Quantitative Characterization of Warpage for Composite Components

Eric J. Martin[1], O. Remus Tutunea-Fatan[2], Ryan Gergely[3] and David A. Okonski[4]

[1]Western University, emarti58@uwo.ca
[2]Western University, rtutunea@eng.uwo.ca
[3]General Motors, ryan.gergely@gm.com
[4]General Motors, david.a.okonski@gm.com

Corresponding author: O. Remus Tutunea-Fatan, rtutunea@eng.uwo.ca

Abstract. While part warpage represents a relatively common occurrence in manufacturing, little research has been directed towards its quantitative characterization. To address this deficiency, five different metrics have been proposed and analyzed in an effort to evaluate the warpage of composite components with small thickness to length/width ratios. The significant common attribute of all these metrics was that they can be reduced to a single number which enables their use in subsequent studies attempting to identify combinations of input parameters yielding a desired output value. To demonstrate the effectiveness of the proposed metrics, they were applied in two case studies involving compression molding of LFT-D. While the analyzed metrics suggested that neither mold temperature nor charge placement play a significant role on part warpage, the comparative analysis of the results obtained revealed that the inherent definition of part warpage plays an important role on any downstream analysis involving it.

Keywords: warpage metric, composite manufacturing, LFT-D process, reverse engineering.
DOI: https://doi.org/10.14733/cadaps.2022.1093-1108

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1 INTRODUCTION

The recent emphasis placed on emission reduction has prompted many automakers to increase their efforts towards a broader adoption of composite components. While composite components can be mass-produced in a variety of ways, the low cycle time of the Long Fiber Thermoplastic-Direct (LFT-D) compression molding makes it a prime candidate for automotive part manufacturing [8]. The LFT material used in this study consists of a polyamide matrix and discontinuous randomly oriented glass fibers. Understandably, composite components are characterized by large warpages owed to the dissimilarities in the thermal expansion of their matrix and fibers. As such, an accurate evaluation of part warpage becomes an issue of paramount importance [2],[3],[10],[16]. Nonetheless, no standard or standardized definition of "warpage" exists.

Part warpage represents one of the important and largely undesirable byproducts of thermal-based part forming processes. The negative connotation of part warpage is sometimes associated with the downstream use of the distorted components, particularly in assembly operations that do not permit large deviations of the mating components from their nominal shapes. For instance, while the forced closing of the gaps that are present between two warped flanges can be attained through clamping, it is relatively easy to anticipate that the stresses to be induced in any of the joining points will be amplified by any prior flange distortions. The extrapolation of this example implies that the assessment of warpage is important since it can provide insight into the potential downstream assembly issues to be faced when using warped components. As such, any effort to reduce the warpage of composite components - or any components, for that matter - seems fully justified. However, one of the first steps towards this goal is the development of quantitative metrics capable of capturing this geometric characteristic.

Typically, part warpage is regarded as the deviation of the fabricated part from its theoretical/nominal shape as captured by its "digital master" (CAD model). When it comes to the numerical quantification of the warpage, one of the obvious possibilities is represented by the maximum amount of deviation between nominal and warped shapes. This specific definition of the warpage is the one that was extensively employed so far in the surveyed literature [4],[6],[9]. While the evaluation of this warpage metric is straightforward, its practical value could be questionable, especially when the vertex associated with the maximum deviation is located outside of the "region of interest" (ROI) of the part (i.e., involved in subsequent manufacturing/assembly operations). Furthermore, in addition to "maximum deviation", other researchers have defined part warpage as the deviation experienced by the part at pre-determined measurement locations. Without providing the absolute maximum deviation, this approach could have more relevance when the predetermined measurement locations have downstream implications [15]. However, no direct applications of this warpage definition have been presented so far. On the other hand, one possible alternative to quantitative approaches is constituted by qualitative approaches. In this case, warpage evaluation relies on the use of color maps in order to better convey deviation magnitude [5]. While this represents a robust approach that is available in commercial software, its applicability to process parameter optimization or investigation remains difficult if not impossible.

While part warpage is a geometric characteristic with important implications on manufacturing and assembly, its quantitative definitions and applicability to process analysis remain rather scarce. To address this deficiency, the current study proposes several quantitative part warpage metric definitions and applies them to test cases in order to obtain insight on the effect of several molding process parameters upon the metrics.

2 GENERAL FRAMEWORK

One of the important prerequisites of warpage evaluation is the digitization of the distorted shape of the part. The digital model of the warped part enables its direct comparison with its nominal counterpart. Presently, one of the most common techniques used to acquire the geometry of the warped part is reverse engineering (RE). A typical workflow involved in warpage assessment involves the use of a laser line probe (LLP) for the acquisition of point cloud data to be subsequently converted into a triangular mesh. Following this, the mesh of the warped component is registered against the theoretical CAD model such that distances between "warped" and "unwarped" meshes can be determined for virtually any vertex of the mesh.

The workflow described above is graphically presented in Figure 1 and it was used to generate five different warpage metrics to be detailed in the upcoming sections. More details on the actual RE process and its settings can be found in a prior study [13]. The geometry of the test part used in this study was a demonstrator seatback outer (SBO), presented in Figure 2. It is important to note that only its top side was scanned for the purpose of this study. The dimensions of the bounding box of

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the sample part were 540 x 480 x 98 mm. The part had a thickness varying between 2.0 and 3.9 mm, depending on the location in the part.

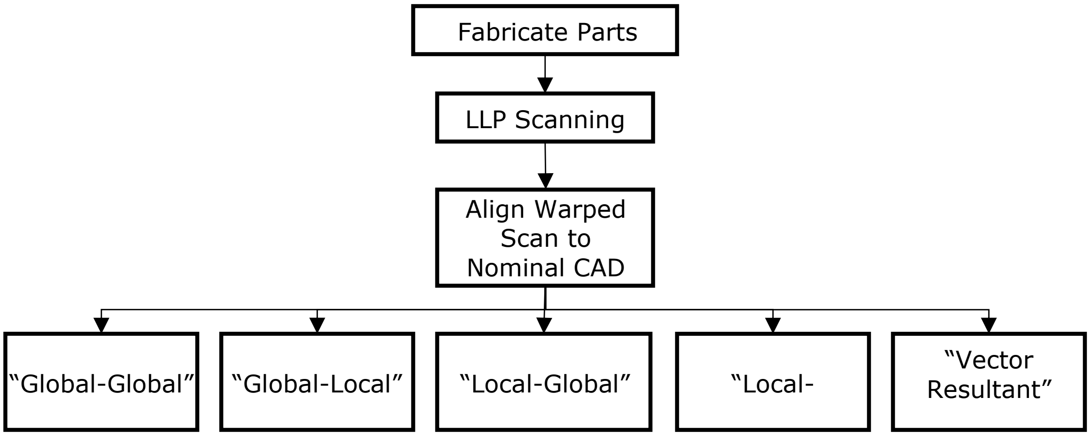
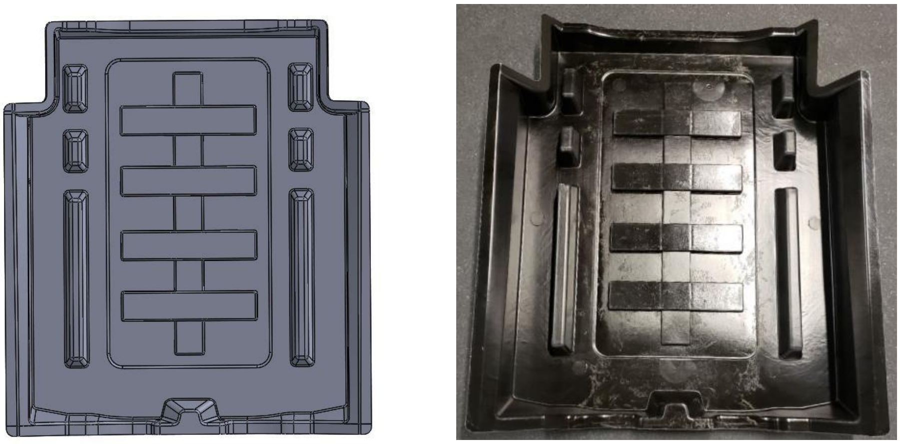


Figure 1: Overview of the study workflow.



a) b)

Figure 2: Seatback outer (SBO): a) nominal model, b) physical component.

3 WARPAGE METRICS

3.1 Background

As indicated above, part warpage can be evaluated in a variety of ways, both qualitatively and quantitatively. However, irrespective of the chosen scenario, warpage assessment is based on the field of deviations between the nominal and deformed geometries. Most commercial RE software generates color maps characterizing the deviation between two overlaid geometries. This represents a valuable tool in warpage evaluation.

The software interprets "deviation" as the distance between the vertex of the reference nominal geometry and its "projection" on the "other" part involved in the warpage evaluation. The actual direction along which the projection is sought is determined as a combination of software algorithms and some (typically limited) user input. Even though the color maps could also serve a quantitative

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role – since the magnitude is displayed for every vertex - the primary use of the color map remains qualitative. The biggest challenge with the quantitative use of the color map is related to the fact that most statistical tools to be used for process parameter analysis and optimization (t-test, ANOVA, etc.) require output variables that are represented as unique numbers, rather than arrays of (*X*, *Y*, *deviation*) values.

Other than color maps, Song et al [15] proposed maximum deviation as the warpage metric to be used to assess the validity of molding simulation results (to be compared against experimental data). The same maximum deviation definition of the warpage was also employed in other studies [4],[6]. However, while this warpage metric worked reasonably well when comparing simulation and experimental data, its relative independence from "regions of interest" on the geometry – *i.e.*, areas that are involved in downstream manufacturing/assembly operations - makes it less suitable for other types of analysis. This study proposes five different metrics to assess part warpage, each to be detailed in the upcoming sections.

3.2 Data Acquisition and Alignment Procedures

As mentioned above, these procedures along with their associated accuracy were presented in detail in a prior study [13]. As such, only some of the most relevant settings will be reiterated here. According to the predetermined procedure, once the raw data was acquired via laser scanning, the points yielded from different passes were combined in a single dataset created by setting the maximum allowable merging distance to 2 mm and the number of iterative blending steps to 15. The dataset was then filtered by means of user-set standard deviation (0.025 mm) that was determined heuristically (via trial and error) in an attempt to eliminate the outliers located outside of the common $\pm 3\sigma$ range. Too small or too large thresholds would yield data that is either too sparse ("full of holes") or with too many outliers ("too noisy").

After the completion of the dataset filtering, point cloud data was converted into a triangular mesh and additional mesh generation controls were used to further improve the quality of the mesh. More specifically, a small rolling ball of 0.5 mm radius was used to further smoothen the geometry and a low reduction rate (2%) was applied in order to improve the flatness of the small near-planar areas that were visible in the data. These parameters were also determined via trial and error and as such they are likely applicable only to the geometry in discussion.

Figure 3: Pre-aligment target area (in red).

Following mesh generation, the warped geometry was aligned to the nominal one by means of a conventional best-fit technique whose robustness was also tested in the past. While from a strict theoretical standpoint, it is possible that mesh registration/ alignment procedures will not yield repeatable results, the robustness of the one employed in this study was previously validated [13]. In brief, the registration procedure relies on the central area of the part that was identified to be less affected by warpage (Figure 3). The core of the alignment procedure implemented in the RE software remains the "iterative closest point" (ICP) algorithm [11].

3.3 Global-Global (GG) Warpage Metric

The first metric to be investigated was termed as "global-global". To ensure the consistency of the terminology used, the following naming convention was adopted for the first four warpage metrics: the first word denotes the size of the area of interest, whereas the second word denotes the number of assessment vertices used. More specifically, the region of interest can be "global" (the entire area of the part) or "local" (a subset of the entire part area, typically with downstream manufacturing relevance). Furthermore, the number of vertices in which the deviation between warped and nominal

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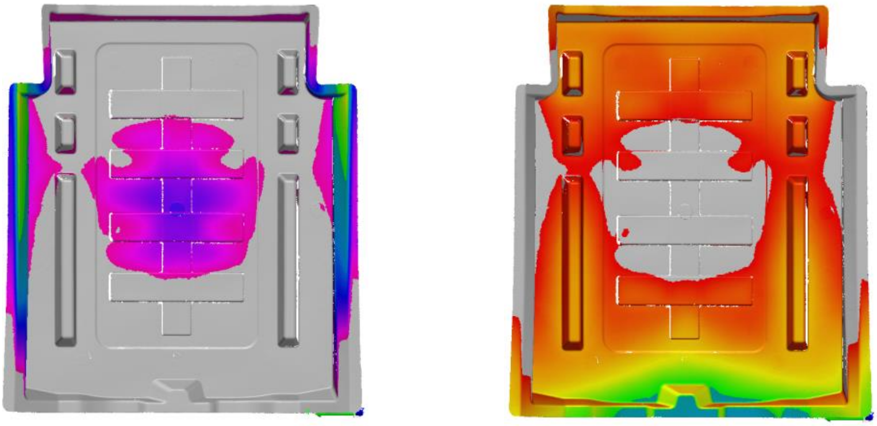
geometries is assessed can be "global" (all vertices in the preset region of interest) or "local" (just a subset of discrete vertices placed in the region of interest).

According to these naming conventions, the global-global metric involves all vertices distributed on the entire area of the part. To reduce the warpage between distorted and nominal part to a single number, all metrics will involve an averaging of the distances measured between distorted and nominal geometries. These distances will be assessed for all vertices corresponding to the metric in discussion and they will be used in absolute values to avoid the bias introduced by the summation of positive and negative values (Figure 4).



a) b)

Figure 4: Separated deviations: a) positive, b) negative.

Values of the global-global metric for a complete series of SBOs fabricated under the same molding conditions are presented in Table 1. The number of vertices included in the evaluation of the metric was approximately 2 million.

Part ID	Average Deviation (mm)
191002-1-1	1.712
191002-1-2	1.755
191002-1-3	1.978
191002-1-4	1.750
191002-1-5	1.826

Table 1: GG warpage metric evaluations.

3.4 Global-Local (GL) Warpage Metric

The global-local metric is similar to the GG metric in that the entire part is evaluated. However, instead of gathering deviation measurements for all vertices, only 26 localized points – in fact small localized areas - were included in the evaluation (Figure 5b). More specifically, distances to vertices located in a 1 mm radius adjacent to the 26 preselected points were averaged to yield a single measurement associated with each point. The 26-point set was chosen based on prior inspection experience. The small localized area was preferred to a single vertex to avoid abnormal deviation values caused by local singularities/outliers. The values of the metric associated with the five-part series are presented in Table 2. The larger values exhibited by the GL metric when compared to the GG metric are likely a consequence of the large number of vertices with small deviations that are included in the evaluation of the GG metric that are not included in the GL metric.

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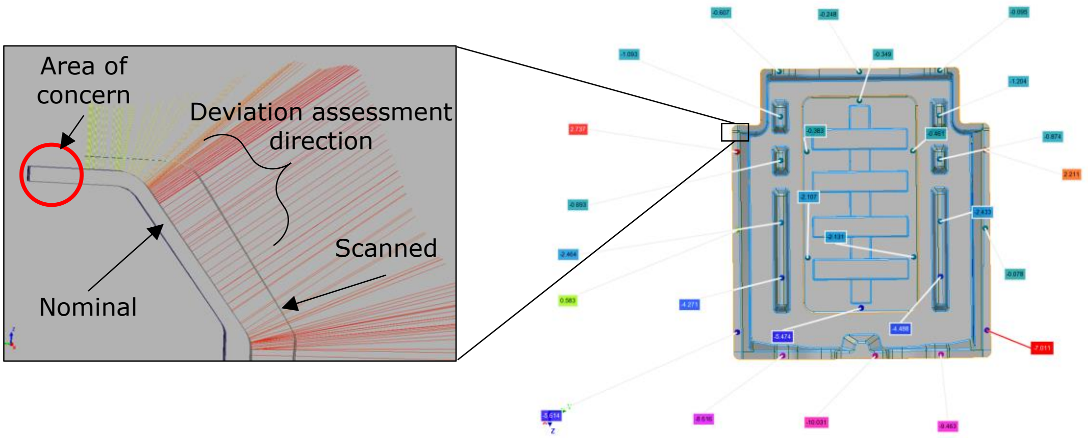
Part ID	Average Deviation (mm)
191002-1-1	2.912
191002-1-2	2.952
191002-1-3	3.265
191002-1-4	3.038
191002-1-5	2.928

Table 2: GL warpage metric evaluations.

While the trend of variation for the GL metric remains roughly similar to that of GG, this new metric assessment technique reveals that – depending on the magnitude and location of the warpage – there might be situations in which the assessment of the deviation between warped and nominal geometry cannot be performed. For example, the final/distorted position of the top corner of the long-left flange makes the evaluation of the deviation virtually impossible since RE cannot establish the correct correspondence between warped and nominal position of the points (Figure 5a).



a) b)

Figure 5: GL metric: a) problematic area, b) evaluation dataset for GL warpage metric.

This problematic area is a consequence of insufficient flexibility permitted by the RE software with respect to the direction along which the "correspondence" between warped and nominal geometries is sought. In most cases, this direction is assumed to be – more or less – normal to the reference/nominal geometry. However, the scenario presented in Figure 5a suggests that this assumption might yield null results in case of vertices that experience large translations along non-normal directions. The accuracy of the GL metric will be typically more affected by these situations than that of GG simply because these instances tend to have a "local" rather than "global" effect.

3.5 Local-Global (LG) Warpage Metric

The local-global warpage metric is determined by deviation assessments considering a specific region of interest (ROI) ("local") for all ("global") vertices located in that region. By assuming that the subsequent assembly operations will primarily involve the long lateral flanges and since qualitative observations suggest that these flanges experience the largest deviations from the nominal geometry, the ROI was restricted to these areas (Figure 6). The data summarized in Table 3 suggests once again that the trend of variation from part to part remains approximately the same as the

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previous two metrics, whereas the magnitude of the LG metric is larger than both GG and GL metrics, a direct consequence of the warpage pattern that is characterized by large deviations on the two long lateral flanges.

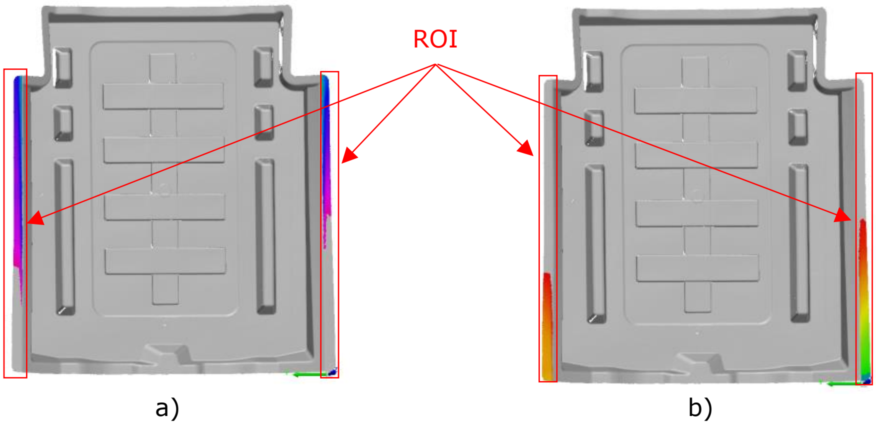

Figure 6: Separated deviations: a) positive, b) negative.

Part ID	Average Deviation (mm)
191002-1-1	4.276
191002-1-2	5.263
191002-1-3	5.815
191002-1-4	4.563
191002-1-5	5.763

Table 3: LG warpage metric evaluations.

3.6 Local-Local (LL) Warpage Metric

This local-local warpage metric is similar to LG, except that a limited subset of the ROI vertices was used for distance measurements (Figure 7). In this particular example, a total of 12 vertices were used (6 per flange). Their location was chosen in such a way to ensure repeatability of the selection as well as to avoid the area at the top corner of the flange where distance evaluations were not possible.

Once again, the warpage data presented in Table 4 exhibits trends similar to the other metrics. When compared to the LG metric, the magnitude of the average deviation for the LL metric is lower. This could be a consequence of the fact that the 12 evaluation points were selected close to the fillet, delimiting the inner edge of the flange (where deviations are lower). This location of the evaluation point was selected in such a way to ensure that distance evaluations are possible. More specifically, if evaluation points would be chosen closer to the free edge of the long lateral flange, some of the evaluations could not be performed due to the phenomenon illustrated in Figure 5a.

3.7 Vector Resultant (VR) Warpage Metric

To avoid the aforementioned issues related to the automatic (*i.e.*, software-based) mapping of the points/vertices between the deformed and nominal geometries (Figure 5a), one possible solution is to revert to a manual/user-controlled mapping. Indeed, the initial position of almost any vertex belonging to the scanned/deformed part can be estimated with sufficient precision by means of direct comparisons with the nominal/un-warped geometry.

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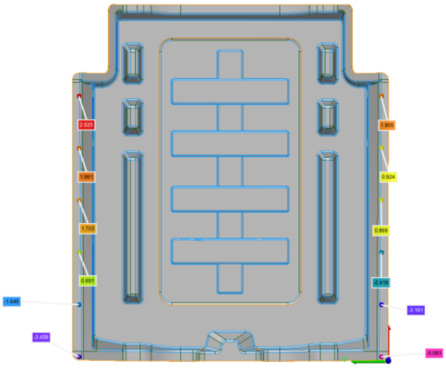
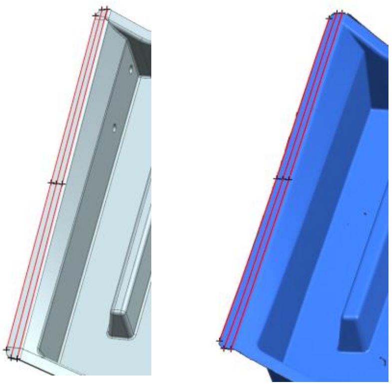


Figure 7: Evaluation dataset for LL warpage metric.

Part ID	Average Deviation (mm)
191002-1-1	2.977
191002-1-2	2.979
191002-1-3	3.578
191002-1-4	1.170
191002-1-5	3.185

Table 4: LL warpage metric evaluations.

For the specific case of the SBO geometry analyzed in this study, a direct mapping of 18 vertices (9 on each of the two long flanges) was performed (Figure 8). To ensure the repeatability of the selection, strict geometric constraints were used. Curvature-based and edge detection methods for tessellated geometry were used to ensure the accuracy/consistency of the evaluation dataset for the scanned/deformed geometry. By contrast, their counterpart on the nominal geometry was determined in a more facile way since the full access to the parametric description of the NURBS-based geometry was possible. While extremely tedious and completely manual at this time, the VR approach practically guarantees that the distance assessment between warped and nominal geometries is always possible. Thus, the proposed VR metric could constitute a more accurate representation of the warpage pattern (Table 5).



a) b)

Figure 8: Evaluation dataset for a) nominal and b) scanned part.

Part ID	Average Deviation (mm)
191002-1-1	7.009
191002-1-2	7.509
191002-1-3	8.201
191002-1-4	7.031
191002-1-5	7.793

Table 5: VR warpage metric evaluations.

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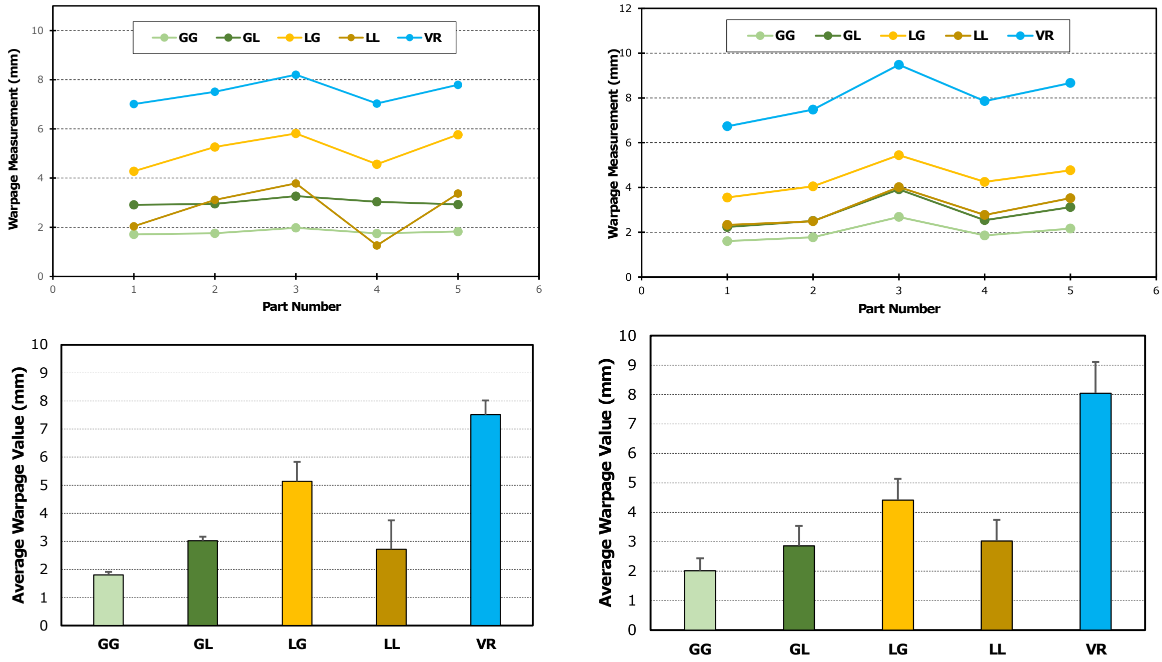
3.8 Comparison of Warpage Metrics

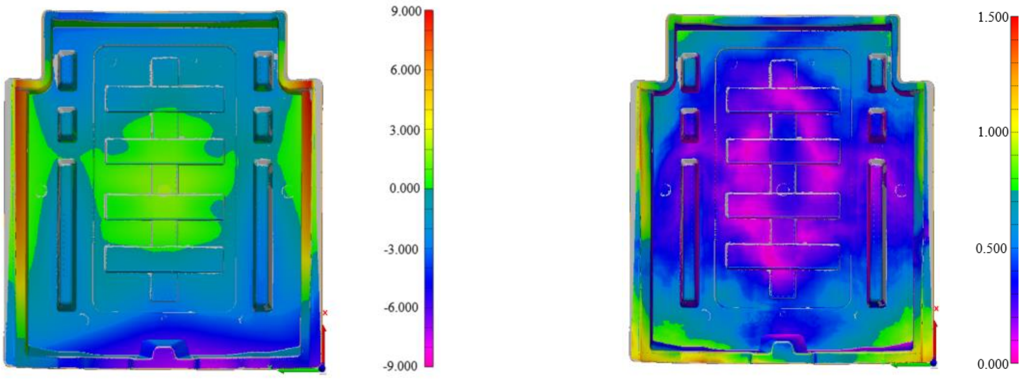
To compare the five proposed warpage metrics, the results of two molding series were analyzed (Figure 9). Each molding series was run with unique molding conditions and produced five parts.



a) b)

Figure 9: Comparative analysis of the warpage metrics for a) Series 1, b) Series 2 (error bars represent one standard deviation).

Several interesting observations can be made with respect to the plots in Figure 9. The first and most obvious observation is that the global approaches (GG, GL) tend to consistently yield low warpage values compared to the other metrics. This is a consequence of the dominant effect played by the large number of vertices located in the central region of the part, an area characterized by relatively low deviations from the nominal geometry (Figure 10a).



a) b)

Figure 10: Series 1: a) averaged deviations, b) standard deviation.

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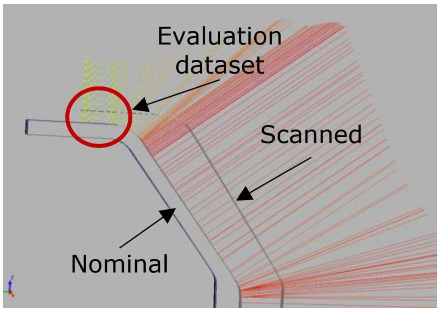
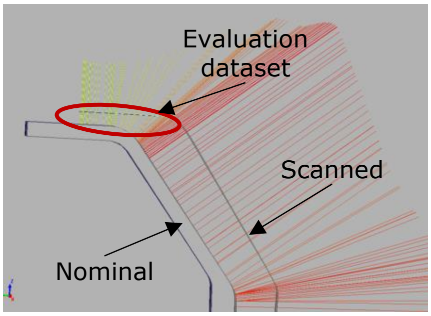
Evidently, whenever the size of the evaluation dataset decreases (GL), so is the dominant effect of the central less warped zone of the part. Because of this, the GL metric consistently results in higher values than the GG metric.

The LL tends to have the lowest values among the remaining three metrics (LG, LL, VR). The main reason for this behavior is related to the geometric constraints placed on the position of the 12 points included in the LL evaluation dataset. More specifically, since these points were positioned close to the filleted boundary of the long flanges (to avoid the null distance condition), the deviation will be found along a predominantly Z and rather small distance (yellow dashed lines, Figure 11a). By contrast, these constraints are not imposed on the LG metric, such that this metric will inevitably yield larger values than the LL metric. In particular, since Y components (horizontal dimension in Figure 11b) will also start to affect the deviations that will eventually compound into the LG metric.



a)



b)

Figure 11: Position of the evaluation dataset for a) LL, b) LG metrics.

Overall, the warpage metric that yields the largest absolute values is VR and Figure 12 illustrates the reason for this behavior. In brief, when manual mapping between pre- and post- deformation vertices is performed, the deviation vectors are often not normal to the surface of the part. As such, their magnitude will increase and thus their average will increase as well. While this process of manual mapping seems to be – intuitively, at least – the most accurate one, it is relatively difficult to justify the utility of the VR metric based on this sole characteristic. Indeed, while VR echoes well the other four metrics, it is the most time consuming one, primarily due to the large amount of manual data processing associated with it.

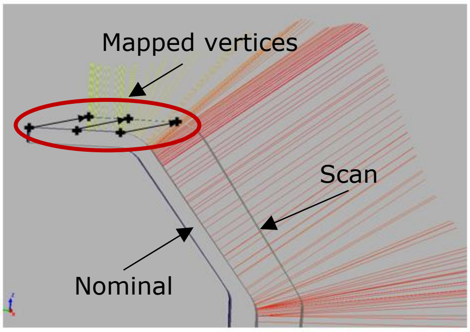


Figure 12: VR warpage metric mapping

When the group of overall global metrics (GG, GL) is compared to the group of local ones (LG, LL, VR), it can be observed that the local metrics are more sensitive to part-to-part variation than the global metrics. This is a consequence of the "tempering" effect played on the GG and GL metrics by the central region of the part that experiences less warpage (primarily because of the manufacturing process used). Another interesting observation stemming from the graphs in Figure 9 is that the parts in Series 2 experience a more notable part to part variation (as captured by the two global metrics). Beyond that, the standard deviation associated with Series 2 is larger than the standard deviation Series 1 (Figure 13). This essentially means that the manufacturing process used for Series 2 is less stable than the one used for Series 1, an observation with important practical applications.

In summary, if the evaluation dataset spans across the entire part (GG, GL), a certain risk of weakening the "warpage signal" exists. On the other hand, the use of a "constant" ROI (LG, LL, VR)

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could omit areas where large deviations are present. Therefore, the local metrics (LG, LL, VR) have a better chance of capturing part to part variations and this increased sensitivity could provide valuable insight on which molding process parameters result in reduced distortion.

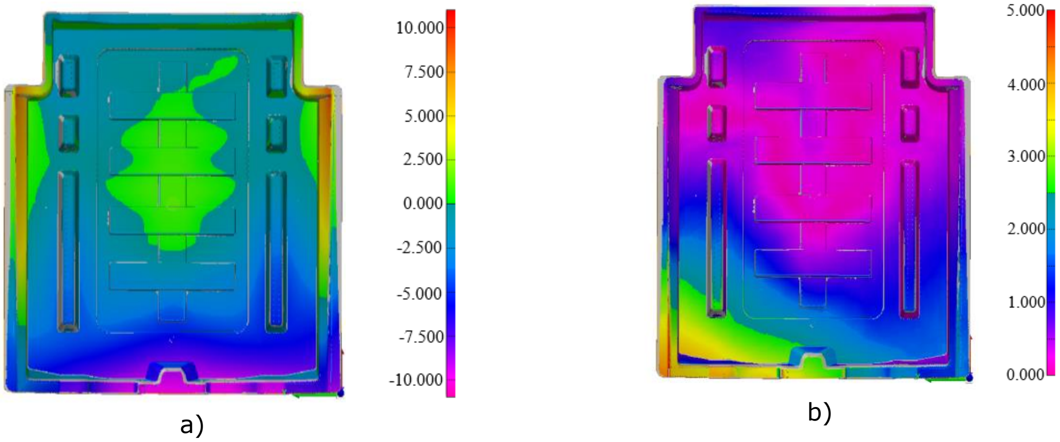

Figure 13: Series 2: a) averaged deviations, b) standard deviation.

4 APPLICATIONS OF WARPAGE METRICS

The applicability of the developed warpage metrics was tested in the context of a simple design of experiments (DOEs) involving one input (molding process parameter, set at either two or three levels) and two outputs (the GG and LL warpage metrics). The purpose of these tests was to investigate any possible dependence between the analyzed input and output of the composite manufacturing process. While any of the five proposed metrics could be used in these simple DOEs, only GG and LL were selected here for further investigation. The main motivation behind this selection resides in the relative generality and evaluation simplicity of the two metrics. While many options exist with respect to input parameters, mold temperature and charge placement were chosen for further analysis. Mold temperature is known to affect warpage in molding due to influence on the part temperature and thermal shrinkage [5],[12],[14]. Charge placement also can affect part warpage through differences in resulting flow induced fiber orientation [1],[7].

4.1 Effect of Mold Temperature on Warpage

In this set of experiments, the effect of mold temperature on warpage was analyzed since prior studies have indicated that this particular process parameter does play a role on the warpage of plastic and fiber reinforced polymer (FRP) components [5],[12],[14]. According to the general understanding of the field, a lower mold temperature is expected to lead to lower warpage. However, if the temperature is set too low, then the part might not fill completely, therefore the temperature cannot be lowered below a certain threshold. Under this investigational idea, all molding conditions were held constant with the exception of mold temperature. Mold temperature was set at two different levels - 150°C and 100°C – both of which produced completely filled parts. A series of 10 identical parts were manufactured for each of the two analyzed temperature conditions. Statistical t-tests were used to determine if temperature alterations lead to warpage changes. A standard 95% confidence interval (CI) was used. Furthermore, the 95% CI sets $\alpha = 0.05$, the null hypothesis being that the two sets are not statistically different from each other. To reject the null hypothesis - and therefore claim that the changed mold temperature leads to a warpage change – the following inequality has to be obeyed: $p \leq \alpha$.

The plot of the GG warpage metric for the two series of parts is depicted in Figure 14a, alongside the average and standard deviation (Figure 14b). Confirming the visual inspection, t-test calculation

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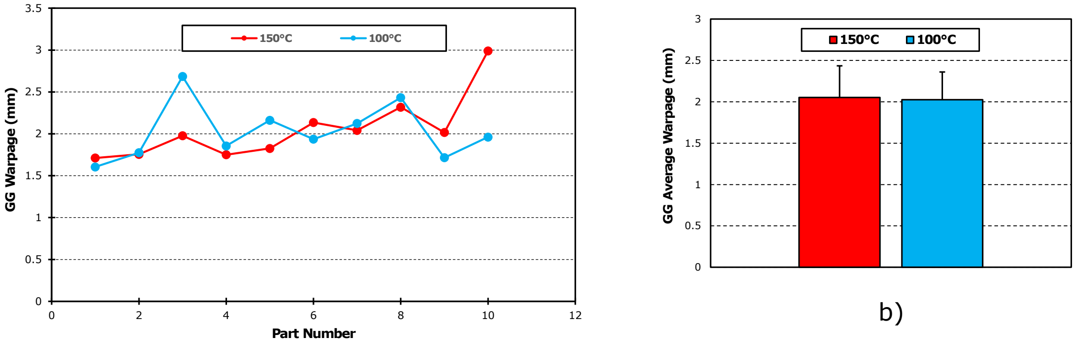
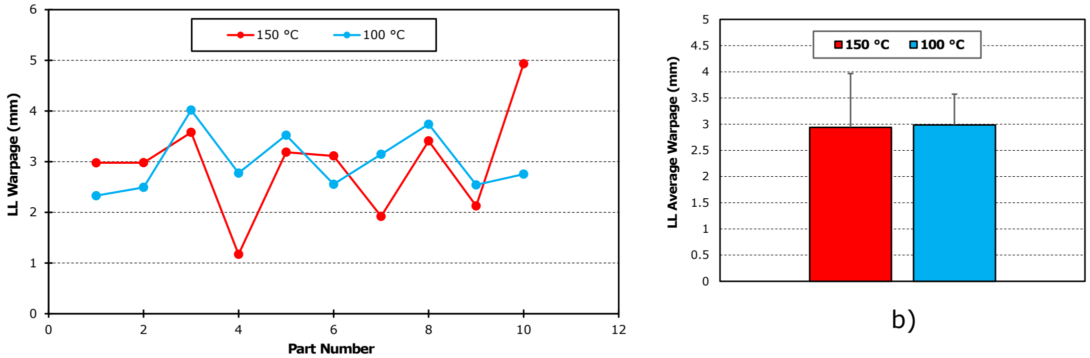
yields p = 0.87 such that it becomes apparent that mold temperature at the values defined in this study does not have a statistically significant effect on the GG warpage metric.



a) b)

Figure 14: Influence of mold temperature on GG warpage metric: a) individual part effect, b) averaged effect (error bars represent one standard deviation).

An identical analysis was performed with LL warpage metric as the output variable which also did not reveal a statistically significant effect (p = 0.9). However, in the case of the GG metric, the 150°C molding condition resulted in slightly higher standard deviation than the 100°C molding condition. The graphical representation of the LL warpage data is provided in Figure 15.



a) b)

Figure 15: Influence of mold temperature on LL warpage metric: a) individual part effect, b) averaged effect (error bars represent one standard deviation).

Taken together, these results suggest that mold temperature does not play a decisive role on either GG or LL warpage and – through extrapolation – on SBO warpage in general. Another important comment to be made is that – as indicated in a previous section – the GG metric does have a tendency to "smoothen" or "level" all deviations such that almost no difference can be detected between the two series of parts (Figure 14b). By contrast, the clear difference between the two standard deviations associated with the LL metric (Figure 15b: 1.03 vs 0.59) suggests – or at least to a certain extent – that when mold temperature is set at 100°C, the left and right flanges (defined as ROIs for the LL metric) will be manufactured with a larger degree of consistency, an observation that could be important for downstream manufacturing operations.

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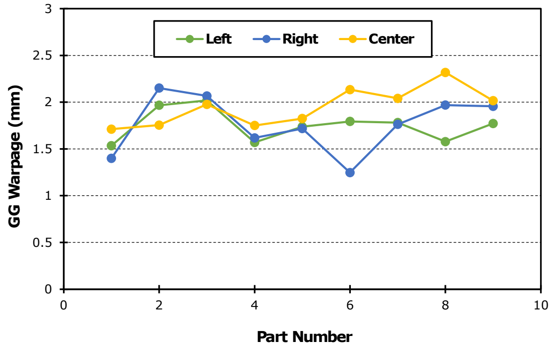
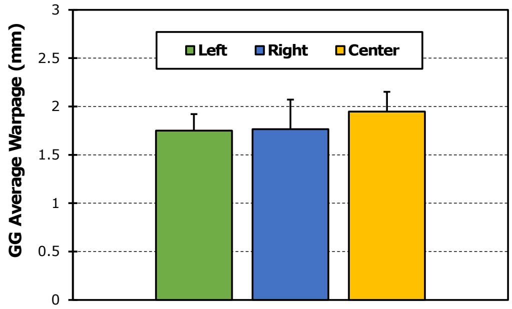
4.2 Effect of Charge Placement on Warpage

One of the steps involved in the LFT-D composite manufacturing process is the placement of the charge in the mold. While this process can be automated, there are instances in which the charge is manually placed by the operator. As a result, charge placement becomes one of the molding process parameters that could be affected by random errors. To determine whether charge placement has an effect on the warpage, three series of LFT-D SBO parts were manufactured with different charge placements (nine parts per series). All other molding parameters were held constant. The three distinct positions of the charge that were tested were simply referred to as "left", "center" and "right". The manual nature of the operation makes it inherently error prone, but the three tested positions were spaced apart generously ("left" and "right" were offset ~100mm from the centerline), such that the effect of the small placement errors associated with each of the three tested locations were deemed negligible. The rough dimensions of the charges were 400 x 100 x 45 mm and the mold temperature used was 150°C. ANOVA was used to determine any statistically significant differences between the three sets, the null hypothesis being that the means of the three series are equal.

The plot of the GG warpage metric for the three series of parts is depicted in Figure 16a, alongside with their average and standard deviation (Figure 16b). Since ANOVA yields a p value of $0.11 > 0.05$, this means that the location of the charge does not lead to a statistically significant effect as assessed by means of the GG warpage metric.

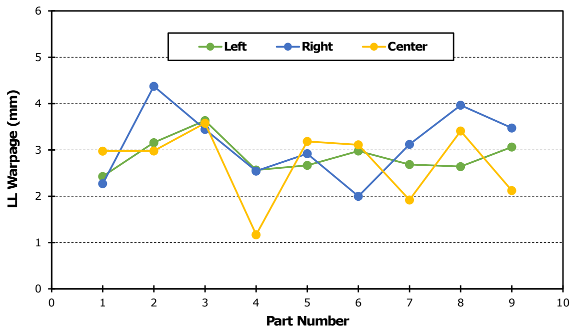


a)

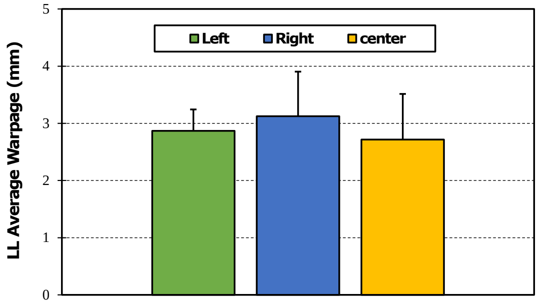


b)

Figure 16: Influence of charge placement on GG warpage metric: a) individual part effect, b) averaged effect (error bars represent one standard deviation).



a)



b)

Figure 17: Influence of charge placement on LL warpage metric: a) individual part effect, b) averaged effect (error bars represent one standard deviation).

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An identical analysis was performed with LL warpage as the output variable and also did not reveal a statistically significant effect (p = 0.56). The graphical representation of the LL warpage data is provided in Figure 17. While these results are, more or less, similar to those associated with GG metric, it can be highlighted that the standard deviation associated with the left charge placement is approximately half of the other two scenarios (0.38 vs. 0.78/0.8). This suggests that left charge placement might be able to produce more stable geometries.

In summary, while small variations in part distortion could be due to charge placement, a difference in the average value of the warpage metrics is not discernable. Furthermore, while the GG metric appears to be completely insensitive to charge placement, LL metric indicates that less variation could be achieved when the left charge placement is used.

5 CONCLUSIONS

Several conclusions and/or suggestions can be made as a result of this study:

- The global metric (GG) that accounts for all vertices of a part tend to "smoothen" any significant warpage "signals" and hence they are less useful due their reduced sensitivity (particularly when the number of vertices is extremely large).
- The GL variant appears to be more sensitive to warpage than its GG counterpart, but its sensitivity remains at low levels.
  Local (LG, LL, VR), rather than global (GG, GL) approaches appear to have an increased sensitivity to part warpage. However, the definition of the region of interest (ROI) plays an important role.
- When selecting an ROI that included areas of the part with relevance in downstream manufacturing operations (LG, LL, VR), the sensitivity of the warpage metric was enhanced.
- The VR metric, involving a manual mapping of the points bypasses common inaccuracies resulting from automatic measurements when using commercial software (Figures 5a and 11).
- When applied to the same series of parts (*i.e.*, produced with identical processing conditions), all five metrics exhibited approximately the same part-to-part variation behavior, and keep roughly the same rank order in terms of their magnitude for the various cases tested in this study: GG < (GL, LL) < LG < VR.
- While none of the analyzed warpage metrics was capable of identifying superior processing conditions for the two input variables analyzed (mold temperature and charge placement location), they could be used to identify series of parts with a more consistent warpage (i.e. smaller standard deviations of the warpage metric).

Future extensions of this work will attempt to extend the use of the proposed metrics to more complex DOE scenarios involving more input molding variables. One other direction to be investigated in the future will be focused on the automation of the procedures underlying VR calculation. Finally, while it is clear that all warpage metrics presented in the current study would have to be adapted to the geometry of the part analyzed in a different manufacturing context, the current study highlights that warpage can be defined in various ways and this might have a direct effect on downstream analyses as well as their conclusions. As such, future studies should attempt to determine more generally applicable definition of warpage, an important manufacturing characteristic that remained under-investigated until now.

ACKNOWLEDGEMENTS

The work presented in this study is the result of the collaboration between Western University (London, Ontario, Canada) and General Motors of Canada. Financial support was provided by Ontario Centers of Excellence (OCE), Natural Sciences and Engineering Research Council (NSERC) of Canada, General Motors of Canada, and Western University.

Eric J. Martin, https://orcid.org/0000-0002-6513-0055

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O. Remus Tutunea-Fatan, https://orcid.org/0000-0002-1016-5103
Ryan Gergely, https://orcid.org/0000-0003-0351-9177
David A. Okonski, https://orcid.org/0000-0003-0485-6749

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