Demand Forecasting and Inventory Management for Spare Parts

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Summary: In this project, we researched the literature to find best practices for companies when dealing with the scope of managing spare parts. In this research, we focused on main topics that companies have to address in this context. The first one is with regards to their demand forecasting practices and the second one is with regards to their inventory management practices. We were able to improve the forecast accuracy in the range of 7% to 14%. Furthermore, we were able to improve the service level by 3%.

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KEY INSIGHTS

1. **Focusing in the demanding planning and inventory management in the spare parts context can lead to an increase in operational performance.**
2. **Following the suggested demand forecasting techniques in the literature for spare parts can lead to accuracy increase.**
3. **Incorporating real world constraints into inventory classification can lead to better inventory management and control.**

Introduction

The management of spare parts is an important activity for companies in many different sectors. The spare parts category tends to have a higher level of demand uncertainty when compared to traditional fast-moving products, given the nature of the demand itself. Customers only look for the product when the current part is not functioning anymore and this can occur within the lifespan of a machinery, which can last for decades. This demand behavior is reflected and characterized by an intermittent pattern (i.e. long periods of time between two demand signals). Furthermore, given the complex nature and variety of machinery, spare parts tend to have a high number of stock keeping units (SKU's). In addition to the aforementioned factors, the fact that many spare parts are critical to the continuity of operations lead companies to hold higher inventory levels in order to mitigate risk.

Gerber Technology is a manufacturing company that designs, sells, and services industrial machines. In addition to the main industrial machines, the company also sells the software that operates them, and the spare parts that support them.

In its spare parts segment, the company faces challenges in its demand forecast quality due to the high uncertainty of customers' orders, caused by the lack of predictability of order pattern. This uncertainty has been negatively impacting the company's inventory costs in recent years, where the actual inventory is consistently higher than what had been targeted. Meanwhile, higher inventory levels are not being translated into higher service level to its customers. In summary, the company has seen increased costs with a lower service level.

The goal of this project was to improve the demand forecast accuracy and the spare parts service level of the company while minimizing inventory costs.

Methodology

We first identified the company's current practices. In the case of demand planning, that meant analyzing each forecasting method currently used for each SKU in each plant. For the supply planning side, that meant analyzing the current SKU categorization in terms of

A, B, C, D, and S classes. The current forecasting method and SKU categorization techniques established the baseline of our study and this baseline served as the basis when comparing the impacts of the proposed changes.

The second step was improving the demand and supply planning. For the demand, we classified each SKU in each plant into one of the four demand categories (erratic, lumpy, intermittent, and smooth), and assigned the suggested demand forecasting by the literature review.

Finally, we compared the results generated by our model with the baseline.

Classification for Demand Forecast

The first step in the analysis phase was to classify each spare part commercialized by the company based in its demand pattern. We classified demand based on two criteria: (i) squared coefficient of variation (CV2), and (ii) average inter-demand interval (p). The first item is calculated based on the demand signals (i.e. when demand is greater than zero), whereas the second item is the average time between demand signals (i.e. how long it takes on average for demand signals to appear). For every SKU, in every single plant, each of these parameters was calculated. Based on their values, the demand pattern was classified into one of four categories: (i) erratic, (ii) lumpy, (iii) intermittent, or (iv) smooth. Demand pattern is said to be erratic if its CV2 is greater than 0.49 and its p is lower or equal to 1.32. For lumpy demand, CV2 is greater than 0.49 and p is greater than 1.32. Intermittent demand is classified by a CV2 is lower or equal to 0.49 and p is greater than 1.32. Finally, smooth demand is classified by a CV2 is lower or equal to 0.49 and p is lower or equal to 1.32.

Classification for Inventory Management

The first step in inventory management was the classification of the SKUs based on business requirements. Using only a single criterion for classification does not serve well in spare parts industry because many spare parts are desired to be in stocks not only to provide higher revenue but also to ensure customers will receive their orders (along with other items) without delay. Such business decisions play a major role in inventory classification in the spare parts industry. Therefore, we decided to use multi-criteria inventory classification, which is believed to yield better results as it considers more parameters that impact inventory holding. We considered 6 parameters: (1) Average Unit Cost, (2) Annual Revenue, (3) Lead Time, (4) Ship Complete, (5) Cost of out-of-stock, and (6) Strategic Importance. To understand how much each of the parameter defined above can influence the classification of each SKU, it is important to know whether the specific parameter impacts the classification directly or indirectly. Hence, we have categorized the 6 parameters into two categories: Direct and Indirect Parameters.

The direct parameters are the ones that have a predefined value for each SKU and cannot be manipulated under usual circumstances. The indirect parameters are the ones whose value can be improved or redefined based on the business situation.

Results - Demand Forecast

Most of the SKU's were classified in the intermittent or lumpy category, with fewer occurrences in the smooth and erratic categories, showing the complexity that the company faces regarding the demand pattern for their spare parts business.

Table 1 - Demand Forecast Results

Plant	Median Improvement RMSE – Positive Cases	Median Improvement RMSE – All Cases
0435	15%	13%
0445	13%	10%
0446	17%	14%
0471	14%	7%
0480	17%	11%

Moreover, many products were not classified in one of the four categories since they did not have enough demand in the past 3 years. This non-classification happens because at least two demand signals are required to calculate an average inter-demand interval (p).
The results were an increase in accuracy measured by the RMSE when using the suggested forecasting methods. However, there are still many SKUs that have their accuracy worsened when changing the current forecasting technique to the suggested. To this reason, we aggregated the results in two ways: (i) calculating the median improvement in RMSE using all SKUs, and (ii) calculating the median improvement in RMSE using only SKUs that had a better forecast. The results can be seen in Table 1.
We were able to increase the accuracy in the range of 7% to 14% in the plants. Accounting only for the positive cases, we see a median range of 13%-17%.

Results – Inventory Classification

Most of the SKUs that were previously classified as A class fall under G1 category. This is expected as the A class SKUs are clearly the most important SKUs in terms of revenue generation and inventory management. However, we also noticed 341 SKUs, previously classified as D class, are now proposed by the model under G1 group. These are the SKUs that despite being small in revenue generation, have a big impact on service level due to other parameters like ship complete. For instance, a D class SKU needs to be shipped together with A class SKU, if out of stock impacts the service level of A class SKU as well. The overall classification can be seen in Figure 1.
Considering ABC classes only, 197 SKUs were proposed to be in higher class while 135 SKUs were proposed to be in a lower class than before.

Conclusions

In this project, we researched the literature to find best practices for companies when dealing with the scope of managing spare parts. In this research, we focused on main topics that companies have to address in this context.
We were able to improve the forecast accuracy in RMSE terms for the company's plants in the range of 7% to 14%, which is reflected in a reduction of the company's safety stock.
Furthermore, we were able to improve the service level by 3% leading to an additional revenue opportunity of approximately $1.3M with the current demand pattern.
We recommend Gerber to do a pilot study with the new forecasting and inventory methods of key SKUs and measure the impact on the business.

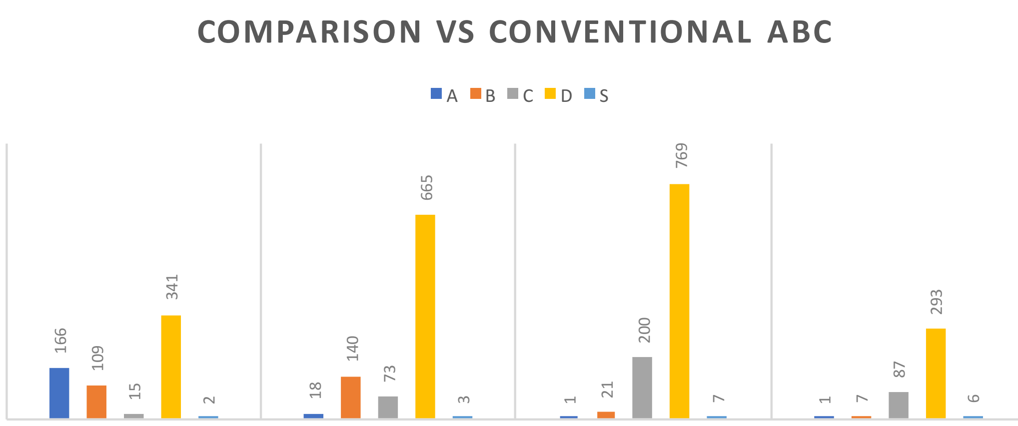

Figure 1 - Original vs New Inventory Classification