Joint Project between IIM Mumbai & Genpact

VISIBILITY AND DISTRIBUTION OF REFURBISHED VS NEW SPARE PARTS

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Executive Summary

The vending machine business has seen remarkable growth across various industries, including FMCG, healthcare, and video gaming/entertainment. A prime example of this trend can be observed in the case of Big Basket, which has introduced the innovative BBinstant vending machine to distribute its products.

Implementation of vending machine is done by either in-house manufacturing or outsourcing it. The advantages are two ways both for the customer and the company. Customers are getting the convenience, product visibility and availability 24 hours & its ease of payment facility. Companies benefit by saving the salaries given to salesperson hired otherwise. Also, Companies are directly connecting with customers which was not the case earlier in the general trade.

But with innovation comes new challenges. It's essential to ensure vending machines are always available to maintain the goodwill from the customer and ensure proper revenue. For this purpose, companies enter into maintenance contract with the vendors or service providers. These contracts are known as AMC (Annual Maintenance contract). AMC visit is done on a periodic basis and parts are replaced or repaired on the basis of their current life cycle and relevance. But there is the issue when parts cannot be predicted for their failures, and this increases the downtime of machines. These maintenances are not scheduled and technician, inventory has to be planned instantly. Therefore, it is essential to get an estimate of these failures and reduce the possibility of downtime.

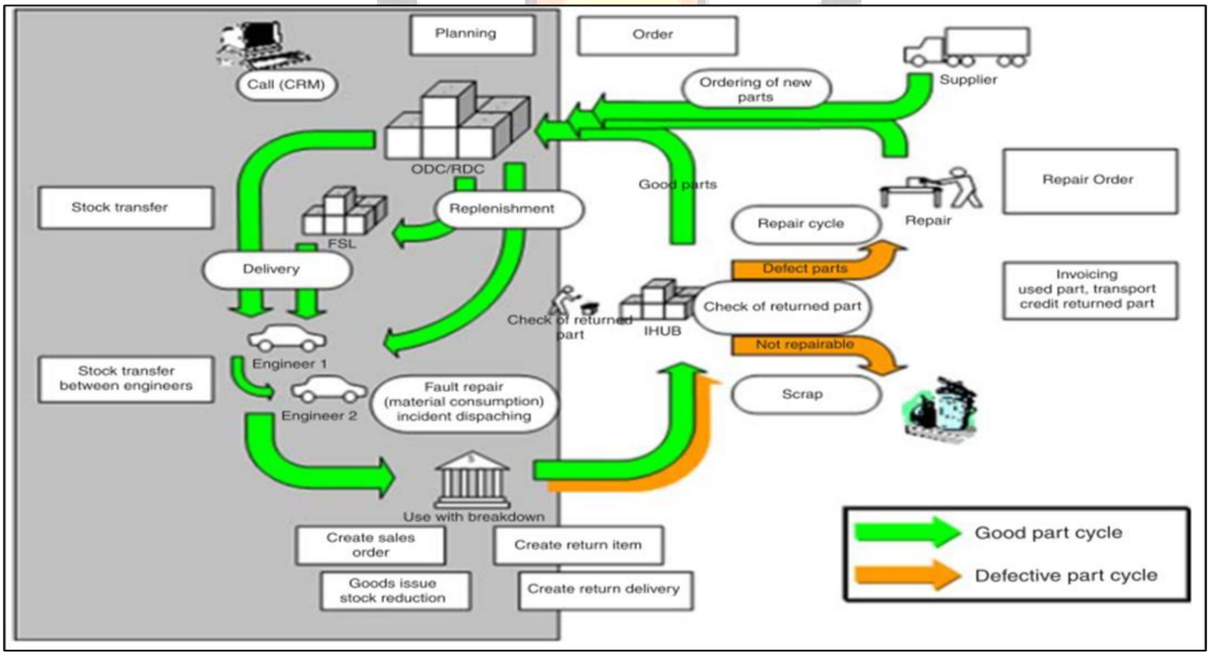
This problem is approached in the paper using unsupervised learning in the performance of spare parts for targeting the problem of unscheduled maintenance. The problem is analysed through preparing a PowerBI dashboard which helped in visualizing parameters like repair time and replace rate along with the criticality of part from the assessment of Bill of material provided by the client. It was then followed by K means clustering to identify three categories of parts in case of unpredictive failures.

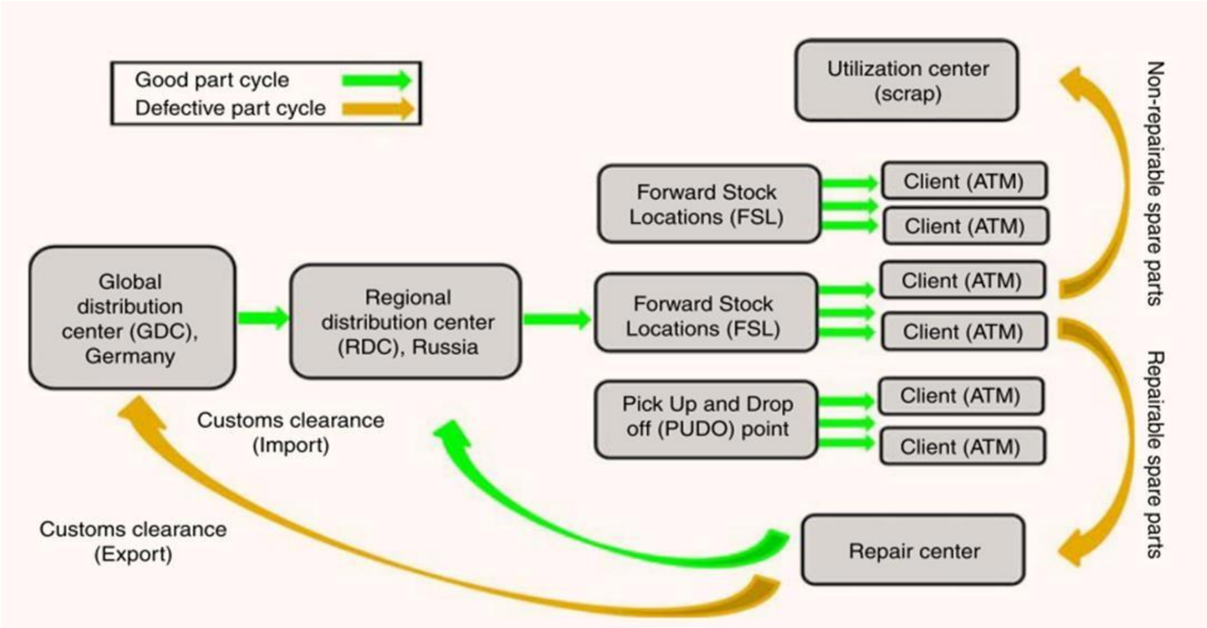
Finally, the analysis gave a focused roadmap for different categories of spare parts failing under unplanned downtime to predict their stocking levels and their placement in the various stages of distribution system. It will result in increasing the availability of machines and improving Overall equipment effectiveness (OEE)

SECTION 1: Introduction

Distribution Systems for Refurbished and New Spare Parts:
The distribution systems for refurbished and new spare parts differ in terms of their channels, processes, and stakeholders involved.

a. **New Spare Parts Distribution**:
New spare parts are typically distributed through well-established networks, involving manufacturers, authorized dealers, distributors, and retailers.
b. **Refurbished Spare Parts Distribution**:
The distribution of refurbished spare parts is more fragmented and diverse. Several distribution models exist, such as *specialized refurbishment centers*, dedicated online marketplaces, and third-party vendors. Refurbishment centers often act as centralized hubs where used parts are collected, refurbished, and made available for sale. Some centers may have direct relationships with equipment manufacturers, allowing them to acquire returned or surplus parts.



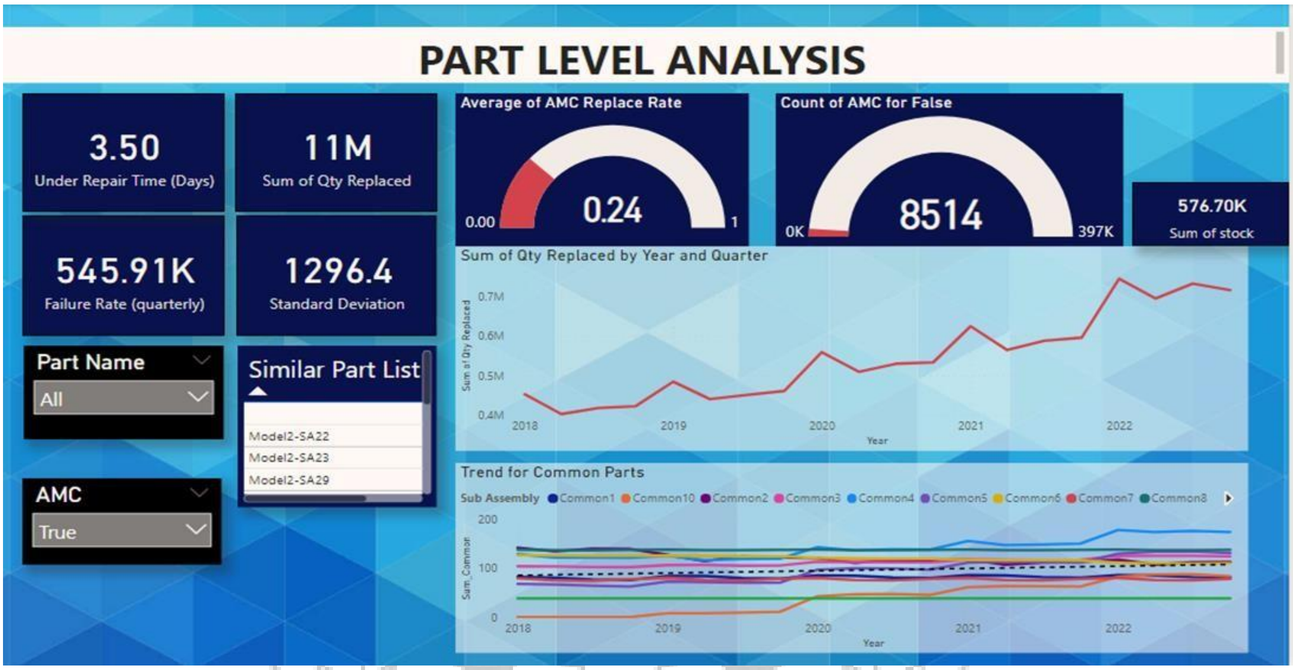


Good part cycle
Defective part cycle
Utilization center (scrap)
Forward Stock Locations (FSL)
Client (ATM)
Client (ATM)
Global distribution center (GDC), Germany
Regional distribution center (RDC), Russia
Forward Stock Locations (FSL)
Client (ATM)
Client (ATM)
Pick Up and Drop off (PUDO) point
Client (ATM)
Client (ATM)
Customs clearance (Import)
Customs clearance (Export)
Repair center
Non-repairable spare parts
Repairable spare parts

SECTION 2: Dashboard

The dashboard provides visibility by providing information and integrating key matrices, thus providing a decision support on selecting part for repair and replacement.

The below snapshot of the dashboard provides an overview of the key metrices that it provides.



The matrices that it provides for decision support are:

1. Average AMC Replace Rate
2. Count of AMC False
3. Quarterly Failure rate
4. Under Repair time in days

Now explaining each key matrices along with the logic that was used in our tool (Power BI) derived from the data shared through BOM, Repair Data and Installation data.

Average AMC Replace Rate:
Average AMC Replace Rate refers to the average rate at which components or parts are replaced during an Annual Maintenance Contract (AMC).
Logic/Function used:
Data set- BOM
Criteria- AMC Replace Rate
Formulae- Average of AMC Replace Rate

Count of AMC False:
"Count of AMC False" refers to the numerical value or tally of instances where an Annual Maintenance Contract (AMC) is deemed invalid or false due to the service provider's failure to fulfil the contractual obligations outlined within the agreement. This count represents the number of contracts that have been identified as false or invalid based on specific criteria or criteria breaches.
When a service provider fails to meet the obligations stated in the contract, such as not providing the agreed-upon maintenance services, not meeting response times, or not delivering the expected level of service quality, the contract can be considered false or invalid. The count of AMC False represents the cumulative number of instances where such breaches occur.
Tracking the count of AMC False can be useful for several purposes. It helps identify the reliability and trustworthiness of service providers, highlighting those who consistently fail to meet their contractual obligations.
Logic/Function used:
Data set- Master Data
Criteria- AMC
Formulae- Count of AMC for False = CALCULATE(COUNTA('Master_data'[AMC]), 'Master_data'[AMC] IN { FALSE })

Quarterly Failure rate:
The Quarterly Failure Rate of spare parts refers to the rate at which spare parts or components experience failures or malfunctions within a specific quarter. It is a metric used to measure the reliability and performance of spare parts during a three-month period.
To calculate the Quarterly Failure Rate, the total number of failures or malfunctions that occurred within the quarter is divided by the total number of spare parts in use or monitored during that period. The result is typically expressed as a percentage or a ratio, representing the proportion of spare parts that failed or malfunctioned.

Logic/Function used:
Data set- Master Data
Criteria- Quantity Replaced , Year of Replacement
Formulae- Failure_rate = SUM(Master_data[Qty Replaced])/((MAX(Master_data[year])-MIN(Master_data[year])+1)*12)*3

Under Repair Time in days:

Under Repair Time in days for spare parts refers to the duration or period of time it takes to repair or service a spare part that has been identified as faulty, damaged, or in need of maintenance.

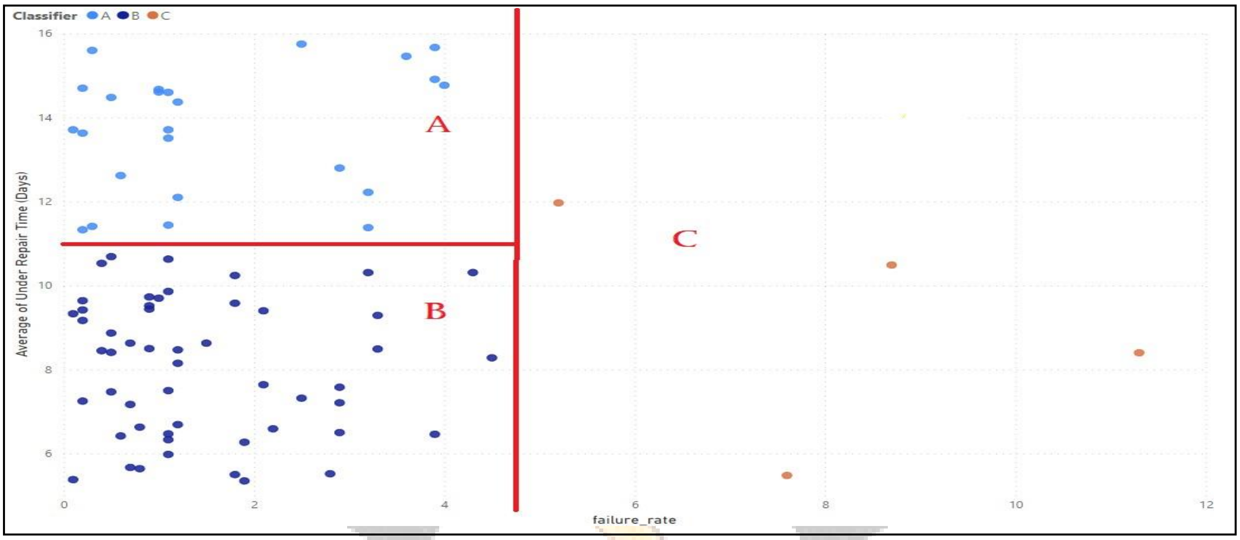
Understanding and managing the Under Repair Time is crucial for several reasons:
1. Minimizing Downtime: The Under Repair Time directly impacts the downtime of machinery or equipment. By reducing the time, it takes to repair spare parts, organizations can minimize operational disruptions and ensure that the equipment is back in operation as quickly as possible.

2. Service Level Agreements: Organizations that provide maintenance services or have service level agreements with customers often have specific targets or commitments regarding the Under Repair Time. Meeting or exceeding these targets enhances customer satisfaction and builds trust in the reliability of the maintenance services provided.

To effectively manage the Under Repair Time, organizations may implement strategies such as establishing streamlined repair workflows, ensuring the availability of necessary repair resources and skilled personnel, optimizing repair scheduling and prioritization, and implementing proactive maintenance practices to reduce the frequency of repairs.

Logic/Function used:
Data set- Master Data
Criteria- Under Repair Time (in days)
Formulae- Average of Under Repair Time (in days)

SECTION 3: Stock Planning



To facilitate efficient inventory management through systematic categorization, the utilization of k-means clustering was employed as a methodology. The objective of this clustering process was to stratify the inventory into three distinct clusters, thereby enhancing organizational inventory control.

This classification was predominantly founded on the analysis of two pivotal variables: firstly, the failure rate, positioned along the x-axis; and secondly, the average repair time, situated along the y-axis. These carefully selected variables served as the primary determinants for the clustering, enabling a structured and data-driven approach to inventory categorization.

The 3 clusters were:

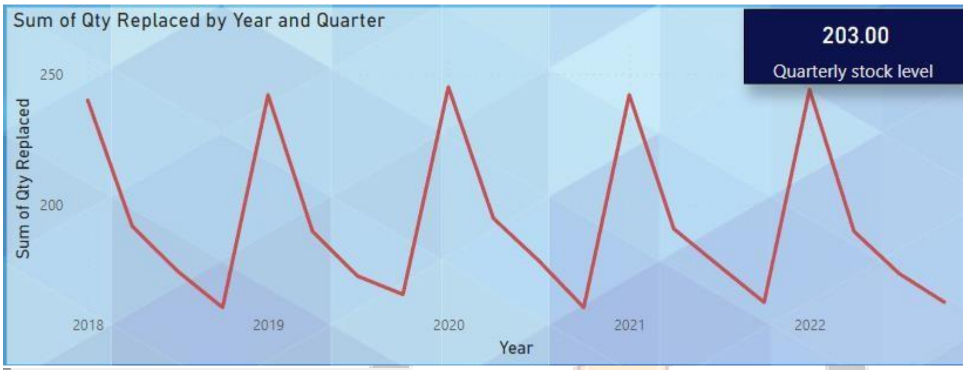
A: failure rate < 5 and average repair time > 11

B: failure rate < 5 and average repair time < 11

C: failure rate > 5

SECTION 4: Recommendations

A cluster: these parts take more time to repair hence they should be kept closer to the machines in local warehouse.
B cluster: these parts take less time to repair, and failure rate is also less hence they can be kept away from the machines in some central warehouse.
C cluster: these parts have very high failure rate so they should be kept very close to machines.



Sub Assembly	Quarter	Max	Min
Model1-SA11	1	245	240
Model1-SA11	2	195	190
Model1-SA11	3	179	173
Model1-SA11	4	166	161

To calculate the stock level for individual parts, replacement pattern was observed quarter-wise and the demand followed a pattern with spike in every first quarter with a dip in last quarter.
Recommendations:

1) For individual parts we can keep average of the maximum and minimum demands that we are getting for a particular pattern.

Average stock = (max + min) / 2 (for Model1-SA11)
= (245 + 161) / 2
= 203

2) The parts that are repaired and replaced in true AMC condition (eg. Common parts) are always come under the accountability of the service provider. Therefore, it is necessary to maintain their stock every time and hence service level should be high.

3) For the Individual parts, the subassemblies are classified in three categories based on failure rates and under repair time as A, B and C. For the stocking, it is recommended that Type A item should be kept at FSL because they have high chances of replacement.
4) The common parts are increasing in the subsequent years, thus there stocking must be done according to the increasing trend and not as averaging as done in individual parts.

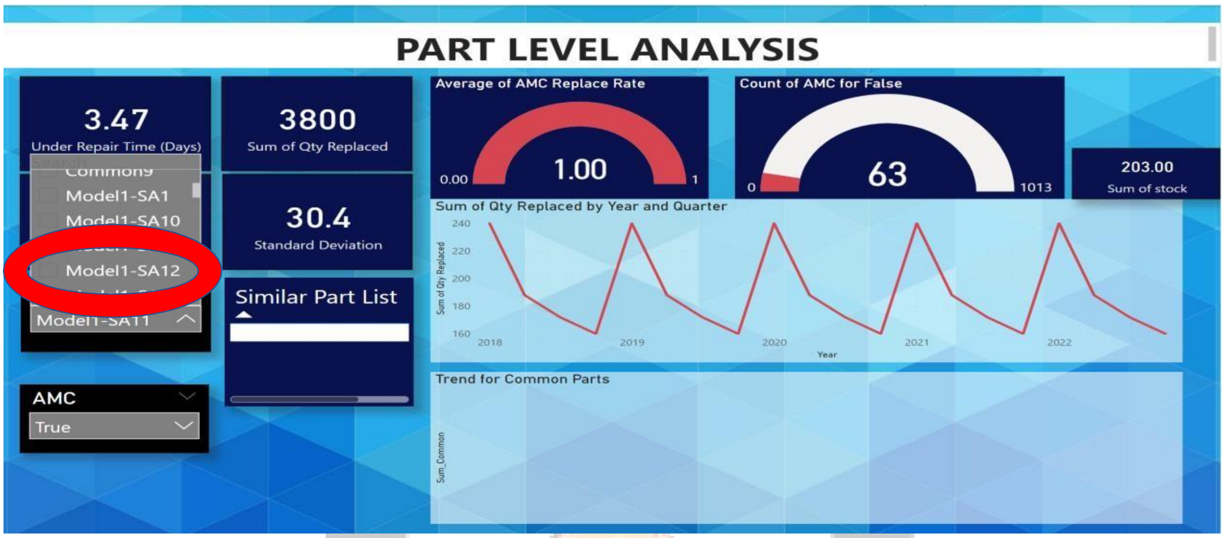
Conclusion

The vending machine industry has seen significant growth, as evidenced by the success of several retailers. This growth benefits both customers and companies, offering customers convenience, product visibility, and constant access while allowing companies to reduce costs and establish direct customer relationships. However, the challenge of ensuring uninterrupted vending machine availability is paramount. Companies often resort to Annual Maintenance Contracts (AMCs) for periodic maintenance and part replacement, but unforeseen part failures can still lead to unscheduled downtime. To address this issue, the paper employs unsupervised learning techniques and a PowerBI dashboard to analyze repair times, replacement rates, and part criticality. Through K-means clustering, parts are categorized, creating a roadmap for spare parts management that mitigates unscheduled downtime and enhances Overall Equipment Effectiveness (OEE).

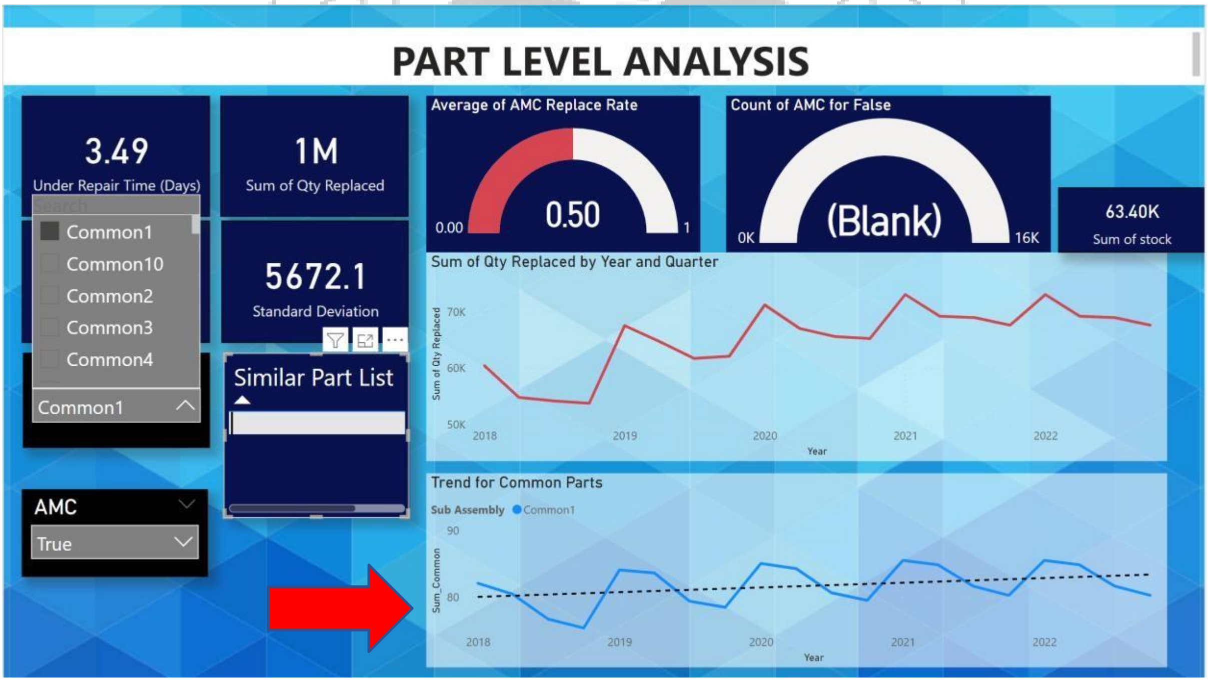
Based on the study's findings, several recommendations emerge. Firstly, in the context of genuine AMC scenarios, where parts necessitate regular repair and replacement, particularly common components, the responsibility for maintaining their stock should squarely rest with the service provider to ensure a consistently high service level. Additionally, individual parts can be better managed by categorizing them into three groups (A, B, and C) based on their failure rates and repair times, with Type A items, having a higher likelihood of replacement, ideally stored at the Forward Stocking Location (FSL). Moreover, recognizing the increasing trend in the number of common parts over subsequent years, it is advisable to adapt stocking strategies for these components to align with this growth rather than resorting to averaging, which is more typical for individual parts.

Annexure

The Tool provides single view decision making to managers and planners by providing critical decision matrices to manage inventory level and improve replace/repair time.



- By Selecting the Part from Drop down will provide the matrices for this part, the user can also select AMC True or AMC False from the Drop Down
- The Trend chart shows the Inventory Levels that needs to be Maintained for this part. But for common part a separate trend chart will show the trend of inventory level that needs to be maintained.



- For Common parts the above chart shows the trends and level for the selected common parts from Drop down, and all the key matrices for decision are displayed same as for the non-common parts.