Integrating Optical Draw-In Measurements with Finite Element Analysis for Enhanced Process Insights in Sheet Metal Forming

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Abstract. Accurate monitoring of draw-in behaviour during sheet metal forming is crucial for understanding material flow, optimizing process parameters, and validating finite element (FE) simulations. This study presents an integrated approach combining high-resolution optical measurement, laser displacement sensors, and numerical simulations to analyse draw-in variations during the first forming operation of an automotive front door inner panel. A dedicated optical system was employed to capture sequential images of the blank edge, which were calibrated and processed using computer vision techniques to extract precise draw-in values at predefined locations. The results demonstrate that optical monitoring provides reliable insights related to the sheet metal forming process, highlighting the influence of real-world process disturbances. Furthermore, the study explores the feasibility of integrating measured draw-in data into an adaptive control framework, applying artificial intelligence techniques to refine process stability. By utilizing experimental data alongside numerical predictions, this methodology enhances process understanding and enables data-driven decision-making in industrial sheet metal forming. The findings contribute to the development of intelligent forming control strategies, bridging the gap between modelling and real-world manufacturing conditions to improve product quality and production efficiency.

Keywords: Sheet Metal Forming; Draw-in; Finite Element Analysis; Artificial Neural Network.

1 Introduction

In industrial sheet metal forming, precise control of material flow is essential to ensure part quality and process stability. Variations in tribological conditions, material properties, and process parameters can significantly influence forming outcomes, leading to defects such as wrinkling, excessive thinning, or splits in the final components [1]. The automotive industry, in particular, demands highly repeatable forming processes, making real-time monitoring and adaptive control strategies increasingly necessary [2].

The blank holder force (BHF) plays a critical role in regulating material flow during forming and has been widely studied for its impact on formability [3]. Traditional approaches to optimizing BHF often rely on offline finite element (FE) analysis, which provides valuable predictions but may not fully capture real-time process variations such as dynamic changes in friction conditions [4]. To address this limitation, integrating experimental draw-in measurements with numerical simulations has emerged as an effective way to improve process understanding and adaptive control [5].

Recent advancements in optical measurement techniques, including high-resolution imaging and laser displacement sensors, have enabled the direct tracking of blank deformation at multiple locations around the part edges [6]. These techniques offer valuable data for analysing material flow and validating FE simulations, helping to identify discrepancies caused by real-world variables such as non-uniform lubrication, tooling compliance, and blank positioning [1]. Furthermore, integrating this experimental data into data-driven models, such as artificial neural networks (ANNs), can enhance prediction accuracy and support adaptive process control strategies [4].

This study investigates the use of optical draw-in measurements combined with FE simulations to monitor and analyse the blank deformation in the first forming operation of an automotive sheet metal forming process. A dedicated optical system was deployed to capture sequential images of the formed part perimeter, allowing for precise draw-in measurements at predefined locations. The collected data was compared against numerical predictions to evaluate sources of deviation and assess the reliability of optical monitoring. Additionally, the potential for integrating these measurements into an adaptive control framework was explored to support real-time decision-making in industrial forming applications.

By combining experimental data with numerical simulations, this research aims to bridge the gap between theoretical modelling and practical manufacturing conditions. The findings contribute to the

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development of more robust forming processes by improving the accuracy of material flow predictions and enabling data-driven control strategies that enhance process stability and product quality [1, 2].

2 Methods

The material used in this study is a 0.7 mm zinc-coated and lubricated mild steel CR4-ZM grade, produced according to VDA 239-100 standard. The mechanical properties were modelled using the Tata Steel Vegter material model, which incorporates strain rate-dependent hardening behaviour to accurately reflect the material's deformation characteristics during the forming process.

The experiments were conducted during the first forming operation of an automotive front door inner component, utilizing industrial stamping equipment under series production conditions [6, 7]. The actual tool geometries of the die, punch, and blank holder were digitized using a HandySCAN 700 3D scanner. The entire geometry of several formed parts and a trapped blank were performed using the same scanning equipment.

To monitor the formed part contours continuously, four high-resolution cameras were positioned to capture the blank edge contours after the first forming operation. The recorded video frames were processed with OpenCV, an open-source computer vision library, to correct for perspective distortions and extract the draw-in pattern of each individual part. The optical measurement system was calibrated using laser-scanned geometry data from several physical parts extracted from the forming process.

A calibrated laser displacement sensor, the optoNCDT 1420-200 from Micro-Epsilon, was used to measure the draw-in at a predefined location. This sensor, operating at a measurement frequency of 4 kHz with a resolution of ±1 µm, provided high-precision displacement data that was manually synchronized with the video recordings, enabling direct correlation between time-resolved and part-specific draw-in variations.

The finite element model (FEM) of the forming process was developed using AutoForm R10 [8], incorporating the Tata Steel Vegter material model alongside the measured surface geometries of the forming tools. The blank was meshed using elastoplastic shell elements with five integration points through the thickness. The initial element size was 20 mm. Automatic remeshing with five refinement levels was applied, corresponding to a minimum element size of 0.63 mm. The initial model comprised approximately 13,000 elements. At the end of the simulation, the adaptive remeshing resulted in a refined mesh of 654,000 elements. The TriboForm friction model was used to account for the influence of friction, incorporating pressure-, velocity-, and strain-dependent effects. The tribological model was defined using the TriboForm friction file "TF - Mild Steel (ZM coated) - Draw Oil" available in AutoForm R10 [8]. The model assumes a uniform sheet surface roughness of 1.0 µm, a uniform tool surface roughness of 0.4 µm, and a uniform lubricant quantity of 1.0 g/m². The FEM simulations were utilized to numerically estimate the effect of blank holder force variations on draw-in behaviour.

3 Results

Fig. 1a illustrates the projection in the XY plane of the positions of the 16 equalizer blocks of the die set used for stamping the part and the projected contours of the draw beads, the trapped blank and of one of the formed parts. The position of the blocks in this plane is indicated with numerical labels. For each of these blocks, a reference point on the trapped blank outer edge was determined as the point closest to the block's centre. The draw-in was defined as the perpendicular distance to the local tangent (illustrated as red arrows in Fig. 1b) towards the edge of the formed part, as shown in Fig. 1b. The laser displacement sensor was positioned approximately at mid distance between blocks 2 and 3 within the forming die set.

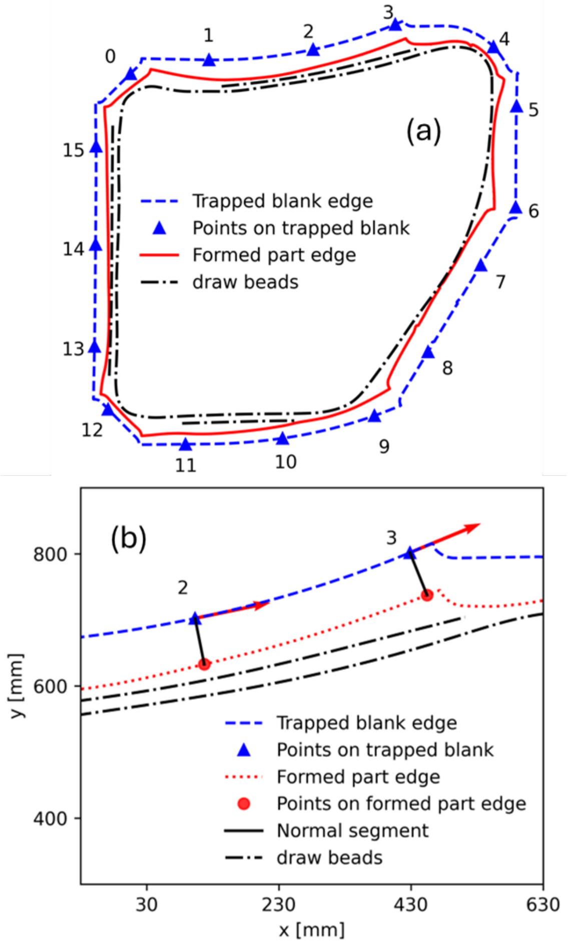

Fig. 1. (a) XY plane projection of the equalizer blocks, selected reference points, and the experimentally measured contours of the trapped blank and the formed part at a blank holder force of 1800 kN. (b) Detailed view illustrating the normal segments used to determine the local draw-in.

The die set contains draw beads, the position of which is indicated in Fig. 1. In addition to a continuous draw bead, the die set incorporates a secondary draw bead. Consequently, in some regions of Fig. 1, two lines are visible. Due to the inclined orientation of the cameras, either the outer or the inner draw bead was visible in the recorded images. The visible part of the draw beads was used where necessary in the analysis.

The images of the formed parts were captured in an idle station immediately following the first forming operation. Fig. 2 presents an example of a raw image (Fig. 2a) alongside its perspective-corrected counterpart (Fig. 2b). From each image, the positions of the part edge and of the draw bead features were extracted. It was observed that the position of the part in the idle station exhibited random variations during industrial production, rendering the absolute edge position in the image unsuitable as a reliable draw-in estimate. To address this, an alternative approach was employed: the draw bead features of each part were utilized as a reference for determining the local draw-in. The relationship between the optically measured dimensions and the actual part draw-in was established by applying a linear translation based on measurements obtained from the 3D contours of three parts sampled from the production line.

Fig. 2. (a) Raw image captured at the location of balance blocks 2 and 3 and (b) the corresponding image after perspective correction. In both images, the formed part appears in light grey, with the draw bead locations highlighted by overexposed white regions, while the surrounding area remains dark.

Fig. 3 presents the draw-in measurements obtained at the laser sensor location for 1630 consecutively pressed parts during the trial. These measurements are shown alongside the draw-in values determined through image analysis. In Fig. 3a, the individual measurements for each part are depicted, while Fig. 3b illustrates the strong correlation between the laser-based and image-based draw-in results, with a correlation coefficient of 0.96 for this dataset. The similar part-to-part fluctuations observed in both methods proves that the optical system provides reliable draw-in data.

A box plot presenting the optical data from Fig. 3 (location 2) together with four additional locations along the formed part contours, labelled similarly to Fig. 1, is shown in Fig. 4. For comparison, the FEM predictions corresponding to ±10% variations in blank holder force are also included in the figure. The experimental results indicate notable differences in relative draw-in across the specified locations: locations 2 and 9 exhibit fluctuations within ±5%, location 6 shows variations up to ±15%, whereas locations 11 and 14 experience fluctuations reaching ±10%. When compared to FEM predictions, the fluctuations at locations 2, 9, and 11 remain within the range predicted by the model. However, at locations 6 and 14, the experimentally observed fluctuations are significantly larger than those predicted by FEM.

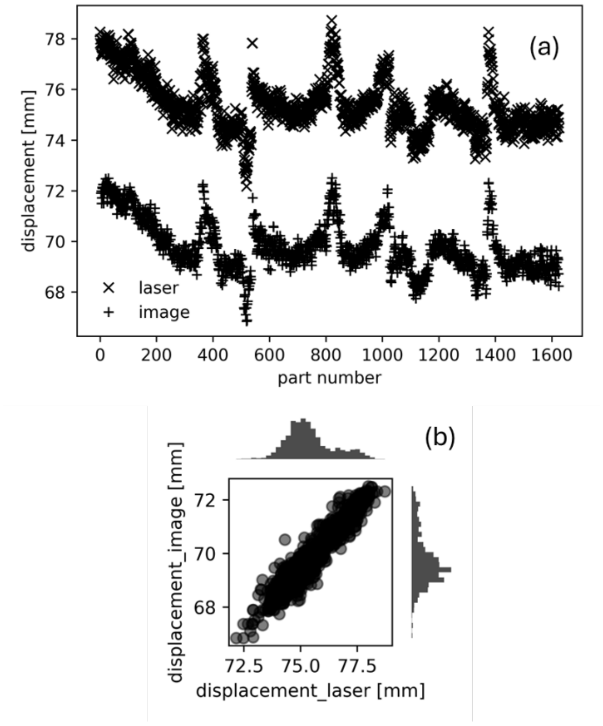

Fig. 3. Draw-in measurements recorded at the laser sensor location for 1630 consecutively pressed parts, presented alongside image-based draw-in determinations. (a) Individual part measurements demonstrate consistent part-to-part fluctuations across both methods. (b) Correlation analysis reveals a strong agreement between the two techniques, with a correlation coefficient of 0.96, confirming the reliability of the optical measurement system for in-process monitoring.

The pair correlation plots of the experimental and numerical data, shown in Fig. 5, illustrate distinct correlation patterns. Strong correlations, with coefficients above 0.8 or below -0.8, are depicted in black or dark grey, whereas moderate and weak correlations are shown in light grey. In the experimental data (Fig. 5a), the five locations along the part edge exhibit weak or negligible correlations. In contrast, the corresponding finite element model (FEM) data (Fig. 5b) demonstrate an almost perfect correlation for the similar locations. The implications of these findings, including the potential role of material variability in influencing the observed fluctuations, are discussed in more detail in the discussion section.

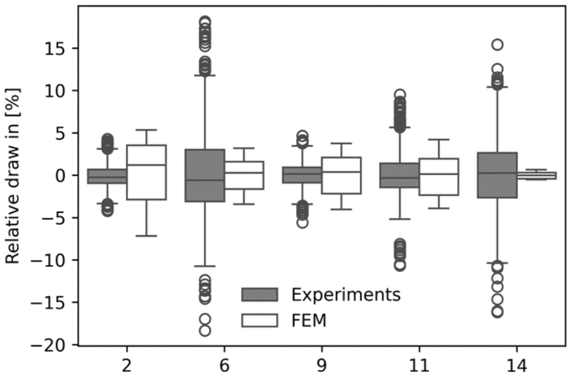

Fig. 4. Box plot comparing experimental optical measurements of relative draw-in at location 2 and four additional contour locations with corresponding FEM predictions for ±10% variations in blank holder force. Outliers, shown as individual circles beyond the whiskers, indicate values lying outside 1.5 times the interquartile range from the lower and upper quartiles.

4 Discussion

The results of this study demonstrate that the optical monitoring system is a reliable and sufficiently accurate tool for tracking draw-in variations during industrial part manufacturing processes. The system successfully captured the draw-in behaviour of 1630 consecutively pressed parts and provided measurements that correlated strongly with data from a laser displacement sensor, achieving a correlation coefficient of 0.96. This consistency indicates that the optical system can serve as a valuable diagnostic tool for monitoring and analysing sheet metal forming processes in an industrial setting.

The study's data were derived from post-processed video recordings. While this method proves effective for process diagnosis and retrospective analysis, its application in automated process control would require alternative real-time measurement techniques. Real-time monitoring could enhance process stability by providing immediate feedback to control systems, allowing for rapid intervention when deviations from the nominal draw-in behaviour are detected.

Despite relying on offline data, the optical monitoring approach offers several practical advantages. First, it presents a cost-efficient alternative to other measurement techniques, such as laser-based sensors. The affordability of high-resolution 4K cameras makes the technology accessible for large-scale deployment. Second, the system is non-intrusive; cameras are positioned on the press frame at a safe distance from the forming process, preventing any disruption to production. Lastly, the system is easily scalable, with the flexibility to integrate additional cameras to track other parameters, such as part geometry or the occurrence of necking, splitting, or buckling.

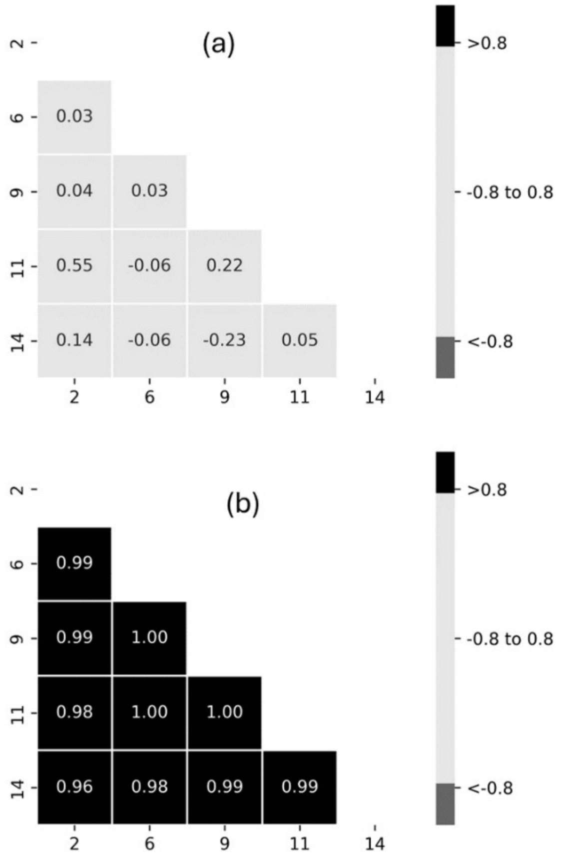

Fig. 5. Pair correlation plots of the draw-in at the five locations from Fig. 4: (a) experimental data, showing weak or negligible correlations, and (b) FEM predictions, exhibiting nearly perfect correlations for the same locations.

The optical monitoring system detected a characteristic gradual drift in draw-in values across all measurement locations during the trial, similar to the patterns shown in Fig. 3a. Both positive and negative drift patterns occurred, along with occasional abrupt changes in draw-in. These instabilities are likely attributable to variations in friction conditions caused by lubricant redistribution and temperature changes during production, material batch differences, blank holder force adjustments, and process interruptions related to blank stack changes and operator breaks. Adjustments to the blank holder force, made within a ±10% range, helped maintain stable forming conditions despite these fluctuations. The approximately 3-hour effective production run was completed without part defects. Throughout the trial, the optical monitoring system operated exclusively in monitoring mode, recording the gradual drift and abrupt draw-in changes without interfering with the manufacturing process.

The optical monitoring system can support the identification of safe draw-in ranges during production. By correlating measured draw-in variations with part quality assessments, reliable control limits can be defined. These limits can be integrated into a part quality control strategy, providing operators with clear, data-driven guidance for adjusting process parameters to maintain consistent product quality. Given these advantages, this system can be feasibly integrated into existing manufacturing lines without significant modifications.

Variations in draw-in correlations were observed between different measurement locations. These differences are likely associated with local variations in contact pressure, influenced by the mechanical stiffness of the press and die set. In practice, operators often adjust the height of the equalizer blocks to locally modulate restraining forces and ensure defect-free production. The optical monitoring system provides location-specific draw-in data, enabling more precise and efficient control of these adjustments.

The discrepancies between experimental measurements and FEM predictions (Fig. 4 and 5) indicate that the current modelling approach does not fully capture the variability introduced by real-world forming conditions. In the experiments, weak or negligible correlations were found between the draw-in measurements at different locations, contrasting with the near-perfect correlations in the FEM data (Fig. 5). This difference indicates that additional variables, such as material variability, friction inhomogeneity, and local contact pressures, contribute to the measured fluctuations. Future work could investigate these aspects in greater depth, potentially enhancing model accuracy through more advanced contact and friction models and adaptive calibration techniques.

The current study relies on established finite element models to predict draw-in behaviour; however, advanced modelling approaches could enhance the understanding of local fluctuations. The complexity of these fluctuations, influenced by factors such as lubricant migration, temperature changes, material variability and local restraining effects, makes accurate modelling challenging. Advances in Artificial Neural Networks (ANNs), a subset of Machine Learning (ML) within Artificial Intelligence (AI), offer promising solutions for capturing such complex behaviour. The combined use of larger datasets and ANN-based models, may become possible to predict draw-in variations more accurately and support the development of adaptive control strategies for improved process stability. The integration of larger datasets with ANN-based models may enable more accurate predictions of draw-in variations, facilitating the development of adaptive control strategies to enhance process stability.

The data obtained in this study serve as a foundation for ongoing work on process monitoring and control. Future research will expand dataset collection and employ advanced modelling techniques, such as ANN-based models, to further quantify relationships between material flow, friction conditions, and part geometry. Additionally, efforts will focus on real-time implementation strategies to enhance industrial applicability.

5 Conclusions

This study demonstrates the feasibility of employing an optical monitoring system to track draw-in variations in an industrial sheet metal forming process. The optical measurements, validated against a laser displacement sensor, achieved a strong correlation coefficient of 0.96, confirming the reliability of the system for industrial diagnostics. Although being based on post-processed video recordings, the monitoring approach offers practical advantages such as cost-effectiveness, non-intrusiveness, and scalability. The results show that the optical system effectively captured the gradual drift in draw-in values observed during the production run, as well as intermittent abrupt changes, indicating the evolving influence of various sources of variability throughout the stamping process.

The comparison between the experimental measurements and the finite element model (FEM) predictions revealed the inherent limitations of the FEM in replicating the complex behaviour of the real manufacturing process. While the FEM serves as a valuable tool for approximating material flow and predicting draw-in trends, it remains a simplification of the actual forming process. In the experiments, variations in draw-in were observed at certain locations, such as positions 6 and 14, where the FEM predictions did not fully capture the magnitude of these fluctuations. These discrepancies underscore the challenge of modelling the dynamic interplay of factors such as material variability, friction conditions, lubricant migration, and local contact pressures, which are naturally present in the industrial process but often approximated in the numerical models. The differences observed highlight the importance of continuously refining the FEM to better align with experimental evidence and accurately reflect the underlying mechanics of the sheet metal forming operation.

The pair correlation analysis provided additional insight into the differences between the experimental observations and the FEM predictions. In the experimental data, weak or negligible correlations were found among the draw-in measurements across different locations, suggesting a more intricate interplay of local frictional and mechanical effects. In contrast, the FEM results exhibited near-perfect correlations, indicating an overly simplified representation of the material behaviour under varying process conditions. These findings underline the importance of incorporating more realistic friction and contact pressure models into future simulation efforts.

The monitoring system, despite operating exclusively in a passive, observation-only mode, effectively documented the draw-in variations without disrupting the manufacturing process. The collected data revealed a pattern of gradual drift and occasional abrupt shifts, emphasizing the potential of optical monitoring systems for detecting and understanding process variations in real-time. The ability to track these variations during normal production conditions suggests that such systems can provide valuable feedback for process optimization and quality assurance.

Future research should focus on implementing real-time measurement capabilities to facilitate immediate feedback and adaptive control in sheet metal forming operations. Enhancing FEM calibration by integrating directly measured contact pressure distributions and refining the lubrication modelling approach will likely improve the predictive accuracy of the simulations.

Additionally, the application of Artificial Neural Networks (ANN) presents an opportunity to better capture the complex relationships between material flow, friction conditions, and part geometry. Further work should also aim to define safe draw-in ranges based on the collected data, enabling the establishment of more robust control limits to support consistent product quality.

In conclusion, this study establishes a foundation for advancing the use of optical monitoring systems in industrial forming processes. The demonstrated correlation with laser-based measurements, coupled with the system's ability to identify draw-in variations, suggests that such systems can be valuable tools for both diagnostic and control purposes. With continued development, including the integration of real-time measurement capabilities and more sophisticated modelling techniques, these systems have the potential to significantly enhance process stability and part quality in automotive sheet metal forming applications.

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