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SIMULATION-BASED DEVELOPMENT OF PARETO-OPTIMIZED TAILORED BLANKS FOR THE USE WITHIN SHEET-BULK METAL FORMING

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1. Introduction

Saving resources, and their efficient use, is one of the key issues of the 21st century and thus the goal of research efforts in various technical disciplines. These include renewable energy, hybrid and fully electrified vehicles or smart grids. Another field with enormous potential for saving resources is lightweight design, which is in particular important for the automotive sector. Downsizing with consistent functionality or increasing the functional density per part are only two approaches to achieve lightweight design [Mallick 2010]. These lightweight design approaches lead to higher requirements for materials and parts in terms of strength, wear resistance and lifetime. For instance, synchronizing rings in vehicle gearboxes are usually made of brass [Song and Jie 2008]. But to meet the increasing requirements they are partially made of steel materials and it is expected that it will continue to rise. Current manufacturing technologies, like slicing, deliver such high performance steel parts but only by means of many sub-process steps and thus at high manufacturing costs [Schneider and Merklein 2011]. This motivates the development of new forming processes to manufacture heavily loaded functional elements on sheet metal parts in few sub-process steps with close geometrical tolerances. For this, a new class of forming processes called sheet-bulk metal forming (SBMF) is being researched [Merklein and Allwood 2012].
In the context of lightweight design, the so-called tailored blanks are more frequently used to improve sheet-bulk metal forming process results. In order to meet the requirements of tailored blank designs for subsequent sheet-bulk metal forming process steps, design engineers can influence many process or geometry parameters. A crucial task for design engineers is to find the optimal process and geometry parameter setting that is an optimal design with respect to multiple design requirements. A simulation-based approach to face this challenge is presented in this paper.

2. Background

2.1 The use of tailored blanks within sheet-bulk metal forming

The manufacturing technology sheet-bulk metal forming (SBMF) is being developed within the transregional collaborative research centre 73 (SFB/TR 73), which is funded by the German Research Foundation (DFG). The overall objective of SBMF is the development of a new forming process technology to manufacture heavily loaded functional elements on sheet metal parts with close geometrical tolerances (see SBMF parts in Figure 1). For this, the sheet operations are extended by bulk-

forming operations within sheet thickness, which leads to overlapping two- and three-axis strain and stress states. [Breitsprecher et al. 2015] In the context of lightweight design, tailored blanks are utilized to improve the SBMF process and thus reduce resources to manufacture SBMF parts. Tailored blanks are semi-finished parts with local material pre-distributions by having more material in locally defined areas of interest and less in other areas of the component.

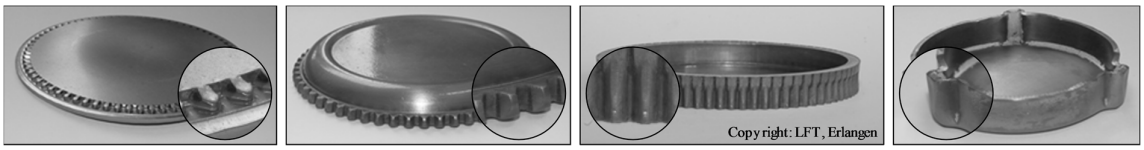

Figure 1. Sheet-bulk metal formed parts [Breitsprecher et al. 2015]

Tailored blanks can be manufactured by various forming processes, like orbital forming. This process was first presented in [Marciniak 1970] as a cold bulk-forming process. It enhances the process limits like the forming force in comparison with, for example, conventional upsetting due to a tilted die with its typical tumbling motion. Using orbital forming instead of conventional upsetting, the forming force can be reduced up to 90 % due to the smaller contact zone between workpiece and tool of up to 70 % caused by the tilted die [Maicki 1977]. In contrast to the established application of orbital forming as a bulk forming process in industry, the tool design presented in [Opel 2013] enables the manufacturing of sheet metal by orbital forming to manufacture tailored blanks with a locally adapted sheet thickness distribution. For SBMF processes, such as combined deep drawing and upsetting process, the general application of tailored blanks has led to an improvement of SBMF parts [Opel et al. 2013].

2.2 Simulation studies, pareto-optimized designs and metamodels

SBMF parts as well as tailored blanks depend on expensive forming tools. During the research of SBMF forming processes, many experiments need to be performed. On this account, virtual experiments (e.g. FEA, CFD and MBS) for digital verification are done before the physical forming tools are manufactured to minimize the costs of tools and machinery. The overall goal of the virtual experiments is to identify tool designs that lead to the production of high precision SBMF parts. For this, tool design engineers need to understand the influences of geometrical characteristics of a tool and forming process settings on SBMF part properties of interest. One approach to reveal these is to perform a simulation study. According to [Kleijnen 1987], the simulation study is defined as the recording of output parameters (target figures) during the iterative run of a simulation program for several input combinations (factors). In case of SBMF processes, there is a parameterized FE-model (geometry and process parameter) of the tailored blank forming process of interest. In order to guarantee a well-distributed combination of all factors within a given interval, design of experiments (DoE) is utilized (see Section 2.3).

In practice design engineers deal with competing target figures, for instance, tailored blank designs need to have much material in locally defined areas of interest, but low effective plastic strain rates to guarantee a successful subsequent SBMF process step. One approach to find a compromise for two or more competing target figures is to use multi-objective optimizations (MOOP). As [Papalambros and Wilde 2000], [Jin et al. 2003], [Kim et al. 2015] show, MOOPs are widely used in engineering design. For a set of given functions $f(x) = \left(f_1(x), f_2(x), \dots, f_n\,(x)\right)^T \; \forall\, x \in \Omega$ the optimization problem is stated as $\min f(x) = \min\left(f_1(x), f_2(x), \dots, f_n(x)\right)$ [Caramia and Dell'Olmo 2008]. In the context of SBMF, the parameter x is a vector that includes all factors (e.g. forming force, sheet geometry). The set Ω describes the valid design space that is all optimization constraints (e.g. valid intervals of factors and constraint functions, which define relations between factors). The functions $f_i, \mathrm{i} = 1, \dots, n$, which depend on the parameter vector x, describe the target figures (e.g. maximum effective plastic strain rate after the SBMF process). Feasible solutions for the MOOP problem are all vectors $x^* \in \Omega$. All vectors $\hat{x} \in \Omega$ are called pareto-optimal, if there are no other vector $x^* \in \Omega$ which reduces one of the functions $f_i(x),\ \mathrm{i} = 1, \dots, n$. The pareto-front is the set of all pareto-optimal vectors that represent feasible "optimal" solutions [Papalambros and Wilde 2000], [Caramia and Dell'Olmo 2008]. In context of

SBMF and tailored blanks pareto-optimized vectors $\hat{x} \in \Omega$ include the settings of a pareto-optimized design.
Despite processing capacity of computers doubles at regular intervals, the computational time of virtual experiment during the optimization iterations are still very high. A common approach to reduce the costs of computation-intensive processes is the usage of mathematical surrogate models, in context of simulation studies also known as metamodels. The name "metamodel" goes back to [Kleijnen 1987]: He describes the simulation model itself as a model of the reality. If we build a model of the simulation model, we call it "model of the [simulation] model". Metamodels have continually been used and applied over the last decades, inter alia, in [Tomiyama et al. 1989], [Emmerich and Naujoks 2004], [Pan et al. 2013]. For this, [Wang and Shan 2007] presents a detailed state-of-the-art review on approximation techniques like metamodeling. In context of SBMF processes metamodels are utilized as surrogates of the expensive virtual experiments. The metamodels (usually one for each target figure) can then be used during the exploration of the design space to find pareto-optimized designs with respect to two or more competing target figures.

2.3 Theory of design of experiments

In order to guarantee a systematic as well as methodical approach for determining an underlying data basis, the theory of design of experiments (DoE) is used. With this methodology an efficient planning, performing and evaluation of experiments is feasible. The aim of this theory is the identification of relevant factors with as minimum effort as necessary [Loper 2015]. Due to a selective variation of the considered factors, relations between these and the target figures can be revealed [Siebertz et al. 2010]. Basis of DoE is a process model shown in Figure 2 on the left side, which contains relevant, separately adjustable input factors (x), disturbing variables and target figures (y) as well as clearly defined system boundaries. A classical full factorial design relays on the chance of one input factor a time. With an increasing number of input factors, the number of experiments increases exponential. The triangles in Figure 2 on the right side show the classical full factorial design, consisting of two settings (+ / –) for each factor. A disadvantage of the full factorial design is the exponential growing number of experiments. For example considering two input factors, each with two settings, four experiments have to be done. When considering three input factors, eight experiments are necessary and with four input factors, 16 experiments are required. However, due to two used settings at the same time, only linear relations between the factors can be revealed [Siebertz et al. 2010].

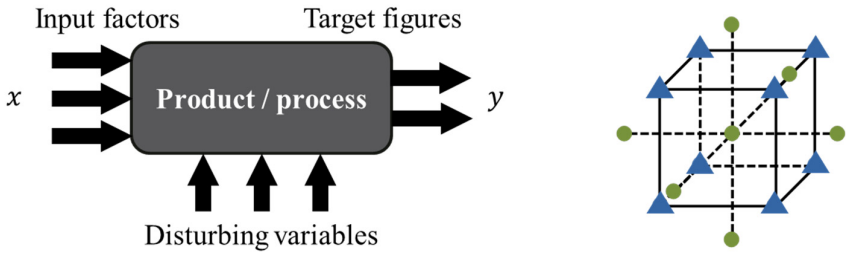

Figure 2. Process model (left), central-composite-design (right)

Therefore, in order to reveal also complex relations by a simultaneously decreasing number of necessary experiments, a central composite design is used. This special enlargement of the full factorial design allows more settings for each input factor and thus the revelation of nonlinear relations between the factors. In Figure 2 on the right side, the model shows a central composite design when combining the triangles and the dots [Loper 2015].

2.4 A constitutive friction law for sheet-bulk metal forming

Due to the various contact configurations (e.g. between punch and sheet), the friction in SBMF processes and tailored blank forming processes has to be taken into account. Contact and friction between bodies is a complex and non-linear problem, which depends on various factors like the surface roughness, the

contact load, or the material. Based on the forming process, different friction models are suitable. For example, the friction law of Tresca models with the friction stress $\tau = m \cdot k_y$, where m is the constant friction factor and k_y is the shear yield stress. This friction law is commonly used for processes in which the yield stress of the workpiece material is surpassed, such as bulk forming. In contrast, for processes with low contact loads, e.g. sheet metal forming, Coulomb's friction law is advisable. The law is defined as $\tau = \mu \cdot p$, where μ is Coulomb's friction coefficient and p is the local contact pressure. The selection of an appropriate friction model complicates, if the contact conditions of both sheet metal forming and bulk forming appear, which is the case in SBMF processes. In addition, as the process considered here is incremental, the plastic smoothing of the workpiece, which changes the contact condition for repeated contact, has also to be taken into account. The constitutive friction law presented in [Beyer et al. 2015b] is able to cope with the special demands of SBMF. The constitutive friction law describes the friction stress for initial contact with

$$\tau = m \cdot k_y \cdot \alpha = m \cdot k_y \cdot \sqrt[n_1]{\tanh\left(\frac{p \cdot C_1}{H}\right)^{n_1}}, \tag{1}$$

where H is the surface hardness of the weaker material in contact and α is the ratio of the real contact area to the apparent contact area. As technical surfaces are rough, contacting bodies get into actual contact only with their surface asperities. The area due to asperity contact is the real contact area, which is only a fractional amount of the apparent contact area. The variables n_1 and C_1 have to be numerically identified, as performed with the use of a half-space model in [Hauer 2014]. If the contact ocurrs repeatedly, the friction stress is evaluated with

$$\tau = m \cdot k_y \cdot \sqrt[n_2]{\tanh\left(\frac{p \cdot C_2}{H \cdot \alpha(p_h)}\right)^{n_2}} \cdot \alpha(p_h). \tag{2}$$

Equation 2 differs from Equation 1 in the variables n_2 and C_2 that also have to be numerically identified. Moreover, Equation 2 also depends on $\alpha(p_h)$, which is the ratio of the real contact to the apparent contact area for the maximum local contact pressure that has been beared by the contact surface. As initial contact is dominated by plastic surface smoothing, reloading a surface is mostly elastic, which is described by $\alpha(p_h)$. Equation 2 is also applicable, if the contact surface is released of the current contact condition.

3. Virtual process chain for the development of pareto-optimized tailored blank designs

The virtual process chain for the simulation-based development of pareto-optimized tailored blanks consist of two sub-processes: the design optimization and post-test calculation sub-process. The design optimization sub-process starts with the design of the experiments (DoE) (see Figure 2). Based on the experimental design the simulation study is performed. For this, a parameterized FE-model of a tailored blanks forming process is used. To speed up the simulation study, Tresca's friction law is used within the FE-calculations that produce the input data for the metamodel computation. During the post-processing of each single simulation of the simulation study the considered target figures (process and geometry parameters) are evaluated and recorded. The DoE design and the target figures are then used to derive a metamodel to reduce the computational cost during the design optimization. The last step of the design optimization sub-process is the multi-objective optimization with regard to one or more target figures. The result of this step is a pareto-optimal design for the tailored blank with respect to the considered target figures. The post-test calculation sub-process consists of simulations with the more accurate constitutive friction model. Due to the significant longer computing time, only a single simulation for the setup of the pareto-optimized tailored blank design is performed. Each process step depicted in Figure 3 will be described in the following sections in more detail. The corresponding section to each step is referenced in Figure 3.

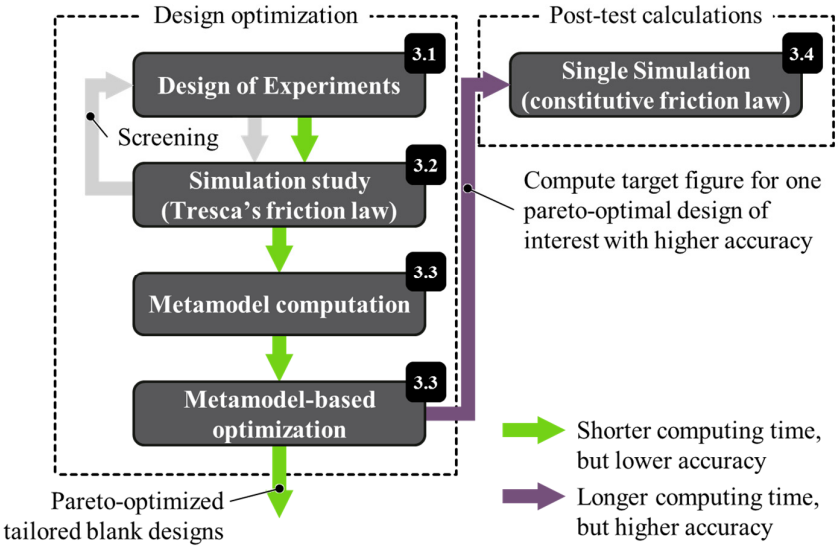

Figure 3. Virtual process chain for the design optimization and post-test calculations of tailored blanks for SBMF parts

3.1 Design of experiments

There is a variety of different experimental designs (e.g. screening designs, full factorial design, fractional factorial design and central composite design, see Section 2.2). The selection of a suitable experimental design, with respect to a compromise between high accuracy and limited time to carry out the experiment is crucial at the beginning of a DoE process. Furthermore, not every parameter in the parameterized FE-model has an influence on the considered target figures. Design of experiments deals therefore with the stipulating of the factors (process and geometry parameters) to be used in the simulation study, the levels of the factors and the design of the experiments. In order to reduce the factors at the beginning, and therefore the overall time to carry out the simulation study, a factor screening is to be done. The goal of the screening is to perform a preliminary simulation study with all available parameters in the parameterized FE-model with as little as possible experiments to identify the factors with a significant effect on the target figures. For this, screening is used to identify all factors with a significant effect on the target figures. The identified factors are to be used during the main simulation study with a central composite design (see Section 2.2).

The purpose of manufacturing tailored blanks of this geometry is, inter alia, to make more material available at the disc margin for further processing and thus improving the components quality. Therefore, the target figures of interest in this contribution is

- the maximum sheet thickness at the disc margin st_{max} in mm and
- the form filling degree ff_{max} in % to measure the efficiency of the used tool (see Figure 4-c).

The target figure st_{max} is measured at the part after the simulation of the orbital forming process. The screening revealed four geometrical factors at the forming tool. These and their defined levels are shown in Table 1.

Table 1. Factors for the simulation study and their levels

Factors	Level 1	Level 2	Level 3	Level 4	Level 5
Step height of die cavities h_s	0.9mm	1.1mm	1.5mm	1.8mm	2.0mm
Angle of each die cavity φ_s	7.5°	12.1°	18.8°	25.4°	30°
Inner diameter of die cavities d_i	60mm	64mm	70mm	76mm	80mm
Number of die cavities a_s	3	6	9	-	-

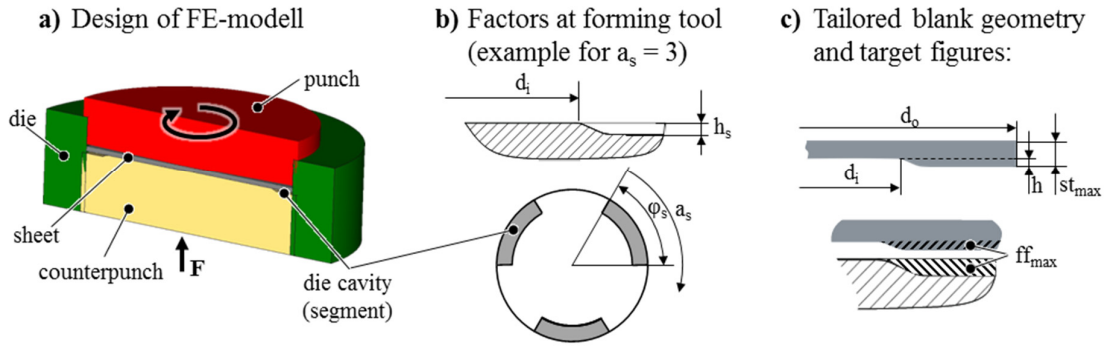

Figure 4. Design of FE-model, factors at forming tool and target figures

3.2 Simulation study

In contrast to the established application of orbital forming as a bulk forming process in the industry, the tool design presented in [Opel 2013] enables the manufacturing of tailored blanks by orbital forming. A conical upper punch transmits the press force in the tool system. The tumbling motion is applied by the lower tool components, the counterpunch and the die (see Figure 4-a). During the orbital forming process, the material is transferred radially from the centre to the outside. A negative imprint of the desired target geometry in the counterpunch enables a local thickening of the sheet. The radial elongation of the tailored blank is prevented by the die thus benefiting the material flow in the die cavity. This process enables the manufacturing of different tailored blank geometries with varying level of complexity by using counterpunches with differing die cavities. Regarding today's necessity for complex components and thus different kind of symmetric or non-symmetric tailored blanks, the use of FEM is predestined for analysing a varied number of geometries. For the investigations in the framework of the paper the parameterized FE-model presented in Figure 4-a) was used in the simulation software Simufact.Forming 11. Due to software issues, the orbital forming process had to be modelled reversely with a rotating and tilted punch and the forming force transmitted by the counterpunch.
According to [Opel 2013], a process force of about 3,000 kN is necessary for realizing a proper filling of the die cavity and thus an adequate sheet thickening. However, regarding the influence of different geometries on the resulting die filling, using a forming force less than 3,000 kN is reasonable for better emphasizing the effects. Thus, a forming force of 2,000 kN was implemented in the FE-model. In Figure 4-b) a detailed view of a die cavity is given with the geometric parameters, which are varied in this investigation, the inner diameter d_i and the height h_s as well as the number of die cavities a_s. A schematic depiction of the thickened tailored blank is given in Figure 4-c).

3.3 Metamodel computation and metamodel-based optimization

The overall objective of the optimization sub-process is to identify a pareto-optimal design for a tailored blank. For this, the metamodels for the considered target figures need to be computed. The input for the training of the metamodels is the result of simulation study, that is, the DoE design with the four factors and the recorded target figures. Several metamodel algorithms are trained based on the simulation study results. These include linear or polynomial regressions, M5P-regression trees or M5R-Rule learners [Quinlan 1992], [Wang and Witten 1997], [Holmes et al. 1999], [Witten and Eibe 2011]. By means of statistical tests the metamodel is selected which fits the data best. In this case, for both target figures the linear regression was selected. Equation 3 represents the metamodel for the maximum sheet thickness at the disk margin st_{max} with a root mean squared error of $\pm$0.07mm. Equation 4 represents the metamodel for the maximum form filling degree ff_{max} with a root mean squared error of $\pm$6.27%. With $x = [h_s, \varphi_s, d_i, a_s]^T$:

$$st_{max}(x) = 1.99 + 0.846 \cdot h_s - 0.00814 \cdot \varphi_s + 0.00644 \cdot d_i - 0.0431 \cdot a_s \text{ in mm} \quad (3)$$

$$ff_{max}(x) = 85.2 + 6.64 \cdot h_s + 0.247 \cdot \varphi_s - 0.430 \cdot d_i + 0.225 \cdot a_s \text{ in \%} \quad (4)$$

The optimization problems are defined as

$$\min f_1(x) = \min(st_{max}(x), ff_{max}(x)),\ \min f_2(x) = \min(-st_{max}(x), ff_{max}(x)),$$
$$\min f_3(x) = \min(st_{max}(x), -ff_{max}(x)) \text{ and } \min f_4(x) = \min(-st_{max}(x), -ff_{max}(x)). \quad (5)$$

In this contribution the "Non Sorting Genetic Algorithm II" (NSGA-II) multi-optimization algorithm [Deb et al. 2002] was used to identify pareto-optimized tailored blank designs. In order to explore the design space, each criteria was iteratively maximized and/or minimized (see Equations 5). The initial individuals were uniformly distributed in the domain of h_s, φ_s, d_i and a_s (see Table 1). For each run, 100 generations with a maximum of 100 mutations where used. The probability for mutation an individual was set to 90%.

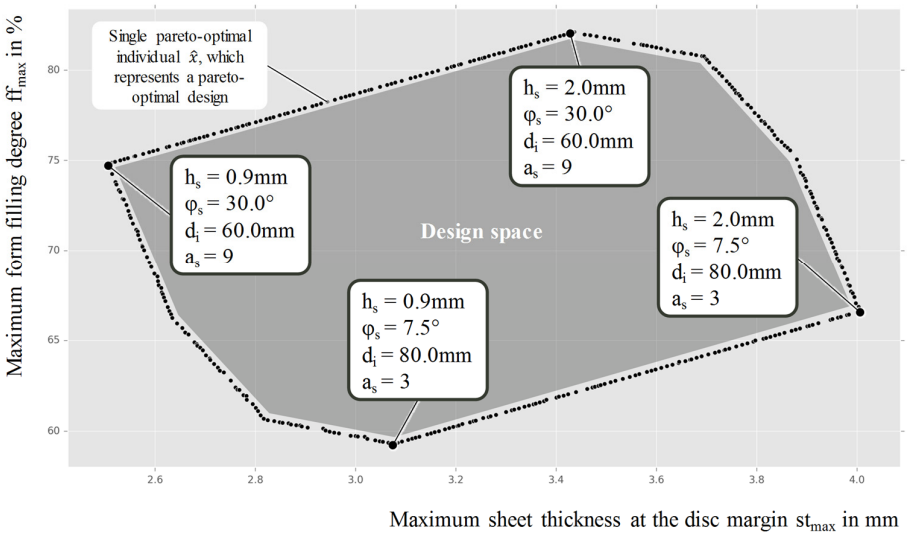

Figure 5. Aggregation of all pareto fronts for the multi-objective optimization for form filling degree ff_{max} and sheet thickness at the disc margin st_{max}

Figure 5 shows an aggregation of four metamodel-based evolutionary multi-objective optimizations for the form filling degree ff_{max} and the sheet thickness at the disc margin st_{max}. The dark gray area represents all valid solutions in the domain of h_s, φ_s, d_i and a_s. Each dot at the border of the dark area represents a single individual of the final generation. All individuals of the final generation create a pareto front, which defines the pareto-optimal tailored blank designs with respect to st_{max} and ff_{max} and the domain of h_s, φ_s, d_i and a_s. If design engineers are interested in a high st_{max} and a low ff_{max}, they can find suitable solutions on the bottom right of Figure 5. The corresponding factor levels of the extremes (highest and lowest st_{max} or ff_{max}, respectively) are written in white boxes. The goal of this contribution was to find a tailored blank design with a high st_{max} and ff_{max}. Suitable designs for this case can be found in the top right of Figure 5. Design engineers need to make a compromise between both design requirements, but their decision is supported by the visualisation of the pareto-front depicted in Figure 5, which represents all possible optimal designs with respect to both design requirements.

3.4 Post-test calculations with the constitutive friction law

A benchmark process for sheet-bulk metal forming, which is described in [Landkammer et al. 2015], has been used to show the applicability of the constitutive friction law. The impact of different friction laws on this process is given by [Schmaltz et al. 2013]. Furthermore, the constitutive friction law has also been used in a bulk forming process in [Beyer et al. 2015a]. In [Beyer et al. 2015a] it is shown that the friction law does not only affect friction stresses, but also process or geometry factors such as the effective plastic strain or sheet thickness at the disc margin. This is also true for the orbital forming process. Figure 6 shows exemplary the resulting sheet thickness changes of the part with Tresca's friction law and with the constitutive friction law after the whole process.

4. Approach for a local adaptive choice of the friction law in simulation studies

The pareto-optimized tailored blank design is based on the design optimization sub-process. As depicted in Figure 6, the used friction law has an influence on target figures like the sheet thickness at the disc margin and therefore affects the optimized design. Thus, it is sensible to use the constitutive friction law during simulation studies. Unfortunately, the application of the constitutive friction law results in a significant longer processing time. On the other hand, the difference between a simulation with the constitutive or Tresca's friction law is not that distinctive in numerous local regions with respect to the sheet thickness, for instance. Keeping the higher processing time in mind, knowing the regions where different friction laws lead to different results would be an advantage. In the following section, an approach is presented, how this difference can be estimated and thus a local choice between one of the friction laws could be applied. This modification leads to a compromise between accuracy and computing time and thus to an improvement of the results of the simulation study.

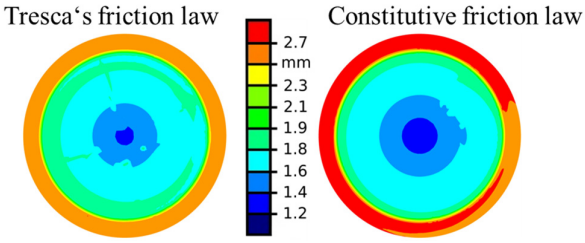

Figure 6. Resulting sheet thickness of a tailored blank forming process

4.1 Friction model adaptivity

SBMF is characterised by locally varying requirements on forming processes. Consequently, the simulation demands are also locally varying in space and time. Designing the simulation to the requirements of the most complex situation leads to high computational costs. Thus, a simulation is needed, which automatically adjusts itself during the simulation run to the given demands. One approach to build such simulations is given by adaptive finite element methods (AFEM). In AFEM the simulation error is approximately defined by a posteriori error estimator. On basis of these estimates, the discretisation as well as the modelling can adaptively be modified to reach a given accuracy with minimal numerical costs. Within this work, we discuss the extension of the pioneering work concerning model adaptivity [Braack and Ern 2003] to frictional contact problems, where we adaptively and especially locally choose the friction law.

With the a posteriori error estimator we want to estimate the error between different given models, which are arranged in a model hierarchy. A typical model hierarchy can be found, for example in [Beyer et al. 2015a]. Within this hierarchy, we have a reference model that is the most accurate model but usually also the one with highest computational effort. Thus, we want to use the computational cheaper but less accurate models in this hierarchy as often as possible. The resulting error has now to be estimated in a user defined error functional J, which could be an integral mean value in a certain region, for instance. Following the ideas of [Rademacher 2015], the estimate consists of the insertion of the solution to the coarser models into the fine model weighted by a so-called dual solution. After applying the trapezoidal rule, neglecting higher order terms and rearranging the remaining expressions, we end up with the following goal-oriented model error indicator η_m:

$$
\begin{aligned}
J(u_h) - J(u_h^m) &\approx \eta_m \\
&= \int_{\Gamma_C} \max\{\tau_r, \|\sigma_{nt}(u_h^m) + c \cdot u_{h,t}^m\|\} \cdot \sigma_{nt}(u_h^m) \cdot \sigma_{nt}(z_h^m)\, do \\
&\quad - \int_{\Gamma_C} \max\{\tau_m, \|\sigma_{nt}(u_h^m) + c \cdot u_{h,t}^m\|\} \cdot \sigma_{nt}(u_h^m) \cdot \sigma_{nt}(z_h^m)\, do \\
&\quad - \int_{\Gamma_C} (\tau_r - \tau_m) \cdot \left(\sigma_{nt}(u_h^m) + c \cdot u_{h,t}^m\right) \cdot \sigma_{nt}(z_h^m)\, do,
\end{aligned} \tag{6}
$$

with u_h being the solution to the reference friction model τ_r, u_h^m the solution to the currently applied friction model τ_m and the corresponding dual solution z_h^m. By $\sigma_{nt}(\bullet)$ we denote the tangential or frictional contact stress and by $u_{h,t}^m$ the tangential displacement.

4.2 Application of the model adaptive algorithm in simulation studies

At first, we outline a standard adaptive algorithm incorporating model adaptivity as well as adaptive refinement. The algorithm starts with an initial choice of a model distribution and a discretization. Then the discrete solution u_h^m is calculated using a suitable numerical solution algorithm. The next step is the determination of the dual solution z_h^m and the evaluation of the error estimators η_m and η_h. If $|\eta_m + \eta_h|$ is below a given stopping tolerance, the algorithm terminates. Otherwise, we conduct a case-by-case analysis. If the discretisation error estimator η_h is dominating, the mesh is locally refined. In the case that the model error estimator η_m is larger than the discretisation error estimator η_h, the model distribution is locally enhanced. If both estimators are nearly of the same size, we modify the mesh as well as the model distribution. Then we calculate a discrete solution u_h^m again and the algorithm continues as described before. A modified version of this algorithm has been implemented in the commercial simulation software Simufact.forming via user subroutines. However, not all required data is available and therefore the calculation was reduced to a nodal evaluation in the post process. Moreover, a dual solution can only be computed with a huge amount of extra work, due to the restricted workflow of the program, such that a simple approximation is used. Using post processing subroutines a graphical output of the model error distribution is created and shows the user where to change the friction model to get better results and where the current model is already suitable.

5. Summary and outlook

This approach offers the potential for design engineers to identify optimal tailored blank designs with regard to competing requirements for the use within sheet-bulk metal forming (SBMF). The current virtual process chain for the simulation-based development of pareto-optimized tailored blank designs consists of two sub-process: the design optimization and the post-test calculation sub-process. Although the application of the constitutive friction law leads to results that are of higher accuracy, it is only used in the simulation of the identified and chosen optimal design within the post-test calculation sub-process. This approach is a compromise between accuracy and computation time. One possibility to reduce the computing time is the application of the presented model adaptive algorithm. However, modifications of the simplified, realised algorithm have to be done, since only a graphical output of the model error distribution is available yet. Thus, an automatic adjustment of simulation is not possible, due to the restricted workflow of the commercial finite element software used.

Acknowledgement

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References

Beyer, F., Blum, H., Kumor, D., Rademacher, A., Willner, K., Schneider, T., "Experimental and Simulative Investigations of Tribology in Sheet-Bulk Metal Forming", Key Eng. Materials, Vol.639, 2015a, pp. 283–290.

Beyer, F., Hauer, F., Willner, K., "Development of a Constitutive Friction Law based on the Frictional Interaction of Rough Surfaces", Tribology in Industry, Vol.37, No.4, 2015b.

Braack, M., Ern, A., "A posteriori Control of Modeling Errors and Discretisation Errors", Multiscale Modeling and Simulation, Vol.1, No.2, 2003, pp. 221–238.

Breitsprecher, T., Sauer, C., Sperber, C., Wartzack, S., "Design-for-manufacture of sheet-bulk metal formed parts", DS 80-4 Proc. of the 20th Inter. Conf. on Eng. Design (ICED 15) Vol.4, Milan, Italy, 2015, pp. 183–192.

Caramia, M., Dell'Olmo, P., "Multi-objective management in freight logistics: Increasing capacity, service level and safety with optimization algorithms", Springer Science & Business Media, 2008.

Deb, K., Pratap, A., Agarwal, S., Meyarivan, T., "A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II", IEEE Transactions on Evolutionary Computation, Vol.6, No.2, 2002, pp. 182–197.

Emmerich, M., Naujoks, B., "Metamodel assisted multiobjective optimisation strategies and their application in airfoil design", Adaptive computing in design and manufacture, Vol.6, 2004, pp. 249–260.

Hauer, F., "Die elasto-plastische Einglättung rauer Oberflächen und ihr Einfluss auf die Reibung in der Umformtechnik", Schriftenreihe Technische Mechanik Band 12, Friedrich-Alexander-Universität Erlangen-Nürnberg, Erlangen, 2014.

Holmes, G., Hall, M., Frank, E., "Generating rule sets from model trees", Twelfth Australian Joint Conference on Articial Intelligence, Springer, 1999, pp. 1–9.

Jin, R., Du, X., Chen, W., "The use of metamodeling techniques for optimization under uncertainty", Structural and Multidisciplinary Optimization, Vol.25, No.2, 2003, pp. 99–116.

Kim, J. S., Jeong, U. C., Kim, D. W., Han, S. Y., Oh, J. E., "Optimization of sirocco fan blade to reduce noise of air purifier using a metamodel and evolutionary algorithm", Applied Acoustics, Vol.89, 2015, pp. 254–266.

Kleijnen, J. P., "Statistical tools for simulation practitioners", Marcel Dekker, Inc, 1987.

Landkammer, P., Loderer, A., Krebs, E., Söhngen, B., Steinmann, P., Hausotte, T., Kersting, P., Biermann, D., Willner, K., "Experimental Verification of a Benchmark Forming Simulation", Key Engineering Materials, Vol.639, 2015, pp. 251–258.

Loper, M. (Ed.), "Modeling and Simulation in the Systems Engineering Life Cycle - Core Concepts and Accompanying Lectures", Springer, Heidelberg, 2015.

Maicki, J. R., "Orbital forging", Metallurgia and Metal Forming, 1977, pp. 265–269.

Marciniak, Z., "A rocking-die technique for cold-forming operations", Machinery and production engineering Vol.117, 1970, pp. 792–797.

Merklein, M., Allwood, J., "Bulk forming of sheet metal", CIRP Annals – Manufacturing Technology, Vol.61, No.2, 2012, pp. 725–745.

Opel, S., "Herstellung prozessangepasster Halbzeuge mit variabler Blechdicke durch die Anwendung von Verfahren der Blechmassivumformung", Meisenbach Verlag, Erlangen, 2013.

Opel, S., Schneider, T., Merklein, M., "Manufacturing of geared sheet metal components using flexible rolled tailored blanks", Key Eng. Mater, Vol.554–557, 2013, pp. 1459–1470.

Pan, F., Zhu, P., Chen, W., Li, C. Z., "Application of conservative surrogate to reliability based vehicle design for crashworthiness", Journal of Shanghai Jiaotong University, Vol.18, 2013, pp. 159–165.

Papalambros, P. Y., Wilde, D. J., "Principles of optimal design: modeling and computation", Cambridge University press, 2000.

Quinlan, J. R., "Learning with continuous classes", Proc. of the 5th Australian joint Conference on Articial Intelligence, Vol.92, World Scientic, Singapore, 1992, pp. 343–348.

Rademacher, A., "Mesh and model adaptivity for frictional contact problems", Ergebnisberichte Angewandte Mathematik, Fakultät für Mathematik, TU Dortmund, Vol.515, 2015.

Schmaltz, S., Landkammer, P., Beyer, F., Kumor, D., Rademacher, A., Blum, H., Steinmann, P., Willner, K., "Vorstellung eines Simulationsbenchmarks für die Blechmassivumformung", 2. Erlanger Workshop Blechmassivumformung 2013, Merklein, M., Behrens, B.-A., Tekkaya, A. E. (eds.), Meisenbach GmbH, 2013.

Schneider, T., Merklein, M., "Sheet-Bulk Metal Forming of Preformed Sheet Metal Parts", Key Engineering Materials, Vol.473, 2011, pp. 83–90.

Siebertz, K., van Bebber, D., Hochkirchen, T., "Statistische Versuchsplanung – Design of Experiments (DoE)", Springer, Heidelberg, 2010.

Song, X., Jie, Z., "A Research on Steel Synchronizer Gear Ring's Precision Forging", Materials Science Forum, Vol. 575-578, 2008, pp. 226–230.

Tomiyama, T., Kiriyama, T., Takeda, H., Xue, D., Yoshikawa, H., "Metamodel: a key to intelligent CAD systems", Research in engineering design, Vol.1, No.1, 1989, pp. 19–34.

Wang, G. G., Shan, S., "Review of metamodeling techniques in support of engineering design optimization", Journal of Mechanical Design, Vol.129, No.4, 2007, pp. 370–380.

Wang, Y., Witten, I. H., "Inducing Model Trees for Continuous Classes", Proc. of the Ninth European Conference on Machine Learning, 1997, pp. 128–137.

Witten, I. H., Eibe, F., "Data Mining – Practical Machine Learning Tools and Techniques", Morgan Kaufmann, San Francisco, 2011.

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