Development of a machine learning algorithm for geometric compensation of Single Point Incremental Forming (SPIF) process

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Abstract. Single Point Incremental Forming (SPIF) is a highly versatile sheet metal forming process that enables the production of complex geometries without requiring dedicated tooling. This flexibility has attracted significant interest, particularly in project prototyping and medium-scale industries. In the medical sector, for instance, where it can be used to manufacture anatomically customized prostheses and in the aerospace sector, where it can be used to produce complex lightweight panels. However, the inherent elastic recovery in SPIF processes presents a significant challenge, often resulting in over- or under-formed components. Conventional linear compensation methods fail to achieve satisfactory geometric accuracy, while iterative geometric modulation compensations are resource-intensive and time-consuming, making them less practical for industrial applications. This study outlines the development of a machine learning algorithm designed to generate optimized CAD geometries, minimizing geometric deviations in SPIF-formed components. The algorithm's performance will be validated through the production of fixed and variable-angled cones and pyramids using AW6082-O aluminium sheets. These formed components will be scanned and compared to their theoretical geometries, demonstrating the effectiveness of the proposed approach.

Keywords: Single Point Incremental Forming; Machine learning; Springback; Geometric compensation.

1 Introduction

In the context of Industry 4.0, research is increasingly focused on sustainable, flexible, and autonomous manufacturing systems that adapt rapidly to market demands with high efficiency and minimal investment. Single Point Incremental Forming (SPIF) exemplifies this trend by incrementally deforming a flexible metal sheet using CNC machines or robotic arms programmed with G-codes, thereby eliminating the need for dedicated dies. Since 2005, advances in hardware and demonstrations of SPIF's ability to exceed conventional forming limits [1,2] have renewed interest in its application for small-batch or prototype production of complex geometries.

However, SPIF is challenged by a lack of standardized procedures, due to variability in machines, materials, and process parameters, and unpredictable outcomes in surface finish, thickness, and springback, which compromise dimensional accuracy in ductile metals. To address these issues, machine learning (ML) techniques (including Support Vector Machine, Convolutional Neural Network, and Multivariate Adaptive Regression Spline) have been employed to predict forming forces, classify part quality, and adjust CAD geometries [3–6]. Given the limited experimental datasets, data augmentation is frequently used.

This work applies ML algorithms to generate a corrected CAD geometry for SPIF-fabricated parts. Specifically, for a single-stage process using AA6082-O sheets with 2 mm thickness, a multivariable quadratic regression model is developed to predict the necessary tool diameter to achieve a truncated cone with a 100 mm diameter, a 60° wall angle, and a 52 mm height. Consistency is maintained by using identical process parameters and collecting data only after complete elastic recovery.

2 Methodology

2.1 G-code Generation and Toolpath Definition

For successful SPIF, selecting a combination of parameters that lead to non-fractured parts is crucial. The toolpath parameters include a fixed feedrate (2000 mm/min) with free spindle speed, a 0.5 mm stepdown, and a spiral strategy. Two G-code paths were generated and run on a Mini-Mill2 machining center, one with a 10 mm tool diameter and another with a 12 mm diameter. Because the study used only 12 mm tool, the

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10 mm path led to a constant 0.5 mm compensation normal to the surface to counteract elastic recovery. It is in order of this compensation that the model will be generated and, therefore, output the needed tool diameter that, running the same toolpath, will achieve the ambitioned geometry.

2.2 Scanning and Geometry Comparison

A Calibri mini handheld scanner was used to capture the part's 3D geometry. The scanner projects blue LED lines to generate a point cloud, which is then processed into a 1.2 mm resolution mesh (with 5 mm hole filling) and exported as an STL file. The part is scanned with its deformed side up, and tracking stickers ensure proper spatial registration. For each produced part, this procedure was repeated 3 times.

In SOLIDWORKS, the scanned mesh is aligned with the theoretical model by defining the undeformed sheet plane (via three selected points) and extracting an intersection curve to determine the axis of symmetry. Radial cuts then provide measurements of wall angles and overall height for comparison. These measurements, 4 angles and 1 height (retrieved from 4 sections) as illustrated in Fig.1, are then concatenated into datasets for further analysis.

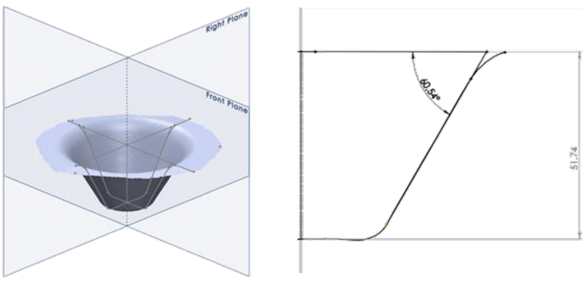

Fig. 1. Scanned geometry analysis: radial cuts of the scan (left); collected measurements of the scan (right).

2.3 Machine Learning for Compensation

Addressing the multivariable nature of SPIF compensation, a predictive regression model was developed to estimate the required tool diameter based on the target wall angle and part height for a fixed toolpath. Due to constant toolpath parameters, the dataset was simplified to three main features—diameter, angle, and height, and processed via three approaches. In the first one, each angle is assigned to its respective height. In the second approach, each scan angle is averaged. In the third option, the angle with the furthest value from the average was eliminated.

The best-fitting model made use of the outlier free dataset, computing an $R^2 = 0.4763$. For this example, the predicted tool diameter is 19.74 mm for a wall angle of 60° and a depth of 52 mm.

3 Conclusions

Although the current model produces results, several limitations must be addressed to develop a robust solution. First, the present approach for diameter compensation is limited, specifically by the availability of the tooling and/or compatibility with the machine's fixation system. Additionally, excessive compensation can cause tool-backplate intersection, potentially damaging the material, support or tool and, as Fig. 2 suggests, that state of compensation is quickly achieved due to the small data sample.

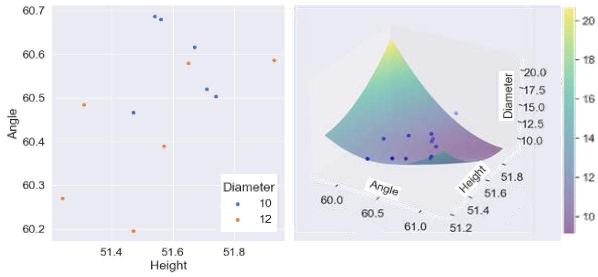

Fig. 2. Disposition of the collected data in a scatter plot (left); Quadratic model surface in a three-dimensional space vs the collected data (right).

Future research will focus on expanding the experimental conditions by producing parts with varied wall angles and heights. This will enable the development of a regression model that predicts an input CAD geometry to obtain the desired part. Additionally, varying toolpath parameters will enable the construction of a correlation matrix to better understand and optimize process influences and allow for a Neural Net generation.

Enhancements in the data collection stage are also critical. Current scanner and mesh generator resolutions are close to the magnitude of the part deviations, challenging the model's accuracy. Adjustments are necessary despite the associated increases in processing time and data complexity.

Lastly, alternative feature extraction methods, for instance, processing the complete scan, should be investigated to further reduce errors, allowing for the study of more complex geometries.

References

1. J. M. Allwood, G. P. F. King, and J. Duflou, Proc. Inst. Mech. Eng. B: J. Eng. Manuf. **219**, 239 (2005).
2. J. Jeswiet, D. J. Young, and M. Ham, Adv. Mat. Res. **6–8**, 409 (2005).
3. P. E. Romero, O. Rodriguez-Alabanda, E. Molero, and G. Guerrero-Vaca, J. Mater. Res. Technol. **15**, 1562 (2021).
4. D. W. W. Low, A. Chaudhari, D. Kumar, and A. S. Kumar, J. Intell. Manuf. **34**, 2373 (2022).
5. D. Chen, F. Coenen, Y. Hai, M. P. Oscoz, and A. Nguyen, in **Lect. Notes Netw. Syst**. (2024), pp. 1–13.
6. A. K. Behera, J. Verbert, B. Lauwers, and J. R. Duflou, Comput. Aided Des. **45**, 575 (2012).