

Then, the Stock Days On Hand measures created from this benchmark enables the planner to visualize stock levels at each location for each classification and use it to make important planning and replenishment decisions.

Stock Days On Hand

Class	Group 1: 1085	1006	1008	1011	1013	1025	1031	1032	Overall
FMov	43	36	56	22	51	36	38	45	102
FMov*	58	72	91	36	51	25	225	30	190
SMov	89	70	106	63	101	85	77	90	152
NotSold	691	136	242	188	231	244	173	190	
Overall	65	59	89	59	79	66	63	76	114

Class	Group 2: 1086	1001	1002	1003	1004	1007	1009	1015	1019	1028	1035	1036	Overall
FMov	44	36	41	27	47	37	35	58	54	44	315	54	102
FMov*	39	45	84	121	33	338	6	51	48	821		89	190
SMov	49	75	74	70	67	88	75	86	93	84	421	102	152
NotSold	967	136	153	140	116	130	204	231	166	147	532	158	
Overall	48	67	59	53	65	70	79	82	87	74	410	99	114

Class	Group 3: 1088	1005	1014	1016	1018	1020	1021	1022	1024	1026	1029	1030	1034	1042	1043	1421	Overall
FMov	63	57	45	60	42	46	57	70	62	55	44	44	73	45	56	88	102
FMov*	20	100	75	128	31	68	74		68		273	40	30		49	33	190
SMov	44	127	110	91	105	88	87	104	88	80	96	91	118	92	101	110	152
NotSold	424	185	200	116	240	191	166	134	151	115	116	147	170	138	114	185	
Overall	60	100	76	85	83	82	97	105	75	100	72	81	111	103	92	128	114

For example, one can see that DC 1035 has significantly high stock days on hand for each class despite belonging to one of the more efficient LC 1086. Scoping into the metrics for the LC, one can view which products are responsible for this overstock situation and shuffle inventory where it can be utilized such as DC 1001, 1003, or 1007. Also, one can observe that the high overall stock days on hand for DCs 1005, 1022, 1026, 1034, 1042, and 1421 is responsible for the high overall stock days on hand of LC 1088. This can not only help the planner find the root cause of low turnover rates to make preventive or corrective adjustments as soon as required but also prevent overstocking or stockout situations occurring in the future.

Finally, we needed to make a small modification when calculating the Sell Through Rates for each location. In case of supplier LCs, although we use the inventory receipts data at a supplier LC to calculate the no. of unit received there, we summed up the inventories sold at the corresponding optimal seller DCs belonging to a supplier LC and the small amounts of inventory sold directly from the same LC to calculate the total no. of units sold there. The underlying assumption for this modification is that LCs inherently are not responsible for any sales and that any sales from the DCs optimally belonging to an LC can be associated to that LC as that is how the supply chain is planned to operate optimally. However, during covid-19, the business experienced low demand and got overstocked at the seller DCs. As operations stabilized, the business thus struggled with low cross-docking rates due to the DCs being overstocking and had to undertake high drop shipping costs to meet demand at these DCs by shipping the SKUs required there from locations other than its optimal LC. Modifying the Sell Through Rate calculation as above lets us compare the actual units received to (and thus shipped from) any LC with the actual units sold by its corresponding DCs (which the LC should have shipped optimally). By doing so, a high Sell Through Rate indicates that for any LC, it sold more units that it optimally received (by its DCs receiving those additional SKUs sold from non-optimal locations) and vice versa. In case of seller DCs, no such modification was needed, and we used the inventory receipts data and zip code sales data to calculate their Sell Through Rates.

Sell Through Rate	Class	Group 1								Overall
		1085	1006	1008	1011	1013	1025	1031	1032	
	FMov	0.22	0.57	0.55	0.57	0.54	0.60	0.63	0.56	0.27
	FMov*	0.27	0.55	0.59	0.84	0.45	0.85	2.13	0.66	0.19
	SMov	0.20	0.53	0.51	0.58	0.54	0.55	0.62	0.52	0.45
	NotSold	0.06	0.37	0.35	0.38	0.29	0.32	0.37	0.32	
	Overall	0.21	0.52	0.51	0.55	0.51	0.55	0.59	0.51	0.30

Sell Through Rate	Class	Group 2												Overall
		1086	1001	1002	1003	1004	1007	1009	1015	1019	1028	1035	1036	
	FMov	1.06	0.58	0.52	0.75	0.55	0.55	0.57	0.53	0.43	0.53	0.59	0.57	0.27
	FMov*	1.17	0.84	0.67	0.66	0.69	0.65	2.69	0.62	0.66	0.31		0.48	0.19
	SMov	0.96	0.54	0.52	0.56	0.52	0.51	0.52	0.54	0.50	0.52	0.52	0.53	0.45
	NotSold	0.08	0.38	0.36	0.39	0.43	0.37	0.33	0.34	0.41	0.38	0.45	0.42	
	Overall	1.01	0.53	0.51	0.62	0.52	0.50	0.50	0.51	0.44	0.50	0.52	0.51	0.30

Sell Through Rate	Class	Group 3																Overall
		1088	1005	1014	1016	1018	1020	1021	1022	1024	1026	1029	1030	1034	1042	1043	1421	
	FMov	1.84	0.65	0.45	0.61	0.76	0.62	0.49	0.57	0.51	0.57	0.57	0.78	0.53	0.54	0.59	1.21	0.27
	FMov*	2.23	0.47	0.53	0.49	1.80	0.58	0.51		0.50		0.47	0.93	0.75		0.67	0.91	0.19
	SMov	2.48	0.54	0.48	0.54	0.56	0.56	0.47	0.52	0.58	0.51	0.55	0.56	0.51	0.48	0.58	1.16	0.45
	NotSold	0.35	0.41	0.32	0.45	0.39	0.37	0.39	0.44	0.35	0.49	0.42	0.41	0.38	0.46	0.47	1.09	
	Overall	1.91	0.56	0.44	0.54	0.62	0.55	0.46	0.50	0.51	0.50	0.53	0.58	0.48	0.49	0.53	1.16	0.30

As revealed from the table above, one can see that the high Sell Through Rates of LC 1088 indicates that its optimal DCs were served by other LCs (particularly LC 1085). The same was confirmed by the planning manager stating that the reason behind it was LC 1088 being closed due to renovation for a few months.

Similar calculations were carried out for the financial metrics and sample data for the gross margins is shown below showing profitability for each classification and/or at each location.

	Class	Group 1								Overall
		1085	1006	1008	1011	1013	1025	1031	1032	
Gross Margins	FMov	0.38	0.41	0.43	0.37	0.40	0.43	0.37	0.41	0.39
	FMov*	0.33	0.44	0.44	0.37	0.44	0.41	0.36	0.43	0.39
	SMov	0.35	0.41	0.41	0.37	0.41	0.42	0.38	0.42	0.35
	NotSold	0.28	0.41	0.40	0.37	0.42	0.41	0.38	0.40	
	Overall	0.37	0.41	0.42	0.37	0.40	0.42	0.38	0.41	0.38

	Class	Group 2												Overall
		1086	1001	1002	1003	1004	1007	1009	1015	1019	1028	1035	1036	
Gross Margins	FMov	0.39	0.39	0.41	0.36	0.39	0.43	0.41	0.38	0.38	0.39	0.40	0.33	0.39
	FMov*	0.37	0.15	0.41	0.41	0.34	0.44	0.37	0.42	0.31	0.31		0.12	0.39
	SMov	0.37	0.40	0.41	0.40	0.41	0.42	0.42	0.40	0.41	0.40	0.42	0.39	0.35
	NotSold	0.31	0.40	0.39	0.38	0.41	0.41	0.41	0.40	0.42	0.40	0.42	0.41	
	Overall	0.38	0.39	0.41	0.38	0.40	0.42	0.41	0.39	0.40	0.39	0.41	0.37	0.38

	Class	Group 3																Overall
		1088	1005	1014	1016	1018	1020	1021	1022	1024	1026	1029	1030	1034	1042	1043	1421	
Gross Margins	FMov	0.41	0.39	0.41	0.42	0.40	0.38	0.42	0.39	0.32	0.41	0.29	0.39	0.41	0.50	0.43	0.42	0.39
	FMov*	0.41	0.50	0.43	0.46	0.37	0.44	0.47		0.33		0.49	0.46	0.43		0.47	0.48	0.39
	SMov	0.38	0.42	0.41	0.43	0.42	0.41	0.43	0.40	0.39	0.41	0.42	0.42	0.42	0.42	0.42	0.43	0.35
	NotSold	0.34	0.41	0.40	0.41	0.40	0.42	0.42	0.38	0.41	0.41	0.41	0.42	0.41	0.41	0.39	0.43	
	Overall	0.40	0.41	0.41	0.42	0.40	0.40	0.42	0.39	0.35	0.41	0.35	0.41	0.41	0.44	0.41	0.42	0.38

Finally, the tables above were dashboarded on Tableau in a user-friendly format as deliverables to the client. Sample Tableau dashboards filtered for LC 1088 are presented as Exhibit 2 below.

The fundamental principles followed in calculating, tabulating, and dashboarding the indicators shown above were useability and utility for the day-to-day operations of the business especially after the project finished which, after multiple iterations of review and rework with the planning manager, compelled us to make them as simple and effective as possible.

EXHIBITS:

Exhibit 1: Auto parts manufacturer categorized products by quantity of historical sales as shown in the chart below. The higher the sales velocity, the SKU will be classified into higher category and vice-versa.

All Brands	
Categorization	**Item Count**
A	60 or more
B	24 to 59
C	12 to 23
D	12 or less

Exhibit 2: Tableau dashboards of KPIs filtered for LC 1088

LC Filter

1088

Inventory Turnover Ratio

Class1	1005	1014	1016	1018	1020	1021	1022	1024	1026	1029	1030	1034	1042	1043	1088	1421
FMov	6.43	8.19	6.06	8.69	7.90	6.40	5.22	5.85	6.63	8.26	8.24	4.97	8.06	6.52	5.81	4.13
FMov*	3.65	4.89	2.84	11.60	5.37	4.96		5.34		1.34	9.19	12.00		7.49	18.35	11.14
NotSold	1.97	1.82	3.14	1.52	1.91	2.20	2.72	2.42	3.17	3.14	2.48	2.15	2.65	3.19	0.86	1.97
SMov	2.88	3.33	3.99	3.48	4.16	4.20	3.50	4.13	4.57	3.80	4.02	3.09	3.97	3.62	8.30	3.31
Total	3.63	4.83	4.32	4.39	4.43	3.78	3.46	4.87	3.65	5.05	4.51	3.30	3.56	3.96	6.11	2.85

Stocks Days on Hand

Class1	1005	1014	1016	1018	1020	1021	1022	1024	1026	1029	1030	1034	1042	1043	1088	1421
FMov	56.8	44.6	60.2	42.0	46.2	57.1	69.9	62.4	55.1	44.2	44.3	73.4	45.3	56.0	62.8	88.4
FMov*	99.9	74.6	128.4	31.5	67.9	73.6		68.3		273.0	39.7	30.4		48.7	19.9	32.8
NotSold	185.0	200.4	116.3	239.7	191.3	166.1	134.2	151.1	115.2	116.3	147.3	170.0	137.9	114.3	423.8	185.3
SMov	126.6	109.6	91.5	105.0	87.7	86.9	104.3	88.5	79.9	96.2	90.7	118.1	92.0	100.8	43.9	110.2
Total	100.5	75.6	84.6	83.1	82.4	96.6	105.4	75.0	100.0	72.3	80.9	110.8	102.6	92.2	59.7	127.9

Sell Through Rate

Class (..	1005	1014	1016	1018	1020	1021	1022	1024	1026	1029	1030	1034	1042	1043	1088	1421
FMov	0.654	0.453	0.614	0.764	0.619	0.491	0.568	0.510	0.570	0.571	0.778	0.528	0.536	0.593	1.841	1.213
FMov*	0.465	0.530	0.486	1.796	0.580	0.514		0.500		0.469	0.930	0.752		0.667	2.233	0.912
NotSold	0.405	0.320	0.449	0.385	0.375	0.394	0.441	0.354	0.489	0.424	0.410	0.385	0.459	0.466	0.349	1.093
SMov	0.537	0.478	0.538	0.562	0.561	0.471	0.516	0.585	0.513	0.552	0.559	0.508	0.484	0.578	2.481	1.164
Total	0.556	0.444	0.542	0.623	0.552	0.455	0.495	0.506	0.502	0.534	0.585	0.484	0.486	0.533	1.910	1.155

Cost
Sales
Profit

Per Unit Metrics

Class (..	1005	1014	1016	1018	1020	1021	1022	1024	1026	1029	1030	1034	1042	1043	1088	1421
	521.3	457.6	439.9	517.8	465.1	449.9	460.9	753.1	405.5	827.5	520.6	483.9	454.9	473.2	491.9	479.5
FMov	856.9	780.9	765.0	856.3	751.3	776.0	759.1	1,105.6	685.4	1,160.1	858.7	814.9	908.3	828.3	827.7	823.9
	335.6	323.3	325.1	338.6	286.2	326.1	298.2	352.5	279.9	332.7	338.1	331.0	453.3	355.1	335.8	344.4
	660.0	684.2	582.4	969.9	592.7	630.7		566.5		587.6	677.2	489.6		655.6	797.5	650.8
FMov*	1,325.2	1,191.0	1,076.6	1,546.1	1,050.1	1,196.0		841.9		1,159.3	1,260.7	863.2		1,232.8	1,359.3	1,240.2
	665.2	506.9	494.2	576.2	457.4	565.3		275.4		571.6	583.5	373.6		577.2	561.7	589.4
	431.0	436.9	416.2	422.6	443.4	468.9	413.5	424.1	424.2	431.5	446.8	435.1	437.0	419.6	547.9	464.3
NotSold	724.8	731.9	704.5	709.5	771.0	810.6	669.3	720.1	713.9	733.8	773.5	737.6	738.6	691.8	825.0	808.1
	293.8	295.0	288.3	287.0	327.6	341.7	255.8	296.0	289.7	302.3	326.6	302.4	301.6	272.1	277.1	343.8
	481.3	451.7	433.0	459.4	421.1	450.1	422.6	545.6	406.6	452.4	458.1	439.0	421.5	428.0	492.3	450.1
SMov	835.7	771.2	755.0	786.7	717.8	784.2	704.1	897.8	684.0	779.3	792.8	753.6	725.5	732.0	796.8	785.7
	354.4	319.5	322.0	327.3	296.6	334.1	281.5	352.1	277.4	326.9	334.6	314.6	304.1	304.0	304.5	335.6
	492.8	454.8	432.3	488.0	444.3	454.8	431.0	653.0	416.0	592.3	481.2	455.6	437.4	438.3	494.2	464.0
Total	828.3	775.1	748.4	817.6	740.2	788.1	708.0	998.9	700.2	916.0	815.7	774.1	786.0	747.0	822.5	804.7
	335.5	320.3	316.1	329.6	295.9	333.3	277.1	345.9	284.1	323.7	334.5	318.5	348.6	308.7	328.3	340.7

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