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# Predicting 2D Data: Using conditional Generative Adversarial Networks in Incremental Sheet Forming

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*Incremental Sheet Forming (ISF) is a flexible sheet forming process which utilizes a moving forming tool to incrementally deform a metal sheet into the desired geometry. The elastic recovery of the material after deformation causes a spring-back effect to occur during the process, which contributes to significant geometrical error in the final shape. In this paper, we present the use of a conditional Generative Adversarial Network (cGAN) trained using empirical data to predict such errors. Using only the 2D depth map of the target geometry, the network generated 2D predictions of the final geometry. This differs from other prediction models in that it doesn't require handcrafting of parameters describing the local geometry, making it more compatible with complex free-form geometries. Experimental investigations reveal that the network was able to generate predictions of untrained geometries with 83.9%-99.6% accuracy. Subsequently, we demonstrate a case study for the use of the prediction to improve geometric accuracy. This paper would be useful to researchers considering empirical modelling of 2D data.*

**NOMENCLATURE**

ISF = Incremental Sheet Forming
cGAN = conditional Generative Adversarial Network
CNN = Convolutional Neural Network
CAD = Computer-aided Design
CAM = Computer-aided Machining
RMSE = Root mean squared error

## 1. Introduction

Sheet metal products are ubiquitous in aerospace, automotive, and marine industries because of their low cost, lightweight, and functional effectiveness [1]. Conventional fabrication of these products is done by stamping, where a rigid punch and die are used to permanently deform a flat sheet into the desired geometry. However, these tools are expensive to manufacture, which makes them economical only in mass manufacturing applications. Consequentially, this makes the process unsuitable for low-volume applications like prototyping, repair, and personalized products.

Incremental sheet forming (ISF) is a flexible sheet forming process that eliminates the need for the die. ISF uses a moving forming tool to incrementally deform a sheet metal over a specified toolpath corresponding to the target geometry. This is advantageous as it not only removes the need to fabricate costly dies, but also minimizes storage costs as products can be stored digitally instead of in dies [2].

While ISF has tremendous potential in this regard, a big problem with the process is the poor geometric accuracy obtained after forming. This largely stems from an assumption made during the forming toolpath generation. ISF toolpaths are commonly made using computer-aided machining (CAM) milling software, which generates a toolpath across the surface of the target geometry. However, this approach assumes that there is no elastic recovery of the sheet material after permanent deformation. Because of this, a spring-back behaviour can be observed on the geometry after forming, causing severe changes in the resultant sheet geometry.

In this paper, we present a novel approach to predict the complex ISF deformation behaviour using a conditional Generative Adversarial Network (cGAN) with Convolutional Neural Networks (CNNs). We first provide a review of relevant literature on addressing the ISF geometric error. Subsequently, we detail our methodology, data curation, and training process. We then report on the results from experimental validation.

### 1.1. Literature Review

Because of the poor forming accuracy, ISF cannot be reliability applied in precision-sensitive applications. Researchers have adopted several approaches to predict the spring-back error, which would be reviewed in this section.

The Finite Element Method (FEM) is a commonly used approach when trying to model the deformation process through mathematical modelling. Moser, et al. [3] used FEM to efficiently simulate double-sided ISF, where they found poor agreement with experimental results. Kulkarni and Mocko [4] also utilized FEM in simulating heat-assisted ISF, which reported an accuracy of 0.378mm root mean squared error (RMSE), albeit with a computation time of 121 hours. Guzmán, et al. [5] proposed the use of the Gurson-Tvergaard-Needleman model in simulating ISF process. The researchers found that whilst the model had shown good agreement for a line geometry, it did not perform as well in a conical geometry. In literature, the FEM approach in modelling ISF is still relatively unproven in complex free-form geometries. Additionally, FEM also consumes a significant amount of time, in most cases forming the part would be faster than numerical simulation.

Instead of using FEM, another approach to generating ISF predictions is by applying statistical models on empirical data. Khan, et al. [6] noted the importance of parameterizing the local geometry for empirical modelling. They proposed a rule-based classifier that predicts deviation using position and 8 qualitative labels of the neighbouring points. Therefore, specific details such as the magnitude of neighbouring points or points outside of these 8 coordinates are neglected. Behera, et al. [7] presented the use of multivariate adaptive regression splines to predict deviation in STL vertices. By separating the target geometry into planar features with the wall angle, the deviation was predicted. This approach is strictly constrained by the combination of features the target geometry must have, greatly reducing its applicability for general use. Möllensiep, et al. [8] reported on the use of exponential Gaussian progress regression in heat-assisted double-sided ISF. The researchers used 8 parameters to predict the geometric deviation at each individual toolpath coordinate. Consequentially, this approach to prediction is strictly constrained by the initially generated toolpath, therefore the geometric deviation of regions outside of these specific coordinates is not visible.

In these works, researchers have shown different approaches to parameterizing forming geometries to predict forming errors. Effective parameterization of the forming geometry appears to be paramount to the accurate prediction of ISF geometric error. However, these approaches lack a means to effectively parameterize the entire forming geometry for error prediction of the entire ISF part. A likely reason might be due to the large size of input data make it challenging to implement on many statistical models.

Recently, artificial neural networks have sparked significant interest in research because of their strength in modelling highly complex systems. Inspired by the biological brain neurons, McCulloch and Pitts [9] first proposed a basic concept which was further refined later by Rosenblatt [10] in the form of a perceptron. When these layers are stacked sequentially, deep learning was realized [11], which greatly improved the capabilities of modern artificial neural networks. In 1980, Fukushima [12] proposed what is now regarded as a Convolutional neural network (CNN), which is a class of artificial neural networks. CNNs use convolution kernels that slide across input features to generate a feature map and are used commonly with image or video data. A well-regarded example of CNN is ImageNet [13], which outperformed other competing networks in classifying a database of 1.2 million images into 1000 different classes. While impressive, such networks purely make a single classification prediction based on an image. In 2014, Goodfellow, et al. [14] conceptualized the Generative Adversarial Network, which generated realistic predictions based on a training set. This was done using a duelling network architecture where a generator is constantly trying to fool a discriminator, which attempts to separate real from generated images. Subsequently in 2016, Isola, et al. [15] utilized a similar network but in a conditional setting to realize image to image translation tasks. Skip connections were added between specific layers to mitigate information loss. They also used a combination of the L1 distance and discriminator for the training objective. In their work, they demonstrated realistic image predictions from a myriad of problem sets.

In this paper, we present the use of cGAN in predicting the resultant ISF formed part given the input CAD geometry. To the best our knowledge, this differs from other published approaches in that the entire CAD geometry is taken into consideration in the modelling and subsequent prediction of the forming error.

## 2. Methodology

We introduce an ISF error prediction framework (Fig. 1) using cGAN which uses 16-bit depth images of the CAD to predict the ISF forming outcomes in the form of another depth image.

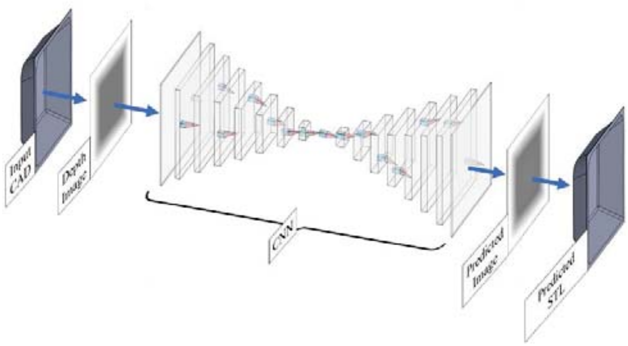


Fig. 1. Prediction model

### 2.1 Generating 2D Depth Images

First, there was a need to convert the 3D forming geometries into a 2D image for use in the cGAN model. First, the CAD data is converted into a triangulated surface and then saved as an STL file format using SOLIDWORKS. A MATLAB script was then developed to fill a 256x256 pixels greyscale image with the depth values of the given STL file. The ray-triangle intersection algorithm [16] was used to determine intersections between these pixels and the triangles. The post-ISF forming images were also generated similarly, with the STL instead generated from PolyWorks metrology software.

### 2.2 cGAN Model

We utilize a well-established cGAN model developed by Isola, et al. [15], which was shown to be effective in performing image to image conversion tasks. The cGAN model uses a generator with a U-Net encoder (C64-C128-C256-C512-C512-C512-C512-C512) and decoder (CD512-CD1024-CD1024-C1024-C1024-C512-C256-C128). The discriminator uses a PatchGAN structure for the discriminator.

A limitation in this original model is the use of only 8-bit images. While this is acceptable in its previous application, this resolution is inadequate when considering its application to ISF. With 8-bit images, the quantization process results in a depth resolution of $234\mu m$ when mapping the 8-bits from a depth range of 0 to 60mm. We adopted 16-bit images instead, which improves this resolution to less than $1\mu m$.

### 2.3 Data curation and model training

A series of forming experiments were conducted to generate data for training. The ISF setup used (Fig. 2) consisted of an ABB robot arm with a 15mm hemispherical ball forming tool attached to the end-effector. The sheet metal used was a 325x325x1mm AL6061, which was annealed and lubricated prior to forming.

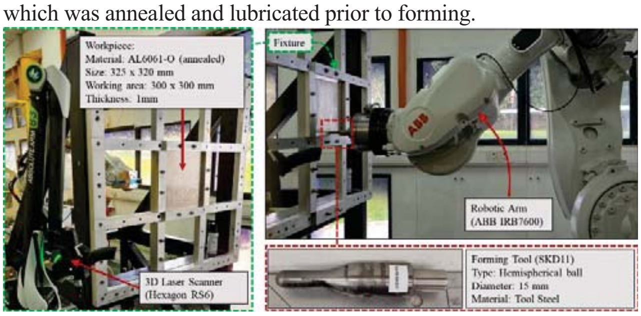


Fig. 2. ISF setup

A wide variety of forming geometries (Fig. 3) was formed for training data. This consisted of geometries with varying wall angles ($40°, 50°, 60°$), fillet radiuses ($7.5, 15, 25, 50mm$) and wall features (straight and stepped). To increase the data collected, these geometries were measured at 10mm intervals up to 50mm. Surface measurement was done on the forming side using a 3D laser scanner (Fig. 2).

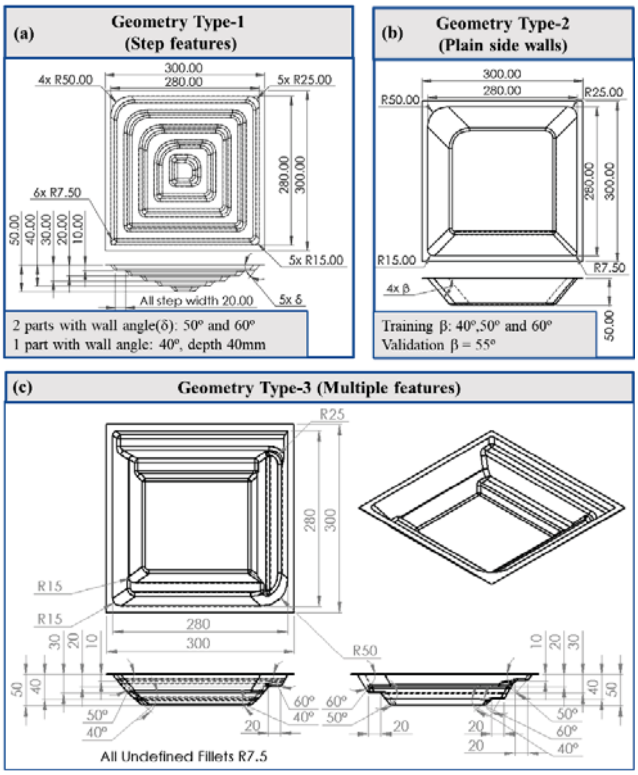


Fig. 3. Forming geometries.

After converting these 3D measurements to depth images (Section 2.1), data augmentation was applied to further increase the amount of data. Specifically, more images were created by rotation and mirroring the images. In total, there were a total of 272 pairs of CAD and post-ISF images for training.

The training was done over 1750 epochs and a linearly decaying learning rate was implemented in the final 1000 epochs. An Intel Xeon W-2113 CPU with NVIDIA Quadro P4000 graphics card completed the training in approximately 15 hours.

## 3. Experimental validation

Experimental validation was performed on two different geometries. Two untrained geometries were used in validation: a wall angle ($55°$) version of geometry type 2 (Fig. 3b) and a new combination of various features of type 4.

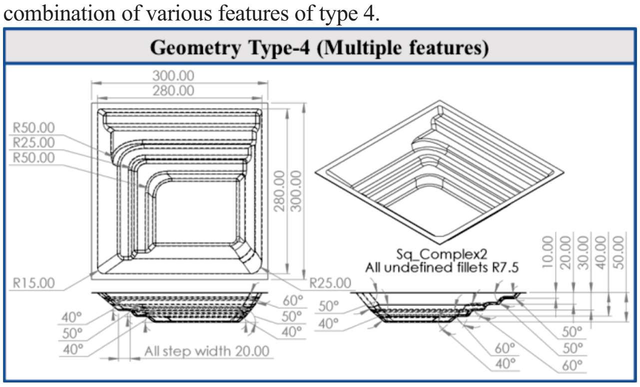


Fig. 4. Validation geometry

The results of the predictions are summarized in Fig. 5, where the actual root mean squared error (RMSE) of each geometry is indicated along with the accuracy of the prediction. In this case, accuracy was determined using (1).

$$\% \, Accuracy = 1 - \frac{|Actual - Predicted|}{Actual} \tag{1}$$

## 4. Early work on improving ISF accuracy

While being able to predict forming accuracy is important for improving the process, a means of improving the forming accuracy would be significantly more beneficial. In the geometries formed, we observed under-formed regions, especially in the angled walls. We theorize that inducing increased forming forces in these regions can have a positive impact on forming accuracy.

Making use of the earlier prediction of geometry type 2 (50°), we inversed the errors of under-formed regions and converted the depth image back into a 3D STL. The accuracy of prediction obtained for this specific geometry was 99.3%. A new forming toolpath was then generated on the morphed 3D STL, and we found a 32.4% decrease in wall RMSE by performing this geometrical compensation (Fig. 6). We hope to complete a more detailed study on this compensation approach in the future.

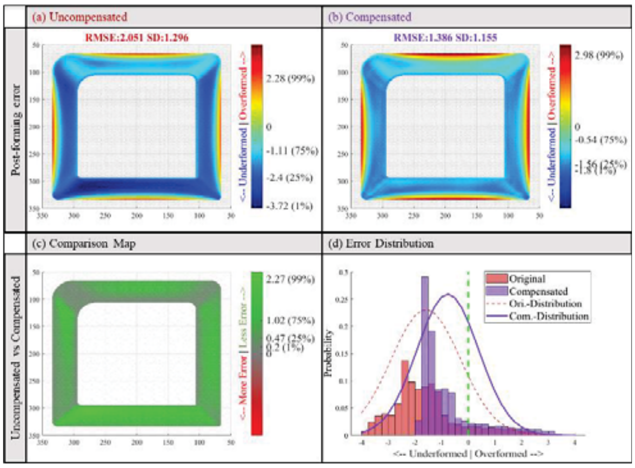


Fig. 6. Compensation results

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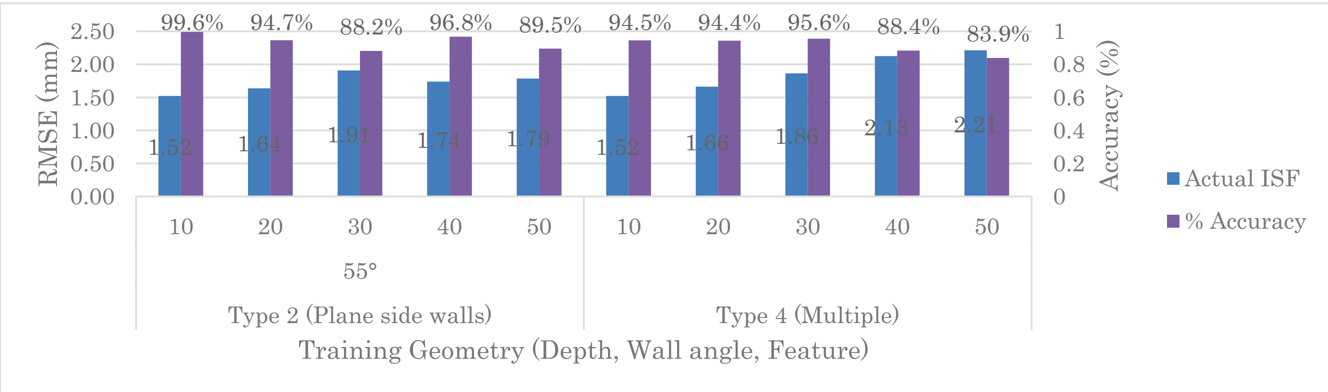


Fig. 5. Prediction results

## 5. Conclusions

When compared to conventional stamping processes, ISF excels in the economical low-volume fabrication of sheet metal products. However, poor geometric accuracy still remains a significant problem in ISF. In the presented work, a CNN based network with a cGAN architecture was used to model post-ISF outcomes. With the error prediction obtained, we also demonstrated the use of selective geometric morphing to realize an improvement in forming accuracy.

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