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Scrap Rate Reduction for a High-Volume Aerospace Bearing Ring Using DMAIC Methodology

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Abstract

To remain competitive within the marketplace, manufacturing companies must seek out opportunities for increased profitability and quality in their production. In order to accomplish these business objectives, efficiency in identifying and solving problems on the production floor is critical. Delays in this process can produce disastrous impacts to the manufacturing plant's bottom line. The DMAIC process, the core to the Lean Six Sigma methodology, is a logical step-by-step process designed to achieve this goal. The DMAIC methodology is applied to resolve an observed high scrap rate of a high-volume bearing ring component. The baseline performance of the process was measured using descriptive statistics and process capability analysis, yielding Cp and Cpk values of 0.311 and 0.175, respectively. Pareto analysis highlighted that 80% of defects were the result of casting defects, undersized outer diameter, and parallelism errors on the bearing ring. Through ideation and a weighted scoring model, the design and implementation of new tooling was a solution to resolve the diameter and parallelism issues. Failure Modes and Effects Analysis was applied to mitigate any risks of the proposed solution. Implementation of the solution conflicted with manufacturing priorities. However, future work is proposed to determine the effectiveness of the solution.

Keywords
Bearings, Manufacturing, Aerospace, DMAIC, Lean Six Sigma

1. Introduction
The success of manufacturing operations is predicated on the efficiency of the processes employed to produce a product. The efficiency of processes used by a manufacturing operation is impacted by factors such as tooling, machinery, trained operators, layout, maintenance, automation, and raw materials. Challenges in any one of these critical areas can produce bottlenecks, added time, and scrap. Ultimately, this results in a loss of revenue and subsequent profits, hindering the success of the business. Scrap, or material waste, is one of the primary key performance indicators manufacturers routinely observe as a metric for the efficiency and profitability of the business. Scrap can be produced at any stage of the manufacturing process and is defined as unusable or non-conforming material. Scrap can be the result of a myriad of factors, from inefficient design, poor use of raw materials, improper inspection equipment, inadequate machinery, unclear instructions, and many other factors. In order to improve the efficiency and profitability of an aerospace bearing manufacturing company, an analysis of scrap rates were conducted to identify the part numbers with the highest scrap volume by USD and quantity. Additionally, emphasis was placed on high-volume part numbers in order to provide the group with adequate opportunities to achieve the goal within the scope of available time. By reducing the scrap rate for a high-volume part number, an improvement to the profitability of the business can be produced.

1.1 Objectives

The goal of this project is to produce a comprehensive assessment of the current process performance, with respect to scrap rate, of a bearing ring component. By observing scrap data for this bearing ring component for the calendar year 2024, the baseline performance can be determined using descriptive statistics. Additionally, the database provides information regarding the cause of scrap at each stage of the manufacturing process allowing the group to hone in on the key factors contributing to scrap for the bearing ring component. Lastly, once the key factors contributing to the scrap of the bearing ring component have been established, solutions to reduce the scrap rate by 20% will be implemented and evaluated to assess improvements in performance.

2. Literature Review

As companies strive to remain competitive in the market, the utilization of Lean Six Sigma methodology is becoming an increasing focal point for a company's continuous improvement practices. The central tenant to the Lean Six Sigma is the DMAIC process. George et al. (2005) describe the DMAIC process as a logical, step-by-step process leading a team from defining a problem to designing solutions in an effective manner. The term, DMAIC, stands for Define, Measure, Analyze, Improve, and Control. Globally, businesses are recognizing the impact Lean Six Sigma can have on improving efficiency and reducing cost, acknowledging if their business is to remain competitive, adoption of Lean Six Sigma is critical.

Marques and Matthé (2017) implemented Lean Six Sigma and the DMAIC methodology to resolve a problem with an aluminum die casting process in the architectural design industry. The research using the practices of Lean Six Sigma aided in the identification of which casting defects were the greatest contributors to scrap or rework in the process. Utilizing techniques, such as Design of Experiments (DOE), they were able to determine what factors produced the observed defects. The improvements they made reduced the defect rate from 79% to 25% increasing cost savings for the manufacturer. Sharma et al. (2018) applied these same techniques to projects in the automotive industry to reduce the rejections of a specific part. The DMAIC methodology allowed the group to identify the root cause of rejections and design a solution improving the sigma level from 2.67 to 4.11.

The process yield from this sigma level increase was raised to 99.6% improving from the baseline 87.8%. Kaid et al. (2016) employed the DMAIC process to improve biscuit production by assessing the increase in flour demand on the production line. The team focused on improving the accuracy of flour usage, with respect to the requirements of the recipe, and was able to improve the process capability from 0.21 to 0.70 during the scope of the project. Mittal et al. (2023) utilized this process to improve the manufacturing of rubber weather strips for a manufacturing company based out of India. Pareto analysis was used during the analyze phase to identify which handful of defects contributed to 80% of all defects. This focused approach, central to DMAIC methodology, enabled the team to hone in on designing improvements for a small number of issues which will result in the greatest impact for the larger process. The demonstrated ability of the DMAIC methodology to solve manufacturing problems indicates the methods applicability in solving manufacturing problems pertaining to the production of bearings and their components.

3. DMAIC Methodology

The DMAIC methodology is the core process for business and teams utilizing six sigma to provide solutions to solve problems. Six sigma gets its name from statistics in reference to standard deviation, or variance, observed in process results. A process capable of producing results with six standard deviations within the specification limits will only produce 3.4 defects per 1 million, or near perfect results. The lean six sigma process employs the following steps towards solving a problem; Define, Measure, Analyze, Improve, and Control. In the define phase, the project charter is produced where a detailed problem statement, goal statement, business case, and timeline are all defined. Accomplishing this step aligns the team with focused direction towards achieving a pre-defined goal. In addition to a project charter, a SIPOC is performed by the team to scope the current process and aid the team in visually identifying all of the key Suppliers, Inputs, Process, Outputs, and Customers pertaining to the project.

The measure phase enables the team to assess the baseline performance of the current process. A data collection plan is defined and followed ensuring the team is able to gather the necessary data points to assess the current-state of the process. Descriptive statistics are utilized to capture and comprehend key metrics associated with the problem and goal statement written in the define phase. Process capability indices, Cp and Cpk, will be calculated to measure the current processes' ability to meet the specification limits.

The analyze phase is where the team will hone in and focus on the root cause of the problem. This stage involves producing a detailed process map, statistical calculations, and root cause analysis. Statistical techniques, such as Pareto analysis, can help the team identify the biggest contributors to a problem. Specifically, what handful of factors contribute to 80% of the observed problem. Furthermore, techniques such as ANOVA and Design of Experiments (DOE) are employed to identify which factors play a determining factor in producing the observed problem. Fishbone diagrams can also be utilized to identify causes for the problem. Ultimately, the goal of the analyze phase is to determine the root cause of a problem.

Solutions are designed and implemented in the Improve phase of the DMAIC process. Producing ideas for solutions should have no limitations. The team, during brainstorming, is encouraged to think of many solutions. Later, these solutions will be evaluated by the team for effectiveness, feasibility, cost, impact, sustainability, and risk in order to select the best solution for the problem. Tools, such as a Pugh Matrix, weighted scoring model, Cost-Benefit Analysis, impact-effort matrix, and Failure Modes and Effects Analysis (FMEA), are utilized to guide the team through this assessment process. Lastly, the solutions are tested and validated using techniques employed in the analyze phase, i.e., Design of Experiments, to determine whether the solution is solving the problem. Once validated, the solutions are implemented into the process.

The last stage, the control phase, involves monitoring the improvements implemented in the process to ensure the problem has been solved and the improvements can be sustained. Control charts can be utilized to visualize the stability of the process over time enabling the team to observe the sustainability of process improvements. Additionally, standard operating procedures (SOPs) and work instructions can be written to ensure the improvements are maintained following the completion of the project.

4. Case Study

4.1 Define

The Bearing Company, an aerospace manufacturing bearing company, has consistently failed to meet its scrap goals, with the manufacturing team missing monthly projections 75% of the time. Part number J2001-33, a ring component for a bearing assembly, is a high-volume part, with at least 150 pieces per lot being scrapped year-to-date (75% of the year). This part accounts for 3% of total scrap dollars and 6% of total scrap pieces, contributing significantly to the company's ongoing scrap challenges.

An indicator of Scrap Rate per Production Lot was used for this project. The initial analysis of scrap rate for each part number will be converted from year-to-date to a per batch metric. When measuring the success of improvements, as production runs of a specific part number go through, the scrap rate will be measured to assess effectiveness of improvements. The goal of this project is to achieve a 20% reduction in the scrap rate for part number J2001-33. Accomplishing a reduction in scrap rate will provide increased efficiencies and quality of products delivered to the customer. Furthermore, the company should see an increase in profitability as a reduced scrap volume will result in an additional revenue for the company.

The SIPOC diagram (Figure 1) outlines the key inputs and outputs for The Bearing Company's manufacturing process for the J2001-33 bearing ring component. Additionally, the process flowchart highlights the key decision points where scrapped parts can be produced. Decision junctions, specifically inspection points, in the process were highlighted as potential focal points investigation.

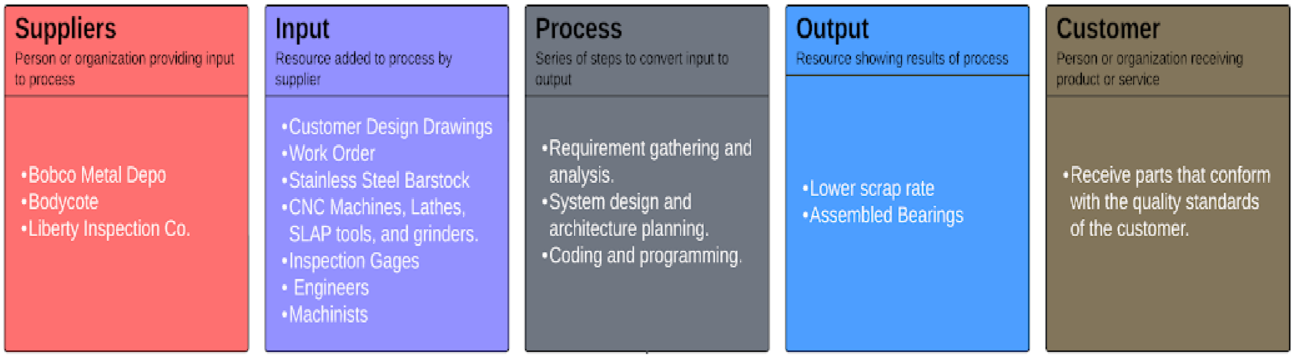


Figure 1. SIPOC diagram detailing inputs, outputs, and key focus areas for reducing the scrap rate for part number J2001-33.

4.2 Measure

Understanding the problems The Bearing Company faces with the production of part number J2001-33 begins with assessing the baseline, current-state performance of the process. Since the project aims to reduce the scrap rate per batch, it will be useful to outline a handful of key operational definitions related to the process.

Batch **-** Production lot, is a single order for a part. All parts associated with a batch have identical characteristics, such as material heat number, which can be traced back to the start of the lot. It is also assumed that all parts manufactured under a specified batch were produced consecutively during manufacturing.

Blanking - refers to the initial forming stage of the manufacturing process where the part is formed into a near-net shape. Blanking for the J2001-33 is done through a casting process of the raw material.

Casting Defect - a catch-all term for manufacturing errors produced during the casting, or blanking, process. It will consist of defects such as gas holes, porosity, inclusions, indications, and cold shuts.

Setup - Any activity, performed by an operator, associated with preparation to conduct the assigned operations.

Ring - A single ring of a bearing assembly. J2001-33 is a ring component which will later be combined with other components to form the bearing assembly.

OD **-** Outer diameter of the ring.

ID - Inner diameter of the ring.

First article inspection - Quality inspection of the first part through a process verifying the process step meets the requirements.

The Bearing Company maintains detailed records and metrics of all production activities at their facility through a database updated in real time. To obtain the relevant data, Mike Kesablian ran a data report extracting the pertinent metrics necessary for assessing the current baseline performance of the process. The data extracted encompassed all batches of part number J2001-33 produced in the calendar year 2024. Each data record contains the order number, quantity produced, quantity scrapped, scrap cause, and scrap source. The scrap percentage was calculated using the below equation. As previously discussed, the percent scrap per batch is the focus for the initial analysis of the process.

$$\% \ Scrap = \frac{Quantity \ Scrapped}{Quantity \ Produced} \ x \ 100\%$$

Descriptive statistics were calculated utilizing the statistical analysis software, JMP. The data, extracted and formatted to a csv file, was uploaded to JMP and the descriptive statistics were computed (Figure 2). A graph of the distribution of scrap rates per batch was also produced and shown in Figure 3. Referring to statistical data, the baseline mean for the scrap rate per batch is observed to be 7.46%. This means, on average, if one were to manufacture a batch of J2001-

33 bearing rings, you would expect to scrap 7.46% of the quantity produced. The standard deviation, however, was found to be 9.17%, which, when compared to the mean, indicates a relatively large spread in the dataset. The median was found to be 5% with a min of 1% and a max of 58%.

Summary Statistics

Mean	0.0738
Std Dev	0.0921155
N	50
Median	0.05
Mode	0.03

Note: The mode shown is the smallest of 2 modes with a count of 10.

Figure 2. Descriptive statistics calculated using JMP statistical analysis software for the production scrap data of part number J2001-33 in the 2024 calendar year.

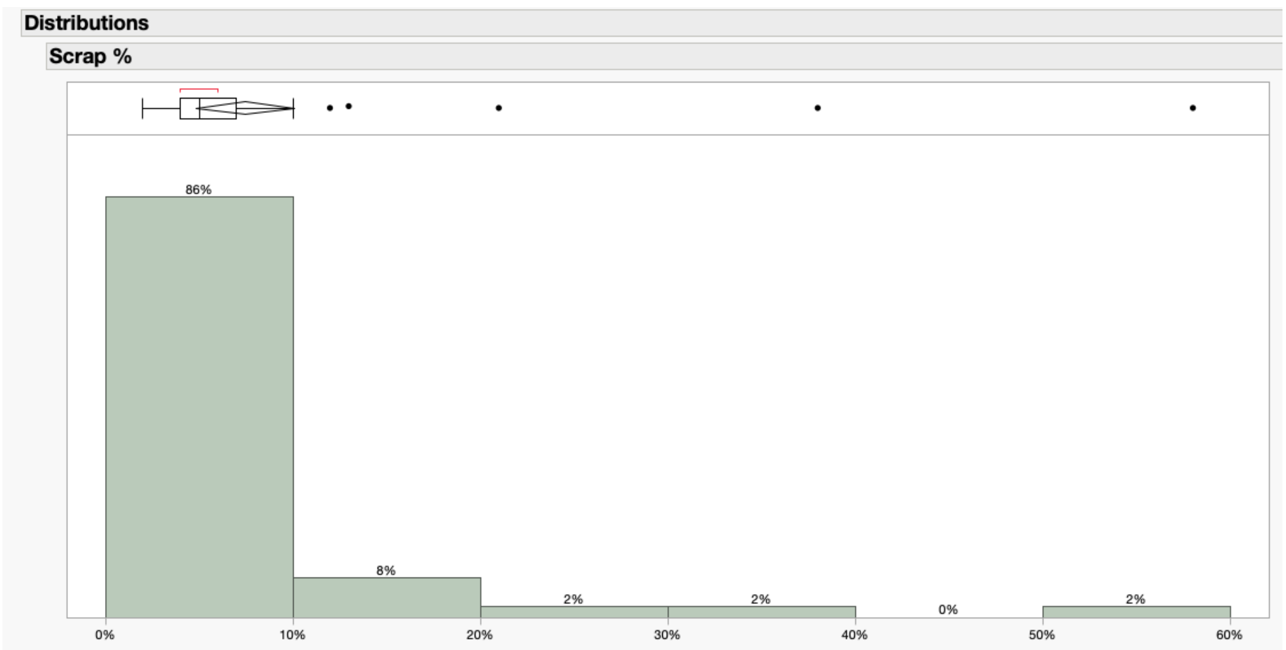
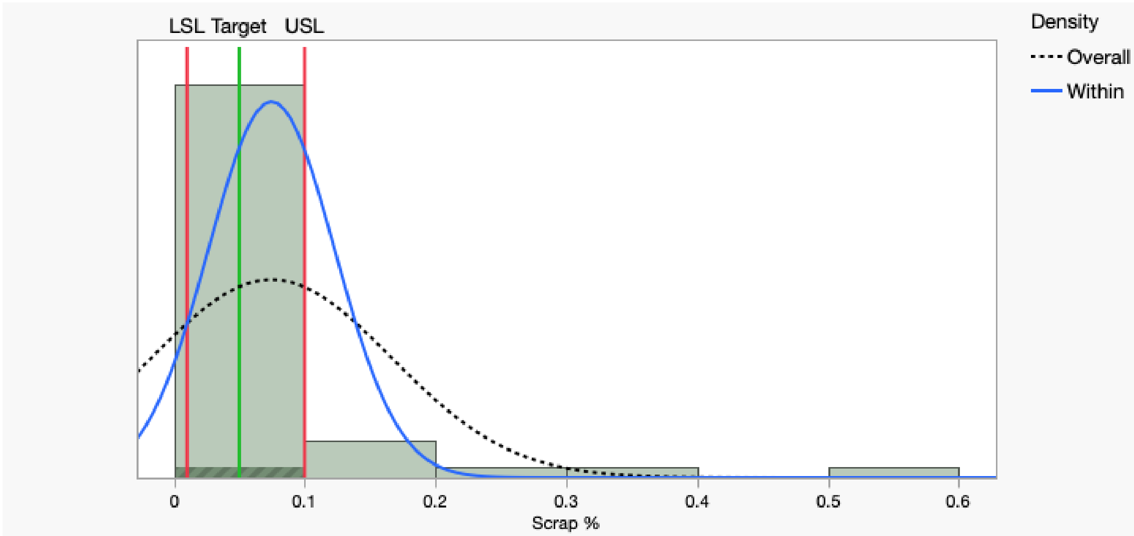


Figure 3. Distribution of scrap percentages per batch for the part number J2001-33 in calendar year 2024. The box and whisker plot above highlights 5 outliers in the dataset.

Process capability indices, Cp and Cpk, were additionally calculated in JMP. While some experimenting was necessary, in order to determine the appropriate distribution of the dataset, it was ultimately determined that a normal distribution was the best fit to analyze the data. A lower specification limit (LSL) and upper specification limit (USL) were defined as 1% and 10%, respectively based on The Bearing Company's standards. A process target value of 5% was also determined. Inputting this information into JMP and running the subsequent calculations yielded Cp and Cpk values of 0.311 and 0.175 respectively. These values indicate the process is performing well below the specification limits. The baseline performance of the process was determined to neither be centered nor capable of meeting the specification limits based on the current distribution.



Within Sigma Capability

Index	Estimate	Lower 95%	Upper 95%
Cpk	0.175	0.073	0.278
Cpl	0.446	0.299	0.589
Cpu	0.175	0.072	0.276
Cp	0.311	0.233	0.388
Cpm	0.246	.	.

Overall Sigma Capability

Index	Estimate	Lower 95%	Upper 95%
Ppk	0.092	-0.002	0.186
Ppl	0.235	0.130	0.337
Ppu	0.092	-0.002	0.186
Pp	0.164	0.131	0.196
Cpm	0.140	.	.

Figure 4. Process capability analysis performed in JMP software.

Results from this stage of the project indicated the current process, with respect to scrap rate per batch, is neither centered nor capable of meeting the process limits. While 86% of batches have a scrap rate within the specification limits, there are outliers noted as having an impact on the distribution of the data. Additionally, a significant challenge was observed in collecting real time production data. In order to collect this type of data, a pause in production would be required and was determined to be out of scope for the project.

4.3 Analyze

The process map for part number J2001-33 can be seen in Figure 5. Within the process, there are multiple checkpoints, typically following machining operations, where the parts will be inspected. In these decision points, if the part does not meet the requirements, and reworking the part is not permissible, the part will be deemed scrap.

A Pareto chart was constructed and analyzed using JMP software to determine which scrap causes resulted in roughly 80% of all scrap (Figure 6). Review of the chart shows that casting defects, undersized OD, and parallelism make up roughly 80% of all scrap for part number J2001-33.Casting defects, while a large contributor to the overall scrap rate, are the result of supplier delivered material. This means there is a little control over this aspect of the process other than providing feedback and data to the supplier for them to resolve the issue. Additionally, a new supplier can be sourced to provide the casting blanks. Moving forward, the focus of the analysis will be on the oversized OD and parallelism causes for scrap defects.

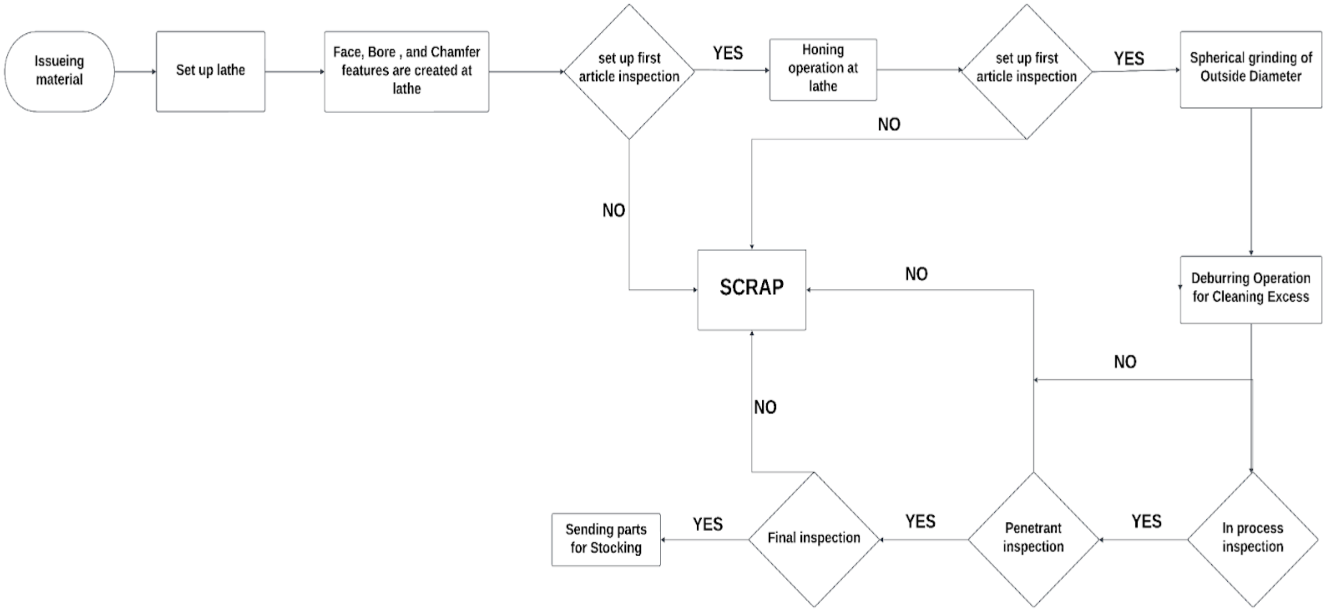


Figure 5 - Process map for part number J2001-33.

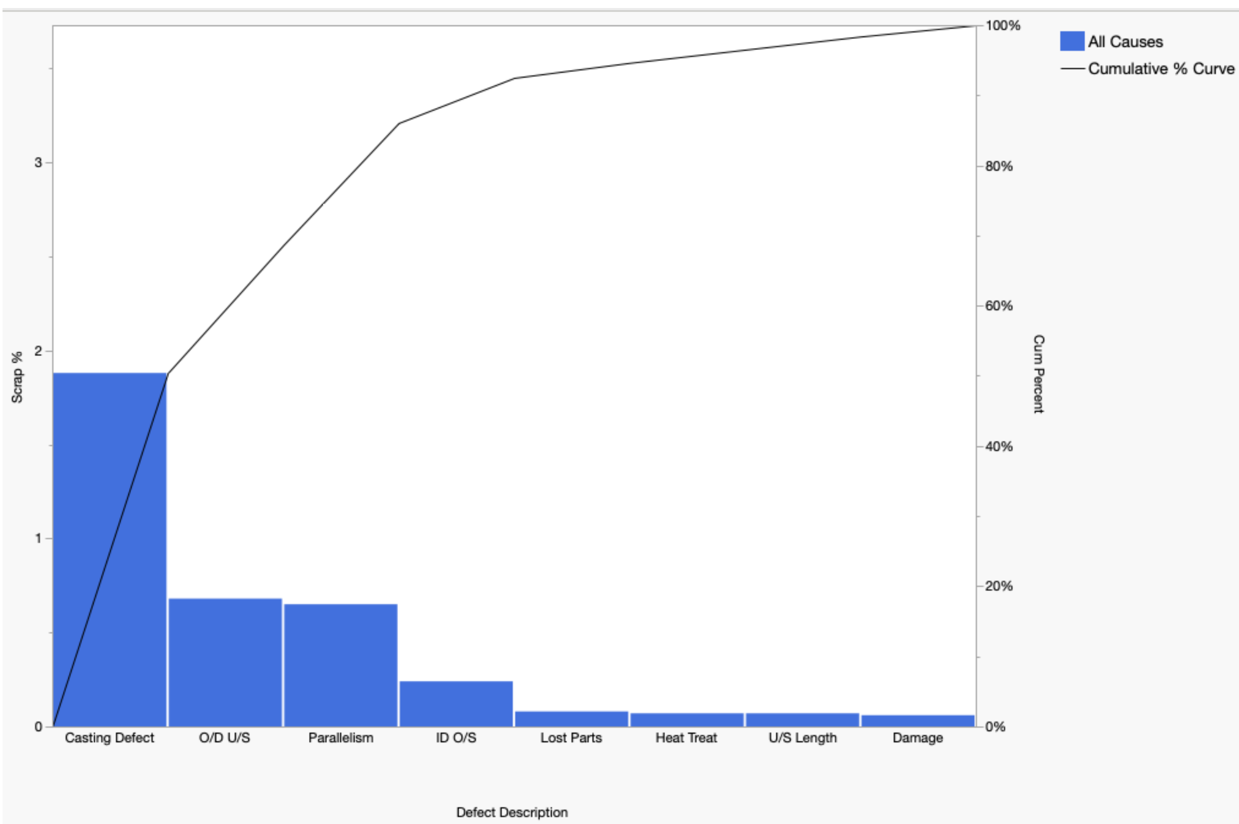


Figure 6. Pareto chart of the causes of scrap highlighting the major contributors to scrap rate in part number J2001-33.

A fishbone diagram can be seen in Figure 7 for both parallelism and oversized outer diameter. From the group's brainstorm session, possible causes, with respect to the 6 key areas, were discussed. The core ideas from this diagram will guide the group towards further investigation of the causes of the problem.

Referring to the fishbone diagram, the group was able to discuss potential areas which could lead to either undersized outer diameter (O/D U/S) and parallelism scrap causes. With respect to People, lack of experience and operator errors can contribute to these manufacturing defects. Machines can have incorrect setup tooling or programs leading to defective parts produced. Inadequate calibration and operator bias can produce measurement errors leading to defective parts. Heat treatment and improper material processing can produce parts unable to meet the specification limits. Lack of control within the environment, such as too high of temperature, can alter the shape of a part resulting in lack of precision during production. Lastly, lack of training or missing instructions, on either the router or drawing, can produce confusion during production resulting in scrap.

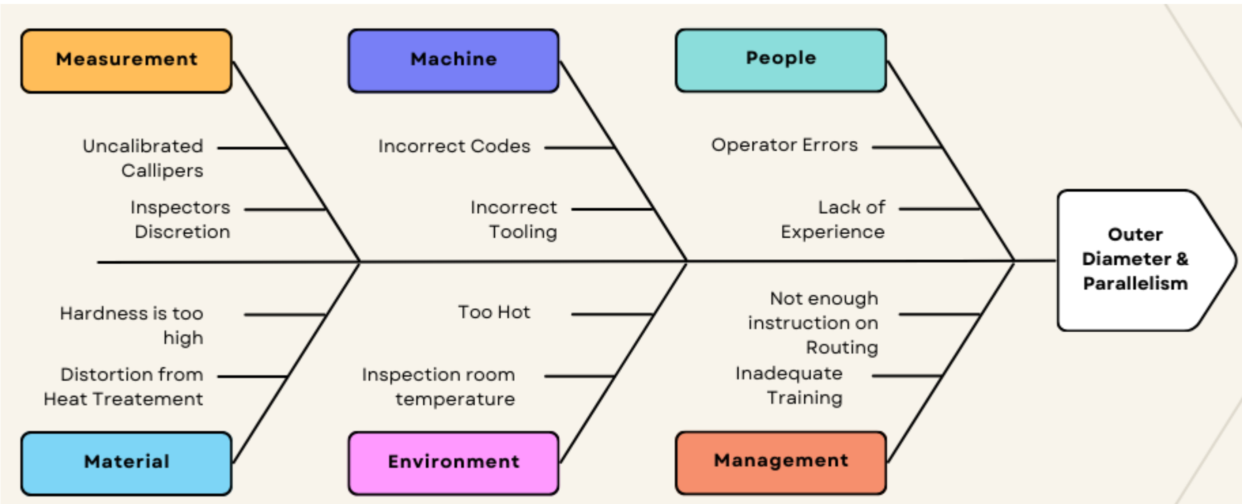


Figure 7. Fishbone, or Ishikawa, diagram for brainstorming potential causes for the outer diameter undersized and parallelism scrap causes.

The analysis of the manufacturing process, for part number J2001-33, has shown that 80% of defects resulting in scrap can be attributed to three causes; casting defects, undersized outer diameter, and parallelism. With respect to casting defects, since this is a supplier-controlled process, the group will have limited impact on improving the quality of parts during the casting process. However, a recommendation can be made to partner with the supplier in an effort to improve quality or identify a new supplier altogether. Moving forward, the group will emphasize improvements made to the production steps producing the outer diameter and parallel faces of the bearing ring component.

4.4 Improve

Solutions were ideated during a brainstorming session aimed at resolving the problems associated with undersized outer diameter and parallelism. A weighted scoring model matrix was used to evaluate each proposed solution and narrow the focus. Those solutions can be identified in Table 1.

Table 1. Weighted Scoring Model for Proposed Solutions

Solution/Criterion	Ease of Implementation	Quick	High Impact	Cost	Total
New Tooling	2	4	4	3	96
Design Change	1	1	5	3	15
Training	3	3	2	4	72

Each solution was given a score from 1-5 across the following areas; ease of implantation, how quick the solution would be to implement, the impact, and the cost. The ratings were multiplied for a total to compare each solution. Based on the weighted scoring model implemented, the solution to design and use new tooling was determined to be the best direction.

A Failure Modes and Effects Analysis (FMEA) was conducted to assess any risks associated with implementing new tooling and design mitigation protocols to reduce the risk. The goal of designing and implementing new tooling is to enable operators to produce finer cuts with greater precision on the bearing's outer diameter to reduce occurrences of undersized OD. With the part being a small bearing assembly with tight tolerances, precision tools are necessary. Using finer end mills for milling operations and finer cutters in the lathe operations, these tighter tolerances can be achieved thus reducing nonconformances caused by undersized OD. These same methods for new tooling can also be implemented for machining the faces to improve parallelism. A summary of the FMEA can be seen in Table 2.

Table 2. FMEA Matrix for New Tooling Solution

Process Step	Machining ID/OD	Machining ID/OD
Failure Modes	Increased lead times.	Increased operator errors.
Failure Mode Effects	Offset cost savings gained by reducing scarp.	Increased scrap rate.
Severity	5	7
Failure Mode Cause	Increased machining time.	Learning curve for operators using new tooling.
Occurance	10	7
Detection (D)	1	4
Risk Priority Number (RPN)	50	196
Recommended Action	Monitor cycle times to ensure cost savings is maintained.	Work instructions and training for new tooling.

Manufacturing constraints resulted in a halt to the progress gained in this project. Due to this, the proposed solution of new tooling was unable to be implemented and the impact could not be measured. As will be discussed in the following sections, when it becomes feasible for manufacturing to test the new tooling solution, future work should be focused on testing the solution's ability to reduce the scrap rate.

5. Conclusion and Future Work

A bearing ring component was observed to produce a scrap rate per production run greater than the desirable scrap rate established by the manufacturing company, The Bearing Company. In order to reduce the scrap rate of part number J2001-33, the DMAIC methodology and Lean Six Sigma practices were applied. Descriptive statistics and process capability analysis highlighted a large spread in the scrap rates for each production ranging from 1% to 58%. Additionally, with Cp and Cpk values of 0.311 and 0.175, respectively, the process is neither centered nor capable of meeting the specification limits. Pareto analysis of the defects pertaining to part number J2001-33 demonstrated that 80% of all defects were due to casting defects, undersized outer diameter, and parallelism non-conformances.

Casting defects, being a supplier related issue, were determined to be out of the scope of this project. Root cause analysis determined outer diameter and parallelism non-conformances were the result of less-than-ideal precision from the current tooling. Thus, the development of new tooling to provide greater precision to the machine of the outer diameter and faces was suggested. Manufacturing constraints prevented the implementation and testing of this solution. However, future work should focus on testing the impact of the proposed solution. Complete success will be predicated on sustaining any achieved improvements observed.

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Biographies

Michael Kesablian is a graduate from California Polytechnic State University Pomona in 2023 with a Bachelor's Degree in Manufacturing Engineering. He now attends California State University Northridge working towards a Master's Degree in Engineering Management. He currently is working for The Bearing Company Corporation in their Aerospace division as a Manufacturing Engineer after transferring from his role as a Quality Engineer. The experience in both roles has grown his knowledge of the entire manufacturing process along with working with customers to meet their standards. His focus in the field is maximizing efficiency and continuous improvement towards eliminating any factors of the manufacturing process that will lead to nonconformances.

Pranshu Kothari holds a Bachelor's degree in Mechanical Engineering from Gujarat Technological University and is currently advancing his education with a Master's in Engineering Management at California State University Northridge. He gained practical experience during an internship at a gearbox manufacturing and assembly firm in India. He is eager to establish a career in the supply chain domain, with a strong focus on logistics, operations strategy, and improving processes.

Calvin Noetzel graduated from California Polytechnic State University San Luis Obispo with a Bachelor's Degree in Materials Engineering in 2016. He is in the process of obtaining his Master's in Materials Engineering from California State University Northridge. He is a Materials and Process Engineer with industry experience developing aluminum and titanium aerospace forging processes and heat treatment of steels. His research interests include additive manufacturing of nickel-based superalloys, fracture mechanics, and high temperature deformation of alloys.

Sepideh Abolghasem is an associate professor in the Department of Manufacturing Systems Engineering and Management at California State University at Northridge. Prior to this appointment, she was an associate professor in the Department of Industrial Engineering at the University of los Andes, Bogotá, Colombia. She earned her B.Sc. degree in Industrial Engineering from Sharif University of Technology, Tehran, Iran and her M.Sc. and Ph.D. degrees in Industrial Engineering from University of Pittsburgh. Her main research interests span the integration of the disciplines of Operations Research and Materials Science. Much of her work has been focused on machining manufacturing process where she tries to improve the understanding on the interrelationships among the process parameters and the microstructure of the materials. Recently, she has been working on the application of machine learning techniques combined with simulation for material properties prediction. She has served as the faculty advisor at IISE and represented the Latin America at INFORMS' International Activities Committee.