

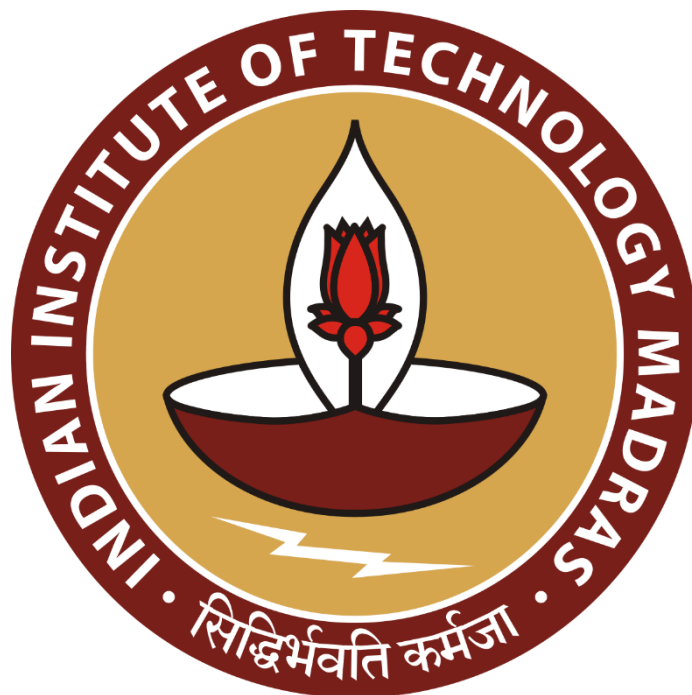
# **Optimizing storage constraints and efficient employment of capital among different categories of products in a versatile shop**

**Final report for the BDM Capstone Project**

Submitted by

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# 1. Executive Summary

The final report contains a comprehensive study addressing the company's challenges and suggesting data-driven recommendations.

The focus of the study is the company's ice cream division. It attempts to shed important information on the seasonality problems with a few products and develop a bulk storage system to address product shortages and price swings.

Twenty-five products—referred to as products of concern (POC)—are identified using Pareto analysis as having the highest income. These products are then given priority. The POCs are divided into four groups according to . There were daily, weekly, and biweekly product demand stability tests. Regression analysis, along with correlation analysis, sheds light on connected POCs' selling trends and the needs that go along with them. The amount of storage space needed for these products can be calculated using the information provided.

The products on which the company is spending the most and their variable pricing are identified by the supply analysis.

After compiling all of the analysis's findings, research was conducted looking at product categories to determine the best storage solution.

Link for the complete Dataset file : <https://shorturl.at/mFHI3>

Based on the study, the following few recommendations are made, which the firm can look into:

- I. The company is spending a lot of money on certain goods that aren't POCs and can be modified to meet their needs.
- II. Certain POCs have relatively consistent demand across a range of time periods and a concurrent change in price. They can be bulk purchased during the off-season, depending on how much storage space they demand.
- III. Non-food product categories like clay, wood, paper, and plastic can be stored with the varnish category of goods without posing a risk of contamination.

A comprehensive list of recommendations is included at the end of this report under the heading "Recommendations".

## **2. Research Methodology**

### **2.1. Products of Concern Identification**

According to the sales data, the firm sells 131 different products only in the ice cream segment. To analyse such a high number of products is neither feasible nor required. It is seen that 20% of the products are generally responsible for 80% of the total revenue. These are the most important products for any business. So, in this project this theory is applied to identify the most important products and are given the name Products Of Concern (POC).

A revenue pareto analysis is useful to validate this 80-20 relationship and hence identify the POCs.

The overall demand trends, demand frequency, storage requirements and price fluctuations of these POCs will help to solve the majority of the issues the business is having.

### **2.2. Categorization of POCs**

Not all POCs hold the same importance in terms of their revenue-generating prowess. So, the POCs need to be further categorized based on their average sales volume and unit price. The product categorization is done on the following basis:

- ❖ Fast selling and Expensive: These products generate the maximum revenue. Their unit price and their average sales frequencies are high. Which means higher revenue and lower inventory days. In terms of storage space, they must be given the highest priority.
- ❖ Fast selling and low cost: These products are sold fast but their unit price is on the lower side. So, their priority in the storage mechanism is lower than category 1.
- ❖ Slow selling and high cost: These products have higher unit prices but they remain idle in the inventory for longer durations (higher inventory days). Depending upon the storage space they consume they are given more or less priority than category 2.

- ❖ Slow selling and low cost: The last category is for products which do not generate much revenue and the chances of them being sold daily are also lower. In the category of the POCs, they are the least prioritized items.

To categorize the POCs in these groups, their standardized packaged price and standardized average daily demand are calculated and a scatterplot between these two variables for all the POCs is plotted. To distinguish the categories median value of the variables is used as a reference.

### 2.2.1. Calculation of standardized daily demand and price

In the following example the method used for calculating the standardized daily average demand and standardized average price is demonstrated.

POC: 37 Pepsi roll

Total quantity sold (in Pieces) = 625, Total business days during Jan-May = 123

Average daily sells (in pieces) =  $\frac{625}{123} = 5.08$

Standard packaging size (in pieces) = 20

Standardized average daily demand =  $\frac{5.08}{20} = 0.254$

Average single unit price (in ₹) = 290.02

Standardized average price of whole package (in ₹) =  $290.02 \times 20 = 5800.31$

## 2.3. Demand Analysis

Demand analysis is simply a time series analysis of the quantity demanded of different POCs. This analysis is done on the daily, weekly and biweekly scale. The different time scales are chosen to analyse the demand trends and forecasting.

Daily demand studies give a good understanding of average daily sales and daily inventory management but are too granular to see any seasonality, trend analysis or forecasting.

Weekly and biweekly demand trends provide a more aggregated view of product demands, which can be useful for strategic planning against market disruption and seasonality aspects.

Although monthly trends were also analysed, it provided too broad a view to get any insights and thus is not taken into consideration.

Demand trends:

- ❖ **Strict Stationary demands:** demand remains stationary over any time scale. In the mathematical sense, the mean, variance and covariance is time independent. Inventory management of products having stationary demand is easy. Since over any time period the demand is constant products can be bulk stored for the entire season considering other parameters like price fluctuation and storage space requirement.
- ❖ **Season Stationary demands:** Seasonality in demand is observed here. On the daily scale, demand remains stationary but on the weekly or bi-weekly scale, non-stationarity in demand is observed. Inventory of products having this type of demand needs to be monitored carefully as overstocking may result in products remaining idle in storage, occupying storage and other resources, at the same time stocking less may lead to loss of revenue.
- ❖ **Non-Stationary demands:** Here the demand is fluctuating in nature suggesting trends in demand. Products which fall in this category are to be minimally stocked.

The most basic method for checking demand trends is to graphically plot the quantity demanded as a function of time and then visually observe for any trends or seasonality, but this method is error-prone, subject to the observing skills and personal bias of the observer.

Thus, a more scientific and unbiased approach will be a statistical hypothesis test which involves a null and an alternate hypothesis. Based upon the time series data for individual products the test will either reject or will fail to reject the null hypothesis.

The statistical test that has been used in this project is called the Augmented Dickey-Fuller (ADF) test.

### 2.3.1. Augmented Dickey-Fuller (ADF) test

The Augmented Dickey-Fuller (ADF) test is an autoregressive time series test which tests for the existence of a unit root in the data. A unit root present in a time series model signifies

non-stationarity. Thus, a tested model having a unit root means the tested component is non-stationary and vice versa.

The test equation is given as,

$$y_t = c + \beta t + \alpha y_{t-1} + \varphi_1 \Delta y_{t-1} + \varphi_2 \Delta y_{t-2} + \dots + \varphi_p \Delta y_{t-p} + \epsilon_t \dots (1)$$

where,  $y_t$  is the variable of interest at the current time  $t$  (in this case quantity demanded), and  $p$  is the lag order of the autoregressive process.

$c$  is a constant,  $\beta$  the coefficient on a time trend,  $\alpha$  is the unit root coefficient and  $\epsilon$  is the error term.

- ❖ Null hypothesis ( $H_0$ ) : time series is **Non-Stationary**, presence of unit root.
- ❖ Alternate hypothesis ( $H_1$ ) : time series is **Stationary**. Series has no unit root.

Conditions to reject Null hypothesis:

- ❖ If the test statistics < critical value of Dickey-Fuller t-distribution and p-value < 0.05  
→ **Reject the Null hypothesis ( $H_0$ )** i.e. time series does not have a unit root, meaning it is stationary and does not have a time-dependent structure.

The python implementation of the testing for a single POC is demonstrated below:

```
#load the required libraries
import numpy as np
import pandas as pd

# Load Statsmodels
import statsmodels.api as sm

# Load Matplotlib for visualization
import matplotlib.pyplot as plt
%matplotlib inline
#loading data Heatmap of Pearson correlation coefficient between POCs

data=pd.ExcelFile("demand trend.xlsx")
week_data=pd.read_excel(data,'weekly demand')
twoweeks_data=pd.read_excel(data,'fortnight demand')
month_data=pd.read_excel(data,'monthly demand')
week_data.index=week_data['Row Labels']
del week_data['Row Labels']
```

```

from statsmodels.tsa.stattools import adfuller
def adf_test(timeseries):
    print (f'Results of Dickey-Fuller Test for item: 37 pepsi roll')
    dfctest = adfuller(timeseries, autolag='AIC')
    dfcoutput = pd.Series(dfctest[0:4], index=['Test Statistic','p-value','#Lags
Used','Number of Observations Used'])
    for key,value in dfctest[4].items():
        dfcoutput['Critical Value (%s)'%key] = value
    return (dfcoutput)
# Call the function and run the test Heatmap of Pearson correlation
coefficient between POCs
print(adf_test(week_data['37 pepsi roll']))

```

*Figure 1: Python implementation of ADF test*

```

Results of Dickey-Fuller Test for item: 37 pepsi roll
Test Statistic          -3.927910
p-value                  0.001839
#Lags Used              9.000000
Number of Observations Used 12.000000
Critical Value (1%)      -4.137829
Critical Value (5%)      -3.154972
Critical Value (10%)     -2.714477
dtype: float64

```

## 2.4. Correlation Analysis

There are twenty-five different POCs and all are required to make a similar type of finished product that is some variety of ice cream or frozen dessert. It is intuitive to think that some products will act as complements to each other and some can substitute one another i.e. there must be a positive and/or negative correlation between products. To efficiently store the product these relations need to be observed. A statistical method called correlation analysis provides the strength of association between different labels.

For simplicity a Pearson correlation coefficient ( $r$ ) is used as the measuring parameter. It measures the linear correlation between two datasets. The correlation coefficient always lies between -1 and +1 i.e.  $-1 < r < 1$ . Once the relationship among the POCs is found, the required quantity of products that need to be stored in the go-downs can be forecasted by a regression analysis.



## 2.5. Regression Analysis

Regression analysis between correlated POCs can uncover how much one product is demanded in terms of the demand of the other products which either complement or substitute this product.

Example: Suppose sales of products 1,2, 3,...,n are related to each other by the relation

$$Q_X = a_0 + a_1 \times Q_1 + a_2 \times Q_2 + \cdots + a_n \times Q_n \quad \text{..... (2)}$$

Where Q is the quantity of demand,  $a_0$  constant and  $a_0, a_1, \dots, a_n$  are coefficients of demand for  $Q_1, Q_2, \dots, Q_n$  respectively.

## 2.6. Purchase Pareto Analysis

Purchasing analysis needs to be done to understand the purchasing pattern of the firm. It reveals which products the firm spends mostly on, are they fall in line with the POCs, their storage requirements etc.

A Pareto analysis of product cost on purchase among different products will be sufficient to answer these questions.

This is very crucial since, if the firm is spending significant capital on some products which do not have a constant demand or are not significant revenue generators, then purchasing and storing them in bulk will result in a blockade of storage space as well as inefficient employment of capital.

## 2.7. Purchase Price Fluctuation Analysis

A regular price fluctuation can cause a significant loss of profit for the business and can also cause supply disruption. Thus a price fluctuation analysis of the purchasing price of different POCs needs to be done.

The ice cream segment of the business is highly competitive due to the highly regulated pricing of the raw materials and competition in the market. Not only competition with the business rivals but competition with the big conglomerates like Amul, Kwality Wall's, Metro,

Mother Dairy and regional semi conglomerates like Arun Ice Cream, Vadilal etc. These players mainly control the ice cream and frozen desserts segment with a vast variety of products, pricing, attractive packaging and certainly with their big brand name. Although the small ice cream manufacturing firms produce comparable quality products, they cannot compete with the sheer infrastructure of these giants and the price at which they offer the finished products. Thus, over the years, the segment has become very sensitive about the prices of the raw materials. Thus profitability of firms like NANDI VARIETY depends solely upon how timely and accurately they manage their inventory and since the margin of profit is around approximately 5 % ( $\pm 1\%$ ) . Thus, any POCs having price fluctuation of greater or equal to 5% has been considered as products with fluctuating price and needs attention.

## 2.8.Product Category Analysis

An efficient storage management needs to utilize all the space it has. During one of the initial surveys, it was observed that the firm does not store anything with the varnish products. This immediately points towards vacant unused spaces which can be used to store non-edible products.

A qualitative analysis of the broader category into which the products can be classified according to their storage needs, storage space requirements and product type needs to be done. Each 131 products can be categorized according to their nature, usage, and storage volume into different categories.

Depending on the type of the products all the products can be categorised into seven categories namely, powder and crystalline products (42 % revenue), Plastic products (28 % revenue), Vegetable Oil (7% revenue), Ice Cream Cones (7% revenue), Essence, food colours, Emulsions and syrups (8% revenue), Wooden products (7% revenue), Paper, Ancillary and Clay products (1% revenue).

### 3. Results and Findings

#### 3.1. Identification of POCs

Revenue side Pareto analysis identifies 25 products of a total of 131 products which generate 80% of the revenue of the ice cream division, they are identified as POCs.

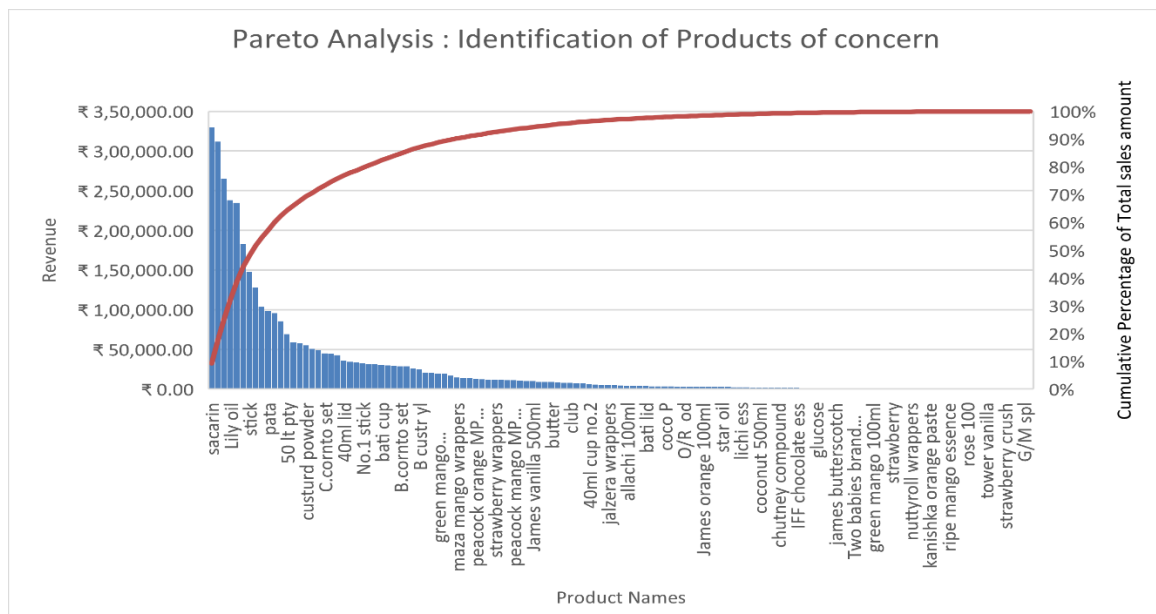


Figure 2: Revenue Pareto chart to identify most revenue-generating products (POCs)

The POCs are listed in following table 1:

sacarin	swtx	mini chocobar wrappers	Lily oil	chocopaste
37 pepsi roll	stick	jack	kulfi wrappers	No.1 CMC
40ml cup	pata	suji	citric	50 lt pty
orange wrappers	glass cup	custurd powder	C.cornito set	No.1 suji
milkbar wrappers	40ml lid	CMC	cocont dst	No.1 stick

Table 1: List of POCs

### 3.2. Categorization of POCs

A scatterplot between the average unit price and average quantity sold daily shows all POCs as data points. The horizontal and vertical line is drawn taking the median standardized average price and standardized average quantity sold daily as the reference.

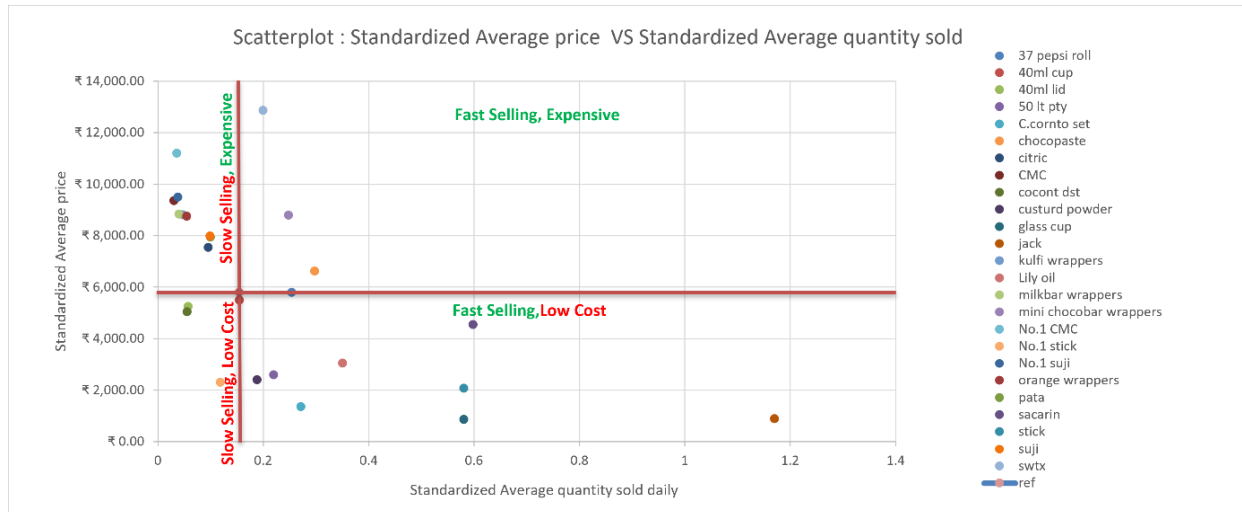


Figure 3: Scatterplot of POCs according to their average price and average daily sales

The reference value of standardized average quantity = **0.154** and standardized average price (in ₹) = **5800.31**

Table 2 shows the priority-wise categorization of the POCs, the priorities are categorized in decreasing order as High, medium and low.

Priority Rating	Demand Type	Price Type	POCs
HIGH	Fast selling	Expensive	<ul style="list-style-type: none"> <li>37 Pepsi roll, Chocopaste, Mini chocobar wrappers, Swtx.</li> </ul>
MEDIUM	Fast selling	Low cost	<ul style="list-style-type: none"> <li>40 ml cup, 50 lt pty, C.cornetto set, Custurd Powder, Glass cup, Jack, Lily oil, Sacarin, Sticks,</li> </ul>
MEDIUM	Slow Selling	Expensive	<ul style="list-style-type: none"> <li>Citric, CMC, Kulfi wrappers, Milkbar wrappers, No.1 CMC, No.1 suji, Orange wrappers, Pata, Suji.</li> </ul>
LOW	Slow Selling	Low Cost	<ul style="list-style-type: none"> <li>40ml lid, Coconut dust, No.1 Stick.</li> </ul>

Table 2: Priority-wise categorization of POCs

### 3.3.Demand Trends using the ADF test

ADF test analysis on the weekly demand data is tabulated in Table 4 using the below test condition. Only the weekly data is tabulated in this report for demonstration, for the complete daily, weekly, biweekly and monthly data please follow this link: <https://shorturl.at/iMSWZ>

Reject Null hypothesis ( $H_0$ ): **P-value < significance level** and **Test statistic < critical value**

Item Name	Test Statistic	p-value	critical value at 5% level
37 pepsi roll	-3.928	0.002	-3.155
40ml cup	-1.265	0.645	-3.031
40ml lid	-0.170	0.942	-3.155
50 lt pty	-3.837	0.003	-3.013
C.cornto set	-3.503	0.008	-3.155
chocopaste	-3.656	0.005	-3.104
citric	-1.406	0.579	-3.155
CMC	-1.893	0.335	-3.013
cocont dst	-9.727	0.000	-3.155
custurd powder	-1.365	0.599	-3.155
glass cup	0.197	0.972	-3.155
jack	29.719	1.000	-3.155

Item Name	Test Statistic	p-value	critical value at 5% level
kulfi wrappers	-5.488	0.000	-3.155
Lily oil	-0.340	0.920	-3.127
milkbar wrappers	-1.441	0.563	-3.155
mini chocobar wrappers	-2.382	0.147	-3.104
No.1 CMC	-4.494	0.000	-3.013
No.1 stick	-2.738	0.068	-3.155
No.1 suji	-3.506	0.008	-3.155
orange wrappers	-1.909	0.328	-3.155
pata	-1.786	0.388	-3.155
sacarin	-2.553	0.103	-3.013
stick	-1.748	0.407	-3.085
suji	-1.354	0.604	-3.155
swtx	-1.094	0.717	-3.155

Table 3: ADF test statistics and p-value at 5% significance level of POCs

Based on Table 3, those POCs for which the Null hypothesis fails are labelled as stationary i.e. their demand remains Stationary in the tested time period and those for which the Null hypothesis holds are labelled as Non-Stationary i.e., they have time-dependent demands.

Table 4 summarises the results obtained for daily, weekly, bi-weekly and monthly data with POCs and their demand labels mentioned with it.

Item Name	Day	week	two weeks	Month
37 pepsi roll	Non Stationary	Stationary	Non Stationary	Non Stationary
40ml cup	Stationary	Non Stationary	Non Stationary	Non Stationary
40ml lid	Stationary	Non Stationary	Non Stationary	Non Stationary
50 lt pty	Stationary	Stationary	Non Stationary	Non Stationary
C.cornto set	Stationary	Stationary	Non Stationary	Non Stationary
chocopaste	Non Stationary	Stationary	Stationary	Non Stationary
citric	Stationary	Non Stationary	Stationary	Non Stationary
CMC	Non Stationary	Non Stationary	Non Stationary	Non Stationary
cocont dst	Stationary	Stationary	Non Stationary	Non Stationary
custurd powder	Stationary	Non Stationary	Non Stationary	Non Stationary
glass cup	Stationary	Non Stationary	Non Stationary	Non Stationary
jack	Stationary	Non Stationary	Non Stationary	Non Stationary

Item Name	Day	week	two weeks	month
kulfi wrappers	Non Stationary	Stationary	Non Stationary	Non Stationary
Lily oil	Stationary	Non Stationary	Non Stationary	Non Stationary
milkbar wrappers	Stationary	Non Stationary	Non Stationary	Non Stationary
mini chocobar wrappers	Non Stationary	Non Stationary	Stationary	Non Stationary
No.1 CMC	Stationary	Stationary	Non Stationary	Non Stationary
No.1 stick	Stationary	Non Stationary	Non Stationary	Non Stationary
No.1 suji	Non Stationary	Stationary	Non Stationary	Non Stationary
orange wrappers	Stationary	Non Stationary	Non Stationary	Non Stationary
pata	Stationary	Non Stationary	Non Stationary	Non Stationary
sacarin	Stationary	Non Stationary	Stationary	Non Stationary
stick	Stationary	Non Stationary	Non Stationary	Non Stationary
suji	Stationary	Non Stationary	Non Stationary	Non Stationary
swtx	Stationary	Non Stationary	Non Stationary	Non Stationary

Table 4: ADF test on demand of POCs on daily, weekly, two weekly, monthly time scale

It can be observed that most of the POCs present stationary demand on a daily scale and non-stationary demands on a monthly scale. Since daily and monthly scales don't provide any insights into the demand trends of the POCs, weekly and two-week data are analysed only.

Based on the data the following inference can be made:

- ❖ **Strict Stationary demands:** Chocopaste.
- ❖ **Season Stationary demands:** 37 Pepsi roll, Citric, Mini chocobar Wrappers, Sacarin, 50 lt pty, C.Cornetto sets, Coconut dust, Kulfi Wrappers, No.1 CMC, No.1 Suji.
- ❖ **Non-Stationary demands:** 40 ml cup, 40 ml lid, CMC, Custurd powder, Glass cup, Jack, Lily oil, Milkbar Wrappers, No.1 Stick, Orange Wrappers, Pata, Stick, Suji, Swtx.

### 3.4. Purchase price fluctuations

Pocs having purchase price fluctuations greater than or equal to 5% are demonstrated in the following charts.

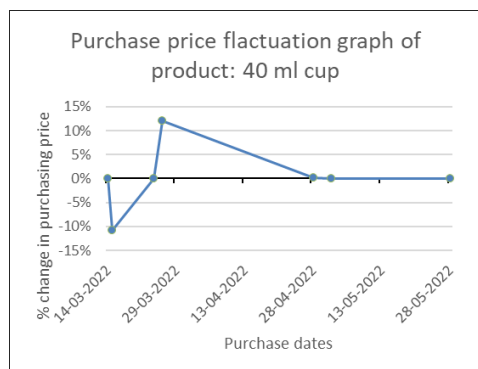


Chart 1: price fluctuation of 40 ml cup

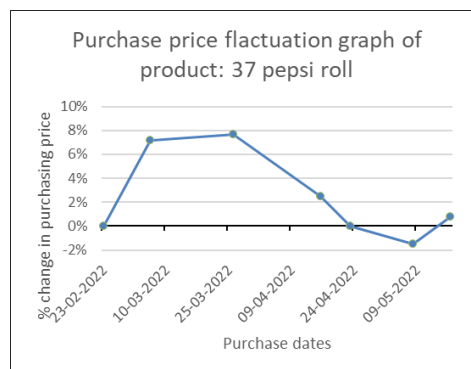


Chart 2: price fluctuation of 37 pepsi roll

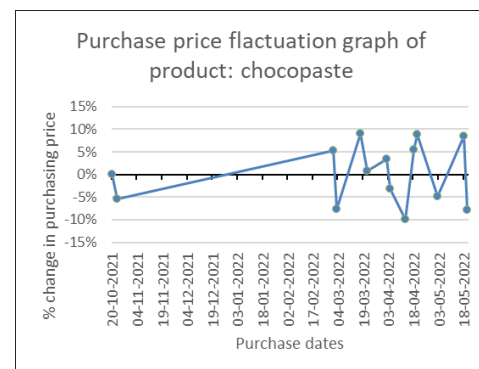


Chart 3: price fluctuation of chocopaste

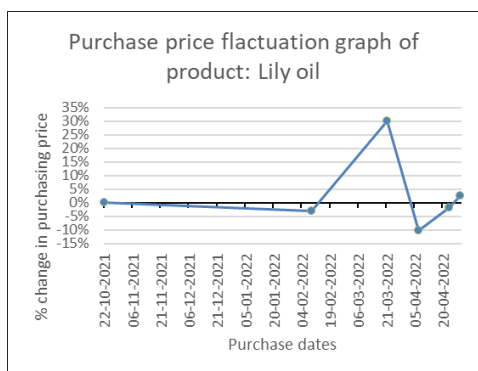


Chart 4: price fluctuation of Lily oil

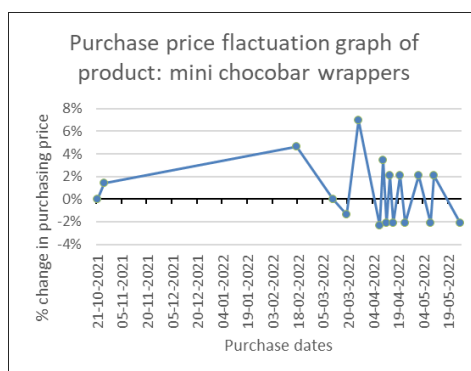


Chart 5: price fluctuation of mini chocobar wrappers

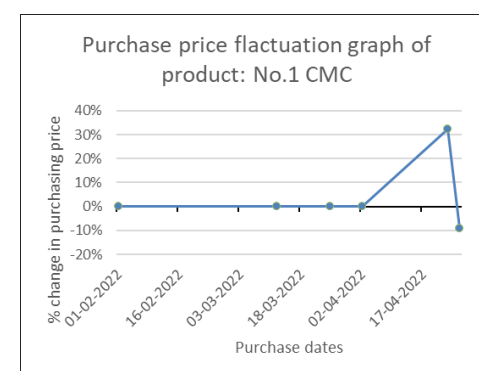


Chart 6: price fluctuation of No.1 CMC

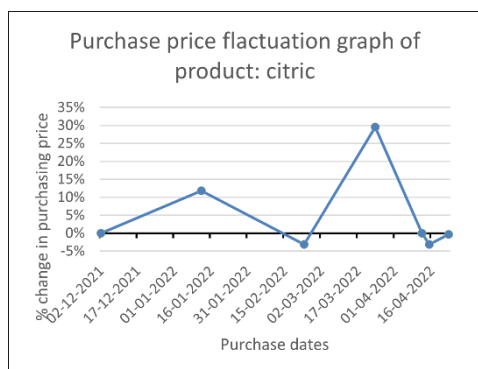


Chart 7: price fluctuation of citric

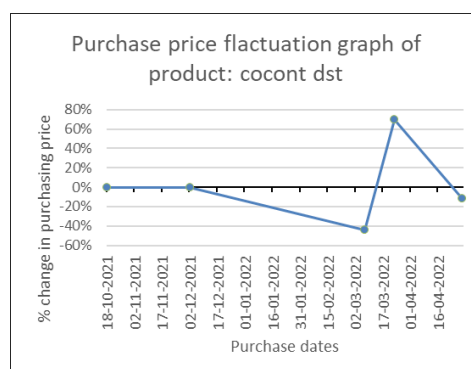


Chart 8: price fluctuation of coconut dust

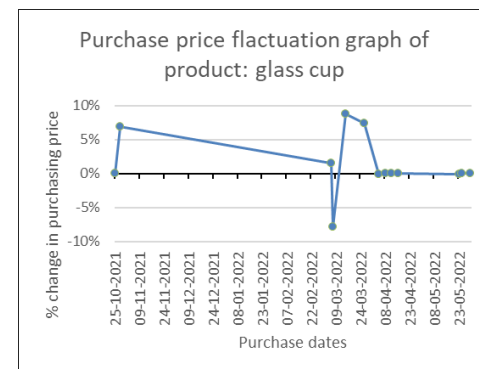


Chart 9: price fluctuation of glass cup

Figure 4: Price fluctuation charts of those POCs whose price fluctuation is 5% or more

POCs identified with fluctuating demands: 40 ml cup, 37 Pepsi roll, Chocopaste, Citric, Coconut dust, Glass cup, Lily oil, Mini chocobar wrappers, No.1 CMC.

POCs whose purchasing prices are fluctuating and/or which are categorized as medium to high priority and/or demand either stationary or season stationary are to be bulk stored during the off season. These are listed in Table 5.

POCs	Priority	demands	price fluctuations
37 pepsi roll	High	season stationary	price swings
chocopaste		Strict stationary	price swings
mini chocobar Wrappers		season stationary	price swings
50 lt pty	Medium	season stationary	stable price
C.cornetto set		season stationary	stable price
Glass cup		Non-staionary	price swings
Lily oil		Non-staionary	price swings
Sacarin		season stationary	stable price
Citric		season stationary	price swings
Kulfi Wrappers		season stationary	stable price
NO.1 CMC		season stationary	price swings
NO.1 Suji		season stationary	stable price
coconut dust	Low	season stationary	price swings

Table 5: List of POCs that needs to be bulk stored in go-downs

### 3.5. Identification of Additional Correlated POCs

Once the identification of POCs that need to be bulk stored is done, any POCs whose demands directly related with these POCs are to be stored such that there is no drop of demand on one essential POC due to the unavailability of its complement POC.

A correlation analysis done on the daily demands of POCs reveal some highly correlated POCs. A heatmap in figure 5 is plotted to demonstrate this

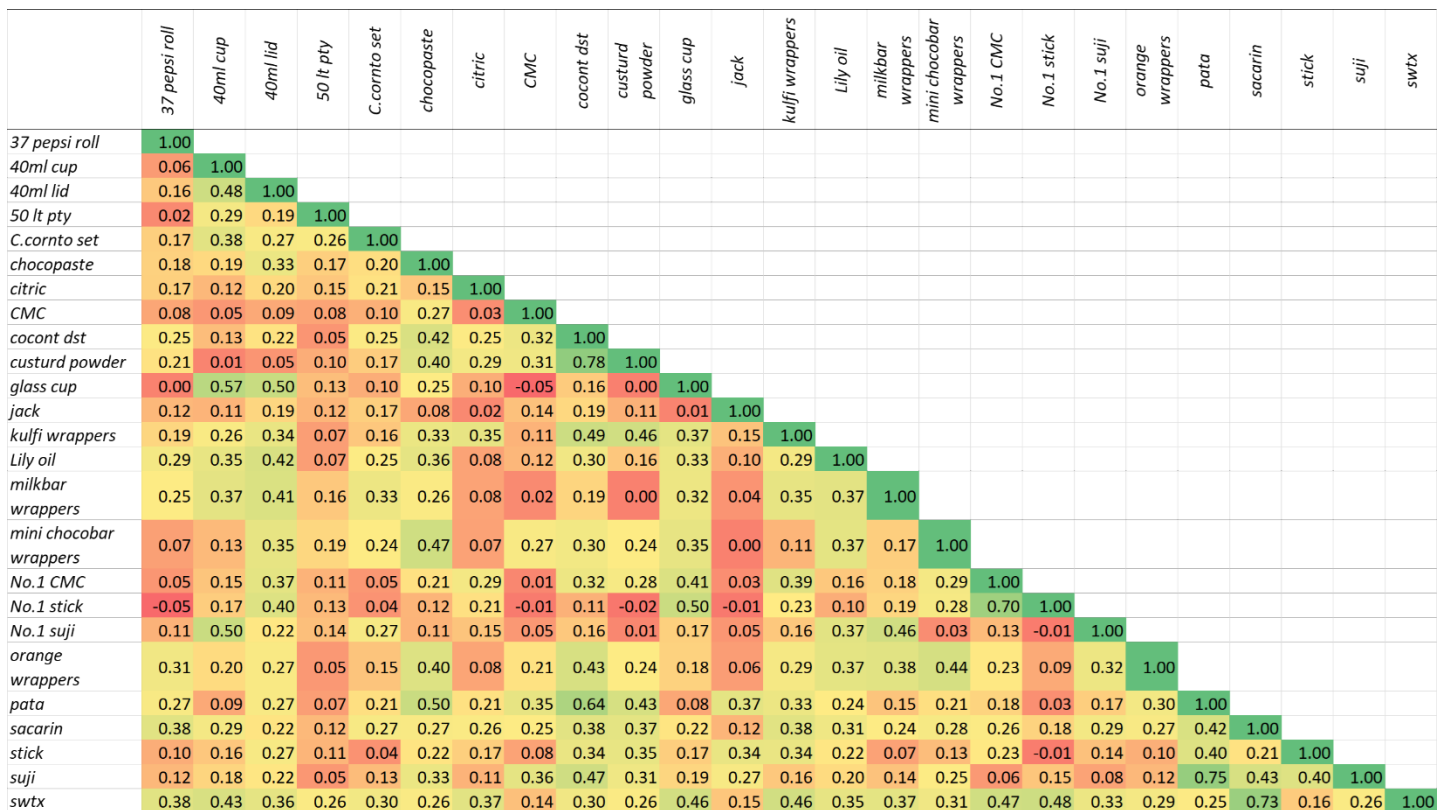


Figure 5: Heatmap of Pearson correlation coefficient between POCs



Based on the correlation analysis following inference can be made:

There are no strong or moderately strong negatively Correlated products which means there are no substitutes for the chosen POCs and all are required to be stored.

- ❖ POCs with strong positive Correlation ( $0.75 < r \leq 1$ ): Custurd powder → Coconut dust.
- ❖ POCs with moderately strong positive Correlation ( $0.5 < r \leq 0.75$ ): pata → Chocopaste, Coconut dust ; Swtx → Sacarin.

### 3.6. Quantization of related POCs

From the Correlation analysis some additional related products are required to be stored such that the sales of the POCs are not hampered. The original POCs are independently stored according to their demands using al the parameters mentioned but for the related POCs whose storing quantity depends on the stored POCs a regression analysis will provide the required quantity of related products that needs to be stored in terms of the independently stored POCs.

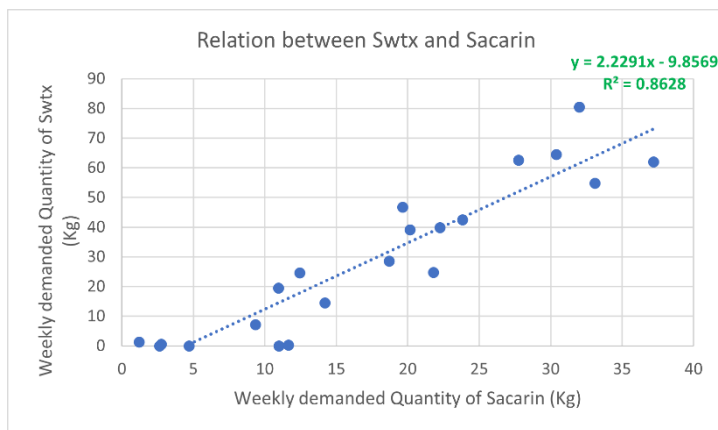


Figure 6: Regression graph between Swtx and Sacarin

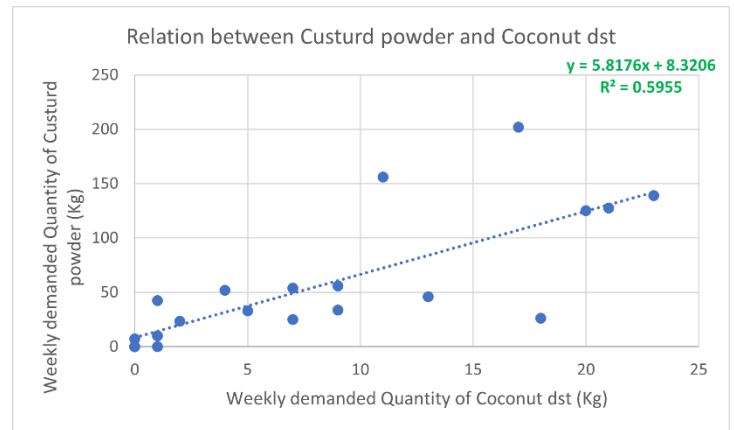


Figure 7: Regression graph between Custurd powder and Coconut dst

From Figure 6 and 7 the below relationships are obtained:

$$\text{Quantity of Swtx (kg)} = 2.23 \times \text{Quantity of Sacarin (kg)} - 9.86 \quad \dots\dots\dots (3)$$

$$\text{Quantity of Custurd powder (kg)} = 5.82 \times \text{Quantity of Coconut dst (kg)} + 8.32 \quad \dots\dots\dots (4)$$

Since Pata has multiple POC dependencies a multivariate regression method is adopted to quantify the demands.

SUMMARY OUTPUT FOR Pata				
<i>Regression Statistics</i>				
Multiple R	0.844282			
R Square	0.712813			
Adjusted R	0.680903			
Standard Error	7.730694			
Observations	21			
<i>ANOVA</i>				
	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>
Regression	2	2670.055	1335.027	22.33846
Residual	18	1075.745	59.76363	
Total	20	3745.8		
<i>Coefficients</i>				
	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	
Intercept	1.002593	2.643216	0.379308	0.708897
chocopaste	0.081364	0.026278	3.096244	0.00623
coconut dst	0.985747	0.244856	4.025823	0.000793

Figure 8: Regression analysis of pata as demand function of chocopaste and coconut dst

From Figure 8, following relationships are established:

$$\text{Quantity of Pata (Kg)} = 0.08 \times \text{Quantity of chocopaste (Kg)} + 0.99 \times \text{Quantity of coconut dst(Kg)} + 1 \quad (5)$$

### 3.7. Purchase Pareto

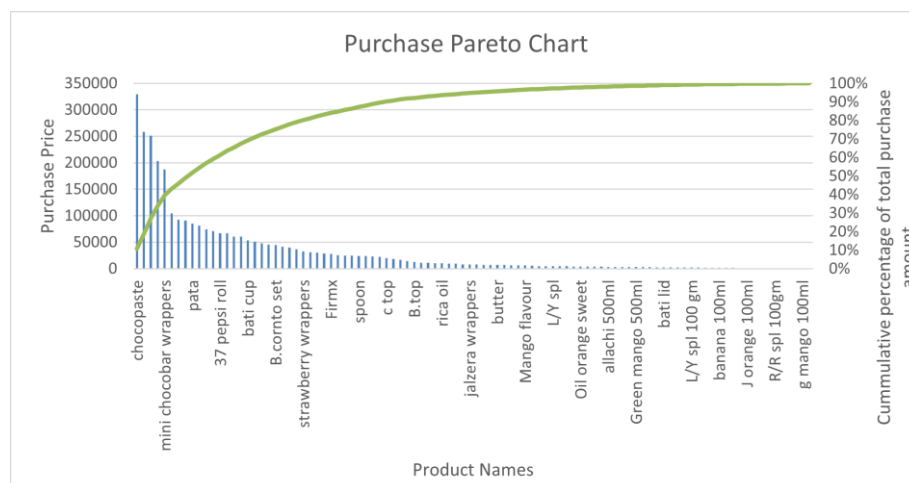


Figure 9: Purchase Pareto Chart

The pareto analysis reveals that other than POCs the firm is spending significant resources on some non POCs e.g : Bati cup, B.cornetto set, Green mango wrappers, James vanilla 500 ml, Strawberry wrappers.

### 3.8. Category wise distribution of Products

A category wise distribution and storage solution is provided in Table 6.

Product Category	Nature	Storage type	Required storage space	POCs	Volume of single unit (Cu. ft)
Powder,paste & Crystalline	Food Grade; contaminable.	Store only with food products	Low Low Medium Medium Medium Medium Medium Medium Medium	1. Chocopaste 2. Sacarin 3. Citric 4. No.1 Suji 5. No.1 CMC 6. Coconut dust 7. Pata 8. Swtx 9. Custurd powder	0.95 0.4 1.78 1.56 1.56 2.37 1.56 3.11 3.95
Plastic products	Non-Food Grade; Non contaminable.	Safe to store with Varnish segment	Medium High High Medium Medium Medium	1. 50 Lt pty 2. Glass cup 3. 40 ml cup 4. Kulfi wrappers 5. 37 Pepsi roll 6. Mini chocobar wrappers	2.99 11.63 11.53 1.78 1.78 1.78
Vegetable Oil	Food Grade; Easily contaminable	Store only with food products	Low	1. Lily oil	0.69
Ice Cream Cones	Directly consumed; Easily contaminable	Store only with food products	Low Medium	1. C.cornetto set 2. Jack	1.4 4.67
Essence, Food colours, Emulsions and Syrups	Comes in sealed boxes; Low chance of contamination	If required, can be stored with Varnish segment	Nil	No POC	Nil
Wooden products	Non consumable; Non-contaminable	Safe to store with Varnish segment	High High	1. No.1 Stick 2. Stick	7.81 7.81
Paper, Ancillary and Clay products	Non consumable; Non-contaminable	Safe to store with Varnish segment	Medium	1. 40 ml lid	1.5

Table 6: Categorization of POCs according to various parameters

The required storage category was divided into Low, Medium and High using the Third Quantile ( $Q_3 = 3.74 \text{ Cu. ft}$ ), Median ( $=1.78 \text{ Cu. ft}$ ) and Interquartile range ( $\text{IQR}=2.18 \text{ Cu. ft}$ ) of all recommended POCs.

Low = volume of single unit < median, Medium = Median  $\leq$  Volume of single unit <  $Q_3 + 1.5 \times IQR$ , High = Volume of single unit  $\geq Q_3 + 1.5 \times IQR$ .

### 3.9. Safety Stock

Safety stock, also known as buffer stock or safety inventory, refers to the additional inventory held by a company or organization to mitigate the risk of stockouts or shortages due to uncertainties in demand or supply. It is a cushion against fluctuation in demand, supply chain disruption, variability in lead time (time between ordering and receiving fresh stocks) and other uncertainties.

Considering the demand to Normally distributed, a service availability of 99% gives a Z score of 2.33 from the standard normal distribution table.

So, the weekly safety stock =  $2.33 \times \text{standard deviation}(\sigma)$  of weekly demand

POCs	37 pepsi rc	50 lt pty	C.cornto se	chocopaste	citric	cocont dst	glass cup	kulfi wrap	Lily oil	mini choco	No.1 CMC	No.1 suji	sacarin
standard deviation	26.4498	2.658146712	7.808256	71.2341	8.234577	7.355529	4.360147	8.960892	42.09976	37.32828	9.586018	5.42039	10.07197
safety stock	61.53143	6.183773953	18.16472	165.7153	19.15649	17.11152	10.14322	20.84615	97.93868	86.83857	22.30041	12.60971	23.4309
unit size	20	1	5	40	25	25	4.5	35	15	35	25	25	5
weekly stocks unit size	4	7	4	5	1	1	3	1	7	3	1	1	5

Figure 10: Weekly safety stocks to be maintained for POCs

Using equation (3)-(5) weekly safety stock for Swtx, Custurd powder and pata are obtained as follows:

POCs	Swtx	custurd powder	pata
safety stock	42.39092	107.9090415	31.19763
unit size	25	50	25
weekly stocks unit size	2	3	2

Figure 11: weekly safety stocks of related POCs

## 4. Interpretation of Results

Key insights from the result are mentioned below:

- I. Efficient storage mechanism can be implemented using parameters like priority, demand trends, price fluctuations and storage volume.
- II. Since a statistical hypothesis test is more accurate to measure the demand trends, graphs of weekly demand trends are not reported, nonetheless they are analysed and available in the following link: <https://shorturl.at/bsvFV>.
- III. Among 25 POCs 13 POCs are identified as essential for bulk storage in the go-downs and are listed in Table 5.
- IV. Conducting a market analysis, the major reason of price swings are found to be due to supply disruption, e.g. citric is speciality chemical and Lily oil is palm kernel oil, they are extensively imported from China and Indonesia respectively. Manufacturing of chocopaste requires Palm oil. Thus, any regulations, international pricing changes or logistics problem can immediately make them unavailable in the market.  
To protect against such problems citric, Lily oil and chocopaste can be bulked stored for the 1-2 months.
- V. 3 additional POCs are closely related to the sales of these 13 POCs, so they also need to be stored. No negative relations in demands detected among the POCs
- VI. The original 13 POCs can be thought of as independent POCs i.e. their demand quantity is independent of other products. Whereas the demand of 3 related POCs depends linearly on the original POCs.
- VII. Using the equation (3)-(5) quantity of these 3 dependent POCs can be estimated for storage.
- VIII. Purchasing side pareto analysis reveals that the firm is spending quite significantly on some non POC products.

## 5. Recommendations

After extensive qualitative and quantitative research, some domain analysis about the nature of the business, conditions of supply market, and applying some basic intuition some key insights are acquired. Based on these some actionable recommendations are made which the firm can look into. These recommendations are scientific, data driven and unbiased.

Based on the research following key recommendations has been made:

- I. Implement an efficient inventory management system that prioritizes storage and handling of the Products of Concern (POCs).
- II. Considering the priority, price fluctuation demand trends and market dependencies the weekly safety stock of **four-eight weeks** should be maintained for **Chocopaste, 37 Pepsi roll, Lily oil, Citric, mini chocobar wrappers**.
- III. Some POCs complement the demand of most important POCs, thus they need to be stored in just the right amount, the quantity of their procurement can be obtained from Figure 11.
- IV. For all other POCs except **glass cup** a safety stocks maintenance of **two weeks** is recommended. Glass cup having non-stationary demand and high storage requirements can should be stored for **one week's** demand.
- V. Firm should reduce the spending of resources in non POC products and purchase should align with demand trends and price fluctuation to optimize capital allocation and minimize storage cost.
- VI. One part of efficient warehouse management is, diversifying the product category based on storage compatibility. The firm should consider storing non-food products which has very low probability of contamination from poisonous varnish products alongside varnish products as shown in Table 6.

By implementing these recommendations, company can optimize storage constraints, enhance capital utilization, and improve overall efficiency in managing diverse product categories within the versatile shop environment. These are in no way promise to solve all the problems the firm is facing but can be a stepping stone towards resolving them.