**Swirltubs – Aftermarket Inventory and Service Strategy Case Part 5 – Team 02 Report**

**Executive Summary:**

Swirltubs offers its clients aftermarket warranty support and repairs. Jim Jenkins, the company's director of aftermarket logistics, oversees a team of about 1000 service specialists that handle these warranty repairs. Their vans keep service parts in case a warranty caller needs a replacement item.

We have found that the recommended truck stock performs well in the face of randomness in part demand concerning cost, service levels, and customer satisfaction. We have recorded 50 trials for random stocking and compared the heuristic recommendation in order to verify the accuracy of our recommendation strategy with random part demand. The results indicate that the recommended truck stock effectively mitigates the risk associated with historical part demand. We have a final truck recommendation with parts having a minimum of 55% accuracy.

**Business Background:**

Swirltubs manufactures various appliances and offers after-market warranty service and repairs.Jim Jenkins manages a network of 1000 service technicians responsible for conducting warranty repairs and carrying service parts inventory on their vans. The cost of holding inventory is a concern for Swirltubs, and Jim is responsible for managing both the costs and customer service provided by the technicians.

**Problem Background/Statement:**

The problem lies in finding an optimal balance between inventory cost and the ability to provide timely repairs. Carrying inventory on 1000 different vans significantly increases the required units of each part, leading to higher costs. However, if parts are not available on the vans, technicians need to order them from the central warehouse, resulting in customer dissatisfaction and wasted technician time. Jim has tried implementing various rules to control inventory but has not achieved desired outcomes.

**Data:**

The dataset provided includes approximately 400 parts that account for 80% of typical technician repair activities over the year. Each record contains the part number, average annual usage, part size in cubic feet, and part cost. From these, we calculated inventory holding cost (25% of part cost), and included technician revisit costs. A smaller 30-part test dataset was also used to evaluate heuristics in a simplified environment before scaling up

**Approach / Methodology:**  
  
Our approach is to identify which parts are most suitable to be stocked in technician vans by considering their usage, size, and cost. The dataset provided includes around 400 parts, each with information on average annual usage, size in cubic feet, and part cost. These factors help us evaluate which parts provide the most value while staying within van space limits and managing inventory costs. Since the stocking decision is a yes or no outcome, this can be addressed using a binomial method, such as logistic regression, which estimates the likelihood that a part will be needed during a service call. To re-optimize truck stock under demand uncertainty, we apply a stochastic optimization model using binomial distribution and Monte Carlo simulation. The goal is to maximize net benefit while maintaining service levels, considering part size, cost, usage variability, and customer satisfaction. This approach allows us to simulate real-world uncertainty and identify parts that offer the highest service value per unit of space.

Average demand per replenishment cycle = 5/250\*Ai

No. of days per replenishment: 5

No. of working days in a year: 250

Number of replenishments per year: 50

Ai = Annual use of individual part

Inventory holding cost: 0.25\*Part cost

Technician random revisit cost = 25\*Random demand

Random Net Benefit value = Random revisit cost - Inventory holding cost/ part sizeRandom Net

Benefit value per cubic feet = Random Net Benefit

As the annual usage of each part is considered uncertain and is binomially distributed, we are randomly generating the demand for each part using Monte Carlo simulation where we analyze past data and predict a range of future outcomes. We are using BINOM.INV() function for generating random annual demand. The probability of success used in this function is average demand per replenishment cycle which is calculated from historical data of average annual use.

After generating random demand, we are calculating random revisit cost and random net benefit value per cubic foot. To automate stocking for 50 trails. Stock the van with a constraint of maximum size 500 cubic feet starting with the highest net benefit value. Assign 1,0 values to the parts which can be stocked in that trail. Sort the table based on part number which gives us a sorted data set of 1,0 stock values for that trail. We have looped this macro for 50 times to stock the van and capture results randomly. We have created a shortcut “ctrl+r” for triggering stock parts. we are calculating the demand per replenishment cycle from past data of average annual use, randomly generating the demand with the BINOM.INV() function. Calculated respective revisit cost, Net benefit per cubic feet for each part. Stocked the van with 500 as constraint for van space and assigning 1,0 based on stocking. With **Heuristic and Trail comparison** sheet we have calculated the frequency of parts that are stocked in 50 trails. We have a **Recommendation Stock** sheet where we have created a final recommendation stock with a minimum accuracy of 55% from 50 trails.

**Objective:**

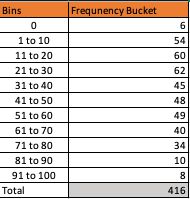
In this scenario, part 5, the goal is to collect 50 random stockings using the heuristic suggested in part three and simulated in part four for the total cost and repair it first percent. We are stocking the van according to the largest net benefit value, as per the heuristic suggested in part 3.

**Constraints:**

The truck's size stays at 500 cubic feet, which is a requirement for stocking parts with significant net benefit values.

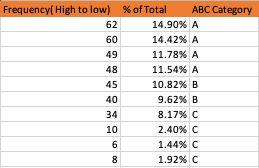
**Results:**

We have generated 50 random stockings using macros and below is the frequency of parts getting stocked in 50 trails.



* We received 06 parts that are not stocked in 50 trials and are not advised by the base heuristic either. Thus, we might move this 06-part recommendation to the lowest priority.
* Only 06 of the 416 components were not filled at least once, indicating that nearly all of the parts were taken into consideration for stocking in random trails.
* A total of 141 parts were stocked more than 40 times across the 50 trials, distributed as follows: 48 parts in the 41–50 range, 49 parts in the 51–60 range, 40 parts in the 61–70 range, 34 parts in the 71–80 range, 10 parts in the 81–90 range, and 8 parts in the 91–100 range.
* 107 parts fall into Medium Frequency group (21–30: 62 parts, 31–40: 45 parts). These represent parts with 40–60% stocking probability, which may vary in priority based on needs.
* 114 parts were stocked infrequently, with 54 parts in the 1–10 range and 60 parts in 11–20.

**Analysis of ABC Categories (Based on Frequency Ranking)**:



* Parts that are stocked the most frequently fall under Category A, accounting for about 52.64% of total inventory.
* Parts with a moderate frequency (around 20.45%) are included in Category B.
* Parts in Category C are the least stocked (around 26.91%).

**Recommendations/ Possible Outcomes:**

The heuristic model proved to be highly effective in balancing overall costs and increasing the "fix-it-first" percentage, as seen in Case Part 4. In Part 5, we refined and validated our heuristic recommendation by simulating 50 random stocking trails. Only six of these trials' parts were never stocked, and the fundamental heuristic did not apply to them either. This shows that these six parts can be safely given the lowest priority, and that the heuristic mostly includes the parts that are used most often.

Our recommendation is to stock all parts with at least 40 occurrences (80% frequency) across the 50 trials in order to develop a data-driven and realistic van stocking plan. 291 high-frequency parts that were regularly stocked in simulations and closely match Category A and top-tier Category B parts from our ABC Analysis are identified by this criteria. These components are probably the most cost-effective and operationally reliable

We advise dividing it up according to:

* Jim’s cost-saving strategies,
* Technician requests and operational requirements, and
* Location-specific part demand that may not be captured through simulations alone.

Importantly, our base heuristic was developed using annual part usage data. However, to better support our main goal of **minimizing total cost while maximizing service efficiency**, we recommend reviewing part usage at least every six months. This more frequent evaluation will help the stocking strategy stay aligned with real-world service demands and technician feedback, ensuring it remains both cost-effective and service-focused.

**Risk assessment based on recommendation:**

We have developed the heuristic based on raw data with historical data of average annual use. Considering the historical data for future recommendation will be one of the risks for this case. Comparing 50 random stockings to base heuristic recommendation of parts will determine our accuracy and risk in recommendation. Neglecting location based sales, repairs and technicians risk while stocking will be risk at individual van level.