NORTHERN ILLINOIS UNIVERSITY

DE KALB, ILLINOIS

MAY 2025

ISYE 640 FINAL PROJECT REPORT

BY

BHAVESHKUMAR CHANDRASEKARAN (Z2006107)

MD ABU NAEEM KHAN (Z1985093)

FOUZAN ABDULLAH (Z1978719)

ADNAN MOHAMMAD ABDUL (Z2009047)

DEPARTMENT OF INDUSTRIAL AND SYSTEMS ENGINEERING

Table of Contents

List of Tables:

List of Figures

INTRODUCTION:

We have been given three categories of data for a manufacturing company. The data is for the Sales, Transactions, and Order data. We need to suggest an inventory replenishment policy for the products of the company. For that, we will need to analyse the data to identify the important SKUs that generate a significant portion of the revenue. Once the SKUs have been identified, we will employ the inventory replenishment methods learned in this course to suggest a relevant policy for the company.

Assumptions:

For the analysis, we took four months' data from 2021 for Feb, Mar, Apr, and May from the Transactions data file. In the Transactions data, we have the item names and quantities relevant to our analysis. We used the Sales data file to calculate revenue. For the analysis, we are assuming that transaction quantity is the demand for the corresponding item. From the sales data, we take the unit cost. Multiplying the quantity in the transaction data with the unit cost in the sales data, we calculated the total revenue for each item.

Objective:

Our objective is to identify the main SKUs and categorize those into ABC units for which we will recommend a relevant inventory replenishment policy for the A and B units to the company.

DATA DESCRIPTION:

There were three data files given, Transaction, Sales, and Order data. Transaction data has 9 columns and over 19,000 rows. Our relevant columns are item names and quantity. In Sales data, we have 10 columns and 40,000+ rows. Our relevant columns in Sales data are Part No (which is the item name) and unit cost. In Order data, we have 5 columns and 100,000+ rows. We are not using the Order data for this analysis. For our ABC analysis, Transaction data and sales data were enough to perform the analysis.

DATA PREPARATION:

The steps of data cleaning that we employed are discussed below:

1. In Transaction data, we identified the unique items from the item name column. 4145 unique items were identified.
2. We calculated the frequency of items (the no. Of times each item was appearing), and the total quantity (summed over all the instances of each item) and sorted it in descending order.
3. In Sales data, we had to first match the item names with the transaction data, because transaction data is our main reference file for this analysis.
4. In the item names column of the Sales data, we utilized the VLOOKUP function to match with transaction data. 4025 items from the sales data item column were matched with transaction data item names.
5. Next, we required the unit cost for each matched item in Sales data. 3485 items, out of those 4025 matched items, had unit cost against them. We decided to go with those 3485 items because they were sufficient for our analysis.
6. We created a new table in which we added item name, frequency, total quantity, revenue, cumulative revenue, and cumulative revenue percentage.
7. From this table, we did the ABC analysis. We found that 80% of the revenue was covered by 516 items, out of those 3485 items.
8. For the sake of maintaining quality and due to time constraints, we only performed inventory analysis on the top 10 items out of those 516 items.
9. From studying the order and sales data, we assumed the lead time for order delivery of all the 10 items under analysis is 7 days (1 week).
10. Order cost is given as $12, and r is 0.12 $/$/month.

SOLUTION APPROACH:

Expected demand during lead time is assumed as the demand of our data range divided by the no. Of weeks (because lead time is one week). Transaction quantity is the demand. We are assuming an order delivery period i.e lead time of 7 days. So, In Order data, we have filtered data from 7 days before Feb 1 till 7 days before May 31. For ease of analysis, we are going to consider all days as business days. So, after cleaning, we have Order data from 21 Jan to 28 May. (It was available only till 28 May).

Only 74 Transaction part names match with order data part names.

Unique items in the transaction data: 4145.

Unique items in order data: 6600

Sales Data:

We have items in sales data but no date. Identify the items from transaction data in sales data. Out of 4145 items in transaction data, only 3485 items were identified straightaway from VLOOKUP approximate in sales data. But more similarities have been identified.

Data Cleaning:

From the unique items identified in the transaction data, we identified the items in the sales data to calculate revenue. We couldn’t find the full list of 4145 items in Sales Data, so we worked with 3485 items in Sales Data.

ABC Analysis:

Among the 3485 items that we finalized for our analysis; we performed the ABC analysis by sorting the data in descending order of Revenue.

A item:

Our 80% revenue is being generated by 516 items. That is 14.81% of the total items. We will perform an inventory policy analysis on the top 10 items in the A items. We decided to go with a continuous review model (s, Q) simultaneous analysis for managing the A items. The stockout cost per event is taken as 80% of the unit cost for each item. Also, we calculated the EOQ for the corresponding 10 parts. The order cost is given as $12. With all the given data we found the reorder point and the quantity to order for the top 10 products with the help of Python code. Here we needed to calculate the converged k value and Q value to come to a stop and use the final value for the calculation. However, for most of the products, the k value is invalid because of the high standard deviation. The standard deviation is calculated by taking the orders placed on each day for the considered period. And STDVE.P() function is used to calculate the standard deviation. Since the standard deviation is too high, the value that comes under the natural log for calculating the k value becomes negative. Since the natural log of a negative is invalid, the iteration stops in the first iteration and the initialization of Q as EOQ comes as the final Q output. This is the reason behind the value of EOQ and the final Q being the same for most of the products. However, for the last two items, we got an output for k and Q.

```
C:\Users\bhave\PycharmProjects\pythonProject\venv\Scripts\python.exe C:\Users\bhave\PycharmProjects\pythonProject\main.py
Converged value of k: 1.1749
Converged value of Q: 9

Process finished with exit code 0
```

Figure 1 Output from python code for A item analysis.

To calculate the safety stock, we had to assume a random k value and calculate the safety stock. Using the safety stock, we calculated the reorder point by adding it with the average demand during lead time.

B items:

For the B items, we considered the products which produce the next 15% of revenue and it came up to 25.29% of the total products. That is around 30% of the total products produces 15% of the total revenue. So, it comes under the category of B items. Among these we selected the top 20 items and calculated the standard deviation for each of the items the same way we figured out for A items.

RESULTS:

A Items:

Table 1 Analysis of top 10 A items

TOP 10 A ITEMS	s	Q	Order Cost	Inventory Cost	Variable Demand Cost	TC
E1840P	62.215	15	$ 24.20	$ 56.83	$ 10.98	$ 92.01
HL2148S	1810.775	459	$ 21.68	$ 1,743.88	$ 0.30	$ 1,765.86
HL2205	1002.7	291	$ 15.51	$ 1,111.97	$ 0.24	$ 1,127.72
R907M	762.45	184	$ 14.67	$ 906.41	$ 0.35	$ 921.43
R9123M	1057.15	445	$ 14.33	$ 1,077.70	$ 0.14	$ 1,092.16
PR34B	6759.95	2787	$ 13.37	$ 7,267.97	$ 0.02	$ 7,281.36
PR656	5429.25	3148	$ 13.22	$ 5,089.68	$ 0.02	$ 5,102.92
RV880X	2462	1541	$ 12.95	$ 2,260.80	$ 0.03	$ 2,273.78
E1839P	10.636132	9	$ 8.42	$ 12.71	$ 7.91	$ 29.03
E1251P	8.254592	10	$ 6.00	$ 11.89	$ 15.36	$ 33.25
		TOTAL	$ 144.34	$ 19,539.82	$ 35.35	$ 19,719.51

Using the found value of the s and Q, we calculated the total cost of each of the products which comprises ordering cost, inventory cost, and variable demand cost. The total cost of the top 10 A items comes up to $19,719.51. Out of the three costs, the inventory costs are the higher ones. But this can be justified as the A items provide the highest value to the organization and we can’t have it being stocked out.

B items:

For the B items, we have decided to go with periodic review systems (R, S) and (R, Q). We selected the desired service level as 80%. With this we calculated the k value, and the k value remained the same for all the 20 B items we selected. At first, we selected cost per stockout event (B1) to be the factor that decides the k value. But, since the standard deviation is erratic the term to calculate the k value becomes negative and the whole value becomes invalid if we proceed further, So, the P1 value is selected to be the criteria that help us to select the safety factor (k). We further decided to implement two periodic review models as (R, S) and (R, Q) models.

(R, S) Model:

In the (R, S) model, the value of R, that is the review period is set to be 1 week. With the help of it and the safety factor, we calculated the order up to level quantity (S) for each of the 20 B items.

Table 2 Order up to level for (S, Q) system.

Top 20 B items	S (Order up to level)
SS3145	6
PR474	1,267
PR342	2,229
EM57	9
RV1082	143
HL1945S	140
FPS108	14
E949P	4
GP103S	24
PR15795S	90
HL1900S	38
E1025P	6
PR441S	224
RV415	25
PR317	489
HPV6	66
EM20G	7
4K408	24
E1761M+15	13
SUM6901	1

(R, Q) Model:

For the (R, Q) model we chose the order quantity to be the economic order quantity (EOQ) and we calculated the review period (R) by dividing the quantity ordered by the corresponding demand for 1 month. Surprisingly the review period is the same for all the B items which is 2 days.

Table 3 EOQ and R for (R, Q) model

Unique Items	Q(EOQ)	R (Review period) in days
SS3145	6.561080935	2
PR474	525.2257314	2
PR342	525.2257314	2
EM57	7.89337038	2
RV1082	197.3855085	2
HL1945S	31.58988759	2
FPS108	3.62261778	2
E949P	3.295469865	2
GP103S	23.40597159	2
PR15795S	52.79636773	2
HL1900S	99.0147543	2
E1025P	3.300851399	2
PR441S	388.2901374	2
RV415	66.08186005	2
PR317	430.9458037	2
HPV6	87.60375908	2
EM20G	1.991652552	2
4K408	17.59486969	2
E1761M+15	33.22277471	2
SUM6901	3.657695991	2

So, we will be ordering EOQ number of items every 2 days for each of the top 20 B items.

Cost Comparison:

Now we compared the total cost per month for each of these two models and the cost comparison is shown below.

Table 4 Cost Comparison for B items

Top 20 B items	(R, S)	(R, Q)
SS3145	110.78	109.1448
PR474	38.89	109.1389
PR342	72.36	109.1389
EM57	16.47	109.1216
RV1082	8.05	109.1192
HL1945S	75.36	109.1168
FPS108	67.34	109.1094
E949P	16.05	109.1034
GP103S	13.75	109.1002
PR15795S	25.82	109.0915
HL1900S	1.72	109.0896
E1025P	28.2	109.0886
PR441S	5.32	109.086
RV415	1.72	109.0796
PR317	15.4	109.0499
HPV6	8.47	109.0407
EM20G	54.32	109.0377
4K408	19.29	109.0367
E1761M+15	1.7	109.03
SUM6901	1.7	109.0221
TOTAL COST/month	**582.71**	**2181.746**

From the above table we can say that the preferred model for B items is (R, S) model as the total cost per month is very low compared to the (R,Q) system.

CONCLUSION:

After a comprehensive study of the given data, and cleaning of the data we have categorized the items given to us to A and B items based on the revenue it contributes to the company. For the A items we decided to go with the (s, Q) model which resulted in a significantly higher inventory cost which can be justified as it provides a greater contribution to the total revenue for the company. For the B items, we decided to go with the periodic review model (R, Q) and (R, S) model where (R, S) proved to be a better option for B items as the total cost is comparatively lower.

Also, we can categorize data by the categories of each item which can be found in the sales data sheet. Further, we can again categorize this into ABC items and do the analysis. It would be an interesting analysis to look at it and we can verify how the data and the chart varies if the categorization of products is done differently.

Moving forward, we can analyse the order data where we can use the project on hand data and we can further analyse it by backorder or lost sales scenario we can also implement inventory management where we can dispose of some of the items that do not contribute much to the organization by salvaging it. We can find it out by figuring out the quantity to be disposed and the cost to dispose and the cost that occurs when we do not dispose.

APPENDIX

Python Code for (s,Q) continuous review system:

```
import math

import pandas as pd

from scipy.stats import norm

file_path = r"sample.xlsx"

try:

    data = pd.read_excel(file_path, sheet_name="Sheet1", nrows=1)

except Exception as e:

    print("Failed to read Excel file:", e)

    exit()

try:

    B1 = data["B1 (stockout cost per event)"].iloc[0]

    sigma_l = data["SD"].iloc[0]

    EOQ = data["EOQ"].iloc[0]

    A = data["Order Cost"].iloc[0]

except KeyError as e:

    print("Column name error:", e)

    exit()

Q = EOQ

tolerance = 1e-6

k = 0

while True:

    log_argument = (B1 * sigma_l * EOQ * EOQ) / (2 * math.sqrt(2 * math.pi) * A * Q *
sigma_l * sigma_l)
```

```
    if log_argument <= 0:
        print(f"Logarithm argument is non-positive: {log_argument}")
        break
    try:
        k = math.sqrt(2 * math.log(log_argument))
    except ValueError as e:
        print(f"Error calculating k: {e}")
        break
    pu_greater_k = norm.sf(k)
    new_Q = EOQ * math.sqrt(1 + (B1 / A) * pu_greater_k)
    if abs(Q - new_Q) < tolerance:
        break
    Q = new_Q
rounded_k = round(k, 4) if k > 0 else "Error"
rounded_Q = round(Q) if Q > 0 else "Error"
print("Converged value of k:", rounded_k)
print("Converged value of Q:", rounded_Q)
```