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Prediction of Geometric Errors of Stamped Sheet Metal Parts Using Deviation Field Decomposition

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Abstract

Stamping process is widely used to fabricate sheet-metal components. Due to the intrinsic nature of sheet-metal parts, it is usually difficult to control the quality of the final shape, surface defects or geometric errors. Additionally, to meet tight GD&T specifications, a proactive prediction technique is required to estimate global/local geometric defects caused by manufacturing steps. Current best practice relies on manual trial-and-error approaches which are far to be optimal and are costly and time consuming. This paper proposes a *model-driven* methodology to forecast geometric errors for given set of process parameters (*forward process*), and consequently optimise (*feedback process*) the process parameters to achieve given quality standards. The methodology is based on: (i) experimental investigation with varying process parameters and subsequently, deviation field extraction by mapping high density Cloud-of-Points with nominal CAD model; (ii) deviation field decomposition; (iii) surrogate model development by mapping decomposed deviation field to process parameters. An industrial case study is used to validate the methodology.

Keywords

Sheet Metal Stamping, Geometric Errors, Deviation Field Decomposition, Surrogate Modelling

1 INTRODUCTION

Sheet metal forming process, such as stamping, is prone to various defects unless the process parameters, forming tools and material variations are optimised and kept under control. Defects can be classified into local (i.e. cracks, wrinkles, cosmetic defects) and global (i.e. dimensional and geometric errors) defects. This paper focuses on geometric errors since they are imputed to impact assemblability and subsequently poor quality of final products [1] [2]. Geometric errors are the result of material or manufacturing process variations such as spring-back errors, fabrication parameter variations [3].

The industrial practice for setting up the process parameters is mainly based on the manual trial-and-error adjustments [4] [5], which involve repetitive experimental tests and multiple parameter tuning. As a consequence, it leads to higher ramp-up time and production cost.

Recently, Finite Element Method (FEM) techniques have been utilised to predict sheet metal defects and to reach optimal and robust design solutions. Many simulation tools are also available to simulate the sheet metal stamping process, such as AutoForm, HyperForm, DYNAFORM, PAM-STAMP, FASTFORM. However, those tools alone does not provide the complete solution to achieve automatic process control and adjustment as demanded by modern manufacturing process (as demonstrated by recent trends in Industry and Academia: Smart Factory, Industry 4.0, Connected Factory, The Factory of the Future [6] [7]). This implies the need

to systematically integrate monitoring strategies (both in-line and off-line sensor data) and *model-driven* process control strategy to achieve near-to-zero defect during manufacturing processes.

Figure 1 shows the general framework for closed-loop process control by combining data (such as dimensional and/or geometric product information collected using surface-based scanners) and *model-driven* process control approach.

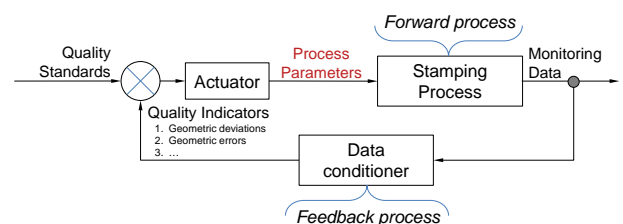


Figure 1 - General framework for closed-loop process control of sheet metal parts.

Model-driven closed-loop process control is understood as capability to keep the process in control by inferring corrective actions through sensing the process (i.e., data collection) and enhancing those data (*data conditioning*) by prediction models. Classical process control strategies are only based on sensing techniques. Although data collection is a necessary step for process control, it is not sufficient for closed-loop control, because of the complex nature of the stamping process along with the inherent variation of *product* (i.e., material thickness) and *process* (i.e., speed, blank holding force) parameters.

This paper provides contribution towards closed-loop process control by identifying the relationship between the geometric errors and product/process parameters. Thereafter, the established relationship can be utilised to isolate the faults and take corrective actions. This will allow to forecast geometrical variations for given set of process parameters (*forward process*), and consequently optimise (*feedback process*) the process parameters to achieve given quality standards.

Current literature is mainly limited to process characterisation with no clear approach to achieve forward and feedback analysis. For example, in order to analyse the dimensional quality of sheet metal parts, Zhou and Cao [8] measured 28 discrete points with varying inner tonnage, outer tonnage and punch speed. The work has then been extended by Majeske and Hammett [4], where they showed the process variation related to 16 discrete output features (point features) for sheet metal stamping. Further, Zhang, et al. [9] investigated the effect of press tonnage, nitrogen pressure and shut height on waviness of the stamped part.

Further, attempts have been made to predict and control springback errors by adapting neural network training based on finite element simulation or experimental data sets. Cao, et al. [10] developed a springback control system using artificial neural networks to control springback in channel forming process. The proposed numerical simulation results are validated experimentally by Viswanathan, et al. [11]. Liu, et al. [12] predicted springback angle of U-shaped parts under varying process parameters. Few closed-loop variation control strategies have been reported in literature [13]. However, the available neural networks approaches fail for complex part geometry and correlation with overall surface quality is missing. Some work has been also oriented to control stamping process by integrating ANN and FEM as documented in [14].

Recently, multivariate statistical techniques have also been adopted to interpret data and extract significant patterns. In [15] the current state-of-art in multiple fault diagnosis based on data-driven methods (such as Principal component analysis (PCA), correlation clustering, least squares, designed component analysis (DCA) and factor analysis) for sheet metal assembly is presented. While PCA is adapted to reduce the large dimensionality of the original data set (measurements), the decomposed orthogonal principal components may not have a physical interpretation related to faults. On the contrary, DCA requires a previous knowledge of the process in order to construct the fault pattern but it offers a close prediction for fault diagnosis and it is lesser sensitive to measurement noise than PCA.

Unfortunately, there is a lack of proper methodology which can correlate the product and process parameters with the entire surface based geometric

errors and it remains unexplored. The following challenges have been identified: (i) unavailability of a parametric approach correlating the measured geometric errors with product and process parameters; (ii) characterisation of the effect of individual process parameters on geometric errors; and, (iii) analytical representation (surrogate model) of the relationship between geometric errors and process parameters.

This paper addresses those challenges by decomposing the captured data into orthogonal error modes and uses the modes as a parametric approach to represent the geometric errors.

The remainder of the paper is organised as follows: Section 2 proposes the methodology, Section 3 demonstrates the methodology with an industrial case study, and Section 4 draws final remarks.

2 METHODOLOGY OVERVIEW

The proposed research methodology is summarised into three major steps as follows:

- *STEP 1* involves the experimental characterisation of the stamping process by varying process parameters. Thereafter, the geometric errors of stamped parts are captured and deviation field is obtained.
- *STEP 2* decomposes the deviation field into orthogonal geometric error modes.
- *STEP 3* develops analytical surrogate model by linking process parameters to decomposed deviation field. The proposed surrogate model can be used to narrow down root causes of failure, usually unforeseen if only based on heuristic approaches.

2.1 STEP 1: experimental characterisation

Design of Experiments (DoE) is adopted to characterise the geometric errors under varying process parameter conditions. To capture geometric errors, 3D optical scanner is used which captures millions of data points (Cloud of Points-CoP) representing the entire surface information. To obtain the *deviation field*, the CoP is mapped onto the nominal CAD model. The nominal CAD model is represented through polygonal mesh geometry. Deviation field is calculated for each node of the mesh model, by using the morphing mesh technique, as originally proposed in [16].

The calculated deviation field is non-parametric by nature which cannot be directly linked to process parameters. Therefore, to develop a parametric model of the deviation field, extraction of geometric features from the deviation field is necessary. Assuming m number of mesh node, and p number of DoE experiments, the deviation field (D) can be expressed as in Equation (1), where, $D_{z,j}$ denotes z th node deviation of p th experimental sample.

$$D = \{D^{(1)} \quad D^{(2)} \quad \dots \quad D^{(p)}\}; \quad D^{(j)} = \{D_{z,j}\} \quad (1)$$

$$\forall z = 1, 2, \dots, m; \quad \forall j = 1, 2, \dots, p$$

2.2 STEP 2: deviation field decomposition

Past research shows that few attempts have been made to develop parametric model for geometric errors. They can be categorised as *Explicit Parametric Models* (EPM) and *Implicit Parametric Models* (IPM).

The Bezier's surface, non-uniform rational basis spline (NURBS) patches, polynomial surface fitting are few EPMS where the geometric errors are directly controlled by key points [17] [18] [19]. These models fail to represent accurate reconstruction of geometric errors as few control points are insufficient to model complex 3D geometry.

On the contrary, IPMs attempt to decompose the deviation fields into functional parameters. IPM uses various function bases (e.g., signal characterisation techniques) to characterise and decompose the geometric errors into parametric error modes [20] [21] [22]. Till date the developed IPM's methods are mainly limited to geometric error characterisation [23] [24] and to assembly processes [25] [26]. However, there is lack of approaches to link error modes with stamping process parameters.

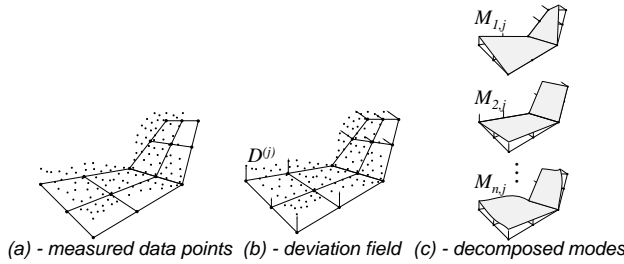


Figure 2 - Pictorial representation of the deviation field decomposition.

This paper implements Geometric Modal Analysis (GMA) [22] to decompose geometric errors into orthogonal error modes. Decomposed modes can be parameterised by means of its values to represent geometric variation associated with the parts produced through varying process parameters. GMA uses 3D Discrete-Cosine-Transform (3D-DCT) as main kernel to decompose the deviation field into significant error modes. Figure 2 shows the main steps to decompose the deviation fields into significant error modes. Due to orthogonality of the error modes, they can be varied independently to fit different set of geometric errors by changing the amplitude of the modes. A set of decomposed modes for p number of experiments is defined as in Equation (2), where n is the number of modes. The transformed modes is expressed as a function of the given deviation field, as in Equation (3), where F denotes the *decomposition function*.

$$M = \{M^{(1)} \quad M^{(2)} \quad \dots \quad M^{(p)}\}; \quad M^{(j)} = \{M_{t,j}\} \quad (2)$$

$$\forall t = 1, 2, \dots, n; \quad \forall j = 1, 2, \dots, p$$

$$M_{t,j} = F(D^{(j)}) \quad (3)$$

2.3 STEP 3: analytical surrogate model

The parametric nature of decomposed error modes shows clear advantage to link with the stamping process parameters, SP (see Equation (4)), where N_{SP} is the total number of process parameters.

To identify the relationship between process parameters and error modes, analytical surrogate model is developed for each error modes.

$$SP = \{SP^{(1)} \quad SP^{(2)} \quad \dots \quad SP^{(p)}\}; \quad SP^{(j)} = \{SP_{s,j}\} \quad (4)$$

$$\forall s = 1, 2, \dots, N_{SP}; \quad \forall j = 1, 2, \dots, p$$

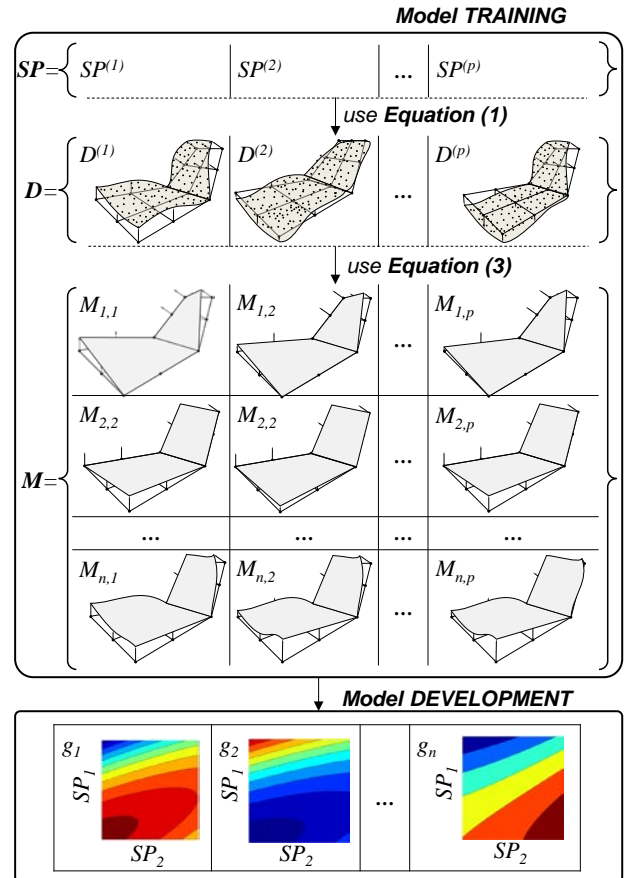


Figure 3 - Pictorial representation of analytical surrogate model development.

The t th mode can be expressed as function (g_t) of a set of stamping parameters ($SP^{(j)}$). The analytical function (see Equation (5)), g_t is computed in two consecutive phases (see Figure 3): (i) model training; and, (ii) model development. *Model TRAINING* uses experimental data from the experimental characterisation (see **STEP 1** of the methodology). *Model DEVELOPMENT* identifies the analytical relationship between process parameters and error modes, as stated in Equation (5). Adaptive

polynomial fitting, spline or Kriging methods can be utilized for this purpose [27].

$$M^{(j)} = g_j(SP^{(j)}), \forall j = 1, 2, \dots, n \quad (5)$$

$$D^{(j)} = \text{inv}F(M^{(j)}) \quad (6)$$

By combining Equation (1) (3) and (5), a parametric relationship can be established between any deviation field and stamping parameters as noted in Equation (6), where, *invF* denotes the *inverse decomposition function*.

3 INDUSTRIAL CASE STUDY

Applicability and effectiveness of the proposed methodology has been demonstrated with an industrial case study. The selected top-hat geometry with nominal polygonal mesh geometry is shown in Figure 4(a). The steps of the methodology are explained as follows:

3.1 STEP 1: experimental characterisation

A set of top hat parts has been stamped varying stamping parameters (see Table 1): (i) material thickness (SP_1); (ii) blank holding force (SP_2); (iii) stamping speed (SP_3).

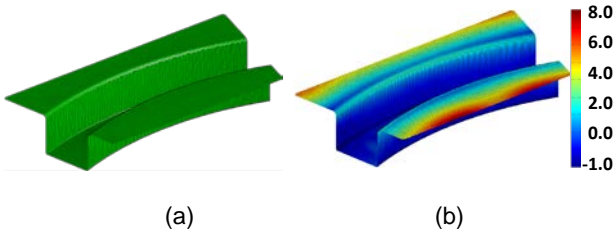


Figure 4 - (a) Top-hat nominal mesh; (b) Deviation field (mm) computation for run $SP^{(1)}$.

	Experimental Runs (p)							
	$SP^{(1)}$	$SP^{(2)}$	$SP^{(3)}$	$SP^{(4)}$	$SP^{(5)}$	$SP^{(6)}$	$SP^{(7)}$	$SP^{(8)}$
Thickness [mm], (SP_1)	0.6	0.6	0.6	0.6	1.2	1.2	1.2	1.2
Holding Force [kN], (SP_2)	150	150	375	375	150	150	375	375
Speed [mm/s], (SP_3)	10	50	10	50	10	50	10	50

Table 1 - Experimental runs with varying process parameters.

Each experimental run has been repeated for 5 times (the average deviation field has been then utilised for further calculations). CoP has been captured using GOM optical scanner (see Figure 5). The deviation field for each experimental treatment has been computed at mesh nodes. For example, Figure 4(b) shows the computed deviation field for experimental run $SP^{(1)}$.

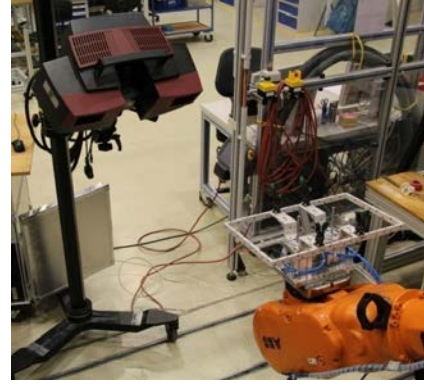


Figure 5 - Experimental setup used to measure CoP of stamped parts.

3.2 STEP 2: deviation field decomposition

The obtained deviation field for each experimental run is decomposed using the GMA. Figure 6 shows a sample set of transformed modes, used as parameters to map with process parameters.

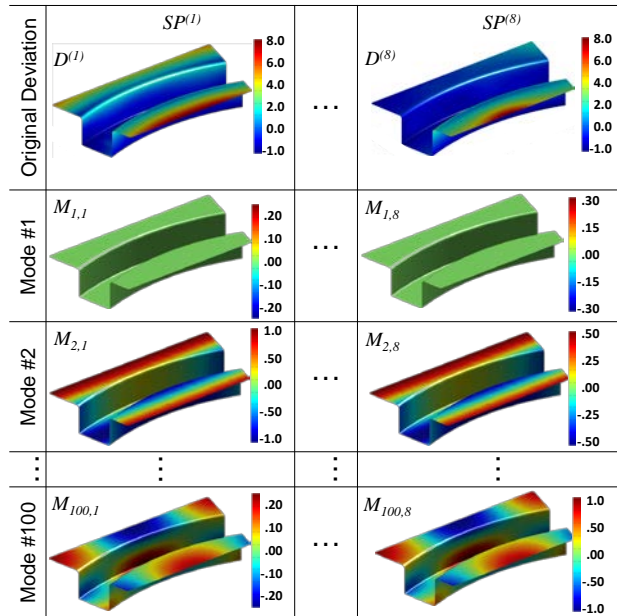


Figure 6 - Deviation field decomposition for each experimental run into error modes.

3.3 STEP 3: analytical surrogate model

For each error mode analytical surrogate model has been developed. For this purpose polynomial regression with automatic degree calculation and robust fitting based on automatic cross validation has been implemented. Figure 7 illustrates the parametric surrogate models (contour plots) for modes in relation with varying blank holding force (SP_2) and stamping speed (SP_3).

In order to prove the accuracy of the proposed methodology the original deviation field has been compared against reconstructed surface by using equation (6). Figure 8 shows the results of original deviations, reconstructed deviations and error plot (between original and reconstructed deviations).

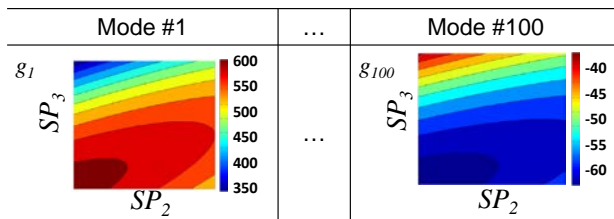


Figure 7 - Surrogate model linking error modes and process parameters (at $SP_1=0.6$ mm).

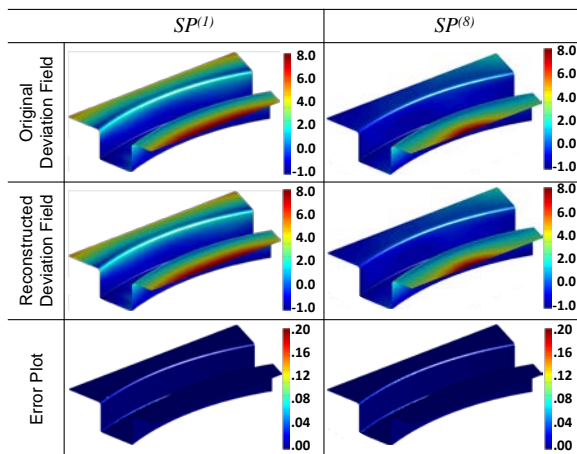


Figure 8 - Original deviation field vs. reconstructed field (deviations in mm).

The proposed methodology is a step forward for predicting geometric errors based on the given set of process parameters (not used during the training step). For example, new parameter set (e.g., thickness, $SP_1=0.6$ mm; blank holding force, $SP_2=250$ kN; and, stamping speed, $SP_3=30$ mm/s) has been selected in between $SP^{(1)}$ and $SP^{(4)}$ to predict the overall geometric deviations [in mm] and is shown in Figure 9.

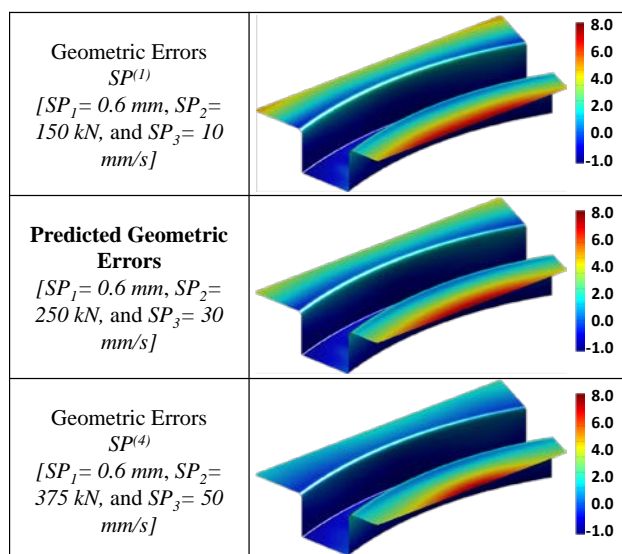


Figure 9 - Prediction of geometric errors for new parameters in between $SP^{(1)}$ and $SP^{(4)}$.

4 CONCLUSION AND FINAL REMARKS

The proposed methodology allows to predict geometric errors by correlating stamping process parameters and monitoring data (such as cloud of points). Geometric errors are defined as deviation field using CoP data which are non-parametric in nature. Therefore, deviation field decomposition has been used to convert CoP data into functional parametric error modes. Subsequently, surrogate model technique has been implemented to link geometric errors and process parameters.

The proposed methodology significantly explores and contributes to the following areas:

- the developed *model-driven* technique represents a step towards automatic closed-loop process control for stamping process;
- costly and time-consuming trial-and-error approaches can be reduced by automatic selection and tuning of process parameters;
- the *model-driven* approach can forecast geometrical variations for given set of process parameters (forward process), and consequently can optimise (feedback process) the process parameters to achieve given quality standards.

Future investigations will be focused on experimental validation of the proposed methodology and root cause identification of global/local geometric errors occurring during production.

5 ACKNOWLEDGMENTS

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