A NOVEL FINISHED-GOODS INVENTORY MANAGEMENT PROCESS FOR BRISA

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Sabancı Üniversitesi

YAEM 2022, Pamukkale Üniversitesi, Denizli

November 26th, 2022

We would like to thank Brisa managers

- Ahmet Günenç,
- Nurhan Cenkmen,
- Melis Küçükerdal,
- Filiz Mert,
- İpek Emeksiz

for their valuable support and cooperation in this work

Brisa

5 **Brands**

Including Bridgestone & Lassa

4 **Sales Channels**

- 1300+ domestic sales points,
- Exports to 87 countries,
- Automotive OEMs

2 **Production Facilities**

- İzmit
- Aksaray

~ 1800 **SKUs**

~ 11 M

Tires produced in 2020

The Objectives

- We developed a novel process to determine the target finished goods (tire) inventory levels
- Triple objectives:
  - Minimize the total finished goods inventory
  - Increase product availability levels
  - Minimize production changeovers
- Three reasons to keep stock
  - **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 OEM channel.

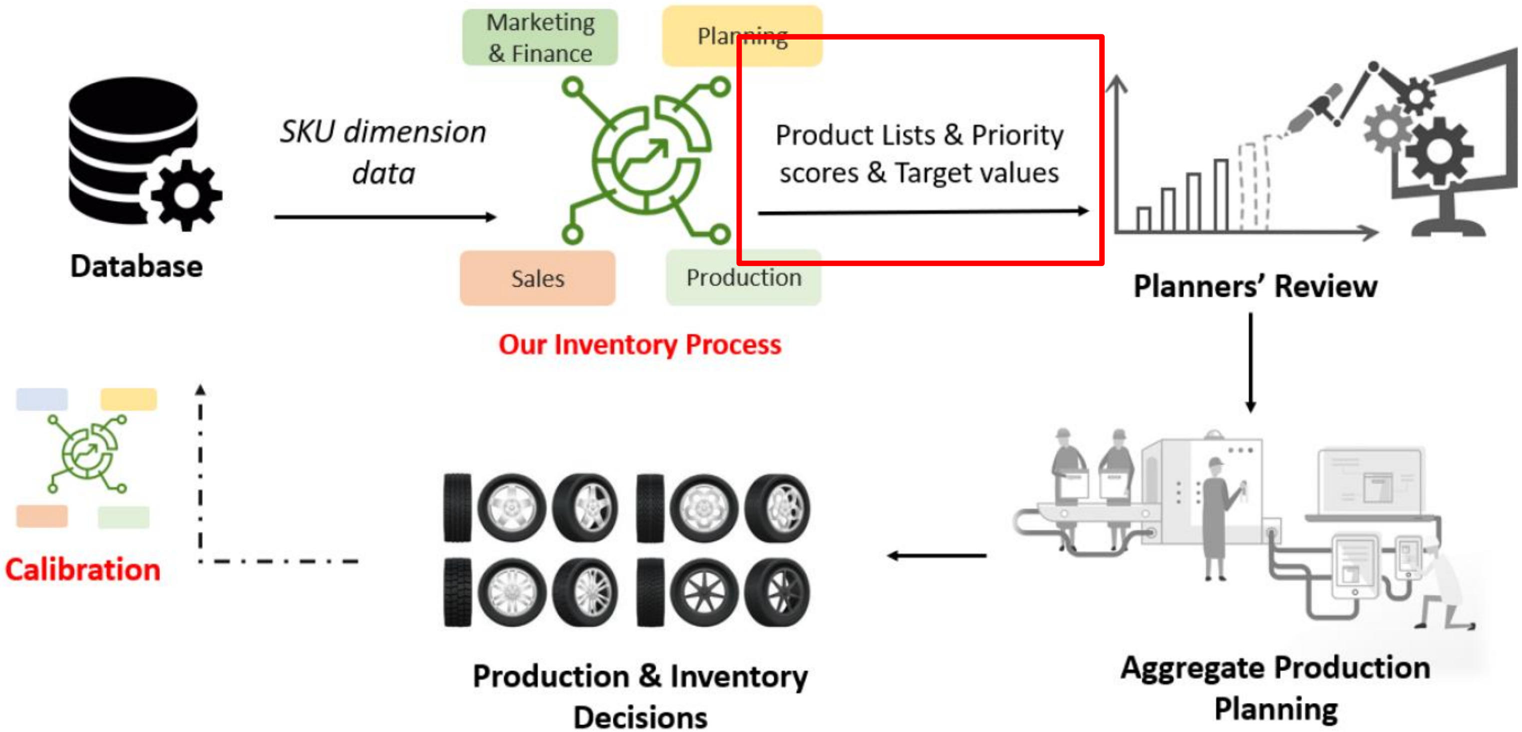
The Setting

- Production capacity 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.
- Production managers prefer producing in large batch sizes, especially for products that exhibit high “production complexity”
- The production rate for each SKU is also constrained by the number of “molds” for the product.
- Total amount of inventory investment is watched carefully.
- It is possible to have backorders in the RL channel, but not in the other channels.

Solution Approach

- For each of the three stock cases, we identified a number of product **dimensions** using which we determine and **prioritize** the candidate products (SKUs).
- 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 methodologies.

Place of Our Work in Company's Planning Process



- **Output**: Prioritized list of SKUs that fall into each of the three stock cases, together with their target weekly-cover values.

Data Description

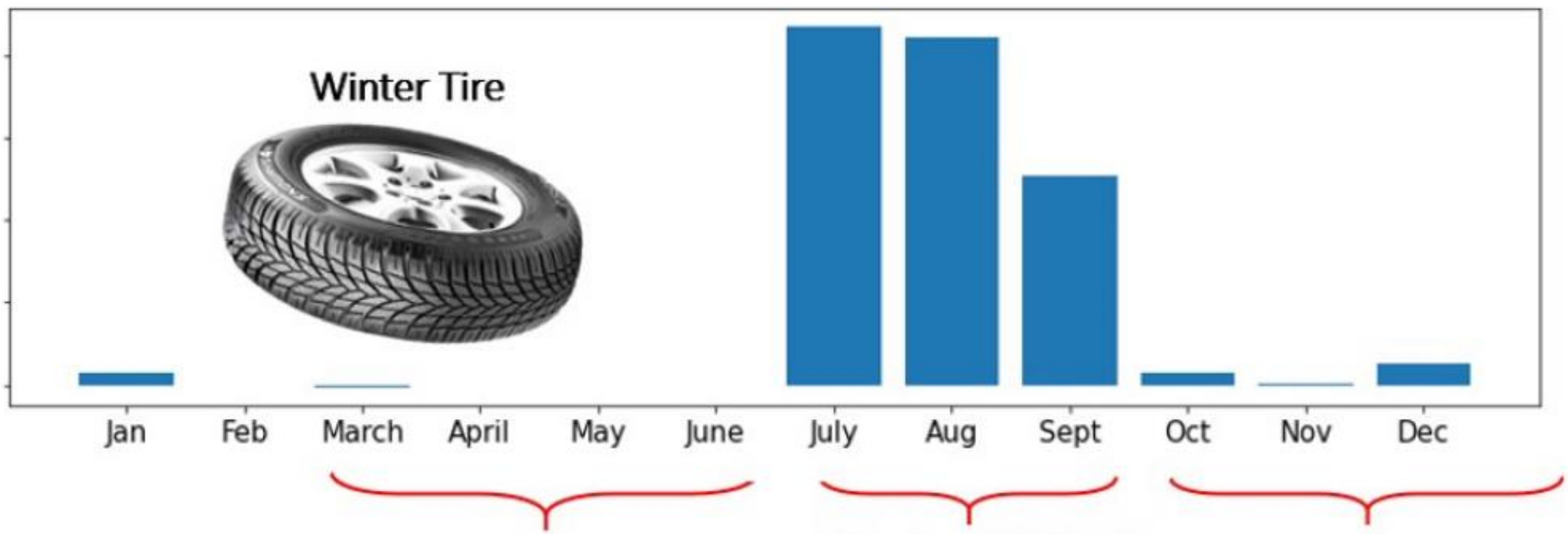
- More than 1000 SKUs, 105 attributes

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

1) Prebuild Stock Study

Demand Seasonality

Figure 3.2 Three Alternatives to Meet the Peak Demand



Pre-build inventory

Incurs inventory cost and risk

Produce within the peak demand months

- SKU-based mold capacity
- Overall capacity

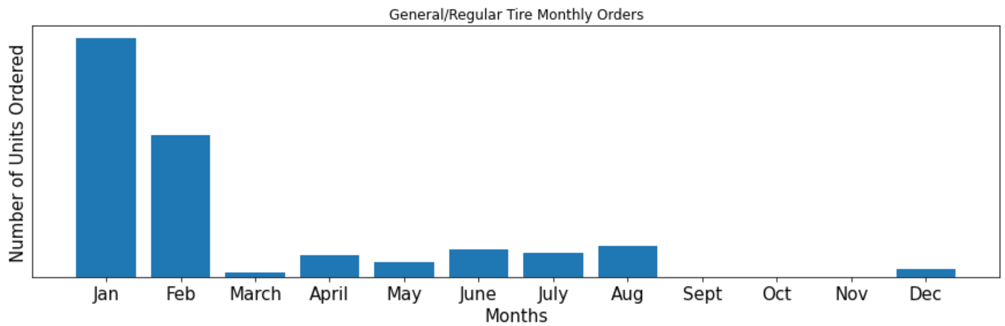
Backorder

- Dissatisfied dealers
- Order cancellations

Product Dimensions Used

1- Annual Sales

2- Seasonality: *The proportion of orders in the the top two months.*

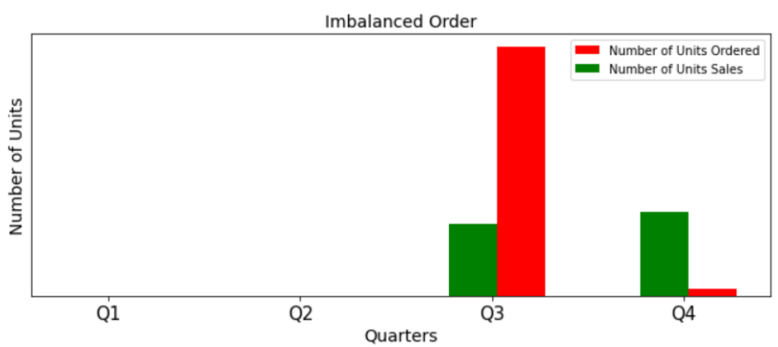


3- Capacity Insufficiency: $\dfrac{\textit{Demand in the peak month}}{\textit{Monthly production capacity in the peak month}}$

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

4- Backorder Tendency

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



The Scoring Approach

Prebuild Priority Score (PPS) $\boxed{= 0.161}$ $\times$ *(annual sales score)* $\boxed{+\ 0.060}$ $\times$ *(seasonality score)* $\boxed{+\ 0.485}$ $\times$ *(capacity insufficiency score)* $\boxed{+\ 0.294}$ $\times$ *(backorder tendency score).*

- Each of the four dimension scores have been **normalized** to [0,1]
- Weights determined through an **AHP study** with Brisa managers

- AHP comparison matrix:

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

Score Normalization for Each Dimension

Table 3.1 Percentile Parameter of Each Dimension

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

Figure 3.7 Annual Sales Dimension Orginal Measurements Box Plot

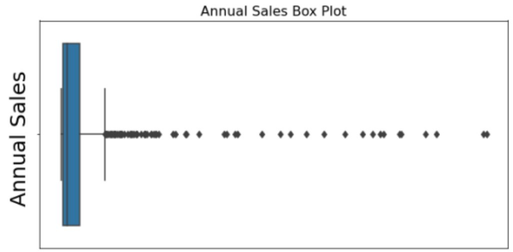
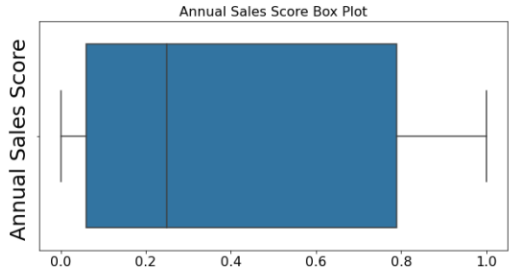


Figure 3.8 Annual Sales Transformed Scores Box Plot



Clustering in 4 Dimensions

- To reflect the different weights of the dimensions, we used a weighted Euclidean distance metric in agglomerative hierarchical clustering.

$$d(p,q,w) = \sqrt{\sum_{i=1}^{4} w_i (q_i - p_i)^2}$$

- Used the following Dendogram to determine the number of clusters (as 4).

Figure 3.12 Clustering Dendogram

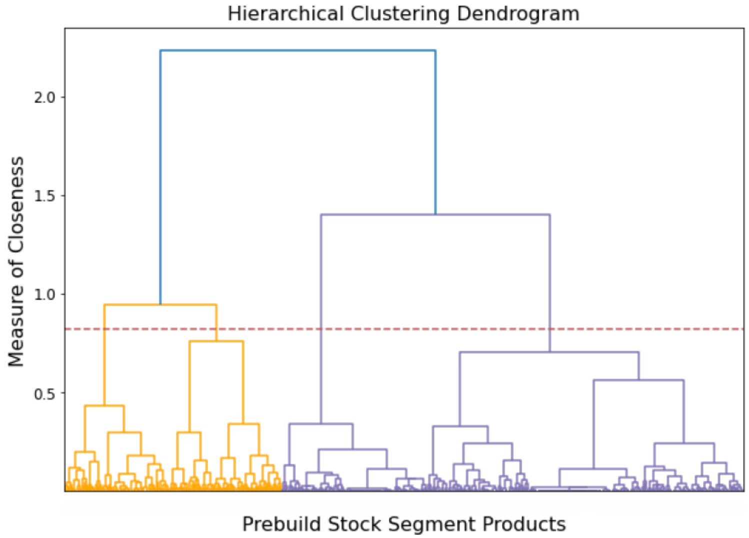


Table 3.6 Clustering with 4 Dimensions

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

Clustering in 3 Dimensions

- Seasonality dimension (6% weight) left out, used as filter
- k-means clustering with Weighted Euclidian Distance

Figure 3.14 Four Clusters Identified with the k-means Method

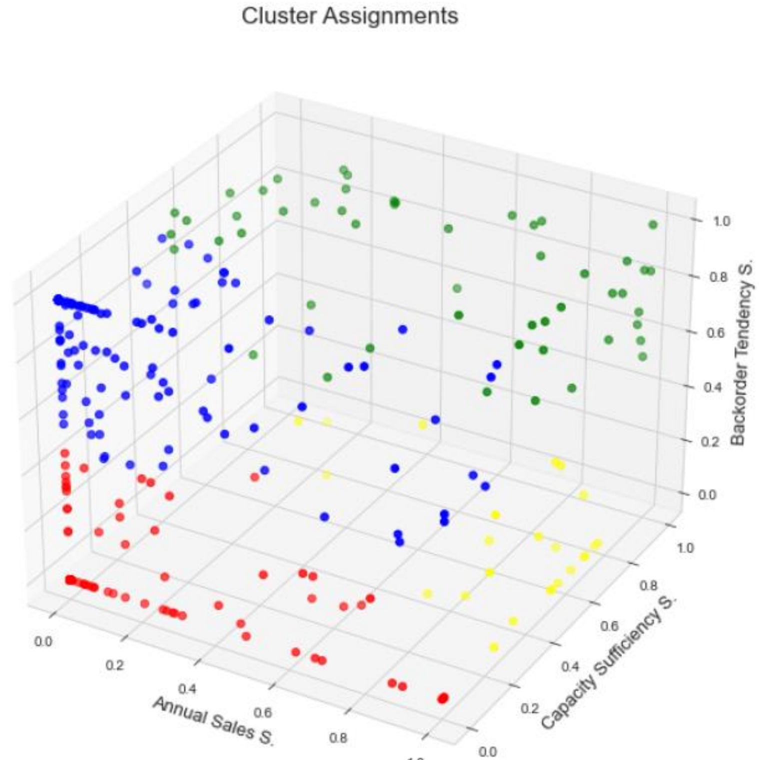


Figure 3.13 The Elbow Curve

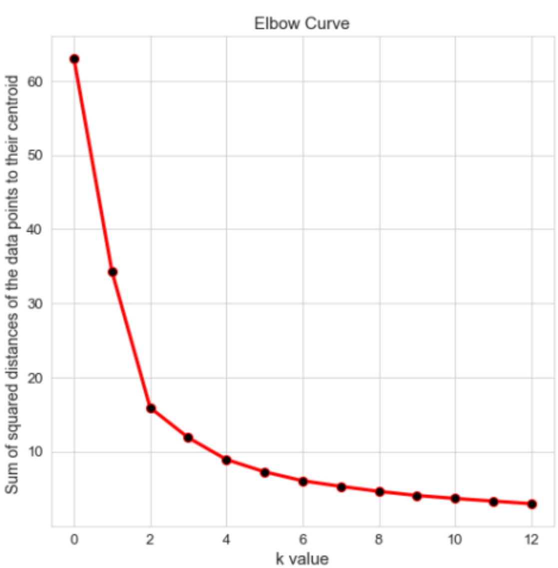


Table 3.7 Clustering in 3 Dimensions

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

Clustering in 2 Dimensions

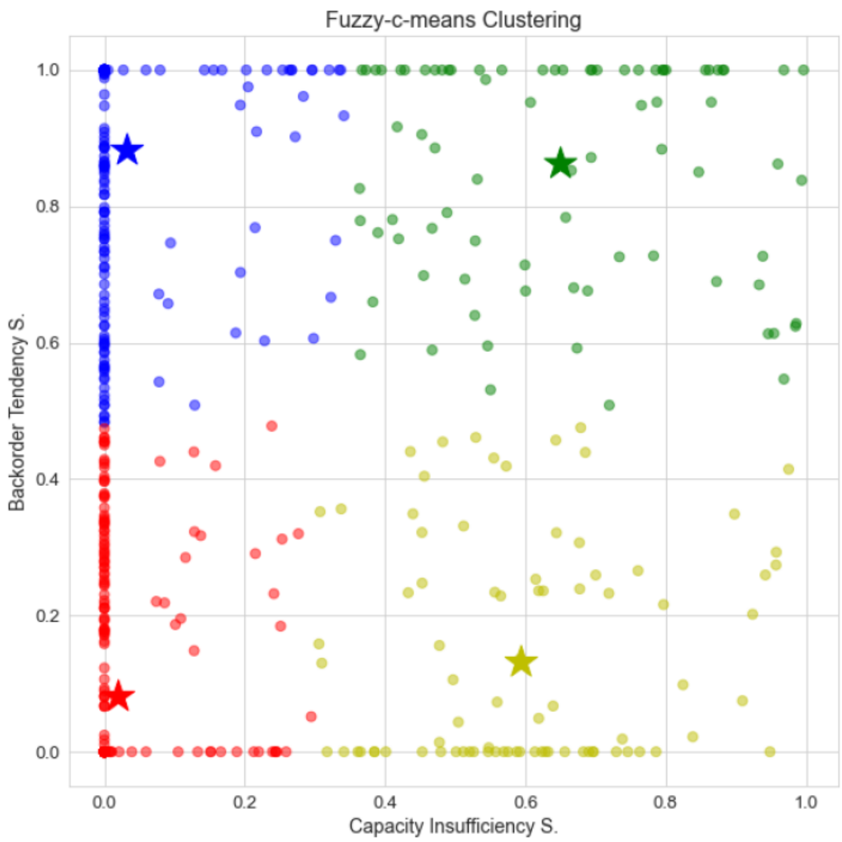
- Fuzzy c-means clustering (a soft clustering algorithm)
- Number of clusters chosen as 4
- Fuzziness parameter m=2 and termination criterion $\varepsilon=10^{-5}$

Table 3.8 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 parantheses.
* corresponds to the number of products in the cluster.

Figure 3.15 Fuzzy-c-means Clusters



Alternative: Decision Tree Classification Based on Non-Transformed Dimension Scores

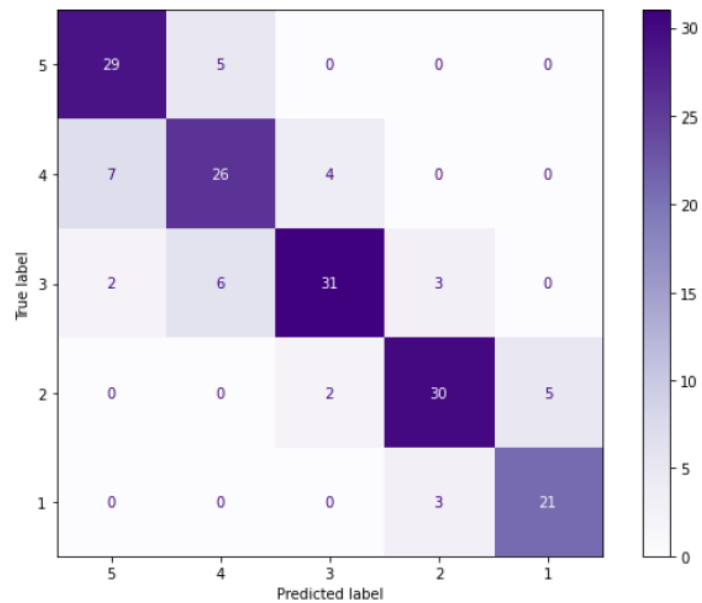
- To be used in new SKUs
- Five classes
- Decision tree classifier
- 70% training, 30% test
- Hyper-parameter tuning to improve the F1 scores of classes 1 and 2

Table 3.12 Decision Tree Classifier Results After Hyper-Parameter Tuni

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

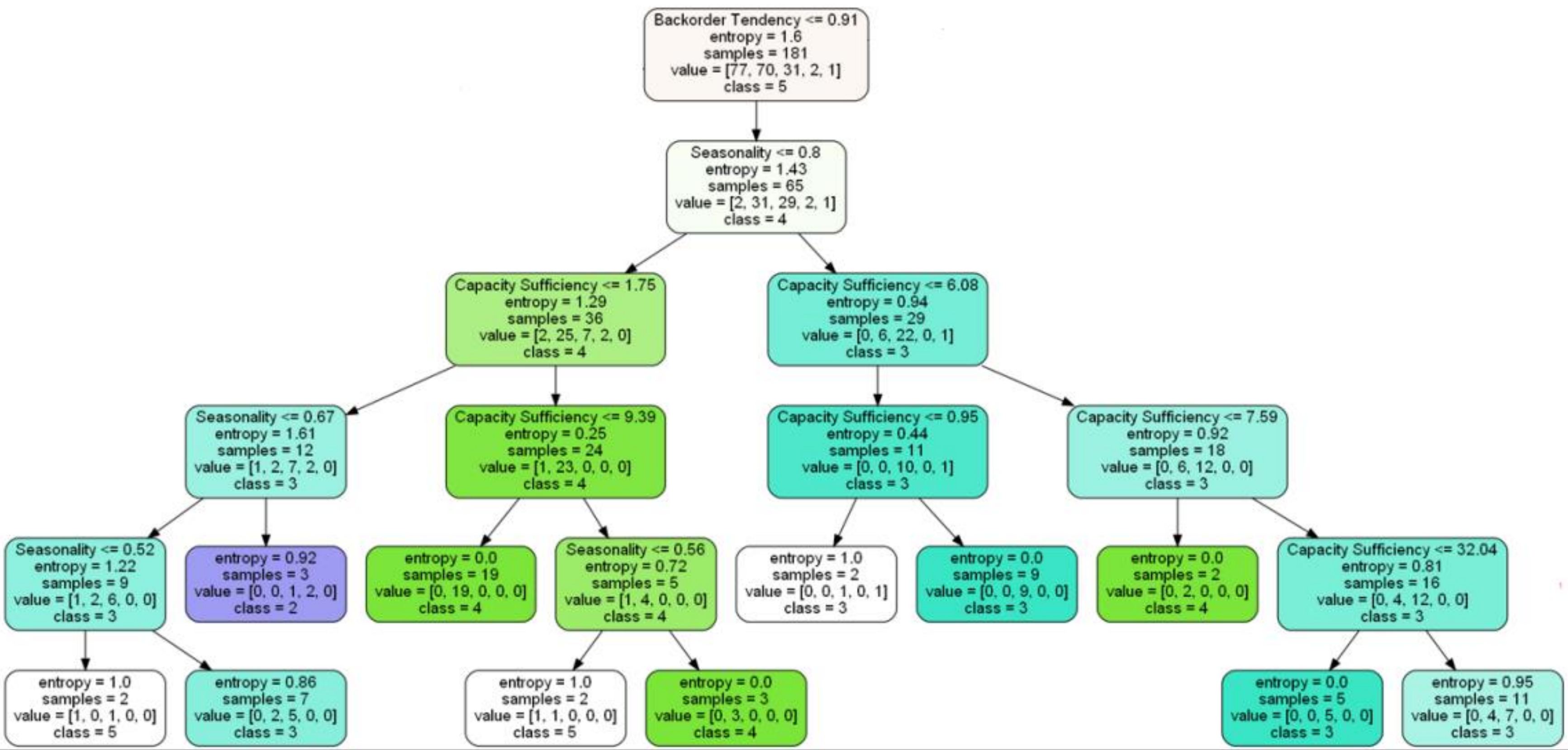
Figure 3.17 Correlation Heat Map

Figure 3.19 Improved Decision Tree Classifier Confusion Matrix



Alternative: Decision Tree Classification Based on Non-Transformed Dimension Scores

Figure 3.20 Decision Tree Classifier



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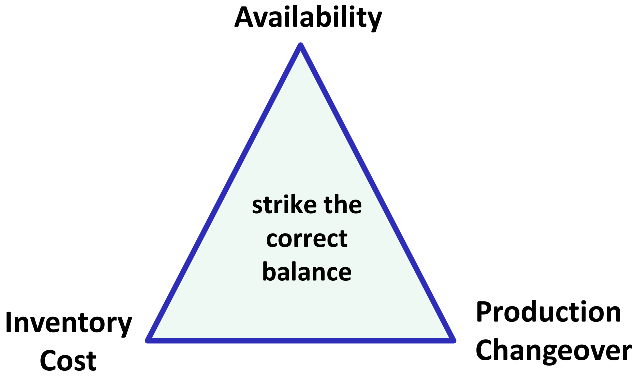
2) Cycle Stock Study

Strategic-Mix Products & Dimensions

Strategic-mix products

- High gross margin
- High importance for the company
- Relatively low sales volume
- Mostly, large-size tires

- Currently, these products are produced in relatively small batch sizes, causing high setup cost
- **Our approach: Produce in larger batch sizes**



Dimensions:

1- Strategic Priority
2- Production Complexity
3- Gross Margin
4- Inventory Turnover

Cycle Stock Priority Score = 0.45 × (strategic priority score) + 0.35 × (production complexity score) + 0.10 × (gross margin score) + 0.10 × (inventory turnover score).

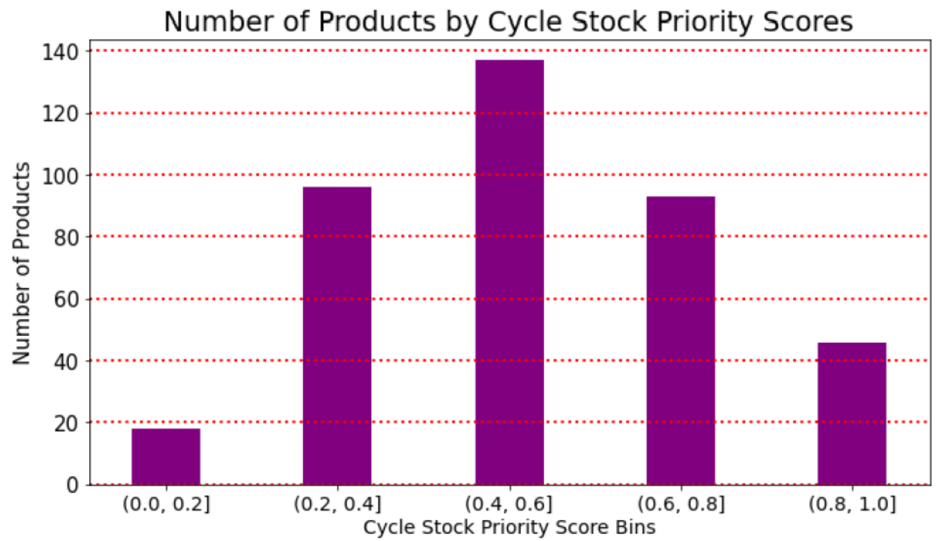


Table 4.2 Cycle Stock Priority Score Details for the Top 20 Products

Product ID	Strategic Priority Score	Complexity Score	GM Score	Inventory Score	Cycle Stoc Priority Scc
1	1.00	1.00	0.71	1.00	0.97
2	0.83	1.00	0.63	1.00	0.89
3	1.00	1.00	0.75	0.07	0.88
4	0.83	1.00	0.56	0.39	0.82

3) Safety Stock Study

Target Weekly Cover Value (TWCV)

- The OEM channel: Auto manufacturers, operating JIT
- Critical to offer high product availability levels
- Frequent updates to orders by OEMs

- Inventory set according to **Target Weekly Cover Value** (TWCV)
- **Current approach:** Keep inventory to cover the 2.5 weeks' forecast.
  - That is, TWCV=2.5 for all OEM SKUs
- **Our approach:** Customized and dynamic TWCV
  - product-dependent (between 2-5 weeks)
  - time-dependent (modified over months based on forecasts)

- Production decision if **Current Weekly Cover Value** (CWCV) < TWCV
  - Production may not start immediately due to constraints.

Capacity Utilization (CU) Definition

For each month t in the horizon, Capacity Utilization (CU) is

$$CU_t = Forecast_t \,/\, ProductionCapacity_t$$

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

Algorithm 1 TWCV Assignment

Data: Capacity Utilization: Forecast/Prod. Capacity

Result: Targeted Weekly Cover Value 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

| $TWCV_t = 5$

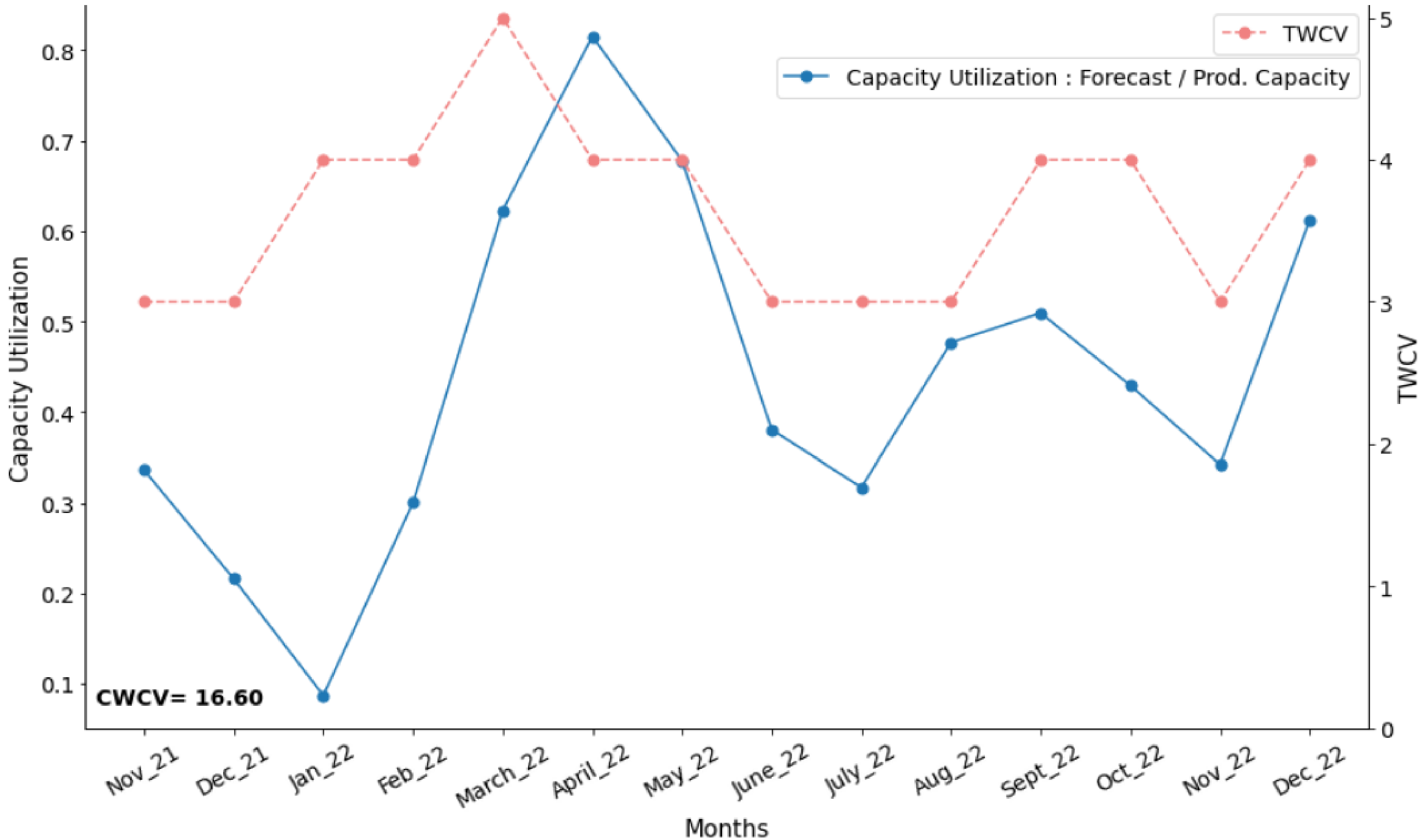
end

update t = t+1

end

W used for smoothing of TWCV values between consecutive months

CU & TWCV for a Sample Product



Discussion & Conclusions

- Current status: Being implemented by the Analytics department of the company

- Other questions that our study sheds light on
  - 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 weekly cover inventory levels?

Discussion & Conclusions

- Other potential product dimensions for segmentation
  - forecast accuracy
  - product substitutability (with alternative tires that the company produces)
  - the lifecycle stage (introduction, ramp up, maturity, soon-to-be delisted etc.)
  - supply risk (related to raw material procurement)

Thanks for your interest ☺
Questions?

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