Optimising towards robust metal forming processes

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ABSTRACT: Product improvement and cost saving have always been important goals in the metal forming industry. Numerical optimisation can help to achieve these goals, but optimisation with a deterministic approach will often lead to critical process settings, such that the slightest variation in e.g. material behaviour will result in violation of constraints. To avoid a high scrap ratio, process robustness must be considered in the optimisation model. Optimising for robustness includes Robust Manufacturing (RM) techniques, Optimisation Under Uncertainty (OUU) methods and Finite Element (FEM) simulations of the processes. In this paper, we review RM and OUU. Subsequently, the combination of Statistical Process Control (SPC), robust and reliability based optimisation methods, and FEM-based process simulation implemented in AutoForm-Sigma is presented. An automotive deep drawing application demonstrates the potential of strategies that optimise towards robust metal forming processes.

Key words: Statistical Process Control, robust optimisation, Finite Element Method, metal forming

1 INTRODUCTION

In recent years, numerical optimisation of forming processes has attracted lots of attention. Optimisation, however, often leads to more critical products and processes, such that natural variation in material, lubrication and process settings will result in a high ratio of unsatisfied constraints. This undesirable situation can be avoided if the process robustness is explicitly considered in the optimisation model, either in the objective function or as a constraint. A robust optimised metal forming process will improve the product quality characteristics and save costs because the number of non-conforming products (scrap) is reduced.

Optimisation towards robust metal forming processes includes two aspects: Robust Manufacturing (RM) and Optimisation Under Uncertainty (OUU), which are only rarely combined in literature.

In this paper, we combine RM and OUU. First, important aspects of RM are reviewed in Section 2. Section 3 addresses OUU and its application to metal forming processes using time-consuming Finite Element simulations. In Section 4, we introduce the AutoForm-Sigma strategy for optimising towards robust metal forming processes and apply it to the deep drawing process of an automotive reinforcement part. Section 5 contains the conclusions and future research topics.

2 ROBUST MANUFACTURING

2.1 Manufacturing variation

A manufacturing process—such as a metal forming process—can be characterised by a P-diagram as shown in Figure 1. In general, the *input* can be categorised as energy, information or material. In case of a metal forming process, all three groups are present: energy for powering the press, information contained by the CAD-drawing, and the undeformed material that is to be deformed by the metal forming process. The *response* is the deformed product or actually, the selected quality characteristics (e.g. the part geometry) of the product. Also entering the process are control variables $\mathbf{x}$ and noise variables $\mathbf{z}$. The *control* variables can be controlled by the process engineer. Examples are the shape of the tools and load paths. *Noise* variables cannot ordinarily be controlled in an industrial setting. An environmental factor like the temperature is a typical example. Note that both the control and noise variables are stochastic variables: a specific material can be chosen and is hence a control variable, although there is always scatter involved.

The presence of noise and stochastic control variables will cause variation in the response, the product characteristics. If the response deviates too much from the intended product characteristics, the product's perfor-

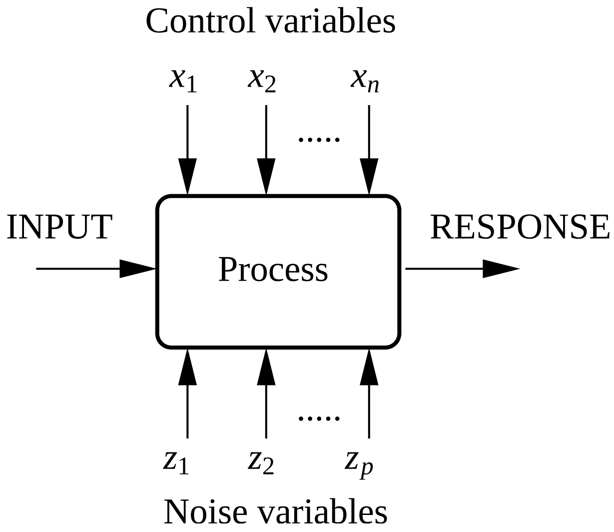

Figure 1: P-diagram [1]

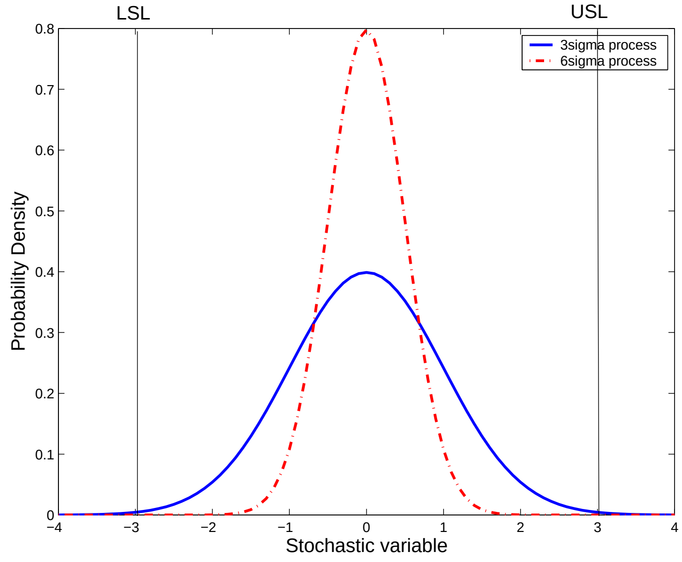

Figure 2: A 3σ- and a 6σ-process

mance is likely to deteriorate, or the product may not be accepted for use at all. The former situation may cause dissatisfied customers or high warranty and replacement costs. The latter situation implies material, time and energy have been spent for nothing. Both cases can be very expensive and should be prevented.

2.2 *Statistical Process Control*

A way to monitor and control the variation within a manufacturing process is using Statistical Process Control (SPC) [2]. An important aspect of SPC is to determine the *process capability ratios*, which indicate the capability of the process to produce acceptable products. Whether the product is acceptable is determined by the user-defined Upper and Lower Specification Limits (USL and LSL) as depicted in Figure 2. Assuming a normal distribution of the response, the process capability ratios C_p and C_pk are defined as [2]:

$$C_\mathrm{p} = \frac{\mathrm{USL} - \mathrm{LSL}}{6\sigma} \tag{1}$$

$$C_\mathrm{pk} = \min\left(\frac{\mathrm{USL} - \mu}{3\sigma}, \frac{\mu - \mathrm{LSL}}{3\sigma}\right) \tag{2}$$

where μ and σ reflect the process mean and standard deviation, respectively. Note that C_p is insensitive with respect to the location of the mean, whereas C_pk is not.

The solid line in Figure 2 presents a 3σ-process for which both the C_p- and C_pk-values equal 1. A 3σ-process implies a production success rate of 99.73%, i.e. if ten thousand products are manufactured, 27 products are defective. The dashed line in Figure 2 is a more robust 6σ-process with a production success rate of 99.9999998% and $C_\mathrm{p} = C_\mathrm{pk} = 2$. Striving for 6σ-robustness is the basis of a very successful quality philosophy that has saved companies billions of euros during the past 20 years [3], which indicates the potential of optimising for robust manufacturing processes.

3 OPTIMISATION UNDER UNCERTAINTY

Two approaches to Optimisation Under Uncertainty are often distinguished: robust optimisation and reliability based optimisation.

3.1 *Robust optimisation*

A robust process is a process which is insensitive to variations in the stochastic variables influencing this process [1]. Robust optimisation aims at reducing the variability in the product quality characteristics, i.e. the response of the P-diagram depicted in Figure 1. As mentioned in the introduction, less variation implies a higher product quality and lower costs. The principle behind robust optimisation is depicted in Figure 3: it is tried to manipulate the control variables in such a way that the variability of the response is minimised. Shifting the entire response distribu-

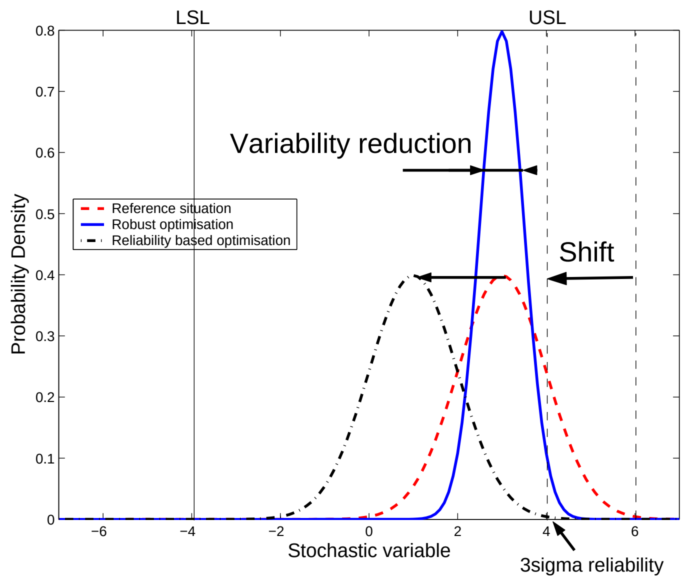

Figure 3: Robust and reliability based optimisation

tion is also possible using robust optimisation, but the main focus is on reducing variability.
A combination of robust optimisation and metal forming can be found in References [4–6].

3.2 *Reliability based optimisation*

Another approach is reliability based optimisation. Reliability based optimisation attempts to find the optimal values of a certain objective function, while at the same time ensuring a predefined (usually small) probability that a product or process fails. The probability that a manufacturing process fails equals the area below the probability density function outside the specification limits as shown in Figure 3 for a 3σ-process. Often the predefined reliability level is achieved by shifting the probability density function of the response, rather than reducing its variability as was the case for robust optimisation.
A typical reliability based optimisation problem is formulated as:

$$\min\ f;\ \ \text{s.t.}\ P[g(\mathbf{x},\mathbf{z}) \leq 0] \leq r \tag{3}$$

in which P denotes the probability, $\mathbf{x}$ and $\mathbf{z}$ are the stochastic design and noise variables as in Figure 1, and r is the reliability level, e.g. 6σ-reliability. g is the *Limit State Function*: the Limit State $g = 0$ separates the regions of failure ($g < 0$) and success ($g > 0$).
Reliability based optimisation is typically applied in aerospace design and automotive crashworthiness design. To predict the reliability accurately a large set of calculations are required. Within metal forming therefore, only a few examples are encountered, see [7–9].

4 A ROBUST OPTIMISATION STRATEGY WITH APPLICATION TO DEEP DRAWING

Next to robust and reliability based optimisation, another robust optimisation strategy is implemented in AutoForm-Sigma. This strategy is illustrated by applying it to the robust optimisation of the deep drawing process of the automotive reinforcement part shown in Figure 4.

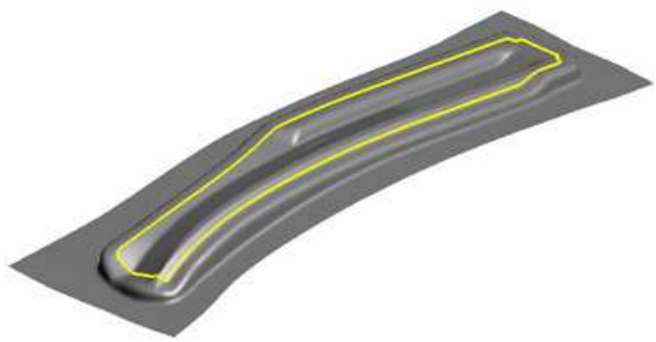

Figure 4: Stamped product with the boundary of the part

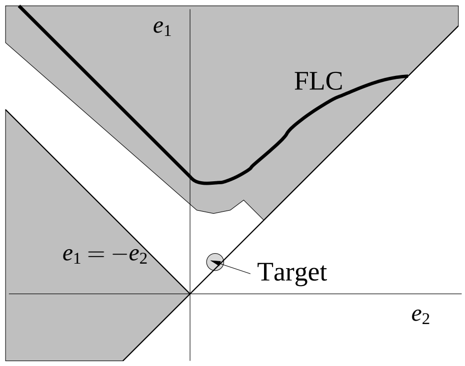

Figure 5: Target function defined in strain space

Keeping in mind the P-diagram of Figure 1, the input is defined as the CAD drawing of the product to be produced; the response is the reinforcement part that should meet the requirements. The parameters that can be varied and must be considered are the control variables and the noise variables, respectively. We propose a two phase strategy for robust optimisation. In a first phase the values of the control variables are defined, this phase we call Robust Design. In a second phase the noise variables are considered, this phase we call Robust Manufacturing.

4.1 *Robust Design*

In the Robust Design phase the control variables are optimised to obtain the best possible production settings. In the case of the automotive part, the restraining forces of three drawbeads, the blank shape and the blank's x- and y-position are defined as the six control variables.

The objective function is based on the Forming Limit Curve (FLC) presented in Figure 5. The dark area at the top and bottom define the area where the process does not yield acceptable products, i.e. $g < 0$ in terms of the reliability based optimisation formulation of Equation 3. The Limit State at the top is the FLC minus a 20% safety margin. Above this Limit State, excessive thinning or necking can occur. The Limit State at the bottom is the line $e_1 = -e_2$, which is the line of constant thickness. Below that line, compression in the sheet material occurs, which indicates a danger of wrinkling.

The objective function is to minimise the distance from the target point presented in Figure 5. Strain points in the dark, unacceptable areas will get a penalty as a function of the distance from the light, feasible area. Strain points in the light area get a bonus the closer they are to the target point.

In the Robust Design phase the optimal settings of the control parameters are found by a genetic algorithm [10]. For the optimisation of the automotive part, 80 simulations of 2 minutes each were needed. They were run in parallel on 4 processors. With the obtained optimal control variable settings, the next phase is entered.

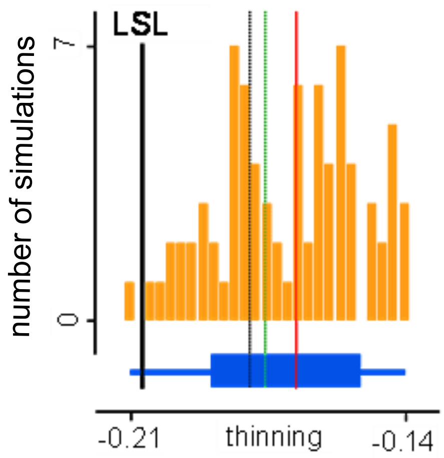

Figure 6: Frequency plot of thinning in the critical area

4.2 *Robust Manufacturing*

In the second phase the robustness with respect to the noise variables will be validated. The noise variables in a deep drawing process are for example the mechanical properties of the material and the coefficient of friction. A material is ordered within a certain tolerance width. The amount of lubricant slightly varies as well. In this analysis the yield stress, the tensile strength, the coefficient of friction as well as the applied blank holder force are defined as noise variables. Another 80 simulations are automatically performed while varying the noise variables according to a normal distribution. The thinning values of all 80 simulations in the most critical area of the part are shown in the frequency plot in Figure 6. The LSL of -0.20 is also indicated in the frequency plot.
The frequency plot shows the response on the scatter of the noise variables. Analysing the frequency distribution with respect to the LSL one directly sees that a danger exists that the thinning will pass the critical value of -0.20. How often failure will occur is quantified by the process capability ratio C_{pk} of Equation 2. However, this definition assumes a normal distribution of the response as mentioned in Section 2.2. One can clearly see in Figure 6 that in case of the automotive reinforcement part the response distribution is not normal. For that reason the non-parametric variant of Equation 2 is used throughout AutoForm-Sigma as defined by DIN 55319, Method M4:

$$\text{lower } C_{pk} = \frac{\text{MED} - \text{LSL}}{\text{MED} - Q_{0.00135}} \tag{4}$$

where MED denotes the median and $Q_{0.00135}$ is the 0.135% quantile. MED $- Q_{0.00135}$ corresponds to 3σ in case of a normal distribution. For the automotive part, this equation results in a C_{pk} value of 0.935 which coincides with a defect rate of about 0.25%. This is an acceptably low defect rate. Thus, the combination of Statistical Process Control with process simulation and robust optimisation has resulted in a robust metal forming process.

5 CONCLUSIONS AND FUTURE RESEARCH

Manufacturing processes possess variability which can deteriorate product quality and increase costs. Statistical Process Control and the 6σ-philosophy can be combined with robust or reliability based optimisation techniques to reduce these problems. A promising approach is AutoForm-Sigma, which consists of a Robust Design and a Robust Manufacturing phase. Its potential has been demonstrated by application to an automotive deep drawing process for which the stochastic variation in thickness was predicted.
In the future, the Robust Design and Robust Manufacturing phases must be integrated to really use robustness evaluations in the determination of optimal process settings. A robust metal forming process benefits from both variability reduction and shifting of the response distribution to a 6σ-level. Hence, both robust and reliability based optimisation principles could further assist in the integration of the Robust Design and Robust Manufacturing phases in AutoForm-Sigma.

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