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TEAM 2

BEANIE LIMITED

WAREHOUSE ORDERING POLICY

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General Project Overview

Beanie Limited's actual policy order is negatively affecting Caserta's warehouse performance, by not having clear guidance.

This report aims to provide solutions and recommendations to **Elisa Bolzano**, director of Caserta's warehouse, to **optimize** the current ordering policy by **minimizing** the amount of stock available while **satisfying** clients' demands.

This new policy consists of a **set of instructions** indicating **when** and **how much** stock to request from Diemen's central office, accounting for different settings and scenarios, supported by quantitative metrics and simulations.

Report Outline

Analysis of the previous year's performance

↓

Ordering Policy

↓

Ordering Policy with Minimum Order Quantity

↓

Fixed Lead Time

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Previous Year Performance

In order to measure the performance of last year, the main metric used is the **Surface Level,** that is the days that the demands of clients were not satisfied since the warehouse was running out of stock.

24% of days Beanie's Limited was in stockout

Previous year stock levels have an excessive variance, causing higher stock amounts in some periods and negative amounts in others (Pending demands). We can see it in **Figure 1**. In the following section, we discuss some of the causes for this.

STOCK MANAGEMENT OVERVIEW	
Mean Stock	359,941.22
Stdr. Deviation	475,980.65
Max stock level	1,361,247.27
Min stock level	-802,079.12

Figure 1

CAUSES

The main and **most relevant cause** of the bad performance in the last period was the **lack of** a **clear ordering policy**. This is reflected not only in a 24% of unsatisfied demand, but also in unstable levels of stock, creating higher warehousing costs. There are two main aspects that should have been tackled:

- When is it necessary to order?
- How much should be ordered?

Another important aspect to see is that the **interval of purchasing orders** does not have relation with the quantity of stock. This can be clearly seen in **Figure 2**.

This also allows us to appreciate how the **quantities ordered** are more or less **stable**, regardless of how much is needed (if the level of stock is very negative, nothing is done differently = no adaptablity)

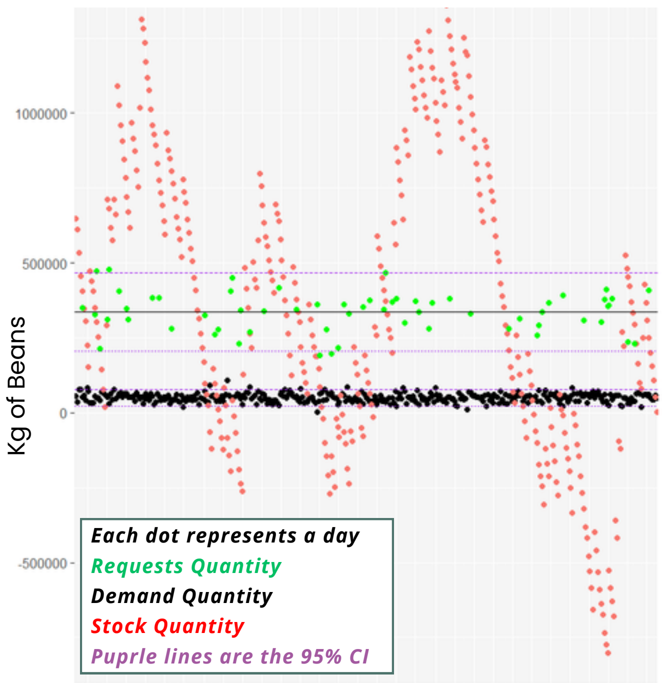
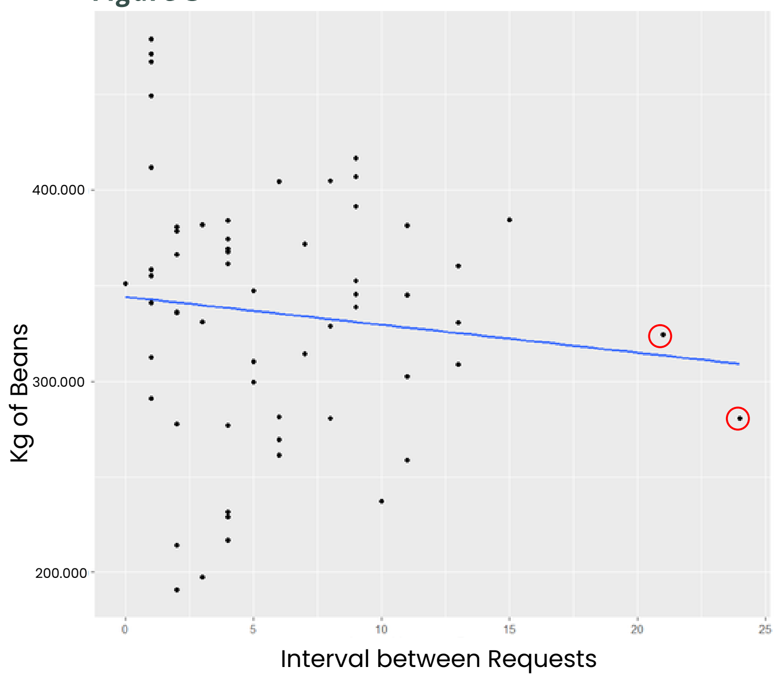


Figure 2

In **Figure 3** we take a deeper look at what the **orders look like**. Apart from seeing that no clear pattern is followed, what strikes the most are the two highlighted dots in the right. These are cases where more than 20 days elapsed between orders. **The consequences of this can be catastrophic** and hard to recover from if a huge order is not placed afterwards, since the stock levels could remain too low.

Figure 3



The mean of the **interval between requests** is **6 days**. If we compute the demand we expect to have for this 6 days (6*50k= 300k), it is roughly the same as the mean of the reorder quantity the company purchases. Thus, when either the demand or the lead time vary (both have a significant standard deviation), stockout issues arise.

Figure 4: Summary historical Data

Historical Data	Demand	Ordered Amount	Lead Time
Average	50,149.19	335,581.7	7.32
Standard Deviation	14,220.76	66,474.37	1.85
Max. level	107,790.97	479,249,85	12 days
Min. level	1,380.98	190,836.06	4 days

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Optimal Ordering Policy

From the previous analysis highlighting the weaknesses of the last purchasing rule, it is clear that there is room for improvement. As we have seen, two of the biggest concerns are **demand variability** and **lead time uncertainty**, and Caserta's warehouse has not been able to define a clear ordering policy in order to account for those facts.

In this section, a new **ordering policy** is going to be presented, with the **goal** of **minimizing the amount of stock** in the warehouse while **fulfilling clients' demand**, achieving a minimum of **95% service level**. The policy is obtained through a simulation-based approach, in order to internalise the randomness of both demand and lead time.

Hence, our methodology will be similar to a Gradient Descendant Algorithm *(see Math Appendix)*. This consists in providing a set of preliminary parameters, based on the **safety stock** and **reorder point** (an approach widely used in *Operations and Logistics*), analyzing the outcome obtained through simulation and repeating again the process with new and more accurate parameters. The aim here is to finally achieve a set of parameters which satisfy our previously depicted goals.

In this fashion, here is our **ordering policy**, consisting of two parameters, the **reorder point** and the **reorder quantity**:

REORDER POINT
442,823.12

»

REORDER QUANTITY
416,924

Figure 5

The first one refers to the **cutoff stock level**. If the current stock level of the warehouse **falls below** this threshold, then Caserta's team **must place a new order**. The second element refers to the **quantity that must be ordered**. That is, once the current stock level has crossed the mentioned threshold, what is the exact amount of stock that should be ordered? Notice that if the amount of stock is above the reorder point there is no need to place a new order, as that level of stock is sufficient to meet demand.

Similarly, in order to successfully complete the simulations, we provide a **initial stock**. In our models, this amount is calculated as the average stock in the historial data multiplied by 2. We establish this number to ensure that enough stock is provided at the beginning of the simulation, and from there, we analyze how the simulation responds. Also, notice that our final approach is tested with different initial quantities, certifying the robustness of our analysis. The conclusion is that our final approach **performs successfully** in each of the different settings considered.

Our final ordering policy is the one depicted in **Figure 5**, which corresponds to the **Approach 7**, located in the appendix. This policy ensures that, through *3,000* simulations, an average service level of **0.95** is achieved, while keeping an average stock level of **234874.20**.

Additionally, a table summarising the different approaches and their metrics can be found in the appendix.

In **Figure 6**, we provide a comparison between last year stock distribution and the one obtained with our proposed ordering policy. As it can be noticed, our results closely follow a normal distribution, with a considerable decrease in both stockout rates and levels of stock.

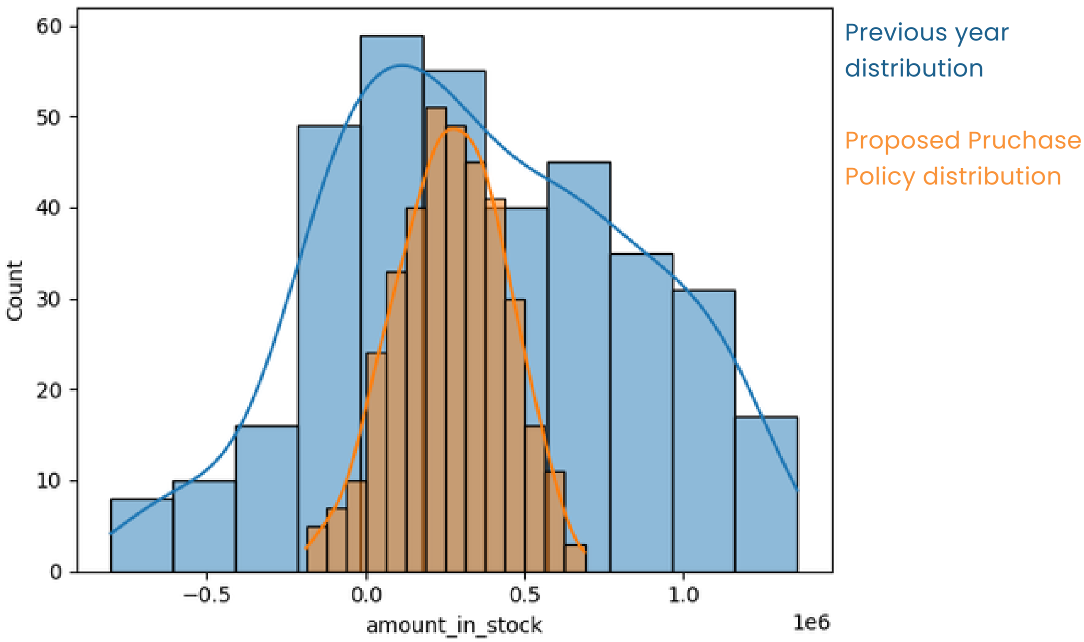

Figure 6

Considering a Minimum Quantity Order

Caserta's warehouse has informed us that a new rule affecting purchasing orders will be implemented soon. This new rule constrains the possible ordering policies, as it imposes a **Minimum Quantity Order** (MQO) of **500,000 kgs** of beans. That is, every time Caserta's warehouse places an order to Diemen's central office, the reorder quantity requested must be of at least that mentioned amount.

Hence, in this section this scenario is also considered and assessed, determining whether the previous optimal policy should be modified or not. The new setting will follow the same methodology as the previous one, but imposing a lower limit of 500,000 kgs to the reorder quantities explored in the simulations.

Recalling our Optimal Ordering Policy

In **Figure 5** we presented our policy, setting a purchasing order of 416,294. However, with the implementation of this last rule, our optimal policy is affected and it is **no longer optimal**.

As a consequence, we need to present a new policy restricting the minimum quantity

New Optimal Ordering Policy with MQO

REORDER POINT
390,000

»

REORDER QUANTITY
500,000

Figure 7

There are these two relevant elements. First, the **reorder quantity**: previously, without MQO, the optimal quantity was lower than 500.000 kg. Therefore, now with this policy the results can not be as good as before. Even though, we can infer that the optimal reorder quantity **cannot be higher than 500.000**. What had to be determined was the **reorder poin**t. To do so, we followed a similar approach as before. The **Approach 5** was the optimal one, as we can see in Figure 11 (Appendix).

Fixed Lead Time vs Uncertain Lead Time

Finally, in this section, we explore the consequences of a possible improvement in lead time stability. A new comparison will be provided, determining whether an ordering policy with a fixed lead time (15 days) could result in a more efficient outcome than the one previously depicted (accounting also for the MQO rule).

Ordering Policy with Fixed Lead Time

With a fixed lead time, the only variable that remains with a certain degree of variability is the demand. In this fashion, we calculate the theoretical values for both the reorder point and the reorder quantity, and then we proceed to develop the corresponding simulations with the same methodology.

REORDER POINT	REORDER QUANTITY
807,314.73	752,237.94

Figure 8

Nevertheless, the results obtained are far from being optimal and far from the outcomes obtained in the previous section. Even though we achieve an average service level **0.98**, the average level of stock skyrockets to **905,790.63**. Therefore, the costs assumed by the Caserta's warehouse with this policy are much greater than the ones obtained before.

Given the fact that the level of stock is too high, we proceed to run the simulations with the *minimum quantity order* of 500,000 kgs, trying to lower the level of stock and its consequently cost. Unfortunately, the **results** are still **far from being optimal**, since the average level of stock is **nearly identical** to the one obtained with the theoretical value.

Fixed Lead Time vs Uncertain Lead Time

Given our results, we conclude that the optimal ordering policy is still the one depicted in **Figure 7**, since it satisfies the required service level while achieving a much **lower stock level**. The reasons for this fact lies on the amount of stock necessary to satisfy client's demand during the awaiting period of 15 days (compared to the simulated lead times with uncertainty).

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PROPOSAL SUMMARY

Based on our previous analysis, find here a concise summary of our main findings and recommendations, given each scenario:

UNCONSTRAINED OP*

REORDER POINT

442,823.12

REORDER QUANTITY

416,924

NEW MQO*

REORDER POINT

390,000

REORDER QUANTITY

500,000

FIXED
VS
UNCERTAIN

Better results with **short but uncertain** lead time, rather than fixed but long

Figure 9

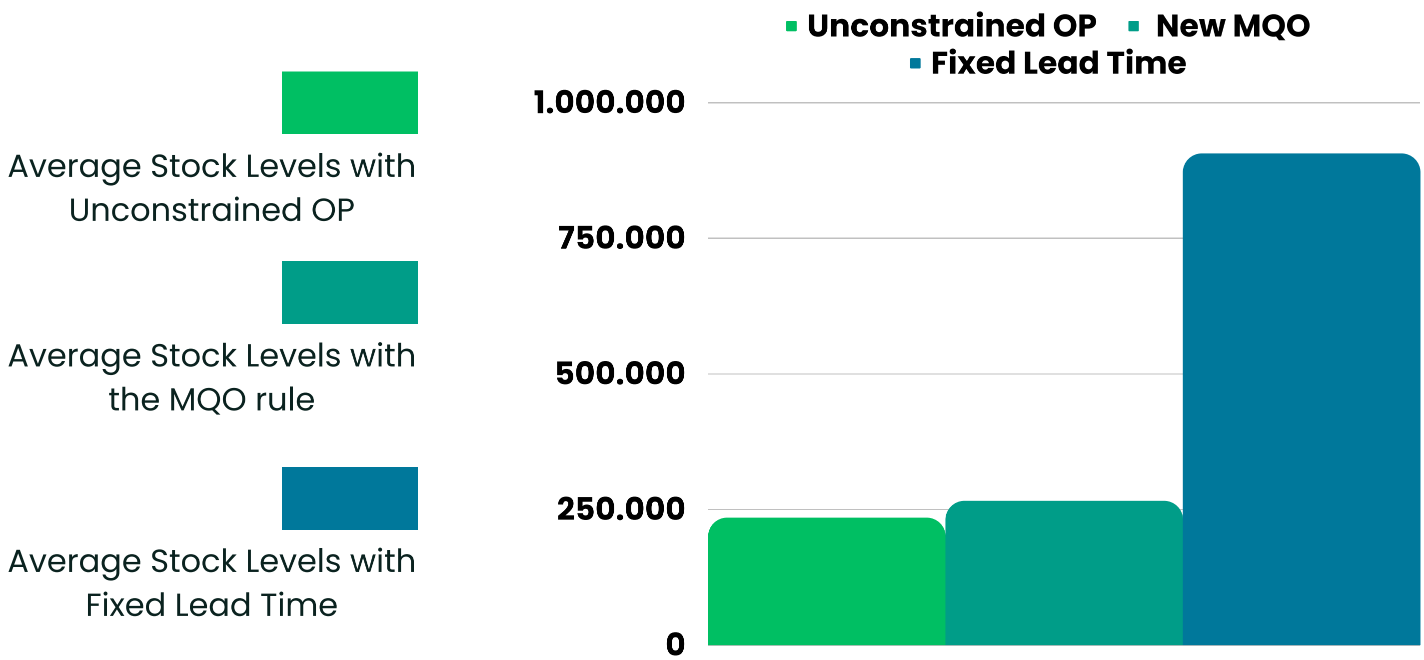

Figure 10

*OP refers to Ordering Policy
*MQO refers to Minimum Quantity Order

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GRADIENT DESCENDANT METHOD

Our simulation optimizing model has been inspired by Convex optimisation procedures. Inside these methods, we find Gradient Descendant Algorithms. Their procedure consists to find the minimum of a function, through iterations, in which each of that steps reports a gradient(vector that minimizes the function most).

Caserta's goal could have been seen as a function that it should be minimised subject to a constraint; Reduce the average stock of the warehouse while serving 95% of the commands through a year.

In our analysis, the initial parameters (2) had been those provided by logistic theory explained before. In our simple approach, we take one of the parameters and increase or decrease their values while maintaining the other fixed until reach 95% Surface Level.

If the increase/decrease of the parameter provides a different result than expected (decrease surface level, increase the stock amount) we reduce/raise quantity provided.

Having achieved this, we seek to minimize the stock level by changing the other parameter. We have been able to report an adjusted stock and a sufficient surface level in 8 iterations.

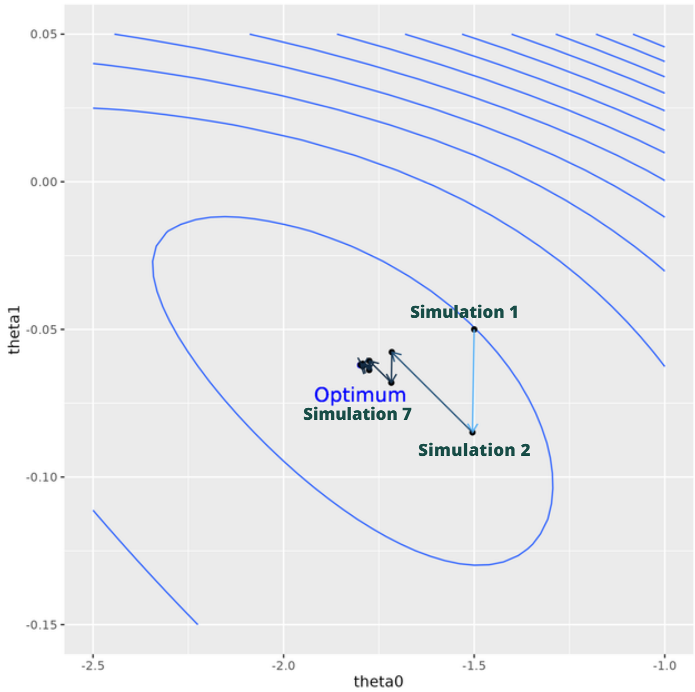

Figure 11

Each iteration consists of 3000 simulations of the whole year

In Iterations 2,3 and 4 the tuned parameter is the reorder quantity. From there up to 7, reordering point is modified, with the final iteration 8, which indicates that it is not possible to minimize more "the function".

Approach	Initial	2	3	4	5	6	7	8
Average Service Level	0.81	0.97	0.95	0.98	0.95	0.95	0.95	0.95
Average Stock Level	127373	296603	246385	340287	241645	242469	234874	247341

Figure 12

MATH APPENDIX

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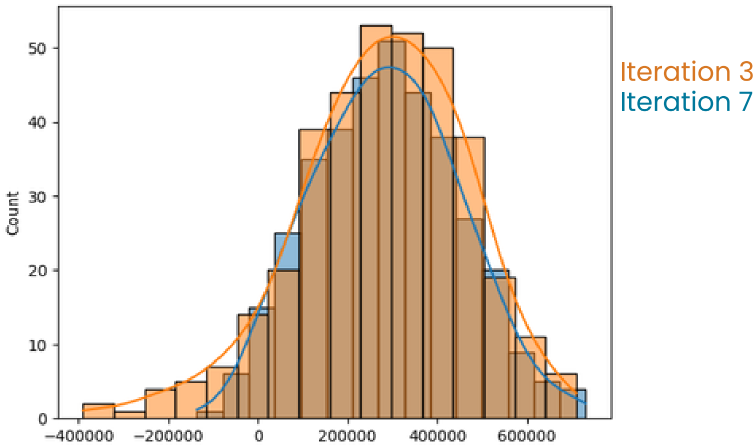
Approach	1	2	3	4	5	6
Average Service Level	0.98	0.98	0.96	0.958	**0.95**	0.94
Average Stock Level	319667	338088	282662	272479	**265853**	263130

Figure 13



Iteration 3 and 7 stock distribution

Figure 14

LOGISTIC FORMULAS

$$\text{Safety Stock (King's Method)} = Z^{*} \times \sqrt{\left(\left(\text{Average Daily Unit Sales} \times \text{Lead Time Standard Deviation}\right)^{2} + \left(\text{Average Lead Time} \times \text{Daily Sales Standard Deviation}\right)^{2}\right)}$$

*Normal distribution Critical Value. In this study is used a 5% level (Z=1.96)

$$\text{Reorder Quantity} = \text{Average Daily Unit Sales} \times \text{Average Lead Time}$$

$$\text{Reorder Point} = \text{Average Daily Unit Sales} \times \text{Average Lead Time} + \text{Safety Stock}$$

TEAM 2

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