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Identifying Sources of Variation in Sheet Metal Stamping*

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Abstract. Manufacturers using traditional process control charts to monitor their sheet metal stamping processes often encounter out-of-control signals indicating that the process mean has changed. Unfortunately, a sheet metal stamping process does not have the necessary adjustability in its process variable input settings to allow easily correcting the mean response in an out-of-control condition. Hence the signals often go ignored. Accordingly, manufacturers are unaware of how much these changes in the mean inflate the variance in the process output.

We suggest using a designed experiment to quantify the variation in stamped panels attributable to changing means. Specifically, we suggest classifying stamping variation into three components: part-to-part, batch-to-batch, and within batch variation. The *part-to-part* variation represents the short run variability about a given stable or trending batch mean. The *batch-to-batch* variation represents the variability of the individual batch mean between die setups. The *within batch* variation represents any movement of the process mean during a given batch run. Using a two-factor nested analysis of variance model, a manufacturer may estimate the three components of variation. After partitioning the variation, the manufacturer may identify appropriate countermeasures in a variation reduction plan. In addition, identifying the part-to-part or short run variation allows the manufacturer to predict the potential process capability and the inherent variation of the process given a stable mean. We demonstrate the methodology using a case study of an automotive body side panel.

Key Words: analysis of variance, designed experiment, dynamic batch mean, sheet metal stamping, variation reduction

1. Introduction

Most passenger vehicles produced today (automobiles, light trucks, and minivans) have a (structural) body that comprises 100–150 stamped metal panels. These panels range in size from small, easy-to-form mounting brackets to large, complex panels such as fenders, hoods, and body sides. The quality characteristics that describe stamped panels are the dimensions of features such as the length of trim edges or the position of a flange used to assemble multiple panels. The typical approach used to measure a panel feature is to determine its deviation from the nominal design specification along a specified plane, for example, fore/aft from front of car, or in/out from the center of car (Roan and Hu, 1995).

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This research provides an analysis methodology to quantify the components of variation for these panel quality features, given the particular characteristics of the sheet metal stamping process.

For each automotive body panel, the sheet metal stamping process requires two distinct types of equipment: the stamping press and a set of stamping dies. The set of stamping dies represents custom manufacturing equipment used to make specific product geometry. The stamping press represents flexible manufacturing equipment, capable of producing many different automotive body panels (hood, door, fender, etc.) simply by changing the stamping dies. Thus, a particular stamping press produces an individual panel in batches, making the setup of the dies critical to controlling the process mean.

To monitor the quality of automotive body panels, most manufacturers apply statistical analysis methods (Montgomery, 1996) such as statistical process control (SPC). In SPC terminology, manufacturing processes contain two types of variation: common cause and special cause. Common cause variation is the natural inherent variation in the process output when all input variables remain stable, that is, independent and identically distributed. Special cause variation represents any increase in product variability above the level of common cause variation. Manufacturers detect special case variation by identifying out-of-control signals on control charts. To correct these out-of-control conditions, and eliminate the associated special cause variation, the manufacturer must have the ability to adjust the process mean.

Many North American (NA) automotive stamping facilities lack the attention to detail in their die setup procedures to control mean shifts after changing the stamping dies. When beginning a panel batch, the manufacturer measures a sample of panels to create an SPC subgroup. If this subgroup plots out-of-control, the stamping processes have no simple adjustment mechanisms to change feature dimensions. This inability to adjust the process mean has frustrated NA automotive manufacturers applying SPC to their stamping processes. Thus, these manufacturers must continually adjust downstream processes (weld fixtures or weld robots) to compensate for changes in the dimensional geometry of stamped panels. However, many Japanese stamping facilities have eliminated out-of-control conditions at die setup by following well-structured die change procedures. By eliminating these out-of-control setup conditions, these Japanese manufacturers have also been able to remove traditional control charts.

2. Measures of stamped panel quality and quality improvement

Manufacturers use control charts to assess stability in the process output. The X-bar and R charts are methods recommended by the Automotive Industries Action Group (AIAG, 1992) for charting a product described with a continuous, random quality characteristic such as panel feature deviation from its nominal measurement. The X-bar chart graphically tracks the sample averages over time to look for changes in the process mean, while the R chart tracks the sample range as a measure of process variability.

While a majority of statistical techniques assume a stable mean over time, some authors have addressed the issue of a nonstable process. Woodall and Thomas (1995) suggest an X-bar chart to track the mean of a process that has two sources of common cause variation (e.g., within batch variation about the mean and batch-to-batch variability in the mean). They also present a model that captures a third component of variation, measurement error. Woodall and Thomas caution against using their techniques "... until every realistic effort is made to remove each of the various sources of what is to be treated as common-cause variability." Sullo and Vandeven (1999) also have studied processes with run-to-run variation. They developed an analytic approach for approving a process setup (run) for production, assuming a quadratic loss function and a 0-1 loss function.

The quality assessment of a panel feature also involves measuring its process capability, the ability to produce products between the upper specification limit (USL) and the lower specification limit (LSL), that is, the design tolerance. Breyfogle (1999) discusses C_p and P_p, two measures of process potential—their values are independent of the proportion of parts within design specification—that share the theoretical definition

$$C_p = P_p = \frac{\mathrm{USL} - \mathrm{LSL}}{6\sigma_x}. \tag{1}$$

The difference between these two indices lies in the assumption regarding process stability and the method(s) used to estimate process standard deviation. The index C_p assumes an in-control process while the measure P_p is considered a "long run" capability index and does not require the standard stability assumption. For C_p, the manufacturer can estimate the process standard deviation with the sample standard deviation as $\hat{\sigma}_x = S$ or from the range chart with $\hat{\sigma}_x = \bar{R}/d_2$. To estimate P_p, the manufacturer should take a sample that captures long run process variation and estimate the process standard deviation with the sample standard deviation as $\hat{\sigma}_x = S$.

3. Sheet metal stamping process characteristics

Sheet metal panels require multiple die operations using either a single press or a series of presses in a press line. Stamping dies and presses have numerous input variables (tonnage, shut height, press parallelism, counterbalance pressure, nitrogen pressure in dies, press speed, etc.) that can influence stamping panel quality, especially during die setup. The resultant geometry of the sheet metal panels depends, in part, on these settings.

Using the same press settings each time a particular die is set would help reduce long run variation in the associated panels. Unfortunately, the relationship of the numerous press settings and other process input factors (incoming material, blank size, etc.) on panel geometry is not well documented or understood by manufacturers. For example, many of the input variable settings use a single value for the entire panel. Individual panels, however, have multiple features in different areas that are not necessarily controlled by the same set of input variable settings. This situation limits the ability to bring the process back to the target value when SPC charts exhibit out-of-control conditions for certain features, especially if other features do not change. In addition, none of the process input variables possess a direct cause-and-effect relationship with a panel feature. For example, increasing the tonnage by some amount will not cause a predictable change in a panel feature, as it does in machining where adjusting the position of a cutting tool has a predictable impact on the process mean.

Hammett, Wahl, and Baron (1999) show how the difficulties resulting from a lack of simple, process input variable adjustments to shift the process mean have led many automotive body manufacturers to apply functional build concepts. Functional build (Majeske and Hammett, 2000) involves delaying the decision to modify a stamping die until assessing the impact of the variation on the downstream assembly process.

The lack of easily adjustable input settings is complicated by the large number of potential significant variables. Numerous case studies describe the complex relationship between sheet metal stampings and their process input variables. Siekirk (1986) suggests "The sheet metal process for high volume production is best described as an art... ." Using two designed experiments to study the relationship between stamping process output quality and process inputs, Siekirk found significance in all five of the process variables studied: blank size, blank location, lubrication, binder force (outer tonnage), and metal thickness.

Zhou and Cao (1994) examined the process of stamping a door inner, and identified two types of variation found in metal stamping: within run and run-to-run. They studied the impact of three process variables (outer tonnage, inner tonnage, and punch speed) on within run variation. Using a designed experiment, they identified levels for these three variables, suggesting better control could reduce within run variation by 54%.

Wang and Hancock (1997) also studied a door inner stamping process. They investigated the impact of 15 process variables on formability (split/no split) of the stamped panels. Using logistic regression, they concluded that three variables influenced the ability to form a panel without splits: surface roughness of the steel, outer tonnage of the press, and the amount of lubricant.

Berry (1996) discussed the relationship between the composition of sheet steel (the raw material) and stamped panel quality. Berry suggests that, in general, Japanese manufacturers run their stamping processes in statistical control while their US counterparts do not. Noting that these manufacturers purchase steel from the same sources, he maintains that US manufacturers should focus quality improvement efforts on nonsteel related variables.

A general conclusion across these various case studies is the existence of a large potential number of significant input variables that are not well understood and hard to control. For example, the true cause-and-effect relationship of the various inputs often is unknown. Rather than exploring the relationship between stamping press parameters and panel geometry, this research develops a method for quantifying the variance in product output based on typical variations observed in the input variable settings. This provides an analytic tool for determining whether a variation reduction plan is necessary.

4. Model development

Manufacturers produce many different panels in the same stamping press by removing one set of stamping dies and inserting another. Placing a die in a stamping press is often referred to as die setup. Die setup involves setting the stamping process variables such as shut height and binder force (tonnage). Thus, die setup signifies a reconfiguration of the stamping process. The quantity of parts produced following a die setup is referred to as a batch.

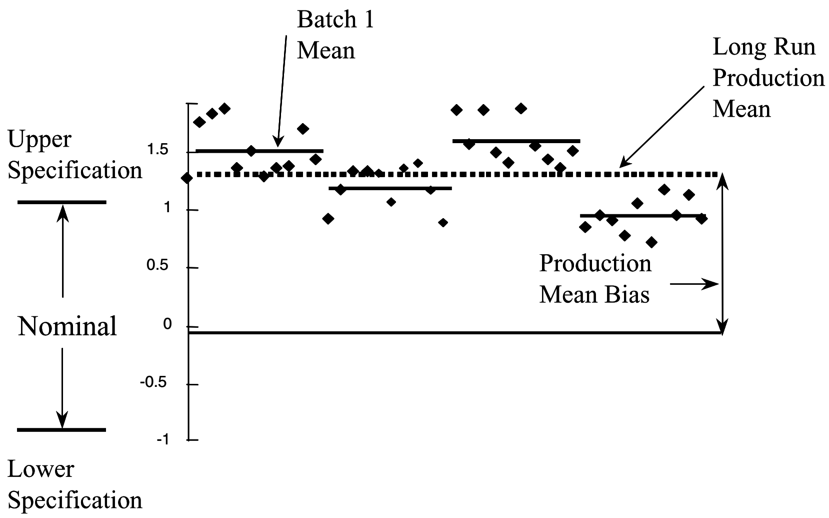

Figure 1. Stamping process data (note: horizontal lines represent batch means).

Figure 1 conceptually shows data from a batch production process. While each batch has its own mean, in the long run, the batch means vary randomly about some overall process mean. The difference between the overall process mean and the design nominal or target value represents the mean bias in the manufacturing process. We define the variability about the current or instantaneous process mean as the natural inherent variability (part-to-part) in the process.

4.1. Total process: TP

TP represents the long run output as seen by the customer. This variable captures all the sources of variation for the quality characteristic X. While not an assumption of this work, historical data shows that for many stamped panels, TP follows a normal distribution. The expected value of TP represents the long run process average for the quality characteristic, $E[TP] = \mu_{TP} = \mu_x$. The variability of TP, $Var[TP] = \sigma_{TP}^2 = \sigma_x^2$, represents the variation delivered to downstream processes and customers. The total process variation represents the variability one should use when assessing the capability of the stamping process to achieve engineering specifications or tolerances.

4.2. Batch mean: B

A large number of stamping process variables affect the mean of a single batch. Press operators and die setup personnel often do not consistently replicate stamping process settings each time they set up the same panel. Several difficult to control input variables, such as steel properties or lubrication levels, could also affect the mean of a batch. Therefore, we model process mean as a random variable where each batch mean, B_i, represents the batch average for the ith batch. Assuming equal batch sizes, the expected value of B, the batch mean, is equal to the long run process average $E[B] = E[TP]$. The variance of B, the batch mean variation, represents the panel variability associated with batch-to-batch mean shifts or $Var[B] = \sigma_{BB}^2$.

4.3. *Within batch mean: WB*

Although B_i represents the average or mean of panels stamped in the ith batch, this model allows for instability of the mean within a batch. In other words, this model allows for a nonconstant or dynamic batch mean. These changes within a batch are believed to be the result of changes in input and process parameters such as differences in steel properties between incoming material lots, or changes in die pressures due to a nitrogen cylinder leak. We let WB represent the instantaneous average or mean of panels stamped in a batch as a deviation from the overall batch average B_i, that is, $E[WB] = 0$. The WB variable captures the changes in batch mean, B_i, during a batch. Therefore, the within batch mean variance, $Var[WB] = Var[B_i] = \sigma_{WB}^2$, represents the variability of the process mean within a batch.

4.4. *Part-to-part: PP*

PP represents the inherent process variation about a given mean value. We assume the stamping process follows a conditional normal distribution, that is, for a given value of the current batch mean, the process produces a normally distributed output. This part-to-part variable is intended to capture any noise variable that would be expected as part of normal process operations. The part-to-part variable has an expected value of zero $E[PP] = 0$ with a variance of $Var[PP] = \sigma_{PP}^2$. The part-to-part variation represents the potential for total process variation or the level of total process variation that could be achieved by eliminating within batch and batch-to-batch variation.

4.5. *Sources of variation model*

This model assumes that the variables are additive or that $TP = B + WB + PP$. We further assume that the components are independent and derive the model by taking the variance $\sigma_{TP}^2 = \sigma_{BB}^2 + \sigma_{WB}^2 + \sigma_{PP}^2$. The part-to-part variation in this variation model represents the short run process variation about the mean. If the manufacturer were to control the stamping process mean, then part-to-part variation would equal the total process variation. We suggest using a statistic

$$C_{PP} = \frac{\text{USL} - \text{LSL}}{6\sigma_{PP}} \tag{2}$$

in consort with P_p to assess stamping process capability. C_{pp} represents the potential capability or the level of C_p the manufacturer would obtain by controlling the process mean.

5. Estimating the model parameters

We suggest estimating the components of variation using a designed experiment or DOE (Box, Hunter, and Hunter, 1978). However, given the nature of the model, the sampling plan cannot be purely random in a statistical sense. The sampling plan should more closely represent the rational sampling used in control charts, that is, taking consecutive parts from the process. While the model does not require observations within a sample to be consecutive pieces, they should be obtained from a relatively short window of parts, for example, every other or every third piece. When conducting the designed experiment, one should allow the process to run the way it normally runs in production. A manufacturer should not attempt to influence any process or steel property variables differently from regular production.

To estimate the parameters of the model we suggest taking observations from b batches or die sets. Taking samples from multiple batches will allow estimating the batch-to-batch variation. Within each batch or die set, a manufacturer should sample the process s different times to estimate the within batch variation in the mean. Finally, a manufacturer should take a sample of size n each time the process is sampled. Taking replications per sampling allows estimating the part-to-part or pure error in the process. This approach results in a total sample of size N, where $N = bsn$. Using the response variable X, this approach will generate data of the form:

$$\begin{aligned} X_{ijk},\quad & i = 1, \ldots, b \text{ (batch)}, \\ & j = 1, \ldots, s \text{ (sample within batch), and} \\ & k = 1, \ldots, n \text{ (observation in sample).} \end{aligned}$$

Fitting the model outlined in this article requires three sample size decisions: the number of batches, the samples per batch, and the replicates or the size of each individual sample. Sample size planning prior to conducting the experiment can assist the manufacturer with obtaining informative results at the lowest cost. To determine the three components of sample size planning, the manufacturer can use a statistical power approach (see Montgomery, 1991). For a random effects model, this requires specifying the magnitude of the variance components the manufacturer would like to detect and the probability (statistical power) that they will detect this condition.

Again, when conducting the designed experiment, one should allow the process to run the way it normally does during normal production. To estimate the components of variation from the experiment, one needs the mean squares batch (MSB), mean squares within batch (MSWB), and mean squares error (MSE). This can be accomplished with a statistical software package by having three variables: the values of the response X_{ijk}, batch (the value of the subscript i), and sample number within the batch (the value of the subscript j). We recommend fitting a nested two-factor random effects analysis of variance (ANOVA) model to the data. One should not include an interaction term, but must nest the sample factor under the batch factor. The software should provide the estimates of the mean squares.

Next, we may estimate part-to-part variation with the mean squared error

$$\hat{\sigma}^2_{PP} = \text{MSE} \tag{3}$$

and within batch variation, if it is significant, using

$$\hat{\sigma}_{WB}^2 = \frac{\text{MSWB} - \text{MSE}}{n}. \tag{4}$$

If within batch variation is significant, estimate batch-to-batch variation as

$$\hat{\sigma}_{BB}^2 = \frac{\text{MSB} - \text{MSWB}}{sn}. \tag{5}$$

However, if within batch variation is not significant, estimate batch-to-batch variation as

$$\hat{\sigma}_{BB}^2 = \frac{\text{MSB} - \text{MSE}}{sn}. \tag{6}$$

Factors that are not statistically significant may be removed from the model and the model refit prior to estimating variance components.

6. Case study: Automotive body side panel

To demonstrate the technique, we utilize data obtained from an automotive body stamping facility. These data represent measurements taken from a body side panel as shown in Figure 2. This particular panel has 16 output features, with the quality of individual features affected by different operations and input variables in the die/press lineup. Thus, although the features may not be truly independent, stamping manufacturers treat these features as independent characteristics. In some cases, manufacturers eliminate significantly correlated features during manufacturing validation prior to the start of regular production. Thus, we first identify the sources of variation for an individual feature.

To study the body side panel stamping process we designed the following sampling plan. To capture batch-to-batch shifts in the mean, we sampled $b = 6$ nonconsecutive batches during a period of two months of production. The manufacturer also felt that this process

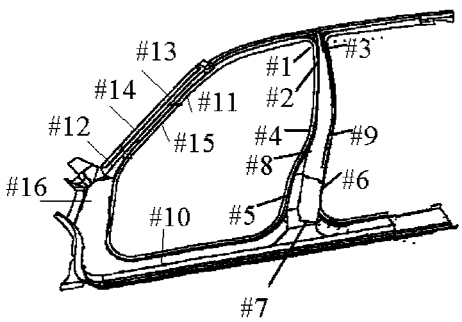

Figure 2. Automobile body side panel.

Table 1. Body side panel data.

Batch	Within batch group	Sample 1	Sample 2	Sample 3
1	1	0.62	0.33	0.51
1	2	0.40	0.18	0.36
2	1	0.24	−0.19	0.17
2	2	0.26	0.28	0.45
3	1	−0.49	−0.45	−0.40
3	2	−0.54	−0.64	−0.22
4	1	−0.19	−0.30	−0.24
4	2	−0.05	0.15	−0.04
5	1	0.13	0.32	0.56
5	2	0.46	0.48	0.48
6	1	−0.27	0.02	−0.20
6	2	−0.31	0.23	−0.13

might have shifts in the mean within a batch due to differences in material properties resulting from changing coils of steel. Since the length of the individual runs is approximately 4 hours, we had a limited time window to detect these within batch shifts. Therefore, we selected $s = 2$ samples per batch taken at the beginning and at the end of the batch to maximize the probability of trapping a mean shift between samples. The last component of sample size planning was to determine the number of replicates. The manufacturer already took samples of size $n = 3$ at the beginning of the batch for SPC. For cost reasons, we choose to augment these samples with an additional sample of $n = 3$ at the end of the batch, rather than generate entirely incremental data for the study.

Table 1 contains the dimensional data, in millimeters, for measurement location #3 on Figure 2 generated from the $N = 36$ body side panels. The manufacturer measures the locations on the body side panel as deviations from the design nominal or the center of the design specification. For example, the first panel in the first subgroup selected from batch 1 deviated 0.62 mm from its target value, that is, the center of the design specification. We use this raw data to construct control charts to assess the stability of the stamping process. We also fit the ANOVA model described in Section 5 to this data to estimate the components of variation.

To assess long run process stability of this body side feature, we constructed control charts for individuals (moving range and individuals charts) as shown in Figure 3. To prepare the charts in Figure 3, we used only the first observation from each sample of three consecutive parts. Here, both charts exhibit statistical control, suggesting that the process has a stable mean and variance. In the context of the components of variation model, the moving range chart estimates the total process variation. Therefore, the individual chart suggests process stability over the long run, rather than a constant mean from batch to batch.

To assess the batch to batch stability of this body side feature, we placed the data on X-bar and R charts as shown in Figure 4. Looking first at the R chart, we see that the variance is

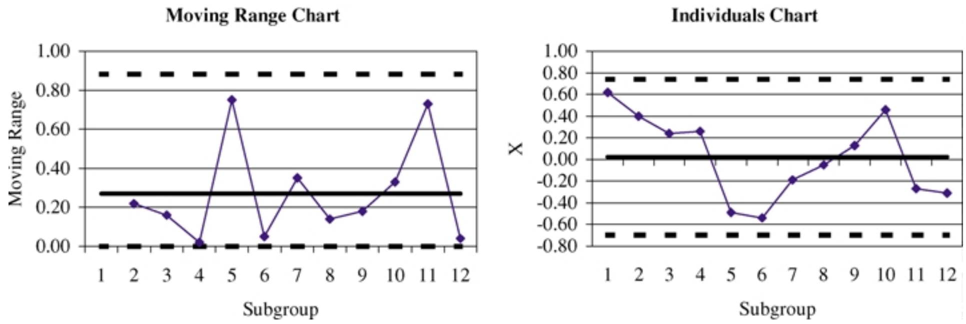

Figure 3. Individual and moving range control charts for body side panel.

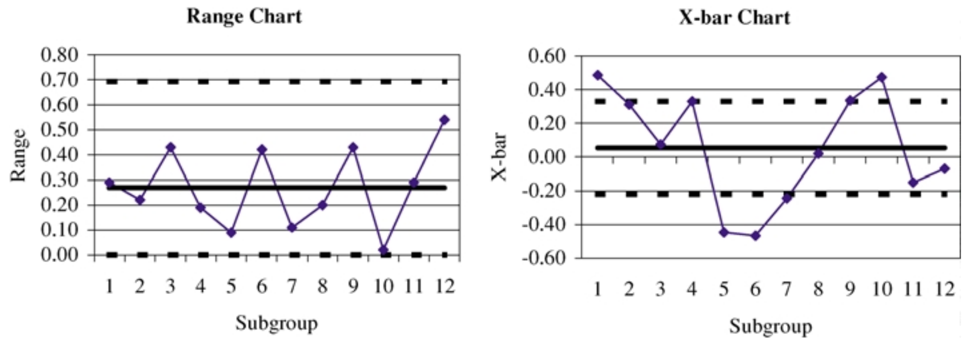

Figure 4. X-bar and R charts for body side panel data.

in statistical control. For the stamping process, this suggests that the part-to-part variation remains stable. Next, we look at the X-bar chart and see that the process mean runs out of control. The special cause variation on this control chart indicates a potential opportunity for improvement.

To quantify the contribution of the variation sources, we recommend fitting the nested two-factor ANOVA model presented earlier. Fitting the ANOVA model (using a Type I error of $\alpha = .05$) to these data allows estimating the mean squares for the batch and within batch factors. Using equations (3) through (6), we estimate the components of variation as shown in Table 2. Note that the body side panel has an insignificant within batch effect, implying

Table 2. Components of variation for quality characteristic.

Component	Variance	Percentage of total variance
Part-Part	0.030	21
Within-Batch	0.000	0
Batch-Batch	0.116	79
Total process	0.146	100

that the mean remains stable within a batch (die set). For the batch factor, changes in the mean between die setups account for 79% of the total process variation. This represents an opportunity to reduce variation and to benefit downstream processes.

Finally, we use these data to assess process capability. Using traditional process capability indices with these data appears to violate the "stable process" assumption. However, given some inherent variability in batch setup, we argue that a manufacturer may predict a certain level of mean shifts over the long run.

Using the data from Table 1, we estimated the process mean as $\hat{\mu}_x = \bar{X} = 0.055$ and the sample standard deviation as $\hat{\sigma}_x = S = 0.3540$. We then used equation (1) to calculate $C_p = 0.942$. This value suggests that the width of the process output distribution is greater than the width of the design specification. In other words, no matter where the process is centered, it will produce panels outside of the design specification. In the automotive industry, a process with a $C_p < 1.67$ is considered incapable (AIAG, 1995) and is targeted for quality improvement.

To assess stamping process potential we used equation (5) to estimate C_{pp} as 1.92. This index suggests that by controlling the process mean, the manufacturer could increase the value of C_p from 0.942 to 1.92, which would be considered a capable process. For this particular feature, the manufacturer must improve the control of the setup operation to reduce the magnitude of the mean shifts between batches.

Table 3. Components of variation for each of the 16 measurement locations.

	Components of variance			
Feature	Part-Part	Within-Batch	Batch-Batch	Total process
1	0.016	0.000	0.022	0.038
2	0.008	0.010	0.018	0.035
3	0.003	0.003	0.044	0.051
4	0.010	0.000	0.019	0.029
5	0.025	0.000	0.000	0.025
6	0.005	0.000	0.019	0.024
7	0.003	0.000	0.046	0.049
8	0.017	0.000	0.008	0.025
9	0.003	0.000	0.019	0.022
10	0.029	0.023	0.000	0.052
11	0.075	0.000	0.154	0.229
12	0.036	0.016	0.062	0.114
13	0.032	0.000	0.083	0.115
14	0.027	0.000	0.145	0.172
15	0.030	0.000	0.116	0.146
16	0.032	0.000	0.032	0.064
Average	0.022	0.003	0.049	0.074
Percentage of total	30	4	66	

7. Overall panel assessment

For large complex panels such as the body side, automotive manufacturers measure a set of features (measurement points). These measurement features, though not necessarily purely independent, are selected to monitor different operations within a press lineup. For example, a manufacturer might select one feature in a particular area to monitor a trim die and another feature on a mating flange to reflect a flange die operation. For large complex panels, manufacturers may select multiple features impacted by the same die operation if the process input variables do not have a consistent influence. For example, if a stamping press is not parallel, the tonnage generated during the forming operation in one of the four corners may differ from another corner, resulting in the potential for nonuniform mean shifts across various panel features impacted by the same die operation.

To analyze the entire panel, we fit the components of variation to each of the 16 measurement locations on the body side panel shown in Figure 2 (see Table 3). To provide an overall assessment of the body side panel using the sources of variation model, we use average variance across the measurement points for each component source. The body side has an average total process variance of 0.074 mm. To assess the panel in terms of standard deviation, we take the square root of the average total process variance or 0.272 mm. From Table 3 we note that the instability in the mean accounts for about 70% of the total process variation. Upon further examination of the location of the features, all the large mean shift problems occur in the windshield opening of the body side panel. By using the sources of

Table 4. Process capability of panel features.

Feature	P_p	C_{pp}	Pass $P_p > 1.67$	Pass $C_{pp} > 1.67$
1	1.71	2.64	Yes	Yes
2	1.79	3.85	Yes	Yes
3	1.48	5.80	No	Yes
4	1.95	3.33	Yes	Yes
5	2.11	2.11	Yes	Yes
6	2.13	4.67	Yes	Yes
7	1.51	5.76	No	Yes
8	2.13	2.56	Yes	Yes
9	2.27	6.19	Yes	Yes
10	1.46	1.96	No	Yes
11	0.70	1.22	No	No
12	0.99	1.76	No	Yes
13	0.98	1.86	No	Yes
14	0.80	2.03	No	Yes
15	0.87	1.92	No	Yes
16	1.32	1.86	No	Yes

variation model, we were able to quantify the magnitude of the various variance components and assess the need for improvement during the setup operation.

While multivariate process capability indices seem appropriate to assess a sheet metal stamping process, automotive manufacturers approve their processes by evaluating the capability of each measurement location independently. Table 4 contains the P_p of equation (1), calculated by estimating the process standard deviation with the square root of the total process variance estimate. Nine of the sixteen features fail to meet the $P_p > 1.67$ quality requirement. Table 4 also contains the C_{pp} of equation (2) using the square root of part-part variance to estimate the short run process standard deviation. Fifteen of the sixteen measurement locations (every location except feature 11) has a $C_{pp} > 1.67$. This suggests that the manufacturer could pass the capability requirement $P_p > 1.67$ on eight of the nine unacceptable features by stabilizing the mean over the long term.

8. Conclusions

For manufacturers using flexible manufacturing equipment, where setup is a significant contributor to overall process variation, this research suggests manufacturers partition variation into three components: part-to-part (the short run variation about a mean), batch-to-batch (die set to die set changes in the mean), and within batch (changes in the mean during a die set). This technique of partitioning variation into three categories provides the manufacturer a clearer picture of the sources of overall product variation. Quantifying the sources of variation and their relative magnitude also provides the manufacturer a guide when developing a variation reduction plan, and helps to isolate the location of the variations in the body panels.

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