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Virtual Hybrid- and Meta-Optimization of Forming Processes

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Virtual Hybrid- and Meta-Optimization of Forming Processes

Rolf Steinbuch

Abstract

Today the optimization of metal forming processes is done using advanced simulation tools in a virtual process, e.g. FEM-studies. The modification of the free parameters represents the different variants to be analysed. So experienced engineers may derive useful proposals in an acceptable time if good initial proposals are available. As soon as the number of free parameters growths or the total process takes long times and uses different succeeding forming steps it might be quite difficult to find promising initial ideas. In metal forming another problem has to be considered. The optimization using a series of local improvements, often called a gradient approach may find a local optimum, but this could be far away from a satisfactory solution. Therefore non-deterministic approaches, e.g. Bionic Optimization have to be used. These approaches like Evolutionary Optimization or Particle Swarm Optimization are capable to cover a large range of high dimensional optimization spaces and discover many local optima. So the chance to include the global optimum increases when using such non-deterministic methods. Unfortunately these bionic methods require large numbers of studies of different variants of the process to be optimized. The number of studies tends to increase exponentially with the number of free parameters of the forming process. As the time for one single study might be not too small as well, the total time demand will be inacceptable, taking weeks to months even if high performance computing will be used. Therefore the optimization process needs to be accelerated. Among the many ideas to reduce the time and computer power requirement Meta- and Hybrid Optimization seem to produce the most efficient results. Hybrid Optimization often consists of global searches of promising regions within the parameter space. As soon as the studies indicate that there could be a local optimum, a deterministic study tries to identify this local region. If it shows better performance than other optima found until now, it is preserved for a more detailed analysis. If it performs worse than other optima the region is excluded from further search. Meta-Optimization is often understood as the derivation of Response Surfaces of the functions of free parameters. Once there are enough studies performed, the optimization is done using the Response Surfaces as representatives e.g. for the goal and the restrictions of the optimization problem. Having found regions where interesting solutions are to be expected, the studies available up to now are used to define the Response Surfaces. In many cases low degree polynomials are used, defining their coefficients by least square methods. Both proposals Hybrid Optimization and Meta-Optimization, sometimes used in combination often help to reduce the total optimization processes by large numbers of variants to be studied. In consequence they are highly recommended when dealing with time consuming optimization studies.

Terms and Definitions

To discuss robust and reliable optimization effectively in the next sections, we have to use the same terms for the same phenomena. As optimization research is done by various groups within various and diverse scientific fields, and also in different regions of the earth, there is the real danger to get confused as the meanings of terms may diverge from group to group. Thus, we must clarify the set of terms used. Most people involved in optimization accept that for an optimization study (Steinbuch, Gekeler, 2016):

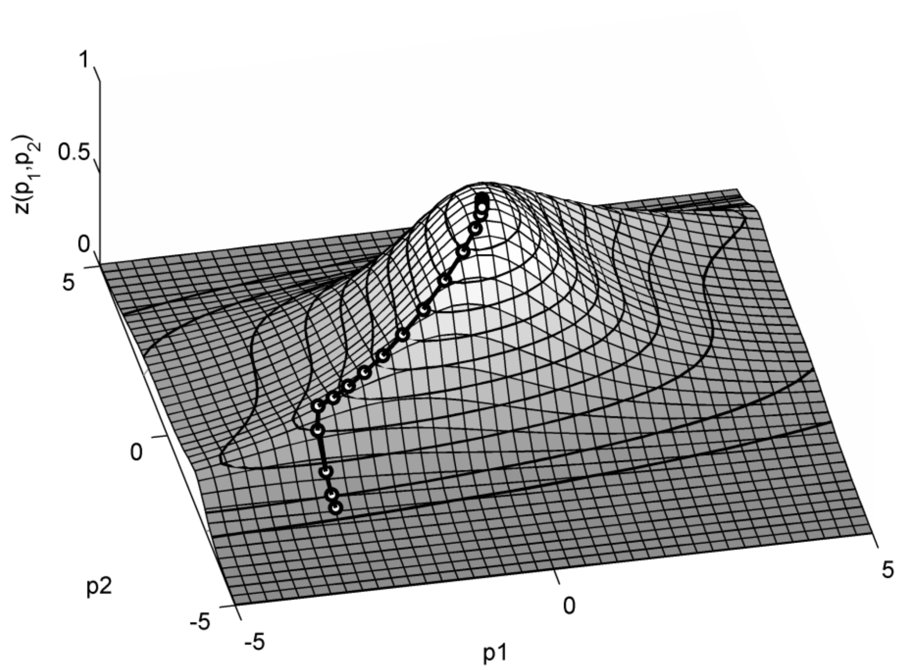
We need a given *goal* or *objective* z.

- This objective z depends on a set of *free parameters* $p_1, p_2, \ldots\ p_n$.
- *Limits* and *constraints* are given for the parameters values.
- There are *restrictions* of the parameter combinations to avoid unacceptable solutions.
- We seek to find the *maximum* (or *minimum*) of $z(p_1, p_2, \ldots\ p_n)$.

To better define our terminology, we use the following conventions and findings:

- The *objective* or *goal* must be defined *à priori* and uniquely. Changing the definition of the goal is not allowed, as this poses a new question and requires a new optimization process.
- We need to define all free parameters and their acceptable *value ranges* we might modify during the optimization studies.
- This *value ranges* or *parameter ranges* are the span of the free parameters given by lower and upper limits. Generally it should be a continuous interval or a range of integer numbers.
- The fewer free parameters we must take into account, the faster the optimization advances. Consequently, accepting some parameters as fixed reduces the solution space and accelerates the process we look at.
- Restrictions, such as unacceptable system responses or infeasible geometry, must be taken into account. But restrictions limit the ranges of parameters to be searched. Such barriers have the potential to prevent the optimization process from entering interesting regions.
- Finding the maximum of $z(p_1, p_2, \ldots\ p_n)$ is the same process as finding the minimum of the negative goal $-z(p_1, p_2, \ldots\ p_n)$. There is no need to distinguish between the search of maxima or minima.

Figure 1. *Climbing up a Hill using Gradient Methods*



Gradient based Optimization Methods

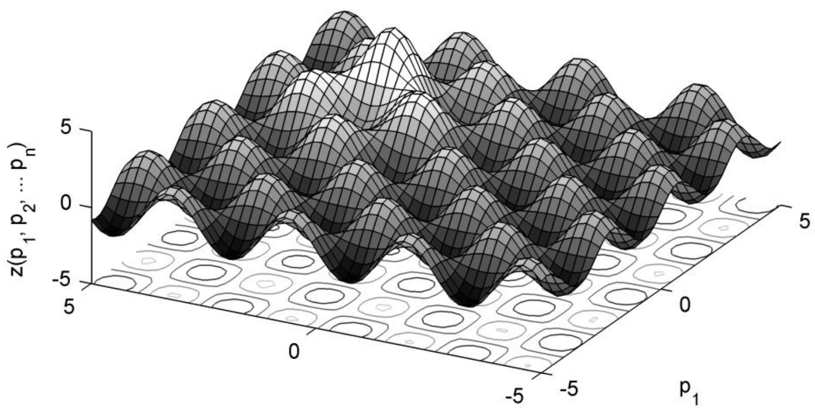
Gradient based optimization methods are the most popular ways to find improvements of given situations. From an initial position, the derivatives of the objective $z(p_1, p_2, \dots p_n)$ with respect to the free parameters are determined. The column of these derivatives defines the gradient. Jumping along this gradient, for example, by using a line search method such as Sequential Quadratic Programming (SQP) (Bonnans et al., 2006), or any related method, has the tendency to find the next local maximum in a small number of steps or iterations, as long as the search starts not too far away from this local maximum (Figure 1).

Optimization using this climbing of the ascent of the gradient is often labelled as a Gradient Method or included in the set of deterministic optimization methods. Here each step is determined by the selection of the starting point. Unfortunately, the numerical determination of the gradient requires $2n + 1$ function evaluations per iteration, which may be an extended effort if the number of parameters is large and the hill not shaped nicely.

Bionic Optimization

Deterministic methods, such as gradient climbing, fail as soon as there are many local hilltops to climb. Only the next local maximum from the starting point is found if problems occur such as the one shown in Figure 2.

Figure 2. *Multi-Hill Landscape with Many Local Optima*

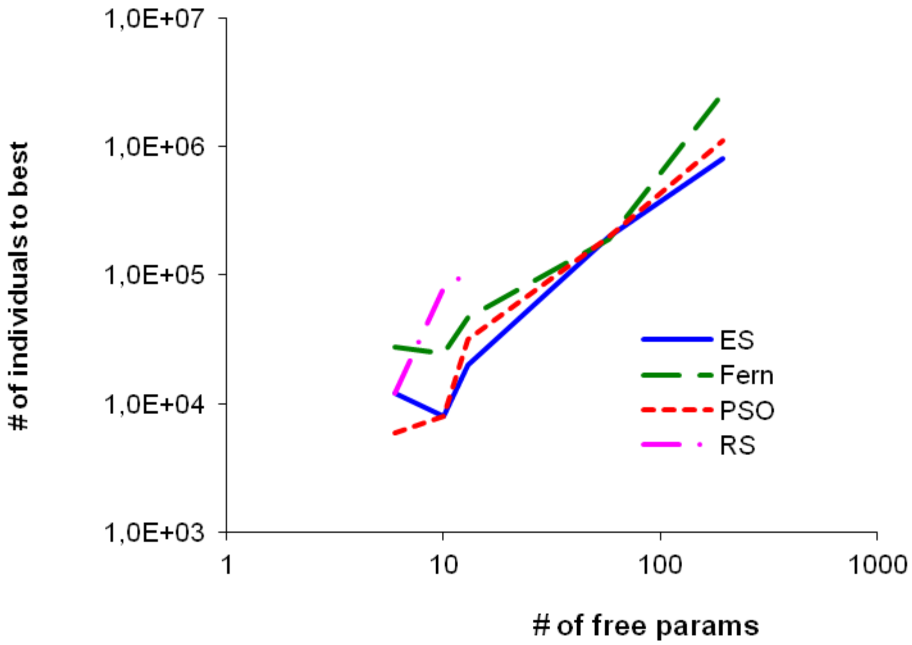


An alternative is using purely stochastic searches, which may consist of randomly placed points in the parameter space. They guarantee discovery of the optimum, but only if we allow for very large numbers of trials. For real engineering applications, they are far too slow. A more powerful class of methods produces some random or motivated initial points into the parameter space and uses them as starting points for a gradient search. As long as the problem is of limited difficulty and does not have too many local optima, this might be a successful strategy. For problems that are more difficult to handle, the bionic methods presented in e.g. in (Steinbuch and Gekeler, 2016) prove to be more successful. They combine randomness and qualified search and have a sufficient potential to cover large regions of high-dimensional parameter spaces. Some randomly or intentionally placed initial designs are used to start an exploration of the parameter space and propose in reasonable time designs that might be outstanding, if not even the best. (Steinbuch and Gekeler, 2016) discuss some of the Bionic Optimization methods and give the basic ideas, examples of applications, and sketches of program structures.

Efficiency of Optimization Strategies

The task to solve optimization problems with a not too small number of free parameters requires large numbers of individual solutions to be evaluated, either to define the gradient or to search the parameter space in bionic optimization. Figure 3 (Gekeler et al., 2012) gives an idea about this number of studies for different bionic and deterministic approaches. We realize that the total computing times will be inacceptable as soon as the evaluation of one individual takes more than small fractures of seconds. In metal forming, where computing times per variant are in the range of hours to days. So the total optimization time would be in the range of many years. Evidently we have to think about efficient acceleration of the processes.

Figure 3. *Efficiency of Different Optimisation Strategies*



Hybrid Optimization

The different optimization strategies show good performance at different problems. There is no doubt, that random or bionic based methods should be used if the goal is represented by a landscape like in Figure 2. For isolated hills (Figure 1) gradient searches will perform better. So it is always a good idea to check, whether switching from one approach to another might be preferable. Typical indications for such a decision could be found by estimating the shape of the goal from the variants studied up to now.

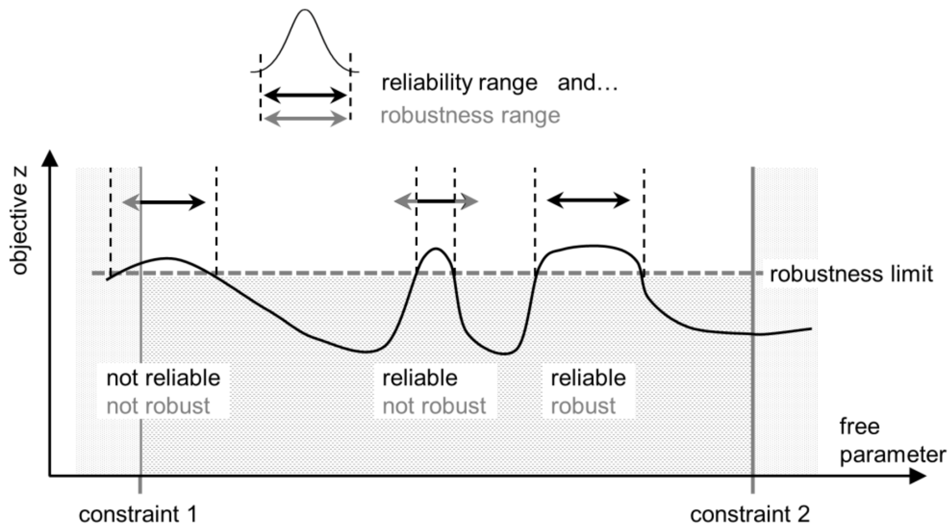
Reliability and Robustness

Uncertainty is inevitable in engineering design. Every component, every material and all load sets are not given by exact data, but tend to scatter around some predefined values. Therefore research about design under uncertainty has been growing over the last years and is now used in a wide range of fields from simple product components to designing complex systems. Terms such as “Robust Design” and “Reliability Based Design Optimization” have been introduced in some design software packages. But their application to parametric uncertainty is difficult and limited. Robust design is mainly exploited to improve the quality of a product and to achieve the required level of performance. This can be done by minimizing the effect of the scatter; however, the causes are not eliminated.

Reliability-based Design Optimization (RBDO), as one paradigm of design under uncertainty searches optimal designs with low probabilities of failure within the expected scatter of the produced parts. Robust design optimization (RDO) seeks a product design which is not too sensitive to changes of environmental conditions or noise. RDO tries to minimize the mean and the variation of the objective function simultaneously under the condition that all constraints are satisfied (Wang et al., 2010; Tu et al., 1999).

For optimization under uncertainty, it is necessary to take both the probabilistic design constraints and the design objective robustness into account. In Figure 4 one can observe in the case of an optimization problem with one free parameter that unreliable parts are not robust, as they fail to comply with the restrictions. This corresponds to unacceptable values of the objective (Gekeler and Steinbuch, 2014). On the other hand there are optima, which are reliable but not robust. Finally robust and reliable optima are what we are searching in most cases.

Figure 4. *Definition of Reliability and Robustness*

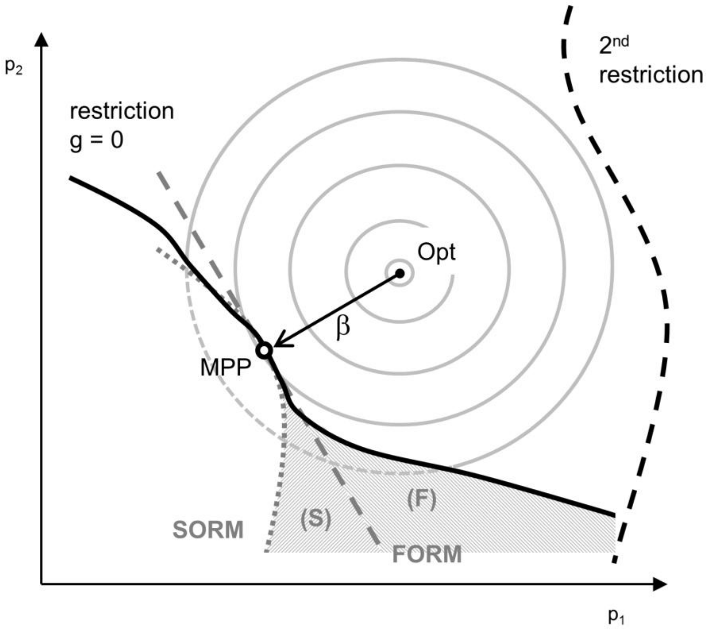


Many engineers use the First Order Reliability Method (FORM) or Second Order Reliability Method (SORM) (cf. Figure 5) successfully to perform optimization and reliability or robustness applications. But, due to some difficulties, they are not suitable for every optimization case. The most important problems related to FORM and SORM are (Gekeler and Steinbuch, 2014):

- scattering input data have to be independent when they are considered as random variables. They must follow a normal distribution or have been transformed into a normal distribution;
- the linear or quadratic approximation of the restrictions hyper-plane may not be conservative. In

Figure **5** (F) indicates the region where FORM is not conservative, while (S) adds the region where SORM is not conservative;

Figure 5. *2nd Restriction and Non-conservativeness of FORM (F) and SORM (S)*



- the normalization of the random variables requires a good guess of the mean and standard deviation of the multidimensional random variables which may be found only after a large number of tests;
- the approaches primarily hold only for one critical restriction, and they may fail or become less applicable as soon as there is a second restriction active as shown in

Figure **5**.

As the proposed approaches to carry out reliability and robustness studies consume much time and computing power, faster steps to come up with acceptable results were proposed (Gekeler and Steinbuch, 2014). These proposals, found by the advanced optimization techniques, may be used as input for manufacturing without having to consider uncertainty at all. To take into account stochastic problems, a more general definition of the robust and reliable optimization was suggested. The objective function of n_p parameters is described as:

$$\mathbf{z} = \mathbf{z}(p_1, p_2, \dots, p_{np})^T, \tag{1.1}$$

where $\mathbf{z}$ is a vector composed of two other vectors, $\mathbf{s}$ and $\mathbf{r}$:

$$\mathbf{z} = (\mathbf{s}, \mathbf{r})^T = (s_1, s_2, \dots, s_{n_g}, r_1, r_2, \dots, r_m)^T, \tag{1.2}$$

Here $\mathbf{s}$ stands for the vector of n_g optimization goals, while $\mathbf{r}$ represents the set of m restrictions. In general there are given limits to the design parameters

$$p_{i,min} \leq p_i \leq p_{i,max}, \qquad i = 1 \dots n_p. \tag{1.3}$$

In addition all p_i may show some scatter indicated by

$$p_i = p_i \pm \Delta p_i. \tag{1.4}$$

Among others (Wang et al., 2010) distinguish sets of non-scattering design or optimization parameters $\mathbf{d}$, scattering design or optimization parameters $\mathbf{X}$, and scattering non-optimization parameters $\mathbf{C}$. If one allows $\Delta p_i = 0$ for some set of parameters and $p_{i,min} = p_{i,max}$ for another set or even the same set of the same parameters, these three classes will be reduced to one set of optimization goals or restrictions $\mathbf{z}$ and parameters $\mathbf{p}$ as proposed in eqs. (1.1) to (1.4). Some of them do not essentially scatter, and some of them are fixed within their tolerances. This allows for a more simple annotation without losing the generality of the idea. Using this approach, the optimization might be done in a relatively compact way.

Metamodeling

The main concern of stochastic mechanics is to use a sufficient amount of test data to provide acceptable probabilistic measures (Doltsinis, 2012). One common and efficient way to solve this problem is using Meta models, e.g. Response Surfaces (RS) in all components of $\mathbf{z} = (\mathbf{s}, \mathbf{r})^T$. These RS provide approximations of the goal and the restrictions. They allow for estimations of the mean and standard deviation of all the components of $\mathbf{z}$.

(McKay et al., 1979; Au et al., 1999; Das et al.; 2000; Matthies et al., 2013; Dubourg et al., 2013; Bourinet et al., 2011).

In this formulation, the goal and the restrictions are defined respectively as $\mathbf{s}$ and $\mathbf{r}$ (cf. eq. 1.1 and 1.2). In many cases, RS are first or second order degree polynomials in the optimization parameters. Since frequently better data are not available, one may use them to perform the reliability or the robustness analysis. The main disadvantage of this approach is that a large number of tests are required (i.e. FE-jobs or experimental measurements). A second order RS could be defined by its coefficients:

$$RS(p_1, p_2, \dots, p_{np}) = a_0 + \sum_i a_i p_i + \sum_i \sum_{k \le i} a_{ik} p_i p_k. \qquad (2.1)$$

The number of coefficients for this second order RS is given by

$$n_c = 1 + n_p + (n_p + 1) n_p / 2, \qquad (2.2)$$

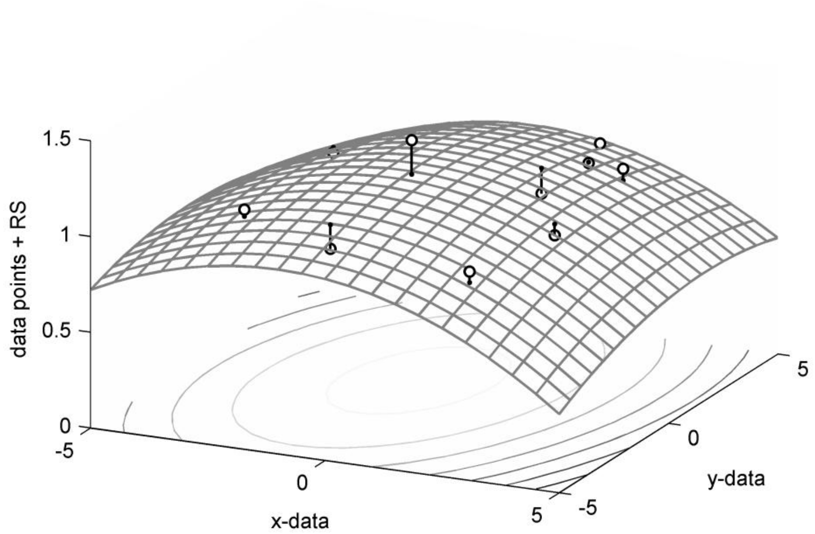
where n_p denotes the number of optimization parameters. To find the RS by a least squares method, the number of tests should be about twice the number of coefficients. In consequence there should be about n_p^2 tests. For nonlinear studies and some (e.g. $n_p = 10$) optimization parameters, where one job may take some hours, the total computation time may become absolutely unacceptable. A reduction of the number of coefficients in eq. (2.1) by omitting the mixed terms to

$$RS(p_1, p_2, \dots, p_{np}) = a_0 + \sum_i a_i p_i + \sum_i a_{ii} p_{ii}^2 \qquad (2.3)$$

may sometimes help accelerate the process, as there are only $2n_p + 1$ unknown coefficients and one has to run about $4n_p$ tests. But this simplification may essentially reduce the quality of the approximation. The response surfaces found by any means may be used to estimate the goal or the reliability as shown in Figure 6. The short vertical lines indicate the test data and their distance to the RS.

In many cases the optimum and the MPP (cf. Figure 5) coincide as the optima often are found to be close to restrictions. If the random variables are following normal distributions, one may find the failure probability at parameter values from the mean and the standard deviation. The reliability close to the MPP and optimum then becomes 50% because $\beta = 0$.

Figure 6. *Approximation of a Goal or Restriction by a 2nd Order Response Surface*

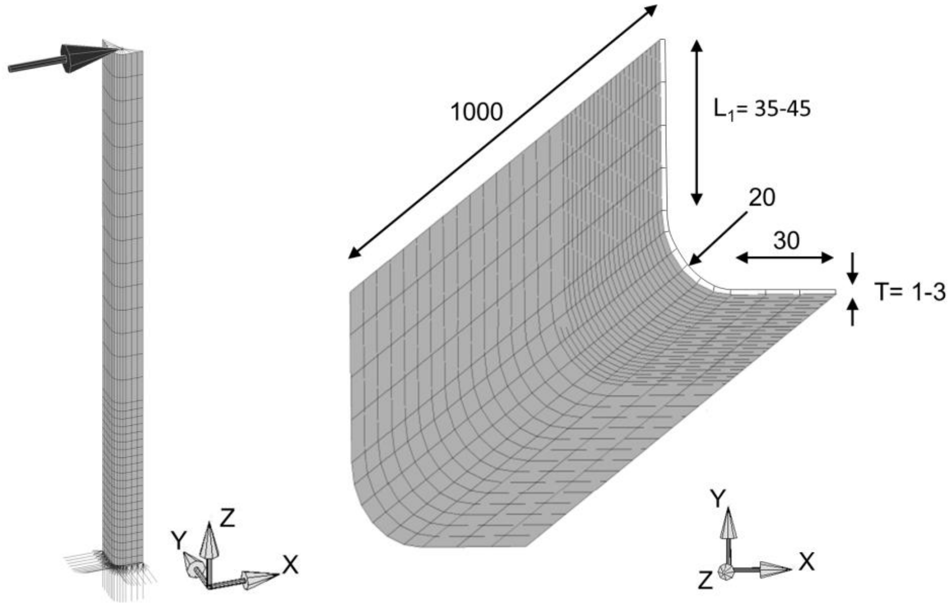


In these cases, neither reliability nor robustness requirements are fulfilled. If such an optimized design does not provide sufficiently high reliability or robustness, its free parameters must be modified to shift it away from the critical regime. This may be done by translating the parameters along a direction close to the normal β or the gradient of the restriction g from the MPP in Figure 5. Studies, such as the ones on the response surfaces, may help to give acceptable representations of the preferable position of the design. Care should be taken in the presence of more than one restriction (

Figure **5**). If other restrictions prohibit feasible solutions near the optimum, we need to search other regions of the parameter space which are large enough to allow solutions that do not violate any restriction.

Example: We analyze the bending of an L-Profile fixed at its lower end while a deflection of the upper end of u_{max} = 400 mm is applied (Steinbuch and Gekeler, 2016). The goal is the minimization of the mass of the L-profile. The length L_1 and thickness T are defined as free parameters (Figure 7).

Figure 7. *L-Profile under Displacement Controlled Bending Load*



a) Overall view b) Free parameters L_1 and T

Figure 8 indicates the meaning of the constraints on the force and energy.

Force $F(u) < F_{max}$,
$F(u_{max}) > F_{min}$,
$W_{mech} > W_{min}$.

In order to generate the corresponding response surfaces, one needs to place variants in the parameter space. Using them Response Surfaces for the goal and the constraints will be generated. Then the restrictions are applied to the Response Surfaces (see Figure 9).

Figure 8. *Definition of Constraints on Force and Energy*

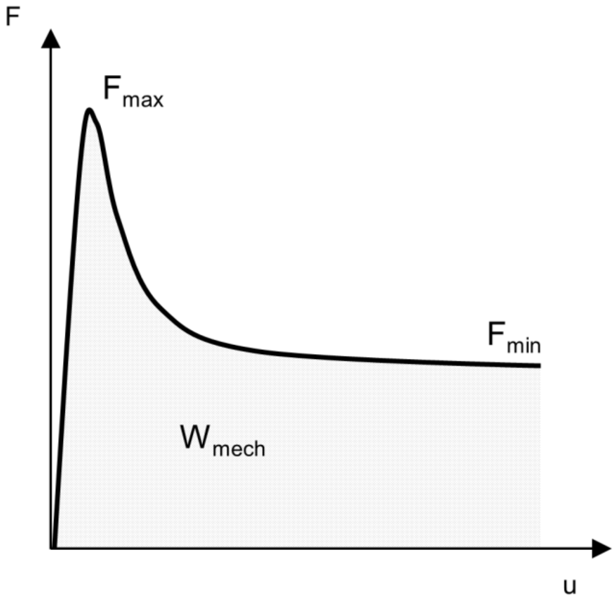
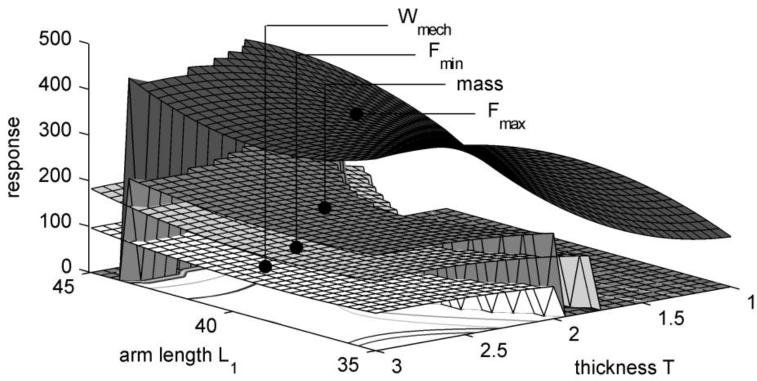
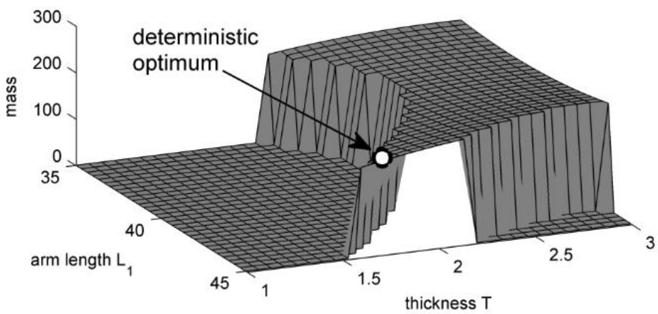


Figure 9. *Response Surface of Goal and Restrictions for L-Profile*



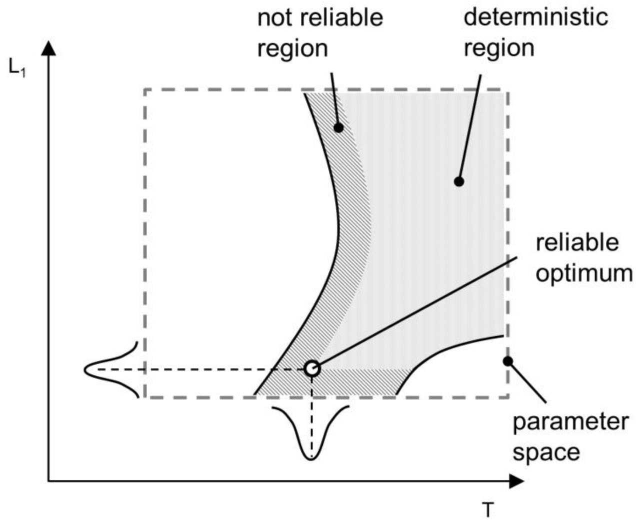
The optimization is done on the response surface of the mass in order to find the deterministic optimum. The optimum without taking into account the scattering is indicated in Figure 10.

Figure 10. *Optimization on RS, which Represents the Mass in the Acceptable Parameter Region*



Now the reliability and robustness of the optimum must be guaranteed. We do it by stepping away from the limits of the allowed parameter region, following the expected scatter (Figure 11). The quantification of this scatter must be provided by real-world experiences of the manufacturing process and the material quality.

Figure 11. *Guess Reliability and Robustness by the Use of the Expected Scatter of the Input Data*



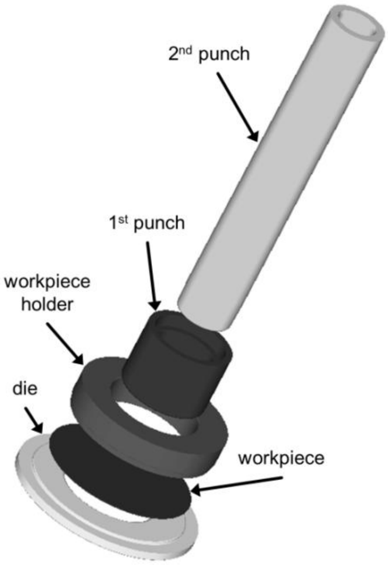
Application to Metal Forming

With growing demands and the high complexity and variety of the products, simulation of forming processes is an increasingly important field. Understanding how the loads will act on a part required to dimension the forming tools and to determine the process borders. Simulations are used to control the quality of the final product at an early stage of the process development. Their flexibility enables quick changes of process parameters, and the evaluation of their effects. Here Robust and Reliable Optimization may help avoid defects in production lines, reduce testing and improve efficiency in the metal forming process.

Deep Drawing of a Can

Deep drawing is a method of sheet metal forming. In this process a sheet metal blank is axially drawn into a hollow cup (can) with a forming die and the mechanical action of a punch. The end form is achieved by redrawing the intermediate form through a series of dies (Ping et al., 2012).

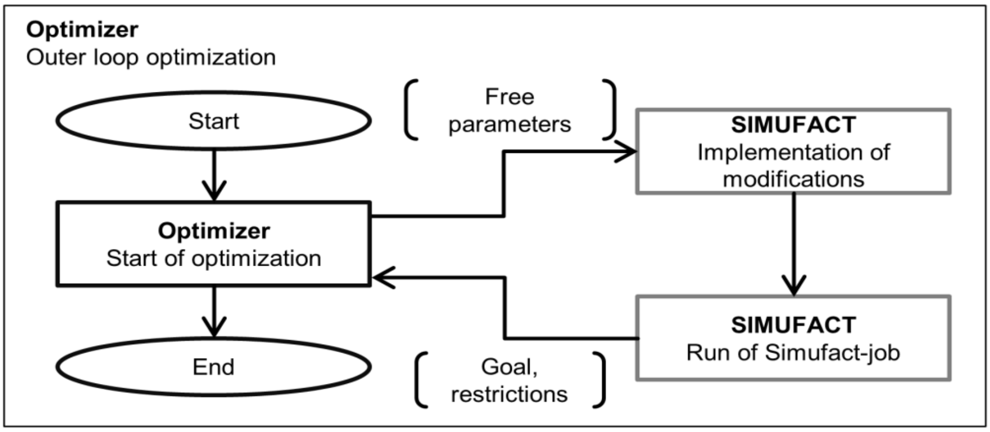
Figure 12. *The First Stage of the Deep Drawing Process (Gekeler et al., 2015)*



a) Tools of the 1st Step of Deep Drawing

b) 1st Intermediate Form of the Workpi – Simulation Indicates the Effective Plastic Strain

Figure 13. *Optimization Workflow for Can Optimization with Simufact (www.simufact.com)*



In our example the workpiece is a blank with predefined dimensions of radius and height. The deep drawing process contains many components and steps. The first forming, shown in Figure 12 uses the following tools: a die (ring), a blank holder (not shown), and two punches, which move together during the first stage. The blank lies between the die and holder. It is drawn into a forming die. In the next stage the tools include a forming die with a smaller diameter, the 1st punch serving now as the blank holder, and a moving 2nd punch. This intermediate form goes through three ring-dies that make the can thinner. The 2nd punch and bottom-die are used on the bottom forming of a can, the last stage, after stretching.

Here, the optimization task is to achieve a uniform wall thickness distribution at the can after the 1st forming stage, dependent on tool friction. The workflow of the optimization process including the optimization step and the FE- simulation tool is shown in Figure 13.

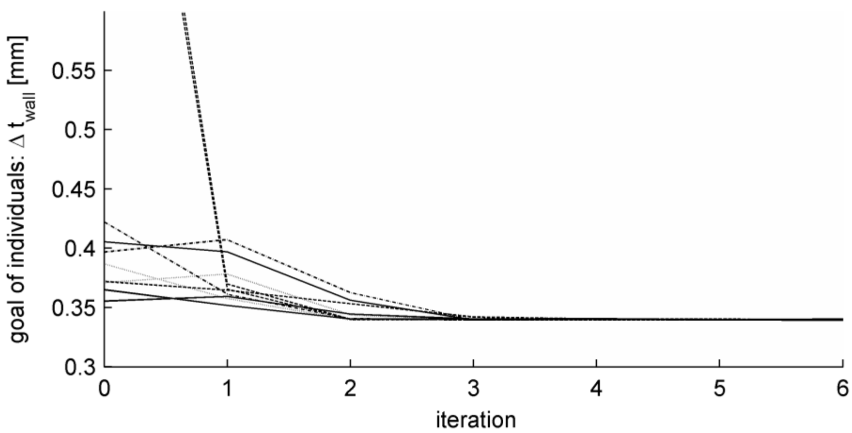
The workflow follows the following steps:

1. The workflow starts with a run of the control program (optimizer). For example the values of input parameters will be selected randomly within a certain range.
2. The changed values are rewritten in the FE-input file.
3. The simulation job is run in batch mode.
4. After a simulation job is finished, the optimizer receives the output file of the last simulation increment, converts it, and reads the results. If these results do not satisfy the restrictions, then the goal value will be modified to comply for the violation of the restriction. This is called a penalization. So the unsuitable set of input parameters will be restricted, and the next cycle of optimization process will be executed. If activated, the program will verify the completed job status by checking a stop criterion, for example. If the tolerance between the new and the old fitness values has been reached, the optimizer will be stopped. Otherwise, the input parameters will be recalculated and next cycle of optimization process will run.

Significant variables or optimization parameters that can be used for optimization of the deep drawing process include:

1. the properties of sheet metal,
2. blank holder force,
3. tool friction,
4. punch speed,
5. the blank diameter to punch diameter ratio,
6. the sheet thickness,
7. the clearance between the punch and the die,
8. the punch and finally
9. die corner radii.

Figure 14. *Optimization of the Can's Wall Thickness Distribution in a Deep Drawing Process using PSO*



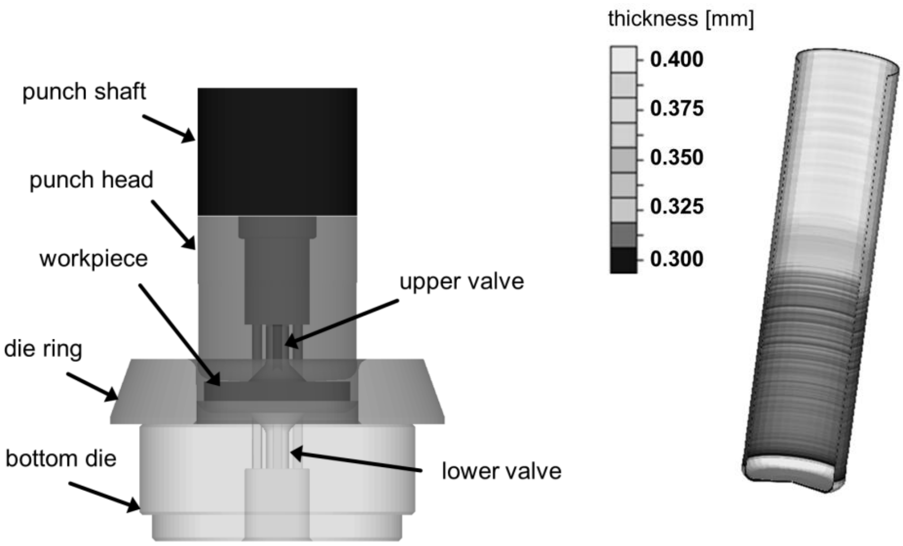
So a total of 9 optimization parameters had to be taken into account. The results found in each cycle had to be tested for their robustness as well. Unsatisfactory responses might be handled by reduction of the goal achieved, we modify the goal to punish the violation, do a penalization.

The convergence behavior and the robust and reliable optimization result are depicted in Figure 14. The figure shows the wall thickness decreasing through the iterative process for different particles in a PSO-study (10 particles, 6 iterations). We realize that the best result is reached after some steps by most of the particles. But it must not be ignored that the total study took about 150 hours on an 8 processor computer.

Backward Extrusion of a Can

Backward extrusion is a widely used cold forming process for the manufacturing of hollow cylindrical products. It is usually performed on high-speed and accurate mechanical presses. The punch descends at a high speed and strikes the workpiece, extruding it upwards by means of the high pressure. The die ring helps to form the tube wall. The thickness of the extruded tubular section is a function of the clearance between the punch and the die (Barisic et al., 2005). A schematic outline of backward extrusion process is presented in Figure 15.

Figure 15. *The Backward Extrusion Process*



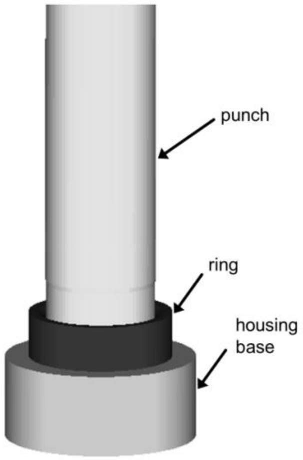
a) *Tools of Backward Extrusion*

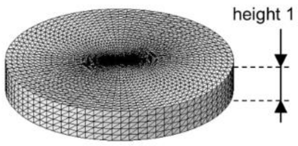
b) *Can - Result of a Backward Extrusion Simulation*

For the simulation of the backward extrusion process, a simplified process model could be used. For instance, all the punch parts could be represented as one single part. All the tools of the backward extrusion process could be divided into three groups according to their functions: punch, ring and housing base. The workpiece is represented by an aluminum blank. Figure 16 illustrates the components of the backward extrusion simulation model.

The output of the process is the can with its wall thickness. The wall thickness distribution depends on the tool dimensions. Parameter variations cause a thickness distribution. Figure 17 depicts all the dimensions of the tools that could be variables for the backward extrusion process optimization. In addition, the thickness of the workpiece may be modified as well.

Figure 16. *Simulation of the Backward Extrusion with a Simplified Model*

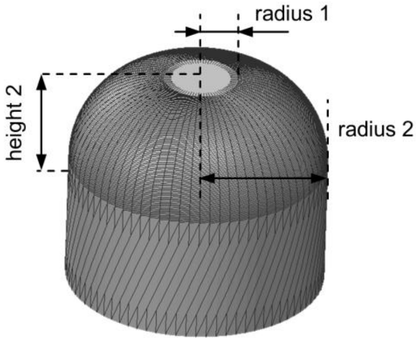


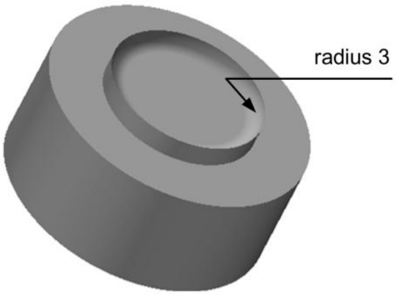


a) *Tools of Backward Extrusion* b) *Meshed Workpiece*

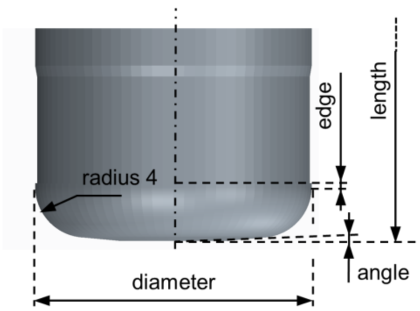
The goal of the optimization is to minimize the mass, here using a PSO study again. As a first restriction the required can length of l = 200 mm should be reached in the backward extrusion process. Furthermore, the final can has to resist an inside pressure of p_2 = 21.6 bar, without large deformations up to p_1 = 18 bar. All restrictions and violations of reliability and robustness are handled using penalty methods. Figure 18 shows the fitness values of different particles through iterations of the PSO (16 iterations x 18 particles = 288 simulation runs, about 600 h of computing time on an 8 processor computer). In this example, the fitness value represents the workpiece mass. Optimization is obtained through modifications to the geometry. The figure contains the worst, average and best particle curves. The Bionic Optimization method finally proposes an 18% mass reduction from the initial mass of 38 g to the optimized mass of 30.0 g. As not all particles have converged, even better results might be expected. To accelerate the further search we used Meta-modeling (c.f. subsection “Meta-models”).

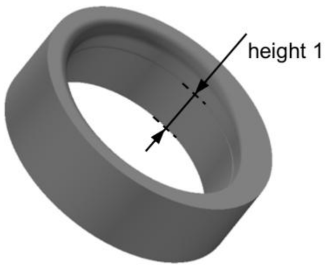
Figure 17. *Free Parameters at Backward Extrusion Tools to Achieve an Optimized Shape of the Can*





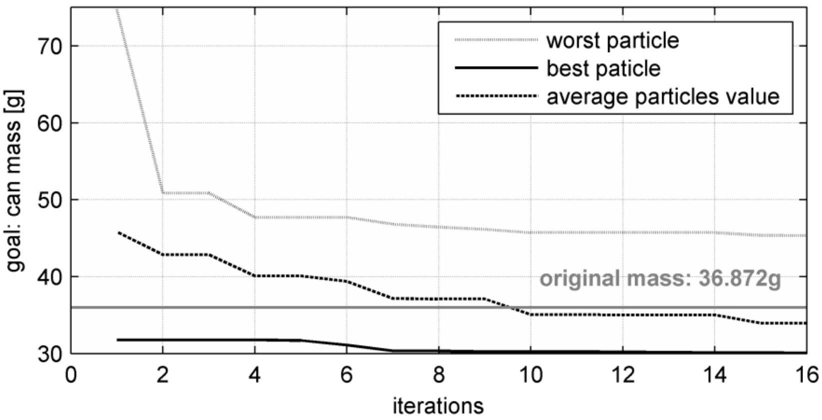
a) *Bottom Forming Tool* b) *Lower Die*





c) *Punch* d) *Ring*

Figure 18. *Minimization of the Can's Mass in a Backward Extrusion Process with PSO*

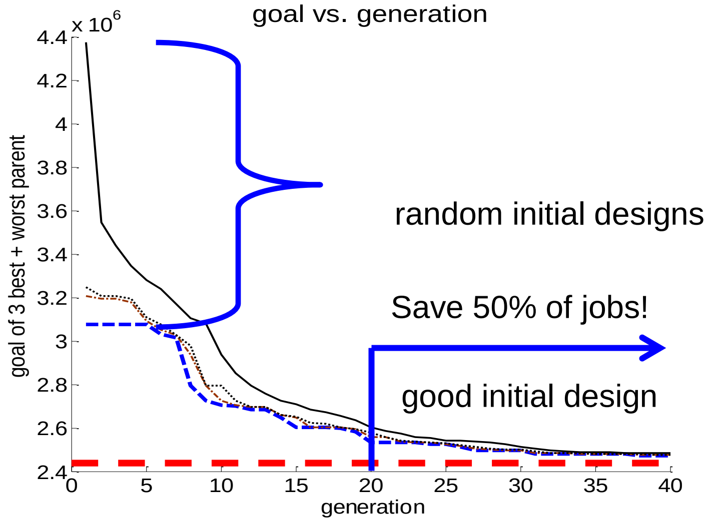


Proposals to Improve Speed

From the definition of the optimization process (subsection "Gradient Based Optimization Methods") it is evident, that the number of free parameters is of central importance for the velocity of the optimization. So if there exists a need to do a study faster, one of the first considerations should be the reduction of the number of these free parameters. In many cases there exist correlations between system variables, so some of them might be represented by others. Furthermore some parameters have no or only little importance in the region of interest. We should remove them. If we want to be sure that the parameters do really not matter, after the optimization has converged, we reactivate them and check, if the assumption to disregard them is justified. In all cases, trying to keep the number of free variables as small as possible will help to accelerate the studies to be performed.

The examples in section "Application to Metal Forming" and Figure 3 indicated that the total time to perform the robust and reliable are not to be accepted in many cases. Therefore methods to accelerate the process have to be introduced. There have been made many proposals. We want to discuss some of them (Gekeler and Steinbuch, 2015).

Figure 19. *Good Initial Designs Reduce the Numbers of Studies Required to Find an Optimum*



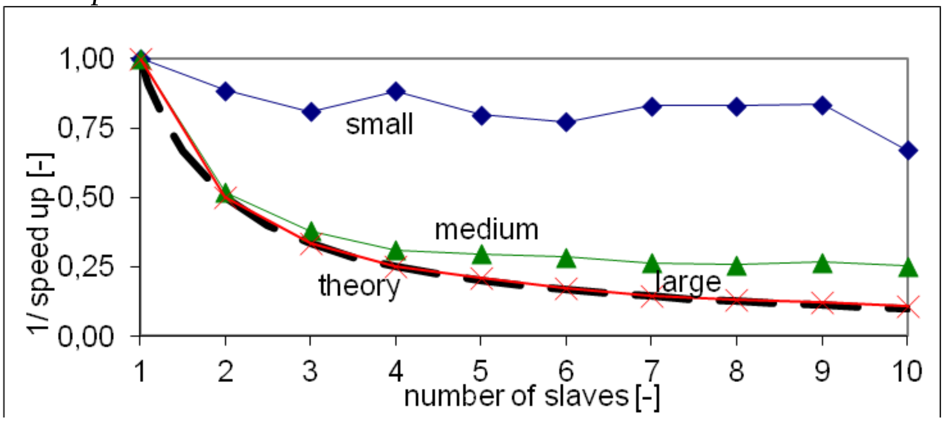
Impact of Initial Design

Figure 19 shows the fitness values of some variants of a bionic optimization process. We realize that most of the early variants represent ideas with poor performance. After about 20 cycles there are acceptable designs to be dealt with. Why shouldn't we reduce the range of initial designs to the region in the parameter space, where good results are to be expected? In many cases this is a very good idea. Starting at a good initial point then climbing up a local hill might yield fast and well performing results, as already indicated in Figure 1. But as soon as we have a non-trivial landscape (cf. Figure 2) we are not sure where to start. So the less or more random driven search of the parameter space as it is done by the bionic optimization methods might propose solutions we would not have thought of initially.

Parallelization

As the total development time is the delimiting criterion in many optimization studies, it is always a good idea to use parallel processing. Distributing the computational task on some or many processors might be done by different ways. The most popular one is to handle all the matrix operations on the different computer cores available. This causes essentially speed up which could be close to the number of cores available if the matrix manipulations are the most demanding part of the study. Figure 20 gives an indication of such a speed up, where here the number of slaves is to be read as the number of cores. The more complex the3 problem is, the more efficient the parallelization becomes as the relative time to administer the sharing of the tasks to different processors becomes less significant.

Figure 20. *Speed up by Use of Parallelization Reduces the Total Development Time*



In optimization we deal with many variants of a base design. So we could accelerate the process by doing the computation of each variant on different cores. Here we will observe essentially accelerations as well, as long as the time for one single study is not too small. Figure 20 might be read as a demonstration of this as well. We realize that for small problems, the time to manage the activation of the different cores causes more delay than the parallelization might gain again.

Finally a combination of the parallelization of the matrix management and the variants would further increase the performance of the optimization process. Unfortunately computing power and software licenses are not for free, so the expansion of the idea might be limited by economic resources.

Meta-models

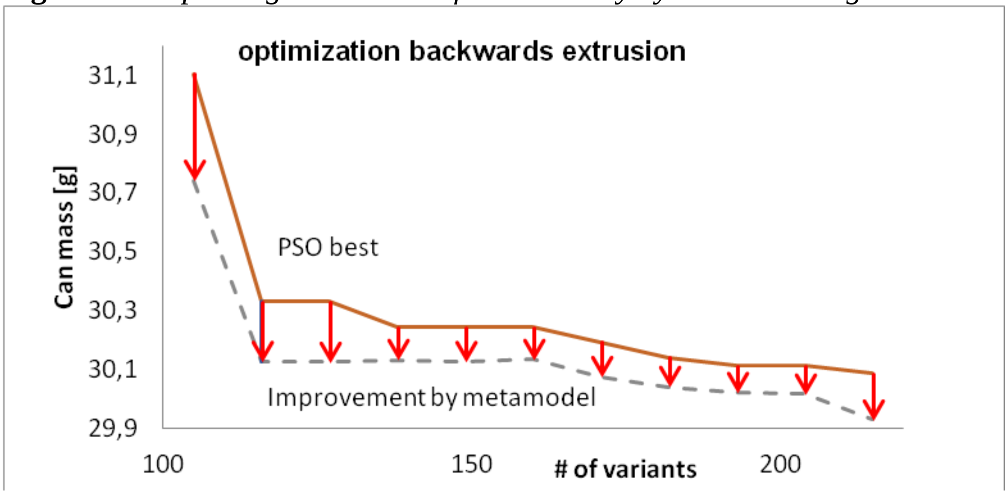
Meta-Models as we introduced in section “Metamodeling” help to find good designs in shorter time as the example outlined. For real problems with larger numbers of design variables this should hold even more. To give an idea about its efficiency we applied meta-modelling to a PSO-study of the backwards extrusion process sketched in subsection “Backward Extrusion of a Can”. We started our study after the first optimization, as we had already decreased the can's mass from 38 g to 31 g. As we had n_{param} = 9 free parameters we needed about (cf. eq. 2.2)

$$n_{test} > 2(1 + n_{param} + \frac{(n_{param} + 1)n_{param}}{2}) = 100$$

studies to find reliable response surfaces of the goal and the restrictions.

Figure 21 indicates the success of the method. After some studies we used the results found up to now to build a RS and find the local optimum. In all cases these optima are essentially better than the one found by PSO. We could have been accelerating the optimization by introducing the solutions found by the RS into the PSO process itself.

Figure 21. *Improving the Results of a PSO-study by Metamodeling*



Hybrid Optimization

In the case of the example discussed in subsection "Deep Drawing of a Can" we used a gradient method to improve the results found in Figure 14. As all particles of the PSO-search converged to the same design, we had only one starting point. In this case the solution found by the PSO was already so good, that switching to the local deterministic optimization methods did not show any essential improvement. This is a relatively rare situation, in most problems the local search like the meta-models find solutions that show at least some improvement.

Conclusions

The question of robustness and reliability in optimization problems under uncertainties must be studied with the aim of providing applicable strategies that may be used in the design process. The proposed methods may help to understand of the basic concepts.

As often only small numbers of test results or data of FE-Jobs are available, the quality of the probabilistic interpretation should be considered with care. Approximations using normal distributions include the danger of being non-conservative and, in addition, may produce large scatter predictions, thus reducing the predicted reliabilities.

Adapted approximations may reduce the scatter and yield more realistic predictions. If many restrictions must be considered, the search for regions with feasible designs may become more tempting than the original optimization. In all cases, the inherent uncertainties of such stochastic approaches need to be taken into account, especially if the safety of human beings or large costs of failures are factors. In every case, the rules of probability must not be disregarded to guarantee a sufficient level of theoretical reliability.

The use of hybrid optimization or meta-optimization often helps to reduce the total time of the optimization. But to find strong criteria for the switch to another method, some knowledge is required, which can only be assembled by preceding or parallel studies. So once more the “no free lunch” theorem holds. Doing optimization especially including reliability and robustness studies is a time consuming job. There are no ways to ignore the limiting factors. Especially the many trials to overcome the convergence laws of probability are always bound to be fruitless.

Nevertheless the ideas of reliable and robust optimization provide tools that enable us to improve the quality of virtual designs essentially. Proposals which are far better suitable to comply with the demands of product lifetime might be found. So the effort required during the design stage is justified by products which are often more reliable at essentially lower costs.

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