Practical Optimization for Automotive Sheet Metal Components

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ABSTRACT:

Forming simulation has now reached an acceptable level of accuracy. It is possible to predict the hardening, the thinning and required forces for sheet metal stamped parts and it is also possible to predict the geometrical defects such as springback, wrinkling and surface appearance problems. Sheet metal forming can therefore be used in a closed loop to help design of parts and required tools in order to achieve a pre-defined geometry and mechanical performance.

The paper presents a practical optimization methodology applied to automotive sheet metal stamped parts. The goal is to automatically optimize tool geometry in order to achieve an optimal part. An optimal part is regarded as a part free of defects. The defects are classified in two categories: material and geometrical. Material defects prevent the forming of the parts which can be in the form of a premature failure or an excessive wrinkling. The geometrical defects prevent the formed part from being assembled to the body structure and are generally referred as "springback". In order to establish this optimization methodology, available tools for optimization and automatic geometry modification were coupled to LS-DYNA [1]. A special attention was paid to the definition of the optimization problem: appropriate selection of design variables, definition of the response functions in order to characterize the possible part defects (material or geometrical) and specification of the required physical constraints. The developed methodology will be demonstrated on actual automotive components

Keywords:

Optimization, Sheet metal forming, Materials

INTRODUCTION

In the automotive industry there is a tendency to shorten development times and reduce the tooling lead times for the production of sheet metal parts. As a result there is limited time for physical try-outs and therefore to a necessity of optimal die designs right from the process layout. This leads to an increasing demand for practical optimization techniques for sheet metal forming processes. These techniques should deliver in a short time the optimal process parameters enabling the forming of a sheet metal part that satisfies tight formability and tolerance requirements. Furthermore, advanced high strength steels are increasingly being used in order to achieve the required weight reduction for the body structure. For these steels, there is a lack of experience among the stamping community. Therefore using systematic optimization techniques can contribute to improving the stamping process layout for such steels.

Using the Finite Element Method (FEM) coupled to optimization techniques provides a solution to such a problem [2-4]. The principle is to use the FEM in order to evaluate the obtained part using a set of process parameters. The process parameters can include the geometry, the material or the process control parameters.

In this paper LS-DYNA is used as a FEM solver for its ability to provide accurate results for the sheet metal forming simulation. LS-DYNA is coupled to the optimization tool of "Hyperstudy" [5].

CHARACTERIZATION OF SHEET METAL FORMING

A mathematical formulation of the problem of numerical optimization of material forming processes requires a characterization of this forming process. It is necessary to define mathematical functions quantifying both the quality of the formed part and the performance of the forming process. The quality of the part is defined through its integrity (safety from cracks and wrinkles), its shape accuracy (no shape distortions or springback) and its surface quality (no wrinkles or surface defects). The performance of the forming process refers to its energy consumption (press forces) and its material utilization.

The so defined mathematical functions also referred to as quality functions can then be used in a scope of a numerical optimization either as objective functions or constraint functions depending on the main target.

In what follows some examples of quality functions will be presented as illustration.

SHAPE QUALITY

The goal of a controlled forming process is to achieve a part with a geometry respecting tight tolerances. Therefore the deviation with regards to the nominal or design geometry has to be kept as small as possible. The function to define in this case should represent this deviation. A general form for this function can be written as following:

$$F_{SH} = \frac{1}{n}\left(\sum_{i=1}^{n}\alpha\left(\frac{X_i^{CAD} - X_i^{NUM}}{X_i^{CAD}}\right)_+^p\right)^{\frac{1}{p}} + \frac{1}{n}\left(\sum_{i=1}^{n}\beta\left(\frac{X_i^{NUM} - X_i^{CAD}}{X_i^{CAD}}\right)_+^q\right)^{\frac{1}{q}} \quad \text{(Eq. 1)}$$

Where

X^{CAD} = coordinates in the nominal or design geometry,

X^{NUM} = coordinate in the geometry obtained after the forming process,

n=number of positions of the part considered for evaluating the distance,

α and β=weighting factors,

p and q define the used norm,

$(.)_+$ is an operator defined as: $(A)_+ = A$ if $A > 0$ and $A = 0$ otherwise.

PRODUCT INTEGRITY

The mathematical function defined for this purpose should allow determining if a part is safe from material defects. These material defects are cracks, excessive thinning or excessive wrinkling, etc.. A simple definition of such a function makes use of the thickness distribution as follows:

$$F_{QP} = \frac{1}{n}\left(\sum_{i=1}^{n}\alpha\left(\frac{h_0 - h_i}{h_0}\right)_+^p\right)^{\frac{1}{p}} + \frac{1}{n}\left(\sum_{i=1}^{n}\beta\left(\frac{h_i - h_0}{h_0}\right)_+^q\right)^{\frac{1}{q}} \quad \text{(Eq. 2)}$$

where the same definitions are used as in (Eq. 1) with h0 representing the initial thickness and hi representing the thickness after forming.

However the definition of (Eq. 2) represents some limitations and a function making use of the forming Limit Curve (FLC) is more appropriate.

A FLC is a piece-wise linear curve which is defined by specifying a list of interconnected points and extrapolated infinitely in both the negative and positive directions of ε2. Normally based on the FLC, three zones are defined presenting cracks area, risk of cracks area and safe area. Points above FLC are in cracks area, in between FLC and 80% of FLC are in risk of cracks area and under 80% of FLC are considered to be in safe area. In order to avoid necking defects, it is necessary to be sure that all points are in the safe area which leads to the optimization constraints as follows:

$$F_{flc0} = \sum_{i=1}^{n} C(i) = 0 \qquad \text{n = number of elements}$$

$$\begin{cases} C(i) = 1 & if \quad \varepsilon_1 \geq 0.8 * \varepsilon_{1\,flc} \\ C(i) = 0 & if \quad \varepsilon_1 < 0.8 * \varepsilon_{1\,flc} \end{cases}$$

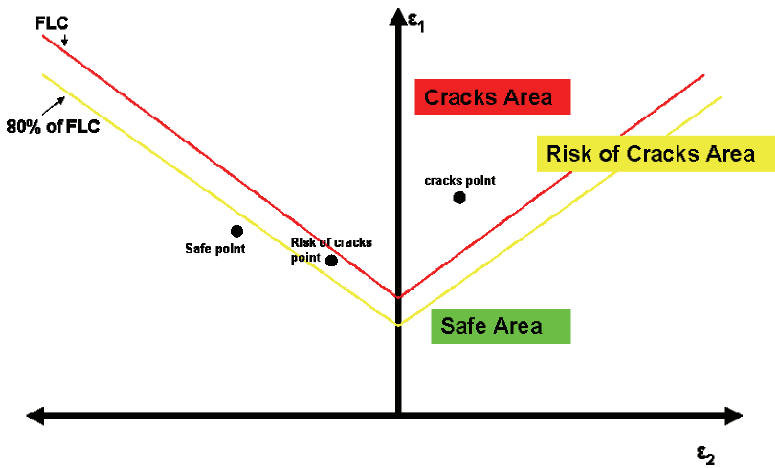

Figure 1: description of FLC

Further, when more defects are taken into account, the extension of FLC is required which includes limit line for excessive thinning, inadequate stretching and excessive wrinkling. The optimization constraints expand accordingly as follows:

$$F_{flc} = \alpha * F_{flc0} + \beta * F_{flc1} + \gamma * F_{flc2} + \theta * F_{flc3} = 0$$

Where F_{flc0} = Necking constraint

F_{flc1} = excessive thinning constraint

F_{flc2} = inadequate stretching constraint

F_{flc3} = excessive wrinkling constraint

α, β, θ and γ = weighting factors,

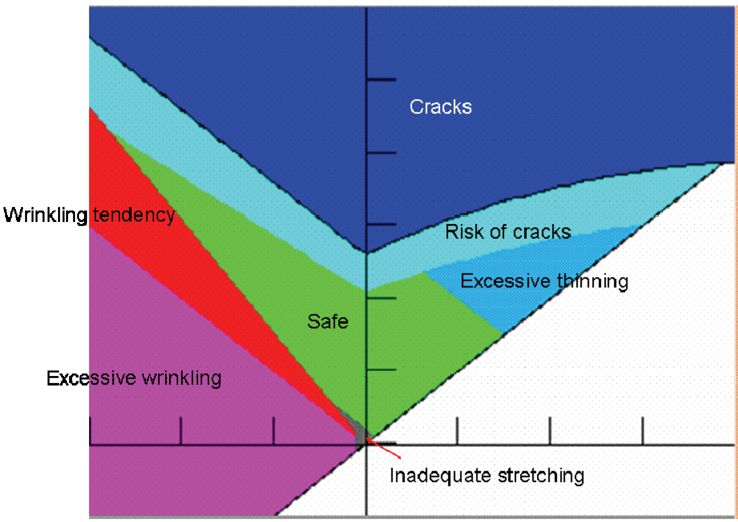

Figure 2: Description of FLD

The definitions of F_{flc1}, F_{flc2} and F_{flc3} are similar to F_{flc0}'s definition. If there is a point across the limit line of certain constraint, it adds one in the constraint function.

OPTMIZATION PROBLEM FORMULATION

The optimization of material forming processes can be formulated as a non-linear mathematical optimization problem as follows:

$$\min_{p} S_0(\mathbf{p},\mathbf{u})$$
$$\text{subject to} \qquad \text{(Eq. 3)}$$
$$\begin{cases} h_j(\mathbf{p},\mathbf{u}) \le 0 & 1 \le j \le n_{ic} \\ g_i(\mathbf{p},\mathbf{u}) = 0 & 1 \le i \le n_c \end{cases}$$

Where n_{ic} is the number of inequality constraints, n_c is the number of equality constraints, **p** is the vector of process parameters and **u** is the calculated displacement field.

The objective function S_0 is a measure of the process performance whereas the constraint functions h_j and g_i are introduced to take into account the technological limitations and the boundaries on the process parameters.

Different techniques are available for the solution of the above formulated optimization problem. One can classify these techniques in two categories, the direct methods and the response surface methods.

The direct methods make use of the exact analysis to evaluate the objective and response functions. The search of the solution can then be performed using local search or global search methods. The local search methods are gradient based and require the evaluation of the gradient of the objective and constraint functions. However the dependency of the different functions to the parameters is implicit, thus the most used way is via finite differences method. As examples to these methods, one can name the FSQP or the BFGS techniques. These techniques can be quite fast to converge if the initial guess for the parameters is close to the optimal solution. However in many situations it is not possible to distinguish between a local optimum and the global one. The global search methods are based on a complete exploration of the solution domain. They require a huge amount of evaluation of the objective and constraint functions but allows finding the global optimum. One of the most used techniques in this category is the Genetic Algorithms method.

The response surface methods (RSM) make use of an approximation of the objective and constrain functions using analytical expressions. The mathematical optimization is then performed on these expressions using one of the above mentioned techniques. The advantage of the RSM is that the number of function evaluation is known in advance. However the success of the method is highly dependent on the initial guess, the domain definition and the chosen approximation.

OPTMIZATION APPLICATION STUDIES

As introduced in previous chapters, the methodology of a closed loop optimization with morphing which enables to achieve a defect-free design by modifying selected geometrical parameters of critical area from initial design is illustrated in Figure 3.

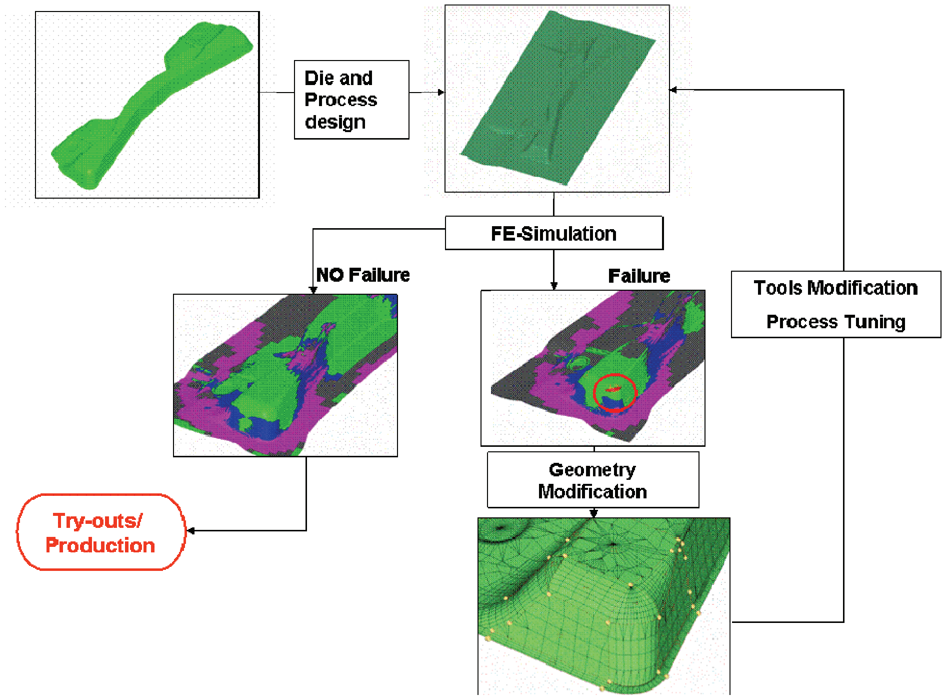

Figure 3: Closed loop optimization with Morphing

FLD is chosen to be the constraint function, where excessive wrinkling and inadequate stretching were neglected. In order to maintain the functionality of the initial design, variation of the shape is defined as the objective function. By optimizing, it is intended to reach the minimal variation of the shape while satisfying the requirements of FLD assuring the formed parts are defect-free.

By implementing Morphing tools "Hypermorph" [6] coupled to LS-DYNA, two case studies, one for academic and the other for industrial investigation, were carried out. The geometry of first application study was shown in Figure.4. The blank is made of DP600 with thickness 1.5mm. The process is in normal friction condition and the binder force is 400KN.

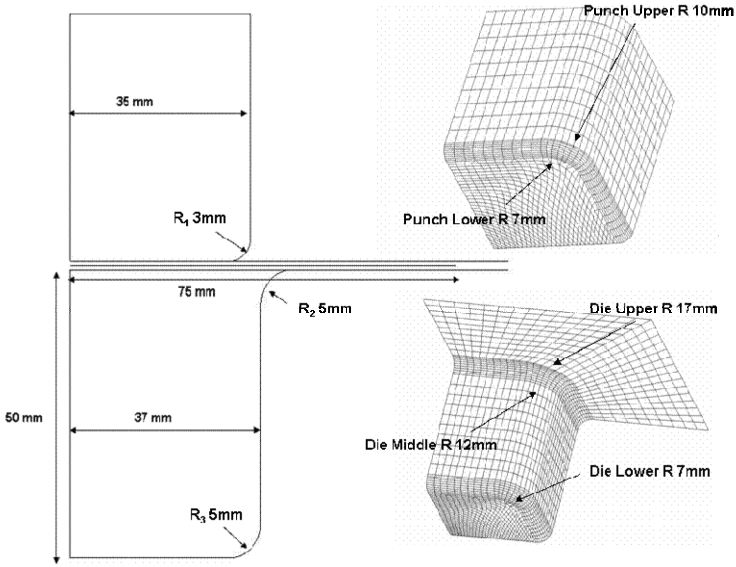

Figure 4: Case study 1- Square Cup

With the first try FE-simulation result, the critical area of cracks risking could be determined and two shape variables are defined in this area as shown in Figure.5. By varying the shapes of the critical area, the necking defect on the corner will be reduced and finally removed. The response surface optimization solver delivers an optimal result after 6 iterations, where both the shape variables are enlarged approximately 30%. Following Table.1 compares the differences of the shape variables in detail. The whole optimization finished in 11 hours which is acceptable for design phase engineering.

	R1 (mm)	R2 (mm)	R3 (mm)	Punch Lower R(mm)	Punch Upper R(mm)	Die Lower R(mm)	Die Middle R(mm)	Die Upper R(mm)
Initial design	3	5	5	7	10	7	12	17
Optimal design	5	7	7	5.7	11.6	5.7	13.6	22

Table 1: Comparison of shape variations

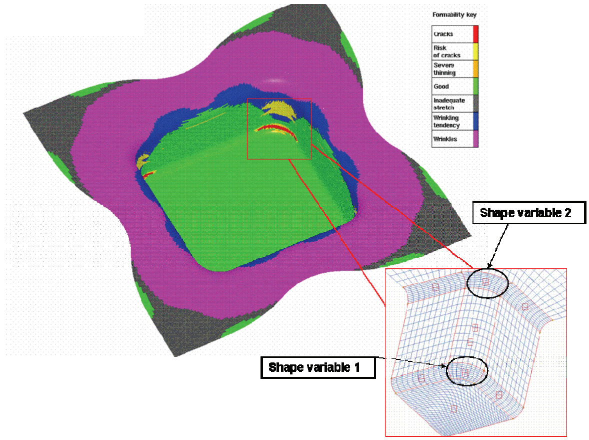

Figure 5: Definition of shape variables for study 1

The other case study was carried out with an automotive sheet metal component, which is originally from benchmark 2 of NUMISHEET 2005 [7] but modified on purpose of this study. Similar approach of optimization was employed in the application study. Since response surface method is dependent of the initial values of variables, the first run optimization did not converge and find the optimal solution. After changing the initial values, the optimization converged with 7 iterations shown in Figure 6.

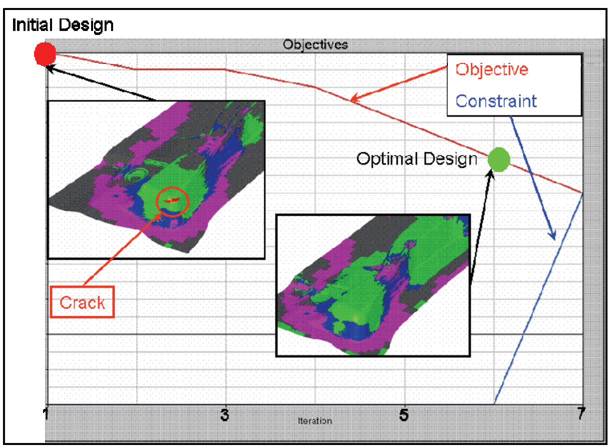

Figure 6: Optimization process of study 2

SUMMARY AND CONCLUSIONS

As the optimization of numerical parameters for forming simulation has been successfully developed and implemented for design engineering, it is attractive to develop an optimization for geometrical parameters which provides effective optimization methodology with acceptable computation time. This is performed by coupling external optimization solvers to LS-DYNA.

Taking advantage of constraints determined by FLD adaptive response surface optimizations were launched which investigate two different types of formed parts where the initial designs have feasibility problem due to necking cracks. Both optimizations deliver the reasonable optimal solution separately without defects, meanwhile robustness and compatibility of the optimization methodology has been proved.

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