Robust optimization of metal forming processes using a metamodel-based strategy

J.H. Wiebenga*, G. Klaseboer† and A.H. van den Boogaard**

*Materials innovation institute (M2i), P.O. Box 5008, 2600 GA, Delft, The Netherlands
†Philips Consumer Lifestyle, P.O. Box 20100, 9200 CA, Drachten, The Netherlands
**University of Twente, P.O. Box 217, 7500 AE, Enschede, The Netherlands

Abstract. Robustness, optimization and Finite Element (FE) simulations are of major importance for achieving better products and cost reductions in the metal forming industry. In this paper, a metamodel-based robust optimization strategy is proposed for metal forming processes. The applicability of the strategy is demonstrated by application to an analytical test function and an industrial V-bending process. The results of both applications underline the importance of including uncertainty and robustness explicitly in the optimization procedure.

Keywords: Metal forming, FEM, optimization, uncertainty, robustness
PACS: 02.60.Pn

INTRODUCTION

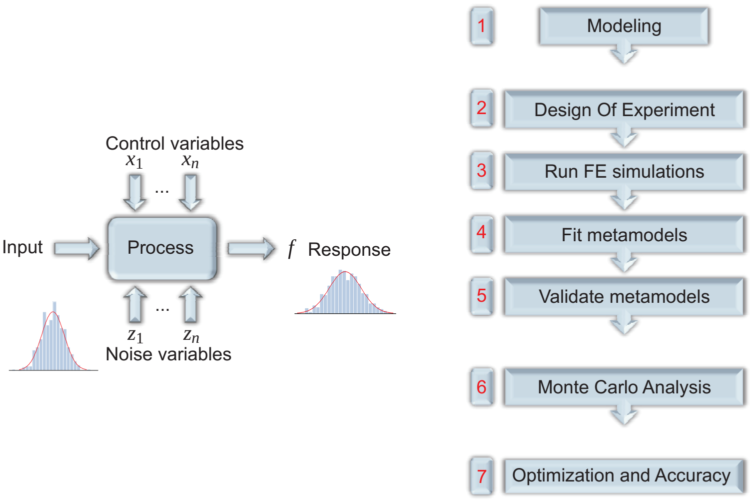
The coupling of optimization techniques and Finite Element (FE) simulations has become a standard procedure in the metal forming industry. First successful results have been reported on improving design quality and reducing development costs. However, these optimization techniques are mostly deterministic of nature, i.e. noise variables and the robustness of the obtained optimal process are not taken into account. In industrial practice on the contrary, including manufacturing variability like material variation is very important for achieving product improvements and cost reductions. In fact, very often an obtained deterministic optimum lies at the boundary of one or more constraints. The natural variation in material, lubrication or process settings might lead to a high number of violations of constraints in the real world, resulting in high scrap rates.

To avoid this undesirable situation, uncertainty has to be taken into account explicitly in the numerical optimization strategy. Next to *control variables* ($\mathbf{x}$), the process is influenced by stochastic variables or *noise variables* ($\mathbf{z}$), see Figure 1(a). The input variation is subsequently translated to the *response* (f) which will now also display a probability distribution instead of a deterministic value only. Process robustness is related to the amount of variation in the process response, i.e. the narrower the response distribution, the more robust the manufacturing process. Robustness is thus a measure for the reproducibility of products resulting from the process. An overview on the most important developments in the field of robust optimization can be found in [1] and [2].

In this paper, a robust optimization strategy is proposed that bridges the gap between deterministic optimization techniques and the industrial aim for robustness. The developed strategy will be introduced first after which the applicability is demonstrated using an analytical test function and an industrial V-bending process.

ROBUST OPTIMIZATION STRATEGY

The proposed robust optimization strategy consists of 7 steps. A flowchart is presented in Figure 1(b). The strategy is suitable for solving optimization problems in a structured way including time–consuming FEM simulations and is implemented in the optimization software OptForm developed at the University of Twente [3]. The software is applicable to any metal forming product or process and is suitable for use with commercially available FEM packages.



(a) (b)

FIGURE 1. (a) Process-diagram and (b) flowchart of the robust optimization strategy

Modelling

The first step is to model the optimization problem under consideration (1). The control and noise variables have to be selected and ranges have to be quantified. For the latter type of variables, a normal distribution is assumed. The stochastic variables can now be expressed by a mean value μ_z and a corresponding standard deviation σ_z. The same holds for the objective function f and constraints $\mathbf{g}$ since they can be influenced by the noise variables. Control variables $\mathbf{x}$ can be treated the same as in a deterministic problem where its ranges are bounded by Lower Bounds (**lb**) and Upper Bounds (**ub**). A typical robust optimization formulation is given by:

$$\begin{aligned} &\text{find } \mathbf{x} \\ &\min \mu_f + k_f \sigma_f \\ &\text{s.t. } \mathbf{LSL} \leq \mu_{\mathbf{g}} \pm \mathbf{k_g} \sigma_{\mathbf{g}} \leq \mathbf{USL} \\ &\quad \mathbf{lb}_x \leq \mathbf{x} \leq \mathbf{ub}_x \\ &\quad \mathbf{lb}_z \leq \mathbf{z} \sim N(\mu_z, \sigma_z) \leq \mathbf{ub}_z \end{aligned} \tag{1}$$

In Equation 1, the objective function is to minimize the weighted sum of both the mean μ_f and standard deviation σ_f of the response, i.e. both the location and the width of the response distribution are minimized simultaneously. A similar type of formulation is used for describing the constraints. Note that using the weighted sum formulation for a constraint can also be interpreted as a reliability constraint that assures a 3σ reliability with respect to a certain Lower Specification Limit (LSL) and Upper Specification Limit (USL) for $\mathrm{k}_g = 3$. If $\mathbf{g}$ is assumed to be normally distributed one can subsequently calculate the scrap rate.

Optimization

Solving the robust optimization problem is performed in the following steps. A (2) Design Of Experiment (DOE) is performed based on a full factorial design combined with a space filling Latin Hypercube Design (LHD). After having run the FEM simulations corresponding to the settings specified by the DOE (3), a metamodel is fitted in the combined control-noise variable space using both Response Surface Methodology (RSM) and Kriging metamodelling techniques (4). In the robust optimization strategy the computationally expensive non-linear FE simulations are thus replaced by a surrogate model. Metamodel validation is performed using ANalysis Of VAriance (ANOVA) techniques [4]. To estimate the performance of the approximate model, leave-one-out cross-validation is used. Each DOE point is selected once as the validation data, and the remaining DOE points as the training data. The level of fit of each metamodel is calculated and used to select the most accurate metamodel with respect to the FE-model response. From the single metamodel, two different models for the response mean and variance are subsequently extracted using a Monte Carlo Analysis (MCA) of 10.000 points (6). The latter step can be performed very efficiently since the MCA is executed onto the metamodel. Both models of the mean and variance can now be used for optimization (7) using a Genetic Algorithm (GA). A final small MCA can be performed using FE simulations to evaluate the accuracy of the optimum.

APPLICATION TO AN ANALYTICAL TESTFUNCTION

The applicability of the robust optimization strategy is tested using an analytical function. The original function as proposed in [5] is slightly adapted by adding an interaction term x-z. Following Equation 1, the goal of the unconstrained optimization problem is to find x for which the weighted sum of the mean plus three times the standard deviation of the response is minimized. The control variable is bounded by $lb_x = 0$ and $ub_x = 10$. A normal distribution is assumed for the noise variable z with $\mu_z = 0$ and $\sigma_z = 1$, the lower and upper bound are set to $\pm 3\sigma$ respectively.

The robust optimization problem has been optimized by running 20 function evaluations. The black dots in Figure 2(a) represent the DOE points. RSM and Kriging metamodels are fitted using the analytically calculated response measurements marked by the blue dots. Resulting from ANOVA, a second order Kriging metamodel is chosen onto which a MCA is applied. By combining the resulting mean μ_f and standard deviation σ_f of the response, the objective function is found as a function of the control variable x, see Figure 2(b). Also the deterministic objective function is depicted, which is in this case simply the mean of the response. Optimization using a GA results in the deterministic and robust optimum reflected by the black and red dot respectively. For this specific analytical function and objective function, a significant shift of the location of the robust optimum is obtained with respect to the deterministic optimum. This underlines the importance of including uncertainty and robustness explicitly in the optimization procedure.

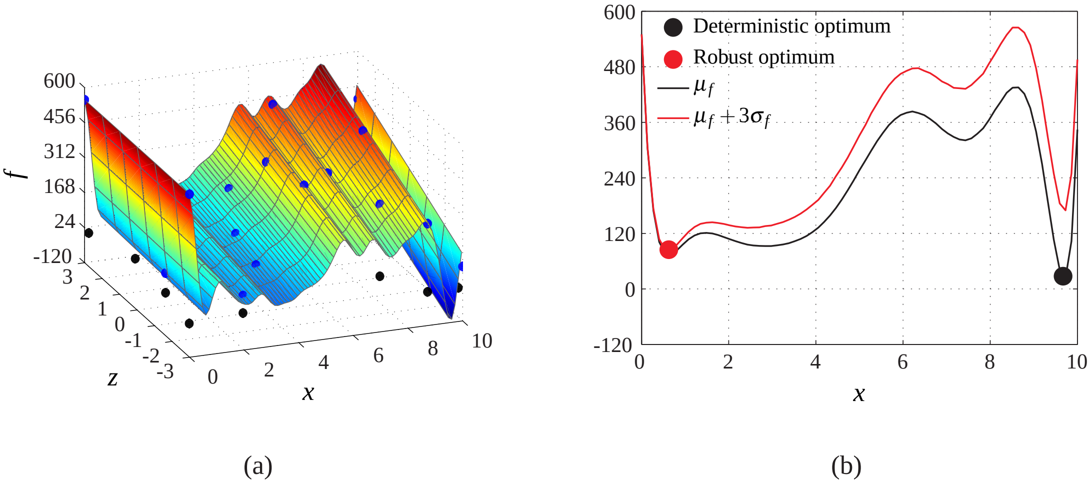


FIGURE 2. (a) Kriging metamodel fitted through the response measurements (blue dots) performed at the DOE points (black dots) and (b) deterministic and robust objective function

APPLICATION TO A V-BENDING PROCESS

The robust optimization strategy will now be applied to optimize an industrial V-bending process. The goal of this optimization study is to gain more insight in the production process. With that, the process can be optimized such that correct products are produced in a robust way. Figure 3(a) shows the 2D FE-model of half of the part, MSC Marc has been used as FE-code. One simulation takes about 7 minutes to perform. Both the die and punch are modeled to be non-rigid such that the real process is represented more realistically.

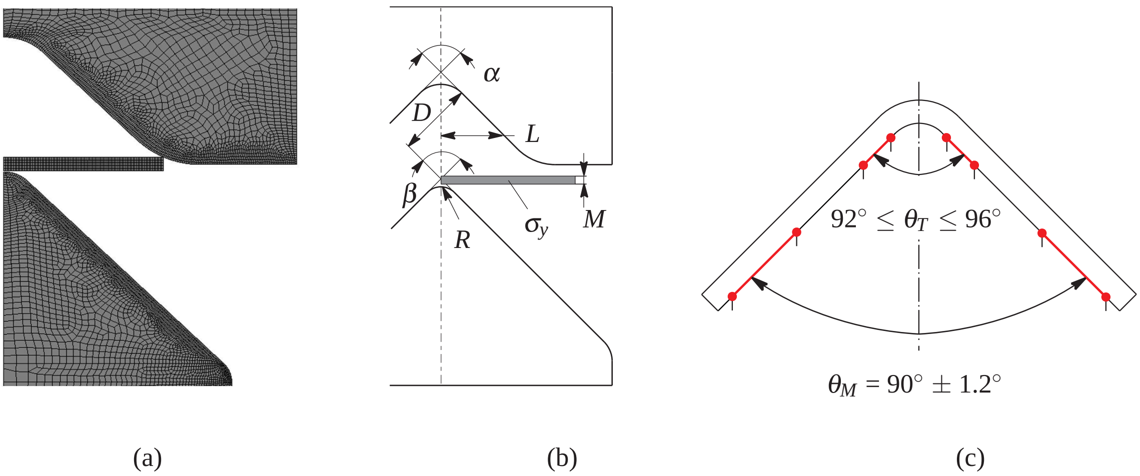


FIGURE 3. (a) 2D FE-model, (b) definition of control and noise variables and (c) constraints on the flange angles

Modelling

A screening step is performed first to reduce the size and complexity of the optimization problem. As a result, the number of variables have been reduced to 3 control variables and 2 noise variables. The variables that have a limited effect on the responses are considered insignificant and can be excluded from the optimization problem. These variables can either be set to their best value with respect to the objective function and constraint or can be set to their current process setting. The latter option has been chosen in this case to minimize the required changes in the current production process.

The remaining set of variables is depicted in Figure 3(b). The control variables are the radius of the die (R), the final distance between the flange of the die and punch (D), the dimensions of the punch (L) and the angle of the die (α) and the punch (β). Since α and β should be equal, both angles can be described by a single control variable. Similar to the process in practice, the material thickness (M) and yield stress (σ_y) are considered uncertain.

To assure a correct performance of the final product, constraints on the flange shape of the product are prescribed. The flange shape is defined by a transition angle θ_T and a main angle θ_M spanned up by the marked line segments, see Figure 3(c). The constraint on the main angle is stricter since this angle is most critical with respect to the performance of the final product. In the current V-bending process, active steering of D is required to obtain products that satisfy the requirements on both angles. The goal of the robust optimization study is to optimize towards a 3σ process for both angles for which active steering of D is not required anymore. The main angle is taken into account as the objective function f while satisfying $\pm 3\sigma$ constraints on the transition angle. The quantified robust optimization formulation reads:

$$
\begin{aligned}
&\text{find } \mathbf{x}\\
&\min\ |(\mu_{\theta_M} - 90)| + 3\sigma_{\theta_M}\\
&\text{s.t. } 92 \le \mu_{\theta_T} \pm 3\sigma_{\theta_T} \le 96\\
&\quad 92 \le x_1 = \alpha = \beta \le 93\\
&\quad 1 \le x_2 = R \le 1.3\\
&\quad 4 \le x_3 = L \le 5\\
&\quad 0.4 \le x_4 = D \le 0.65\\
&\quad \mu_{z_1} - 3\sigma_{z_1} \le z_1 = M \sim N(0.51, 0.01) \le \mu_{z_1} + 3\sigma_{z_1}\\
&\quad \mu_{z_2} - 3\sigma_{z_2} \le z_2 = \sigma_y \sim N(350, 6.66) \le \mu_{z_2} + 3\sigma_{z_2}
\end{aligned}
\tag{2}
$$

TABLE 1. Current and optimized process settings

Parameter	Current process settings	Optimized process settings
α	92 °	92.4°
β	92 °	92.4°
R	1.15 mm	1.16 mm
L	5 mm	4.8 mm
D	adaptive	0.55 mm

Results

As a basis for the metamodel, a DOE of 300 points is constructed in the combined 5D control-noise variable space. The FE-simulations are performed on 4 parallel processors reducing the total calculation time to approximately 9 hours, all simulations can thus be performed overnight. Using ANOVA, a second order Kriging model resulted in the most accurate fit for both f and g. Impressions of the metamodels are given in Figure 4.

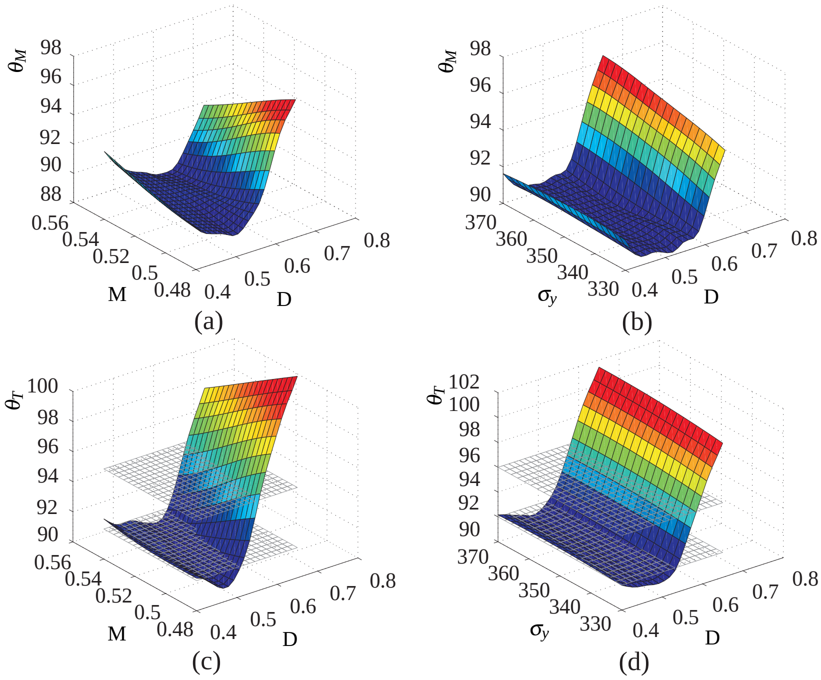


FIGURE 4. Kriging metamodel impressions of the (a,b) main and (c,d) transition angle

Figure 4(a) and 4(b) show the metamodels of the main angle as a function of the distance D and the material thickness M and yield stress σ_y respectively. For visualization,the remaining variables are set to their current process settings as depicted in Table 1. Note that for small D the main angle approaches the tooling angle which is caused by the flattening of the material. For large D, the main angle increases since the material is solely bended. In between these extreme process settings, an area can be observed in which both the influence of the distance D and both noise variables is small. For this specific setting, this could potentially yield a process which is robust with respect to noise. Moreover, by looking at the slope of the metamodel in the noise direction it can be seen that the standard deviation increases for increasing D. A similar behavior is observed for the transition angle, see Figure 4(c) and 4(d). Note that especially the lower constraint on the transition angle significantly reduces the feasible area also excluding the use of the robust area.

The metamodels are subsequently used for optimization by applying a GA. The initial optimization approach did not result in a 3σ process. This is mainly caused by a non-robust behavior of the transition angle in the feasible design space. Therefore, the 3σ constraint on the transition angle is slightly relaxed to a 2σ constraint. The optimal process settings of the revised optimization problem are given in Table 1. The results of the optimized process are depicted in Figure 5 in which the main and transition angle are plotted as a function of D. The vertical bars represent the

$\pm 3\sigma$ bounds caused by the influence of the noise variables. The optimal distance D is found to be 0.55 mm which corresponds to a mean value of the main angle of 90.39° and a standard deviation of 0.1°. Note that the modified 2σ requirement for the moment matching constraint on g has been satisfied.

In case of deterministic optimization, neglecting the influence of the noise variables will result in an optimum that lies at the boundary of the lower constraint on θ_T for $D = 0.52$ mm. The variation in M and σ_y would in this case lead to a high number of violations of the constraint in the real V-bending process, resulting in high scrap rates. From this, it can be concluded that the effect of adding noise is significant if one compares both optimal settings for D. The ultimate result is a 2σ robust V-bending process for which active steering of the distance D is not required anymore.

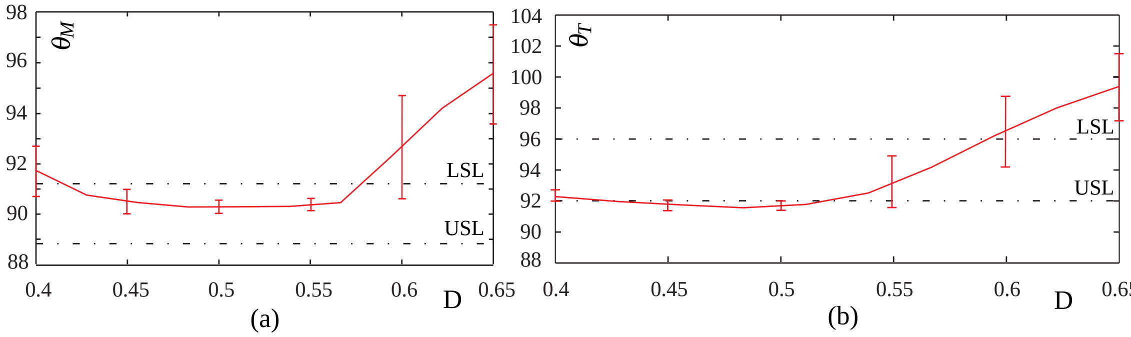


FIGURE 5. Optimal process results for the (a) main and (b) transition angle as a function of the distance D

CONCLUSIONS AND FUTURE WORK

Applying the robust optimization strategy presented in this paper allows for modeling and solving robust optimization problems in the metal forming industry including uncertainties such as material variation and process settings. More than solely deterministic strategies and algorithms, it assists the metal forming industry in achieving robust and reliable mass production processes.

Important process insights are obtained, among others by visualization of the metamodels used in the strategy. However, it is important to realize that the robust optimization results are based on a metamodel approximation of the response measurements resulting from FE simulations. Small errors in the metamodel or FE model can have a significant effect on the final robust optimum. Future work will therefore be focused on implementing a sequential optimization strategy. It is to be expected that adding additional DOE points in the control-noise variable space will significantly increase the metamodel accuracy and with that the robust response prediction. More in general, we will focus our research efforts on efficiently including manufacturing variability, process robustness and reliability during optimization.

ACKNOWLEDGMENTS

This research was carried out under the project number M22.1.08303 in the framework of the Research Program of the Materials innovation institute (www.m2i.nl).

REFERENCES

1. H.-G. Beyer and B. Sendhoff. Robust optimization - A comprehensive survey. *Journal of Computer Methods in Applied Mechanics and Engineering*, 196:3190–3218, 2007.
2. G.-J. Park, T.-H. Lee, K.-H. Lee, and K.-H. Hwang. Robust design: an overview. *Journal of the American Institute of Aeronautics and Astronautics*, 44:181–191, 2006.
3. M. H. A. Bonte. *Optimisation strategies for metal forming processes*. PhD thesis, University of Twente, 2007.
4. R. H. Myers and D. C. Montgomery. *Response surface methodology*. John Wiley & sons, 2002. ISBN 0-471-41255-4.
5. K.-H. Lee and G.-J. Park. A global robust optimization using Kriging based approximation model. *Japan Society of Mechanical Engineers International Journal*, 49:779–788, 2006.