CONSTRUCTION AND PRAXIS OF SIX SIGMA DMAIC FOR BEARING MANUFACTURING PROCESS –NABARUP GHOSH (22GG10028)

Introduction

In today's competitive landscape, achieving sustained performance hinges on delivering high-quality products at minimal cost. Statistical Quality Control (SQC) offers a systematic approach to this challenge, with 'process capability' analysis playing a pivotal role. By quantifying a process's ability to yield acceptable results, organizations can prioritize improvements and reduce costs. This study employs the DMAIC approach to enhance the bearing manufacturing process at Kirloskar Oil Engine Ltd., focusing on Pareto analysis, process evaluation, and Taguchi's robust design methodology to identify critical parameters. The goal is to drive operational excellence through strategic quality control measures.
Cp - Capability index
Cpk - Process performance capability index

Literature Review

2.1. Process Capability

The notion of process capability was introduced by the statistical community but gained traction with the dissemination of Japanese manufacturing methods in the United States (Sullivan, 1984). The Cp and Cpk indices, along with their statistical features, were devised to quantify the degree of process variation in relation to specification limits. Cp reflects the process variation in respect to specification limits, while Cpk considers both process variance and mean position. These indices provide a static goal for performance and serve as crucial metrics for continuous process improvement.
One key metric in assessing process capability is the capability ratio, denoted as:
Capability ratio = 6σ variation/tolerance width

This ratio directly links customer specifications to process variability, emphasizing the supplier's obligation to meet these requirements (J. M. Juran & Gryna, 1993). While capability indices offer advantages over capability ratios, such as rising values with process performance improvement, they provide valuable insights into both process location and variation (Stoumbos, 2002). Historical contributions from Shewhart (1931), Juran, Gryna, and Bingham (1974), and J. M. Juran and Gryna (1993) laid the groundwork for determining specification limits using process capability indices, recommending a maximum tolerance range of six sigma.
Palmer and Tsui (1999) summarized process capability indices and provided guidelines for index interpretation and process improvement, while Stoumbos (2002) detailed various capability indices linked to process parameters. Brugger (1992) outlined a procedure for conducting process capability studies to determine inherent process variation and underscored the benefits of such studies. Gitlow, Gitlow, and Oppenheim (1989) delved into detailed discussions on process capability and improvement studies, particularly focusing on attribute process parameters.

2.2. Six Sigma and DMAIC

Six Sigma, initially developed by Motorola, serves as both a philosophy and a method for minimizing process variance and enhancing organizational quality and performance. The DMAIC approach, a cornerstone of Six Sigma, focuses on Define, Measure, Analyze, Improve, and Control to drive process capability improvements. Antony and Banuelas (2002) highlighted the effectiveness of DMAIC in implementing Six Sigma successfully. Taguchi's robust design methodology, integrated into the DMAIC approach, facilitates the analysis and optimization of critical-to-quality (CTQ) characteristics. Srinivasan et al. (2014) demonstrated the combined use of Six Sigma and Taguchi's robust design to optimize process parameters and reduce fault rates.

2.3. Taguchi Robust Design

The Taguchi robust design methodology, developed by Genichi Taguchi in 1980, is a widely utilized statistical method for optimizing process parameters and product quality characteristics. Gopalsamy, Mondal, and Ghosh (2009) discussed its application in investigating surface finish and tool life in end milling processes. Li, Al-Refaie, and Yang (2008) concluded that integrating Taguchi's robust design into the DMAIC approach is effective for enhancing process capability. Pareto analysis is another valuable tool employed to identify critical causes of rejection, separating the significant factors from the trivial ones.

DMAIC methodology, results and discussion

3.1. Define Phase

The study focuses on half engine bearing manufacturing, encompassing the charting of machining operations across thirteen process workstations, with two inspection points post the tenth workstation. Table 1 outlines the system specifications. Rejection data collection spanned a calendar year, identifying fifty-nine defects, of which twenty defects, representing over 1% of total rejection, were earmarked for further scrutiny. Monthly rejection data informed Pareto analysis, revealing nine defects contributing to nearly 80% of rejections (Fig. 1).

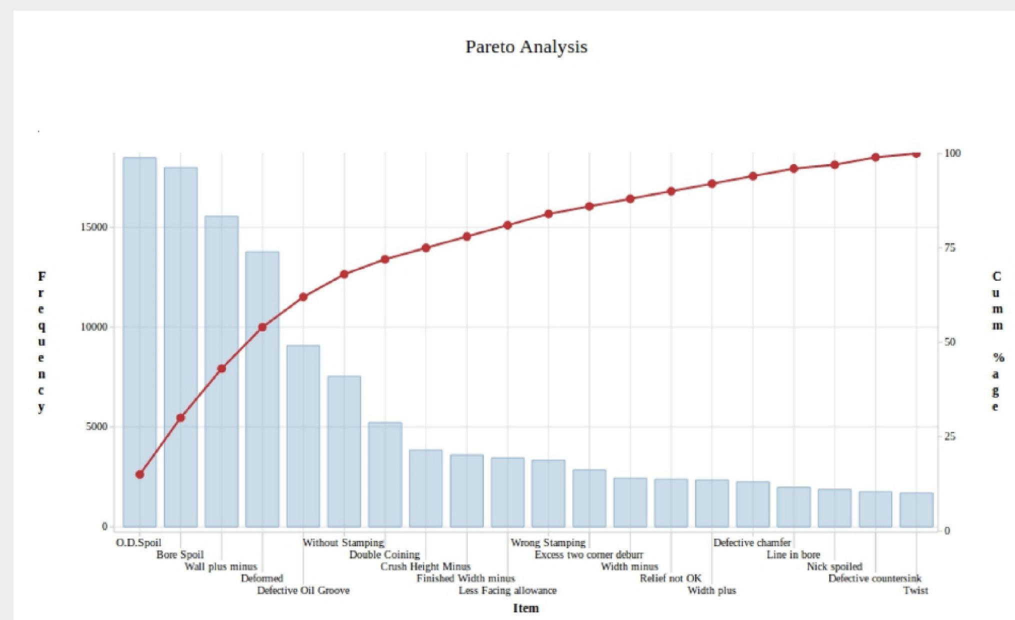


Fig. 1. Pareto analysis for defects.

3.2. Measure Phase

The 'Measure' phase entailed evaluating current performance concerning critical quality characteristics (CQC). A data collection system was established for each CQC, with 30-day rejection data for attribute parameters and 60 data points for variable parameters. Defect classification and process capability studies are summarized in Table 3.

Table 3
Classification of defects according to inspection method and process capability study.

Sr. No.	Defects	Quality characteristics	Inspection Method	Type of process capability study
1	O.D. spoil	Marks on outer diameter	Visual	Attribute
2	Bore spoil	Bore spoiled	Visual	Attribute
3	Wall plus minus	Finish wall thickness at crown	Wall thickness measurement machine	Variable
4	Deformed	Deformed	Visual	Attribute
5	Defective oil groove	Chip embedded in groove	Visual	Attribute
6	Without stamping	Stamping operation missing	Visual	Attribute
7	Double coining	Double coining	Visual	Attribute
8	Crush height minus	Crush height	Height measurement machine	Variable
9	Finished width minus	Finished width at crown	Micrometer	Variable

Selected parameters underwent process capability assessment, categorized as variables or attributes based on evaluation method. Attribute parameters underwent P chart analysis based on daily production over thirty days, while measurable parameters underwent Cp and Cpk analysis using standard formulae.

Table 4 showcases rejection in Parts Per Million (PPM) for attribute parameters, while Table 5 presents process capability indices for variable parameters. While parameters like 'Crush height' and 'Finished width at crown' exhibited satisfactory Cp and Cpk values, 'Finish wall thickness at crown' fell below acceptable levels, necessitating process improvement actions. With Cp and Cpk values critically lower than the desired 1.33, significant enhancements were earmarked for the 'Auto bore broaching workstation'.

Table 4
Rejection in PPM for attribute parameters.

Sr. No.	Attribute parameter	Rejection in PPM		
		Average	UCL	LCL
1	O.D. Spoil	4090	5769	2412
2	Bore Spoil	3814	5434	2193
3	Deformed	2920	4339	1501
4	Defective Oil Groove	747	1466	28
5	Without Stamping	1933	3089	778
6	Double Coining	968	1786	150

Table 5
Process capability indices for variable parameters.

Sr. No.	Parameter	C_p	C_{pk}
1	Finish wall thickness at crown	1.170	0.976
2	Crush height	3.630	2.540
3	Finished width at crown	3.050	1.870

3.3. Analysis Phase

Upon reviewing the Measure phase, it became apparent that the current process performance, particularly regarding 'Finish wall thickness at crown', was unsatisfactory and necessitated improvement. Utilizing a fishbone diagram (Fig. 2), common causes such as unskilled operators and improper machine settings were identified and rectified. Factors like cutting speed and cutter roundness, previously optimized during product development, were excluded from further analysis. The most influential causes—clamping pressure (CP), worn-out cutter or usage of the cutter (UC), and length of bimetallic strip (LBS)—were pinpointed for further investigation.

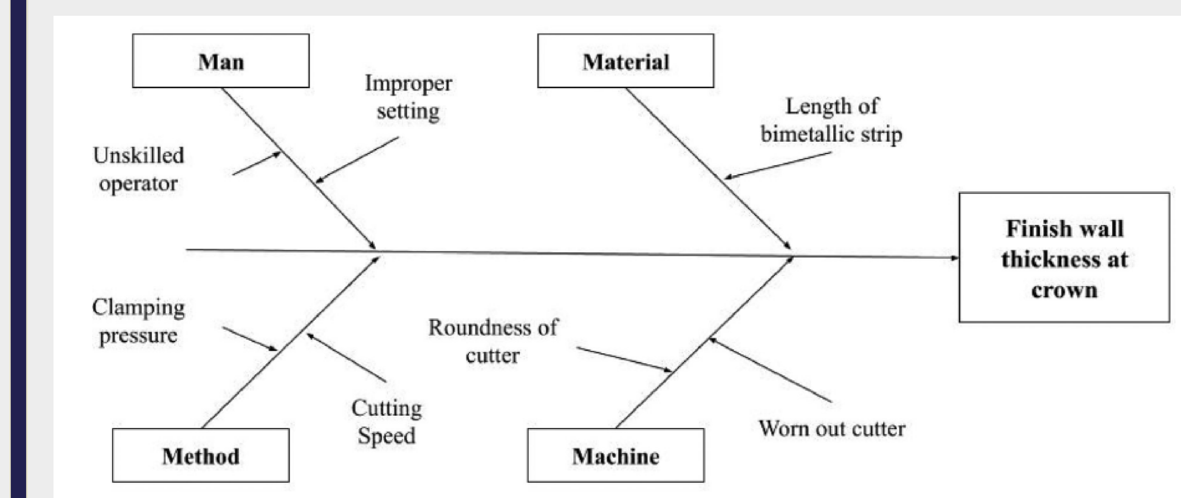


Fig. 2. Fishbone diagram.

3.4. Improve Phase

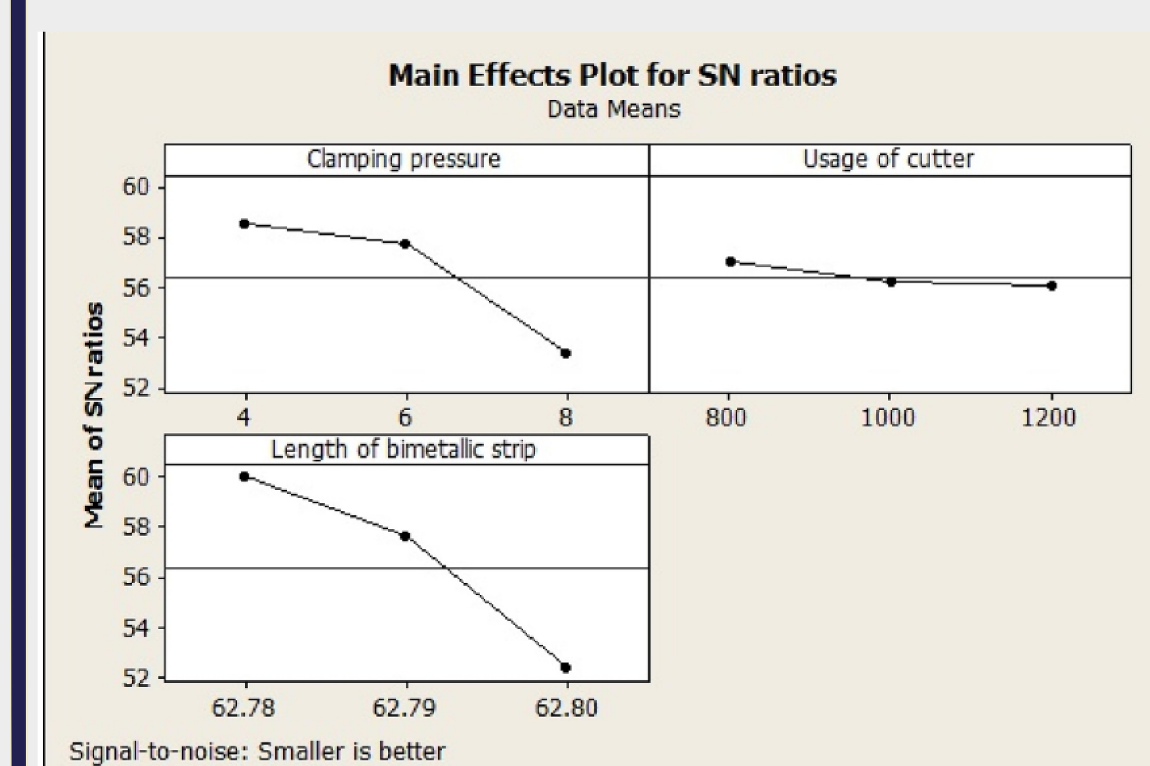
This phase focused on optimizing the CP, UC, and LBS values, crucial for improving 'Finish wall thickness at crown'. An experiment was designed using an L27 orthogonal array (OA) (Table 6) and analyzed using ANOVA. Levels for factors were selected, with Level-I representing lower values, Level-II representing actual values, and Level-III representing higher values. Through randomizing trials, control over variables was maintained to avoid confounding. ANOVA was employed to discern the significance of factors. The response diagram revealed optimal settings for 'Length of bimetallic strip' at 62.78 mm and 'Clamping pressure' at 4 bar. Residual plots confirmed the linear relationship between actual and fitted values, validating the simple linear regression model. Interaction plots highlighted the impact of factors on response, guiding further adjustments.

Table 6
Factors along with its levels.

	Factor	Unit	Level-I	Level-II	Level-III
A	Clamping pressure (CP)	Bar	4	5	6
B	Usage of cutter (UC)	–	1200	1500	1800
C	Length of bimetallic strip (LBS)	mm	62.78	62.79	62.80

3.5. Control Phase

Following the Improve phase, optimal factors and levels for 'Finish wall thickness at crown' were determined. A trial run with 50 units, set to the identified optimal parameters, confirmed Cp and Cpk values (2.78 and 2.23 respectively) within the acceptable range. This successful optimization ensures a minimal rejection rate, underscoring the efficacy of the selected factors and levels.



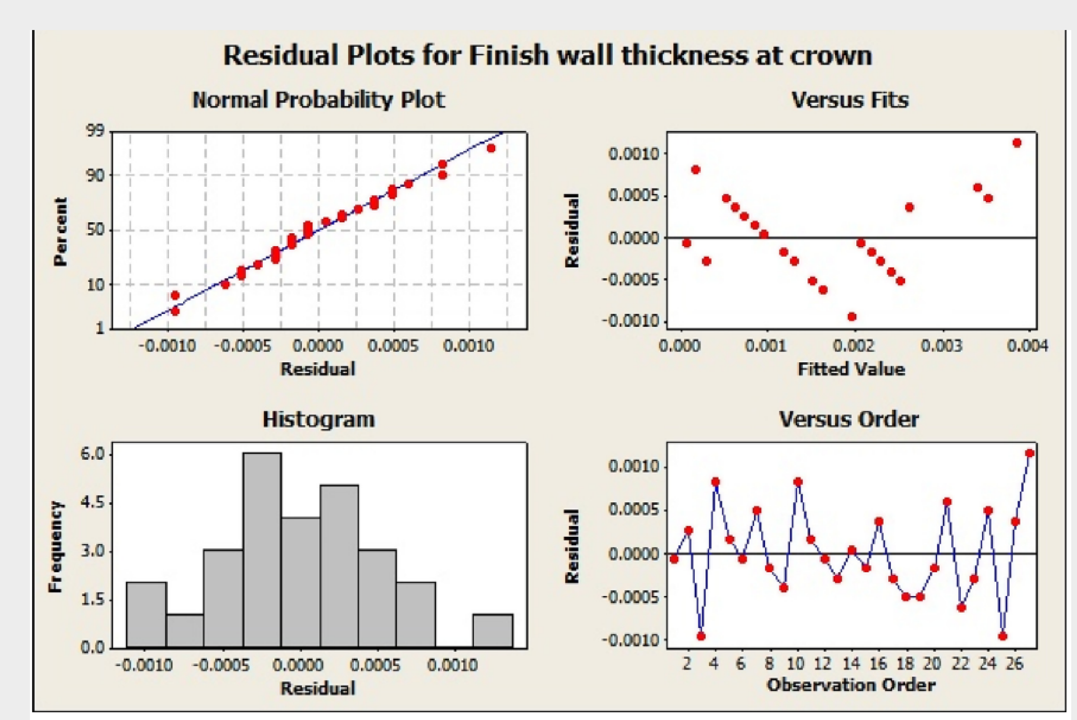


Fig. 4. Residual plots for finish wall thickness at crown.

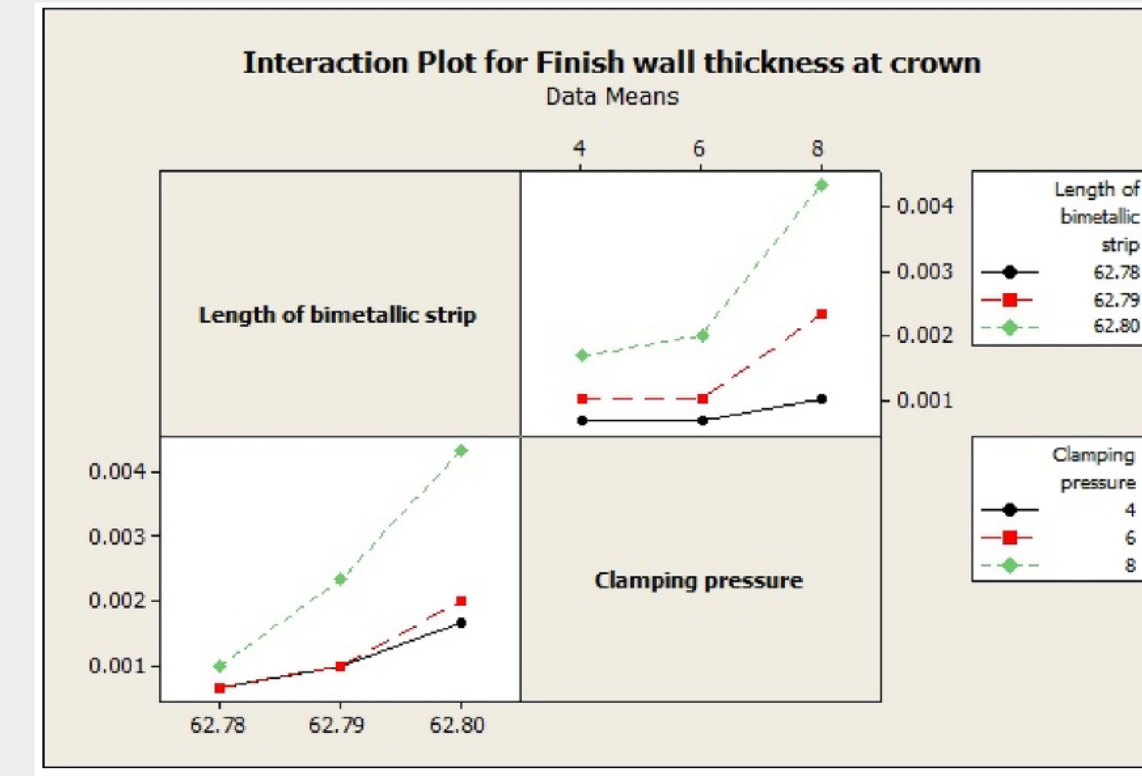


Fig. 5. Interaction plot for Finish wall thickness at crown.

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Conclusions

The integration of the Taguchi method within the Six Sigma DMAIC framework proved instrumental in systematically analyzing process parameters' effects on the bearing manufacturing system's process capability. Through process capability studies, significant improvements were achieved, addressing the primary causes of rejection and enhancing Cp and Cpk values for critical-to-quality (CTQ) characteristics.

The 'Define' phase effectively identified critical defects, with nine defects contributing to nearly 80% of rejections.
During the 'Measure' phase, process capability indices revealed deficiencies, notably with Cp and Cpk values for 'Finish wall thickness at crown' falling below acceptable levels.
In the 'Analyze' phase, the fishbone diagram identified clamping pressure, cutter usage, and length of bimetallic strip as influential factors affecting 'Finish wall thickness at crown'.
The 'Improve' phase utilized an L27 orthogonal array and ANOVA analysis to refine process parameters, highlighting the interaction between 'length of bimetallic strip' and 'clamping pressure' as critical.
In the 'Control' phase, validation runs under optimal conditions demonstrated significant improvements, elevating Cp and Cpk values for 'Finish wall thickness at crown' from 1.170 and 0.976 to 2.78 and 2.23, respectively.
These findings underscore the effectiveness of the DMAIC approach coupled with the Taguchi method in enhancing process capability, reducing rejection rates, and ultimately improving overall manufacturing quality.

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