Evaluating Multi-Dimensional Sheet Metal Assemblies Using A Biased Sample of Stamped Components

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Abstract

Evaluating the sources of assembly variation (stamped components versus the assembly process) is an important time consuming activity when setting up a new process. Automotive body manufacturers often attribute variation in assembly dimensions to deviations in the stamped components. For non-rigid sheet metal components, however, empirical and theoretical studies have shown that assembly processes are often robust to stamping variation. One problem in assessing robustness is that manufacturers must correlate multiple stamping input dimensions to multiple assembly dimensional outputs. This paper presents an algorithm which combines multiple dimensions into a single response variable. It then provides a case example which uses the algorithm to identify biased samples of stamped components in order to assess assembly robustness. Applying this algorithm can significantly improve variation reduction efforts during the critical pre-production phase of launching a new vehicle.

Introduction

A timeless dimensional control problem in automotive body manufacturing is identifying the primary causes of assembly variation. Body assembly personnel frequently attribute variation problems to deviations in the stamped components. They usually support this position using stamping data which typically show both dimensional means deviating from their nominal specifications and process variation which is larger than allowed by part design tolerances. Stamping personnel, in defense, have long held that in the case of non-rigid parts, design specifications are unnecessarily stringent because assembly processes are often robust to the typical observed levels of stamping variation. Thus, reducing the variability in the stamped components may not lead to a reduction in assembly variation.

Evaluating assembly robustness is one key aspect of the production approval process for new assembly tooling with potentially expensive ramifications. During the production approval process, unacceptable assembly quality is corrected either through changes to stamped components or the assembly process. Changes to alter stamped component geometry might entail die rework, or adjustments to the forming process (cycle rate, binder pressure, etc.). Assembly process changes might include changing the number or location of spot welds, clamping locations, part locating (datum use), or weld gun and clamping pressures. The assembly quality level cannot be ascertained until the robustness of the assembly process is evaluated for the range of variation expected from the stamping process on each dimension. Unfortunately with random selection, a very large sample would be required before a complete cross-section for all the dimensions' distributions are obtained. For this reason, it is recommended that a structured procedure be followed that creates a biased sample of part dimensions that can expediently evaluate robustness.

Several studies, both theoretical [1] and empirical [2] have found that variation in flexible sheet metal components does not necessarily increase during assembly (i.e., additive theorem of variance), and in some cases even may decrease. This phenomenon occurs because many stamped components (particularly non-rigid, complex-shaped parts) continue to deform or change dimensionally during subsequent welding operations. For example, non-rigid dimensions may conform to the dimensions of a more rigid mating part. The robustness of welded assemblies to stamping deviations, however, often is not reflected in the assigned tolerances for component dimensions. These tolerances typically assume that nominal specifications add linearly and that variation stacks, resulting in the need for assembly tolerances which are wider than the components.

Even though most body manufacturers accept that many non-rigid areas of components do not necessarily affect assembly quality, stamping plants continually rework dies in pursuit of dimensional capability requirements. This die rework may occur irrespective of whether the manufacturer knows if it will actually improve assembly dimensional quality. These rework decisions follow the principle that "perfect parts make perfect assemblies". Unfortunately, the ability to make a perfect part has long alluded stamping manufacturers for several reasons. First, due to limitations in predicting metal flow during forming operations, die manufacturers rarely can produce dies such that the mean of every dimension is at its nominal specification. Second, no simple adjustments exist to shift these off-target mean dimensions back toward their nominal specifications. Finally, manufacturers rarely can eliminate all stamping mean shifts which typically occur between die set-ups or after changes in material lots [3]. Even with these concerns, manufacturers still have been able to produce acceptable assemblies because of robust weld processes.

Evaluating robustness for a single part characteristic or dimension is fairly simple. Manufacturers could compare the measurement values for the characteristic before and after assembly. Figure 1 provides an example comparison. This stamping dimension experienced a mean shift (0.5mm to 1.5 mm) resulting in two significantly different measurement distributions. This figure suggests, however, that the observed range of assembly variation (Range = 1mm) would unlikely change regardless of whether the mean shift occurred in stamping. Thus, the assembly process appears robust to this mean shift. Examining assembly robustness, however, becomes more complicated when considering multiple stamping input dimensions and assembly outputs.

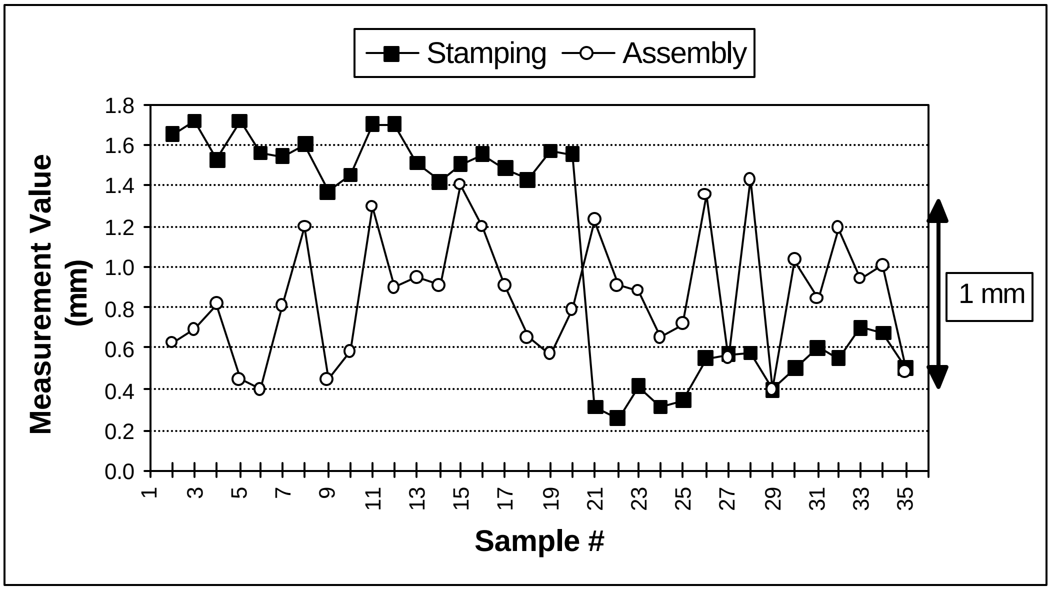

Fig. 1: Robustness of assembly measurements to stamping variation for a single dimension

In this paper, we propose a methodology to examine assembly robustness for multiple stamping input dimensions. First, we review the concept of biased sampling. Next, an algorithm is presented to assess overall variability across multiple dimensions of a part in order to identify a biased sample of stamping dimensional measurements. We then apply the algorithm to two case studies to examine the robustness of an automotive body subassembly to variability in the detail stamped components. We evaluate robustness by creating two samples of component measurements: one biased sample with less variation than the overall process and a second sample with variation representative of the process. By comparing the resultant assemblies from these two samples, we assess whether reducing stamping variability across multiple dimensions would result in significantly lower assembly variability. Finally, we discuss other potential applications for the biased sampling algorithm in automotive body manufacturing.

What is a Biased Sample?

When conducting a design of experiment (DOE), investigators typically seek a random sample of observations [4]. A random sample is where any observation has an equal chance of being selected from the entire population. In some cases, however, experimenters may prefer a non-random or biased sample. Consider the histogram of measurements in Figure 2. In a biased sample, an experimenter would examine only a particular area of the distribution. For example, they may choose to evaluate the lower 25% of the population, the middle 50%, or the upper 25%. One example of the use of biased sampling theory is in reliability testing [5]. Here, engineers may test only the lower 25% of the population. If these observations meet reliability requirements, engineers then assume that all samples above the lower 25% will also meet the requirements. In this example, biased sampling allows reliability engineers to reduce sample size and still perform an effective analysis.

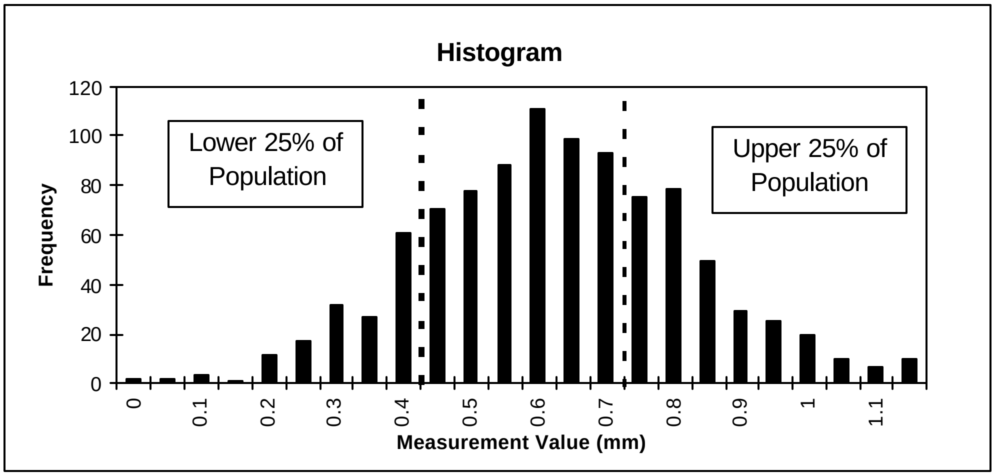

Fig. 2: Histogram of measurements for a stamping dimension

The use of biased samples has several potential applications in automotive body manufacturing. For instance, manufacturers could use biased samples of stamped components to evaluate welded assemblies during a product launch. Manufacturers typically make minor adjustments to assembly tooling locators to accommodate stamping dimensions which are off target. If manufacturers randomly select stamping panels for this welder "tune in" process, they could potentially select panels which do not truly represent the center of the dimensional distribution of the stamping measurements. By using a biased sample, they would use more representative panels to help make final adjustments.

In the next section, we demonstrate the use of biased sampling to evaluate assembly robustness to stamping variation. The need to evaluate assembly robustness arises primarily from the fact that most manufacturers experience some mean shifts (for example, between die sets) in their stamping processes. These mean shifts are readily apparent using traditional Shewhart X-bar and Range control charts. Rather than assuming that any stamping dimensional mean shift will create an assembly problem, manufacturers should examine the assembly process robustness to determine acceptable levels of stamping variation.

A Biased Sampling Algorithm

Choosing a biased sample of stamped panels with minimal variation about the center of the distribution is relatively simple for any single dimension. For example, if a manufacturer measures one part dimension over a sample of thirty panels, they could simply choose the panels closest to the center of the distribution to create a lower variance sample. In practice, however, companies collect dimensional data on several areas of a part. Figure 3 shows several measurement locations for a body side panel which we will use later in a case study.

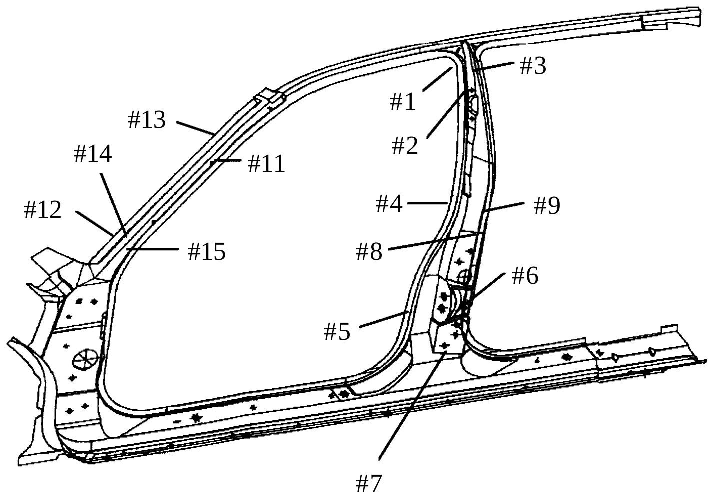

Fig 3: Measurement check point locations for a body side component

Choosing a biased sample around the center of a distribution becomes increasingly complicated when considering multiple dimensions. Different panels may be closest to the center of the distribution depending on the check point. For example, the measurement of one panel may be closest to the distribution center for check point 1, while another panel may be closest for check point 2. One approach for selecting a biased sample for multiple dimensions is to find the one panel or panels which best reflect the center of the distribution for all check points considered.

To illustrate the selection of a biased sample for multiple check points, we first consider the case of two check points on mating flanges. Figure 4 provides a scatter plot of measurement data for these points. The rectangular box in this figure represents the area where the panel measurements for both check points are simultaneously closest to the center of their respective distributions. By choosing panels inside this box, we expect to generate a sample of panels whose individual dimensions have significantly less variation while maintaining the same distribution center.

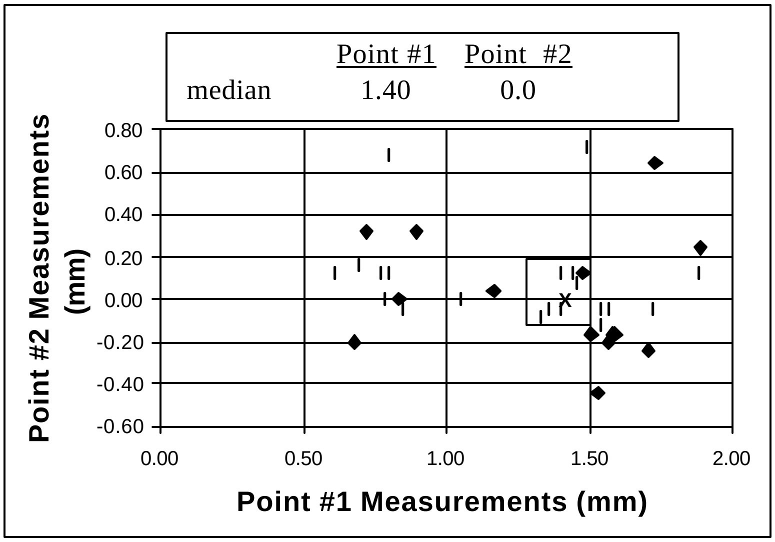

Fig 4: Biased sample of minimum variation for Two Dimensions

As we consider more check points, identifying a biased sample of panels whose measurements are simultaneously close to the center of their respective distributions becomes increasingly complicated. To accomplish this task, we propose a new descriptive statistical index, Rp, in Equation 1. The objective of the Rp index is to simultaneously measure the variation of several component dimensions with respect to a particular panel. The hypothetical data structure for k check points on n panels is shown in Table 1. Rp is obtained by computing the squared deviation of each measurement value from its check point median and then averaging these deviations based on the number of check points considered. We use the statistical median instead of the mean to represent the center of the distribution for the following two reasons. First, since observed stamping measurements often are not normally distributed due to unstable means, the statistical median provides a more robust measure of the distribution center [6]. Second, the intent of a biased sampling approach is to select physical panels, and the median more closely relates to actual observed measurements than a calculated mean value. In the Rp equation, we square the deviations from the median in accordance with the assumption that deviations from a target follow a quadratic loss function [7]. An alternative reason for squaring the deviations is that the Rp index essentially finds the Euclidean distance between the location of each panel in k-dimensional space to the center of k-space (defined by Md_1, Md_2, .. Md_k). The Rp index defined here resembles a leverage calculation [6]. One main difference, however, is that leverage seeks to find statistical outliers whereas Rp seeks those observations closest to the center point.

$$Rp_j = \sqrt{\frac{\sum_{i=1}^{k} (X_{ij} - Md_i)^2}{k}} \qquad \textbf{(1)}$$

where,

X_{ij} = deviation from nominal specification for check point i of panel j.

Md_i = the median of the distribution for check point i.

i ={1,2,...,k} check points.

j $=\{1,2,...,n\}$ panels.

Check Point	Panel 1	Panel 2	Panel 3	Panel 4	...	Panel n	Mdi
1	X_{11}	X_{12}	X_{13}	X_{14}	...	X_{1n}	Md_1
2	X_{21}	X_{22}	X_{23}	X_{24}	...	X_{2n}	Md_2
...	...	...	...	...	...	...	...
k	X_{k1}	X_{k2}	X_{k3}	X_{k4}	...	X_{kn}	Md_k
	Rp_1	Rp_2	Rp_3	Rp_4	...	Rp_n	

Table 1: Sample matrix for measurement data (k check points, n panels)

After computing Rp for each panel, we then rank order the panels according to their respective index values. Figure 5 shows a distribution of Rp index values for a study involving 35 sample panels. The panels with the smallest Rp values are those whose individual measurements are closest to their respective medians. We have arbitrarily chosen the smallest 20% of the values to represent a biased sample. Thus, for a sample of 35 panels, the 7 panels (20% x 35 =7) with the smallest Rp values represent a biased sample of panels. (Note: the most representative panel is the one with smallest Rp value or the minimum$\{Rp_{\text{panel 1}}, Rp_{\text{panel 2}}, ..., Rp_{\text{panel n}}\}$. Large Rp values will typically indicate panels which have outlier measurements for certain check points or are related to mean shifts. For example, the large jump in Figure 5 is the result of a mean shift for several stamping dimensions.

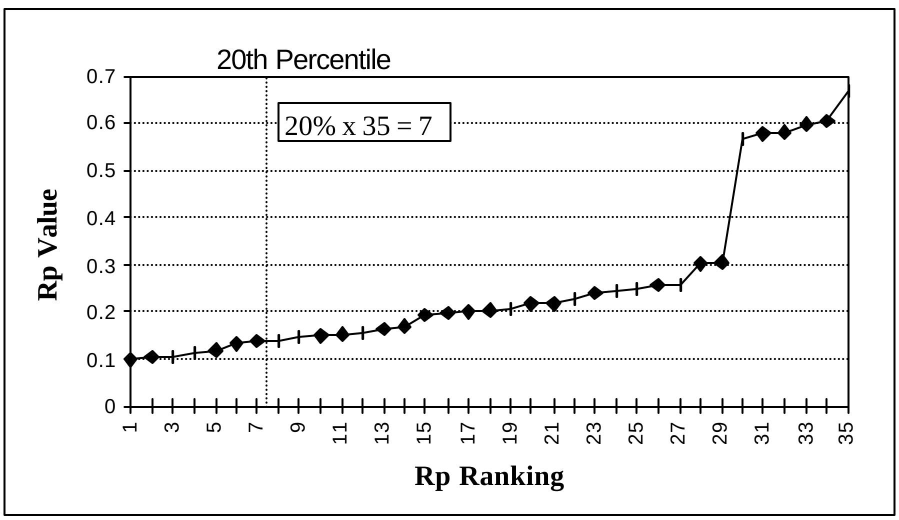

Fig. 5: Distribution of Rp values (ranked in ascending order, sample size = 35)

Case Examples - Using Biased Samples to Evaluate Assembly Robustness

To illustrate the use of biased samples to test assembly robustness, we present the following two case examples from a body side assembly study. The first case example examines the robustness of the body side assembly to variation in both the center pillar reinforcement and body side components. The second case example examines the relationship between the windshield reinforcement and the body side component.

Case Example 1: Center Pillar Reinforcement and Body Side Component

We measured 35 panels from both the body side and center pillar reinforcement. Figure 6 shows the location of nine check points on the body side and six check points on the center pillar. All of these check points are measured in the in/out body plane. The panels were selected from six different die sets to capture some long run process variation.

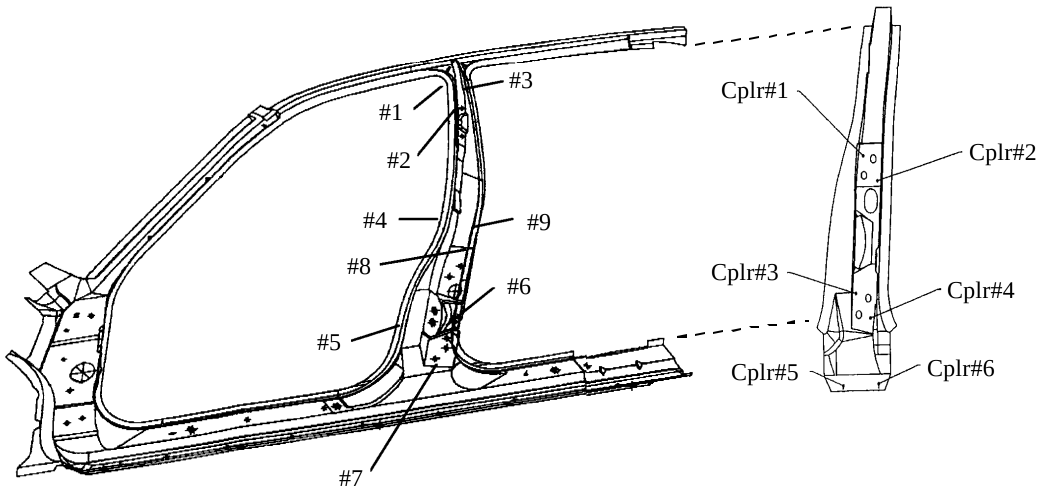

Fig. 6: Body side and center pillar stamped components

Body Side Component					Center Pillar Component			
Check Point	Median	Std Deviation	Six Sigma		Check Point	Median	Std Deviation	Six Sigma
BS#1	***0.35***	***0.33***	***1.99***		Cplr#1	0.44	0.08	0.48
BS#2	***0.24***	***0.32***	***1.91***		Cplr#2	0.28	0.09	0.55
BS#3	***0.13***	***0.35***	***2.09***		Cplr#3	0.12	0.14	0.83
BS#4	-0.85	0.22	1.35		Cplr#4	0.16	0.16	0.97
BS#5	-0.07	0.15	0.92		***Cplr#5***	***0.12***	***0.68***	***4.08***
BS#6	-0.19	0.18	1.05		***Cplr#6***	***-0.44***	***0.66***	***3.94***
BS#7	-0.28	0.17	1.05					
BS#8	-0.60	0.14	0.83					
BS#9	-0.55	0.14	0.81					

Table 2: Data summary of 35 panels

Table 2 provides a statistical summary of the measurement data for the check points in the center pillar area. Five check points have unacceptably large variation: points #1, #2, and #3 on the body side component; points #5 and #6 on the center pillar. We now demonstrate the use of the biased sampling algorithm from the previous section to test if the assembly process is robust to this dimensional variation.

For each of the 35 panels, we compute its Rp index and then rank order the panels from smallest to largest (see Table 3 for the body side component Rp values). A small Rp index suggests that the individual measurements for the various check points across a particular panel are close to their distribution medians. We chose the smallest 20% of Rp values for both the body side and the center pillar panels to represent a biased sample (refer to Figure 5). The smallest 7 panels represent this 20th percentile (20%*35 total panels = 7). Next, we match the biased sample of body side panels with the biased sample of center pillar reinforcement panels in the construction of body side assemblies. By matching panels in this manner, we expect to obtain either of the following two results.

1. If the biased samples produce significantly less variation than the rest of the panels in the sample, we would conclude that reducing stamping variability in these dimensions should reduce assembly variation.

2. On the other hand, if these biased samples do not produce assemblies with significantly less variation, we conclude that the assembly process is robust to this observed level of stamping variability.

Panel #	Rp_j	Rank		Panel #	Rp_j	Rank
10	0.097	1		22	0.140	8
8	0.104	2		25	0.145	9
24	0.106	3		...	...	...
9	0.113	4		3	0.580	32
23	0.119	5		5	0.597	33
26	0.131	6		7	0.605	34
21	0.138	7		2	0.670	35

Table 3: Rp index by panel number for body side component
(Note: table does not show panels ranked 10-31)

Table 4 compares the difference in variation by check point between the biased sample of stamped components and the rest of the population. For the five check points with unacceptably high variability (Body Side: #1,#2,#3 and Center Pillar: #5, #6), the biased sample yields significantly less variation. For the rest of the check points, their biased sample variances are significantly less than or equal to those of the other panels. This table confirms that the biased sampling algorithm has produced a sample with minimal variation about the median of the distribution. Although the biased sample has less variance, the median or center of the distribution is similar for both the biased sample and the other panels.

Body Side Measurements						Center Pillar Measurements		
Check Point	Median (Biased)	Median (Others)	Std Deviation (Biased)	Std Deviation (Others)		Check Point	Std Deviation (Biased)	Std Deviation (Others)
BS#1	0.31	0.37	***0.11***	0.37		Cplr#1	***0.06***	0.12
BS#2	0.21	0.32	***0.13***	0.35		Cplr#2	0.15	0.18
BS#3	0.13	0.09	***0.18***	0.38		Cplr#3	0.13	0.14
BS#4	-0.80	-0.87	0.15	0.24		Cplr#4	0.11	0.17
BS#5	-0.04	-0.08	0.13	0.16		Cplr#5	***0.13***	0.75
BS#6	-0.25	-0.19	0.11	0.19		Cplr#6	***0.16***	0.72
BS#7	-0.31	-0.28	***0.09***	0.19				
BS#8	-0.58	-0.61	0.11	0.15				
BS#9	-0.55	-0.56	***0.06***	0.15				

Table 4: Comparison of stamping variation between biased sample and others panels
(Note: bold and italicized values indicate statistically less variability)

The next task is to assemble the panels. First, we assemble the biased sample of body side component panels with the biased sample of center pillar reinforcements. Then, for the non-biased sample, we recommend randomly matching the remaining panels to simulate normal production conditions. Next, we measure the assemblies. Using these measurements, we compute the Rp index for the critical assembly dimensions. Table 5 shows the rankings of the biased sample before and after assembly. Since the lower ranked stamped panel did not result in lower ranked assemblies, these data indicate that the biased sample does not result in assemblies with significantly less variation. We further examine this robustness in Table 6 by comparing the variability of the seven critical subassembly dimensions measured in the center pillar area of the body side assembly. This table shows that none of the assembly dimensions for the biased stamping samples resulted in significantly less variation (based on F-tests with an alpha of 0.05).

Panel #	Rp_j	Rank (Stamping)	Rank (Assembly)
10	1.215	1	30
8	1.325	2	35
24	1.007	3	6
9	1.299	4	34
23	1.199	5	24
26	1.187	6	23
21	0.952	7	5

Table 5: Rp index of the panel assemblies

Assembly Measurements			
Assembly Dimension	Std Deviation Biased Sample	Std Deviation (Others)	Significantly Different
ASM#1	0.40	0.41	no
ASM#2	0.44	0.42	no
ASM#3	0.48	0.43	no
ASM#5	0.17	0.28	no
ASM#6	0.29	0.28	no
ASM#7	0.26	0.25	no
ASM#8	0.35	0.42	no

Table 6: Comparison of assembly variation between biased sample and others

Interestingly, the variability of the biased sample increases from stamping-to-assembly, while the variability of the rest of the sample decreases. We conclude that the assembly process is robust to these observed levels of stamping variability for this area of the part. In other words, reducing the stamping variation for these dimensions is unlikely to significantly reduce assembly variation.

Case Example #2: Windshield Reinforcement and the Body Side Component

We now explore assembly robustness for the windshield area of the body side component. Here, we have eight check points on the windshield reinforcement component and five check points on the body side (see Figure 7). All measurements are taken in the in/out body plane.

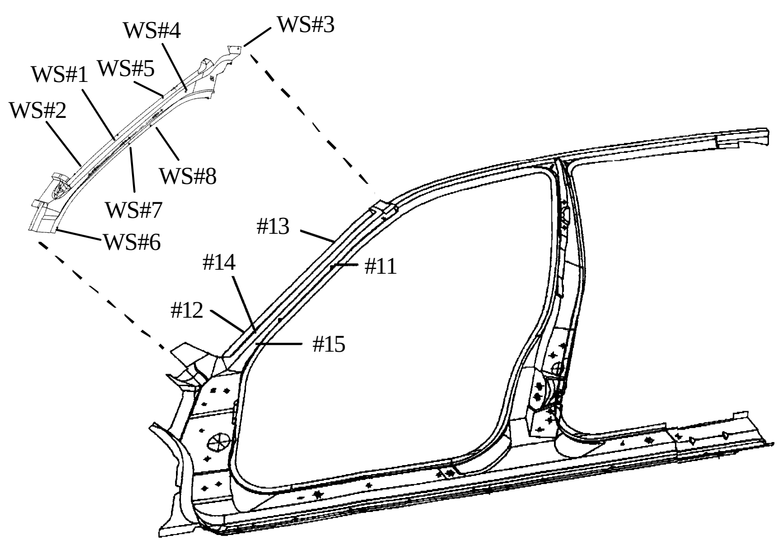

Fig. 7: Body side and windshield reinforcement stamped components

Table 7 provides a summary of the measurement data. The variability in the body side component check points are higher than those in the windshield reinforcement. The primary reason for this larger variability is a mean shift between two of the six die setups. The magnitude of the mean shift is 1 to 1.5 mm.

Check Point	Median	Std Deviation		Check Point	Median	Std Deviation
BS#11	-0.11	0.57		WS#1	0.00	0.24
BS#12	1.40	0.39		WS#2	-0.76	0.41
BS#13	2.59	0.68		WS#3	-0.36	0.20
BS#14	-1.16	0.59		WS#4	-0.40	0.13
BS#15	-0.31	0.50		WS#5	-0.40	0.20
				WS#6	-0.60	0.21
				WS#7	0.12	0.22
				WS#8	-0.88	0.29

Table 7: Data summary for body side windshield frame reinforcement

Again, we use the biased sampling algorithm to identify two samples of components: a biased sample with minimal variability and another with larger variation. Table 8 summarizes the differences in stamping variation between these two samples. This table shows a greater disparity between the biased sample and the other panels than observed in case example #1. This disparity occurs for both the body side component and the reinforcement panel.

Check Point	Std Deviation (Biased)	Std Deviation (Others)		Check Point	Std Deviation (Biased)	Std Deviation (Others)
BS#11	***0.11***	0.63		WS#1	***0.08***	0.27
BS#12	***0.12***	0.43		WS#2	***0.12***	0.45
BS#13	***0.20***	0.74		WS#3	***0.13***	0.21
BS#14	***0.19***	0.64		WS#4	***0.04***	0.14
BS#15	***0.11***	0.56		WS#5	0.14	0.21
				WS#6	***0.08***	0.23
				WS#7	***0.02***	0.24
				WS#8	***0.08***	0.32

Table 8: Comparison of stamping variation between biased sample and others panels

(Note: bold and italicized values indicate statistically less variability)

Next, we construct assemblies for both the biased and non-biased groups of panels. Table 9 indicates that by matching components using biased sampling, we may reduce the overall assembly variation. Table 10 further illustrates this effect by comparing the average sigma of the stamping and assembly dimensions for both the biased and non-biased samples. Here, the larger variation of the non-biased sample was not reduced from stamping to assembly. In contrast with the first example, these assembly dimensions are not robust to the stamping variability. For the mating of the body side component and the windshield reinforcement, we conclude that the elimination of the stamping mean shifts in excess of 1 mm will likely result in reduced assembly variability.

Assembly Dimension	Std Deviation Biased Sample	Std Deviation (Non-biased)	Significantly Different
ASM#11	0.23	0.32	no
ASM#12	0.15	0.32	yes
ASM#13	0.22	0.50	yes
ASM#14	0.11	0.31	yes
ASM#15	0.24	0.65	yes
Average	0.19	0.42	

Table 9: Comparison of assembly variation between biased and non-biased samples

	Average Std Dev Biased Sample	Average Std Dev (Non-biased)
Stamping	0.11	0.37
Assembly	0.19	0.42

Table 10: Comparison of stamping and assembly variation by group

Other Body Manufacturing Applications of Biased Sampling

This paper provides examples of the use of biased sampling to evaluate the robustness of assembly processes to stamping variability. Another potential application of biased sampling is during the validation phase of automotive body development. Many companies construct one or two master bodies during stamping and assembly validation. These master bodies provide physical evidence of assembly build conditions. Many companies use these bodies to make decisions regarding final tooling changes to produce a dimensionally accurate final body.

One danger in constructing master bodies is that companies may not use representative panels in their construction. In many cases, component panels for the master body are selected randomly. The biased sampling algorithm provides a method to identify those panels for each component which are most representative of the center of their measurement distributions. By using representative panels, manufacturers are better able to evaluate the stack-up of mean dimensions for a subassembly.

Conclusions

Understanding the dimensional relationships between stamping input dimensions and their respective assembly outputs is critical to building a dimensionally accurate and repeatable automotive body. One challenge in understanding these relationships is that manufacturers must simultaneously examine multiple stamping input dimensions and multiple assembly outputs. This paper provided a technique to examine assembly robustness to component dimensional variation. By matching biased samples of mating components, we were able to assess the potential impact of reducing stamping variation. In the first example, we found that reducing stamping variation would unlikely affect the assembly. In the latter example, the mean shifts observed between two of the die sets were sufficiently large to induce additional assembly variation. These case studies show the potential of using biased sampling to evaluate assembly robustness.

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