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The effect of clamping sequence on dimensional variability in sheet metal assembly

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Finite element (FE) modelling techniques have become a popular tool for exploring welding and clamping sequence dependence in sheet metal assemblies. In the current paper, the dimensional variability associated with different assembly clamping sequences is investigated with a FE contact modelling approach implemented in the commercial code Abaqus. A simplified channel section assembly consisting of a top hat and bottom plate is the case study investigated. Expected variation modes of bow and twist were used to simulate key variability sources in the main structural component under investigation; the top hat of the channel section. It was found that final assembly variability can change considerably depending on clamp sequence selection. It was also found that different clamp sequences can control particular modes of variation better than others, and that there is not one particular clamping sequence that is the best for containing all variation modes. An adaptable assembly process is therefore suggested, where given the shape of input components the best available clamping sequence is selected. Comparison of the performance of the proposed adaptable clamping sequence to traditional fixed clamping sequences shows improvements for the dimensional control of variability in non-rigid components. While introducing such a method in production would require inspection of each component being assembled and investigation of the alternative clamping sequences, given access to fast and detailed dimensional inspection technology such as optical coordinate measuring machines (OCMM's), the approach shows promise for future application.

Keywords: Automotive body; Assembly; Flexible manufacturing

1. Introduction

A recurring problem with sheet metal assemblies is the dimensional variation that occurs. In order to control this variation, the sources of variation and their respective influence on final assembly variability must first be identified. While variation propagation in rigid component assemblies can be described by the additive theorem of variance, this law does not apply to non-rigid assemblies due to the ability of components to bend and distort during the assembly process (Takezawa 1980). In order to capture and predict the deformation effects of flexible sheet metal

assemblies, the mechanistic behaviour must be taken into account. Finite element simulation approaches for the modelling of variation propagation in sheet metal assemblies have therefore become a key focus area. Differing levels of realism of these mechanistic models have been presented, ranging from simple linear beam models (Liu and Hu 1995; Liu and Hu 1997), through to non-linear contact models (EAVS software, a GM in-house package (Cao *et al.* 2001)), and even approaches that consider thermo mechanical effects of spot welding zones (SysWeld). Linear approaches are popular as they require significantly

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less computational time. Liu and Hu developed a particularly useful linear approach to assembly with the mechanistic assembly variation simulation model that can be easily combined with stochastic modelling (Liu and Hu 1997). Non-linear contact and thermo-mechanistic approaches may correspond more closely to the physical process but can be very time intensive and have convergence issues. While these mechanistic approaches have added to the understanding of sheet metal assembly, owing to the precise nature and complexity of assembly, it is not always possible to model these processes to the required levels of accuracy: tolerance predictions based on these models can therefore also suffer in terms of accuracy. The term 'functional build' has been used to describe a practice where components are accepted for production according to their ability to produce assemblies that are within tolerance, even if they do not meet original part specifications or tolerances. This approach is often still needed even with the advanced tolerance prediction tools available (Majeske and Hammett 2000). However, FEM still provides a valuable tool for virtual prototyping of assembly processes, and was used as a basis for this study.

Estimates of variability of sheet metal components are often used as inputs to FE simulations as actual component variation data is not available at the design stage. In some approaches, component variability is estimated by each surface sample point, or node in an FE mesh, being set to vary independently. Surface continuity conditions such as mechanistic properties of components usually dictate that there will be some level of correlation between point and nodes of a surface, and therefore allowing each point to vary independently is an inaccurate representation of component variability. Inaccurate simulation inputs can result in redundant results. This characteristic of surface continuity or correlation has been explored in the past (Liao and Wang 2005, Liao 2005). Merkley (1998) investigated the use of Bezier curves to represent free form surfaces and profile tolerances, in order to account for the 'geometric covariance that arises from constraints on random variation in mating surfaces due to surface continuity conditions'. Camelio *et al.* (2004) extracted linear variation modes from assembly component measurement data using principal component analysis, and using the mechanistic variation simulation model (Liu and Hu 1997) determined the sensitivity of the final assembly to these component variation modes or patterns. For this study, expected dominant variation modes such as bow and twist are used to simulate more realistic occurrences of component variability by taking into account geometric covariance of surfaces.

Finite element modelling (FEM) techniques allow for rapid virtual prototyping of assembly processes and have been used to explore key characteristics and sources of variability in sheet metal assembly. Liu and Hu (Liu and Hu 1995, Liu and Hu 1997) used simple beam assembly models

to investigate different join types and the major sources of variability associated with them. Liao (2005) combined FE simulation with a genetic algorithm for optimising spot weld locations in order to maximise dimensional build quality of sheet metal assemblies. Cao *et al.* (2001) compared the dimensional variation of five different clamping schemes for a wheelhouse assembly using FE simulation software. Optimum fixture positioning for the minimization of assembly variability has been explored by Camelio *et al.* (2004). This study applies a non-linear contact FEM to investigate the dimensional variation associated with different variation modes and clamping sequences, and demonstrates the ability of an adaptable clamping sequence to control overall dimensional variability in sheet metal assemblies.

2. The case study

A simplified cross-member structure assembly, consisting of a hat section and flat bottom plate, was chosen as the focus for this experimentation: it is representative of a larger class of parts including chassis rails and structural cross-members. An illustration is presented in figure 1. The part is located by a pin and slot at opposite ends along one flange, and three evenly spaced locating clamps down each flange (six clamps in total). Locator positions remain fixed throughout the study. The channel is 1000 mm long, 50 mm high, has 25 mm flanges, with a sheet metal thickness of 0.8 mm.

2.1 Finite element modelling approach

This study utilizes a non-linear contact FE simulation model implemented in Abaqus (ABAQUS). This model accounts for deformation induced contacts that linear models cannot capture, and was selected as it is a more accurate representation of the assembly process. The FE model used a multi-step framework, consisting of the following stages:

1. Datuming of parts using the locating pins and rest surfaces;
2. Applying clamps;
3. Performing welds;
4. Releasing the clamps;
5. Re-clamping in measurement fixture.

These stages have often been referred to as the place, clamp, fasten, and release cycle in literature (Chang and Gossard 1997). An example FE simulation setup is illustrated in figure 2. The pin 'P' and slot 'S' are located at opposite ends along one flange. Locating clamp locations and their sequence are indicated by numbers 1 through to 6. Welding

Figure 1. Channel section case study, consisting of a top hat and bottom flat plate. The assembly is located by a pin, slot and three clamps down each flange.

locations are indicated by the letters a through x (note that weld sequence is not altered for this study).

2.2 Component variation modes

The key input part variation modes of bow and twist were selected for this study. These variation modes account for surface co-linearity, providing a more realistic representation of part variability. For bow, there is a constant bow radius throughout the length of the part. Twist was created by rotating cross-sections throughout the length of the part. It should be noted that only hat section variation is considered (and not the flat bottom plate). This is because the hat is the primary structural member, and has much greater influence on final assembly variability than the bottom plate. Also, only hat nodal displacements were considered for data analysis. For the purposes of this paper, twist will be described by the twist angle illustrated in figures 3 and 4, and bow will be described by middle deflection as illustrated in figures 5 and 6.

2.3 Clamp sequences

There are 720 possible clamp sequences with a six clamp configuration. Testing each of these sequences is unrealistic, particularly considering the selection of a non-linear FE model for assembly simulation. Sixteen clamp sequences were initially chosen from four logical groups of: clamping down one flange and back up the other, clamping from one end to the other, clamping the outer ends and then the middle, and clamping the middle and then the outer edges (see figures 7–9). FE simulations were run for these 16 clamp sequences to gather basic measures of variability. In consideration of these results, a final subset of five clamping sequences from this group of 16 was then chosen for detailed investigation. This selection process is presented in the following section.

2.4 Clamp sequence selection

As stated earlier, 16 clamp sequences were initially chosen. One discrete example from each variation mode was then

Figure 2. Example FE simulation set-up. Locating pin and slot locations are indicated by 'P' and 'S', numbers 1–6 show clamp locations and sequences, and letters a–x are weld locations.

Figure 3. Example silhouette of negative twist.

selected: positive bow of 2.6 mm, negative bow of -2.6 mm, positive twist of 3° , and negative twist of -3° . Simulations were then run for all clamp-sequence/variation-mode combinations. The average displacements from the nominal final assembly shape were calculated for each of these clamp-sequence/variation-mode combinations. These figures provided an indicator of the sensitivity of assembly variability to input variation modes for each of these combinations, allowing for a ranking of the performance of each clamp sequence for each variation mode (see Appendix for comparison table). Here it was assumed that the closer an assembly shape is to the nominal, the better the shape is. These results were then used to select a subset of five clamp sequences to investigate in more detail. Firstly, the clamp sequences that resulted in the minimum average displacement for each variation mode were selected. For example, clamp sequence 621 had the lowest average displacement figure for negative bow at 0.27 mm, and was therefore selected. Secondly, the best and worst overall (across all variation modes) clamp sequences were selected. The overall measure was taken as the sum of the average displacements for all variation modes. For example, clamp sequence 634 had the highest overall value of 1.09 mm and was therefore selected as the worst overall sequence. Coincidentally, clamp sequence 641 was the best for positive bow and overall. The results for the final subset of 5 clamp sequences are presented in table 1.

Figure 5. Example silhouette of positive bow.

From table 1 it can also be seen that there is a substantial difference in the average displacement values when comparing the best and worst sequences. For example, for negative bow, the increase from the minimum average displacement to the maximum average displacement is 33%, suggesting that selection of clamp sequence is an important factor for the control of dimensional variability in flexible assemblies. This increase is much higher for the other variation modes.

2.5 Modelling the response of the assembly to input part variation modes

The study presented in the previous section only considered a single example or instance of each variation case. While this provides some indication of the relationship between input variation and output assembly shapes, it does not provide a good estimation of this relationship throughout the entire range of variation mode magnitudes. For example, while the responses of the assembly to clamp sequence 611 and a positive bow of 2.6 mm is known, how do you estimate the response of a positive bow of 1 mm or 3 mm? To provide a better estimation of this, a parametric study across a range of the each of the selected variation modes was undertaken for each of the five selected clamp sequences. A piecewise polynomial (or spline) regression technique was then used to determine the relationship between the component variation modes (predictors) and

Figure 4. Twist angle measure (degrees) for the variation modes positive twist and negative twist.

Figure 6. Middle deflection measure for the variation modes positive bow and negative bow. (Units: mm).

Figure 7. Example clamp sequence 611 (down one flange and back starting near the locating pin). Numbers indicate clamp location and sequence, 'P' and 'S' the pin and slot locations.

assembly variation (responses). This was chosen over a basic linear model owing to the presence of non-linear relationships in the data and its flexibility (see figure 10).

To put this study into more practical context, the type of data seen in real-life production situations, such as the measurement of samples from a production run, was simulated for analysis. To create such large data sets for

detailed inspection, random samples for each of the variation modes were created using a Gaussian random number generator, and responses calculated using the previously described models. The input variation was chosen such that maximum input values corresponded to reasonable final assembly maximum displacements. For example, the maximum positive bow of 2.71 mm corresponded to a final assembly displacement of approximately 2.32 mm for clamp sequence 621 (see table 2). figure 11 displays a histogram of random part variation for positive bow.

3. Results

The results are presented in three sections. Firstly, the variation associated with each clamping sequence and each of the four variation modes (positive/negative bow and twist) is assessed individually (i.e. this section is looking to identify the best clamping sequence for each of the individual variation modes). Secondly, the variation associated with each clamp sequence across all variation modes is assessed (i.e. this section is looking to identify the best clamp sequence for containing the variation modes overall).

Figure 8. Clamp sequence 612 (down one flange and back starting at the locating slot), and clamp sequence 621 (middle and then the outer ends).

Figure 9. Clamp sequence 634 (one end to the other), and clamping sequence 641 (outer ends and then the middle).

Finally, the concept of an adaptable clamping sequence is proposed, where given the shape of each part to be assembled, the optimal clamp sequence can be selected for that assembly case.

3.1 Individual variation modes

In this section, the variation associated with each clamp sequence is assessed for each particular variation mode. As the distributions of the assembly variables were highly skewed, a histogram is used to estimate the 90th percentile spread of data. The average of this value across all variables (or nodes) is used as an assessment of the overall population variability. This is illustrated in figure 12.

To highlight the differences in variation of the final assembly for the different clamping sequences, figure 13 shows the percentage differences between the maximum and minimum average spread values of each clamp sequence for each variation mode. The results show that different clamp sequences can result in considerably different final assembly variation. For example, for positive bow the worst clamp sequence results in an average spread value that is 80% more than the best clamp sequence.

Table 3 shows which clamp sequences were the best and the worst at containing variation in the final assembly. An interesting observation is that each variation mode has a different lowest variation sequence. Another is that the lowest variation sequence for positive bow is the highest variation sequence for negative bow (and vice versa). These results show that the best clamp sequence for containing variability depends on which variation mode is present.

For further demonstration of the differences between the clamping sequences, a comparison of the maximum differences between final assembly shapes for each clamp sequence given the same input part shape (positive bow of 2.71 mm) was undertaken. It can be seen that by altering the clamp sequence, the final assembly shape can be quite different, with a maximum difference of 2.14 mm between

Figure 10. Plot of an example non-linear relationship between the input variation mode (positive bow middle deflection) and final assembly nodal displacement. The spline model passes through all data points, whereas the linear model (dotted line) is a poor approximation.

clamp sequences 641 and 621 (table 4). A plot of the differences in shape is shown in figure 14.

3.2 Combination of all variation modes

While the last section presented assessments of the variability associated with individual variation modes, this section looks at which clamp sequences are the best for containing variation across all variation modes. Here it is assumed that part variation consists of all four variation modes, with each variation mode having an equal likelihood of occurrence, and the distribution and sample size for each variation mode is as stated earlier (i.e. there are 800 samples in total for the combination case). Average standard deviation, maximum standard deviation, and maximum displacement from nominal were used to assess the performance of each clamp sequences in terms of dimensional

Table 1. Final assembly average displacements from nominal for selected clamp sequences. As seen in the table, each clamp sequence was tested against each variation mode.

Sequence description	#	Final assembly average displacement from nominal (mm)				Indicator for overall clamp sequence variation Row total (mm)
		Negative bow (−2.6 mm)	Positive bow (2.6 mm)	Negative twist (−3°)	Positive twist (3°)	
Down and back (pin)	611	0.36	0.35	0.13	0.08	0.91
Down and back (slot)	612	0.32	0.36	0.09	0.11	0.88
Middle to out	621	0.27	0.43	0.10	0.09	0.89
One end to other	634	0.31	0.29	0.21	0.28	1.09
Out to middle	641	0.34	0.22	0.11	0.18	0.84
% Increase from min to max values		33%	95%	133%	250.00%	30%

Table 2. Parameters used to generate variation modes.

	Positive bow	Negative bow	Positive twist	Negative twist
Standard deviation	1 mm	1.6 mm	2°	2°
Mean	0 mm	0 mm	0°	0°
Samples	200	200	200	200
Max. value	2.71 mm	-4.75 mm	4.86°	-4.80
Max. assembly displacement	2.32 mm	4.03 mm	2.15 mm	1.91 mm

variability. table 5 presents the maximum and minimum performance values and the respective sequences. When looking at average standard deviation, it can be seen that sequence 621 is the best at controlling variability overall. When looking at maximum standard deviation and maximum displacement sequence 621 appears to be the best at controlling variability in the final assembly. The table also shows considerable differences in the performance of the best and worst clamping sequences across each of the performance measures. For example, the percentage increase in the maximum displacement value from the best to worst clamping sequence is 71%.

3.3 Adaptable clamp sequence for dimensional control

The previous sections revealed some key factors. Firstly, differences in final assembly variability can be quite large when comparing different clamp sequences, both for cases where part variation consists of a single variation mode, and in cases where part variation consists of multiple variation modes. Secondly, different variation modes do not share the same best clamp sequence. This behaviour is best shown in the case of positive and negative bow, where a clamp sequence

Figure 11. Example random distribution of inputs for positive bow. Note that only half of the Gaussian distribution is used for generating the random data set for each variation mode, and the nominal part shape is the most likely shape.

that is best for containing variability in one variation mode (621 for positive bow), is also be the worst at containing variability for another variation mode (621 for negative bow). This means that for a case where multiple variation modes exist, the best overall clamp sequence might not be the best clamp sequence for each individual variation mode. This section poses the concept of an adaptable clamping sequence for minimizing dimensional variability in assemblies in light of these learnings. The proposed method for this approach requires the following key facilities:

1. Models that can relate input part shapes to the final assembly shape for a range of clamp sequences: Earlier in this paper, parametric FEM studies combined with regression modelling techniques were used to develop this relationship. This relationship could also be established from statistically significant production studies where input components and their respective assemblies are measured for a range of clamp sequences, although the resource requirements for this would be quite substantial.
2. The facilities to measure 100% of incoming parts to an assembly cell: If an input part can be measured, the final assembly shapes for the range of available clamping sequences can be calculated, and the best sequence selected for assembly.

While the requirements for implementing an adaptable clamping process are quite demanding, improvements in technology, particularly in terms of optical measurement systems, provide the opportunities for such a technique. The next section provides a demonstration of this method and the possible advantages to be gained.

3.3.1. Demonstration of method. The previous sections have already developed regression models for the five different clamp sequences over 4 different variation modes. This means that given an input part shape, the final assembly shape can be calculated for all five possible clamping sequences. For this illustration of an adaptable clamping sequence, input part shapes were matched to the clamping sequence that resulted in the lowest average displacement from nominal of the final assembly. The process can be described as follows:

Figure 12. Histogram of an example variable from the final assembly, highlighting the 90% spread of data measure, indicated by the filled bars. Note that the measure of spread includes the peak-end of the data and omits the tail-end.

Figure 13. The percentage difference between the maximum and minimum average spread values of each clamp sequence.

1. measure input parts;
2. determine the expected final assembly shape for each available clamping process using the previously developed regression models;
3. identify the clamping sequence that results in the lowest average displacement from nominal for the final assembly;
4. use this best sequence to assemble this particular part; repeat above for each part to be assembled.

This process was followed using the same input part population case as the combination of variation modes

Table 4. Maximum difference between final assembly shapes for each clamp sequence, for the example input part shape:

Positive bow, 2.71mm middle deflection. For example, the value in row 641, column 621 shows the maximum difference between the final assembly shape of clamp sequences 641 and 621, which is 2.14 mm.

612	1.07 mm			
621	1.09 mm	1.01 mm		
634	1.03 mm	2.10 mm	2.12 mm	
641	2.01 mm	2.12 mm	2.14 mm	1.8 mm
Clamp sequence	611	612	621	634

presented earlier. A comparison of the adaptable assembly process with the best and worst traditional fixed clamp sequences is shown in table 6. It can be seen that the adaptable process shows considerable improvements in final assembly variability: average and maximum standard deviations for the best fixed clamp sequence are roughly 20% more than for the adaptable clamping sequence. Table 6 also shows that the average standard deviation of the worst fixed clamp sequence is 54% more than for the adaptable process, which highlights the possible extent of benefits by adopting an adaptable clamping sequence for the control of dimensional variability in assemblies. It should be noted that the Maximum displacement value for the best fixed clamping sequence and the adaptable clamping sequence is the same (2.35 mm).

Table 3. The lowest and highest variation clamp sequences for each variation mode. It can be seen that different variation modes do not share the same lowest variation (or best) sequence.

	Positive bow	Negative bow	Positive twist	Negative twist
Lowest variation sequence	621	641	611	612
Highest variation sequence	641	621	634	634

Figure 14. Final assembly shapes for clamp sequence 621 (light) and 641 (dark) overlaid to highlight differences ($10 \times$ magnified displacements from nominal).

Table 5. Performance measures for assessing variability of clamping sequences for the case where part variation consists of multiple variation modes.

	Average standard deviation (mm)	Maximum standard deviation (mm)	Maximum displacement from nominal (mm)
Min	Sequence 612: 0.15	Sequence 621: 0.51	Sequence 621: 2.35
Max	Sequence 634: 0.19	Sequence 634: 1.17	Sequence 634: 4.03
% Increase from min to max values	25%	126%	71%

Table 6. Comparison of adaptable clamping process with the best and worst fixed-clamping-sequences (in terms of final assembly variability).

	Average standard deviation (mm)	Maximum standard deviation (mm)	Maximum displacement (mm)
Minimum values for fixed clamping sequences	Sequence 612: 0.15	Sequence 621: 0.51	Sequence 621: 2.35
Minimum values for fixed clamping sequences	Sequence 634: 0.19	Sequence 634: 1.17	Sequence 634: 4.03
Adaptable clamping sequence	0.12	0.43	2.35
% Increase from adaptable to min	23%	21%	0%
% Increase from adaptable to max	54%	173%	71%

4. Discussion

This study shows that different clamp sequences can result in different final assembly variation levels, and that an adaptable clamping sequence can provide quite considerable improvements over traditional approaches where the clamping sequence is fixed. A major limitation of this approach is the resources and facilities required to set up such a process. However, through the usage of mechanistic simulation, and the advent of new in-line inspection technologies, opportunities to gather the required data for this approach are arising. This adaptable clamping sequence

approach highlights the concept of optimizing an assembly process for each particular part shape to be assembled, rather than focusing on a global optimization for the entire population. Clamping sequence is one aspect of the assembly process that can have an influence on assembly variability. Other aspects such as welding sequence and locator setup have been shown to have an influence on assembly variability. Global optimization studies (i.e. fixed process for all part shapes) have been undertaken for welding sequence and locator layout (Camelio and Hu 2004, Liao 2005). Looking into furthering this concept of an adaptable assembly process to welding sequence and locator

layout could further enhance the dimensional control capabilities of such approaches. For example under a flexible fixturing framework (where assembly process including clamp sequence, locator layout, and welding sequence can be altered for each assembly), a highly adaptable assembly process could be implemented that optimizes a process specifically for each part being assembled.

5. Summary

In the current paper, the dimensional variability associated with different assembly clamping sequences is investigated with a FE simulation models. It was found that final assembly variability can change considerably depending on clamp sequence selection. It was also found that different clamp sequences can control particular modes of variation better than others, and that there is not one particular clamping sequence that is the best for containing all variation modes. An adaptable assembly process is therefore suggested, where given the shape of input components the best available clamping sequence is selected. Comparison of the performance of the proposed adaptable clamping sequence to traditional fixed clamping sequences shows improvements for the dimensional control of variability in non-rigid components. While introducing such a method in production would require inspection of each component being assembled and investigation of the alternative clamping sequences, given access to fast and detailed dimensional inspection technology such as optical coordinate measuring machines (OCMM's), the approach shows promise for future application.

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Appendix

Table A1. Average displacement from nominal of the final assembly for each input variation mode example and clamp sequence combination.

Clamp sequence	Negative bow (−2.6 mm)	Positive bow (2.6 mm)	Negative twist (−3°)	Positive twist (3°)	Row total (mm)
611	0.36	0.35	0.13	0.08	0.91
612	0.32	0.36	0.09	0.11	0.88
613	0.33	0.25	0.14	0.15	0.87
614	0.36	0.26	0.16	0.15	0.93
621	0.27	0.43	0.10	0.09	0.89
622	0.30	0.27	0.24	0.22	1.03
623	0.27	0.43	0.10	0.10	0.89
624	0.30	0.27	0.22	0.24	1.03
631	0.27	0.24	0.18	0.23	0.93
632	0.28	0.25	0.23	0.18	0.93
633	0.31	0.30	0.27	0.21	1.09
634	0.31	0.29	0.21	0.28	1.09
641	0.34	0.22	0.11	0.18	0.84
642	0.33	0.23	0.23	0.17	0.95
643	0.35	0.22	0.17	0.11	0.84
644	0.34	0.24	0.16	0.22	0.95
Min	0.27	0.22	0.09	0.08	0.84
Max	0.36	0.43	0.27	0.28	1.09
Range	0.09	0.21	0.19	0.21	0.25
Max/min-1 (%)	34.41%	96.28%	221.14%	275.10%	29.99%