

1 INTRODUCTION

Saving resources is a crucial objective in the 21st century and is motivating intensive work in various research fields such as renewable energy, hybrid (or fully electric) vehicles or smart electrical grid. Lightweight design is another example that is particularly important for the automotive sector and can be achieved by different approaches: Decreasing the volume of specific parts (key components) or increasing the functional density per part are only two possibilities (Mallick, 2010). However, these lightweight approaches place new demands on key components which have to operate at their limiting capability due to increased loads and/or stresses. For example, the synchronizer rings in vehicle transmission units which feature precisely arranged gear teeth are in general made of brass. But to cope with higher loads they should in future be made of steel to benefit from higher strength and improved wear resistance (Song, 2008). In many cases current production processes are only able to deliver these new high performance components by means of many different sub-process steps and thus at high costs (Merklein, 2011). This motivates the research for new forming processes to produce high quality sheet metal components with heavily loaded functional elements. One possibility is to apply bulk forming operations to sheet metals which has led to a new class of forming processes with the overall designation sheet-bulk metal forming (SBMF) (Merklein, 2012). Exemplary sheet-bulk metal parts with different design features are depicted in Figure 1. Breitsprecher and Wartzack (2013) have described a detailed classification system for those features.

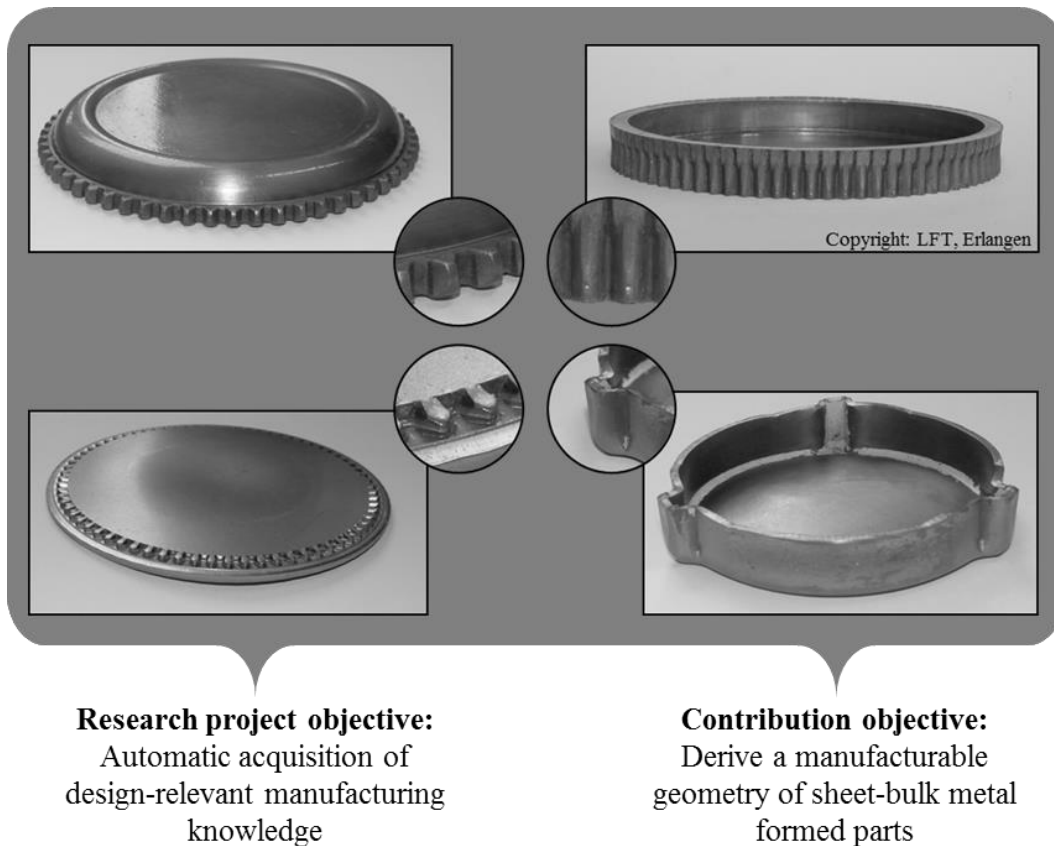


Figure 1: Sheet-bulk metal formed parts from manufacturing experiment. The overall research goal is an automatic acquisition of design-relevant manufacturing knowledge.

In order to establish this new technology the potential of SBFM from the engineering design point of view has to be revealed. Most of this potential resides in a broadened design space for secondary design features (teeth, engaging pieces, locking elements). However, in the sense of integrated product development, e. g. according to Andreasen (1987) and Ehrlenspiel and Meerkamm (2013), this requires an early acquisition of design-relevant manufacturing-related knowledge and implementation within the engineering design process. Furthermore, this knowledge has to be updated by the time the forming process evolves.

This objective is pursued through the development of the Self-Learning Engineering Assistance System referred to as SLASSY that supports the design engineer during the design process of sheet-bulk metal formed parts. For details please refer to Section 2.2 and to Breitsprecher (2012). In the current development stage SLASSY offers the design engineer assistance through a knowledge-based *analysis* (in accordance to Weber (2005)) of sheet-metal parts regarding manufacturing process related parameters.

The very next step is done with this contribution as seen in Figure 1. Our objective is to enable a knowledge-based *synthesis* of SBMF-parts. Why this objective calls for a multi-objective optimization (MOOP) and how such an optimization approach can be realized is shown in this contribution.

The paper starts with a brief description of sheet-bulk metal forming and how manufacturability can be expressed for that process. Furthermore, well-known works regarding (multi-objective) optimization in the field of engineering design are highlighted (Chapter 2). The optimization procedure which bases on the utilization of metamodels derived from the KDD-process and evolutionary optimization algorithm is shown in Chapter 3. Our use case shows the application of MOOP for a specific sheet-bulk metal formed part (Chapter 4) before the paper is concluded in Chapter 5.

2 BACKGROUND AND RELATED WORK

2.1 Design-for-manufacture in 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), funded by the German Research Foundation (DFG). This technology will unite the advantages of sheet and bulk metal forming processes to manufacture geometrically complex parts with variants and functional elements from thin sheet metal through forming. The objective is to manufacture these high–precision elements with close geometrical tolerances in which the geometrical details of the variants are in the range of the sheet thickness. The variants to manufacture are carriers and gearings derived from synchronizer rings and seat slide adjusters. The manufacturing of such variants out of sheet metals requires the overlapping or the sequence of two– and three–axis strain and stress states. To realize this, various sheet and bulk metal forming processes have to be combined (Merklein, 2012). For the development of SBMF processes, the process combinations “deep drawing – upsetting“, “deep drawing – extrusion“ and “cutting – deep drawing” will be investigated within SFB/TR 73. Exemplary SBMF-parts are shown in Figure 1.

The process engineers use and combine different methods to develop their manufacturing technology, for example forming experiments (Merklein, 2014), finite element process simulations (Schneider, 2011) and design of experiments (Fisher, 1995). The result of a SBMF process is acceptable, i.e. the SBMF part is manufacturable, if certain process parameters do not exceed upper and/or lower bounds. Depending on the part (see Figure 1) and the process, different parameters can be defined. The following list is a qualitative selection. Distinct values cannot be named since they depend inter alia on the forming machines, materials and the design features.

- forming force F_f [kN]: A forming force (mostly axial) is necessary to induce sufficient stress within the material and allow two- and three-dimensional strain rates. Depending on available forming machines a maximum value cannot be exceeded.
- horizontal loads F_h [kN] on the forming punch: In case of non-symmetrical sheet-metal parts, the vertical forming force will induce horizontal forces on the forming punch which lead to a lateral shift of the punch resulting in geometric errors of the formed part. A maximum value is not to be exceeded.
- total equivalent plastic strain ϕ [-]: It measures the increase of dislocation density and the mutual hindering of dislocation, that is, the increase of flow stress. If it exceeds a material specific value the part fails during manufacturing or operation, e.g. due to micro cracks.
- contact ratio c / mould filling volume V [%]: The specific function of a part (e.g. torque transmission) is fulfilled, if the functional features (e.g. teeth of a gear) are shaped correctly. For forming processes this can only be achieved if the material flows into the mould and fills it as much as possible. A contact ratio of 1.0 indicates that the whole mould surface is in contact with flown material, that is the process engineer strives for that value.

- sheet thickness reduction t_{Δ} [mm]: The necessary material flow and the inevitable volume constancy cause a local thinning of the sheet-metal. A maximum value $t_{\Delta,max}$ shall not be exceeded or the part will fail during operations.

Notice that each part from Figure 1 is assigned to different process parameters. The deep-drawn cup (lower right corner in Figure 1) will be evaluated, e.g. by checking F_f , ϕ and t_{Δ} , whereas the plate in the upper left corner is evaluated with F_f , ϕ and c (Figure 2 as an example). However, these are general discussions and specific values have to be assigned through discussion between the process and the design engineer. Both can influence each process parameter with specific attributes. The manufacturing engineers may use different extrusion oils to influence the tribological boundary conditions during the forming process. Also the usage of deep-drawing dies with different inlet geometries has a high influence on the forming force (Schneider, 2011) and the number of die reinforcements is often increased for more allowable forming cycles. On the other hand design engineers change the geometry of the SBF part (synthesis step) to ensure the fulfilment of a specific function, e.g. the geometry of locking teeth similar to a synchronizer ring (see Figure 2). SLASSY predicts the process parameter based on the geometry parameters and the mentioned metamodels (analysis step). Figure 2 shows how process parameters change according to different geometries.

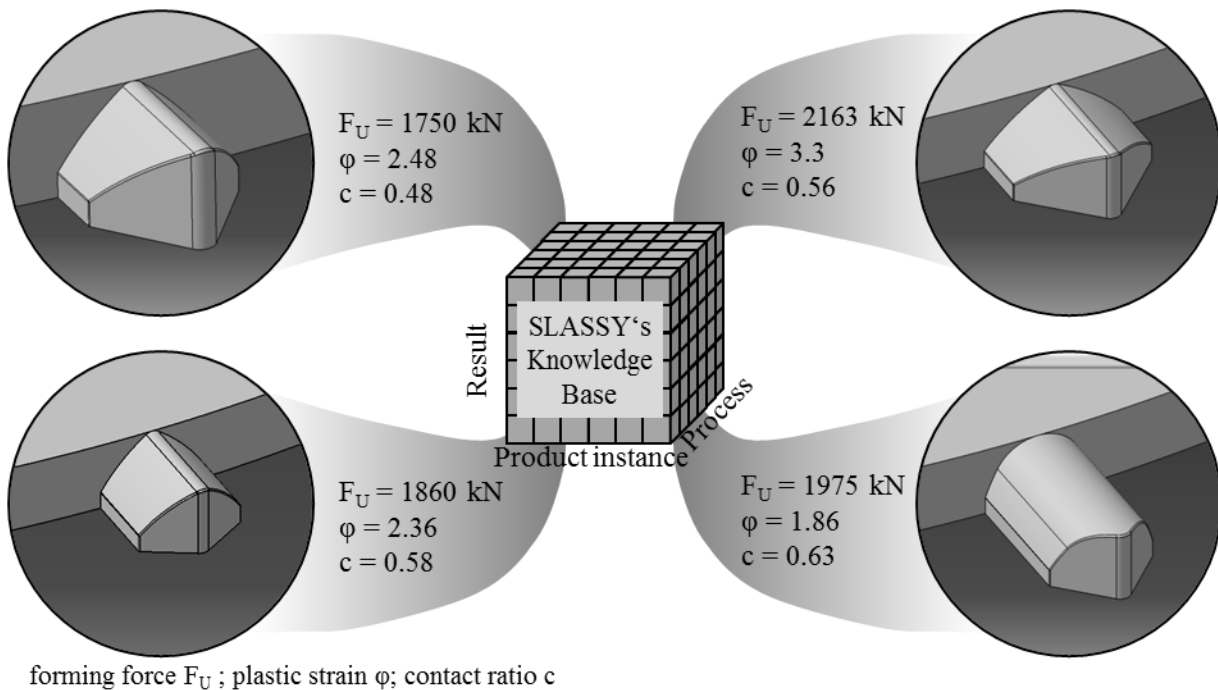


Figure 2: Different variants of sheet-bulk metal formed parts with predicted corresponding process parameters. The cube represents the knowledge base that has been derived via the KDD-based self-learning process.

Now the question is: How does a design look that meets the design-for-manufacture requirements? This is a "classical" optimization problem: For a given function $f: \Omega \rightarrow R$ from a set Ω we wish to find at least one element x_0 for which we can state $f(x_0) \leq f(x) \forall x \in \Omega$ or $f(x_0) \geq f(x) \forall x \in \Omega$, that is, we seek for minimization or maximization, respectively. From the SBF perspective each x represents a specific forming process configuration (lubrication concept, inlet geometry, reinforcement concept, etc.) in combination with specific sheet-metal part geometry (length, width or height of a tooth, etc.). $f(x)$ represents a resulting process parameter as described above. However, since the manufacturability of each SBF part is evaluated with at least two parameters, hence, the goal of deriving a design-for-manufacture design becomes a Pareto- or multi-objective optimization (MOOP) problem. A further challenge is the mixture of discrete and continuous attributes (set of x). While geometrical product characteristics (e.g. length, width, angles, etc.) can be set to values $x \in \mathbb{R}$ (e.g. 1.5mm, 12.65mm, 65.3°) other attributes can only have discrete settings (e.g. extrusion oil A, B or C; 1, 2 or 3 layers of reinforcements). These aspects have to be taken into account during the search for a suitable optimization approach.

2.2 SLASSY at a glance

SLASSY is an engineering assistance system developed for the purpose of helping the product developer to design parts that are to be manufactured by sheet-bulk metal forming. The assistance is in accordance to the understanding of Weber (2005) of the design process that consists of iterations between the phases synthesizing and analysing. The synthesis step is supported by offering feature elements both for the primary design features (cups, plates, etc.) and the secondary design features (teeth, carriers, knurls, etc.) to the design engineer. The knowledge which is necessary for the analysis of a product regarding its manufacturability is acquired automatically and stored in SLASSY's knowledge base. In summary, the development of SLASSY addresses the well-known challenge of knowledge acquisition in the field of expert systems. The term "self-learning" refers to the implemented Knowledge Discovery in Databases (KDD) process which uses data from the manufacturing process development (Röhner, 2011). After this KDD-process the knowledge is represented by means of linear or polynomial regression functions, M5P-regression trees or M5R-Rule learners (Witten, 2011). By means of statistical test methods SLASSY selects user-independently the metamodel (out of 24) which has the best data fit. In the current development stage SLASSY offers the design engineer assistance through a knowledge-based *analysis* (in accordance to Weber (2005)) of sheet-metal parts regarding manufacturing process related parameters.

2.3 Metamodelling and Optimization in Engineering Design

The development of computer technology constantly increases computing capacities and recent advances in quantum computers may offer much more potentials in the future. However, the high computational costs of virtual experiments (FEA, CFD, MBS, etc.) call for a more efficient solution when it comes to design optimizations that rely purely on computer-based system evaluation.

A well-known and mature approach is the usage of mathematical models that map the system's behaviour and produce an output which shows a sufficient accuracy. Since the origin of such mathematical models is the simulation model itself they can be considered as a "model of the model" (Kleijnen, 1986). Therefore, the term *metamodel* is often used, but further terms can be found in literature such as surrogate, reduced order, regression, approximation or response surface model.

Metamodelling techniques have been utilized and constantly improved over the last decades. Overviews and applications can be found, inter alia, in Tomiyama et al. (1989), in Barton (1994), in Simpson et al. (1997), in Emmerich and Naujokos (2004) and in Pan et al. (2013). The issue of model fit estimation is discussed in detail by Jin et al. (2001). A metamodel can be used for different purposes, such as sensitivity analysis (Chen 2005), robust design (Sanchez, 2000) and design exploration (Ligetti and Simpson, 2005). Wang and Shan (2006) present a detailed review on different metamodeling approaches. To these works we will add this contribution with the focus on design-for-manufacture in the context of sheet-bulk metal forming.

In section 2.1 we derived the necessity for a multi-objective optimization approach to deal with the given problem of a knowledge-based synthesis of SBMF parts. Such optimizations are widely used in engineering design as Papalambros (2000) shows. A crucial step in design optimization is to model the system that is to be improved. Here one can make use of metamodels, too. They offer a drastic reduction of computational loads that accompany large, comprehensive or multi-domain models of a system. Metamodel-based optimization has been used, inter alia, by El-Beltagy and Keane (1999) for minimizing the energy level of an excited beam structure for a certain excitation frequency, by Sasena et al. (2000) to find a set of design variables for a midsized hybrid electric passenger car that minimizes the fuel consumption, by Jin et al. (2003) to show how metamodels can contribute to optimization problems with uncertain design parameters, by Hu et al. (2008) to increase the energy absorption in crash-relevant sheet-metal parts and by Kim et al. (2015) for deriving shapes of fan blades that emit less noise.

3 METAMODEL-BASED OPTIMIZATION OF SHEET-BULK METAL FORMED PARTS

We have shown that our objective of deriving a design-for-manufacture geometry of sheet-bulk metal formed parts can only be achieved via multi-objective optimization. A variety of optimization approaches and procedures are available for that purpose, see e.g. Papalambros (2000) and Nelson et al. (2001), however, there are some restrictions we have to take into account which will limit the scope

of usable algorithms. Beside the restriction/requirements that were described in the last paragraph of chapter 2.1 further aspects can be named. A single forming process simulation takes approximately not less than two days, including pre-processing, solving and post-processing (Schneider, 2011). Costs for a forming tool range from four- to five-digits (Euro) depending on the design. A metamodel-based approach is thereby inevitable. Furthermore, we have to consider the metamodels (objective functions) which are available in our project. These functions can show multiple local minima, non-continuity and/or discrete behaviour. While the manufacturing process is constantly improved over time the process engineers, of course, gain more and more experience. Those heuristics contain valuable knowledge that should be taken into account during the optimization.

With these restrictions in mind we did extensive literature reviews and decided to focus on evolutionary algorithms (EA). EAs use the principles of biological evolution and involve (re)production of groups of individuals (population) via mutation, recombination (or crossover) and selection (Back, 1997). This procedure is repeated several times, whereas the population of each iteration is the generation. Furthermore, memetic algorithms as presented by Moscato (1989), a subgroup of EAs, have gained our attention. Weicker (2007) explains that memetic algorithms combine population based algorithms and local search strategies to overcome the disadvantages of both. The former tend to research the design space in its whole width, however, they are very slow and need to create many generations to find the global optimum. On the other hand, local methods can move (evolve) quickly but tend to get trapped in a local optimum. The term memetic (or meme) originates from the field of behaviourism and describes the behavioural element of an individual that can be inherited but, in contrast to a gene, can be changed in every next generation, e.g. through imitation. The basic idea of most memetic algorithms is to optimize all evolutionary created individuals locally and only afterwards add them to the population, if they show a better behaviour than their predecessor.

3.1 Deriving the fitness function

An important step is the formulation of the objective or fitness function. This function can be understood as the formal (computer-interpretable) representation of the optimization problem. Each individual's quality is evaluated by means of this fitness function to ensure comparability, whereas a single individual corresponds to a specific variant of a SBMF-part. As described in section 2.1 the term "manufacturable" means that part specific process parameters do not exceed upper and/or lower boundaries. These process parameters can be calculated via metamodels that are the result of the KDD-based self-learning process. The self-learning component of SLASSY (automatic acquisition tool) stores the metamodels by means of text-based representations that can only be interpreted by the inference machine of SLASSY. Since the optimization is carried out in the Matlab[®] environment the representation from SLASSY's knowledge base have to be converted in an appropriate format (parsing). After that parsing at least one m-function is available that accepts an input vector x (product and/or process attributes) and returns a scalar value for a specific process parameter (e.g. F_f , φ or t_Δ). In case of a single-objective optimization this m-function can be easily processed by any optimization toolbox. The fitness function for a MOOP can be expressed as an aggregation function, a weighted sum of the different process parameter objectives. Another possibility is to create multiple m-functions for each process parameter and to hand them over to the evolutionary or memetic algorithm.

3.2 Taking into account functional and further constraints

A functional constraint in our context describes the consideration of a design features's function during the optimization process. This function is ensured via a specific geometry. The teeth in Figure 1 (lower left corner) are inspired by the teeth of a synchronizer ring from a drive train gear. They have to prevent the synchronizer ring from slipping back after it has matched the new gear ratio between drive-shaft and driven-shaft (details in Kuchle, 2010). Therefore the geometry of the teeth shows specific angles and geometrical proportions.

Furthermore the manufacturing process data has to be taken into account. This data was elicited via parameter variation studies with upper and lower boundaries of the input parameters. The metamodels that are derived afterwards from the data (KDD-process) can predict the process parameters (e.g. F_f , φ or t_Δ) both for values that are beneath (interpolation) and above (extrapolation) those boundaries. However, extrapolation should be treated with caution, because predictions "outside" of the variation study range are not reliable.

Such constraints can be taken into account via different approaches (see Weicker, 2007 for details): *restrictive* methods will either reject invalid individuals immediately (so called “crib death”) or try to turn them into valid ones (repair strategy). *Tolerant* approaches will allow invalid individuals, however, those will be discriminated against the better ones during selection. The *decoder approach* chooses the coding in a way that a valid individual can always be assigned to each genotype.

4 USE CASE AND EVALUATION

In this use case a non-manufacturable design of a SBMF-part is chosen to be optimized. This design draft is created in SLASSY by synthesizing a primary design feature (deep-drawn cup) with secondary design features pattern (locking teeth). The default (initial) geometry is set as shown left in Figure 25. The self-learning process of SLASSY has acquired metamodels for the process parameters forming force F_f , total equivalent plastic strain ϕ and the contact ratio c . Each model is parsed into a Matlab processible format, whereas this operation has been automated via a short script we developed. The optimization objective is to maximize the contact ratio and minimize the forming force plastic strain. As a next step the constraints have to be derived. Figure 3 shows a sketch of the secondary design feature “locking tooth” with geometric characteristics (R0, R1, R2, H1, H0, L0, W0, A0), referred to as attributes and several constraints to ensure functionality. These attributes will be tuned during the optimization in order to find a design that is better with respect to manufacturability than the initial. Within the Matlab optimization toolbox environment the behaviour of the algorithms can be tuned inter alia by varying the numbers of generations and the size of each population. We tested several configurations and found that for the given example 800 generations with a population of 150 (black triangles in Figure 4) and 1200 generations with 400 individuals (grey rhombus in Figure 4) have shown the best results. Figure 4 shows a pareto chart of the forming force and the contact ratio with different optimization configurations. It can be seen that the mentioned configurations densify to what can be interpreted as a pareto front, whereas the remaining configurations are more loosely spread right of the pareto front.

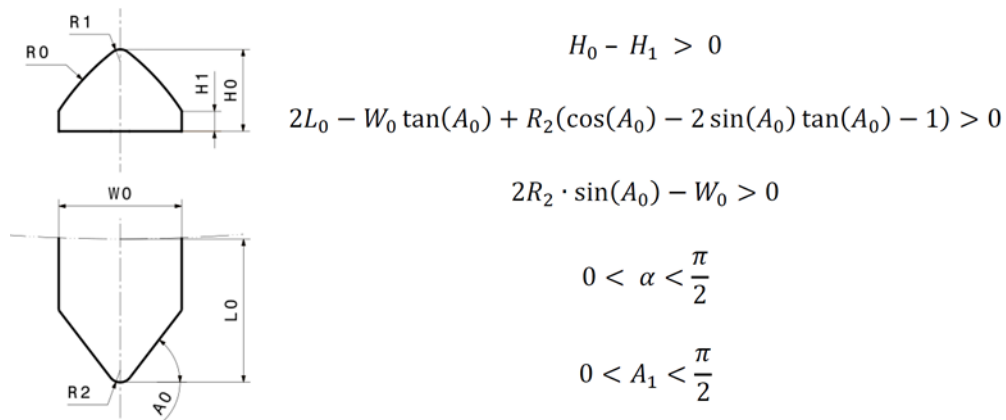


Figure 3: Constraints of the use case “locking tooth”. The constraints ensure both functionality of the SBMF-part and failure-free CAD-model creation.

The result of a MOOP is a set of pareto-optimal points each of which represents a SBMF-part design that is optimal with respect to the process parameters F_f , ϕ and c and that meets the previously determined constraints. The design engineer can independently choose an individual from this set and transfer it to the synthesis tool of SLASSY in order to display this specific solution and discuss it with manufacturing experts. A complete automation and the output of a single optimization solution are not expedient, because the user loses the control over the assistance system and cannot comprehend its decisions. According to Stokes (2001) this is a major cause of failure for knowledge-based systems. The users tend to avoid dealing with the system and start to develop their own workarounds on the longterm. We developed the functions *thinningPareto* and *explorePareto* in Matlab to either reduce the size of the set or to search the individuals selectively.

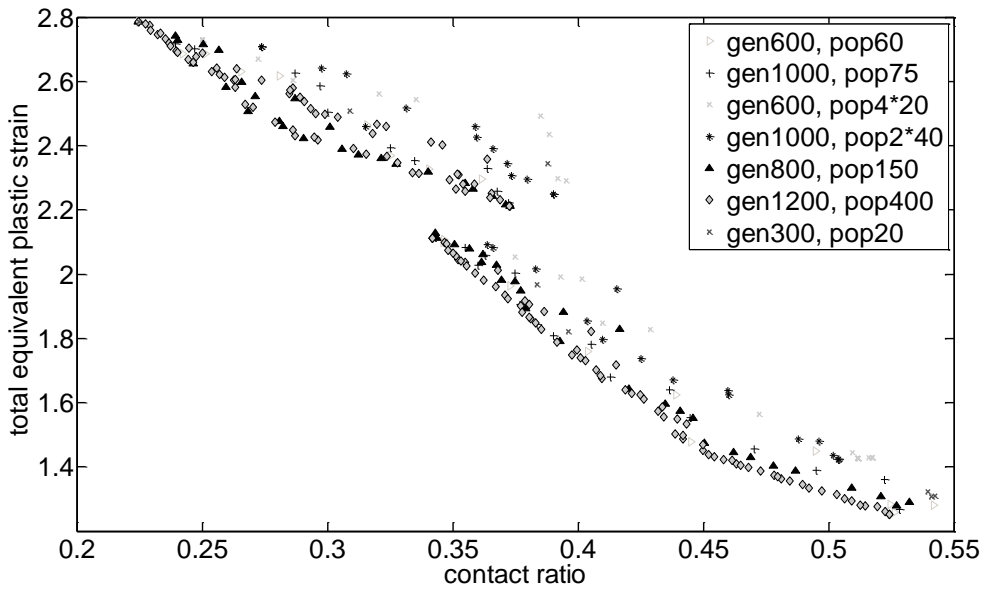


Figure 4: Pareto chart of plastic strain and contact ratio with different optimization configurations (pop= size of population, gen= number of generations).
The configuration that is represented by triangles and rhombus turned out to deliver good results in a short time (40s).

Figure 5 shows an optimized individual with the values of the according attributes and the resulting process parameters. Both the forming force and the plastic strain have been reduced by 11% (F_f) and 37% (ϕ), however, the contact ratio increased by 10%.

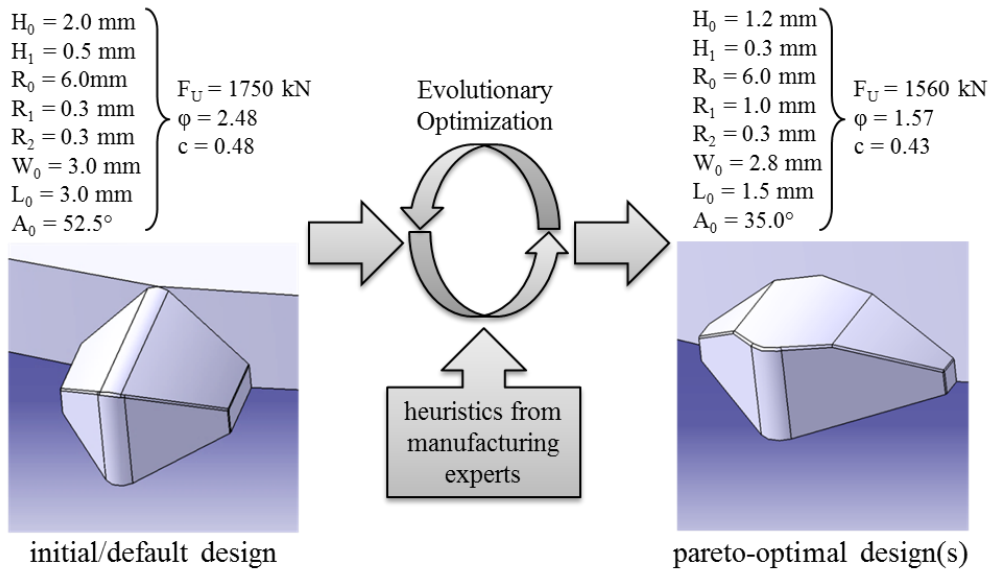


Figure 5: Initial and an optimized version of the locking teeth with according process parameters. Note, that there is mostly more than one pareto-optimal design.

5 SUMMARY AND OUTLOOK

This research is concerned with the problem of knowledge-based engineering of sheet-bulk metal formed parts. Sheet-bulk metal forming is a new manufacturing technology that offers potential for the design engineer, however, the design-relevant and manufacturing related knowledge has to be acquired and integrated into the product development in an early phase of process development. This is done by an automatic KDD-based self-learning process. The knowledge is formally represented by means of metamodels which have been used for the knowledge-based *analysis* of SBMF-parts. We showed that the goal of a knowledge-based *synthesis* corresponds to a multi-objective optimization

problem. MOOP has been used for many engineering design problems and can be achieved via different approaches. For this contribution we focussed on evolutionary and memetic algorithms which are available in toolboxes, e.g. in Matlab[®]. We extended such a toolbox to customize them for our purpose and to ease their usage. Beside the presented example we analysed different algorithms regarding their fit for our purposes. Table 1 concludes our findings.

Table 1: Comparison of evaluated algorithms with respect to the fulfilment of requirements regarding the optimization of our sheet-bulk metal formed parts.

requirement	memetic algorithm	genetic algorithm	genetic multi-objective algorithm
Multi-objective optimization	with aggregation function	with aggregation function	yes
Optimization with discrete attributes	via fitness function	yes	yes
Optimization under constraints	yes	yes	yes
approx. runtime (s)	1	0,5	40

For a given SBMF-part design we started a multi-objective optimization process and derived a set of pareto-optimal designs that also met function related constraints. The presented example is straightforward and kept simple to ensure proof-of-concept and will be extended with further aspects in future works. Nevertheless, we set the basics for aspects like integration of manufacturing heuristics which result in local search strategies (memetics) during the optimization process. Since sheet-bulk metal forming is still in an early development stage, the process simulation models are extended by further aspects (e.g. friction models, material fatigue models, structured tool surfaces) step by step. This leads to continuous simulation studies being performed and continuous simulation data being created. From this data SLASSY will acquire metamodels which represent the “new” knowledge for a specific SBMF-part. Eventually SLASSY tackles the well-known bottleneck of knowledge acquisition within the development of knowledge-based systems as described in Hayes-Roth (1983).

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