A Systematic Approach to Internal Spare Parts Management

by

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B.S. Industrial and Systems Engineering, Georgia Institute of Technology, 2007

Submitted to the MIT Sloan School of Management and the Engineering Systems Division in Partial Fulfillment of the Requirements for the Degrees of

Master of Business Administration

and

Master of Science in Engineering Systems

In conjunction with the Leaders for Global Operations Program at the Massachusetts Institute of Technology

June 2014

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Abstract

Internal spare parts management is a universal issue faced by all manufacturers, and involves decision-making and planning across a highly complex and heterogeneous group of thousands of items. Spare parts exhibit intermittent demand and a variety of prices, lead times, and potential downtime costs that pose challenges for planning and control. Managers can facilitate spare parts decision-making through the utilization of classification methods to prioritize critical parts and forecasting tools to better establish inventory policies. This thesis explores a classification method to evaluate the criticality of spare parts using the Analytic Hierarchy Process and applies bootstrapping forecast techniques to better inform safety stock levels. A joint classification and forecasting model is developed and validated for use by supply chain and maintenance teams in the organization. Through improved safety stock settings, an inventory savings of up to 39% is identified while maintaining or increasing service levels for critical spare parts. For most manufacturing companies, the approaches and findings discussed in this thesis are applicable and can be used to aid efforts in establishing a systematic approach to internal spare parts.

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Special thanks to my advisors Juan Pablo Vielma and Bruce Cameron, who helped me to strike the right balance between academic rigor and implementable impact. Thanks to the Leaders for Global Operations (LGO) Program for all of the opportunities, including this project, through which I have been able to better understand myself and develop as a leader.

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Most importantly, I owe many thanks to my beautiful and supportive wife Rachel. Her encouragement and, perhaps more importantly, patience have helped me to achieve heights that I never thought possible. Throughout this project and beyond, she has pushed me to challenge myself while serving as a constant reminder that there is always a reason to smile.
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1 Introduction

The purpose of this thesis is to assess and recommend a systematic approach to internal spare parts management, with a focus on classification and inventory policies. With these recommendations, manufacturers can more intelligently prioritize and manage spare parts inventories and planning decisions. This can lead to reduced inventory holding costs while maintaining or improving critical parts service levels from the spare parts warehouse. This research was performed as a part of the Leaders for Global Operations program at the Massachusetts Institute of Technology under the sponsorship of a partner company. To protect proprietary information, the researched company's name, location, and identifiable characteristics have been disguised. The following section provides context for the performed spare parts research.

1.1 Company Overview

Company X is a Fortune 500 consumer products manufacturer. The company operates production facilities across the world and employs more than 50,000 people. Production is typically segregated by product family, driven by technology differences. Current production is focused on paper-based consumer goods, requiring a variety of mechanical processes including fiber conversion, cutting, adhesion, and bagging. While the company has over 60 facilities across the world, the focus of this analysis is on a particular geographic division.

1.2 Division Overview

The studied division spans two continents and is structured into four regions, each of which includes multiple countries and production facilities. The full product family portfolio is produced by 20 mills across 11 countries, while the studied product family is produced in 8 of these mills across 8 countries. The facilities support sales networks in over 20 countries for a total of approximately $3.6 billion in net sales. Spare parts for the facilities are sourced from a mix of global and local suppliers, including an internal centralized global warehouse based in the United States. The focus of this analysis is on
four particular sites manufacturing a single product family, but the results are applicable to the remaining production facilities in the company portfolio as well as any general manufacturing sites which manage internal spare parts.

1.3 Problem Statement

The division has benefited from multiple years of accelerated sales growth at a pace of over 10% per annum and, as a result, has expanded production through new machine installations and purchases of existing independent manufacturing facilities. Organizational priorities have been focused on ensuring adequate supply for the climbing demand. However, the complexity of the operations has accelerated in line with the expanded production, and spare parts working capital has expanded at a compound annual growth rate of 34% per year over the past two years. In addition, the sheer variety of SKUs has risen and the division now catalogs over 80,000 spare parts in the inventory system.

Individual production facilities manage an average of 7,700 unique parts SKUs each. Inventory decisions are made on an individual part basis and are typically managed by a single warehouse supervisor. Maintenance teams provide guidance on the criticality of stocking parts, but this guidance is ad hoc and solely experiential. This complexity and nonsystematic approach have led to a high percentage of non-moving and slow-moving parts. 40% of stocked spare parts inventory by value have not been used in the last three years, tying up significant working capital and increasing obsolescence risk. While slow and erratic demand is common for spare parts, the accelerated growth of the operational complexity and inventory levels has resulted in 20% of the region's working capital being held in spare parts. The division leadership has prioritized reducing this spare parts working capital, with one region targeting a 20% reduction over the next year.
1.4 Project Goals

The primary goal of the project is to reduce spare parts working capital while maintaining or improving critical part availability. To accomplish these goals, a two-pronged effort has been developed. First, a benchmarking study performed across four production sites will serve to identify and codify best practices in spare parts management within the region. These efforts will not be extensively discussed in this document due to the company-specific nature of the practices, but will instead be referenced when relevant. In addition, the current state of the division will be examined through the study performed at these four sites. The second focus of the project is to develop a systematic approach to managing spare parts. To accomplish this, classification and inventory management techniques will be explored. A decision-aiding tool will be discussed and initial outcomes from a pilot test will be used to show how spare parts can be effectively managed through a systematic approach.

1.5 Thesis Structure

Chapter 1 provides context relevant to the project and identifies the primary goals and approach for the analysis.

Chapter 2 describes the behavior of spare parts and identifies the current state of the company’s spare parts processes.

Chapter 3 discusses spare parts management practices, as established by literature, and relevant case studies focused on spare parts.

Chapter 4 reviews the current state of the spare parts classification process, opportunities for improvement, and recommendations.

Chapter 5 reviews the current state of the spare parts inventory policies, opportunities for improvement, and recommendations.

Chapter 6 discusses the developed model to jointly classify and forecast spare parts SKUs, including results of a pilot study.

Chapter 7 summarizes the project, identifies considerations for implementation, and assesses general applicability of the research findings.
2 The Spare Parts Process

Due to the unique characteristics of spare parts relative to traditional products studied in supply chain research, it is beneficial to review spare part behavior and processes. This chapter will review the nature of spare parts with examples from the studied division, sources of demand generation for spare parts, and the current spare parts management process in the division.

2.1 Spare Parts Characteristics

Because spare parts must encompass almost all components of a complex production process, the types and number of spare parts are significant. As seen in Table 1 below, spare parts span a wide spectrum of electrical and mechanical supplies. The division uses the specified material groups to consolidate similar types of spare parts, although these groups are in themselves quite large and mixed. In total, there are over 80,000 individual SKUs in the SAP management system.

<table>
<thead>
<tr>
<th>Material Group</th>
<th>Examples</th>
<th># of SKUs</th>
<th>% of SKUs</th>
<th>% of Stock Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chains and Belts</td>
<td>Roller chains, timing belts</td>
<td>11,361</td>
<td>13%</td>
<td>8%</td>
</tr>
<tr>
<td>Electrical Supplies</td>
<td>Servo motors, sensors</td>
<td>11,339</td>
<td>13%</td>
<td>10%</td>
</tr>
<tr>
<td>OEM Materials</td>
<td>Pumps, control modules</td>
<td>8,644</td>
<td>10%</td>
<td>19%</td>
</tr>
<tr>
<td>Bearings</td>
<td>Rolling pins, ball bearings</td>
<td>8,466</td>
<td>10%</td>
<td>6%</td>
</tr>
<tr>
<td>Fasteners</td>
<td>Clamps, screws</td>
<td>6,516</td>
<td>7%</td>
<td>1%</td>
</tr>
<tr>
<td>Fluid Power</td>
<td>Pumps, filters</td>
<td>4,416</td>
<td>5%</td>
<td>5%</td>
</tr>
<tr>
<td>Hoses, Fittings, Joints</td>
<td>Vacuum hoses, flex joints</td>
<td>3,960</td>
<td>4%</td>
<td>2%</td>
</tr>
<tr>
<td>Seals, Gaskets, O-Rings</td>
<td>Mechanical seals, O-rings</td>
<td>3,867</td>
<td>4%</td>
<td>1%</td>
</tr>
<tr>
<td>Electronic Equipment</td>
<td>Amplifiers, vector controls</td>
<td>3,745</td>
<td>4%</td>
<td>10%</td>
</tr>
<tr>
<td>Instrumentation</td>
<td>Processors, sensors</td>
<td>3,733</td>
<td>4%</td>
<td>4%</td>
</tr>
<tr>
<td>All Other (75 Groups)</td>
<td>Cutting knives, tubing</td>
<td>22,342</td>
<td>25%</td>
<td>34%</td>
</tr>
</tbody>
</table>

Table 1: Overview of Spare Parts Material Groups
To further complicate spare parts management, there is also challenge in accurately assigning groups due to subjective technician interpretations of the material group definitions. For example: servo motors appear in 5 different material groups, pumps appear in 7 different material groups, and cutting knives appear in 11 different material groups. Standardization is difficult across multiple sites when many of the material groups are closely related, such as in the case of electrical supplies versus electronic equipment.

Spare part demand behavior varies the full spectrum, from non-moving to very fast-moving. Even within a specific type of spare part, demand patterns can be heterogeneous. Figure 1 below highlights a range of demand patterns for ball bearings at a particular site. 23% of stocked ball bearing SKUs have had no consumption in the previous three years, whereas the fastest-moving ball bearings have been consumed several hundred times each.

![3-year demand pattern](image.png)

Figure 1: Example of Demand Distribution, Ball Bearings

The slow-moving and intermittent behavior seen in the ball bearing SKUs is representative of the full spare parts portfolio. At one particular site in the division, 43% of parts had zero demand in the previous three years and 18% had only one demand

---

1 The largest bubble represents 44 SKUs with zero demand in the previous 3 years
instance. The remaining SKUs exhibiting more than one demand instance can be categorized according to the recognized cross-section of average inter-demand interval and coefficient of variation suggested by Syntetos et al. [1] in the field of intermittent demand forecasting. Average inter-demand interval is the average interval between two demand events, whereas coefficient of variation is the standard deviation of demand divided by the average of demand. Figure 2 below summarizes the distribution of SKUs according to the classifications proposed by Syntetos et al. From this analysis, it is clear that most SKUs with greater than one demand instance fall into the “Lumpy” or “Intermittent” demand categories. These categories exhibit many periods of zero demand, and the ability to forecast and control these parts is challenging at best.

![Figure 2: ADI versus CV^2 Comparison, Site A SKUs](image)

In addition to intermittent and erratic demand patterns, costs and lead times are also highly variable. At one site, 18% of spare parts cost under $10 while 17% cost over
$500. Part costs at the same site range from a minimum of $0.01 to a maximum of $19,000. In addition, repairable parts are typically capitalized, representing approximately 4% of SKUs. Lead times vary depending on specificity and origin country. Specially-made OEM spare parts are typically imported from across the world and can require lead times of several months. In the case of this particular site, 29% of parts require a lead time of 60 days or more, 35% of parts require 30 to 45 days, 3% require less than 30 days, and 32% have unknown lead times because they are infrequently ordered. Supplier management is also difficult, with each site in the division managing an average of over 150 suppliers for spare parts alone.

The end result of this combination of factors is that spare parts are extremely complex to plan and control. Long and often unknown lead times, wide-ranging costs, a multitude of suppliers, and various demand patterns ranging from non-moving to highly intermittent all contribute to the challenge of setting inventory policies and making decisions regarding spare parts. The difficulty of this management process is exacerbated when management is accomplished via informal and ad hoc approaches. It is difficult to manage thousands of heterogeneous spare parts with sophisticated systems and controls, but nearly impossible to intelligently manage thousands of spare parts through an informal basis. For this reason, it is of the utmost importance to define a systematic approach to managing spare parts.

2.2 Demand Generation through Maintenance

To understand the underlying demand behavior of spare parts, it is beneficial to examine the demand drivers. Demand for internal spare parts is triggered by work orders from maintenance technicians as they repair sections or pieces of the production machinery. There are three common types of maintenance work orders as summarized in Table 2, depending on the purpose of the activity.
These three maintenance types are dependent on one another. For example, effective preventive maintenance programs can ensure that machines produce for longer periods prior to breakdowns. This is similar to changing oil in a personal car every 3,000 miles. Should the preventive oil changes not take place, the engine of the car may seize, which would create a more costly emergency breakdown work order. Extraordinary maintenance activities can also include one-time project work, such as a machine upgrade or new technology installation.

In addition, part failure rates can follow a relatively deterministic nature or a stochastic nature. Cutting knives, for example, physically wear down every few thousand cuts. On the other hand, electronics fail in a stochastic manner that is difficult to predict. Failure rate and life cycle distributions such as the Weibull distribution can assist technicians in planning for the failure of parts with a stochastic nature, but this remains a challenge.

### 2.3 Spare Parts Management: Current Process

The management of spare parts in the division is a cooperative effort between the supply chain and maintenance teams. Supply chain is responsible for the service level performance, warehouse operations, supply management, and inventory levels. Maintenance is responsible for planning future resource requirements, managing technical information, and providing technical expertise when needed for purchases. While the exact organizational structure varies by site within the division, the general segregation of duties remains the same.

<table>
<thead>
<tr>
<th>Work order type</th>
<th>Event Timing</th>
<th>Repair Timing</th>
<th>% of Work Orders, Site D</th>
<th>% of Spare Parts Spend, Site D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Emergency breakdown</td>
<td>Unknown and unplanned</td>
<td>Immediate due to downtime costs</td>
<td>14%</td>
<td>25%</td>
</tr>
<tr>
<td>Short-term corrective</td>
<td>Unknown and unplanned</td>
<td>Short-term horizon; schedulable</td>
<td>75%</td>
<td>59%</td>
</tr>
<tr>
<td>Preventive</td>
<td>Known and planned</td>
<td>Routinely scheduled</td>
<td>11%</td>
<td>15%</td>
</tr>
</tbody>
</table>

Table 2: Maintenance Types and Distribution
The primary flows in the spare parts management process are outlined in Figure 3 below. Maintenance work orders are generated as described above, which then lead to job scheduling and part requisition. If the maintenance activity can be planned in advance, the spare parts may be ordered for consumption on delivery. Otherwise, spare parts must be obtained from the parts warehouse from the site’s inventory. Spare parts inventory control and purchasing is managed through a combination of manual Excel-based spreadsheets and automatic material resource planning (MRP) orders via the SAP system. Orders in the MRP system are triggered when the physical inventory, less planned maintenance taking into account delivery lead times, is lower than the safety stock as set in the system for each SKU.

![Figure 3: Overview of Spare Parts Process](image)

### 2.4 Summary

Although the heterogeneous and intermittent behavior of spare parts increases the complexity of inventory policy decision-making, it does not preclude quantitatively-driven approaches. A systematic method of prioritizing and setting inventory policies through classification and forecasting can be applied to reduce uncertainty in setting spare parts inventory decisions.
3 Literature Review

While the issue of internal spare parts management has existed since the early years of manufacturing, the literature surrounding spare parts has accelerated primarily in recent decades. Efforts have been made by Kennedy et al. [2] and Rego and Mesquita [3] to corral recent literature on spare parts. As seen from their summaries, the majority of literature is focused on challenges such as intermittent demand forecasting, devising classification systems, and determining inventory stocking policies.

3.1 Maintenance and Spare Parts Management Practices

Because maintenance activities are the primary driver of spare parts demand, it is beneficial to consider maintenance planning processes. Maintenance handbooks such as that of Palmer [4] highlight practices in planning, scheduling, and controlling maintenance activities. In addition, maintenance reviews such as those performed by Wang [5] and Chase [6] identify potential maintenance policies and improvements regarding work flow processes and structure. While maintenance practices are not the focus of this study, it is important to be familiar with these policies given the dependency of spare parts usage on maintenance activities.

In addition, there have been general efforts focused on the full spectrum of spare parts decision-making. Cavalieri et al. [7] propose a five-step decision-making framework to aid in spare parts management, including part coding, part classification, part demand forecasting, stock management policy, and policy test and validation. Driessen et al. [8] propose a planning and control framework for spare parts management which groups decisions into common topics such as supply management and order handling. Slater [9] suggests inventory reduction actions and management policies based on industry experience. These frameworks provide structure and guidance for the described systematic approach to spare parts management.

3.2 Spare Parts Classification Models

Classification models have been extensively reviewed in literature given the importance of applying a structured approach to large and heterogeneous groups of spare parts. For classification, it is beneficial to consider the purpose of classification systems, the criteria used as inputs, the process used to analyze these inputs, and the recommended outputs from these models.

As described by Syntetos et al. [10], classifying SKUs is critical to facilitate the decision-making process, and can benefit a variety of areas from forecasting to inventory policies. In addition, Syntetos et al. highlight that classification enables time-constrained management teams to focus their efforts on the parts which matter most.

Inputs for classification models have been explored in a variety of studies. Bacchetti and Saccani [11] provide a helpful review of 25 published classification approaches and the factors that were most commonly used across these research initiatives. Figure 4 below summarizes the most common factors used in these studies. Interestingly, the definition of the most common factor, criticality, can vary significantly. Syntetos and Boylan [12] identify criticality as a factor that can be defined formally or informally, and that it is typically more important for technical systems, such as the system in this study. An important distinction in semantics is the usage of the term “criticality.” In the summary of Bacchetti and Saccani, criticality is meant in terms of the part’s technical criticality to the production line. In this study, we define criticality as the holistic importance of the part to the overall system. We refer to the technical criticality as “machine impact” to avoid confusion with nomenclature at the company’s site level.
Factors used in classification methods

<table>
<thead>
<tr>
<th>Factor</th>
<th>Number of studies using factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Part criticality</td>
<td>15</td>
</tr>
<tr>
<td>Part cost</td>
<td>15</td>
</tr>
<tr>
<td>Demand volume/value</td>
<td>13</td>
</tr>
<tr>
<td>Supply characteristics</td>
<td>12</td>
</tr>
<tr>
<td>Demand variability</td>
<td>8</td>
</tr>
<tr>
<td>Other</td>
<td>6</td>
</tr>
</tbody>
</table>

Number of studies using factor

Figure 4: Common Factors Used in Other Classification Studies [11]

With the inputs defined, another important step in classification analysis is how to process these factors. A variety of methods are applied to process the inputs, ranging from linear optimizations such as those discussed by Ng [13] to Analytic Hierarchy Process (AHP) as discussed by Molenaers et al. [14], Gajpal et al. [15], and Braglia et al. [16]. AHP is a method to combine quantitative and qualitative factors through pairwise comparison rankings, as proposed by Saaty [17]. The advantage of an approach such as linear optimization is that it is purely objective, while the advantage of an approach such as AHP is that it can include both quantitative and qualitative factors.

Once inputs are processed, it is necessary to define an output by which spare parts can be classified and organized. Traditional ABC analysis is typically based on a single factor, but as Braglia et al. [16] highlight, this is insufficient to address the many control parameters of heterogeneous spare parts populations. A popular method of classifying spare parts is the VED method discussed by Gajpal et al. [15], where parts are either Vital, Essential, or Desirable. This level of criticality is associated with downtime costs and losses due to non-availability in event of part failure. More nuanced methods are also discussed, such as the 12-group system proposed by Bacchetti et al. [18].
3.3 **Spare Parts Forecasting Models**

In addition to classification models, there is also an abundance of literature on spare parts forecasting and intermittent demand forecasting in general. Callegaro [19] highlights a variety of methods discussed in literature, ranging from single exponential smoothing to neural networks. Syntetos, Boylan, and Croston have published a number of studies on intermittent demand forecasting with a focus on Croston’s method and the Syntetos-Boylan Approximation [1], [12], [20]–[22]. These studies also explore and evaluate other methods for intermittent demand forecasting, such as Poisson and gamma distributions.

Willemain et al. [23] identify a bootstrapping method to address the challenging spare parts tendency to exhibit many periods of zero demand. The approach leverages Markov processes to model and exploit autocorrelation that is common in spare parts demand behavior. The bootstrapping method is compared against Croston’s method and exponential smoothing across nine industrial datasets, and is found to perform favorably.

3.4 **Relevant Case Studies**

Given the pervasiveness of spare parts management issues across manufacturing companies, there exist a number of case studies focused on spare parts planning and control. These case studies cover an assortment of spare parts issues and provide beneficial insight into the implementation challenges that companies face when attempting to translate recommended spare parts management systems into practice.

There are a variety of case studies, though a few of the more relevant cases to this study will be listed here. These include:

- Porras and Dekker’s inventory control study at a refinery [24]
- Velagic’s classification and outsourcing study at KLM [25]
- Van Duren’s inventory policy work at KLM [26]
- Verlinden’s supply chain collaboration study at DAF Trucks [27]
- Thompson’s inventory management work at Alcoa [28]
Many other case studies exist, but the studies listed above were most useful in the development and execution of this particular project.

3.5 Summary

Given the abundance of spare parts literature across classification, forecasting, and other focus areas, it may be surprising that the various sites at Company X have little familiarity with the studies listed above. Optimistically, this translates to an abundance of opportunity that can be achieved through the application of more rigorous methods. However, this also means that maintenance and supply chain teams may be reluctant to experiment with "academic" approaches applied to their domains of expertise. It is for this reason that it is critical to find approaches that are not only rigorous and valuable, but that also can be understood and embraced by the teams that must implement and own them.
4 Classification

As described in the literature review, classification approaches are critical to applying structured and differentiated decisions to the broad and heterogeneous set of spare parts. The following reviews the current state of classification in the studied company division, issues that arise from these approaches, and recommendations for improvement.

4.1 Current Classification Approach

Classification methods are currently set at the site level and, as a result, vary within the division. Of the four locations studied, all four segregate spare parts by material group; however, practices vary regarding strategic classifications. Two sites do not currently employ classifications to spare parts inventories, while the other two sites employ classification methods based on demand and inventory value characteristics. No classification information is currently used for proactive actions such as setting logistics or stocking policies at three of the sites. Site A leverages the classifications to prioritize items for consignment targeting, but does not apply the classifications to other decisions or actions.

<table>
<thead>
<tr>
<th>Location</th>
<th>Spare Parts Classifications</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Site A</td>
<td>• ABC based on stocked value</td>
<td>A: Top 80% of inventory value</td>
</tr>
<tr>
<td></td>
<td>• 123 based on demand frequency</td>
<td>B: Next 15% of inventory value</td>
</tr>
<tr>
<td></td>
<td></td>
<td>C: Remaining 5% of inventory value</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1: Consumed 10-24 months of past 2 years</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2: Consumed 1-9 months of past 2 years</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3: Not consumed in past 2 years</td>
</tr>
<tr>
<td>Site B</td>
<td>• System based on last stock movement date</td>
<td>Active: Stock movement in past year</td>
</tr>
<tr>
<td></td>
<td></td>
<td>L1: Stock movement in last 1-2 years</td>
</tr>
<tr>
<td></td>
<td></td>
<td>L2: Stock movement in last 2-3 years</td>
</tr>
<tr>
<td></td>
<td></td>
<td>L3: No stock movement in past 3 years</td>
</tr>
<tr>
<td>Site C</td>
<td>None</td>
<td>None</td>
</tr>
<tr>
<td>Site D</td>
<td>None</td>
<td>None</td>
</tr>
</tbody>
</table>

Table 3: Current Classification Methods

2 Excludes material group classifications, which are discussed in Chapter 2
Classification analyses are conducted by the warehouse managers approximately once per quarter at Sites A and B using activity and value reports from the SAP system. These reports are reviewed by maintenance and supply chain management to gauge the health of the stocked spare parts inventories. Reactive decisions, such as deciding to write off obsolete inventories if the value of non-moving parts has increased substantially, may be taken by management based on the outcome of these reports.

4.2 Issues with Current Classifications

Classifying solely by material group, such as the case for Sites C and D, is useful in allocating decision-making authority within maintenance technician groups. For example, technicians with electrical expertise can provide better guidance on sensors and amplifiers than technicians with mechanical expertise. Although this allocates a smaller set of spare parts to each maintenance technician, a substantial number of SKUs remains to be managed. As seen in Figure 5, each technician must still make decisions regarding an average of 750 parts. Maintenance technicians at the site indicate that these decisions, ranging from stocking levels to criticality, are difficult to manage on a broad scale of SKUs such as this. In reality, the technicians focus efforts on work orders and maintenance tasks rather than dedicating time to set logistics or inventory policies.

![Number of different parts managed](image)

**Figure 5: Number of Parts Managed by Technician, Site A**
In the case of Site A, classifications involving stocked inventory value and SKU velocity are also employed. As discussed in the literature review, ABC analysis is a common method used in classifying traditional products, but is less useful for internal spare parts management. This is primarily due to spare part criticality requiring a combination of multiple inputs. For example, a $0.50 fuse required for a critical machine would be classified as a “C” product if judged by demand volume. However, in a stockout event this part would result in a machine stoppage, leading to excessive downtime costs relative to the part’s value. On the other hand, the 123 analysis based on part consumption can be useful for identifying spare parts that are fast-moving. The primary limitation with this type of classification is that many spare parts are slow-moving, especially relative to the cutoffs used at Site A. Only 8% of parts at Site A are classified as fast-moving with these parameters, limiting the value of this analysis when applied to the full spectrum of spare parts to manage.

In the case of Site B, classifications are applied according to the most recent stock movement date logged in SAP. This can include both purchases and consumption stock movements. The primary motivator for this classification method is to monitor stock levels that hold high risk for obsolescence. While this classification is beneficial for this type of monitoring, in this particular case the methodology is flawed. Because activity can be driven by either purchasing or consumption, there is a bias towards classifying parts as active which may not be so in reality. To reduce obsolescence risk for new parts and leverage return and buyback policies, activity should be analyzed according to consumption with newly-purchased parts segregated from parts with historical demand. Current analysis at Site B indicates that 66% of stocked parts are “Active”. However, when consumption is used as the primary indicator of activity rather than all stock movements, only 40% of parts have been consumed in the past year. 43% of all stocked parts have never been used, indicating a high potential for obsolescence. Classification based on demand frequency can be useful for monitoring obsolescence risk, but must be performed on the basis of consumption. In addition, the applicability
of demand activity in isolation is not enough to make stocking decisions, as discussed previously.

In addition to the previously discussed limitations of the current classification approaches, organizational power in decision-making is also valuable to consider. The supply chain organization is interested in maintaining sufficient part availability while also reducing inventory levels by not stocking unnecessary items. However, because spare parts depend on more than part value and demand frequency, decisions in stocking spare parts are heavily driven by technician expertise. Because the maintenance group is primarily judged on overall equipment effectiveness and not on stocked spare parts working capital, technicians have an incentive to stock more parts in the warehouse than may be truly required in a risk-balanced, system-wide approach. Classification methods which incorporate criticality can aid supply chain groups in quantitatively assessing spare parts decisions, and provide decision-aiding guidance to both organizations as they plan and control spare parts.

4.3 Proposed Changes to Classification System

4.3.1 Classification Criteria

Incorporating multiple factors to predict part criticality and subsequently determine required service levels can improve systematic decision-making for spare parts in the organization. The focus on criticality as an output of the classification is driven by the unique nature of spare parts. To determine the appropriate inputs into the classification approach, aspects such as the goals of the classification, applicability to these goals, and data availability must be considered. Leveraging criteria suggested by past literature as a starting point, these evaluative aspects were considered for each criterion to arrive at four selected inputs. Table 4 below summarizes the assessment of potential classification criteria for the studied division.
### Goal of classification: Predict criticality of spare parts to allow prioritization for management focus and to set service levels in inventory policies

<table>
<thead>
<tr>
<th>Criterion</th>
<th>Applicability</th>
<th>Data Availability at Company X</th>
</tr>
</thead>
<tbody>
<tr>
<td>Machine impact (stoppage)</td>
<td>• Potential downtime</td>
<td>Known, but codification needed</td>
</tr>
<tr>
<td></td>
<td>• Service levels</td>
<td></td>
</tr>
<tr>
<td>Lead time</td>
<td>• Safety stock</td>
<td>✔️ Available in SAP</td>
</tr>
<tr>
<td>Failure predictability</td>
<td>• Ability to plan in advance</td>
<td>✗ Unknown and unavailable</td>
</tr>
<tr>
<td>Unit volume</td>
<td>• Forecast method</td>
<td>✔️ Available in SAP</td>
</tr>
<tr>
<td></td>
<td>• Order policy</td>
<td></td>
</tr>
<tr>
<td>Demand frequency</td>
<td>• Forecast method</td>
<td>✔️ Available in SAP</td>
</tr>
<tr>
<td></td>
<td>• Order policy</td>
<td></td>
</tr>
<tr>
<td>Life cycle</td>
<td>• Forecast method</td>
<td>✗ Unknown and unavailable</td>
</tr>
<tr>
<td></td>
<td>• Obsolescence risk</td>
<td></td>
</tr>
<tr>
<td>Part price</td>
<td>• Order policy</td>
<td>✔️ Available in SAP</td>
</tr>
<tr>
<td></td>
<td>• Centralization</td>
<td></td>
</tr>
<tr>
<td>Specificity</td>
<td>• Repair options</td>
<td>Can be predicted by material group and valuation type</td>
</tr>
<tr>
<td></td>
<td>• Supplier options</td>
<td></td>
</tr>
</tbody>
</table>

**Table 4: Assessment of Classification Factors**

As seen from the above assessment, criteria such as life cycle and failure predictability can be useful, but are difficult to assess for thousands of parts given the current state of the division’s maintenance practices. Based on the combined assessment of data availability and applicability, the four criteria determined to be most useful in assessing criticality are machine impact, demand frequency, lead time, and part price.

Lead time, demand frequency, and part price are readily available in the company’s SAP system. Lead time is critical as the division’s sites are located in developing countries where lead time can commonly be several months. Demand frequency is preferred to unit volume as it is more indicative of machine breakdown events. However, unit volume will be considered in setting safety stock levels via the forecasting calculations. Part price can serve as a useful proxy for specificity and importance, although this is not always the case so should not be considered as a standalone factor.
Machine impact is more difficult to gather, but is a key determinant of part criticality. The Department of Defense Reliability Analysis Center identifies criticality analysis as "A procedure by which every potential failure mode is ranked according to the combined influence of severity and probability of occurrence" [29]. While this is an ideal target state, it is more realistic to leverage machine stoppage as a proxy for failure modes and severity. After discussions with the maintenance department, it was determined that a binary assessment of machine stoppage versus no machine stoppage could be easily assessed across the full set of spare parts. In the future, more dimensions may be useful to capture partial machine impact, such as production waste or machine slowdown rather than full stoppage. Due to time and resource constraints, however, the binary assessment can be used in the short term to provide the required information.

4.3.2 Criteria Weighting and Processing

In order to apply the four identified factors in predicting part criticality, relative weights must be understood. Decision-making studies such as Hajkowitcz [30] evaluate pairwise comparisons as highly useful in understanding tradeoffs between factors, though highlight this method as difficult to perform with a large number of factors. Because there are only four factors in this case, it is reasonable that the assessments will not be too complex to perform. Analytic hierarchy process, developed by Saaty [17], has been established as an effective pairwise comparison approach to weighting a combination of quantitative and qualitative criteria. This approach is explored in spare parts studies by Sharaf and Helmy [31], Gajpal et al. [15], and Braglia et al. [16].

Application of the AHP approach requires decomposition of the assessment’s goals into a hierarchical structure. This structure, as seen in Figure 6, outlines the classification objective, four key criteria, and alternatives for each criterion. Alternatives can be established through analyzing the spare parts database systems for common groupings and through discussing typical ranges with the procurement, supply chain, and maintenance teams.
Once the key criteria and alternatives have been identified, AHP then requires a pairwise comparison across each key criterion and each alternative. For example, lead time must be compared to demand frequency and lead times of more than 60 days must be compared to lead times of 31 to 59 days. From Saaty [17], we can apply the pairwise ranking options seen in Table 5 to each set of criteria and alternatives.

<table>
<thead>
<tr>
<th>Intensity of importance on an absolute scale</th>
<th>Definition</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Equal importance</td>
<td>Two elements contribute equally to the objective</td>
</tr>
<tr>
<td>3</td>
<td>Moderate importance of one over another</td>
<td>Experience and judgment slightly favor one element over another</td>
</tr>
<tr>
<td>5</td>
<td>Essential or strong importance</td>
<td>Experience and judgment strongly favor one element over another</td>
</tr>
<tr>
<td>7</td>
<td>Very strong importance</td>
<td>One element is favored very strongly over another, its dominance is demonstrated in practice</td>
</tr>
<tr>
<td>9</td>
<td>Extreme importance</td>
<td>The evidence favoring one element over another is of the highest possible order of affirmation</td>
</tr>
</tbody>
</table>

Reciprocals: If activity $i$ has one of the above numbers assigned to it when compared with activity $j$, then $j$ has the reciprocal value when compared with $i$.

Rationals: If consistency were to be forced by obtaining $n$ numerical values to span the matrix.

Table 5: AHP Scale for Performing Pairwise Comparisons [17]
Pairwise comparisons were collected independently from six expert users. Independent assessments help to reduce groupthink and ensure each user is represented equally. In addition, it is important to gauge the criteria from the perspectives of the key stakeholder groups. Therefore, three supply chain representatives and three maintenance representatives were involved in the pairwise comparison process.

In the pairwise comparison assessments, it is important to ensure consistency at a defined threshold. For example, if Factor A is extremely more important than Factor B and Factor B is extremely more important than Factor C, it is consistent that Factor A should be extremely more important than Factor C. In order to assess the comparisons for consistency, pairwise comparison matrices are constructed and eigenvalues are calculated against a tolerance threshold as described in further detail by Saaty [17].

After each expert user assesses the criteria and alternatives, the evaluations are combined and normalized. Outputs of the AHP process are framed in percentage terms, with each set of comparisons adding to a total of 100%. Figure 7 below illustrates the AHP results for individual user assessments and the combined and normalized evaluations for the four main criteria. As expected, machine impact is identified as the most critical factor by five of the six expert users. The large margin by which machine impact is considered most important is reasonable, considering that parts which do not cause machine stoppage will not lead to significant downtime or costs to the company. Demand frequency, lead time, and part cost carry some disagreement across users; overall, however, these three factors were considered to be approximately equal, with demand being most important and part cost being least important.
In addition to relative importance across the four key criteria, the alternatives for each criterion are also evaluated against each other. As seen in Figure 8, the importance of the alternatives in evaluating criticality can vary significantly. The clearest example of this is seen in machine impact, where users universally rate machine stoppage as extremely more important than no machine impact. Demand frequency importance is bifurcated, with most importance placed on parts with more than one event per year on average. Lead time clearly diverges with parts that have lead times greater than 60 days being identified by all users as most important, with relatively little difference between parts that have less than 60 days of lead time. Finally, part cost varies across values, with two users identifying low cost items as least important and four users identifying high cost items as most important. This difference is explained by function, as the users identifying low cost items as most important are supply chain team members. In their perspective, it is more critical to stock lower cost items due to the lower contribution to inventory value levels.
To derive final weightings, the percentage importance for each key criterion is multiplied by the alternative exhibited by the part and then summed. A demonstration of this calculation for an example material is shown in Figure 9 below.

**Figure 8: AHP Results for Criteria Alternatives**

**Figure 9: Example Calculation of Aggregate AHP Score**
4.3.3 Outputs of Classification System

With the established weightings, spare parts SKUs can be almost immediately evaluated and assigned an aggregate AHP score. The result in this particular exercise is a spectrum of scores from 11% to 80%, depending on the combination of alternatives that the selected spare part SKU exhibits. The minimum score of 11% represents the case of a part with no impact on the machine, a lead time less than 30 days, no demand history in the previous three years, and a part cost of less than $50. The maximum score of 80% represents the case where a part stops the machine on failure, has a lead time greater than 60 days, exhibits a demand frequency of greater than once per year on average, and costs more than $500 per unit. Criticality can be estimated through the scale of each part's AHP score.

As discussed in the literature review, a classification output system of Vital-Essential-Desirable is commonly used for spare parts systems. Definitions for each classification and the associated service level implications are described in Table 6 below. In order to determine the appropriate classification by aggregate AHP score, expert users must identify critical path examples as in Gajpal et al. [15].

<table>
<thead>
<tr>
<th>Classification</th>
<th>Definition</th>
<th>Implications for Service Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vital</td>
<td>Non-availability will result in very high losses due to production downtime and/or a very high cost will be involved if the part is procured on an emergency basis</td>
<td>High service levels may be required to safeguard the technical integrity of the facility</td>
</tr>
<tr>
<td>Essential</td>
<td>Non-availability will result in low/moderate production losses or low/moderate costs to procure on an emergency basis</td>
<td>Moderate service levels should be justified by tradeoffs of penalty costs with holding costs</td>
</tr>
<tr>
<td>Desirable</td>
<td>Parts can be allowed to remain temporarily out of operation without having a serious effect on operations. Non-availability will cause only minor disruptions with no significant loss in production</td>
<td>Low service levels or no stock may be needed</td>
</tr>
</tbody>
</table>

Table 6: Definitions of Vital, Essential, and Desirable Criticality
In this case, a part is considered desirable if it does not stop the machine, no matter what lead time, cost, or price it carries. This is because parts that do not impact the machine on failure will not lead to expensive downtime should they not be in stock, so it is acceptable to maintain lower service levels. Vital parts, on the other hand, are defined by stopping the machine on failure, having long lead times of over 60 days, having at least some history in the past three years, and having any cost. The determination of this cutoff is primarily driven by the effects that long lead times and demonstrable demand history have in regards to stocking a part. If it will stop the machine and take a long time to replenish, combined with being likely to fail again in the near future, then it should be Vital. Given these definitions, cut-offs can be established for the aggregate AHP score, and distributions of spare parts can be examined. Figure 10 below shows the distribution of scores and associated cut-off points for Vital, Essential, and Desirable classifications. In addition, the allocation of SKUs classified through a pilot test is shown. Application of the classification method on this set of pilot SKUs will be discussed further in Chapter 6.

<table>
<thead>
<tr>
<th>Minimum</th>
<th>Cut-off</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>- No machine stoppage</td>
<td>- No machine stoppage</td>
<td>- Stops machine</td>
</tr>
<tr>
<td>- No demand history</td>
<td>- &gt;1 demand per year</td>
<td>- &gt;1 demand per year</td>
</tr>
<tr>
<td>- Lead times &lt;30 days</td>
<td>- Lead times &gt;60 days</td>
<td>- Lead times &gt;60 days</td>
</tr>
<tr>
<td>- Price &lt;$50 per unit</td>
<td>- Price &gt;$500 per unit</td>
<td>- Price &gt;$500 per unit</td>
</tr>
</tbody>
</table>

21% of pilot SKUs | 49% of pilot SKUs | 30% of pilot SKUs

Figure 10: Distribution of AHP Scores and Cut-off Points
4.4 Summary

The studied division of Company X currently employs a variety of classification methods that are dependent on the selected site. However, none of these methods are effective in helping site management to make proactive decisions regarding spare parts prioritization and stocking policies. Through the application of Analytic Hierarchy Process, quantitative and qualitative factors can be combined to evaluate spare part criticality. Determining this criticality is beneficial in setting logistics and inventory policy decisions, such as service level, which will be discussed in the following chapters.
5 Inventory Policies

Because a substantial portion of spare parts demand is stochastically driven, it is beneficial to set and maintain risk-based inventory policies for the parts warehouse. As in-use parts fail and are replaced, safety stock alerts in the SAP system trigger additional orders for replacement. Should these safety stock levels be too high, non-value-added inventory will consume excess working capital and clog the warehouse. However, should they be set too low, costly downtime can result from maintenance's inability to fix broken equipment. The following will discuss how the sites currently set safety stock levels, identify issues with this approach, and propose recommendations that can improve inventory decision-making.

5.1 Current Inventory Policies

As seen in the review of classification methods, inventory policies also vary at a site level. Policies are determined through a negotiation between the supply chain management and maintenance management leaders, although final stocking decisions are typically controlled by the maintenance team.

5.1.1 Sites A and B Inventory Policies: Formula-based Approaches

Safety stock levels at Site A are determined by the warehouse supervisor through Excel spreadsheet calculations. The safety stock is currently calculated by the following formula, where $D_{ij}$ is the demand for SKU $i$ in month $j$ and $L_i$ is the estimated lead time in months for SKU $i$:

$$SS_i = L_i \left( \frac{1}{12} \right) \sum_{j=1}^{12} D_{ij} \quad \forall SKUs$$

Effectively, the safety stock levels for spare parts at Site A are set according to average monthly demand from the previous year considering the estimated lead time. Values are rounded up to the closest integer to ensure whole unit levels. The maintenance technicians can provide input into the final level of safety stock, but this option is not
typically exercised. Orders are executed weekly, with the warehouse supervisor placing orders for any items with existing inventory levels below the calculated safety stock levels. The order-up-to level is the safety stock level unless there are adjustments for minimum order size, packaging counts, and known near-term maintenance plans that will require supply of the part.

Safety stock at Site B is set according to the built-in SAP safety stock calculation tool. The safety stock is calculated by the following formula for each SKU $i$, where $k$ is the safety factor determined by the specified service level, $W$ is the delivery time by forecast period ratio, and $M$ is the mean absolute deviation for the part's historical forecast accuracy:

$$SS_i = k_i \sqrt{W_i M_i} \forall SKUs$$

In this case, the delivery time is determined by historical deliveries from the supplier and can be manually adjusted. For all items, service levels are set to the system default of 95%. In addition, the forecasting software within SAP is not being employed by the site; as a result, the MAD for each item is always calculated as if the original forecast had been zero. This significantly increases the safety stock levels, as will be discussed in the subsequent section. As with Site A, orders are placed weekly according to the safety stock comparison against physical inventory.

### 5.1.2 Sites C and D Inventory Policies: Feedback-based Approaches

In the cases of Sites C and D, no standard formulas are employed in calculating safety stock. Rather, the engineering and maintenance teams take responsibility for determining and setting the safety stock levels.

Maintenance teams at Site C set a safety stock level of zero for all new items, which helps to ensure manual review of the items in the future once demand history has been accumulated. Safety stock levels for established items are revised based on feedback loops, with the MRP supervisor identifying potential orders to the maintenance teams. Should the orders be justified, safety stock levels are kept at current
levels; should the orders be unnecessary, safety stock levels are reduced so that the automatically triggered orders are eliminated.

The engineering team at Site D segregates spare part responsibility across each process step of the production equipment. The engineers are also responsible for setting preventive maintenance routines for their respective sections, and thus plan the preventive demand generation for the spare parts. Historical demand and stock-out events are analyzed to determine safety stock levels for established parts. Stock-out events in the warehouse are assigned one of three event types: 1) Incorrect delivery time quote, 2) No demand history and product code, and 3) Incorrect safety stock level. The engineering team reviews all stock-out events with the safety stock level code to determine if safety stock levels should be increased. There are no processes in place to identify high safety stock levels except in the event of eliminating a current technology that has specific parts associated with the production process.

5.2 Issues with Current Inventory Policies

In addition to the overarching issue that inventory policies vary significantly within a single division, there are also issues with the methodologies being employed by the sites. Concerns with the approaches of Sites A and B focus on the misuse of traditional safety stock calculations, while concerns with Sites C and D focus on the reactive nature and limitations in identifying overstocked parts.

Sites A and B have inventory policies associated with Periodic Review, Order-Up-To-Level systems. Silver et al. [32] identify a standard policy as the following\(^3\), assuming Normal demand with mean \(x\) and standard deviation \(\sigma\):

\[
S = x_{L+R} + k\sigma_{L+R}
\]

In the case of Site A, it is apparent that the quantity during lead time and review, as represented by \(x_{L+R}\), is the value being used to set safety stock levels. The true safety

\(^3\) Silver et al., pp 240
stock level, represented by \( k\sigma_{LR} \), is absent from the methodology of Site A. The result of this omission will be, for parts following a Normal distribution, that service levels will be approximately 50%. This will result in a significant number of stock-outs for these parts.

However, many spare parts are slow-moving with intermittent demand, violating principles associated with Normal distributions. If, for example, a slow-moving part followed the Poisson distribution, the stock-out rate would be lower than 50%. A hypothetical part with an average of 2 demand occurrences per year and a lead time of 60 days would result in a rounded-up safety stock of 1 under this approach. Reviewing the Poisson distribution’s cumulative distribution function, we can see that this would result in an average 95.6% service level. Given this lower level of stock-outs and the tendency for slow-moving parts to follow a distribution similar to Poisson [20], it can be seen why the warehouse would believe there are no issues with this approach. However, under this approach we would find that fast-moving parts will remain understocked and slow-moving parts may be overstocked, depending on their respective underlying distributions.

In the case of Site B, the automatic safety stock calculation employed by SAP is fundamentally correct. However, there are two main issues with the site’s utilization of this approach. First, all service levels are set to the default level of 95%. While acceptable for some parts, it is likely that not all parts require a 95% service level, such as those not impacting the production of the machine upon failure. Second, the site is not actively using the forecasting tool within SAP. As a result, the mean absolute deviation for the safety stock calculation will always be excessively high. This will lead to an exceptionally high level of safety stock as the system assumes that forecasting is at a 0% accuracy level. Because of these high levels of calculated safety stock, the site has a low adherence to the reordering program. Currently, 43% of spare parts SKUs at Site B are held at a physical level under the calculated safety stock. Until the site adopts the forecasting tool in SAP or changes the underlying methodology, it will continue to be misguided for the site to follow the system’s recommended orders.
In the cases of Sites C and D, the primary challenge in solely relying on feedback loops is that it creates a reactionary approach. Issues are only discovered after they occur, rather than predicted in advance based on mathematical models leveraging part behavior. In addition, reliance on feedback loops creates significant non-value added burden on the engineering and maintenance teams. For example, the MRP accuracy at Site C averages just 19%. On average, 1,703 orders are automatically generated by the system according to safety stock levels versus physical inventory; upon review, only 320 are executed. The high level of inaccuracy makes effective feedback difficult, resulting in large batches of incorrect orders continuing to be automatically generated every week. When feedback is effectively executed, the primary problems uncovered are only those with low safety stock levels. Issues of high safety stock are not identified, resulting in overstocking. At Site D, approximately 2,000 SKUs have safety stock levels higher than one but also have had no demand in the past three years; this is likely due to a lack of high safety stock level reviews, and leads to higher obsolescence risk and working capital requirements.

5.3 Proposed Changes to Inventory Policies

As discussed in the literature review, there exist a multitude of intermittent demand forecasting approaches. These methodologies range from assuming that underlying demand behaviors are well-reflected by Poisson or Normal distributions to applying complex neural network formulations.

A key consideration for this area is feasibility of implementation, which is affected by the level of involvement from the end-users in developing the new approach. Given these concerns, complex approaches that may be mathematically sound but difficult for the organization to grasp become less attractive as potential solutions. As a result, bootstrapping through the Willemain et al. method is an attractive solution in this scenario. The bootstrapping algorithms are easily implementable in an Excel spreadsheet tool, and are also easily understood, at least from a high level, by maintenance and supply chain users due to the empirical approach.
Bootstrapping is a method that assumes historical behavior is indicative of future behavior, and models an empirical probability distribution function based on this historical data. For example, if a particular part has been consumed on ten occasions over the past three years and has a replenishment lead time of 60 days, then bootstrapping can be used to estimate the number of consumed items over the part’s lead time period. A simulation of the part’s behavior is executed many times by combining probabilities with the historical information. In this particular example, a bootstrapping simulation with 2,500 runs predicts that in 1,375 instances no consumption occurs, in 846 instances one part is consumed, in 220 instances two parts are consumed, in 52 instances three parts are consumed, and in 7 instances four parts are consumed. These outcomes can then be used to derive the stock required for a certain service level percentage. If this part requires a 95% service level, then a safety stock of 2 parts is needed.

An advantage of this empirical approach is that bootstrapping can actively adapt to each SKU’s predicted underlying distribution. In the case of a highly heterogeneous population of SKUs, a self-tailoring approach such as this maintains simplicity of implementation while ensuring reasonable predictions for underlying demand behavior.

To apply the Willemain et al. approach, it is necessary to obtain inputs related to demand frequency, unit volume, lead times, and service level. In this case, service levels can be determined by the classification model output as a corollary to part criticality. Through discussions with supply chain and maintenance leadership, as well as references to common service levels cited in supply chain research, the following service levels were assigned to each criticality:

- **Vital**: 98% service level
- **Essential**: 90% service level
- **Desirable**: 70% service level
Demand history and lead times can be readily obtained from SAP system data. In the case of the studied division, three years of history are available for analysis. According to the Willemain et al. approach, the following steps should be applied for the bootstrapping process:

1. Import historical demand data from SAP system
2. Using a two-state zero versus non-zero Markov model, estimate transition probability matrices for each SKU
3. Apply random number generation against the transition probability matrices to determine a zero versus non-zero expectation across each day in the item's lead time, conditional on the previous day's demand
4. Randomly sample from historical unit volumes to assign quantities to all non-zero instances
5. Sum all values across the lead time horizon to obtain an estimate for demand during lead time
6. Repeat the calculation many times, in this case a default of 2,500
7. Apply service levels defined by the classification model to identify correlating safety stock levels, and recommend to user

With the assistance of Visual Basic macros in Excel, these steps can be carried out simultaneously for a large group of products. In the pilot case, 2,500 bootstrap trials across 2,460 SKUs took an average execution time of 30 seconds. As spare parts data sets become larger, web-based applications with back-end processing can be explored to more appropriately manage the processing load.

5.4 Summary

The studied sites in Company X employ a mix of approaches to setting safety stock levels, ranging from mathematical approaches to feedback loops. When applying mathematical approaches, it is important for the sites to consider the correct application of the underlying models. Feedback loops, while useful, should be combined with mathematical modeling to help increase the site's proactive abilities to set inventory
levels and to identify items with excessively high safety stock levels. The Willemain et al. bootstrapping method is a useful statistical approach to setting inventory levels due to the ability to tailor assumptions of underlying distributions across a variety of SKUs and the ability to effectively build buy-in from end-users who must understand the rationale for the approach.
6 Joint Classification and Forecasting Model

In order to aid implementation of the outlined classification and safety stock recommendations, a joint classification and forecasting model was developed and tested at a pilot site within the division. The following chapter reviews the joint model's inputs and outputs, assesses the tool's classification prediction accuracy, and evaluates inventory opportunities highlighted by the model.

6.1 Model Components

The purpose of the joint classification and forecasting model is to answer the following questions for each SKU:

- Given the SKU's lead time, demand history, price, and impact on the machine, what are the predicted criticality and service level?
- Given the SKU's service level, lead time, and demand history, what is a prediction of the expected demand during lead time and what should the safety stock level be as a result?

Given the overlap of inputs for both the classification prediction and forecasting calculation, it is beneficial to develop a single integrated tool. An Excel spreadsheet with supporting Visual Basic macros is the preferred method in this case due to the near-universality of Excel usage. Expert users indicate comfort with this type of tool, and this approach enables modification should future improvements be identified. Figure 11 below highlights the overarching flow of the joint tool. Safety stock recommendations, when combined with expert knowledge of upcoming maintenance needs and already-scheduled maintenance jobs, can optimize the spare parts inventory level in the site's warehouse.
In addition to basic SKU information, the key inputs into the joint tool are demand history, lead time, part cost, and machine impact. Inputs into the joint model are primarily captured from the SAP system and include demand history, part cost, and lead time. Demand history for each SKU includes all goods issues and returns for the previous three years. Return events are leveraged to eliminate unnecessary goods issues and thus provide an accurate representation of actual consumption. Part cost is sourced from the most recent purchase transaction of the SKU. Lead time is sourced from the SAP master record of the SKU, which is updated periodically by the purchasing department.

In addition, machine impact is manually assessed by a team of maintenance technicians. While more manually intensive than a system data pull, this assessment is only required once unless subsequent changes are made to the production technologies or processes. As discussed in Chapter 4, machine impact is coded in a binary approach, with 0 representing that the machine will not be stopped if the part fails and 1 representing that the machine will be stopped if the part fails.

Because the inputs for both the classification prediction and the forecasting calculation overlap, all inputs can be sourced initially prior to tool execution. Error
checks are built into the tool to ensure that any suspicious SKU data, such as overall negative demand, are addressed prior to tool execution.

6.2 Classification Process and Output

Once all inputs are imported into the tool, an aggregate AHP score is calculated and a predicted classification is assigned per the methodology outlined in Chapter 4. Because it is useful to include maintenance expertise for certain SKUs, maintenance technicians have the option to manually change the suggested classification. However, in order to manually change a classification, the user must provide the rationale for the change. This ensures that changes are justified, and the feedback can be captured for future improvements to the tool’s methodology.

The tool leverages the previously discussed AHP methodology to instantly predict the criticality of each analyzed SKU. As part of the effort to jointly build and develop the tool, a pilot selection of 2,460 SKUs was analyzed for criticality. Figure 12 below summarizes the calculated AHP aggregate score distributions and highlights the cut-offs established by the initial pairwise comparisons and AHP methodology.

Figure 12: Distribution of AHP Scores for Pilot Set of Spare Parts SKUs
From this distribution, it can be seen that the pilot assessment identified ~20% of SKUs as Vital, ~50% of SKUs as Essential, and ~30% of SKUs as Desirable. These classifications can be used to prioritize management attention and set appropriate service levels for forecast calculations.

It is beneficial to compare the predicted criticality of the SKUs with the traditional criticality assessments of the maintenance experts in order to build credibility and ensure that the tool is accurate enough to aid in decision-making. In order to test the accuracy of the approach, 200 SKUs were randomly selected from the pilot SKU set. Two maintenance experts were provided with this list of SKUs along with the basic data from the system such as supplier, lead time, price, demand, and machine stoppage. No information was included on the predicted classifications, but rather the definitions of each class were agreed upon as described in Chapter 4. The maintenance experts then blindly assessed each SKU using their own expertise regarding the SKUs and the data available. Outputs from the manual assessment were compared against the tool predictions and are summarized in Figure 13 below.

![Tool accuracy assessment diagram](image)

**Figure 13: Accuracy of Tool Classifications and Reasons for Discrepancies**
From the comparison, two outcomes should be noted. First, the accuracy of the tool in predicting classifications is very high at 87%. While it should be noted that accuracy in this case is relative to the perspective of the maintenance technician and may not reflect reality, it is the best assessment of accuracy that is available in any event. Second, the inaccuracies of the tool can provide valuable feedback to the purchasing and supply chain teams. This is especially true in the cases where the maintenance team does not agree with the lead times recorded for the SKUs. With this information, the teams can validate or disprove these concerns and make corrections to the system data accordingly.

6.3 Forecasting Process and Output

Once the user reviews and agrees with the classification output, the tool assigns suggested service levels according to the criticality of each part. The next step in the forecasting process is to run the bootstrapping algorithm, which is encoded into the spreadsheet through Visual Basic. The bootstrapping algorithm follows the Willemain et al. process outlined in Chapter 5, using lead time, demand frequency, and unit volume history as primary inputs to simulate lead time demand behavior. The default number of trials per SKU is 2,500 as this balances computer processing time and bootstrap sampling accuracy, although the user can specify any number of bootstrap trials in the tool’s control panel. Upon completion of the bootstrapped trials, the service level is used to identify the percentile of the 2,500 instances and suggest a resulting safety stock level.

Suggested safety stock levels are compared to existing system safety stock levels so that the user can review any increases or decreases in suggested levels. Similar to the classification output, if the user has additional information that can be used to determine a more appropriate safety stock, this can be applied as long as the corresponding rationale is noted. Figure 14 below summarizes the differences between existing system safety stock and recommended safety stock levels for the 2,460 pilot SKUs.
As can be seen from the comparison, the result of the forecasting outcome is a risk-balanced shift in inventory levels rather than a pure reduction across all categories. For those items deemed to be vital to the operation, safety stock is increased for approximately 50% of the SKUs. This is driven by the higher service level requirements, and implies that not enough critical parts are being stocked under the existing method. However, inventory reductions can be seen in both the Essential and Desirable SKU sets. Given that these parts typically have a lower impact on the machine or have low demands and lead times, the service levels allow for stock-outs in some instances so that inventory can be reduced. The overall impact of the inventory reallocations are summarized in Figure 15, and highlight an overall inventory reduction opportunity of 16% to 39%. The wide range of savings is dependent on how conservatively the site approaches Vital parts with no demand history. A portion of these parts are likely “insurance parts,” which have very low demand frequency but are critical to the production process. However, the remaining portion is composed of parts that could be potentially important, but are too expensive to justify holding given the low rate of demand.
6.4 Assessment of Joint Classification and Forecasting Model

The two outcomes of the tool, a classification for each SKU and a suggested safety stock level, answer the key questions identified as the main purposes of the project. The suggested classifications can be used to prioritize management attention on efforts such as lead time reduction, data cleanliness, supplier negotiations, and production technology improvements. In addition, the safety stock levels help to monitor all SKUs, both those with and without demand, so that the appropriate safety stocks can be set for the appropriate SKUs.

The classification tool’s effectiveness stems from the ability to quantify and structure the classification techniques that are typically performed “in the heads” of the expert maintenance users. By translating these techniques to quantifiable and repeatable methods, we can ensure that all SKUs are assessed in an equivalent manner. In addition, this quantification provides negotiating leverage to the supply chain team. As the groups work together to reduce inventory levels, the quantification of the part criticality can enable a two-sided conversation that does not rely solely on personal experience and technical expertise from the maintenance perspective.
A significant benefit of the outlined process is the involvement of the supply chain and maintenance teams. This involvement of the expert users, combined with the simplicity of the tool, increases the tool's credibility and enables future implementation across the division. Because of the buy-in across the organization, the tool is being rolled out across all four sites in the country where the pilot was conducted. In addition, sites in a neighboring country will also be using the tool by the end of Q1 2014, with plans to expand to additional sites in the coming year.

6.5 Summary

The joint classification and forecasting model leverages the Analytic Hierarchy Process and Willemain et al. bootstrap forecasting algorithm to predict SKU classifications and recommend safety stock levels. The developed Excel tool can be used for both processes simultaneously and can be shared across the supply chain and maintenance organizations.
7 Conclusions and Recommendations

7.1 Conclusions for the Project

Because spare parts are highly heterogeneous and exhibit challengingly intermittent demand patterns, it is beneficial to structure spare parts management in a systematic manner. In this case, classification and forecasting tools are the primary methods to provide additional information and guidance for decision-makers. By applying these tools to existing spare parts catalogs, the sites can better prioritize limited management attention on the most critical parts, reduce spare parts working capital while maintaining or improving service levels for critical parts, and increase the dialogue between the key stakeholder groups of supply chain and maintenance.

Classifications which combine qualitative and quantitative criteria can assist managers by rapidly predicting criticality for thousands of SKUs at a time. Decision-making strategies such as Analytic Hierarchy Process can be applied to transform these factors into meaningful weights, while Excel spreadsheets or similar tools can quickly translate these weights and the individual SKU characteristics to a predicted criticality. These criticalities can then be leveraged in setting management priorities and allocating inventory policies such as service levels to individual groupings. In this case, the 20% of parts identified as Vital can be targeted for consignment opportunities, supplier negotiations, and production technology improvements to reduce inventory costs and logistics challenges. Similarly, the 30% of parts identified as Desirable can be, in many cases, eliminated from the warehouse and deprioritized by the maintenance leadership.

Once service levels have been identified through the classification approach, forecasting methods can be applied to appropriately determine safety stock levels. In this case, the Willemain et al. bootstrapping method is preferred due to its ability to tailor to each SKU's underlying distribution and its acceptance as a rational method by the users who will be responsible for these analyses. Through the combination of criticality-based service levels and forecasting, safety stock inventories can be reallocated in a risk-balanced method so that working capital investments are focused
on critical parts. Inventory reductions can be achieved through reduction of safety stock levels for less important parts as the stockout costs carry less risk to production and the site.

The buy-in expressed by the users involved in this process is driven by the desire to reduce complexity in their management decisions and in the clear value that can be derived from systematic decision-making. As the joint classification and forecasting tool is expanded to other sites and countries in the division, there will likely be further improvements. In addition, the standardization of the site approaches will aid leadership in setting direction for the division overall and can help the sites collectively share improvements and management practices.

7.2 Applicability and Recommendations

The challenges and approaches discussed in this study are applicable to any manufacturing sites with internally managed maintenance and spare parts systems. While the exact nature of the spare parts may vary depending on the production equipment and the site dynamics, the overarching behaviors will be the same. As a result, developing a systematic approach through classification and forecasting can be beneficial for any maintenance manager or supply chain manager struggling with the complexities of managing a multitude of spare parts choices.

In the journey to systematically structure spare parts management, there are many pitfalls. The heterogeneous nature of spare parts leads to many exceptions, which can impede efforts to create tools applicable to the broader set of parts. In these cases, it is important to manage the exceptions individually while managing the bulk of the parts through standard processes. Additionally, efforts can be focused on excessive evaluation of classification and forecasting methods, as many exist. Instead, managers should prioritize approaches that both have literature support and are understandable and credible with the teams who must use the tools. In this way, action and incremental improvement can be enabled as systematic approaches are designed and implemented.
References

[28] K. M. Thompson, “Total cost reduction through an improvement of the use and inventory management of consumables and spare parts,” Massachusetts Institute of Technology, 1996.