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RELIABILITY BASED ECONOMICAL OPTIMIZATION OF SHEET METAL FORMING PROCESSES

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ABSTRACT: In metal forming, optimization under uncertainty, e.g. by Reliability Based Design Optimization (RBDO), in combination with the results of FEM simulations has been recently opened. In RBDO, optimal process solutions should be robust with respect to uncontrollable or unpredictable variations of working conditions. Many try to solve the problem of optimizing some sort of objective function, under a reliability constraint. However, to the author's knowledge, all the objective functions previously presented are expressed in terms of part quality (e.g. thickness uniformity) or process robustness with respect to failures (wrinkles, tears, etc.). In this paper a new approach is proposed for design optimization, under uncertainty, based on the minimisations of direct variable industrial costs (namely the material costs and the failure costs) rather than quality or reliability. It is called Reliability Based Economical Design Optimization (RBEO), and is demonstrated using the #1 benchmark case of Numisheet 1993. A simple cost model is used in order to build an economical objective function, which directly correlates the traditional technological design variables of the stamping process (e.g. the blank holder force) to the manufacturing costs.

KEYWORDS: deep drawing, epistemic uncertainty, industrial costs

1 INTRODUCTION

In the sheet metal forming industry, the rapid improvement of computational capabilities offers the opportunity of running massive simulation campaigns on fast computers. As a consequence, the field of optimization in the presence of uncertainty has been opened up for process design. The role of uncertainty in process optimization is crucial. In fact, very often deterministic optima fall on the boundaries of the process feasibility windows [1], determining as a potential consequence a large number of scraps, failed parts or reworks. A large number of applications and techniques of optimization under uncertainty can be found in the field of plasticity [2] and sheet forming [3]. Many recent papers deal with the problem of optimal design of sheet forming processes under uncertainty, often called RBDO, Reliability Based Design Optimization. All the previously proposed RBDO approaches deal with the optimization of an objective function which is related to the technological performance of the stamping or deep drawing process, either in terms of part quality (e.g. uniformity of thickness or principal strains, amount of maximum thinning, geometrical distance from a target shape, etc.) or process robustness with respect to failures (wrinkles, necks, tears, etc.). Arguably, this should not be the most important goal of plant managers, who probably prefer to implement an economically optimal solution, provided that the part is sound or provided that a given level of quality or customer satisfaction is guaranteed. Conversely, a perfectly safe solution might determine a process which is more expensive than strictly necessary. The scientific literature on cost modelling of sheet forming is very scarce, set apart a few exceptions [4]. An economic analysis performed in the framework of the ULSAB project (www.worldautosteel.org) has shown that, for a set of typical auto-body stamped parts, the percentage material cost, which is a direct and variable cost, plays a major role, accounting for more than half of the total industrial cost and being much higher than the total of fixed costs. These figures refer to processes which have been already industrialised, i.e. where the reliability is under control (e.g. less than 0.5% stamping reject rate) and the corresponding cost is negligible. Any economically based design optimization should be mainly targeted at minimizing the material requirements for each part, i.e. the size of the initial blanks. Unfortunately, changing the size of stamping blanks generally has a significant effect onto the feasibility or failure risk of the process. Therefore, the economical optimization problem is mainly a trade off choice between costs of material and costs of process failure.

The process planning of sheet metal forming operations involves several iterations, with decreasing level of epistemic uncertainty as production gets nearer. Epistemic uncertainty is a subjective and reducible kind of uncertainty that stems from lack of knowledge or data about the process or the materials [5]. At the early stages of CAE-based design, most engineers and managers agree that any decision might have a great impact on

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manufacturing costs but it must be taken under a significant level of epistemic uncertainty and the effect of random uncertainty is negligible [6].

In this paper, a new approach, called Reliability Based Economical Optimization (RBEO) is proposed for early design optimization of sheet metal forming processes under epistemic uncertainty, based on the minimisation of direct variable industrial costs, rather than quality or reliability. In Section 2, the case study is presented. In Section 3, the method and its results are presented.

2 THE CASE STUDY

The new RBEO approach is demonstrated using the well known benchmark #1 case of Numisheet 1993 (the deep drawing of a square panel). This case has been often used by different authors [7-8] for the development of new computational or optimization methods, mainly because, despite being very simple and computationally inexpensive, it contains most of the relevant features which are typical of sheet metal forming processes: the part may fail either by excessive draw-in, wrinkling, excessive thickening or thickening and by fracture. Deep drawing of a square panel is a process very sensitive to the draw-in, which in turn is influenced by friction, blank holding force and material anisotropy; the process is less sensitive to hardening parameters and initial sheet thickness. Clearly, the draw-in is also affected by the initial dimensions and shape of the blank. According to the benchmark reference geometry, the blank is square with a maximum 170 mm side length *l*. If this length is reduced, while keeping constant the blank holder force, the friction forces decrease and, as a consequence, the amount of draw-in increases. As an example, in Figure 1 the draw-in is shown for a simulation run at nominal conditions with different initial blank length *l*=170 mm and holding force *BHF*=58.7 kN. The cost of material C_{m_s} [€/part] for this successful stamping operation can be calculated by the simple following equation:

$$C_{m\_s} = M_b \cdot p_b - M_s \cdot p_s; \qquad M_b = l^2 \cdot \bar{t}_0 \cdot \rho \qquad (1)$$

where M_b [Kg/part] is the nominal mass (i.e. calculated by the nominal initial sheet thickness $\bar{t}_0$) of the initial blank, M_s is the actual mass of the trimmed scrap, p_b and p_s are the sheet buying and selling prices [€/Kg], respectively, of the raw sheet material and of the scrap material; ρ [kg/mm^3] is the specific weight of the steel sheet. The value of M_s cannot be calculated before running the analysis and it might be considered as a response of the simulation which, in principle, depends on all process parameters, including the two main design parameters *l* (blank side length) and *BHF* (blank holder force). The part shown in Figure 1 is free of defects but, more generally, the process may fail for one or more of three reasons: a) the outer edge of the formed part may fall outside the trimming line at the end of the forming phase, b) fracture may occur, c) wrinkling may occur. The risk of fracture can be measured through the final maximum thinning $th_{\%}$ measured anywhere on the formed part within the trimming line: a part is considered to be failed by fracture when $th_{\%}\geq 0.335$. The risk of wrinkling can be measured through the final maximum thickening, measured anywhere on the formed part within the trimming line: a part is considered to be failed by wrinkling when $th_{\%}\leq -0.225$.

An Hill '48 isotropic hardening model has been used in FEM simulations, with the strain hardening law $\bar{\sigma} = (\varepsilon_0 + \bar{\varepsilon})^n$ and orthotropic properties determined by the three Lankford's coefficients r_0, r_{45}, r_{90}. Simulations have been conducted with a commercial solver with explicit time integration scheme, shell element formulation with reduced spatial integration and 5 points of through-the-thickness integration. Due to the double symmetry of the process, FEM simulations can be simplified by analysing only a quarter of the model actual geometry. In Table 1, the input data used in the simulations are listed (values referred to the full model, e.g. the blankholder force value BHF used in simulations is ¼ of the value shown in Table 1). Punch stroke *S* has been kept constant to a value of 45 mm.

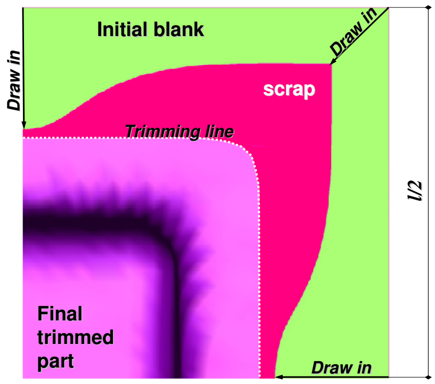

Figure 1: *Top view of blank (l=170 mm,* BHF *58.7 kN, ¼ of the full model) and formed part; the portion of the part out of the trimming line will be sold as scrap*

Table 1: *main reference data of the case study; nominal values are printed*

Process Variables			Values
Maximum blank side length			*l* = 170 mm (max. value)
Initial sheet thickness			$\bar{t}_0$ =0.79 mm
Anisotropy coefficients	R_0=1.79	R_{45}=1.41	R_{90}=2.27
Flow stress law parameters	ε_0=0.007	*K*=561 MPa	*n*=0.259
Friction coefficients	punch-blank f_p=0.14	blankholder-blank f_{bh}=0.14	die-blank f_d=0.14

3 RBEO AT AN EARLY STAGE

In order to calculate to optimal values of the blank size *l* and the holding force *BHF* at an early design stage, the total uncertainty (epistemic and random) about the actual values of the relevant process variables must be taken into account. In Table 2, a summary of all variables

involved in the proposed cost optimization technique is given. Two variables play a role in the proposed model:
- a vector $\underline{x}$ of 2 process control design variables to be designed and optimized, $x_1=l/2$ and $x_2=BHF/4$ in Tab. 2 (1/4 of the blankholder force is used because of the double symmetry of the process),
- a vector ξ of 10 process variables (normally and independently distributed random variables with mean equal to the nominal values given in Table 1 and given coefficients of variation) which can be controlled only to a limited extent and may be affected by variation (t_0, R_0, R_{45}, R_{90}, ε_0, K, n, f_p, f_{bh}, f_d in Tab. 2).
Table 2 reports also the assumed *c.o.v.* for each random variable. The *c.o.v.* are quite large because of the early timing of the design stage, and larger values are assumed

Table 2: *type of variables in the cost optimization model and coefficients of variation for random variables*

Process Variables	Type of Variable	Range of Values
Blank side length l	control design	158÷170 mm
Blankholder force BHF	control design	4.8÷78.4 kN
		c.o.v.
Initial sheet thickness t_0	random	11%
Anisotropy coefficients	random	R_0 R_{45} R_{90} 11% 11% 12%
Flow stress law parameters	random	ε_0 K n 11% 12% 11%
Friction coefficients	random	f_p f_{bh} f_d 17% 16% 16%

for the friction coefficients, because they are usually less controllable than other factors.
A set of computer experiments has been designed with varying values of the control vector $\underline{x}$, according to the data ranges provided in Table 2. For each of the N=36 planned values of $\underline{x}$, n=3 different simulation runs have been repeated (to a total of $n \cdot N$=108 runs), in order to account for the process variability induced by the non deterministic values of ξ. For each single run, the values of ξ have been selected using a Montecarlo approach, i.e. randomly extracting them from a normal distribution with given mean and coefficient of variation (reported respectively in Tables 1 and 2). At the end of each simulation run, with given values of the vectors ($\underline{x}$,ξ), a post processing routine extracts the following values:
- $th_{\%+}(\underline{x},\xi)$: maximum value of engineering thinning measured in the part after trimming; it must fall below the 0.335 limit in order to have a safe part;
- $th_{\%-}(\underline{x},\xi)$: the minimum (negative) value of thinning measured in the part after trimming; it must fall above the -0.225 limit in order to have a safe process;
- $D_{di}(\underline{x},\xi)$: a binary variable which indicates whether the draw-in has exceeded the boundary of the trimming line (D_{di}=1) or not (D_{di}=0);
- $M_t(\underline{x},\xi)$: mass of the outer trimmed portion of the part;
- $\overline{M}_t(\underline{x})$: mass of the outer trimmed portion of the part, averaged on the n simulation replicates for each value of $\underline{x}$ and normalized with respect to the nominal thickness:

$$\overline{M}_t(\underline{x}) = \bar{t}_0 \cdot \sum_{i=1}^{n} M_t(\underline{x},\underline{\xi}) \Big/ \sum_{i=1}^{n} t_0 \qquad (2)$$

- $D(\underline{x},\xi)$: a binary variable, calculated for each simulation run, which indicates whether the process is defective (D=1), i.e. the draw-in or thinning or thickening have exceeded their limits, or not (D=0);
- $P_f(\underline{x})$: the probability of failure, valid for a given value of the control vector x, calculated after all simulations runs; the probability $P_f(\underline{x})$ has been calculated with a statistical method called binary logistic regression [9].
The material cost expressed by equation (1), which was valid only for a successful stamping operation, can now be rewritten as a more general value which takes into account the possibility of failure:

$$C_m(\underline{x}) = M_b(\underline{x}) \cdot [p_b - P_f(\underline{x}) \cdot p_s] - \overline{M}_t(\underline{x}) \cdot [1 - P_f(\underline{x})] \cdot p_s \qquad (3)$$

As previously stated, the material cost is by far the most significant for simple stamping or deep drawing operations. For this reason, any economically based design optimization should be targeted at minimizing the material requirements for each part, i.e. the size of the initial blanks. Unfortunately, changing the size of stamping blanks generally has a significant effect onto the feasibility of the process. Therefore the economical cost function to be minimized must be formulated in order to incorporate the cost of potential failure as well:

$$C_{tot}(\underline{x}) = C_m(\underline{x}) + P_f(\underline{x}) \cdot c_f \qquad (4)$$

The coefficient c_f is a constant value which quantifies several costs "wasted" as a consequence of the production of a defective and unprofitable part: the allocated portion of all overhead costs (including manpower, tooling and equipment) and the direct variable costs (including energy consumption, tool wear, lubricants), etc. Once $C_{tot}(\underline{x})$ has been calculated for each of the N $\underline{x}$-values, a relation between the output C_{tot} and the input $\underline{x}$ can be meta-modelled with a second order polynomial regression. Indeed, in order to increase the fit of the regression, expressed through the R^2 correlation coefficient, and to reduce the numerical errors, a transformation $\underline{X}$ of the original input $\underline{x}$ has been used: $X_1=x_1^2/10000$; $X_2=x_2/10$. Using the transformed input variable $\underline{X}$, the meta-model of cost can be written as:

$$\hat{C}_{tot}(\underline{X}) = a_1 X_1 + a_2 X_2 + a_3 X_1^2 + a_4 X_2^2 + a_5 X_1 X_2 + a_6 \qquad (5)$$

For instance, in Figure 2, the plot of the meta-model vs. the calculated cost $C_{tot}(\underline{x})$ and vs. the input design variable $x_1=l$, $x_2=BHF/4$ is shown, for given values of the coefficients c_f, p_b and p_s. This demonstrates that for any given combination of material buying cost p_b, scrap selling price p_s and failure cost c_f, an optimal solution (l^*, BHF^*) can be found in terms of initial blank length and blankholder force which minimises the total direct variable production cost. For the data in Figure 2, the optimal values are x_1= 83.08 mm, x_2= 11.60 kN.
The meta-modelled cost expressed as in Equation (5) can be optimised with respect to the design variables X_1 and X_2, by taking the first and second partial derivatives of

the polynomial. Transforming the optimal $\underline{X}^*$ back into the length and blankholder force values, the optimum values of l^* and BHF^* can be finally obtained. In Figure 3, the dependence of l^* and BHF^* on the model coefficients c_f, p_b and p_s is shown. The selling price p_s of the scrap material is given as a percentage of p_b. This shows that the optimal length l^* is not very sensitive to a change in the price and cost coefficients, especially when the cost of producing a defective part increases (e.g. c_f>3 €/unit). On the contrary, the optimal force BHF^* increases significantly as the material cost p_b increases and as the scrap price p_s and c_f decrease.

4 CONCLUSIONS

A method has been presented for Reliability Based Design Optimization of the deep drawing or stamping process, based on an economic objective function. The method, named Reliability Based Economic Optimization (RBEO), is suited for early design optimization of the process, where the epistemic uncertainty plays an important role. The method is based on the knowledge of 3 cost coefficients, which are dependent on the specific conditions of each production: p_b, the sheet buying price [€/Kg]; p_s, the re-selling prices of scrap materials [€/Kg]; c_f [€/part], the cost of a defective part, a constant value which quantifies several costs "wasted" as a consequence of the production of an unprofitable part. The method has been applied to a benchmark case study. The proposed method becomes more useful, with respect to a conventional RBDO approach, especially when the buying price p_b of the sheet metals and/or the dimensions of the stamped parts and/or the dimensions of the process feasibility window increase or the cost c_f of defective parts decreases.

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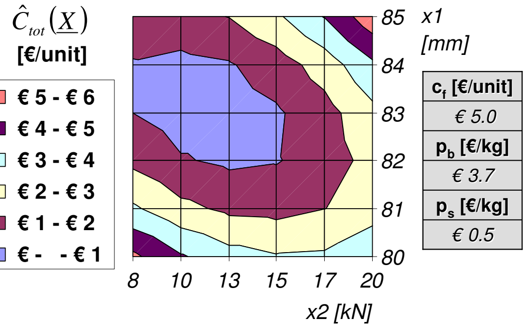

Figure 2: Plot of the meta-modelled total cost vs. the input design variables x_1 *and* x_2

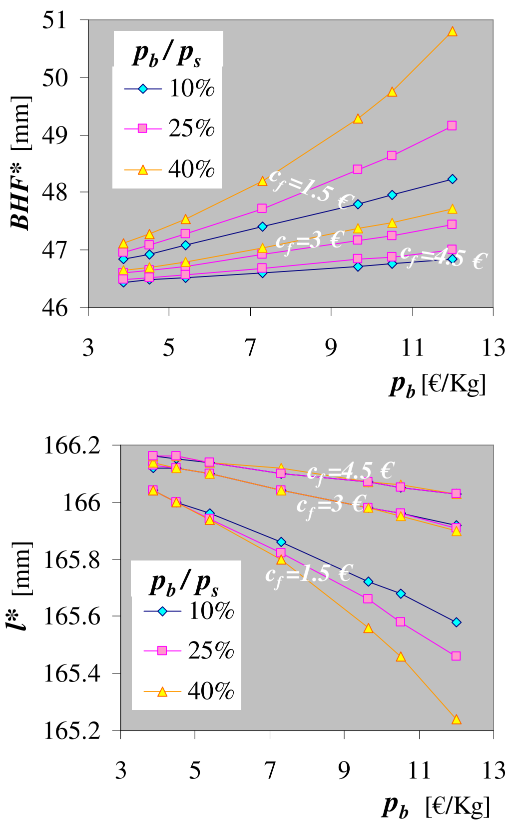

Figure 3: Optimum BHF- *and* l-*values for different combinations of* c_f, p_b *and* p_s