A NOVEL FINISHED-GOODS INVENTORY MANAGEMENT PROCESS FOR A TIRE MANUFACTURER

by
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ABSTRACT

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Keywords: Inventory management, Production planning, Product segmentation, Tire manufacturing, Machine learning

In this thesis, we develop processes to determine the finished goods inventory levels and associated production decisions for a tire manufacturer. Studying the business practices and the needs of the company in its different sales channels, we identified three cases for keeping inventory: Prebuild stock for products that face highly seasonal demand, cycle stock for the strategic mix products, and safety stock to guard against fluctuations in the automotive manufacturer orders. For each case, we used scoring and machine-learning based approaches to segmentize and prioritize the tire SKUs based on product dimensions that span finance, sales, marketing, production and planning functions of the firm. In doing so, we also developed a number of novel metrics to capture product characteristics such as demand seasonality and capacity insufficiency.

ÖZET

BİR LASTİK ÜRETİCİSİ İÇİN YENİLİKÇİ BİR BİTMİŞ ÜRÜN STOK YÖNETİM SÜRECİ GELİŞTİRİLMESİ

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Anahtar Kelimeler: Envanter yönetimi, Üretim planlama, Ürün segmentasyonu, Lastik üretimi, Makine öğrenmesi

Bu tez çalışmasında, lastik üreticisi bir firmanın bitmiş ürün stoklarının belirlenmesi ve üretim planlama kararları üzerine yeni bir süreç geliştirilmiştir. Çalışmada, şirketin farklı satış kanallarındaki iş süreçleri ve ihtiyaçlarını inceleyerek, bitmiş ürün stoğu tutulması gereken üç durum belirledik: Talebi yüksek oranda sezonsallık gösteren ürünler için stok biriktirme, stratejik ürün listesindeki ürünler için çevrim stoğu ve otomotiv üreticilerine satılan ürünler için güvenlik stoğu. Üç durumun her biri için, lastik SKU'larını segmentize edecek ve önceliklendirecek skorlama ve makine öğrenmesi tabanlı yöntemler geliştirdik. Bu yöntemler, firmanın finans, satış, pazarlama, üretim ve planlama departmanları ile ilgili çok sayıda ürün boyutuna bağlı olarak çalışmaktadır. Çalışmamız sırasında talep sezonsallığı ve kapasite yetersizliği gibi bazı ürün özelliklerinin ölçümüne yönelik yeni bazı ölçütler de geliştirdik.

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To lifelong learners

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1. INTRODUCTION

In this thesis, we develop a novel process to determine the target finished goods inventory levels for a leading global tire manufacturer located in Turkey. For purposes of confidentiality, the name of the company will not be mentioned in the thesis and the data as well as certain business practices has been masked.

Studying the business practices of the company, we identified three reasons to keep inventory as prebuild stock, cycle stock and safety stock in different sales channels. For each of the three cases, we identified a number of product *dimensions* using which we determine the candidate products. The dimensions we consider span marketing & finance, planning, sales, and production functions of the company, providing a holistic picture. We develop a scoring-based approach and also discuss how the approach can be extended using Machine Learning approaches.

1.1 Information on the Company

The company produces more than 1000 different tire SKUs and more than 10 million tires per year. Products are sold through the following *sales channels*:

Replacement Channel (RL): This is the independent retail outlet (dealer) channel. Because dealers also keep inventory, it is possible for the company to backorder dealer orders to some degree.

Original Equipment Manufacturer Channel (OE): This is the channel through which tires are sold directly to auto manufacturers (OEs) to satisfy all agreed-upon orders from stock without backordering. The OEs often require just-in-time delivery to their factories. They provide forecasts of their tire needs for the coming months.

Export Channel (EXP): The company sells tires to a high number of countries through this channel. Customers in this channel do provide sales plans in advance, but they do not preorder.

The production capacity of the company is utilized at high levels. Thus, the company needs to be careful about when and how much to produce each tire SKU. In particular, they want to know which SKU to produce when an opportunity arises in the busy production schedules of the production lines, which are grouped according to tire size.

Production managers prefer producing in large batch sizes, especially for products that exhibit the so-called high *production complexity*. This is natural given that the typical setup time for production is around 8 hours. Minimum production quantities are around 400 units. In addition to production-line-related constraints, the production rate for each SKU is also constrained by the number of molds for the product. As we explain in Section 5.2, our results can help the company in making more informed decisions on their mold purchases.

1.2 Our Approach

Through interviews with the management, we discovered that the company cares about the following three objectives: (1) Maximize the service level (finished goods availability level), (2) Minimize the inventory cost (to minimize the cash tied to inventory and to minimize the risk of unsold stock), (3) minimize production changeovers (by using large production lot sizes, because production capacity is totally utilized). We aim to strike the correct balance between these three conflicting objectives of the company by developing customized inventory policies for tire SKUs.

To this end, we carefully analyzed the production, sales, and planning processes of the company. This allowed us to understand the drivers for keeping (if any) finished goods inventory at the SKU level. We identified three cases for keeping inventory as follows:

- **Prebuild stock**: To build inventory prior to high-order months for high-volume products in the RL and EXP channels.

- **Cycle stock**: To minimize the number of production setups for the strategic mix products.
- **Safety stock**: To guard against order fluctuations in the OE channel.

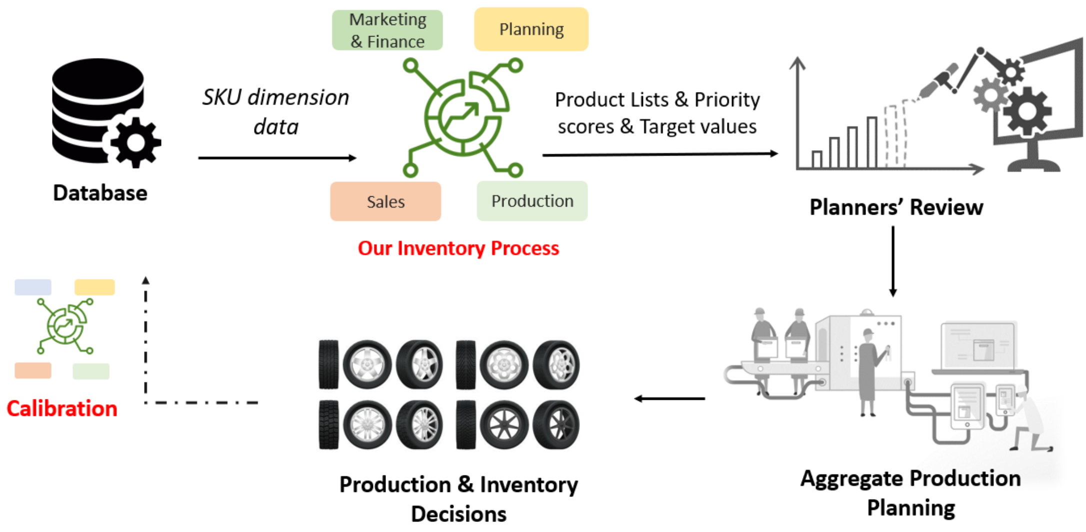
Once our process is implemented, the company will not be keeping planned inventory for an SKU that does not fall into one of the three cases above. Definitely, it will take some time for the current slow-moving inventory of certain SKUs to fall down to targeted levels.

As the company does not want to tie cash to inventory, the total amount of inventory at any given time will be constrained by company-wide policies. In addition, the overall production capacity of the firm is highly utilized, which introduces further constraints on how much a given SKU can be produced at a given time. To address these issues, we decided to prioritize products for each of the inventory cases mentioned above. To do that, we developed a scoring based approach where for each candidate SKU we calculate a weighted score based on eight *product dimensions* that characterize the SKU in relevance to the inventory case on hand. The dimensions are relevant to different functions and departments of the company including sales, planning, production, marketing, and finance. Some of these dimensions such as annual orders and gross margin are relatively straightforward; whereas others such as backorder tendency and capacity insufficiency are novel ones that we developed for this thesis. The dimensions are explained in detail in Chapters 3 and 4.

Our approach is an example of product segmentation. Product-driven segmentation often brings important benefits to firms as explained in a McKinsey reports (Protopappa-Sieke et al., 2017). For instance, through product-driven segmentation in its lighting products, Phillips Europe decreased the probability of stocking out from 40% to 5% while also decreasing the level of inventory by one-third (Roy et al., 2017). In another reported example, outdoor power products producer Gardena reduced its inventory levels by 15% and transportation costs by 5% (Dahlhaus et al., 2017).

The output of this thesis to the company will be a list of SKUs that fall into each of the three stock cases, together with their priority scores and target levels. After the planners' review, this information will become the input for the aggregate production planning process that determines the production and inventory levels of the company. Once the process is implemented, its results will be periodically reviewed and the SKU lists will be calibrated as needed, as explained in Figure 1.1.

Figure 1.1 Place of Our Work in The Company's Planning Process



As a result of this change, the suggested inventory or backorder levels of some products may decrease and that of some others may increase. Ultimately, it may be possible to achieve both higher product availability levels and lower total inventory cost. In addition, the novel product dimensions we identify in the context of this study are likely to offer further directions for operational improvements. Lastly, the data that we collected, organized and cleaned from multiple functions of the company will be an asset for future potential analytic-based studies.

1.3 Data Description

The company delivered the dataset for this thesis in the form of more than 30 distinct MS Excel spreadsheets. Using these, we created our own dataset for the purpose of understanding and interpreting each SKU. After following the data pre-processing steps, we are left with more than 1000 SKUs with 105 attributes. The attributes and their explanations are given in Table 1.1. For each month of year 2020, for each SKU, the data includes product description and group, sales season, production facility, brand, gross profit margin, marketing and sales based strategic priority, channel-based sales and order data, production quantity, production capacity, beginning and ending inventory levels.

Table 1.1 Data Description

Attribute	**Explanation**
SKU_code	a unique identifier for each SKU
product_description	description of the product
product_group	product main group
season	sales season
prod_facility	the production facility
brand	brand
gm	gross profit margin
strategic_priority	marketing and sales based priority of the product
jan_rl_sales ... dec_rl_sales	monthly sales quantities to RL
jan_oe_sales ... dec_oe_sales	monthly sales quantities to OE
jan_exp_sales ... dec_exp_sales	monthly sales quantities to EXP
jan_rl_order ... dec_rl_order	monthly order quantity from RL
jan_oe_order ... dec_oe_order	monthly order quantity from OE
jan_exp_order ... dec_exp_order	monthly order quantity from EXP
jan_production ... december_production	monthly production quantity
jan_prodcap ... december_prodcap	monthly production capacity
jan_BI ... dec_BI	monthly beginning inventory level
jan_EI ... dec_EI	monthly ending inventory level

2. LITERATURE REVIEW

2.1 Literature on Segmentation

The most popular method for product segmentation in operations management has been the traditional ABC analysis. This analysis is often based on the annual sales of the end products. Extensions, such as the ABC-XYZ analysis add one or more dimensions to the classification, such as the forecast accuracy, lead time or profit margin (Ramanathan, 2006; Zhou and Fan, 2007). These approaches; however fail to realize significant sufficient cost and service achievements as they ignore other relevant characteristics of the products. (Ernst and Cohen, 1990).

Our work contributes to the literature in this aspect. We take a holistic view and consider eight different product dimensions (characteristics) that are relevant to different business functions of the firm including sales, finance, marketing, planning and production. We believe this to be an important consideration as these functions often have conflicting views about the production and inventory decisions, which are traditionally resolved in high-level Sales and Operations (S&OP) meetings. To the best of our knowledge, no study in academic literature takes such different product dimensions into account in developing inventory policies. The conventional dimensions such as sales volume and variability (D'Alessandro and Baveja, 2000), lead-time variability, profit margin and product life cycle stage have been utilized in various approaches (Aitken et al., 2003). In addition to using numerous dimensions, we also contribute to the literature by developing a number of novel dimensions.

We use a product-driven segmentation approach to develop customized production and inventory policies. A segment consists of a set of products that are determined based on certain features such as customer requirements and product characteristics (Alicke and Forsting, 2017). Based on product segmentation, one can develop customized operations management strategies that meet the needs of the customers and/or products for every segment (Childerhouse et al., 2002; Godsell et al., 2006; Lovell et al., 2005). In operations management, segmentation has been shaped around three main approaches which are the market-driven, the product-driven, and the combined market-and-product-driven approaches (Protopappa-Sieke et al., 2017).

Segmentation constitutes the approach to not only develop customer orientation but also cope with the variety in customer needs (Smith, 1956). One of the pioneering approaches of market-driven segmentation was proposed by Hill (1995) who recommends offering customized customer service by embracing various strategies of manufacturing. To Hill, manufacturing seeks to maintain proper responses for the requirements of every segment. Thus, the author offers diversified manufacturing strategies which conforms with the customer segment-specific requirements instead of one single strategy. Customer service which includes topics such as quality, accuracy of orders, availability and delivery time should consider requirements' variation based on the type of customer (Hill, 1995). Similarly, Lambert and Sharma (1990) suggests a market segmentation that is formed on requirements of customer service. In a more general form, Lovell et al. (2005) offers a market-related variables list which may influence decisions on design, selection of supply chain and market segmentation.

As for product-driven segmentation, different characteristics of products have been taken into consideration. Fisher (1997) sets off the product segmentation in terms of categorizing the products based on their demand characteristics. Later, various researchers also argue that such distinctive characteristics of products have to be met with various supply chain strategies (Frohlich and Westbrook, 2001; Schnetzler et al., 2007). Considering the uniqueness and complexity of the products, Lamming et al. (2000) broadens Fisher's model to segment the products. As an addition to the demand uncertainty (i.e, low vs. high), Lee (2002) offers to segment products according to supply uncertainty. Christopher and Towill (2002) presents a three-dimensional classification system that examines supply and demand characteristics concurrently. They categorize products based on product's type (standard or special), its demand (stable or volatile) and the replenishment lead time (short or long).

Because both product features and customer requirements have substantial impact on operational decisions, the segmentation approaches mentioned before may be combined. In that regard, Fuller et al. (1993) note that companies have to establish market-specific operation management strategies but these researchers also highlight the use of product characteristics (e.g., sales volume or unit value) in segmenting products. To illustrate this approach, a dual segmentation approach is presented by Godsell et al. (2011). In this approach, first, significant product-centring variables such as the stage in the product life cycle, delivery lead time, variety and variability and volumes are used. Then, based on the variability in their demand and their order volumes, customers are split into two different groups. Following Godsell et al., other researchers have contributed to this approach by combining the market and order characteristics into a segmentation framework.

2.2 Literature on Inventory Management

In inventory management, two important decisions are when to order and how much to order. If these decisions are correctly made, both the average inventory level and the probability of stocking out can be decreased. The academic literature addresses this problem by considering quantity-based policies such as the well-known (Q, R) and (s, S) policies (Nahmias and Olsen, 2015; Silver et al., 1998). The (Q, R) policy assumes an infinite horizon with continuous review and replenishment which means that the inventory position (on-hand inventory plus inventory on-order) can be observed at all times, and an order can be placed anytime. An order of size Q is placed as soon as the inventory position falls below the reorder level R. The products in the order, which can be a production order or a purchase order, will be received after a certain lead time. Demand is probabilistic but stationary, which means that the demand distribution does not change over time.

The (s, S) policy is a periodic ordering policy, which means that the inventory position is checked periodically at certain points in time such as once every week. If the inventory position is found to be lower than s, an order of is given to increase the inventory position back to level S. Otherwise, no order is given in that period.

Such quantity-based policies assume demand distribution to be stationary, that is not to change over time (Nahmias and Olsen, 2015; Silver et al., 1998). Stationary demand distribution assumption is not a suitable one for most real-life cases, especially for products that exhibit strongly seasonal demand or demand with spikes due to bulk ordering, as is the case for the company we consider. Demand may change over time based on the product life-cycle stage, marketing activities, competitor activities or cannibalization due to the introduction of a substitute product of the firm.

A practical alternative to quantity-based policies that can handle nonstationary demand is the cover-based policies (Hoppe, 2006). These are also known as *Inventory days of supply*. In a cover-based policy, the target inventory level is expressed not as a quantity but as the number of time units (days, weeks or months) for which the inventory level shall cover the forecasted demand (King and King, 2017) in the subsequent time periods. Cover based policies are especially popular in business practice due to their ability to handle non-steady demand, as well as their ease of application in ERP systems and ease of explanation. Our suggested inventory management process is based on weekly cover values.

3. PREBUILD STOCK STUDY

Some of the tires that the company sells in its Replacement (RL) and Export (EXP) channels exhibit high seasonality in demand, that is, in orders from dealers within Turkey and from abroad. For regular tires, the peak orders typically arrive in Winter months as shown in Figure 3.1.

Figure 3.1 Monthly Order Quantities for a Sample Regular Tire

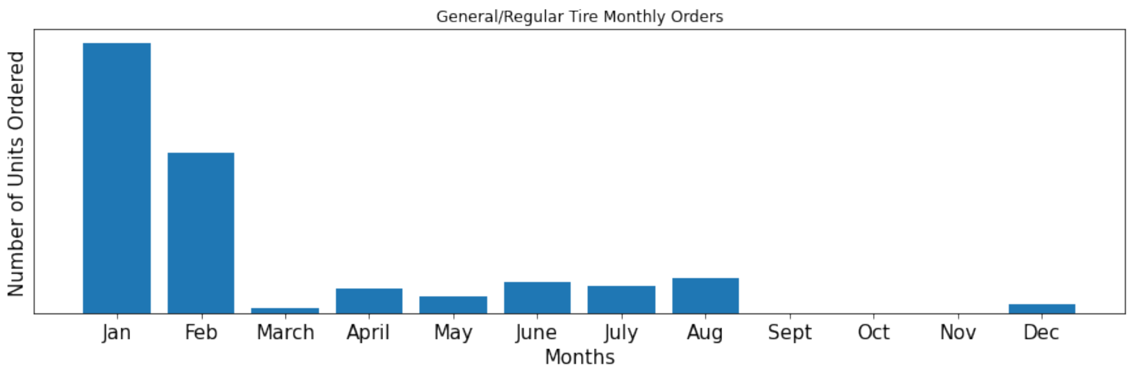
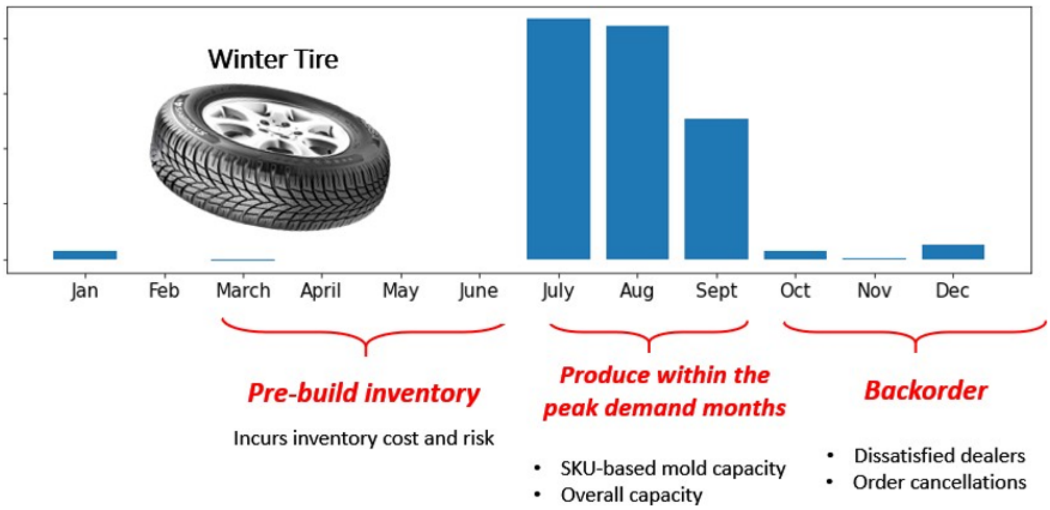


Figure 3.2 shows the monthly order quantities of a sample winter tire product. We observe most orders to arrive around July, August, and September. One might consider three options to meet this peak period demand. First, one can produce within the peak demand months. However, SKU-specific mold capacity and overall production capacity may place constraints. Second, one can build inventory prior to the peak demand period and use this to satisfy part of the peak demand. This option, however, leads to inventory costs and inventory risk. Third, one can backorder part of the peak demand such that this demand is met with production of the subsequent months. This policy, however, results in dissatisfaction with dealers and can lead to potential order cancellations and lost sales.

Figure 3.2 Three Alternatives to Meet the Peak Demand



This seasonality in demand can be problematic if the SKU-specific production capacity, that is, the mold capacity is not sufficient to allow quick production of required quantities within the peak demand periods and the customers of the tire do not accept backordering. This leaves prebuilding of the inventory prior to the peak demand period as the only feasible solution. Accordingly, such a product's inventory level will reach to relatively high levels before its peak-order months; however, the inventory level may be low, even zero in other months.

In this study, we first tried to segmentize candidate products as low-medium-high priority classes using clustering and decision tree approaches. This method did not give good-enough results; yet we chose to report it first. Next, we explain a scoring-based prioritization process to determine which SKUs in the RL and EXP channels are candidates for inventory prebuilding, and in which priority order. Finally, we outline an alternative Machine-learning based methodology.

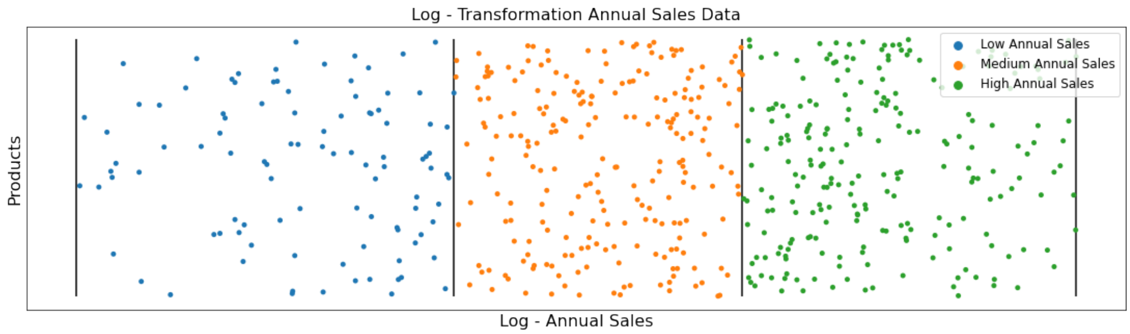
3.1 Clustering & Decision Tree Approach

Initially, we used standard multi-dimensional clustering approaches such as k-means and fuzzy-c-means to segmentize the products along all (or most of) our eight dimensions. Our initial results, however, were not encouraging as the segments that were formed were difficult to map into the business practices of the cpmpany. To prevent this, we proceed with two alternative methodologies as explained next.

We cluster products along each dimension separately. We use Fisher–Jenks algorithm (Jenks, 1967) for a single dimension classification. The algorithm reduces the variance within classes and maximizes the variance between classes. For instance, when some products are separated in terms of their 2020 annual sales into low, medium and high classes, most products ended up in the low class as seen in Figure 3.3 (note that the sales quantity values in the horizontal axis have been masked for confidentiality purposes). This is because there are a small number of products that have very high or high sales quantities. To solve the issue, we classified the products based on a logarithmic translation of the original data as shown in Figure 3.4.

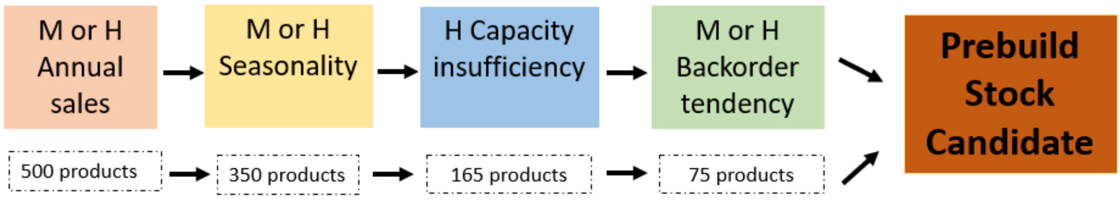
Figure 3.3 Clustering on Original Data

Figure 3.4 Clustering on Log-Transformed Data



After repeating this procedure for each product dimension separately, and thus labeling each product as low, medium or high along each dimension, we used the decision tree approach to determine the SKUs for which safety, cycle or prebuild inventory should be kept. The approach uses certain splitting and filtering rules for which the parameters were defined by us. Figure 3.5 illustrates the process for the Prebuild Stock decisions of a partciular product category where L, M and H correspond to low, medium and high labels. We observe 75 out of the 500 products in this product category to be identified as candidates for Prebuild Stock with this approach.

Figure 3.5 Decision Tree Approach Applied to a Particular Product Category



3.2 Priority Scoring Approach

The production capacity may not be sufficient to produce the required prebuild quantities in certain times of the year, especially in the busy January-February and July-August terms. To prioritize the production in such cases, we calculate a prebuild priority score as the weighted average of normalized scores from four separate product dimensions as explained below. For each dimension, a higher score indicates the SKU being a better candidate for keeping prebuild stock. The weights were determined together with the company managers through an Analytic Hierarchy Process (AHP) study as explained in Section 3.3. Next, we discuss the dimensions in detail.

The Dimensions

- **Annual Sales:** This is the total number of units sold in all relevant sales channels annually. We used the annual sales in year 2020.
- **Seasonality:** This dimension measures the level of seasonality in demand. To this end, we calculate the proportion of total orders taken during the the top two highest order months. For a hypothetical extreme product that receives an equal amount of orders in every month, this measure would be 1/6. If all demand is concentrated in two months, the measure would be 1.
- **Capacity Insufficiency:** This dimension measures the insufficiency of mold capacity during the peak order month to meet that month's demand. A given month's mold-based production capacity is calculated as

  *Monthly Production Capacity = (number of molds) * (daily production per mold) * (number of working days in month) * (production yield).*

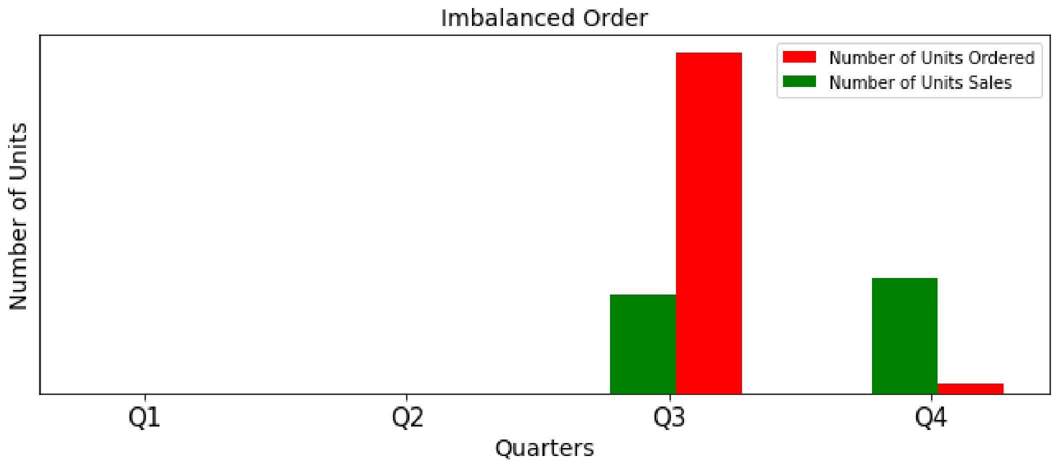
Capacity Insufficiency is calculated as *(demand during the peak order month)/(mold-based production capacity during the peak order month)*. If the capacity insufficiency value of a product is high, this means that in the absence of beginning inventory the company is not likely to meet the expected peak demand. Thus, such a product becomes a candidate for inventory prebuilding.

- **Backorder Tendency:** This dimension shows the observed backordering tendency for the product, which we measure with Equation 3.1. Specifically, we calculate the maximum differences between quarterly (where Q1 refers to the months of January, February and March) orders and sales for each of the four quarters of the last year, and divide this with the total annual sales for normalization. A high value indicates a higher case of realized backordering.

$$\max\left[\frac{order_t - sales_t}{\sum_{t=1}^{4} sales_t}\right], \qquad Quarter\ t = 1,2,3,4 \tag{3.1}$$

Figure 3.6 shows the imbalance between quarterly orders and sales for a sample tire. We observe high quantity of orders arriving in Quarter-3, most of which were not met and backordered. Part of the backordered orders are seen to be met within Quarter-4.

Figure 3.6 Quarterly Orders and Sales for a Sample Product



In order to be able to calculate weighted priority scores, we first transformed the calculated values for each dimension to normalized scores that range between 0 and 1 as follows:

if *Measure* $\leq$ *MinPercentile* **then**
Transformed Score = 0

if *MinPercentile* $<$ *Measure* $<$ *MaxPercentile* **then**
Transformed Score = (measure - min measure)/(max measure - min measure)

if *MaxPercentile* $\leq$ *Measure* **then**
Transformed Score = 1

To prevent one dimension from being dominant over another dimension, we determined min and max percentile to have closer lower quartile, mean, and upper quartile values between the dimensions. Table 3.1 shows the percentile parameter of each dimension. The mean value of each transformed dimension is 0.50.

Table 3.1 Percentile Parameter of Each Dimension for Prebuild Stock Study

Dimension	MinPercentile	MaxPercentile
Annual Sales	5	65
Seasonality	10	85
Capacity Insufficiency	11	42
Backorder Tendency	5	80

As an example, Figures 3.7 and 3.8 show the box plots of the original and transformed Annual Sales dimension scores.

Figure 3.7 Annual Sales Dimension Original Measurements Box Plot

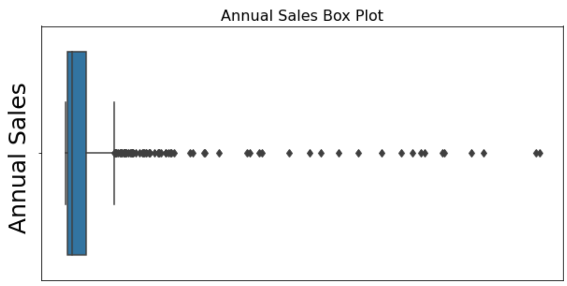
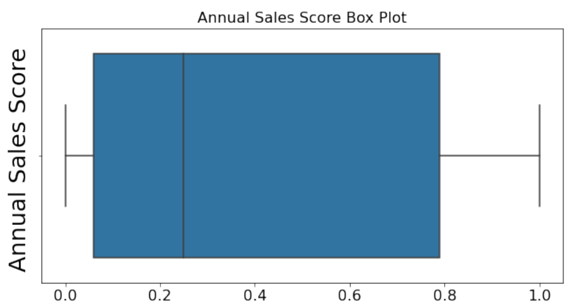


Figure 3.8 Annual Sales Dimension Transformed Scores Box Plot



Figures 3.9 and 3.10 present the distribution of Annual Sales Dimension scores before and after the transformation. Note, again, that we mask the x-axis quantity labels for confidentiality purposes.

Figure 3.9 Annual Sales Dimension Original Measurements Distribution

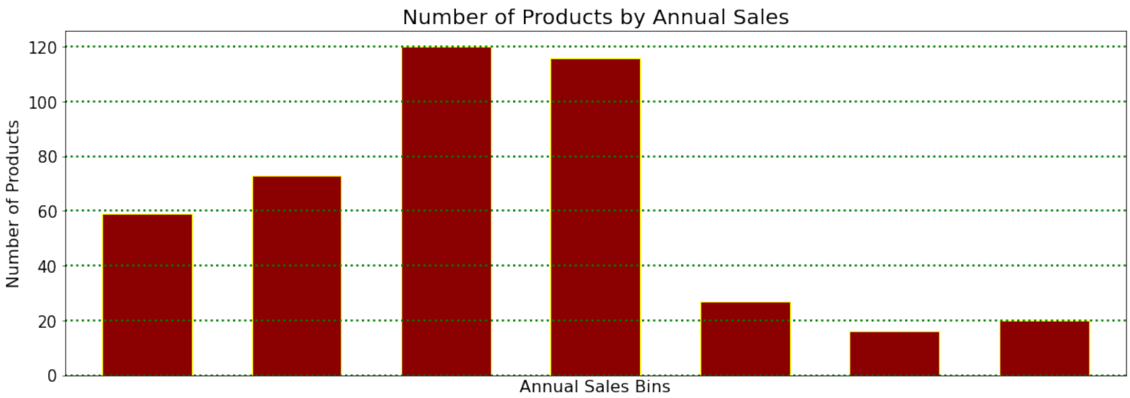
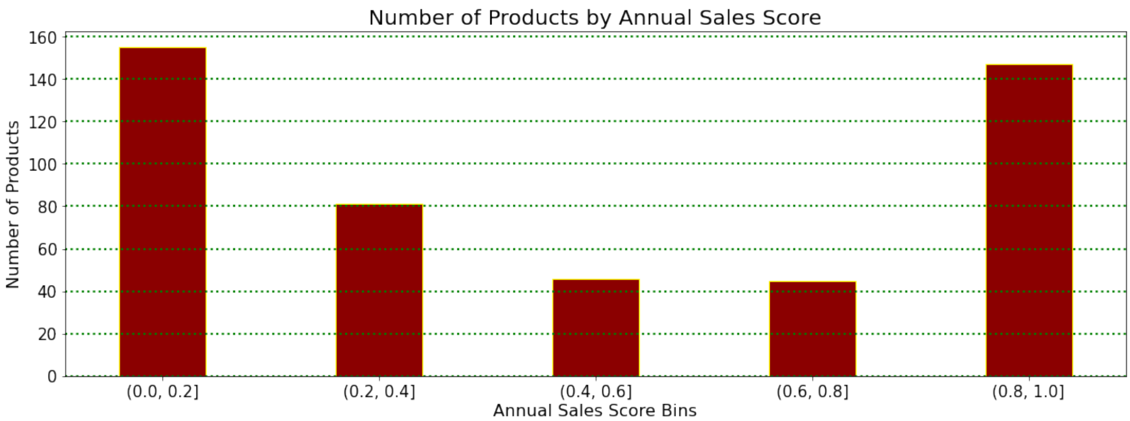


Figure 3.10 Annual Sales Dimension Transformed Scores Distribution



3.3 Combining Dimension Scores Using AHP-determined Weights

The Analytic Hierarchy Process (AHP) is a pairwise comparison measurement theory that derives priority scales based on the assessments of experts (Saaty et al., 2008). These scales determine the relative importance of different objectives or decision alternatives. In our study, we use the AHP approach to determine the relative weights of the four dimensions. In comparing two dimensions, we use the absolute judgment scale of Saaty et al. given in Table 3.2. The pairwise comparison values are entered into a comparison matrix, and the weights of the attributes are then calculated using matrix algebra.

Table 3.2 Saaty Scale

Intensity of Importance	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective.
2	Weak or slight	
3	Moderate importance	Experience and judgement slightly favour one activity over another.
4	Moderate plus	
5	Strong importance	Experience and judgement strongly favour one activity over another.
6	Strong plus	
7	Very strong or demonstrated importance	An activity is favoured very strongly over another; its dominance demonstrated in practice.
8	Very, very strong	
9	Extreme importance	The evidence favouring one activity over another is of the highest possible order of affirmation.

The company managers conducted pairwise comparisons among the four dimensions of the prebuild stock study under our guidance. The resulting comparison scores are given in Table 3.3. As an example, the comparison score of 3 in the first row, second column of this matrix indicates that the decision maker thinks that the annual sales dimension is "moderately more important" compared to seasonality dimension in determining the overall prebuild stock score of an SKU. Note that the comparison score for the opposite comparison, that is between seasonality and annual sales, automatically becomes 1/3.

Table 3.3 Relative Importance of Dimensions for the Prebuild Stock Study

Dimensions	Annual Sales	Seasonality	Capacity Insuff.	Backorder T.
Annual Sales	1	3	1/2	1/3
Seasonality	1/3	1	1/6	1/5
Capacity Insufficiency	2	6	1	3
Backorder Tendency	3	5	1/3	1

Next, based on this matrix, we calculate the weights of the four dimensions using the *Eigenvenctor Method* of (Saaty, 2003). Table 3.4 shows the resulting weights and the corresponding ranks. The matrix achieved a consistency ratio of 0.082, which indicates a sufficient level of consistency in pairwise comparisons.

Table 3.4 Weights of the Prebuild Stock Priority Scoring Dimensions

Dimension	Weight	Rank
Annual Sales	16.1%	3
Seasonality	6%	4
Capacity Insufficiency	48.5%	1
Backorder Tendency	29.4%	2

Accordingly, we used the following equation to calcuate the overall Prebuild Priority Score (PPS) of SKUs:

Prebuild Priority Score (PPS) = 0.161 × (annual sales score) + 0.060 × (seasonality score) + 0.485 × (capacity insufficiency score) + 0.294 × (backorder tendency score).

Figure 3.11 shows the distribution of the PPS priority score among the related products. Table 3.5 lists the dimension scores as well as the weighted priority scores of the top-20 products.

Figure 3.11 Distribution of Prebuild Stock Priority Scores

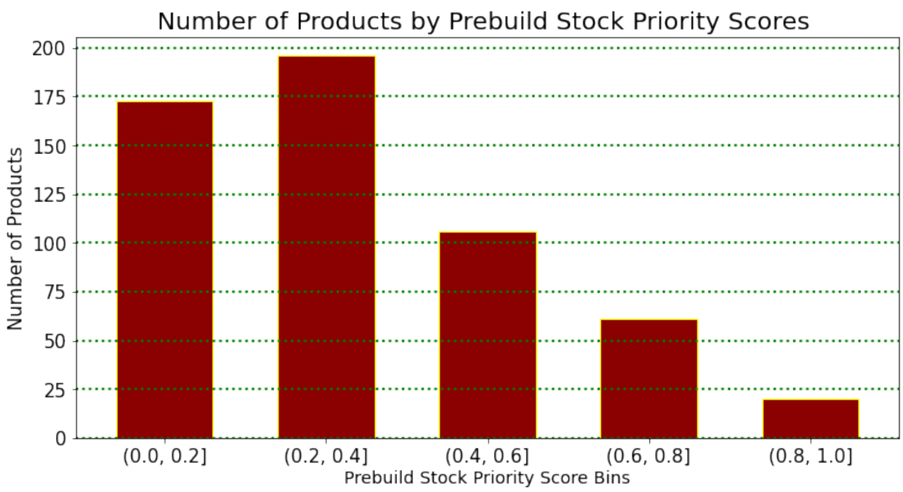


Table 3.5 Prebuild Stock Priority Score Details for the Top 20 Products

Product ID	Annual Sales Score	Seasonality Score	Capacity Insufficiency Score	Backorder Tendency Score	Prebuild Stock Priority Score
1	1.00	0.78	1.00	1.00	0.98
2	1.00	0.82	0.97	1.00	0.97
3	1.00	0.71	0.99	0.84	0.93
4	1.00	0.52	0.96	0.90	0.92
5	1.00	0.58	0.86	0.95	0.90
6	0.77	0.82	0.88	1.00	0.89
7	0.69	1.00	0.87	1.00	0.89
8	0.76	0.70	0.86	1.00	0.87
9	1.00	0.48	0.94	0.73	0.86
10	1.00	0.53	0.85	0.85	0.85
11	1.00	0.59	0.93	0.69	0.85
12	0.97	0.94	0.70	1.00	0.85
13	0.82	0.86	0.79	0.95	0.85
14	1.00	0.23	0.99	0.63	0.84
15	1.00	0.15	0.98	0.62	0.83
16	1.00	0.65	0.97	0.55	0.83
17	1.00	0.62	0.95	0.55	0.82
18	1.00	0.26	0.79	0.88	0.82
19	0.23	0.97	0.83	1.00	0.79
20	1.00	0.13	0.88	0.61	0.78

3.4 Machine-Learning-based Clustering

In this section, as alternative to combining the four dimension score into a single priority score, we will discuss how we cluster the products based on both the scores they obtained in the four dimensions and the weights through AHP study.

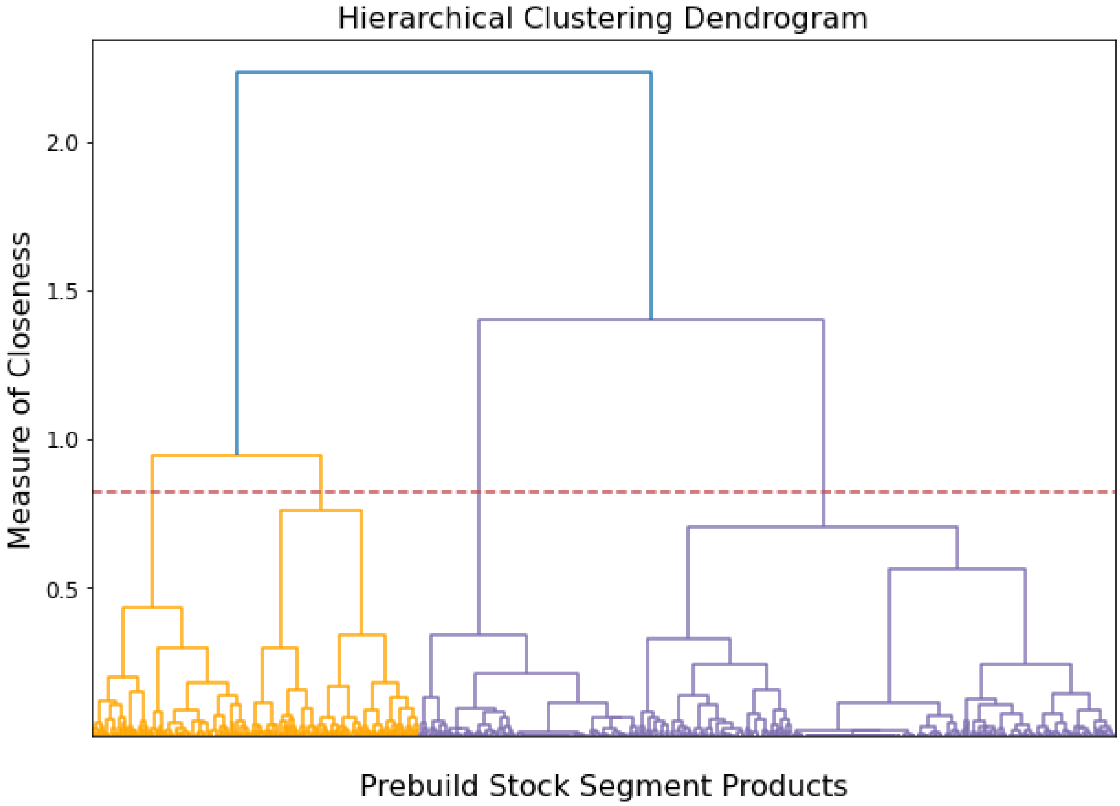
In Section 3.4.1, we cluster the products in four dimensions by hierarchical clustering algorithm. In Section 3.4.2, we eliminate seasonality dimension that has the least weight (6%), and we cluster the products in three dimensions by k-means clustering algorithm. In Section 3.4.3, we cluster the products in the two most important dimensions, capacity insufficiency (48.5%), and backorder tendency (29.4%), by fuzzy-c-means clustering algorithm.

3.4.1 Clustering in 4-Dimensions

We label the products based on the dimension weights that we obtained with the AHP study. To reflect the different weights of the dimensions, we used weighted euclidean distance metric in agglomerative hierarchical clustering. The Weighted Euclidean distance measure is calculated as $d(p, q, w) = \sqrt{\sum_{i=1}^{4} w_i (q_i - p_i)^2}$ where w_i is the AHP-determined weight of dimension i.

When deciding how many clusters to create, dendrograms can be useful. There is no "correct" answer to the "how many clusters?" question because this is an unsupervised learning process, so keep in mind that Figure 3.12 is a tool for decision making process. Based on the measure of closeness of either individual data points or clusters, we decided to cut the hierarchical clustering dendrogram given in Figure 3.12 at the dashed red horizontal line to obtain four distinct clusters.

Figure 3.12 Prebuild Stock Clustering Dendogram



After cluster assignment, we consider the average of all dimensions scores for each cluster to label the products. Table 3.6 shows the number of products and average scores of the dimensions in each cluster.

Table 3.6 Prebuild Stock Clustering with 4 Dimensions

Cluster	Annual Sales Score	Seasonality Score	Capacity Insufficiency Score	Backorder Tendency Score	Number of Products
1st consideration for prebuild inventory	0.62	0.53	0.54	0.89	92
2nd consideration for prebuild inventory	0.89	0.18	0.63	0.25	86
3rd consideration for prebuild inventory	0.18	0.66	0.01	0.90	119
4th consideration for prebuild inventory	0.35	0.46	0.04	0.16	259

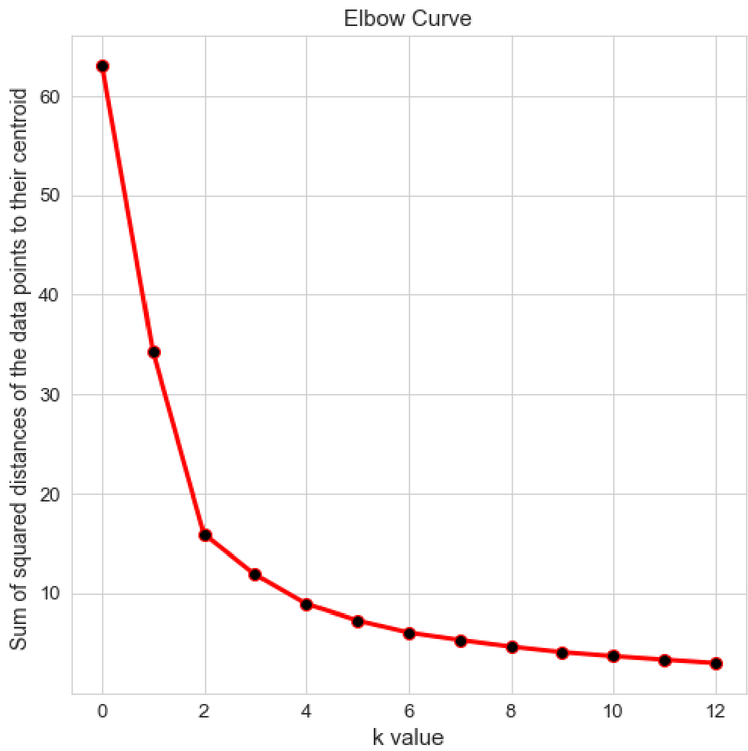
The four clusters we identify are as follows:

- **1st consideration for prebuild inventory:** All dimension scores are above the overall score averages (0.50 as mentioned in Section 3.2) in the group. Therefore, these products would be the first to be considered for prebuild inventory.
- **2nd consideration for prebuild inventory:** Annual sales and capacity insufficiency scores are above the overall score averages, however their seasonality, and backorder tendency scores are below the score averages. Therefore, these products would have the second priority for prebuild inventory.
- **3rd consideration for prebuild inventory:** The group includes the products with high seasonality and backorder tendency scores, however their annual sales and capacity insufficiency scores are relatively low. Such products can be produced within the peak order months. Accordingly, they have only the third priority for prebuild inventory.
- **4th consideration for prebuild inventory:** All dimension scores are below the overall score averages in the group. Therefore, these products have the lowest priority for prebuild inventory.

3.4.2 Clustering in 3-Dimensions

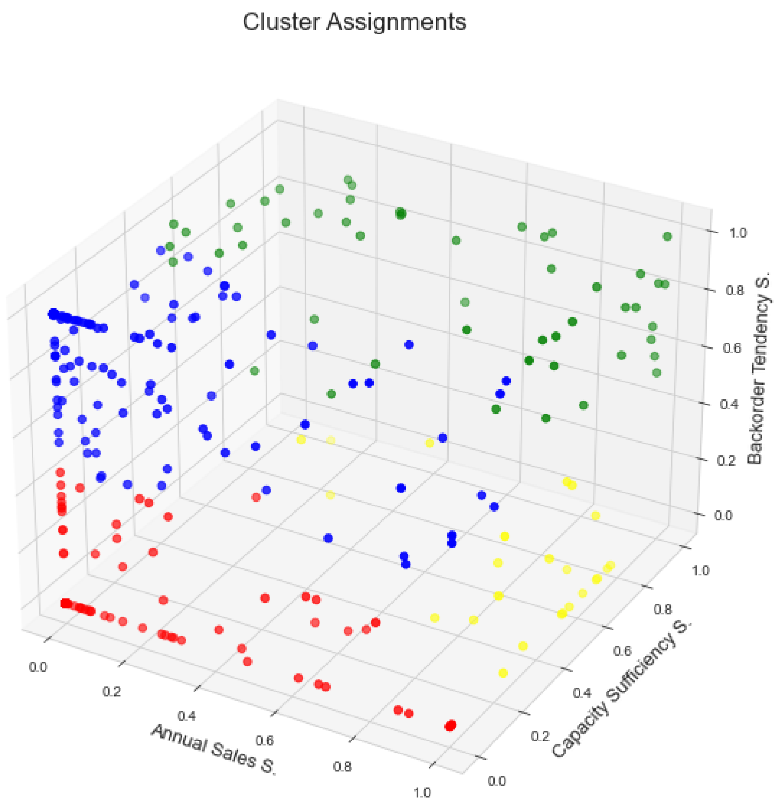
Out of the four dimensions, seasonality is the one that has the least weight (6%). Therefore, we decided to first use seasonaltity as a filter (considering only the products that have a seasonality score greater than 0.25), and then conduct a 3-dimensional k-means clustering study based on the remaining three dimensions. We use Weighted Euclidean distance measure as $d\left(p,q,w\right) = \sqrt{\sum_{i=1}^{3} w_i \left(q_i - p_i\right)^2}$ where w_i is the AHP-determined weight of dimension i. We select the k value as 4 based on the elbow approach shown in Figure 3.13.

Figure 3.13 The Elbow Curve



Figures 3.14 present the products with 3 dimensions after the clustering.

Figure 3.14 Four Clusters Identified with the k-means Method



After cluster assignment, we label the products based on the dimensions' average scores as shown in Table 3.7.

Table 3.7 Prebuild Stock Clustering in 3 Dimensions

Cluster	Annual Sales Score	Capacity Insufficiency Score	Backorder Tendency Score	Number of Products
1st consideration for prebuild inventory (Green)	0.60	0.68	0.90	51
2nd consideration for prebuild inventory (Yellow)	0.87	0.53	0.14	24
3rd consideration for prebuild inventory (Blue)	0.19	0.04	0.88	133
4th consideration for prebuild inventory (Red)	0.15	0.02	0.08	125

3.4.3 Clustering in 2-Dimensions

Next, we conduct a clustering study based only on the two most important dimensions, capacity insufficiency and backorder tendency dimensions. Different from our other clustering studies, we used the fuzzy-c-means clustering method, which is a popular algorithm used in health (Hou et al., 2007) and inventory segmentation studies (Aydin Keskin and Ozkan, 2013) among others.

As a soft clustering algorithm, fuzzy-c-means assigns a membership degree of 0 to 1 to each data point in order to determine the degree to which the data point is a member of the cluster. We chose the number of clusters as 4. The fuzziness parameter m should be higher than 1, because if m is chosen as 1, the algorithm converges to k-means in the limit. Therefore, 2 is commonly used as a fuzziness parameter in the literature (Hathaway and Bezdek, 2001). To stop the algorithm, a termination criteria $0 < \varepsilon < 1$ should be used. Considering literature, we set the termination criterion at $\varepsilon = 10^{-5}$ and the fuzziness parameter m at 2.

Figure 3.15 shows the clusters according to the maximum membership degree. The stars are the centroids of the clusters. The labeled products are illustrated in Table 3.8.

Figure 3.15 Prebuild Stock Fuzzy-c-means Clusters

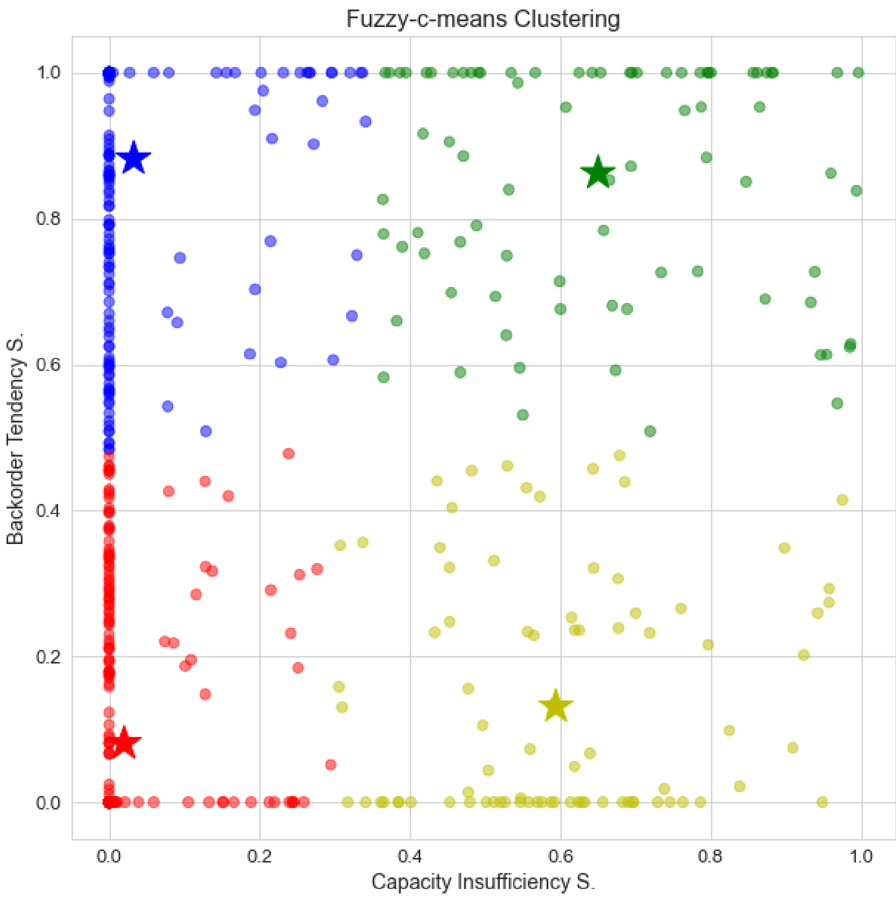


Table 3.8 Prebuild Stock Fuzzy-c-means Cluster Explanations

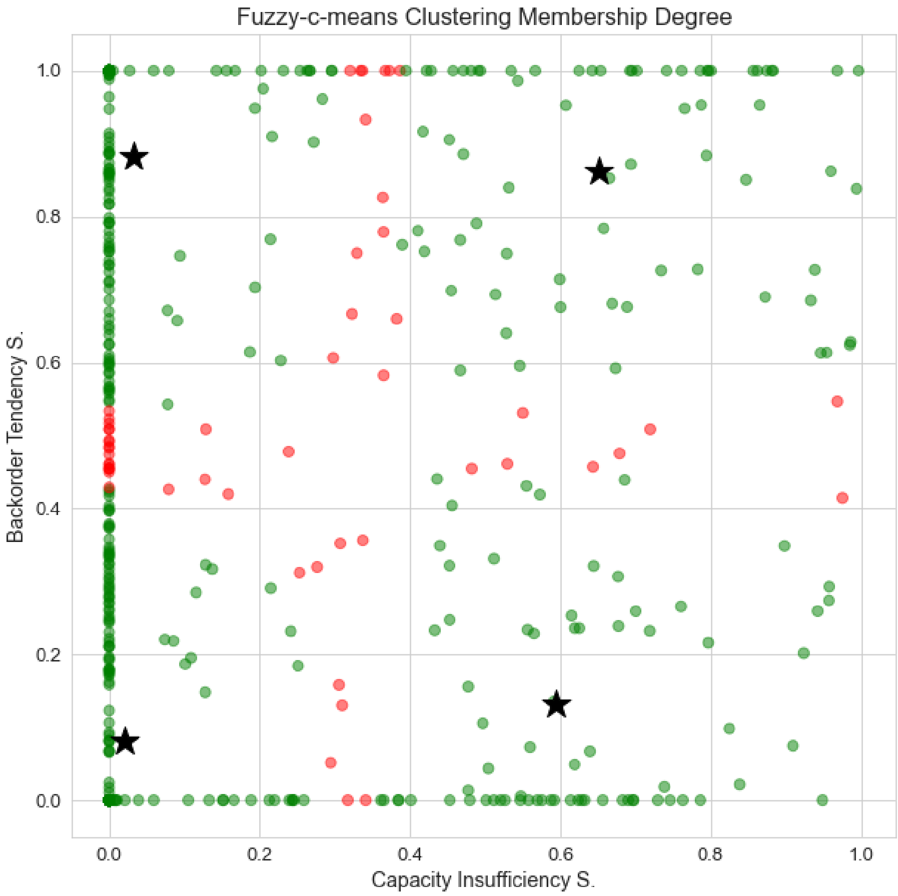
Low Capacity Insufficiency (0.04), High Backorder Tendency (0.85), *171	High Capacity Insufficiency (0.66), High Backorder Tendency (0.85), *80
Low Capacity Insufficiency (0.03), Low Backorder Tendency (0.12), *223	High Capacity Insufficiency (0.60), Low Backorder Tendency (0.15), *82

Notes: Average values, centroids, are given in parentheses.
* corresponds to the number of products in the cluster.

Some SKUs cannot become a member of a cluster with a high membership degree. For such SKUs at the boundaries, we analyze the difference between the maximum two membership degree. The green data points in the Figure 3.16 below represent cluster members who have a membership degree that is at least 0.2 greater than that of a member of another cluster. Here, the threshold value of 0.2 was determined by us. The red data points are the members of their own cluster whose membership degree is less than 0.2 away from the next cluster's degree. For instance, an SKU that has final membership degrees as 0.7, 0.1, 0.1, 0.1 for the four clusters is shown as green. On the other hand, if the final membership degrees of an SKU are 0.45, 0.35, 0.1, 0.1; such SKUs are represented as red because $0.45 - 0.35 < 0.2$. Such

SKUs should be clearly distinguished before making clustering based decisions due to their higher membership degrees for various clusters. We found 53 SKUs at the boundaries.

Figure 3.16 Prebuild Stock SKUs that have the Closest Membership Degrees to Different Clusters



3.5 Machine-Learning-based Classification

The weighted score calculation and the associated transformation operations explained in Section 3.2 are rather time consuming. Hence, we decided to investigate whether a machine learning algorithm can classify the products based on their non-transformed dimensions. This approach would be especially practical when new SKUs need to be classified.

To this end, we defined five classes of products based on their priority scores that were given in Figure 3.11.

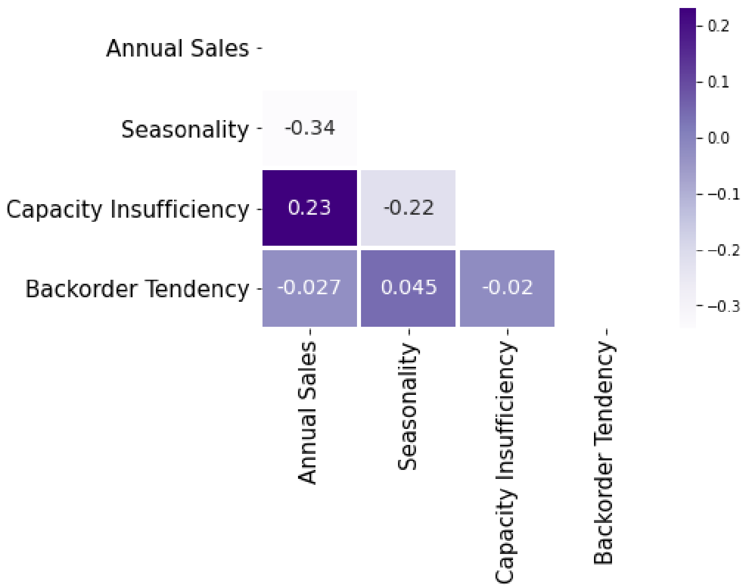
The threshold value 0.15, 0.30, 0.40, and 0.60 were chosen such that the number of SKUs in each class are close to each other.

Table 3.9 Class Assignment

Prebuild Priority Score	Class	Number of Products
Above 0.60	1st consideration for prebuild inventory (1)	81
0.40<PPS≤ 0.60	2nd consideration for prebuild inventory (2)	106
0.30<PPS≤ 0.40	3rd consideration for prebuild inventory (3)	116
0.15<PPS≤ 0.30	4th consideration for prebuild inventory (4)	123
PPS≤ 0.15	5th consideration for prebuild inventory (5)	130

The four chosen dimensions are independent of each other as suggested in the correlation heat map of Figure 3.17.

Figure 3.17 Correlation Heat Map



We split the data into 70% training and 30% test sets with stratified samples. Using the lazypredict library, we obtain 27 classifiers' accuracy and F1 scores as shown in Table 3.10.

Table 3.10 Lazy Classifier Initial Results

Model	Accuracy	F1 Score
RandomForestClassifier	0.83	0.83
LGBMClassifier	0.83	0.82
BaggingClassifier	0.82	0.82
ExtraTreesClassifier	0.80	0.80
XGBClassifier	0.79	0.78
DecisionTreeClassifier	0.78	0.77
ExtraTreeClassifier	0.65	0.65
NuSVC	0.64	0.65
LabelPropagation	0.56	0.56
AdaBoostClassifier	0.55	0.49
KNeighborsClassifier	0.55	0.55
LabelSpreading	0.54	0.54
QuadraticDiscriminantAnalysis	0.47	0.40
CalibratedClassifierCV	0.52	0.47
LinearSVC	0.51	0.47
GaussianNB	0.44	0.36
Perceptron	0.51	0.49
SVC	0.49	0.49
LogisticRegression	0.48	0.46
SGDClassifier	0.46	0.46
PassiveAggressiveClassifier	0.41	0.35
NearestCentroid	0.42	0.42
RidgeClassifier	0.41	0.38
RidgeClassifierCV	0.41	0.38
BernoulliNB	0.37	0.33
LinearDiscriminantAnalysis	0.40	0.36
DummyClassifier	0.24	0.23

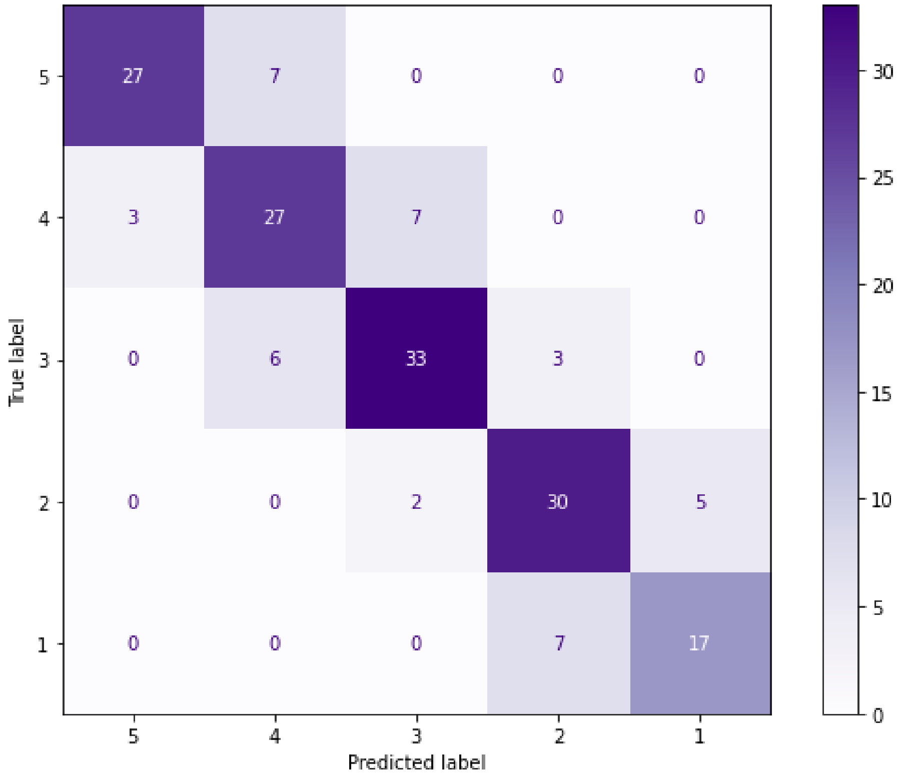
We chose the Decision Tree classifier because it gives close-enough accuracy to the other classifiers while being easy to visualize and explain. Using the default parameters of the Decision Tree classifier from sklearn library (Pedregosa et al., 2011) (criterion: gini, max_depth: None, min_samples_split: 2, min_samples_leaf: 1 etc.), the initial results we obtained are presented in Table 3.11.

Table 3.11 Decision Tree Classifier Initial Results

Class	Precision	Recall	F1 Score
1	0.77	0.71	0.74
2	0.75	0.81	0.78
3	0.79	0.79	0.79
4	0.68	0.73	0.70
5	0.90	0.79	0.84
weighted avg.	0.78	0.77	0.77

Figure 3.18 shows the confusion matrix obtained from the initial Decision Tree Classifier for the five classes.

Figure 3.18 Initial Decision Tree Classifier Confusion Matrix

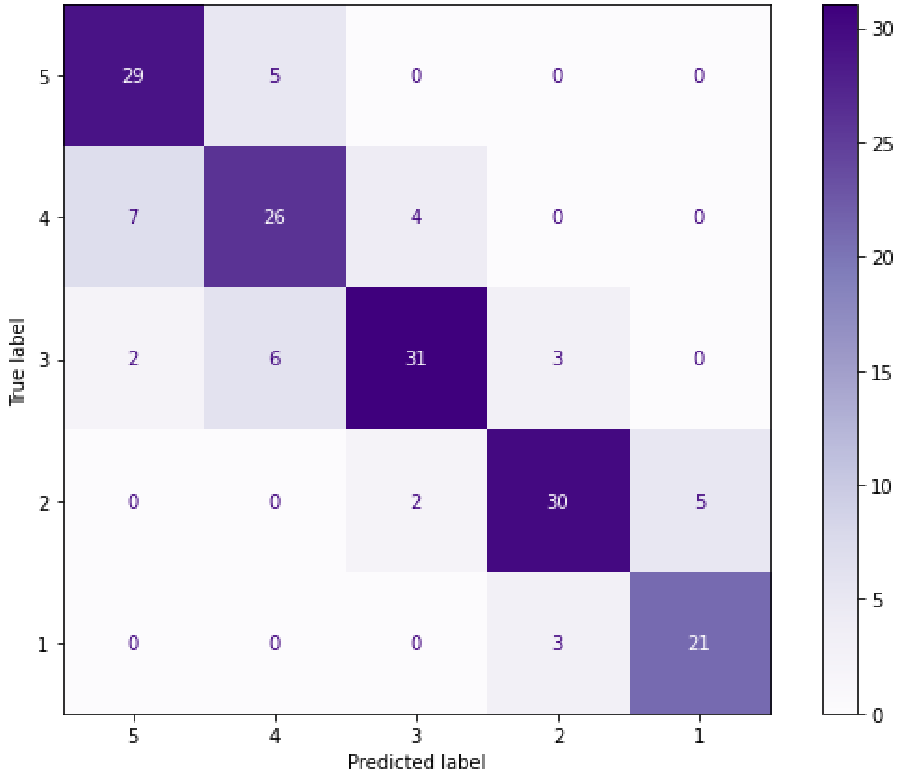


We want our classifier to differentiate classes 1 and 2 (corresponding to the 1st and 2nd considerations for prebuilding) better than the other classes. To this end, we conduct a hyper-parameter tuning study where classes 1 and 2 are the "positive classes" and classes 3, 4 and 5 are the "negative classes". Accordingly, a false positive is defined as a true class 3, 4 or 5 product predicted as a class 1 or 2. A false negative is a true class 1 or 2 product predicted as a class 3,4 or 5 one. Ideally, we aim to increase both the *precision* (that is, reducing false positives) and the *recall* (that is, reducing false negatives) of the classification model; however, these two metrics are often conflicting. Therefore, we tried to maximize the F1-score which considers the harmonic mean of precision and recall. After hyper-parameter tuning study with GridSearchCV with 10-Fold cross validation, and tree-pruning by selecting the right parameters for tree-depth and leaf-size to prevent overfitting of decision tree (Best parameters: criterion: entropy, max_depth: 6, max_features: 3, min_samples_split: 4, splitter: best, min_samples_leaf: 2), we obtained the results in Table 3.12. The corresponding confusion matrix is shown in Figure 3.19.

Table 3.12 Decision Tree Classifier Results After Hyper-Parameter Tuning

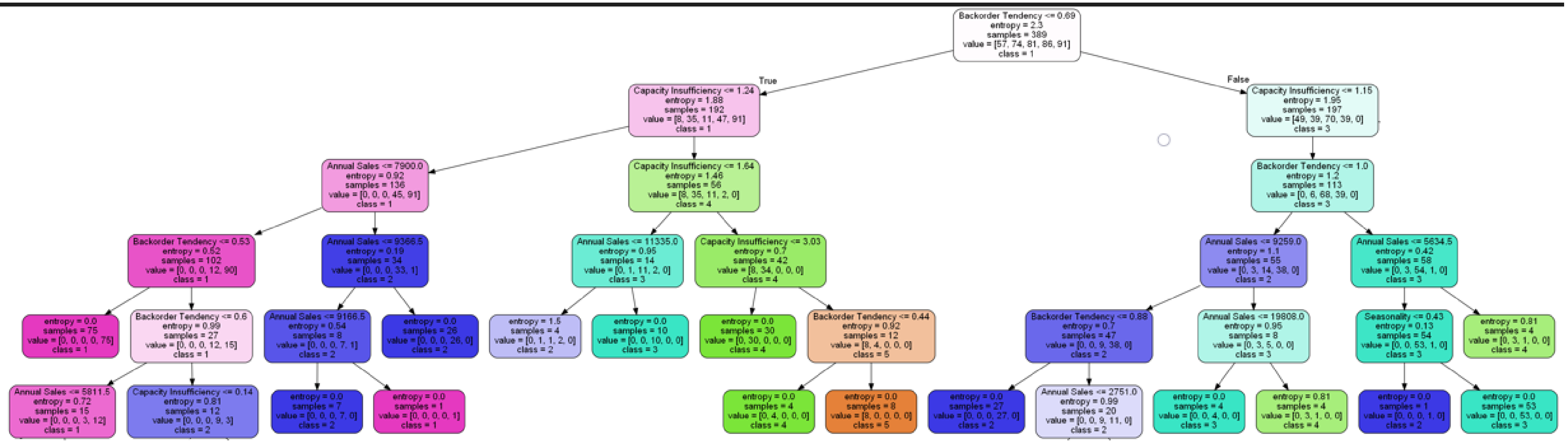
Class	Precision	Recall	F1 Score
1	0.81	0.88	0.84
2	0.83	0.81	0.82
3	0.84	0.74	0.78
4	0.70	0.70	0.70
5	0.76	0.85	0.81
weighted avg.	0.79	0.79	0.79

Figure 3.19 Improved Decision Tree Classifier Confusion Matrix



With this tuning, we were able to increase the F1-scores of class 1 from 0.74 to 0.84 and that of class 2 from 0.78 to 0.82. As a result, we can conclude that our optimized model shown in Figure 3.20 is successful in predicting the classes by using non-transformed dimensions. Hence this model can be used to evaluate unclassified products' consideration priority for prebuild inventory decisions. Figure 3.20 shows sample part to explain the decision tree.

Figure 3.20 Decision Tree Classifier



4. CYCLE STOCK STUDY

The company refers to tire SKUs that have high profit margin, high importance for the company, but relatively low sales volume as the *strategic mix*. These are usually large-size tires. Given the high profit margin and importance of these products, and the sensitivities of the dealers and end-customers, the company aims to satisfy the demand for these products from stock. Unlike most other tires, dealers often do keep stock of these SKUs and expect quick delivery from the company when demand arises from an end-customer. Currently, because their sales volumes are relatively low, these products are produced in relatively small lot sizes. This causes significant time lost due to manufacturing setups, which is an important concern given the overall high capacity utlization in the manufacturing plant.

In the process we developed, the tires in the strategic mix will be manufactured in relatively higher lot sizes to minimize the number of setups and production complexity. This will lead to keeping planned *cycle stock* for these products. Together with the company managers, we determined a policy in which for each SKU in the strategic mix, sufficient number of products will be manufactured to meet the demand of, say 3, or 6 subsequent months in horizon. The "number of months to cover" parameter can be decreased if the company chooses to reduce inventory levels, which may be preferred if production complexity becomes a lesser issue.

4.1 Priority Scoring Approach

While the target is to produce x-months worth of inventory for each product in each production run, the total production capacity may not be sufficient to meet this goal in certain times of the year. Thus, we developed a scoring rule to determine the production priorities that will be used when the company has limited production capacity for these products.

For each dimension, a higher score indicates the SKU being a better candidate for keeping cycle stock. The weights were determined together with the company managers through an Analytic Hierarchy Process (AHP) study as explained in Section 4.2. Next, we discuss the dimensions in detail.

The Dimensions

- **Strategic Priority:** This dimension indicates the subjective importance of the product in the eyes of the sales and marketing managers. It is calculated based on the average evaluation of managers from these departments. This is a rather subjective evaluation that is based on factors such as the growth potential of the product, the prestige of carrying the product or the value that dealers attach to the product. For products for which we could not get evaluations, we used a distance based clustering algorithm, hierarchical clustering, to establish similarity with an evaluated product. To do so, we considered annual orders, product group, season and the rim size. If the products are similar, in other words they are coming from the same tree in hierarchical clustering, we used the priority score of the evaluated product.

- **Production Complexity:** This dimension is related to the production setup costs and setup time of the SKU, which can be as high as 8 hours. While other factors may also be effective, a rule of thumb is that products that have larger rim sizes have higher production complexity. Accordingly, we measured production complexity dimension based on the tire's rim size.

- **Gross Margin:** This is the standard gross profit margin value, which is an indication of the profitability of the product. It is calculated as *(total revenue − total cost)/(total revenue)*. Gross profit margin comes into picture as the company prefers not stocking out with a product that has high profit margin.

- **Inventory Turnover:** We use the realized inventory turnover ratio, which is calculated as *(annual sales)/(average inventory)* as an indication for the riskiness of the product. A high inventory turnover ratio indicates that the SKU has been sold relatively fast compared to its average inventory level, thus it is likely to have low risk of being unsold.

In order to calculate the weighted average values, the measures from each of the four dimensions were normalized to scores between 0 and 1 as we did in Section 3.2. Table 4.1 shows the percentile parameter of each dimension. The mean value of each transformed dimension is 0.50.

Table 4.1 Percentile Parameter of Each Dimension for Cycle Stock Study

Dimension	MinPercentile	MaxPercentile
Strategic Priority	10	80
Production Complexity	2	83
Gross Margin	15	85
Inventory Turnover	10	70

4.2 Combining Dimension Scores Using AHP-determined Weights

We use the AHP approach to determine the relative weights of the four dimensions as we did in Section 3.3. In comparing two dimensions, we use the absolute judgment scale of Saaty et al. given in Table 3.2. The pairwise comparison values are entered into a comparison matrix, and the weights of the attributes are then calculated using matrix algebra.

The company managers conducted pairwise comparisons among the four dimensions of the cycle stock study under our guidance. The resulting comparison scores are given in Table 4.2. As an example, the comparison score of 2 in the first row, second column of this matrix indicates that the decision maker thinks that the strategic priority dimension is "weak or slight more important" compared to production complexity dimension in determining the overall cycle stock score of an SKU. Note that the comparison score for the opposite comparison, that is between production complexity and strategic priority, automatically becomes 1/2.

Table 4.2 Relative Importance of Dimensions for the Cycle Stock Study

$$
\begin{array}{c c}
\textit{Dimensions} & \begin{array}{cccc} \text{Strategic Priority} & \text{Production C.} & \text{Gross Margin} & \text{Inventory T.} \end{array} \\
\begin{array}{c} \text{Strategic Priority} \\ \text{Production Complexity} \\ \text{Gross Margin} \\ \text{Inventory Turnover} \end{array} & \begin{pmatrix} 1 & 2 & 2 & 1/2 \\ 1/2 & 1 & 1 & 1/4 \\ 1/2 & 1 & 1 & 1/4 \\ 2 & 4 & 4 & 1 \end{pmatrix}
\end{array}
$$

Next, based on this matrix, we calculate the weights of the four dimensions using the *Eigenvenctor Method* of (Saaty, 2003). Table 4.3 shows the resulting weights and the corresponding ranks. The matrix achieved a consistency ratio of 0.00, which indicates full consistency in pairwise comparisons.

Table 4.3 Weights of the Cycle Stock Priority Scoring Dimensions

Dimension	Weight	Rank
Strategic Priority	25%	2
Production Complexity	12.5%	3
Gross Margin	12.5%	3
Inventory Turnover	50%	1

Accordingly, we used the following equation to calcuate the overall Cycle Stock Priority Score (CSPS) of SKUs:

Cycle Stock Priority Score $=$ *0.25* $\times$ *(strategic priority score)* $+$ *0.125* $\times$ *(production complexity score)* $+$ *0.125* $\times$ *(gross margin score)* $+$ *0.50* $\times$ *(inventory turnover score).*

The highest weight is inventory turnover score as one of the goals with this study is to minimize the inventory holding costs, and unsold products' inventory risk. The weight of strategic priority score is also relatively high as this study is concerned with the strategic mix products. The weights of gross profit margin and production complexity is relatively smaller. According to this study, products with high strategic priority, high production complexity, high gross margin and high inventory turnover will be given priority in production.

Figure 4.1 shows the distribution of the resulting Cycle Stock Priority score among the related products. Table 4.4 lists the dimension scores as well as the weighted priority scores of the top-20 products.

Figure 4.1 Distribution of Cycle Stock Priority Scores

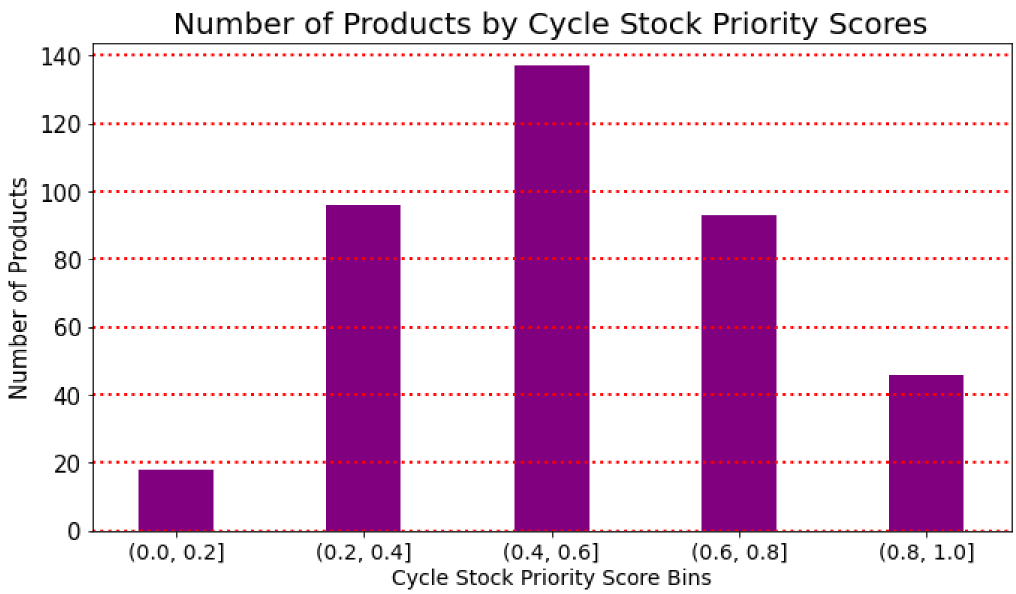


Table 4.4 Cycle Stock Priority Score Details for the Top 20 Products

Product ID	Strategic Priority Score	Complexity Score	GM Score	Inventory Score	Cycle Stock Priority Score
1	1.00	1.00	1.00	1.00	1.00
2	1.00	1.00	1.00	1.00	1.00
3	1.00	1.00	1.00	0.98	0.99
4	0.93	1.00	0.84	1.00	0.96
5	1.00	1.00	0.71	0.99	0.96
6	0.91	1.00	0.81	1.00	0.95
7	1.00	1.00	0.54	1.00	0.94
8	1.00	1.00	0.48	1.00	0.93
9	0.96	0.45	0.98	1.00	0.92
10	1.00	0.35	0.96	1.00	0.91
11	0.96	0.35	0.99	1.00	0.91
12	1.00	0.45	0.73	1.00	0.90
13	0.67	1.00	1.00	0.95	0.89
14	0.83	0.45	1.00	1.00	0.89
15	1.00	0.45	0.91	0.92	0.88
16	0.81	1.00	0.40	1.00	0.88
17	1.00	0.45	0.98	0.89	0.87
18	1.00	0.35	0.64	1.00	0.87
19	1.00	0.35	0.60	1.00	0.87
20	1.00	0.45	0.92	0.88	0.86

4.3 Machine-Learning-based Clustering

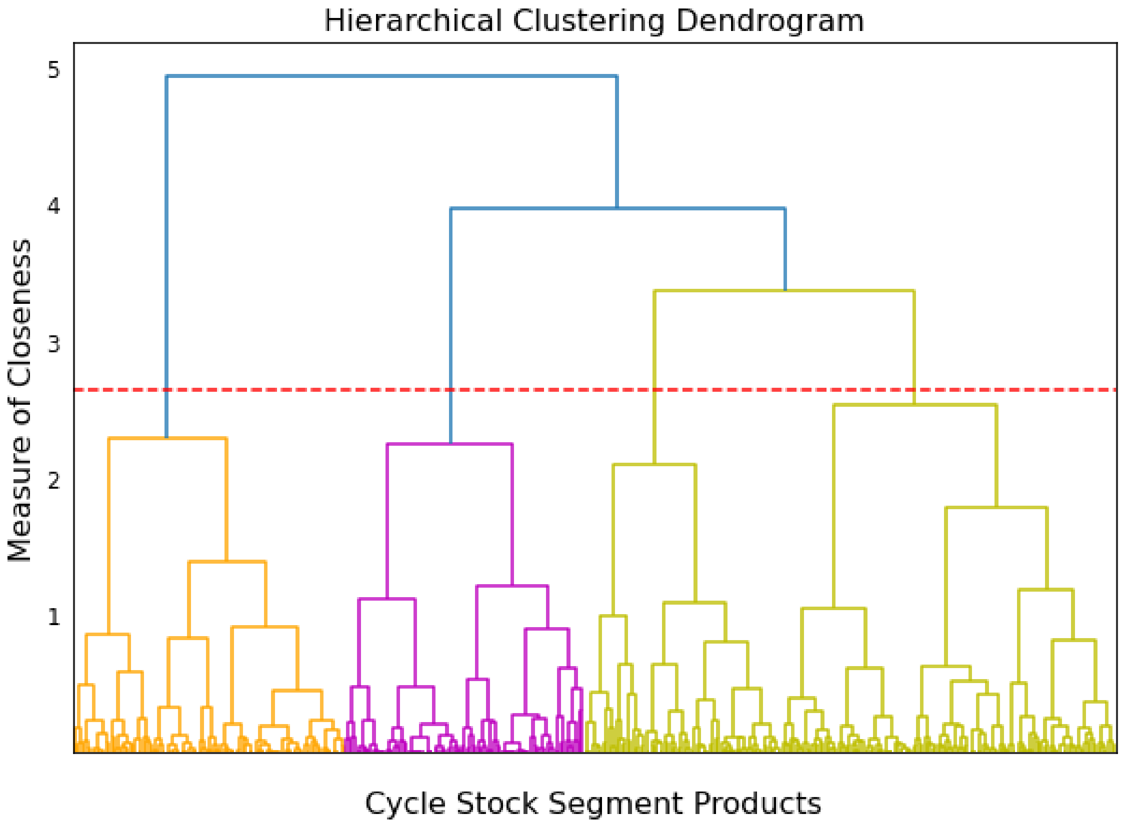
In this section, as an alternative to combining the four dimension score into a single priority score, we will discuss how we cluster the products based on both the scores they obtained in the four dimensions and the weights through AHP study.

In Section 4.3.1, we cluster the products in four dimensions by hierarchical clustering algorithm. In Section 4.3.2, we cluster the products in two dimensions, gross margin and inventory turnover, by fuzzy-c-means clustering algorithm.

4.3.1 Clustering in 4-Dimensions

As we did in Section 3.4.1, we used weighted euclidean distance metric in agglomerative hierarchical clustering. Based on the measure of closeness of either individual data points or clusters, we decided to cut the hierarchical clustering dendrogram given in Figure 4.2 at the dashed red horizontal line to obtain four distinct clusters.

Figure 4.2 Cycle Stock Clustering Dendogram



After cluster assignment, we consider the average of all dimensions scores for each cluster to label the products. Table 4.5 shows the number of products and average scores of the dimensions in each cluster.

Table 4.5 Cycle Stock Clustering with 4 Dimensions

Cluster	Strategic Priority Score	Production Complexity Score	Gross Margin Score	Inventory Turnover Score	Number of Products
1st consideration for cycle stock	0.72	0.75	0.64	0.91	82
2nd consideration for cycle stock	0.54	0.63	0.48	0.76	86
3rd consideration for cycle stock	0.18	0.46	0.19	0.38	103
4th consideration for cycle stock	0.17	0.26	0.14	0.12	119

The four clusters we identify are as follows:

- **1st consideration for cycle stock:** All dimension scores are above the overall score averages (0.50 as mentioned in Section 4.1) in the group. Therefore, these products would be the first to be considered for cycle stock.

- **2nd consideration for cycle stock:** Strategic priority, production complexity and inventory turnover scores are above the overall score averages; however, the gross margin score is slightly below the score averages. Therefore, these products would have the second priority for cycle stock.

- **3rd consideration for cycle stock:** This group includes the products with moderate production complexity and inventory turnover scores, but relatively low strategic priority and gross margin scores. Accordingly, they have only the third priority for cycle stock.

- **4th consideration for cycle stock:** All dimension scores are far below the overall score averages in this group. Therefore, these products have the lowest priority for cycle stock.

4.3.2 Clustering in 2-Dimensions

We conduct a fuzzy-c-means clustering (with the same parameters in Section 3.4.3 based only on gross margin, and inventory turnover dimensions. Figure 4.3 shows the clusters according to the maximum membership degree. The stars are the centroids of the clusters. The labeled products are illustrated in Table 4.6.

Figure 4.3 Cycle Stock Fuzzy-c-means Clusters

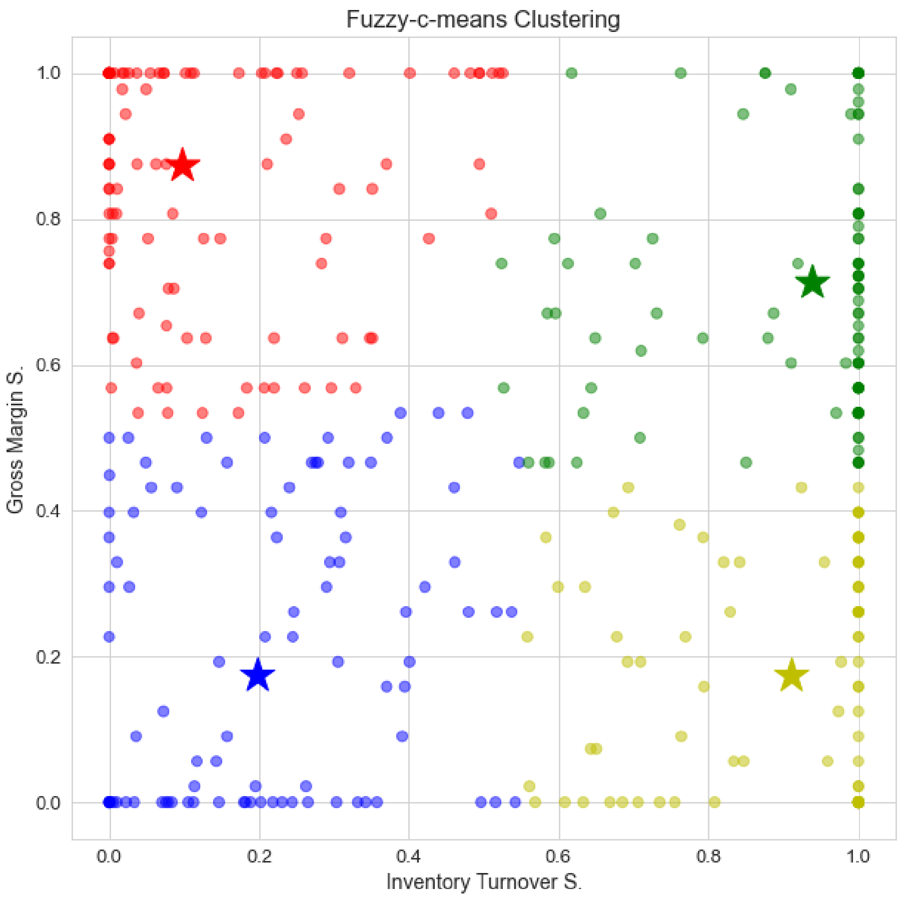


Table 4.6 Cycle Stock Fuzzy-c-means Cluster Explanations

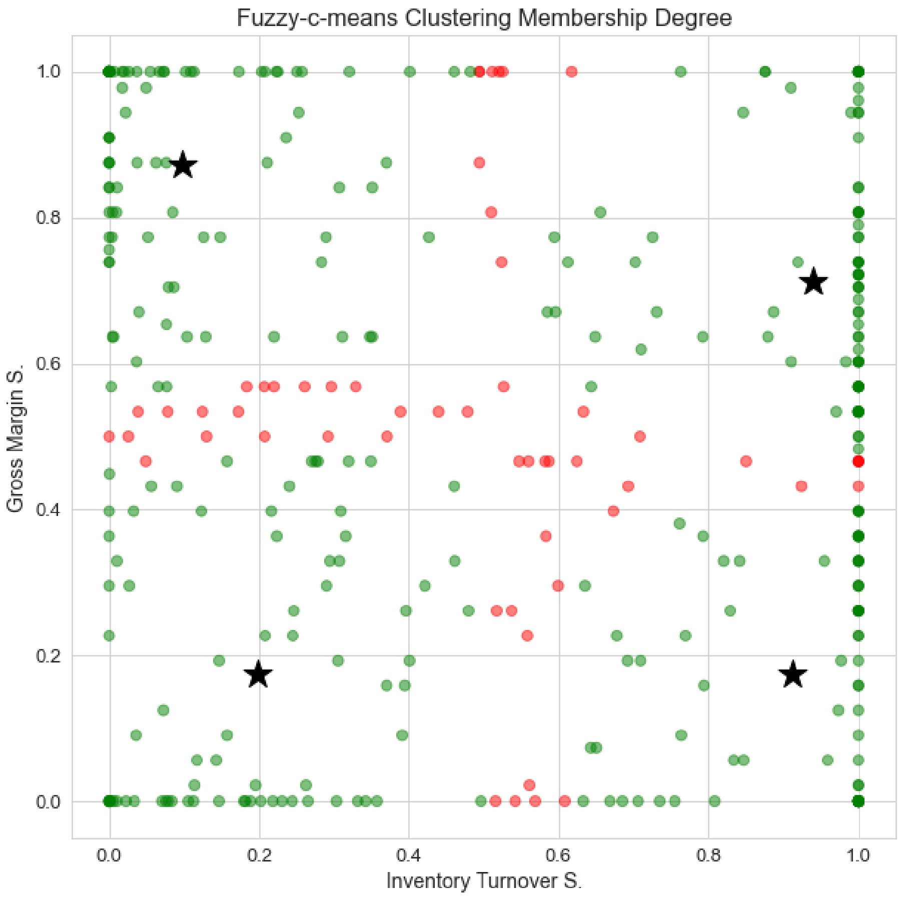
Low Inventory Turnover (0.13), High Gross Margin (0.85), *110	High Inventory Turnover (0.91), High Gross Margin (0.72), *101
Low Inventory Turnover (0.21), Low Gross Margin (0.18), *92	High Inventory Turnover (0.89), Low Gross Margin (0.17), *87

Notes: Average values, centroids, are given in parentheses.
* corresponds to the number of products in the cluster.

Some SKUs cannot become a member of a cluster with a high membership degree. For such SKUs at the boundaries, we analyze the difference between the maximum two membership degree as we did in Section 3.4.3.

The green data points in the Figure 4.4 below represent cluster members who have a membership degree that is at least 0.2 greater than that of a member of another cluster. Here, the threshold value of 0.2 was determined by us. The red data points are the members of their own cluster whose membership degree is less than 0.2 away from the next cluster's degree. Such SKUs should be clearly distinguished before making clustering based decisions due to their higher membership degrees for various clusters. We found 56 SKUs at the boundaries.

Figure 4.4 Cycle Stock SKUs that have the Closest Membership Degrees to Different Clusters



5. SAFETY STOCK STUDY

5.1 The Current Process

Stocking out in the OE channel would have serious consequences for the company as the auto manufacturers operate with close-to-zero inventories and depend on timely deliveries of tires for their production schedules. Although the OE customers provide their monthly orders in advance, they may need to update the delivery schedules of the tires to their factories, causing fluctuations in demand.

To cover such fluctuations, the company aims to keep sufficient inventory on hand to cover the coming x-week's (where the true x value is masked) forecasted demand for each SKU that is sold to OE customers. We refer to this policy as using a *Target Weekly Cover Value (TWCV)* of x-weeks. If the number of weeks whose demand can be covered with the current inventory, that is, the *Current Weekly Cover Value (CWCV)* falls below this threshold, a production run needs to be initiated, but this may not start quickly due to production constraints.

At the beginning of each month, the company calculates both the CWCV and the projected weekly-cover values for the coming months in the planning horizon, taking into account the current inventory level, the monthly production quantities and capacities, and the monthly forecasts for the subsequent months. The company plans for production in the months in which the CWCV is projected to fall below the TWCV of x-weeks. If that month's production capacity is not sufficient, the capacity of previous months are used to build inventory. In that case, the projected CWCV of certain months can turn out to be higher than the targeted x-weeks. Minimum production quantities or lot sizes can also cause the projected CWCV to be over the TWCV. As can be seen, this policy affects not only the finished-goods inventory level, but also the production planning of the tires sold in the OE channel.

5.2 The Process We Developed

In this study, we improved the aforementioned process in two aspects. First, instead of pursuing a fixed x-week-coverage for every product, we set customized TWCV for each product between 2 and 5 weeks, taking product characteristics into account. Second, we allow the monthly TWCV for a product to dynamically change throughout the year. We expect these modifications to help the company in several ways. Customized TWCV allow higher inventory levels for products whose demand fluctuates more, and lower inventory values for products whose demand is less risky. Dynamic TWCV allows building inventory in anticipation of high demand months considering the monthly production constraints arising from SKU-specific mold-capacities in advance. The approach also highlights cases where production will be sufficient even with inventory prebuilding; in which case new molds may need to be purchased. The company needs to know these requirements in advance, as it takes around 3 months for an ordered mold to be delivered.

As discussed in Section 3.2, the monthly production capacity for the product is calculated as *(Number of molds)*(Daily production per mold)*(Number of working days in the month)*(production yield).*

For instance, a sample passenger vehicle tire has 4 molds each of which can produce 70 tires per day with a production yield of 95%. Given this, the production capacity for that tire in January 2022, which has 25 working days, is calculated as $4 \times 70 \times 25 \times 0.95 = 6650$ units.

Next, for each month in the planning horizon, we calculate the ratio of that month's demand forecast to the production capacity, which we refer to as the *Capacity Utilization (CU).* The idea is to calculate, how long a production run would be needed in that month to cover that month's demand forecast without using the available inventory. For instance, a CU value close to 0 means there is excess production capacity to meet unexpectedly high demand in that month; hence TWCV can be low for the month. On the other hand, a capacity utilization value that is above indicates a stockout risk in the absence of beginning inventory, hence the TWCV is set to a higher value to increase the safety stock of the product. Note that the beginning inventory value for the month is not used in the TWCV calculation. The beginning inventory value is used in the calculation of the CWCV of the month, which will be compared against the TWCV.

In our sample calculation, for each product we used the beginning inventory levels as of November 2021, and the monthly demand forecasts and production capacity values from November 2021 to December 2022. Table 5.1 summarizes how the calculated capacity utilization values are related to production decisions. The threshold values 0.25, 0.50, 0.75 arise due to the simplified month-week conversion: If the CU is less than 0.25, then at most one-week of production would be sufficient to meet the forecasted monthly demand. Note that we add a buffer of one week to obtain the assigned TWCV values for each group in the table.

Table 5.1 Production Decisions Based on the Capacity Utilization (CU) Values

Capacity Utilization	Required production weeks	Assigned TWCV
0.00 to 0.25	At most one-week	2
0.25 to 0.50	At most two-weeks	3
0.50 to 0.75	At most three-weeks	4
Above 0.75	At most four-weeks	5

TWCV for the t months in the decision horizon is calculated with the procedure below.

Algorithm 1 TWCV Assignment

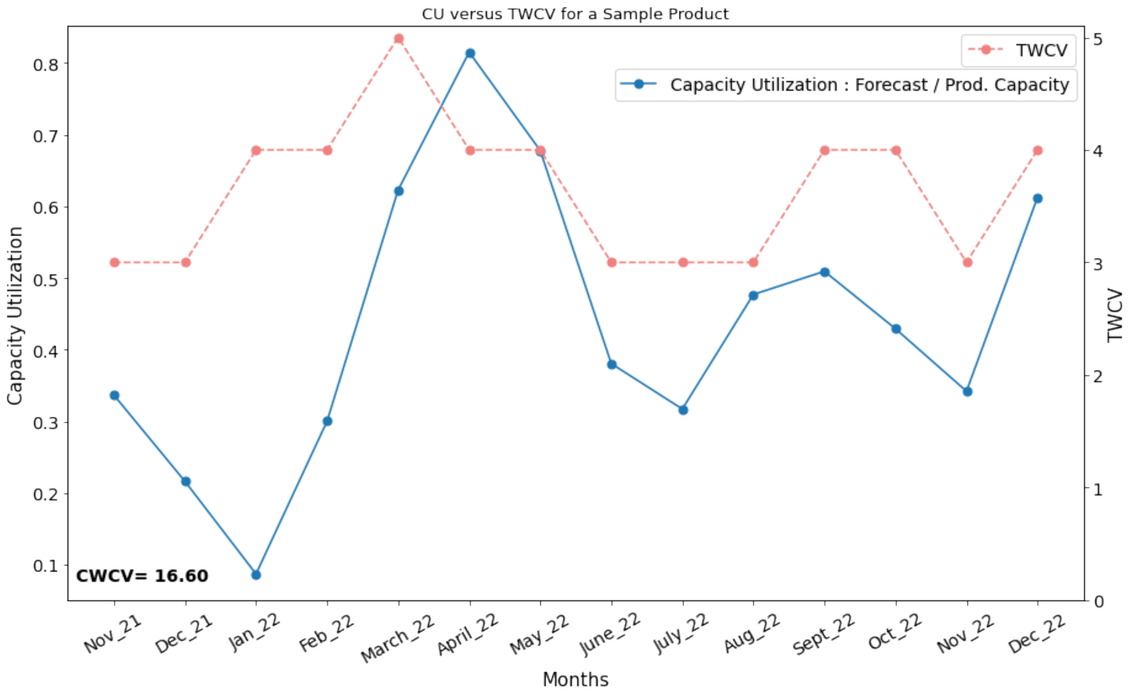
Data: Capacity Utilization (CU): Forecast/Prod. Capacity
Result: Targeted Weekly Cover Value (TWCV) for the t months
initialization: t=1, weight W such that $0 \leq W \leq 1$
while *length of decision horizon* $\geq t$ **do**
  if *length of decision horizon* $- t \geq 3$ **then**
    $C_t = W \times \max\{CU_t, CU_{t+1}\} + (1-W) \times \max\{CU_{t+2}, CU_{t+3}\}$
  else if *length of decision horizon* $- t = 2$ **then**
    $C_t = W \times \max\{CU_t, CU_{t+1}\} + (1-W) \times CU_{t+2}$
  else if *length of decision horizon* $- t = 1$ **then**
    $C_t = W \times CU_t + (1-W) \times CU_{t+1}$
  else
    $C_t = CU_t$
  end
  if $0 \leq C_t \leq 0.25$ **then**
    $TWCV_t = 2$
  else if $0.25 < C_t \leq 0.50$ **then**
    $TWCV_t = 3$
  else if $0.50 < C_t \leq 0.75$ **then**
    $TWCV_t = 4$
  else
    $TWCV_t = 5$
  end
  update t = t+1
end

Here, the weight W is used for smoothing the potential fluctuation of TWCV between consecutive months. To achieve smoothing, the algorithm considers the CU values in four months, and takes a weighted average of the maximum of CU_t and CU_{t+1}, and the maximum of CU_{t+2} and CU_{t+3}. By doing so, we allow the monthly TWCV to change by a maximum of 1 week consecutive months. In the absence of such smoothing it would be difficult to ramp up the inventory to targeted values.

Next, we illustrate the capacity utilization *(forecast / production capacity)* and TWCV calculations for the 14-month horizon for our sample product. The left axis and the blue line in Figure 5.1 show the capacity utilization values; whereas, red dashed line, and the right axis show the targeted weekly cover values. As for the weight value W is chosen as 0.60.

We observe the CU values to decrease until January, and then increase significantly until April, after which they decrease again. To prepare for this increase in capacity utilization, the algorithm increases the TWCV from November until March, and decreases them afterwards till August.

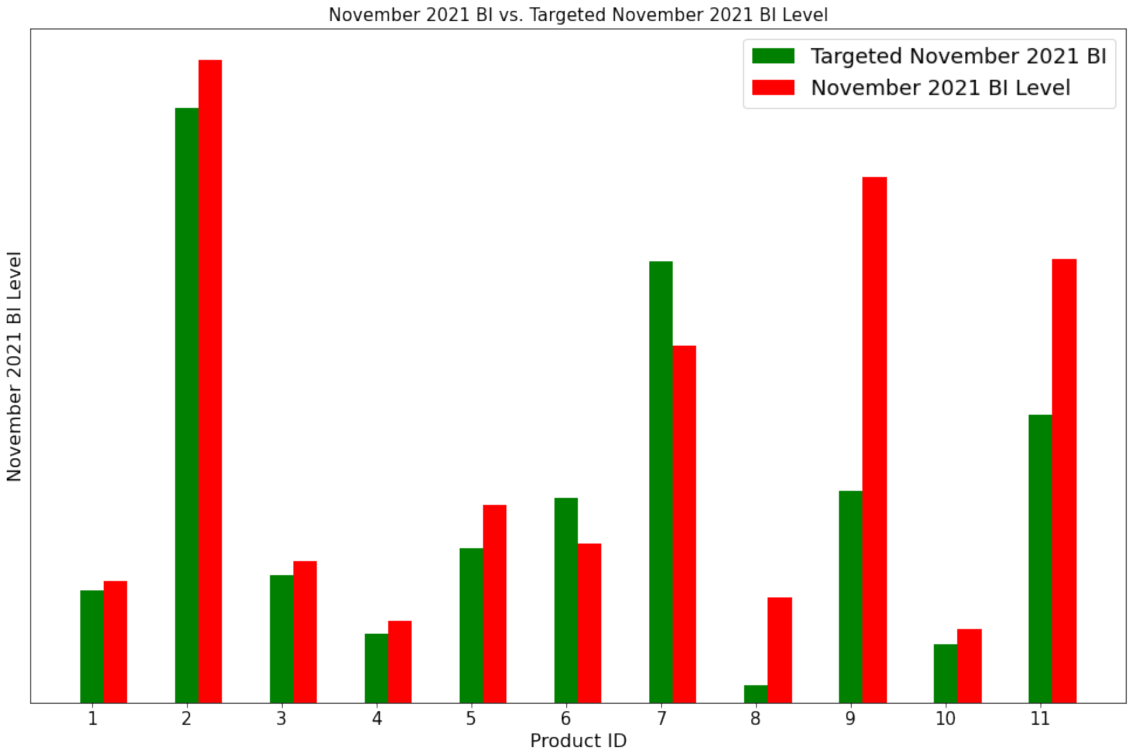
Figure 5.1 CU versus TWCV for a Sample Product



Next we discuss how this process will be used to determine production quantities. At the beginning of each week, for each product that is sold in the OE channel, the current and target weekly cover values will be compared. Products for which $CWCV < TWCV$ will be flagged for production. Even though the company gives priority to OE channel products, there may not be sufficient overall production capacity to produce all of the required products in the coming weeks. Hence, each product will be assigned a production priority score that is based on the difference between TWCV and CWCV, customer priority and the gross profit margin of the product.

Next we compare the inventory levels that would be realized under our suggestion with the realized values as of November 2021. Figure 5.2 compares these for 11 popular products from passenger tire category. We observe that for most products, our procedure would have resulted in lower amounts of inventory while for some products the opposite is the case.

Figure 5.2 Targeted vs. Observed Beginning Inventory Levels for November 2021



6. DISCUSSION AND CONCLUSIONS

In this thesis, we have developed a data-based solution approach to address the production planning and finished goods inventory policies of a leading tire manufacturer. This segmentation approach can also help answer other important questions for the company. For instance, for which SKUs shall the company purchase more molds, hence, increase production capacity? For which SKUs the preorder incentives to dealers shall be increased or decreased? Which SKUs shall be promoted in sales channels in certain times of the year, based on their ongoing weekly cover inventory levels?

Beyond the eight product dimensions we utilized, we conceptualized some other dimensions as well. These were not utilized in this thesis due to lack of data in the company or lack of time. Examples include forecast accuracy, product substitutability (with alternative tires that the company produces), the lifecycle stage (introduction, ramp up, maturity, soon-to-be delisted etc.), and supply risk (related to raw material procurement). Inclusion of such dimensions can further improve the applicability and accuracy of our methods.

In the course of our interaction with the company, we have made numerous suggestions to address some of the root-cause issues that affect the inventory and production related performance of the company. For instance, we believe that most of the ordering and backorder related issues in the replacement channel can be mitigated through a better channel policy that takes dealer incentives and dealer inventories into account. Or, recording the root causes of order cancellations, which is currently not done, can give significant clues for improvement. We were not able to address these issues in the scope of this thesis study but they offer valuable opportunities for further studies.

We have developed our solutions in collaboration with the company's production planning managers, reflecting their views and preferences in certain choices. The company is currently implementing our solution to their business processes. To this end, we have shared our Python codes with the Analytics department of the company. Once our solution is implemented, the company may develop a dynamic tracing system which will track SKU inventory performance over time. Periodically (say, every 3 months), the target inventory level of the SKU may be modified based on the realization (say, over a 6 month period data) of certain measures such as, how timely and complete the orders were shipped, the realized inventory levels in weekly cover terms, level of dealer inventory in the RL channel, and the production queue status of the relevant production lines.

Similar to most analytics projects, we spent most of our time to understanding the business processes, gathering data from various sources in the company, and cleaning and preparing the data. Another challenge we experienced is the abnormality of the business environment in recent years due to a number of “black swan” events including the covid pandemic, global supply chain shortages, the war in Ukraine and changing economic conditions in Turkey and in the export markets. Despite all the challenges experienced, I am happy to have conducted a real-life analytics project based on novel operations approaches. The fact that our findings will be implemented in the company’s business processes adds to my satisfaction.

BIBLIOGRAPHY

Aitken, J., Childerhouse, P., and Towill, D. (2003). The impact of product life cycle on supply chain strategy. *International Journal of Production Economics*, 85(2):127–140.

Alicke, K. and Forsting, M. (2017). Supply chain segmentation scientific frameworks. In *Supply Chain Segmentation*, pages 5–13. Springer.

Aydin Keskin, G. and Ozkan, C. (2013). Multiple criteria abc analysis with fcm clustering. *Journal of Industrial Engineering*, 2013.

Childerhouse, P., Aitken, J., and Towill, D. R. (2002). Analysis and design of focused demand chains. *Journal of Operations Management*, 20(6):675–689.

Christopher, M. and Towill, D. (2002). Developing market specific supply chain strategies. *The international journal of logistics management*, 13(1):1–14.

Dahlhaus, V., Menges, S., Alicke, K., and Lennartz, C. (2017). Gardena's segmentation in a volatile and seasonal market. In *Supply Chain Segmentation*, pages 47–54. Springer.

D'Alessandro, A. J. and Baveja, A. (2000). Divide and conquer: Rohm and haas' response to a changing specialty chemicals market. *Interfaces*, 30(6):1–16.

Ernst, R. and Cohen, M. A. (1990). Operations related groups (orgs): a clustering procedure for production/inventory systems. *Journal of Operations Management*, 9(4):574–598.

Fisher, M. L. (1997). What is the right supply chain for your product? *Harvard business review*, 75:105–117.

Frohlich, M. T. and Westbrook, R. (2001). Arcs of integration: an international study of supply chain strategies. *Journal of operations management*, 19(2):185–200.

Fuller, J. B., O'Conor, J., and Rawlinson, R. (1993). Tailored logistics: the next advantage. *Harvard Business Review*, 71(3):87–98.

Godsell, J., Diefenbach, T., Clemmow, C., Towill, D., and Christopher, M. (2011). Enabling supply chain segmentation through demand profiling. *International Journal of Physical Distribution & Logistics Management*.

Godsell, J., Harrison, A., Emberson, C., and Storey, J. (2006). Customer responsive supply chain strategy: an unnatural act? *International Journal of Logistics: Research and Applications*, 9(1):47–56.

Hathaway, R. J. and Bezdek, J. C. (2001). Fuzzy c-means clustering of incomplete data. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, 31(5):735–744.

Hill, T. (1995). *Manufacturing strategy: text and cases*. Macmillan International Higher Education.

Hoppe, M. (2006). *Inventory optimization with SAP*, volume 477. Sap Press Gaithersburg, MD.

Hou, Z., Qian, W., Huang, S., Hu, Q., and Nowinski, W. L. (2007). Regularized fuzzy c-means method for brain tissue clustering. *Pattern Recognition Letters*, 28(13):1788–1794.

Jenks, G. F. (1967). The data model concept in statistical mapping. *International yearbook of cartography*, 7:186–190.

King, P. L. and King, J. S. (2017). *Value stream mapping for the process industries: Creating a roadmap for lean transformation*. CRC Press.

Lambert, D. M. and Sharma, A. (1990). A customer-based competitive analysis for logistics decisions. *International Journal of Physical Distribution & Logistics Management*.

Lamming, R., Johnsen, T., Zheng, J., and Harland, C. (2000). An initial classification of supply networks. *International Journal of Operations & Production Management*.

Lee, H. L. (2002). Aligning supply chain strategies with product uncertainties. *California management review*, 44(3):105–119.

Lovell, A., Saw, R., and Stimson, J. (2005). Product value-density: managing diversity through supply chain segmentation. *The International Journal of Logistics Management*.

Nahmias, S. and Olsen, T. L. (2015). *Production and operations analysis*. Waveland Press.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., and Duchesnay, E. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830.

Protopappa-Sieke, M., Thonemann, U., and Thonemann, U. W. (2017). *Supply Chain Segmentation*. Springer.

Ramanathan, R. (2006). Abc inventory classification with multiple-criteria using weighted linear optimization. *Computers & operations research*, 33(3):695–700.

Roy, S., Alicke, K., and Forsting, M. (2017). Philips segmentation case study. In *Supply Chain Segmentation*, pages 27–36. Springer.

Saaty, T. L. (2003). Decision-making with the ahp: Why is the principal eigenvector necessary. *European journal of operational research*, 145(1):85–91.

Saaty, T. L. et al. (2008). Decision making with the analytic hierarchy process. *International journal of services sciences*, 1(1):83–98.

Schnetzler, M. J., Sennheiser, A., and Schönsleben, P. (2007). A decomposition-based approach for the development of a supply chain strategy. *International Journal of Production Economics*, 105(1):21–42.

Silver, E. A., Pyke, D. F., Peterson, R., et al. (1998). *Inventory management and production planning and scheduling*, volume 3. Wiley New York.

Smith, W. R. (1956). Product differentiation and market segmentation as alternative marketing strategies. *Journal of marketing*, 21(1):3–8.

Zhou, P. and Fan, L. (2007). A note on multi-criteria abc inventory classification using weighted linear optimization. *European journal of operational research*, 182(3):1488–1491.