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APPLICATION OF SENSITIVITIES ON SIMULATION-DATA-BASED METAMODELS DURING THE PRODUCT SYNTHESIS

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1. Introduction

In accordance to [Weber 2005] the relevant core-activities during the product design process can be identified as product synthesis steps and product analysis steps, respectively. In the synthesis step the product characteristics and parameters are generated with respect to the requirements whereas the product properties and thus the fulfilment of the requirements are evaluated in the analysis step.
If the product does not fulfil the demanded requirements a further synthesis step (design interaction) is needed. For this step it is important for the designer to know the correlations between the characteristics which he can specify directly and the properties which result from the specified characteristics. This knowledge enables him to identify the relevant and decisive characteristics and parameters in order to optimize the product.
Prerequisite for knowing the correlations is a knowledge transfer between the analysis expert and the designer. Due to the fact that the necessary analyses (simulations or tests) are time consuming (lack of information in early design phases, external service companies need external flow of information, experts are not available, etc.) the iteration loops between synthesis and analysis and thus the product optimization process can be considered to be quite slow. Consequently new ways have to be found to support the product developer by analysing the product's properties and to provide him the correlation between characteristics and properties.

1.1 Objectives

Thus, the aim of this research work is to develop a methodology to support the designer during the product synthesis and optimization. This methodology is based on metamodels, which represent the correlation between characteristics and properties. Based on this simplified representation the product properties will be predicted. Furthermore the metamodel should be used to determine the sensitivity of single characteristics influencing distinct properties. Knowing these sensitivities supports the product developer designing a robust and optimized product.
In chapter 2 the correlations between characteristics and properties are theoretically formulated within a product model. At first the useful and decisive parameters have to be analysed. This has direct and indirect influence on the following procedure, since the quality of this analysis can be directly transferred to the quality of the correlation analysis. Before processing the simulation or a test, an appropriate sampling (the number of the simulations, the range of the varied input parameters and their allocation in the range) is needed. The sampling has a direct influence on the calculation error in the following steps. The correlation between input and output parameters will be formulated in a mathematical relation – the so-called metamodel. This metamodel can be analysed by a pool of methods (e.g. sensitivity analysis). In chapter 3 the sensitivity analysis is introduced, which derives the

most sensitive correlations between characteristics and properties. In this paper two different approaches on sensitivity analysis will be used. Both sensitivities are basing on different mathematical approaches on calculating the influence of an input parameter (in this case a characteristic) on a function value (a property). Afterwards the sensitivities will be compared and applied on a case study and their differences and individual advantages and disadvantages will be discussed. The paper closes with a short conclusion and an outlook.

2. State of the art

2.1 Characteristics properties modelling and property-driven development (CPM/PDD)

The modelling of product information is adopted from [Weber 2005] and his allocation to characteristics and properties, which is an european approach on product development. The CPM approach gives a model for the relations R between characteristics and properties and PDD gives a methodology, how to optimize the product with regard to the properties. Characteristics can be influenced directly (e.g. geometry, material), whereas, the properties are not directly adjustable. This paper focusses on the computational modelling of the relations between characteristics and properties.

2.2 Identifiying of characteristics, properties for simulation-modelling

The product development methodology of Weber fits very well with simulations because the characteristics can be identified with the input parameters and the properties with the output parameters of the simulation. In a first step the relevant characteristics for the considered properties should be identified. Therefore the number of parameters in the simulation can be reduced, because every considered parameter increases the number of simulation steps needed to calculate a useful metamodel. The range of the input parameters has to be adapted to useful characteristics, too (e.g. limits to the length of a geometrical parameter). The study in this paper is limited at both, input and output parameters, to real values (e.g. geometry parameters of a product or the forming force of a tool). There is no analysis of noncontinuous parameters (e.g. like a materials density). Another limitation at this paper is that the variation of the characteristics is not known from the production process, so the method can be adopted to early phases of the product development. This implies that the input parameters of the simulation are exactly adjustable and no distributions of input parameters have to be considered.

2.3 Metamodelling

Metamodelling is a statistical approach in the context of data mining, a common kind of knowledge acquisition and creation, which for example is discussed in [Röhner 2011]. It is an automatic knowledge acquisition method, which extracts knowledge from simulation data.

A metamodel is a regression model giving an approximate solution for the relation between the input parameters x to the output parameters y. The metamodel enables a prediction of the output parameters which are related to combinations of input parameters that were not considered in the simulation-sampling before, and due to that it compensates the scattering of the simulation.

The first regression models were calculated with the method of least squares, introduced in the late 18th century by C.F. Gauss, which can derive a regression model from overestimated linear systems of equations (overestimated means, there are more equations than variables). This is the case for normal simulations. With this method the linear regression model was introduced. It fits very good for linear relations between input and output space and it has a lot of advantages due to the simplicity. It is, however, limited to linear relations between input and output. When there are nonlinear correlations, there are some ways how to extend the linear regression model, of which two are shown in the following. The first way is to divide the input parameter space into suitable cuboids and to fit in independent linear regression models. This metamodel is called the M5 Model Tree [Quinlan 1992]. The advantages both are a better prediction of the output values and – within the range of the cuboids – a simple model. In contrary the loss of a global metamodel and due to that the loss of continuity are disadvantages. Another approach would be to approximate the correlations with polynomial regression, which is an universal approximator. This means, it is capable to approximate every nonlinear continuous relation between input and output space when the order of the polynom just gets high enough. In the last decades several additional universal approximators had been developed. A very well known is a member of the neural network family: the multi-layer perceptron network (MLP) [Rumelhart 1986]. The last universal approximator is called support vector regression (SVR) [Müller 1997], which was developed from a classification model by Vapnik. It transforms the parameter space into a higher dimensional space, fits in a linear regression model and transforms it back to the original space (so called kernel trick). MLPs and SVRs are black-box-models, which mean that the internal working of the model can not be interpreted by the designer. They just return the output parameters for a chosen combination of input parameters, which is a big disadvantage. Another problem of metamodels (aside of the linear models) is overfitting, which means the model fits nearly perfect to the simulation data but doesn't give a good prediction of the output parameters. There are a couple of ways to counteract this problem. However, there is no silver bullet metamodel. If the correlations are linear, the linear regression model is surely the best one. If the relations are nonlinear the universal approximators MLP and SVR are both suitable models. With restriction also the polynomial regression can be used. However, it is more important to understand the process of deriving a metamodel with all the possible adjustments rather than being able to choose the best model from a set of derived metamodels.

2.3.1 Sampling for metamodelling

A metamodel needs a suitable sampling for the simulation. Sampling is the number of simulations, the range of the varied input parameters and their allocation in the range. In the 1920s, the first systematical studies called Design of Experiment (DOE) were carried out. The first detailed publication was [Fisher 1935], the method became worldwide common in engineering in the 1980s. DOE includes due to the sampling also the interpretation of the results in a formalized manner. Here the sampling method is considered. A 3^n-design e.g. divides the range of n single input parameters to three values and combines them. For two input parameters e.g. this is shown in Figure 1, there are $3^2 = 9$ samples.

At DOE, there are a few disadvantages. A classical full factorial design would give not enough points in the input parameter space to fit other models than linear regression in a useful manner. At this design the allocation of the parameter combinations is unfortunate if an input parameter has a small influence on the output parameters. Because for every unneccesary input parameter the number of useable simulations halves.

To avoid this the Latin Hypercube Sampling (LHS) [McKay 1979] was developed at the end of the 80s. LHS is a stratified sampling, based on the Monte Carlo method. The Monte Carlo method uses random-numbers in the range of the input parameters (Figure 1), while the parameter combinations are randomly distributed in the parameter range. LHS separates the ranges of the single input parameters in different areas, picks for every sample for an input parameter one random number from each of these areas and combines the points.

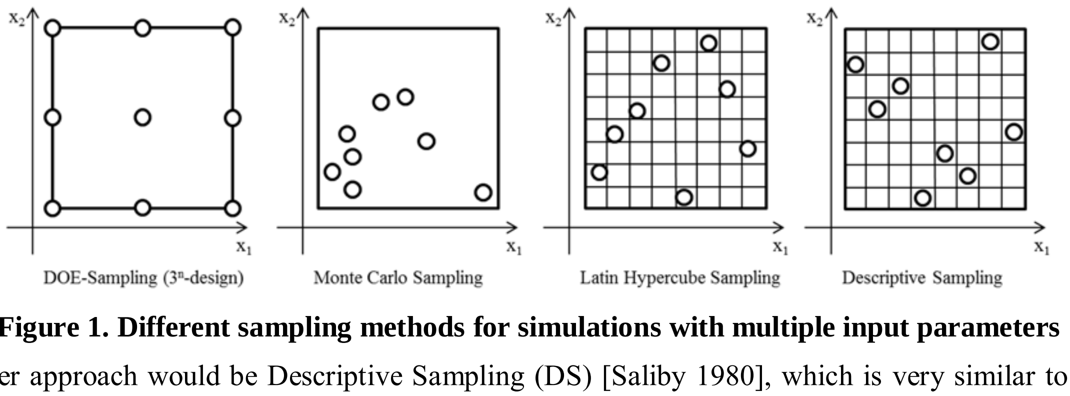

Figure 1. Different sampling methods for simulations with multiple input parameters

Another approach would be Descriptive Sampling (DS) [Saliby 1980], which is very similar to LHS from the systematic approach but is a deterministic, not a random sampling. At DS the input parameter points are placed at the middle of the areas, as seen in Figure 1. Both, LHS and DS converge for a high number of samples against the same limit. For using metamodelling, both approaches give an uniform

allocation of points in the inner input parameter space and the more knowledge about the parameter correlations are available, the better the samples can be chosen. DOE places more points on the borders of the input parameter space, which can result in a higher stability of the metamodel. The number of samples needed depends on the number of input parameters (DOE). However, the remaining sampling methods underlie no further restrictions.
A last point to the number of samples: It surely should be a compromise between simulation runtime and quality of the metamodel. But the more the simulation results spread and the more the correlations are complex, the more samples are needed. If there are noncontinuities, the number nearly will explode. But that isn't the focus of this paper, even the used metamodels are not able to map such correlations. If the simulation runtime is very short, there also can be used common Monte Carlo sampling.

2.3.2 Mathematical formulation of the metamodel

The input parameter space is a cuboid, defined by $Q = [x_1^u; x_1^o] \times \ldots \times [x_n^u; x_n^o]$, where $n \in \mathbb{N}$ is the number of input parameters. To normalize the input parameter space, it will be transformed using a mapping Φ to $\Omega := [0;1]^n$. The metamodel is a mapping from a point $x = (x_1,\ldots,x_n)$ in Ω to $\mathbb{R}^m$ with a vector valued function $f : \Omega \rightarrow \mathbb{R}^m$ with $f(x) = (f_1(x_1,\ldots,x_n),\ldots,f_m(x_1,\ldots,x_n))$, where $m \in \mathbb{N}$ is the number of output parameters and furthermore $f \in C^\infty(\Omega)$. If the derivation of the metamodel can not be easily calculated (like with black-box-models) derivations were approximated by the difference quotient. Figure 2 shows a metamodel based on a simulation with eight samples of one input and one output parameter. The common RSM-method e.g. calculates also a kind of metamodel.

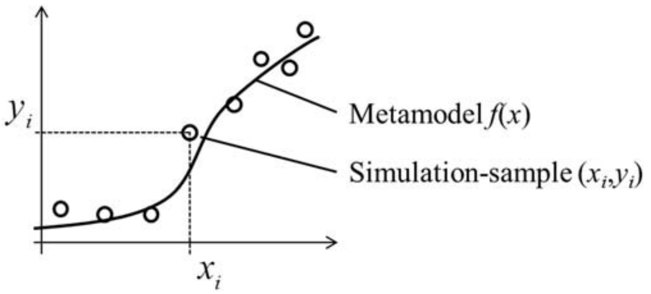

Figure 2. Metamodel based on one input and one output parameter

The product developer wants to know how he has to design the product to satisfy the requirements. In the context of WEBER, applied on simulation data, therefore the influence of the input parameters of the simulation on the output parameters has to be analyzed. This can be achieved by analyzing the simulation data or as in our case by analyzing the metamodel. Therefore the influence of the single variables to the function values of the metamodel have to be identified. Sensitivity analysis e.q. can be performed to identify the input parameters with the most important influence to the output parameters.

3. Framework

The whole framework is depicted in Figure 3. The subsequent procedure is as follows: At first the parameters and sampling for a simulation are selected. The parameter analysis is not part of this paper. The method works for static input and output values (so the input and output parameters are not time-dependent). The simulation data is then transferred to a design support tool, which analyses the data and calculates an appropriate metamodel. The metamodel can calculate for every parameter combination of the input parameters of the simulation (in their range) an approximation of the output parameters. Subsequently, the metamodel is analysed by sensitivity analysis. In the following, two sensitivities are introduced, for the second sensitivity a sampling must be chosen.
The product developer chooses a combination of characteristics, puts it into the design support tool and the metamodel inside calculates an approximation for the correlated properties. As the intention of the product developer is to design an optimal and robust product, the tool supports him at both tasks.

The sensitivity analysis of the design support tool can point out recommendations for better characteristics combinations. The sensitivity analysis also suggests which characteristics deviation has to be controlled to obtain low deviating properties.

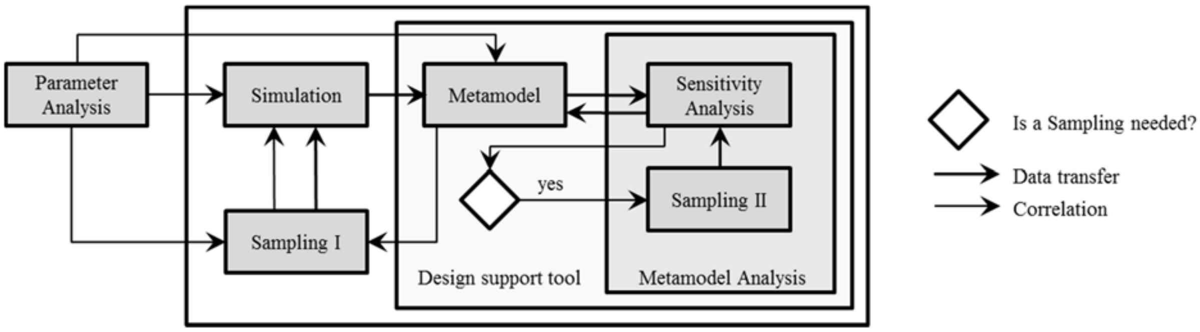

Figure 3. Framework for sensitivity analysis of simulation-data based metamodels

3.1 Sensitivites

The word sensitivity means in general, how sensitive something is on changing conditions. In different fields of research it is in detail used for very different objects. However, it bases on the same intuitive understanding of the word. In this paper sensitivity is seen more general as in the common Sensitivity Analysis (SA) [Saltelli 2000]. In SA sensitivity is defined as the influence of the variances of the distributions of the input parameters of a model to the output parameters. Since no distributions are given, this definition doesn't hold in this case. But a very well known method from SA can be adopted to our case, a modified SOBOL sensitivity. There will be two different kinds of sensitivities introduced in the following. The sensitivity at the starting point is called Derivation-based, the sensitivity at the neighbourhood of the starting point is called variance-based sensitivity due to SALTELLI. Both have advantages and disadvantages, who will be discussed later.

Calculating the sensitivity from the determined metamodel instead of directly based on the performed simulations is an advantage when the simulation runtime is high, since the prediction of the simulation output parameters by metamodels calculates very fast. In a first step, the area in the input parameter space where the sensitivity will be calculated has to be selected. When the metamodel is the linear regression, the following introduced sensitivities are independent from the considered area. However, in the case of other metamodels, the sensitivities depend on the area. The chosen area directly follows from the procedure of the product developer: Starting with a first combination of characteristics, it is useful to calculate the derivation-based sensitivity at this parameter combination point. During the next step the sensitivity of the starting points neighbourhood will be calculated. Mathematical formulated for a parameter combination $x^0 \in \Omega$ an useful neighbourhood is $A = \left\{ x \in \Omega \,\middle|\, \| x - x^0 \| \le r \right\}$, where $0 < r \le 1/2$ is the radius of the area. The norm $\|\cdot\|$ is interpreted here as a distance-measurement between points x and the center point x^0. The norm can be chosen in different ways (useful would be the 1, 2 and sup-norm).

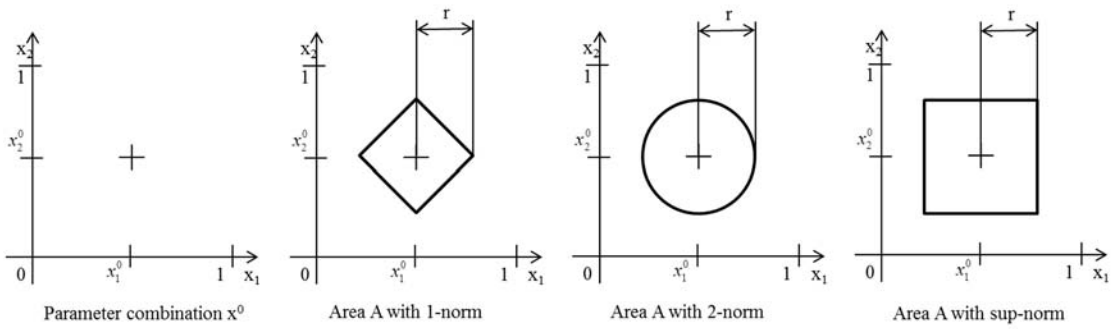

Figure 4. Area *A* in the input parameter space at different norms

Figure 4 shows the difference of area *A* at the three norms in the case of two input parameters around the center point x^0 with radius r. As the input parameter space is normalized, the borders are 0 and 1. The 1-norm results in a rhombus, the 2-norm in a ball and the sup-norm in a square. The difference between the sensitivity value of these three areas will be seen in the following chapter considering the variance-based sensitivity.

3.1.1 Derivation-based sensitivitiy (DBS)

The derivation-based sensitivity is the Jacobian matrix of the metamodel f. For $i \in \{1,\ldots,n\}$ and $j \in \{1,\ldots,m\}$ the value $D_i f_j$ of the Jacobian matrix implies, in which scale each output parameter f_j changes for a small variation of the input parameter x_j. The value $D_i f_j$ is defined by

$$D_i f_j(x) = \lim_{h \to 0} \frac{f_j(x_1, x_2, \ldots, x_i + h, \ldots, x_n) - f_j(x_1, x_2, \ldots, x_i, \ldots, x_n)}{h} \tag{1}$$

Figure 5 details the quotient (1) for an one-dimensional case with the corresponding slope-triangle. With the limit $h \to 0$, $D_i f_j$ converges against the slope of f at x^0. The Jacobian matrix has i rows and j columns. As the input parameter space is transformed with Φ, the argument in the metamodel-function f has to be differenciated, so the Jacobian must be $D_i f_j \partial_i \Phi$. Another approach would be the normalization of the Jacobian matrix. So there is a qualitative sensitivity as a mapping from $[0;1]^n$ to $B_1(0)$. This will be achieved by normalizing every Df_j – dividing it by its length. Since the Jacobian matrix is derivation-based, the problem arises that for very nonlinear metamodels a small variation of the considered parameter combination could result in a totally different Jacobian matrix. So the point-based sensitivity is not very robust towards appearing deviations. However, it can help to optimize the output parameters in a small region around the chosen center point.

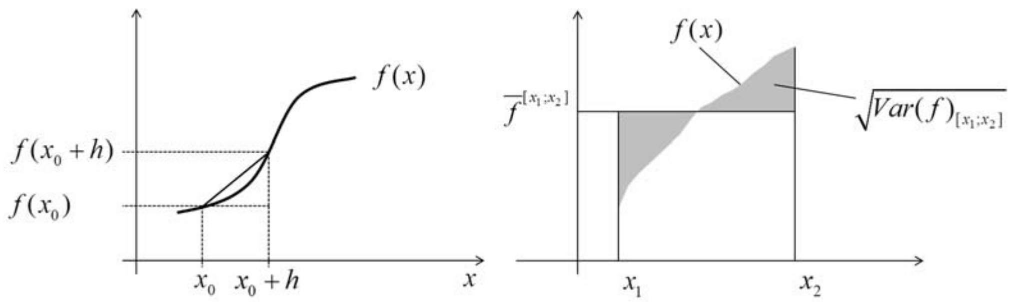

Figure 5. Derivation of f at the point x^0 and variance of f in the region $[x_1; x_2]$

3.1.2 Variance-based sensitivity (VBS)

In the following the variance-based sensitivity model of SOBOL [Sobol 1990] is adopted. This sensitivity can be calculated with a couple of different algorithms (Sobol, Jansen, FAST, EFAST etc.). The SOBOL-VBS originally deals with distributions of input parameters giving the influence of the variances of the input parameter variations to the variance of the output parameter variation. Therefore, the distributions of the input parameters must be known. With VBS the main effect and the total effect of the input parameter variances can be calculated. The main effect qualifies the effect of a single input parameter on an output parameter. The total effect also takes into account parameter interrelations with additional input parameters, too [Saltelli 2000].
When the variations of the input paramters are not known, the adaption of VBS on the metamodel becomes a different meaning. Then the distributions can be used to define the area in which the sensitivity is calculated. The indicator function of A is

$$I_A(x) = \begin{cases} 1 & \text{for } x \in A \\ 0 & \text{else.} \end{cases} \tag{2}$$

By dividing I_A by the volume of A, this quantity receives the characteristics of a distribution. The integral of a distribution over the parameter space is 1 and its values are bigger or equal to zero. This quantity enables the adaption of the SOBOL-sensitivity, since this sensitivity requires a distribution of the input parameters. Due to [Sobol 1990] the metamodel f has to be separated to a sum of single terms

$$f(x) = f_1(x_1) + f_2(x_2) + ... + f_n(x_n) + f_{12}(x_1, x_2) + ... + f_{12...n}(x_1, ..., x_n) . \tag{3}$$

In order to determine the VBS, the variances of the single terms within the area A have to be calculated and divided by the variance of f within the area A. The variance $Var(f)_A$ of a function in an area A is a measure for the deviation concerning its mean $\overline{f}^A$ in the area. The resulting variance is the square of the grey area, as shown in Figure 5.
The chosen area A of the input parameter space is defined by its center x^0 and a corresponding radius r. The decided norm influences, how much interrelations between the input parameters will be considered by the sensitivity. With the sup-norm interrelations have the biggest influence, with the 1-norm the smallest. The radius can be defined by the product developer. It classifies two things, which are naturally opposed: How general the calculated sensitivity as well as how precise the given information is. The size of the radius r has the following consequences:

- From small r the sensitivity indicates the influence of the input parameters to the output parameters near the center point.
- With increasing radius the sensitivity becomes more and more an analysis of the average influence of the input parameters to the output parameters in the neighbourhood of the center point.

If the product developer wants to change the characteristics of the product significantly, the sensitivity in an area with wider range is interesting. A technical problem there appears: The area A must be in different input parameter dimensions adopted to the range. For the first parameter (range from 2000°C to 3000°C) a width of 5°C is small. However, for the second parameter (range of 3 mm – 12 mm) a width of 5 mm is significant. Therefore, the input parameter space was normalized to Ω. Going back to sampling methods for metamodels, it must be said that LHS and DS are just available for an area A with sup-norm or with 1-norm (with a translation and rotation of the sampling after the creation) but not in the case of 2-norm. There, a classical monte carlo sampling must be chosen. Table 1 shows the differences between the introduced sensitivities. The derivation-based sensitivity and the variance-based sensitivity have less in common. The DBS is a value calculated at the center point (a zero-dimensional area) with a quantitative value. It is not robust against variation of input parameters and the different output parameters can not be compared with each other. In contrast, the VBS is calculated at a n-dimensional subarea A of the input parameter space. It is a qualitative measure for the influence of the single input parameters, robust against variation and the different output parameters can be compared to each other. However, the normalized derivation-based sensitivity has some similarities to both of them.

Table 1. Differences between the introduced sensitivities

	Derivation-based sensitivity	**Derivation-based normalized sensitivity**	**Variance-based sensitivity**
Area in the parameterspace	point	point	solid
Dimension	0	0	n
Kind of statement	quantitative	qualitative	qualitative
Robust to variation of the input parameters?	no	no	yes
Comparability of different output parameters?	no	yes	yes

3.2 Interpretation of the sensitivities

The product developer receives two n×m matrices for n characteristics and m properties. He can interpret them by lines or columns. The lines show the influence of a products characteristic on different properties. The columns details the influence of all characteristics towards a single property. A appropriate visualisation can be achieved using e.g. bar diagrams. Finally, at the normalized DBS or the VBS the sensitivity of the characteristics on different properties can be compared (since they are normalized). This is the base for a possible multi-parameter optimization. However, this topic is very complex (it would exceed the framework of this paper). A simple procedure is to rank the properties by their importance, optimize the most important property by changing the characteristics with the highest sensitivity. When the properties value fulfills the given requirements, the second property can in the next step be optimized e.g. by its most influencial characteristic.

4. Application example

4.1 Sheet-bulk metal forming

The transregional collaborative research centre 73 (SFB/TR 73) aims to connect the advantage of cold bulk forming and thin sheet metal parts and therefore creates a new manufacturing technology, named "sheet-bulk metal forming" (SBMF). It is defined as the "plastic change of the shape of a plain semi-finished product with both two- and three-axial strain and stress conditions" [Röhner 2011]. Parts produced with this production method should stand out with lightweight design and the conjunction of multiple functions. Furthermore material and energy-usage in the manufacturing process would decrease. The subproject B1 "Self-learning engineering assistance system" of SFB/TR 73 is the basis for the automatic and data-mining based knowledge-aquistion that is done in this paper.

4.2 Application of sensitivities on simulation-data-based metamodels of SBMF

For this application example a FEA (using the software Simufact Forming v9.0) was performed. The simulation combines deep drawing of a thin sheet metal and in a second step extrusion of teeth at the border of the part. The demonstrator is rotational symmetric, so only a 10° sector of the part was modeled to reduce the computational expense. The FE-mesh of the formed part at three following timesteps of the simulation is shown in Figure 6.
The left picture shows the FE-mesh of the sheet metal part before the forming process. Half the forming process is performed as the center-picture was created. On the right side the teeth are seen as the forming tool is near its final position. For further information concerning the simulation see [Röhner 2011].

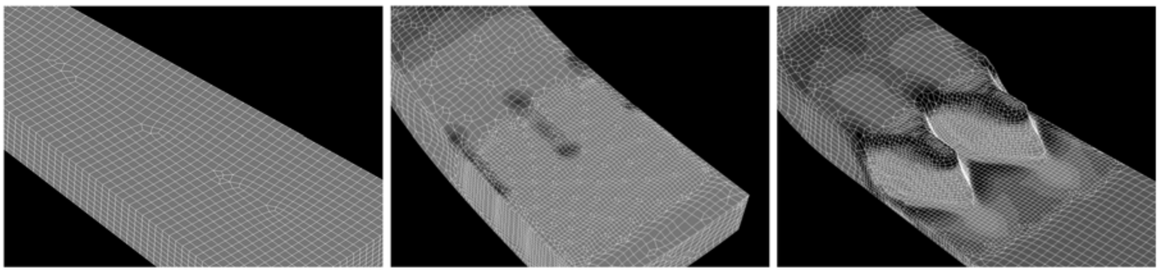

Figure 6. FE-mesh of the teeth in three simulation time steps

Table 2. Input parameters of the simulation

Name	Symbol	Unit	Range	Mean
Tooth width	w	mm	[1.8;3.2]	2.4
Tooth length	l	mm	[2.4;3.1]	2.75
Forming velocity	v	mm/s	[0.1;0.6]	0.35
Sheet thickness	t	mm	[1.9;2.6]	2.25

Two geometrical parameters of the teeth (tooth width w and tooth length l), the thickness of the sheet metal t and the forming velocity v of the simulated tool (manufacturing parameter) vary, see Table 2. The contact ratio (CR) and the forming force (FF) are measured (output parameters). The sampling is performed using LHS, the metamodel is a polynomial regression model. Since the simulation is quite time-consuming 20 simulations were performed. Therefore, the polynomial regression is limited to second order to prevent the metamodel from overfitting (see 2.3 Metamodelling).
The product developer usually defines the mean values of the geometry parameters (tooth width and length) as well as the sheet thickness and forming velocity. The corresponding point in the input parameter space is x^0 = (0.35, 2.25, 2.4, 2.75). The range of the robustness analysis (with variance-based sensitivities) is choosen half of the samplings range, what is equal to r = 0.25. As the robustness analysis is supposed to be a worst-case scenario, large deviations of all input parameters need to be taken into account. Consequently, the sup-norm (cubic area, see Figure 4) will be used for the variance-based sensitivity analysis. A design support tool calculates the associated sensitivities and returns a appropriate result visualization as seen in Figure 7.

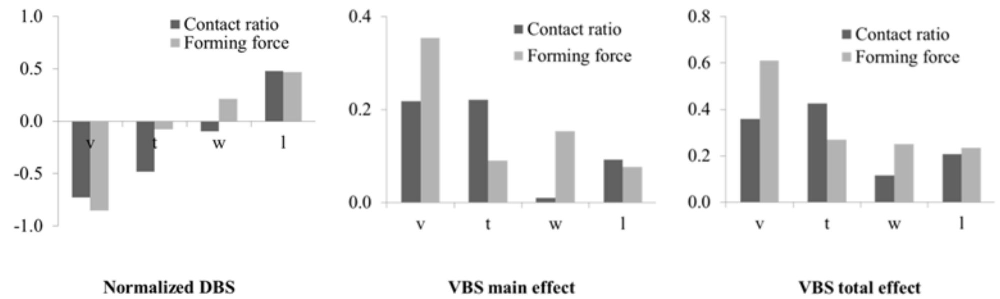

Figure 7. Results of the calculated sensitivities normalized DBS, VBS main effect and VBS total effect at the considered point x^0 (and with the radius r at VBS)

Three recommendations can be derived:
The first impression the product developer takes notice of, is the appearence of both positive as well as negative DBS-values in contrast to just positive VBS-values. Since the variance-based sensitivity only accepts positive values, an indirect proportionality can not be identified by the product developer. In this case, e. g. the results lead to the assumption, that an increasing forming velocity goes hand in hand with an increasing contact ratio. However, this is not the case. Hence, the variance-based sensitivity can be used to identify correlations between input and output parameters, but it’s still missing the information about the correlation’s direction. *Therefore the use of VBS Analysis should be considered carefully, especially in the case of complex technical systems and/or the lack of experience concerning the system’s behavior.*
Considering the situation, that the contact ratio does not fulfill given requirements but the forming force is still very high. If the product developer considers the derivation-based sensitivity, there are three possibilities to increase the contact ratio significant: to decrease the forming velocity v, to decrease the sheet thickness t or to increase the tooth length l. Both decreasing v and increasing l would also lead to an increasing forming force (that should be avoided). So these are no suitable options, although the two parameters have the highest influence on the contact ratio. Decreasing the sheet thickness t would just have a minor influence on the forming force, making it the most appropriate action. *When the value of a property has to be changed and one or several other properties have to be restricted to a certain limit, not necessarily changing the most sensitive characteristics is the most suitable action.*
Assume the contact ratio is appropriate after slightly changing the sheet thickness l. The final task is now to perform a robustness analysis. At first the product developer considers the total effect of the variance-based sensitivity of the contact ratio. The forming velocity v and the sheet thickness t have the highest influence. The total effect VBS of the forming force indicate v as the highest deviation contributor. So for controlling the process quantities CR and FF the deviation of the sheet thickness l as well as the forming velocity v have to be limited. Finally the strong differences between the main

and total effect values at VBS for both CR and FF are considered. This indicates interactions between the input parameters w,l,v and t. This is an indicator that the control of the deviations of CR and FF could be a problematic task in practice. *The VBS total effect is a useful indicator for control factors. A large difference between the main and total effects indicates that problems during the process control of the analysed properties can be expected.*

5. Discussion and outlook

The application example revealed that both the derivation-based and the variance-based sensitivities have advantages as well as disadvantages. For manual product optimization the derivation-based sensitivity tends to be more useful (due to the considered direction of correlation). However, for robustness analysis without knowledge about the appearing deviations, the variance-based sensitivities are obviously better (consideration of product property deviations due to the Area A).
The crux of the matter with metamodel-based analyses is the approximation quality of the metamodel. All analyses based on metamodels are very sensitive to approximation errors. Therefore metamodels can be analysed in multiple ways – not only by sensitivity analysis – e. g. visualization is another suitable option. A sensitivity analysis is not restricted to a manual product optimization. An automatically performed optimization could be realized by Newton's method (application of the derivation-based sensitivity) with a robustness side condition (variance-based sensitivity without normalization, see [Sobol 1990]). Furthermore multi-objective optimizations (in case of two or more properties) induce multiple optimal solutions from which one must selected in an additional step.

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