

Introducing Statistical Process Control Techniques into a Headliner Subassembly Process

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Abstract

Customer demand is a constantly changing variable that suppliers must be able to accommodate to stay in business. Being able to properly assess the output of a process is key to determining capability. The focus of this paper is to determine and improve the quality level of a headliner manufacturing line using statistical quality control tools. It will analyze observational data to determine whether the process is in control and measure the capability of the process to meet an increased demand. QC tools such as control charts, analysis of variance (ANOVA) and Pareto analysis will be used as the means for collecting and analyzing data, measuring the results and then identifying root causes. These tools will then be used to identify how to improve the process to meet the demand.

Keywords

Control chart, Sigma level, Analysis of variance (ANOVA), Pareto analysis

1. Introduction

Statistical quality control (SQC) tools were originally developed to evaluate process performance in manufacturing environments. These techniques have since been expanded to measure more atypical subject matter such as advanced warning systems in vehicles (Liu and Ho, 2017). Other divergent uses include evaluating the performance of Precise Point Positioning used for GPS navigation systems (Cheng, et. al., 2017). SQC is being implemented in the health profession as well. Oncology researchers have utilized SQC tools as a method to quantify quality of life in cancer trials (Hamel, et. al., 2017). It has also been used to improve neonatal care in hospitals (Gupta and Kaplan, 2017).

Quality control (QC) refers to the practice of monitoring a process to ensure the product is meeting requirements as well as detect and reduce any variance in the product or process. QC utilizes many tools designed to help gather and analyze data with the goal of improving operational efficiency in a system. Variance is a value that is studied closely in QC because variance is a good indicator of poor quality. To measure variance in a process, statistical tools are applied frequently for quality control purposes (Montgomery, 2013).

A headliner for a vehicle line (Fig. 1) is built using both a batch and sequence process. The side facing down in Fig. 1 is called the A surface. This is the side that can be seen when you look up inside a vehicle. The other side is referred to as the C surface. This is the side that connects to the roof of the car and contains all the wire harnesses and connections. Stiffeners and head impact countermeasures (HIC) are installed on the C surface by robots or automatic machines in batch. Customer use items such as grab handles, overhead consoles and dome lamps are applied by manual glue process along with wire harnesses and other unseen items.

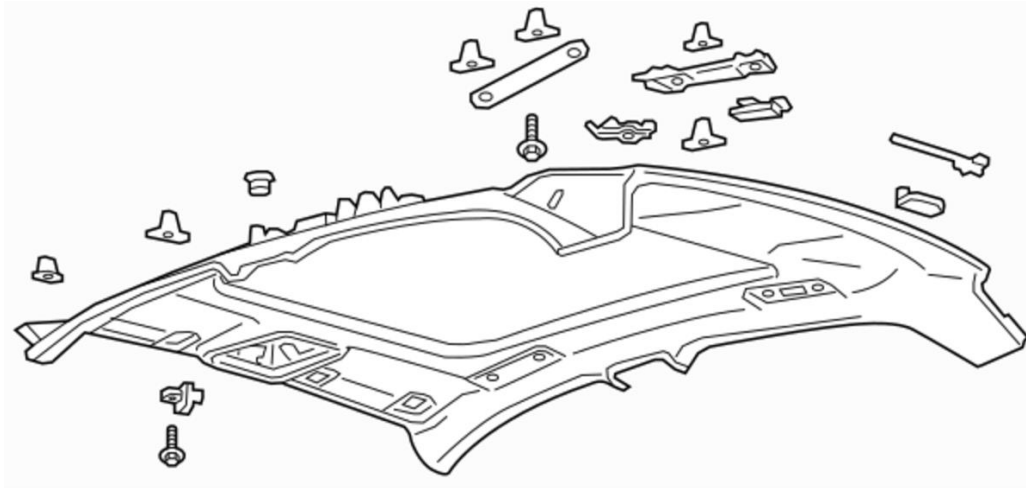


Figure 1. Exploded assembly of headliner.

In this paper, we will look at this build line using statistical analysis tools to determine whether this process is in control and how it can be improved to meet customer demand. We will utilize QC tools for a statistical analysis of the process and its yield.

2. Methodology

Sample data for 31 days of production was taken to analyze the performance of the line. We will utilize several QC tools such as control charts, a process capability study and ANOVA analysis to diagnose this build line (flow chart in Fig. 2). The data will be evaluated to determine whether the headliner process can meet and increase in the demand. If necessary, we will also use Pareto analysis to determine the root cause of the failure and give recommendations.

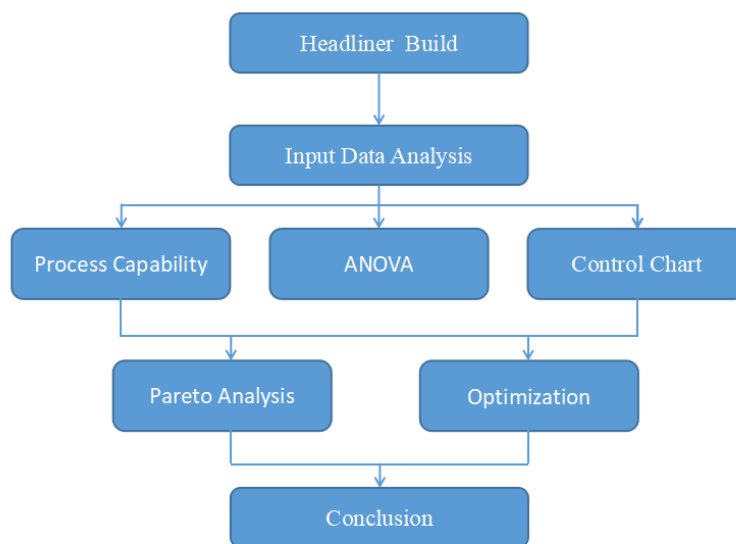


Figure 2. Flow chart of methodology used in this case study.

2.1. Control Chart

Control charts utilize mean variance data to determine a lower control limit (LCL) and upper control limit (UCL) for a set of data. Sample process data is then plotted against these limits. Multiple data points outside of these control

limits indicates an out-of-control condition of the process. If analysis of the control chart indicates that the process is currently under control, then there is a decent chance that no corrections or changes to process control parameters are needed or desired (Montgomery, 2013).

There are 2 main types of control charts: characteristic and attribute. For the purpose of this case study, we will be using attribute chart which tracks the amount of non-conforming parts if the quality data is qualitative rather than quantitative (Aslam et. al., 2016). In addition, data from the process can be used to predict the future performance of the process. If the chart indicates that the monitored process is not in control, analysis of the chart can help determine the sources of variation.

2.2. Capability Study

The process capability is a measurable property of a process to the specification, expressed as a process capability index (Pal, 2011). Again, we will be utilizing attribute data, so this capability study will include:

- 1) finding the current sigma level of the line, and
- 2) comparing to the required sigma level to meet the increased rate

The sigma level is a value used to convey the overall quality of a process. It is converted from a value of parts per million (ppm) defective in a sample either using an equation or extrapolating from a sigma conversion table such as Table 1 below (Swinney). The million opportunities that define this number represent each opportunity for a defect, not just each part. One part may have several different opportunities for a defect (Montgomery, 2013). The number of defects per million opportunities (DPMO) corresponds to a sigma level indicating the overall quality of the process.

Table 1. Sigma level performance table (Swinney)

Sigma Level	Defects Per Million Opportunities (DPMO)
1	690,000
2	308,537
3	66,807
4	6,210
5	233
6	3.4

As shown in the figure, a sigma level of 1 indicates an inefficient process producing 690,000 defects per million opportunities, or a defect rate of 69%. Whereas a sigma level of 6 indicates a high-quality process producing only 3.4 defects per million opportunities, or a defect rate of 0.00034%.

2.3. ANOVA Analysis

Analysis of variance (ANOVA) is used to analyze the differences within and between groups of data typically to determine the cause of variance in a process (Popescu, et. al., 2016). It is also used to determine the effect of individual parameters on results (Nandagopal and Kailasanathan, 2016). This method uses a hypothesis test to determine whether there is a statistical difference in the mean data from multiple groups. The null hypothesis assumes that all factors have equal significance. Tests to disregard this hypothesis assume 1 or more factors has more of an effect on the data (Montgomery, 2013).

If the null hypothesis is rejected, then it can be assumed that 1 of the means is different from the others (Loman, 2000). However, it does not tell us which mean is different from the others. In this case, a Tukey HSD test would need to be conducted. The Tukey HSD (Honestly Significantly Different) test allows the user to test each group mean against each other group mean using the standard t-test formula below (Urdan, 2005). The equation for the Tukey test is shown on the next page.

$$HSD = \frac{\bar{X}_1 - \bar{X}_2}{s_{\bar{X}}}$$

$$\text{where } s_{\bar{X}} = \sqrt{\frac{MS_e}{n_g}}$$

and n_g = the number of cases in each group

This calculates the difference in the means of the 2 groups over the standard error $s_{\bar{X}}$. The standard error is defined by taking the square root of the mean squares error MS_e over the number of cases in each group. The user would then compare the observed Tukey value for each group with a critical value, Q, found in a Q value table compared to a 0.05 significance level (Urdu, 2005).

2.4. Pareto Analysis

Pareto analysis is used in cases where multiple defects are seen to identify those that most need to be addressed to resolve most of the problems (Pal, 2011). This method typically utilizes a Pareto chart, which gives a distribution of the different types of defects based on how often they occur (Montgomery, 2013). Once the most frequent causes of defects are identified, it can be determined if a) the most frequent defects are truly the most important and b) how to begin resolving the line's issues.

3. Problem Description

The headliner line has been experiencing a high number of defects resulting in scrapped parts over the last year. The build for this line is scheduled to increase from 48 parts per shift to 98 parts per shift. There is concern that, at the current defect rate, the line is incapable of meeting the new demand. The purpose of this research and experiment is to use quality control tools to determine if the line is capable of building 98 parts per shift at its current defect rate and if not, what can be changed to make it capable.

4. Data Analysis

The defects produced by this subassembly process are not quantitative, so all data collected was attribute data and calculations were made using a binary setup. Only non-conformances that caused parts to be scrapped were documented for the purposes of this case study. Reworked parts were not taken into account. Data was collected from 31 days of production covering two 8-hour shifts.

4.1. Sample Data

To perform the analysis, sample data of 2601 production parts was taken. Because headliner is a soft trim piece, most reasons for scrapping a part are empirical so we used attribute data, basically a conforming or nonconforming system, to tally results. The data is given in Table 2 on the next page.

Table 2. Attribute data for 31 days of production

Sample			Sample		
#	Build	Scrap	#	Build	Scrap
1	69	10	17	72	14
2	77	8	18	85	38
3	84	12	19	82	0
4	70	39	20	91	0
5	117	30	21	101	0
6	83	0	22	33	0
7	81	21	23	78	35
8	81	7	24	81	8
9	74	0	25	87	0
10	96	25	26	87	53
11	86	0	27	88	0
12	82	34	28	66	27
13	95	28	29	79	27
14	89	10	30	104	0
15	96	8	31	84	14
16	103	13			

The data collected gives a basic overview of the production line and its current performance. This process builds an average of 83.9 parts per day with a current defect rate of 0.1772.

4.2. Control Chart

The first test was to determine whether the process was in control. To do this, we take the sample scrap data from Table 2 above. As stated, a conforming or nonconforming classification system will be used for this data instead of numerical due to the nature of these parts. Because of this, a np control chart is best for this exercise. The equations below give the lower control limit (LCL) and upper control limits (UCL) as well as the centerline of the control chart where n equals the number of trials observed and \bar{p} is the sample mean of the defective parts.

$$LCL = n\bar{p} - 3\sqrt{n\bar{p}(1 - \bar{p})} = 4.39$$

$$Centerline = n\bar{p} = 14.89$$

$$UCL = n\bar{p} + 3\sqrt{n\bar{p}(1 - \bar{p})} = 25.39$$

Because the data samples tracked full days of production, each sample was a different size. An average sample size was calculated to determine limits for the control chart shown in Fig. 3 on the next page.

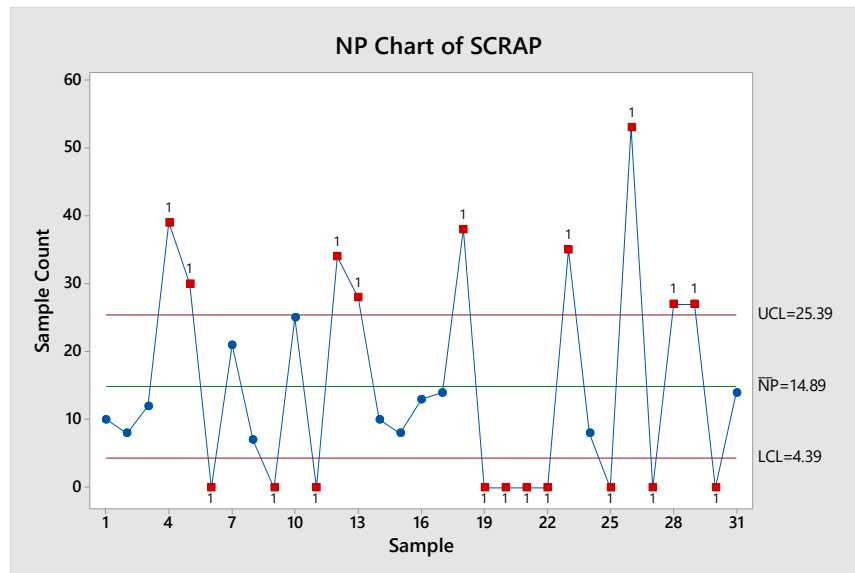


Figure 3. Control chart using average sample size.

The chart clearly shows an out-of-control process with 19 points outside of the control limits. However, because there are several plot points near the control limits, the samples using variable-width limits are also charted in Fig. 4 below.

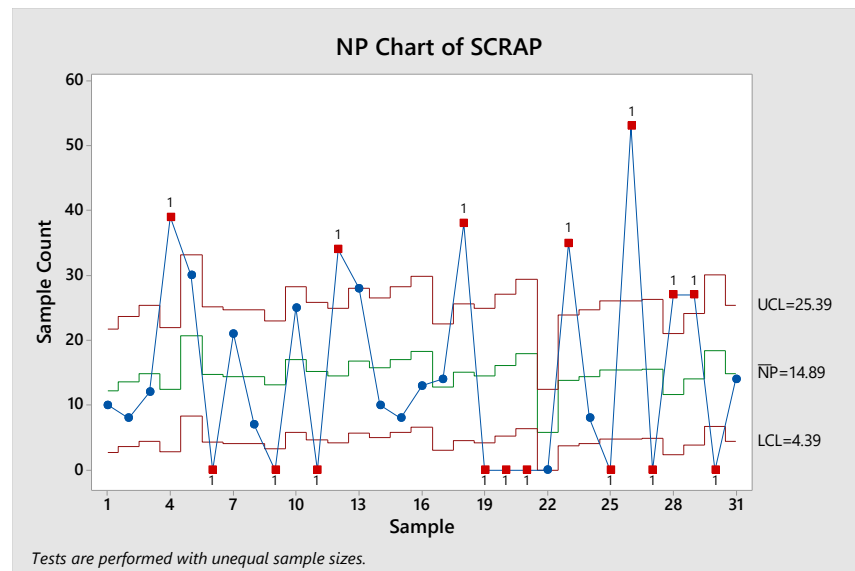


Figure 4. Control chart using variable sample sizes to determine limits

Variable sample sizes given by the builds of each day result in moving control limits. Despite this, the variable-width chart shows with certainty that the process is out of control with 16 of the 31 points outside of these limits. So, it is already apparent that improvements will be needed regardless of whether we can prove capability.

4.3. Process Capability

The gross capability of the line with 0 defects is 14 parts per shift. Based on this, we will determine the highest defect rate possible while still meeting the build requirements. Since the required net build rate is 98 parts per shift, the necessary sigma level of the line can be found using the calculations below. In an 8-hour shift, there are 2 10-minute breaks, resulting in 7.6 hours of actual work time.

$$\text{Required Build Rate} = \left(\frac{98 \text{ parts}}{7.6 \text{ hours}} \right) = 12.8947 \text{ JPH}$$

$$\text{Required Defect Rate} = \frac{14 - 12.8947}{14} = 0.0789$$

This required defect rate computes to a required defects per million opportunities (DPMO) value of 78,947.37. This number is typically calculated using the equation below.

$$DPMO = \frac{\text{Total \# of defects}}{\# \text{ of units} * \# \text{ of opportunities}} * 10^6$$

However, we backed into the required DPMO value by using the knowledge of the line's raw capability and the calculations on the previous page. This calculated DPMO converts to a sigma level of 2.912.

Next, we calculate the current sigma level based on samples of daily builds from Table 2 from pg. 4. This data gives a sample defect rate of 0.1772 and a DPMO of 177,239.5 using the given equations. This means the build line is currently at a sigma level of 2.426 which is less than the necessary sigma level. At the current defect rate, the process is not capable of meeting the required demand.

4.4. Analysis of Variance (ANOVA)

There are 4 main types of headliners. Base is the basic headliner without special features. Moon is the headliner to accommodate cars with a moonroof. Lyric is the material used for the basic package in the vehicle. Alcantara is a far more expensive velvet-like material. The first priority was to see if the style of the headliner had any impact on the defect rate. For this, year-to-date data for the headliner build was used to get a large enough sample of each type. Table 3 below shows the data for each style.

Table 3. Scrap data per headliner style		
TYPE	BUILD	SCRAP
MOON	9749	1704
BASE	3194	469
LYRIC	9051	1836
ALCANTERA	3892	337

The most common part built is the lyric material with a moon roof opening. This combination, as expected given the high usage, also produces the highest amount of scrap parts. However, the information sought here is whether any of the defect rates per type are statistically dissimilar to the remaining types. The following hypothesis test was used to determine significance where τ_i represents the relevant factors.

$$H_0: \tau_{MOON} = \tau_{BASE} = \tau_{LYRIC} = \tau_{ALC} = 0$$

$$H_1: \tau_i \neq 0 \text{ for at least 1 factor}$$

Using a 95% confidence interval, the level of significance (α) is 0.05. The p-value of the variance determined using Minitab is 0.741 (Table 4).

Table 4. Minitab output of ANOVA analysis

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Factor	3	0.1750	0.05833	0.42	0.741
Error	196	27.3800	0.13969		
Total	199	27.5550			

As stated previously, this case study is using attribute data so the scrap data from Table 3 above was entered in Minitab in a binary format, with “1” meaning good and “0” meaning scrap. Each cell represented a separate trial. Since the p-value is greater than 0.05, headliner type has no significant effect on the defect rate.

5. Optimization

This study determined that the process was not capable of meeting the 98 parts per shift requirement. Based on the sigma level, the defect rate needs to decrease by 0.0983. For optimization, we looked for methods to improve the defect rate using Pareto analysis. This allows us to see which type of defects are causing the most scrap and allows us to focus our efforts to improve the process.

5.1. Pareto Analysis

To determine the problems that can be confronted first, a Pareto analysis was completed of the various reasons for scrapping headliners. Fig. 5 shows the breakdown.

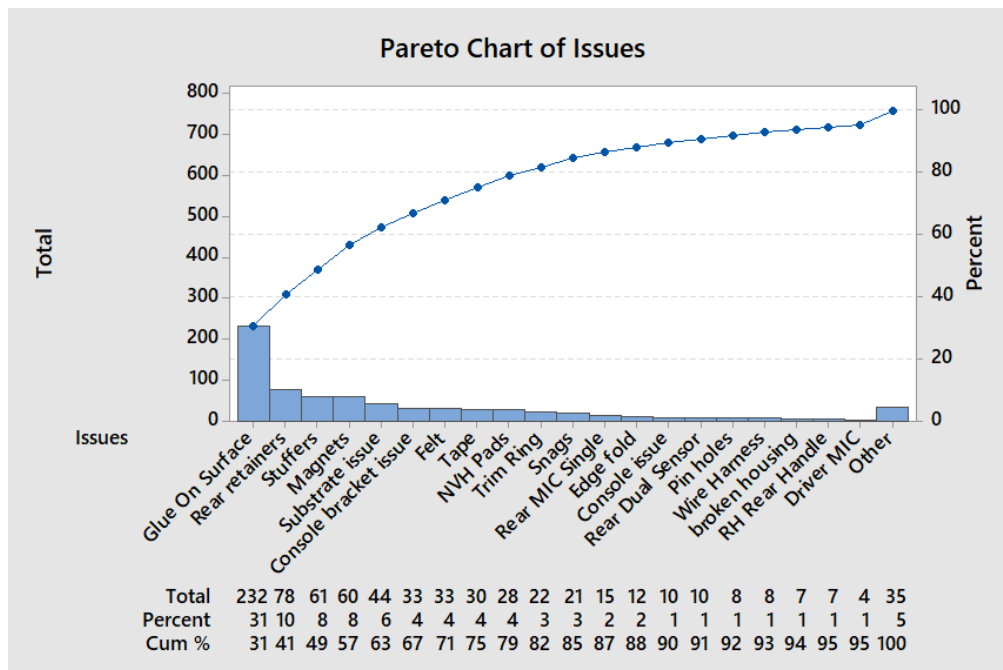


Figure 5. Pareto analysis of defects causing headliner scrap

The Pareto chart above shows that the largest issue causing scrap is glue on the surface of the substrate accounting for 31% of defects. Glue is applied to the headliner at several different points on the line, both robotically and manually. After speaking with the quality team, this issue comes about mostly from the manual processes when applying the wire harness and noise, harshness and vibration (NVH) pads.

To apply these pads, the operators use handheld glue guns and follow laser lines projected onto the headliner from above the table to guide them as to where to lay the glue. This setup is shown in Fig. 6 on the next page.

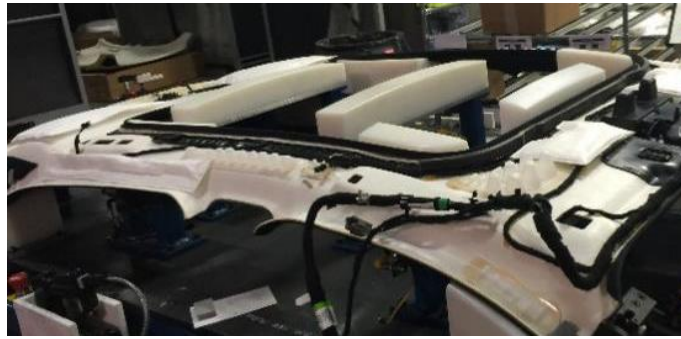


Figure 6. Wire harness installation table in headliner line

The issue arises once the trigger on the glue gun is released. The flow stops but strings of the glue just laid can remain adhered to the glue still inside the gun nozzle. This creates thin strands of glue smaller than a millimeter that end up on the headliner. Because this glue application happens on the C surface (unseen side) of the headliner, most of these glue strands end up where no customer will see them. But there are multiple holes and openings in the headliner that allow the glue to end up on the A surface (visible side) which ends up being scrap.

If this problem can be solved, perhaps by utilizing temporary shields for the parts, it would reduce the defect rate to 0.1158. This is certainly better, but it is not enough to meet the demand and only takes the process to a sigma level of 2.696. So, we will need to look at a secondary issue as well.

Referring back to the Pareto chart in Fig. 5, the next highest issue is the rear retainers. Specifically, the rear retainers being installed out of location tolerance. The retainers are installed automatically by a machine which places them using a nest. This substrate material for the headliner is placed into this machine using a 2-way and 4-way locator. The retainers end up out of location when the part is not properly placed onto these locators. We can eliminate this issue by adding a proximity (or prox) sensor to detect whether the part is fully located onto the 2-way and 4-way.

To combat the problem, a sensor was added to the nest to ensure the headliner substrate is properly placed in the machine. We were unable to find a shielding strategy that prevented glue leaking onto the A surface while still allowing for proper glue appliance, but we were able to find a cleaning solution that would adequately take the glue off of the substrate material without harming the A surface cloth. After these modifications, we monitored the scrap data for another 300 samples. With this data, we discovered that solving the rear retainer issue solved a few other issues causing scrap. The alignment issues with the rear mic, rear dual sensor and driver mic from the Pareto chart above are no longer significant problems. With these 2 changes, we were able to reduce our scrap rate to 0.0867 yielding a sigma level of 2.86.

5.2. Further Suggested Work

The above adjustments to the line improve the scrap rate but still falls below the required sigma level of 2.912. To meet the required demand, we need to eliminate the next cause in the Pareto analysis which would yield a scrap rate of 0.0722 and a sigma level of 2.96 all other factors ignored. This next cause is actually counted against us as a supplier instead of something that happens on our line. The stuffers fall off of the headliner in transit or at any point between our line and the customer line and the entire headliner gets scrapped as it is unusable.

Stuffers are foam blocks with adhesive backing that are applied to the C surface of the headliner to aid in proper installation of the headliner to the vehicle. They also help reduce noise and vibrations in the cabin. If missing, they can interfere with the connections of the wire harnesses in the vehicle or the fasteners that adhere the headliner to the steel roof of the car. A proposed solution to this issue is to have the supplier remove the adhesive backing from these parts and they would simply be applied using the same glue we use to apply the wire harness, HICs and NVH pads. Not only would this be of minimal cost to the company but it would also reduce the piece price for these parts.

6. Cost Savings

The cost of scrapping just 1 headliner can cost as much as \$493.01. Extrapolating the year-to-date scrap data, the current defect rate is costing the company on average \$958,647.80 per year. The alcantera substrate material alone costs \$438.76 to scrap. In a worse-case scenario analysis, the company could be losing over \$1 million a year in scrap. By increasing our sigma level from 2.436 to the necessary 2.912, we could save at minimum \$526,024 per year. This is savings is further explained in Table 5 below.

Table 5. Yearly cost savings achieved by meeting goal Sigma level

Headliner Type	Average Scrap Cost per Part	Previous Scrap Cost per Year	Current Scrap Cost per Year	Goal Scrap Cost per Year
Alcantera	\$472.43	\$578,635.29	\$283,113.32	\$257,642.91
Lyric	\$132.97	\$380,012.52	\$185,931.63	\$169,204.22
Total		\$958,647.80	\$469,044.95	\$426,847.13

As stated, Table 5 above shows the cost savings associated with improving this process to our goal scrap rate. The lyric headliner is 70% of the take rate for the total yearly build. It also cost \$340 less to scrap. The cost for alcantera vs. lyric headliner scrap is broken out due to the significant difference in cost. Reducing the scrap rate the goal of 0.789 would save an average of \$538,800.67 a year based on the average take rates of lyric and alcantera and the current build volume of 48 parts per shift.

7. Conclusion

Using the statistical analysis tools, we were able to determine that the headliner process is highly out of control. More importantly, it is incapable of meeting the newly increased demand at its current scrap rate. The increased demand requires a sigma performance level of 2.912. The current process misses this performance by about 10 parts per shift. In manufacturing, you must above all be able to meet the demand of the customer. It is also necessary keep the scrap rate low enough so that costs are not paid out of pocket. Currently, this process is unable to do either. The company is losing an average of more than \$950,000 a year due to scrap. To improve the line's yield, we made modifications to the process to achieve significant improvements to the process in multiple areas as identified in the Pareto analysis. However, there will still need to be changes made to reach the necessary quality level. It is unlikely that we will eliminate 100% of the defects mentioned even with error-proofing so further analysis into the defect causes will need to be done to decrease scrap to a reasonable level for the line.

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Biography

Torie Rose is a graduate student in the Industrial Engineering program in the A. Leon Linton Department of Mechanical Engineering at Lawrence Technological University, Michigan, USA. She will complete her Masters' degree in the Summer of 2019. She earned Bachelor of Science in Mechanical Engineering from University of Michigan, Michigan, USA in 2013. She is an industrial & manufacturing engineer with five years of experience working for Integrated Manufacturing & Assembly, LLC and Dakkota Integrated Systems, LLC. She has participated in kaizen and six sigma events throughout those five years in the industry. She has participated in Manufacturing Day events to help spread interest in the STEM fields at both jobs as well as at the University of Michigan. She has been a member of SWE and NSBE since 2010.