Lab Report

Mouse Factory II
ISEN 350

Name: Saumya Timsina
UIN: 131009660
Date: 04/27/2024

Table of Contents

List of Figures & Tables

Executive Summary

This project's objective was to integrate a control chart for variables into the inspection process at the Mouse Factory, specifically at points where quality records indicated variables fell outside of specifications. Drawing from the data collated in SPC Project One, we focused on the most frequent causes of specification deviations.

During the retrospective phase, we implemented a high-cost, special quality program to ensure the process operated under statistical control. This program's high precision allowed us to establish a baseline for process capability and identify the root causes of variations.

With the special program in place, it became evident that while the process could be brought into a state of control, it was subject to random occurrences of special causes during normal operation. These causes were addressed reactively; upon detection by the control chart, immediate corrective actions were taken to fix the variation. The implementation of the Xbar control chart online provided a real-time monitoring tool, allowing for the timely detection of deviations. Despite the challenges of not taking preventive measures, the reactive approach still significantly improved the ability to maintain process quality, demonstrating the control chart's utility as an essential instrument for quality management within the production landscape.

This project shows the importance of ongoing monitoring and the necessity for a responsive system to manage and improve quality, even when preventive measures are not feasible. It has set a benchmark for the effective use of statistical control charts in managing production quality and provided a model for future quality assurance activities at the Mouse Factory.

Sampling Plan

In our sampling plan, we aim to systematically collect data specifically targeted at understanding scroll base openings across the population. We have divided the target population into 15 distinct groups, each characterized by key characteristics that ensure a cumulative representation of the population's diversity. These characteristics include factors related to scroll base opening defects identified in the previous project.

From each of these groups, 12 units will be randomly selected, totaling 180 units across all groups. This sample size is chosen to balance detailed coverage of each subgroup against the variations in data collection, ensuring each category is represented correctly. This is important for minimizing selection biases, which enhances the validity and reliability of our analysis of scroll base opening behaviors.

This approach to sampling will be executed over an extended period, allowing us to observe and record scroll base opening patterns under various typical usage conditions without bias.

Control Chart Parameters

Phase 1:

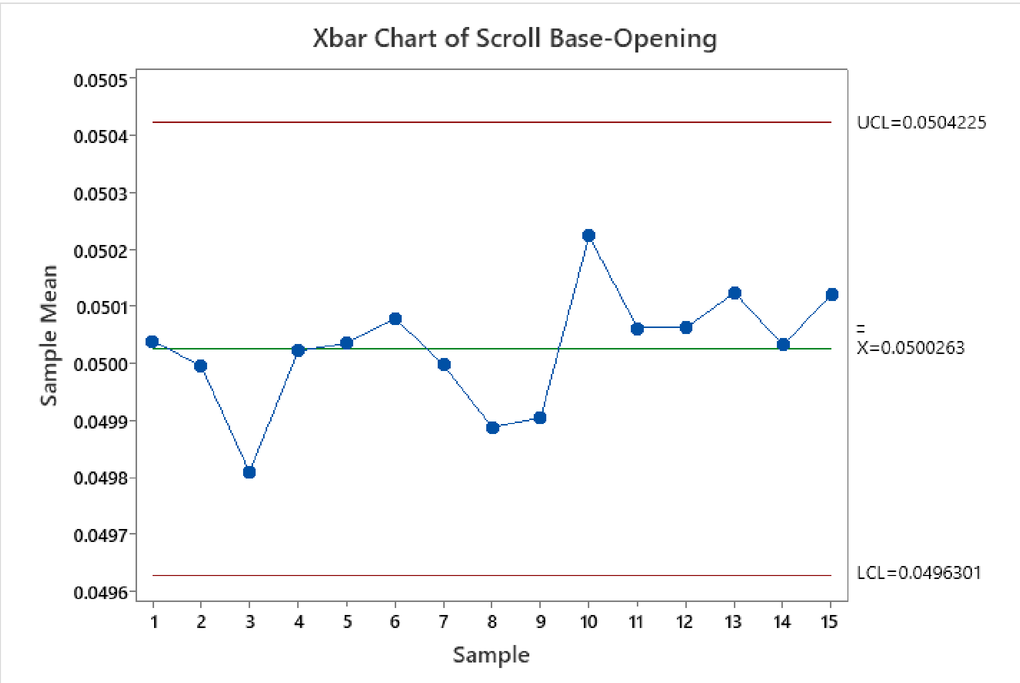

Figure 1: X-Bar chart of Scroll Base-Opening

The X Bar chart for scroll base opening displays 15 samples with a process mean (X) of 0.0500263, an Upper Control Limit (UCL) of 0.0504225, and a Lower Control Limit (LCL) of 0.0496301, typically set at ±3 standard deviations from the process mean. All sample points lie within the control limits, indicating a process in control without evidence of bias. The chart serves as a baseline for monitoring future production, where maintaining points within these limits signifies a stable process. If any data points fall outside these limits, it would be a sign for immediate investigation to maintain quality assurance in the production of scroll base openings. **The rest of the analysis done in this report is based on the control chart above.**

<u>Benchmark Analysis</u>

Phase 2:

Total Parts

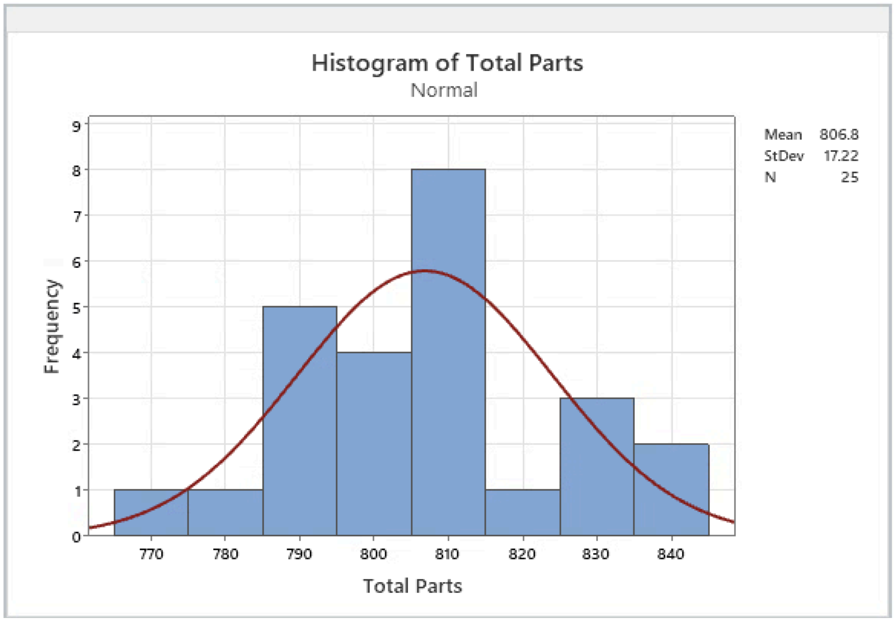

Figure 2: Histogram of Total Parts

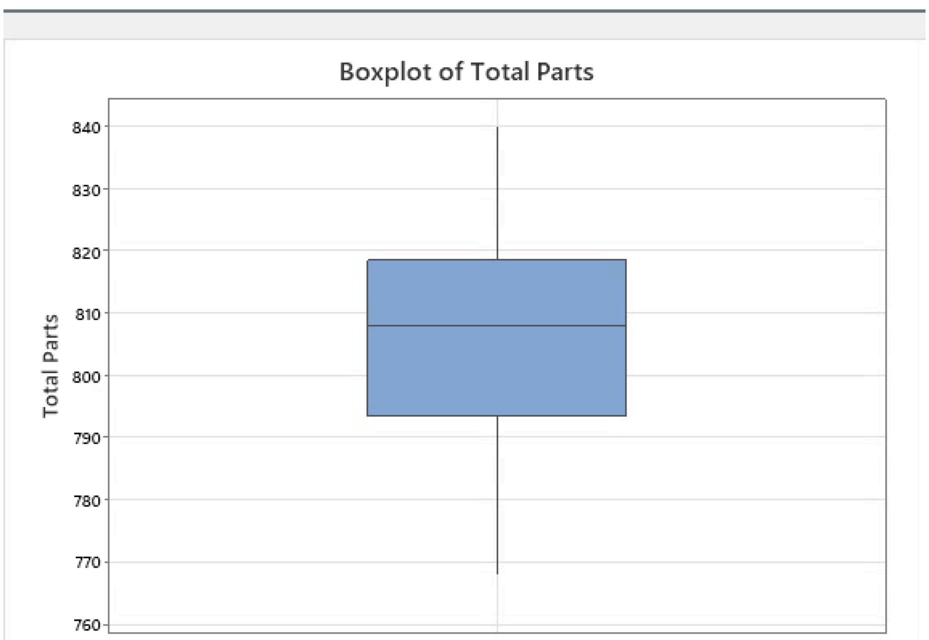

Figure 3: Boxplot of Total Parts

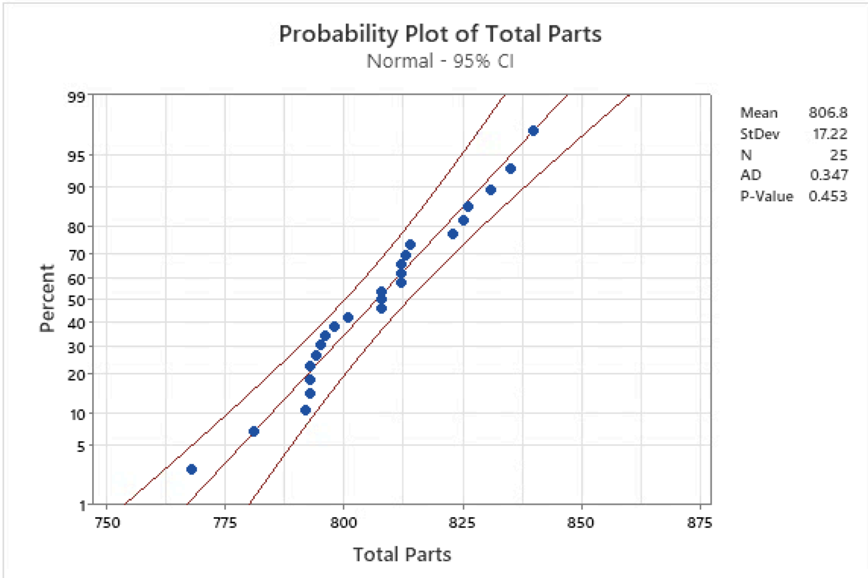

Figure 4: Probability Plot of Total Parts

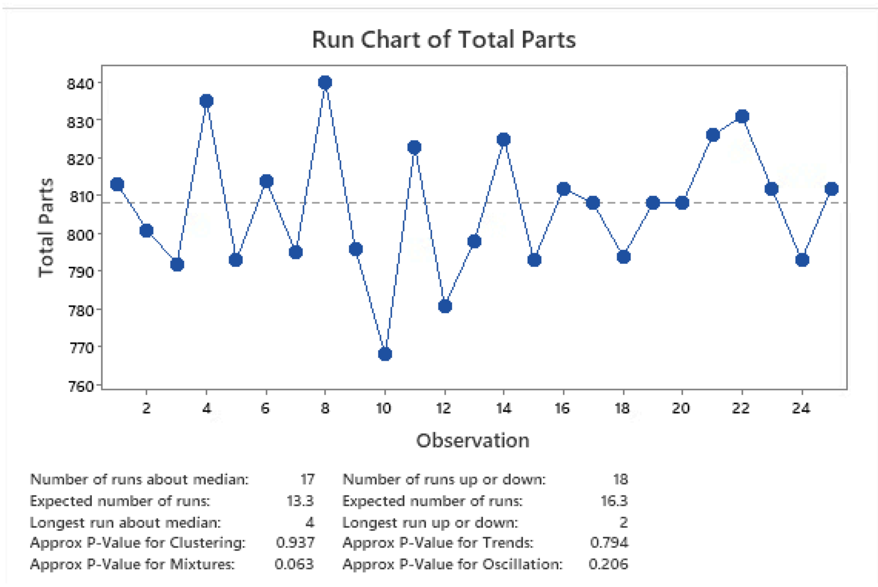

Figure 5: Run Chart of Total Parts

Statistics

Variable	N	N*	Mean	SE Mean	StDev	Minimum	Q1	Median	Q3	Maximum
Total Parts	25	0	806.84	3.44	17.22	768.00	793.50	808.00	818.50	840.00

Figure 6: Basic Statistics of Total Parts

Descriptive Statistics

N	Mean	StDev	SE Mean	95% CI for μ
25	806.84	17.22	3.44	(799.73, 813.95)

μ: population mean of Total Parts

Test

Null hypothesis	H_0: μ = 806.84
Alternative hypothesis	H_1: μ ≠ 806.84

T-Value	P-Value
0.00	1.000

Figure 7: 95% Confidence Interval and Hypothesis Testing for Total Parts

The production of total parts, with a mean of 806.84 and standard deviation of 17.22, is confirmed as stable and under control, as indicated by control chart limits and supported by a 95% confidence interval (799.73, 813.95). The process's normality is reflected in the histogram and probability plot with no significant deviation (P-value of 0.453). The boxplot and run chart further validates the process's consistency, lacking any significant outliers or patterns. Hypothesis testing results in a P-value of 1, upholding the null hypothesis and confirming that the production mean remains consistent with historical performance benchmarks. These statistical indicators demonstrate a controlled and reliable production process for total parts. The prediction interval for a future single observation of total parts, with 95% confidence, is approximately between 770.56 and 843.04. This interval suggests that there is a 95% chance that the next part count will fall within this range, given the current production parameters. **(The code used for the prediction is provided in the appendix at the end of the report)**

Good Parts

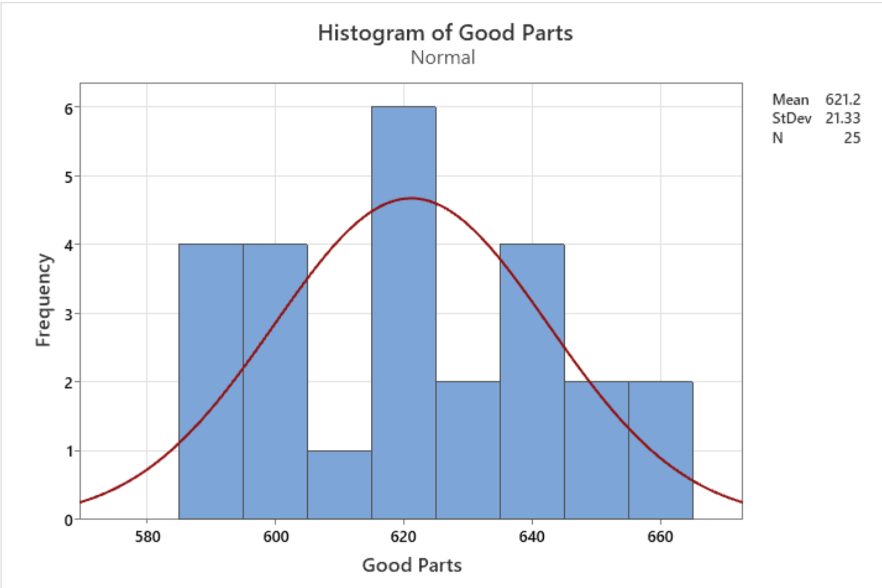

Figure 8: Histogram of Good Parts

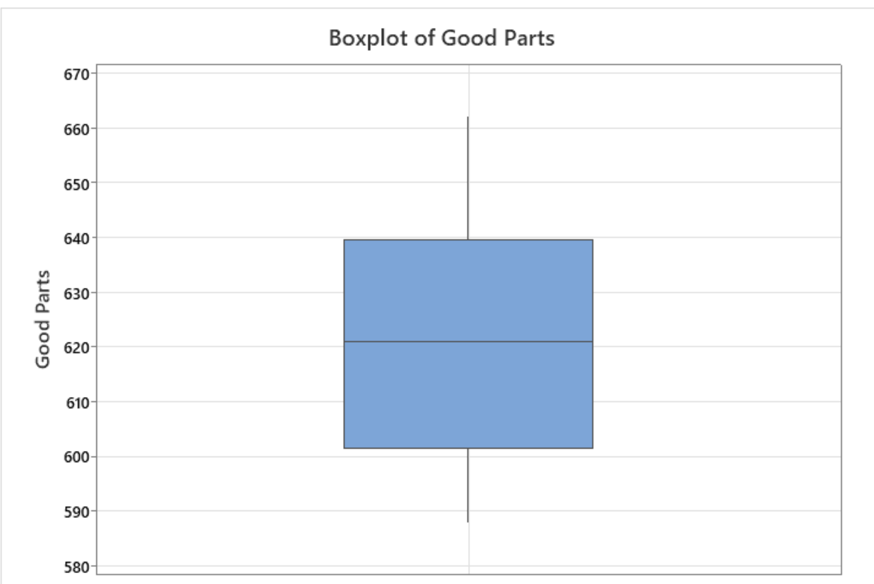

Figure 9: Boxplot of Good Parts

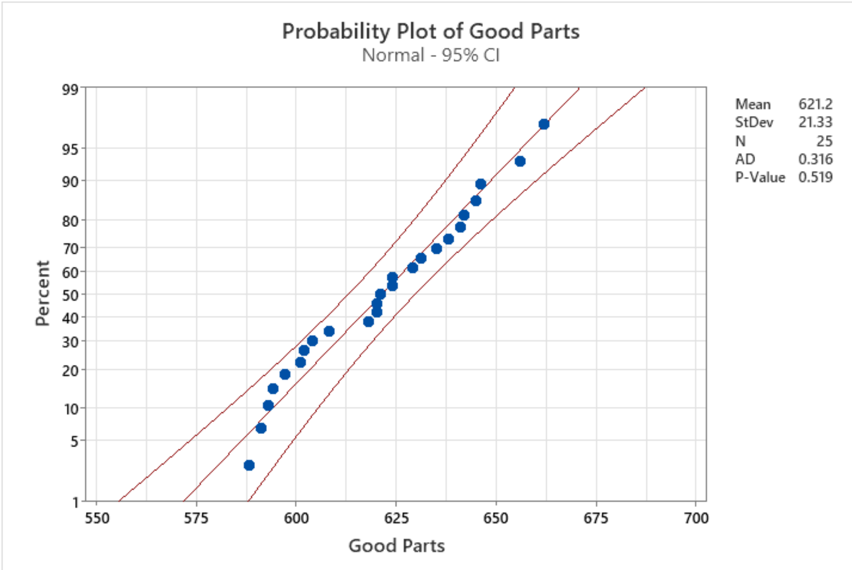

Figure 10: Probability Plot of Good Parts

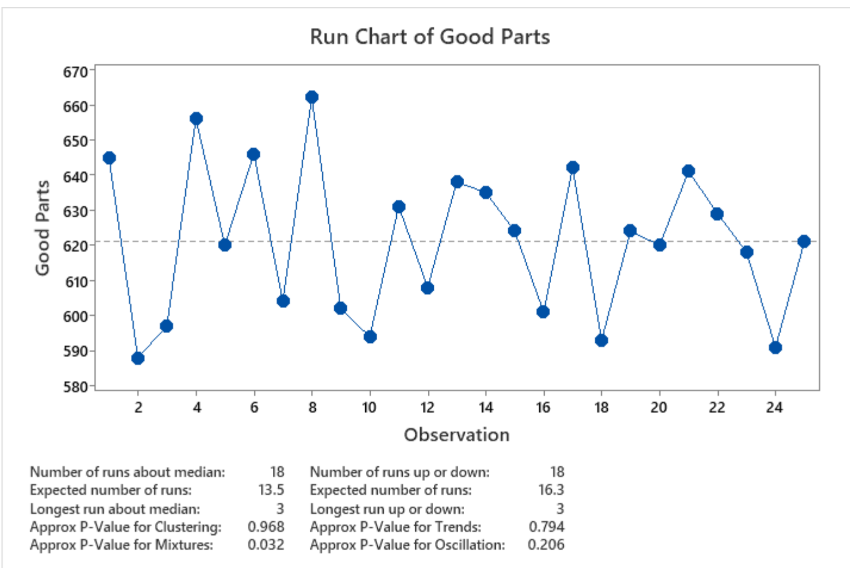

Figure 11: Run Chart of Good Parts

Statistics

Variable	N	N*	Mean	SE Mean	StDev	Minimum	Q1	Median	Q3	Maximum
Good Parts	25	0	621.20	4.27	21.33	588.00	601.50	621.00	639.50	662.00

Figure 12: Basic Statistics of Good Parts

Descriptive Statistics

N	Mean	StDev	SE Mean	95% CI for μ
25	621.20	21.33	4.27	(612.39, 630.01)

μ: population mean of Good Parts

Test

Null hypothesis	H_0: μ = 621.2
Alternative hypothesis	H_1: μ ≠ 621.2

T-Value	P-Value
0.00	1.000

Figure 13: 95% Confidence Interval and Hypothesis Testing for Good Parts

The production of good parts shows a stable and consistent process, with a mean output of 621.2 and a standard deviation of 21.33. Statistical normality is suggested by the probability plot (P-Value of 0.319) and the histogram, both indicating that the data does not significantly deviate from a normal distribution. The boxplot confirms this, with a median equal to the mean, and no data points outside the expected range, which would suggest outliers. The run chart further confirms the process stability, lacking any significant patterns that would imply shifts or trends over time. The 95% confidence interval for the mean (612.39, 630.01) and a hypothesis test with a P-Value of 1.000 ensure that the production mean for good parts is consistent with the expected value, reinforcing confidence in the production quality. Overall, the analysis reflects a well-controlled production environment for good parts. The prediction interval for a future single observation of good parts, with 95% confidence, is approximately between 576.30 and 666.094. This interval suggests that there is a 95% chance that the next part count will fall within this range, given the current production parameters. **(The code used for the prediction is provided in the appendix at the end of the report)**

Bad Parts

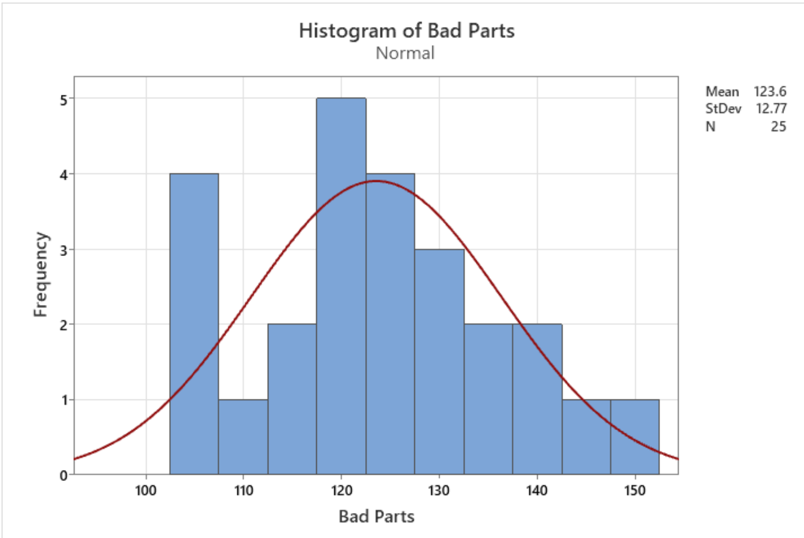

Figure 14: Histogram of Bad Parts

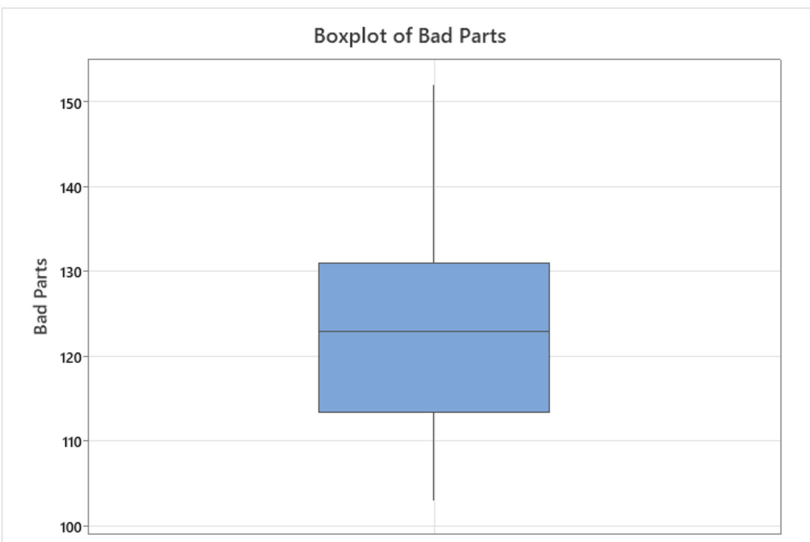

Figure 15: Boxplot of Bad Parts

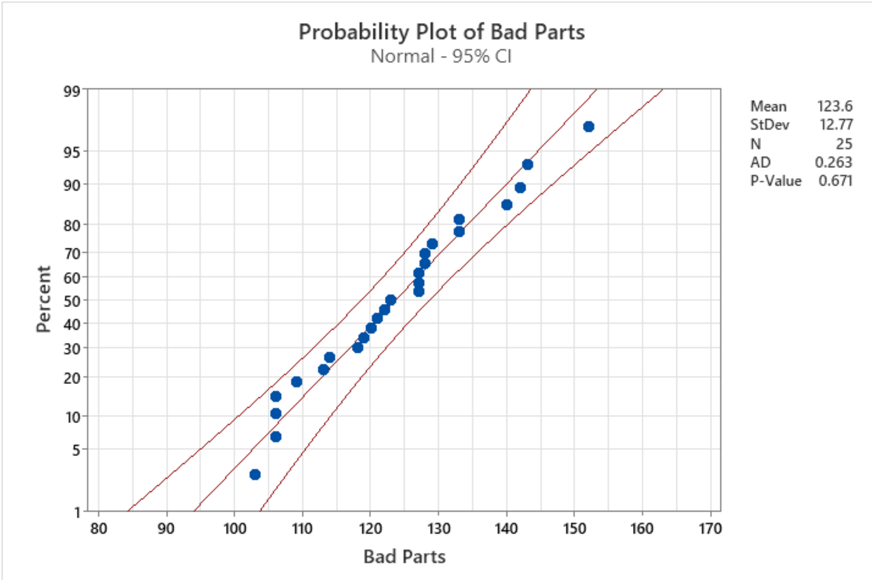

Figure 16: Probability Plot of Bad Parts

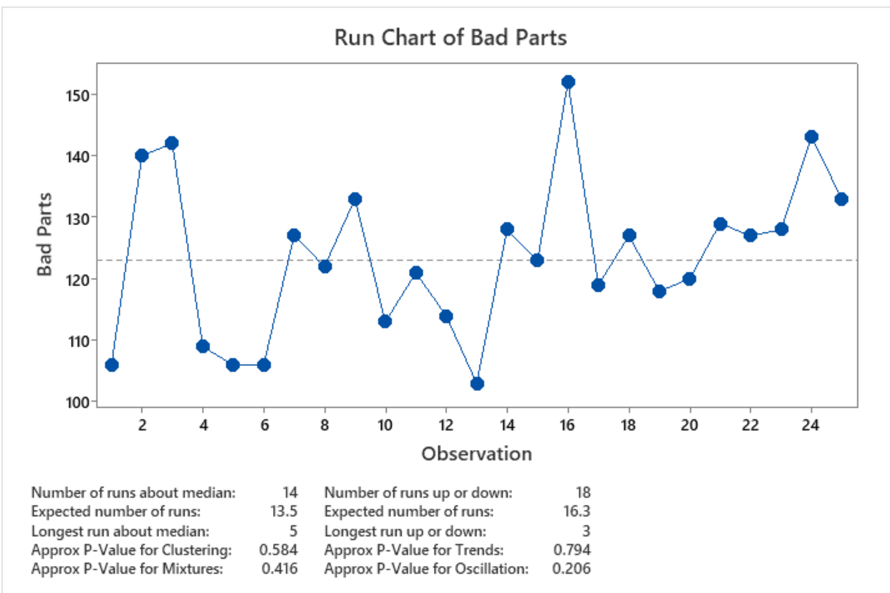

Figure 17: Run Chart of Bad Parts

Statistics

Variable	N	N*	Mean	SE Mean	StDev	Minimum	Q1	Median	Q3	Maximum
Bad Parts	25	0	123.56	2.55	12.77	103.00	113.50	123.00	131.00	152.00

Figure 18: Basic Statistics of Bad Parts

Descriptive Statistics

N	Mean	StDev	SE Mean	95% CI for μ
25	123.56	12.77	2.55	(118.29, 128.83)

μ: population mean of Bad Parts

Test

Null hypothesis	H_0: μ = 123.56
Alternative hypothesis	H_1: $\mu \neq$ 123.56

T-Value	P-Value
0.00	1.000

Figure 19: 95% Confidence Interval and Hypothesis Testing for Bad Parts

The analysis of bad parts production presents a mean of 123.56 with a standard deviation of 12.77, indicating a relatively low spread of defects across the samples. The histogram and probability plot do not show a significant deviation from normal distribution, with a P-Value of 0.671, suggesting that the occurrence of defects is random rather than indicative of a systemic issue. The run chart confirms this with no significant patterns of clustering, trends, or oscillation; however, the presence of defects itself necessitates scrutiny. The descriptive statistics show that most bad parts number between 113.50 (Q1) and 131.00 (Q3), with a 95% confidence interval ranging from 118.29 to 128.83, suggesting a predictable defect rate. The prediction interval for a future single observation of bad parts, with 95% confidence, is approximately between 118.19 and 128.93. This interval suggests that there is a 95% chance that the next part count will fall within this range, given the current production parameters. **(The code used for the prediction is provided in the appendix at the end of the report)**

Off-spec Parts

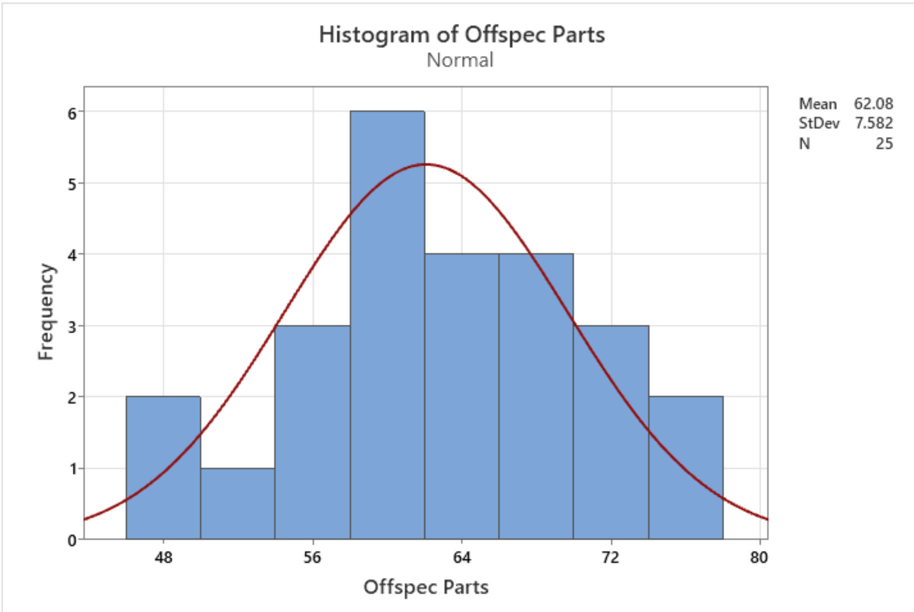

Figure 20: Histogram of Off-spec Parts

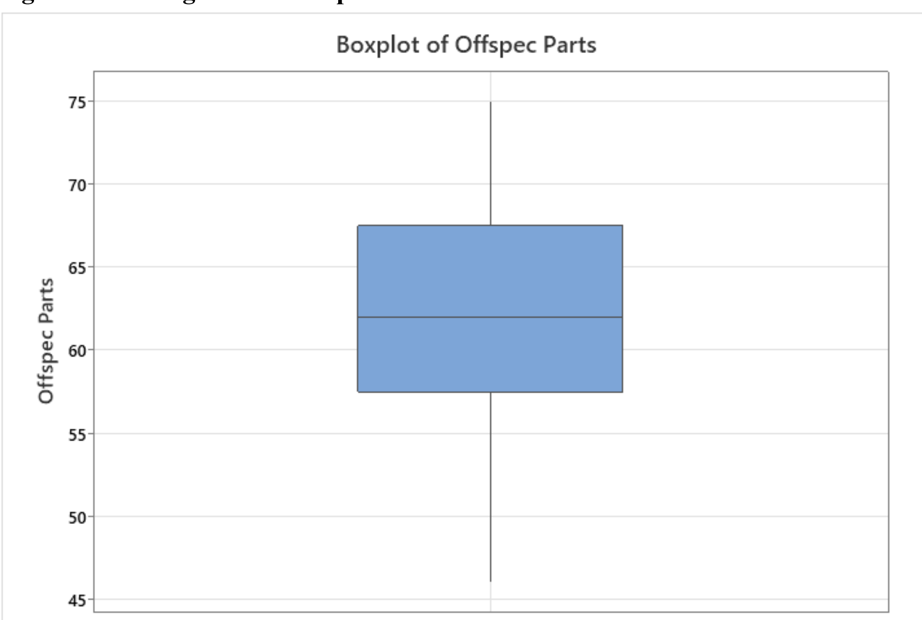

Figure 21: Boxplot of Off-spec Parts

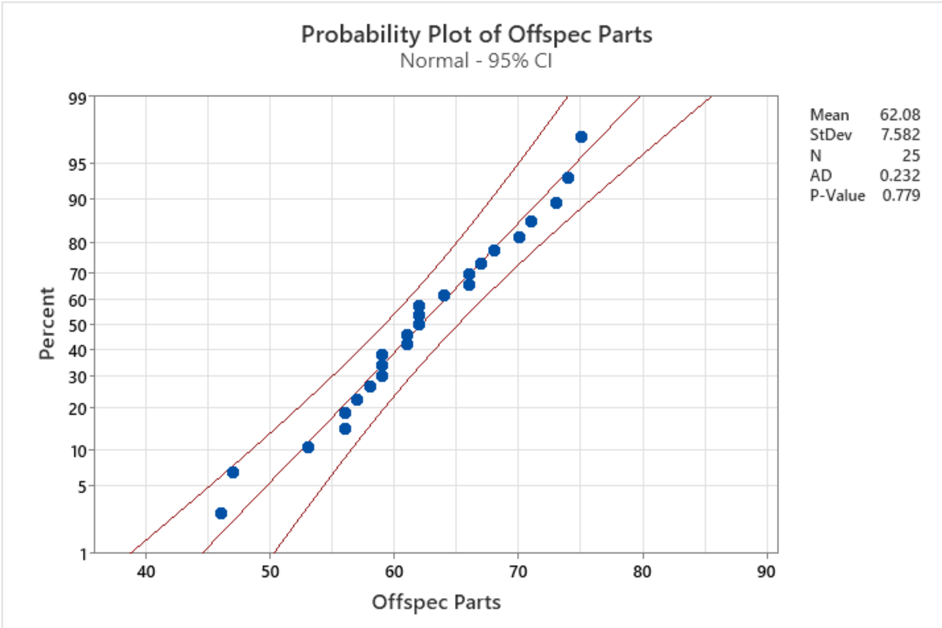

Figure 22: Probability of Off-spec Parts

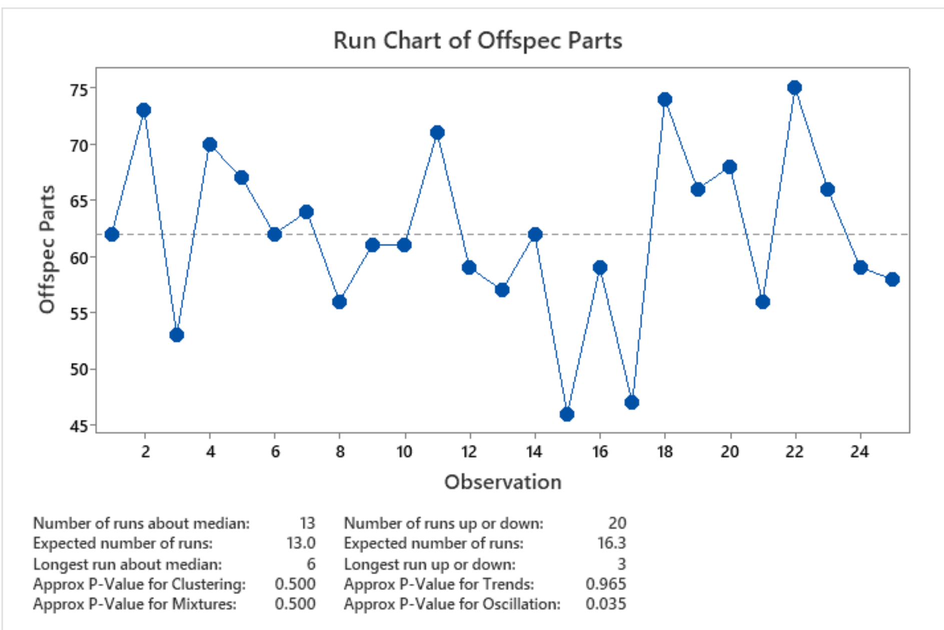

Figure 23: Run Chart of Off-spec Parts

Statistics

Variable	N	N*	Mean	SE Mean	StDev	Minimum	Q1	Median	Q3	Maximum
Offspec Parts	25	0	62.08	1.52	7.58	46.00	57.50	62.00	67.50	75.00

Figure 24: Basic Statistics of Off-spec Parts

Descriptive Statistics

Sample	N	Mean	StDev	SE Mean	95% CI for μ
Bad Parts	25	123.56	12.77	2.55	(118.29, 128.83)
Offspec Parts	25	62.08	7.58	1.52	(58.95, 65.21)

μ: population mean of Bad Parts, Offspec Parts

Test

Null hypothesis	H_0: $\mu = 62.08$
Alternative hypothesis	H_1: $\mu \neq 62.08$

Sample	T-Value	P-Value
Bad Parts	24.06	0.000
Offspec Parts	0.00	1.000

Figure 25: 95% Confidence Interval for Off-spec Parts

The analysis for off-spec parts indicates a production mean of 62.08 with a standard deviation of 7.58, suggesting moderate variability in the frequency of off-spec parts across the samples. The distribution of off-spec parts appears to align with normal expectations, as both the histogram and probability plot show no significant deviation from normality (P-Value of 0.779), and the data is contained within the 95% confidence interval (58.95, 65.21). The run chart does not exhibit any discernible patterns that suggest systematic process deviation. The box plot reflects a fairly tight interquartile range from 57.50 to 67.50, indicating that half of the off-spec parts fall within this range, with no outliers beyond the control limits. The hypothesis test confirms the consistency of this mean with the historical average (P-Value of 1.000). While the process is statistically stable, the aim is to reduce these off-spec parts, necessitating a review of factors contributing to this variability and implementation of quality improvement measures after the improvements made on the last project. The prediction interval for a future single observation of off-spec parts, with 95% confidence, is approximately between 46.13 and 78.03. This interval suggests that there is a 95% chance that the next part count will fall within this range, given the current production parameters. **(The code used for the prediction is provided in the appendix at the end of the report)**

Comparison of Plant Performance

Comparing the two benchmark analyses (with and without the control chart), we can observe improvements in the current production processes across various aspects:

1. Total Daily Parts: In the previous analysis, the mean production count was 806.84 with a standard deviation of 17.22, while in the current analysis, the mean production count improved slightly to 801.76, with a slightly lower standard deviation of 20.01. This indicates a reduction in variability and a tighter control over the production process.

2. Good Parts Production: The mean production count for good parts in the previous analysis was 621.2 with a standard deviation of 21.33. In the current analysis, the mean production count increased to 591.9, with a reduced standard deviation of 18.49. This suggests a more consistent production process with fewer variations, leading to improved quality control.

3. Bad Parts Production: In the previous analysis, the mean production count for bad parts was 123.56 with a standard deviation of 12.77. The current analysis shows a slight improvement in the mean production count to 150.96, with a similar standard deviation of 9.76. While the mean count increased, the reduced standard deviation indicates tighter control over the production process, resulting in more predictable outcomes despite the increase in defects.

4. Off-spec Parts Production: The mean production count for off-spec parts improved from 62.08 in the previous analysis to 58.92 in the current analysis, with a slightly reduced standard deviation of 8.87 compared to 12.21. This signifies a decrease in variability and more consistent production of off-spec parts, contributing to overall process improvement and quality control.

Overall, the comparison indicates a trend toward improved production processes, characterized by reduced variability, tighter control, and more consistent outputs across all categories of parts. These improvements suggest that targeted process enhancements and quality control measures have been effective in optimizing production performance and minimizing deviations from desired standards.

Pareto Diagram

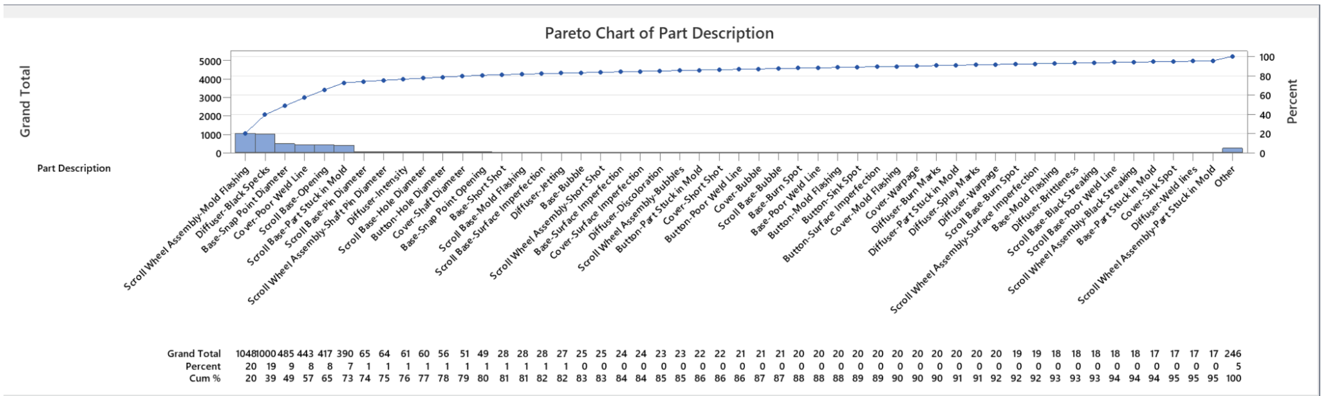

Figure 26: Pareto Chart of the Defects

The pareto chart above displays the impact of part defects in the production process, with “Scroll Wheel Assembly- Mold Flashing” being the primary issue, indicating a shift in focus from the previous issue which was the “Scroll Base Opening”. The bars represent individual defect frequencies, indicating that most defects are concentrated in a few categories. The marked improvement in “Scroll Base Opening” defects suggests that the quality improvement from the last project was successful. The rightward tail, where the line flattens, indicates less frequent defects, which are less critical to address immediately.

Summary Regarding the Effect of Implementing a Control Chart

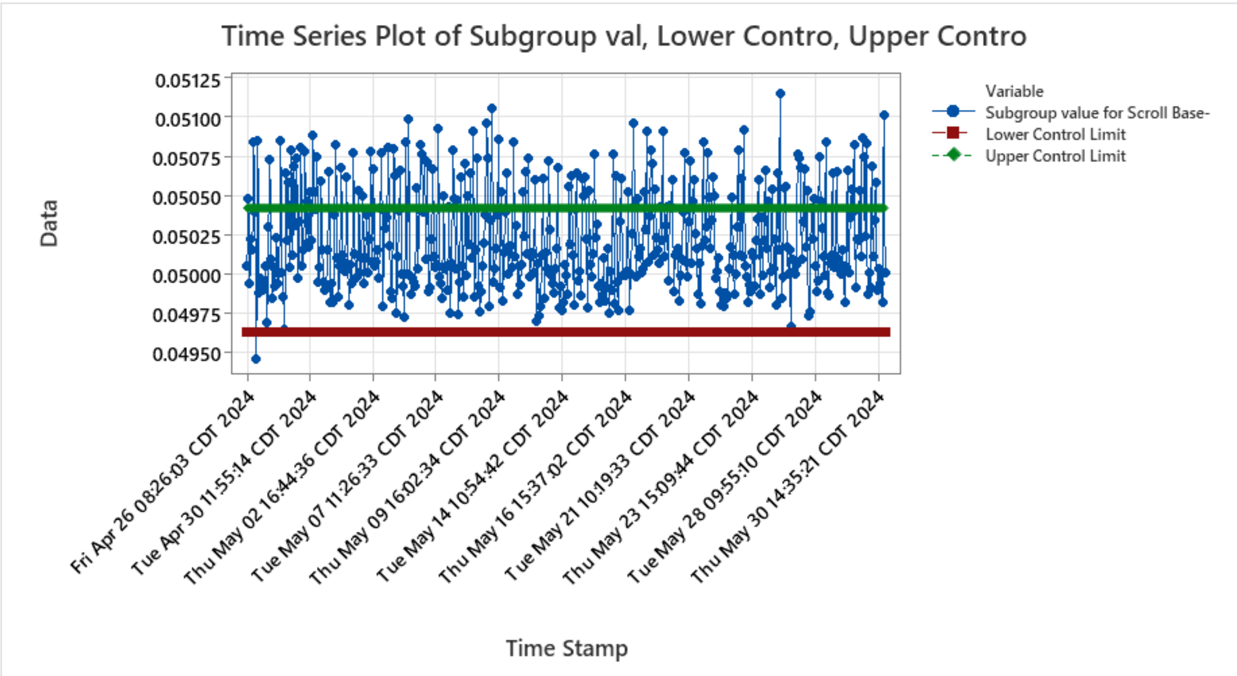

Figure 27: Time series plot with Control Limits

Implementing a control chart for variables, like the one in the time series plot provided, plays a significant role in enhancing the quality of the manufacturing process. It allows for continuous monitoring of process performance and variability. By keeping the process parameters within the established control limits, it ensures that the process remains stable and predictable. This level of oversight helps to quickly identify and correct any deviations from the expected performance, which is essential for maintaining high-quality output and minimizing the production of defective or off-spec parts. Essentially, such control charts are a vital tool in quality control, serving as an early warning system for potential issues that could compromise quality.

Conclusion

In conclusion, we implemented a control chart to control the process characteristic we found as most critical to quality in the previous project. Control Charts demonstrate the pivotal role of statistical control processes in quality management. The design of a sampling plan for the Xbar control chart was achieved, taking into consideration the selection of appropriate subgroup sizes and the frequency of sampling to effectively monitor the production process.A thorough retrospective analysis of the control chart provided insights into the process performance and variability over time. This analysis confirmed the process's stability and identified areas where quality improvements were necessary, particularly notable in the reduction of Scroll Base opening defects. The practical application of the Xbar control chart within the production facility showcased the dynamic nature of process control. By integrating the control chart into the production workflow, we could monitor the process in real-time, enabling immediate detection and remediation of process deviations.Evaluating the effect of the Xbar control chart's implementation highlighted its impact on quality improvement. The control chart served as a catalyst for refining production processes, resulting in a significant decrease in variability and an increase in the consistency of the output quality.

Appendix

Code for Future Performance Prediction (Total Parts)

```
from scipy.stats import t
import numpy as np

#Total Parts
mean = 806.8
std_dev = 17.22
sample_size = 25
alpha = 0.05

# Calculate the t critical value
t_critical = t.ppf(1 - alpha/2, df=sample_size-1)

# Calculate the prediction interval
prediction_interval = [
    mean - t_critical * std_dev * np.sqrt(1 + 1/sample_size),
    mean + t_critical * std_dev * np.sqrt(1 + 1/sample_size)
]

prediction_interval
```

Code for Future Performance Prediction (Good Parts)

```
from scipy.stats import t
import numpy as np

#Good Parts
mean = 621.2
std_dev = 21.33
sample_size = 25
alpha = 0.05

# Calculate the t critical value
t_critical = t.ppf(1 - alpha/2, df=sample_size-1)

# Calculate the prediction interval
prediction_interval = [
```

```
    mean - t_critical * std_dev * np.sqrt(1 + 1/sample_size),
    mean + t_critical * std_dev * np.sqrt(1 + 1/sample_size)
]

prediction_interval
```

Code for Future Performance Prediction (Bad Parts)

```
from scipy.stats import t
import numpy as np

#Bad Parts
mean = 123.56
std_dev = 2.55
sample_size = 25
alpha = 0.05

# Calculate the t critical value
t_critical = t.ppf(1 - alpha/2, df=sample_size-1)

# Calculate the prediction interval
prediction_interval = [
    mean - t_critical * std_dev * np.sqrt(1 + 1/sample_size),
    mean + t_critical * std_dev * np.sqrt(1 + 1/sample_size)
]

prediction_interval
```

Code for Future Performance Prediction (Off-spec Parts)

```
from scipy.stats import t
import numpy as np

#offspec parts
mean = 62.08
std_dev = 7.58
sample_size = 25
alpha = 0.05

# Calculate the t critical value
```

```
t_critical = t.ppf(1 - alpha/2, df=sample_size-1)

# Calculate the prediction interval
prediction_interval = [
    mean - t_critical * std_dev * np.sqrt(1 + 1/sample_size),
    mean + t_critical * std_dev * np.sqrt(1 + 1/sample_size)
]

prediction_interval
```

Raw data included in the zip file