Field meta modelling for process design in complex sheet metal forming

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Abstract. Actually, new applications of machine learning methods like variance-based sensitivity analysis take place for developing complex sheet metal forming and joining processes. The application of this methods will help to quickly start of production when the simple numerical designing of the processes becomes too complicated. Two investigated examples show the application of the method for complex planning situations. The first one uses variable functions of force and motion during deep drawing to extend the process limits. The second one describes the complex clamping of an assembly of different sheet metal parts. Field meta modelling approaches are shown to automate tasks, visualize results and support engineers to plan and run different complex processes regarding sheet metal parts.

1. Introduction

First goal of the field meta modelling approach is the visualization of correlations and prediction of a proper process design with an interactive graphical user interface. Second goal is process optimization to achieve the greatest possible insight with the fewest possible calculations. A third goal is to stabilize critical processes with fast calculations on the field meta model in a closed-loop control system.

The limits of deep drawing processes can be extended with complex movements (e. g. superimposed pulsations) on servo presses [9]. These deep drawing technologies use a lot of process parameters (12). Therefore, it is difficult to design such processes. The presented examples show that trial-and-error is often difficult to achieve success. Also in a process chain (e.g., deep drawing, clamping, joining) many parameters have cross-correlations and strongly influence the result [13].

Field meta models calculated with the variance-based sensitivity analysis describe important parameters of complex processes. This approach helps to systematically find a suitable parameter set for which a minimum sheet thickness at the weak point is not fallen short of in order to prevent failure cracks. Another criterion is to minimize the deviation from the desired geometry at a certain point of the sheet metal part.

For calculating the field meta model the challenge will be to spatially correlate input and output of all simulations and experiments. For example the outlines of the resulting finite element mesh vary over different simulations of deep drawing processes [1]. That is why an automatic workflow for the variance based sensitivity analysis with different software tools was developed to extract results at certain locations of the sheet metal parts.
2. Application of field meta models

The objective is to achieve a three-dimensional representation of statistical measures on finite element meshes. Thereby, simulations are run with different variants, which have e. g. in deep drawing scattered material parameters, sheet thickness values or blank positions [4]. A comparable solution approach is used in the publication by Wärmefjord et al [5].

The purpose of the study is to develop a method based on principal component analysis (PCA) that can be used to determine the effects of manipulated and disturbance variables (e.g., friction or forming speed) on the part quality from the deep drawing to the assembly process. Based on this, Wolff [6] and Gerbino [7] independently perform numerical (with Finite Element Method – FEM) variance-based sensitivity analyses for sheet metal parts. Influences of material (e.g., sheet thickness) and design parameters (e. g., drawing speed, blank holder force) on the part quality are investigated. In both cases, field meta models are used for the three-dimensional representation of the sensitivities on the FE mesh surface. In a separate study [8], a PCA-based method is proposed to enable part-based visualization of variance-based sensitivities for finely discretized FE meshes in numerical parameter studies. Using a front flap inner part, it is demonstrated that by using a field meta model the influence of process parameters on specific state variables such as strain or spring back can be represented for FE meshes with over one million elements on the drawn part surface.

3. Method used for field meta modelling

Here, the method described in [8] is used for field meta modelling. A variance-based sensitivity analysis is the core of the method. The data comes from the finite element geometry and calculated results (strain, stress, plate thickness) out of the variant simulations, see 1st step in Figure 1. As described in the 2nd step, the field meta modelling uses data reduction by principal component analysis (PCA). The mathematical approach of PCA consists in a linear transformation of the original data into a new coordinate system. As a result, the variance structure of the original data can be summarized with the help of a small number of meaningful linear combinations, the so-called principal components.

After identifying the new transformation basis, the input data for dimensionality reduction is projected onto the principal components previously ordered by variance proportions, resulting in the data reduction. Based on PCA, the surrogate models are then built in the reduced feature space and by means of a variance-based sensitivity analysis, the percentage influences of the input parameters on the dimensional fluctuations or other post-size values of the FE networks are estimated (3rd step). The back transformation (4th step) of the reduced data enables the field metamodeling and the 3-D visualization of the sensitivities on the entire component FE surface mesh (5th step).

![Figure 1. Overview of the method behind field meta modelling [8]](image-url)
4. **Toolkit for automatic field meta modelling**

**Overview of the developed software concept**

Experimental and numerical development of deep drawing processes with variable force and motion functions are complex tasks regarding the settings of the press machine control and the parametrization of the FEM simulation, respectively.

![Diagram](Figure 2)

**Figure 2.** Developed software concept for automatic field meta modelling with advanced simulation models for deep drawing processes

Field meta modelling should help to systematically find a proper solution. That is why we setup a software concept using different tools and a data management system for field meta modelling. The developed toolkit as shown in Figure 2 is an interdisciplinary product from mathematics, computer sciences and classical mechanical engineering. The purpose of the toolkit is to automate the calculation of field meta models and simplify the pre- and post-processing for engineers.

The input is based on the process parameters (e. g. in BDD: amplitudes, forces) and the drive capabilities of the press machine. It is possible to calculate any kind of deep drawing processes with variable force and motion functions. The software concept provides an interface to an external FE solver (e. g. LS-DYNA) for the advanced forming process simulation [11]. The FE models are independent for the workpiece, the tool and the machine. This flexible concept allows to build fast and reliable simulation models for any deep drawing process. The advanced forming process model [11] will be automatically assembled, calculated and evaluated depending on the selected inputs for each design.

The developed software concept in Figure 2 is independent from any FE solver. Other solutions like e. g. AutoForm Sigma have only interfaces to the AutoForm Solver. This does not allow advanced forming simulations with variable force and motion functions to be performed. The data extraction of
MetaField is compared to other solutions (AutoForm, Deform, Simufact) much more flexible for any kind of production process because it is not restricted to numerical FE data. For example, MetaField can calculate models based on experimental data (e.g. welding micrograph structure [15]), on mixed data - numerical and experimental (see chapter 6), on process chains (consisting of several operations, e.g. in car body construction), on freely selectable formats for input and output (e.g. curves, surfaces, visual images, discrete values).

**Description of the graphical user interface**

The computer program DYNAMO (see (Figure 3a)) calculates the input data for the simulation and the control commands for the press machine. The force and displacement functions are calculated in such a way that any deep drawing process will be realized with minimum time requirements. Thus, high productivity will be achieved.

Another important task of DYNAMO is the automation of numerical variance-based sensitivity analysis for deep drawing processes. The program supports the user at a high level in the pre- and post-processing of each process design.

**Figure 3.** Graphical user interface (a) for the process design tool DYNAMO and for the field meta modelling tool MetaField with model accuracy plot (b) and slider tool (c) for prediction

The development workflow should reduce the development times for deep drawing processes. Based on the flexible software concept from Figure 2, various tasks can be securely outsourced. The input and output data are given by interfaces. The graphical user interfaces (Figure 3b and c) connects all individual results and shows the field meta model to get the optimal deep drawing process.

Further this allows different departments in a company to easily work together, even though everyone is in their own area of expertise. Further developments will integrate measurements from the production process as a continuous feedback loop to improve the prediction.
5. Example for planning a complex deep drawing process

**Short description of the Bidirectional-Deep-Drawing (BDD) process**

As described in [10] a cylindrical cup evolves a characteristic weak point at the bottom radius during the deep drawing process. High tensile loads cause excessive thinning in the area with of least stressability. To avoid local material instabilities, one should increase the strain hardening near the bottom radius. Earlier published papers detailly shows the extension of the forming limits for a cylindrical cup [2] and a cross die [10].

BDD has a complex variable force and motion function. The sheet is clamped between blankholder and die. An upper punch fixes the bottom of the part onto the lower drawing punch. The Figure 6 in [2] shows, how the effective plastic strain increases with each alternating bending movement of the die. All details of the BDD process are described in [2] and [10]. The papers provide material properties for the simulation as well. The pre- and postprocessing of the simulation are explained in [10] for the calculation of the field meta model.

The motion function will be calculated by DYNAMO as shown in Figure 3a. The software was fully written in PYTHON at Fraunhofer IWU [3, pp. 93-104] based on the software concept from Figure 2. It is quite complicated to find a proper motion function for a specific part, which will increase the effective plastic strain in the right area. To solve this problem numerically, we use a variance-based sensitivity analysis with the Fraunhofer IWU tool MetaField (see Figure 3b and c). Based on that, we can perform a parameter study for different motion functions as described for the BDD process in [10].

**Parameter study with predicted results based on the field meta model**

With the bidirectional deep drawing (BDD), the work hardening can be locally adjusted by the process parameters. The Figure 4. Predicted effective plastic strain (a/b) for different motion functions (c/d) based on the field meta model [10] illustrates the parameter study, which is based on the field meta model as described in [10]. The predicted values for the effective plastic strain will increase with larger amplitudes and more bending operations during BDD.

![Figure 4](image-url)
Nevertheless, the failure prediction based on the forming limit curve is currently not reliable for bidirectional deep drawing processes due to the nonlinear strain paths as shown in [10, Fig. 4]. Therefore, we cannot perform an optimization task based on this field meta model.

6. Example for clamping an assembly of sheet metal parts

The variations of the clamps in car body manufacturing have been studied for a long time [14]. The field meta modelling approach can help to find a suitable solution for this problem. The method is quite the same as explained above, only the data preparation had to be adjusted for the following investigations. The assembly, which consists out of 4 individual sheet metal parts as shown in Figure 5a, was experimentally and numerically evaluated in [13]. In the experiment each surface of the 4 single parts on 5 parts each was optically measured and digitalized. These twenty 3D-surfaces were used as parameter variations in the simulation without any known causes (e.g. property variations of the material or deep drawing parameters). In the clamping simulation the crucial clamp and two bolts were numerical varied on the assembly as shown in Figure 5a. Then the deviation between the calculated and the desired surface of the assembly was calculated.

![Figure 5. Location of the varied clamp and bolts on the assembly (a) and model accuracy (b) with plot of local sensitivity indices for all input parameters in MetaField](image)

The Figure 5b visualizes the influences of the individual parameters according to their importance. The result data are plotted onto the investigated assembly. Figure 5b shows the prediction quality with the Coefficient of Determination (COD). The value describes how much of the result variation can be explained by the input variations. In the slider tool of MetaField (Figure 6) one can play around with the field meta model to quickly find a suitable clamping situation without any remarkable delay. This variation of the input parameters, shown here manually, can be taken over by an optimization algorithm in case of a concrete target.
7. Conclusion

For the field meta-modelling approach based on the sensitivity analysis of variances it will be necessary to automate the pre- and post-processing of experiments and simulations. The method is characterized by the design of experiments, the data generation and the result extraction.

The presented examples show how one can systematically find a suitable process design for complex or different sheet metal parts using variance-based sensitivity analysis with field meta-modelling. The process design with trial-and-error has a bad cost versus effect ratio. Often the data acquisition can be the biggest cost driver. What is sought is the analytical model that achieves the best process description at the lowest cost for simulation and measurement. Therefore, the combination of numerical and experimental data is an important topic for the modelling.

Such an analytical model is then used as a basis for the automatic control of processes based on the developed software workflow via suitable actuators.

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