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Concurrent Optimization of Springback and Failure in Stamping Processes

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1. Abstract
One of the biggest challenges in automotive industry focuses on weight reduction in sheet metal forming operations, in order to produce a high quality metal part with minimal cost production. Stamping is the most widely used sheet metal forming process; but its implementation introduces several difficulties such as springback and failure. A global and simple approach to circumvent these unwanted process drawbacks consists in optimizing the process parameters with innovative methods. The aim of this paper is to prevent and predict this two phenomena. For this purpose, the simulation of the stamping of an industrial workpiece is investigated to estimate the springback and the failure. To optimize this two criteria, a global optimization method was chosen, namely the Simulated Annealing algorithm, hybridized with the Simultaneous Perturbation Stochastic Approximation in order to gain in time and in precision. Indeed, the general optimization of the stamping process is by nature multi-objective and springback and failure are among most used criteria, and they are known to be conflicting.To solve this kind of problems, Normal Boundary Intersection and Normalized Normal Constraint Method are two methods for generating a set of Pareto-optimal solutions with the characteristic of uniform distribution of front points. We have performed many benchmark problems, and compared the results with those of the NSGA-II Non-dominated Sorting Genetic Algorithm. Then, the comparison was led for the two criteria stamping problem. The results show that the proposed approaches are efficient and accurate in most cases.
2. Keywords: Sheet metal forming. Springback. Failure. Multi-objective optimization. Pareto-optimal solutions.

3. Introduction
Considering the actual economic requirements, the advantage of stamping, compared to other processes, is its capability to involve complex, precise and useful workpiece at high production rates. However, its implementation is difficult. This operation is carried out in manufactories with the classical experimental method of trial and error which is a slow and expensive method, and numerical simulation of the stamping process with finite element method is an alternative to predict many problems related to metal forming process. In the present work, the industrial aim is the prediction and the prevention of the springback and failure. These two phenomena are the most common defects in stamping process. They present much difficulties in optimization since they are two conflicting objectives. The forming test studied in this paper concerns the stamping of an industrial workpiece stamped with a cross punch. To solve this optimization problem, the approach chosen was based on the hybridization of an heuristic and a direct descent method. This hybridization is designed to take advantage from both disciplines, stochastic and deterministic, in order to improve the robustness and the efficiency of the hybrid algorithm. For the multi-objective problem, we adopt methods based on the identification of Pareto front. To have a compromise between the convergence towards the front and the manner in which the solutions are distributed, we choose two appropriate methods. These methods have the capability to capture the Pareto front and have the advantage of generating a set of Pareto-optimal solutions uniformly distributed. The latter property can be of important and practical use in optimization of, generally, several industrial problems and, precisely, problems in sheet metal forming. By reformulating the multi-objective problem into single-objective subproblems and with few points, these two methods can compute a rather uniform distribution of Pareto-optimal solutions, which can help designer and decision maker to easily choose a Pareto solution in the design space. It is important to notice the need for solving the single-objective subproblems with global optimization approaches whereby we can obtain a global Pareto front, whereas the resulting optima using a gradient-based local optimization algorithm are only local Pareto-optimal solutions. To assess the efficiency of these multi-objective approaches, classical numerical benchmarks

were used to compare the obtained results with those obtained with a well-established technique in multi-objective optimization called Non-dominated Sorting Genetic Algorithm II (NSGAII). This paper is structured as follows: Section 4 presents the test case used to calculate our two criteria. Section 5, develops the principle of the global optimization approach, which is based on the hybridization of a methaheuristic algorithm which is The Simulated Annealing (SA) [1] and a descent method which is the Simultaneous Perturbation Stochastic Approximation (SPSA) [2] and discusses the advantage of the used two multi-objective optimization methods, which are the Normal Boundary Intersection (NBI) [3] and The Normalized Normal Constraint Method (NNCM) [4], to generate a set of well-distributed Pareto-optimal solutions. Then a conclusion and perspective views are provided in Section 6.

4. Finite Element Analysis of an industrial workpiece

The sheet metal forming requires the understanding of a wide range of technical knowledge, manufacturing application standards, interaction of processing and material properties . . . [5][6][7][8]. The stamping process is commonly used to manufacture sheet metal products. During this process, initially curved or flat blank material is clamped between the die and the blank holder. When the punch is pushed into the die cavity, the blank is plastically deformed and the specific shape of the punch and the die is transferred to it. The quality of the final product depends on the proper tools design, choice of the blank material, the blank-holder force, the lubrication and some other process parameters in sheet metal forming. The finite element simulation of sheet metal forming is a powerful tool, which allows cheap and quick testing trials of the stamping process parameters. In recent years, finite element analysis (FEA) has maturated enough to be an effective tool for simulating the stamping process and predicting the springback and failure. The latter are complex physical phenomena which are very sensitive to numerous factors (process parameters, material properties, contact parameters, sheet and tooling geometry, yield function, hardening law, integration scheme . . .). These criteria are not easily accessible in FE formulations. Various assumptions in material behavior, simplified elastic plastic anisotropy and work hardening, can be other reasons for significant deviation of the numerically predicted springback and failure from that observed in real practice. It is extremely difficult to develop analytical models for these phenomena including all of these factors. Also, the difficulty with the analytical approach is the lack of explicit form of the stress distribution throughout the sheet, which limits the analytical method to simple geometry and simple deformation cases.

4.1. Finite element model with LS-DYNA

Numerical simulation of metal forming processes is currently one of the technological innovations which aim to reduce the high tooling costs and facilitates the analysis and the resolution of problems related to the process. In this study, the commercial FEA code, LS-DYNA, was used to simulate the stamping of an industrial workpiece. LS-DYNA is an explicit and implicit Finite Element program dedicated to the simulation and analysis of highly non-linear physical phenomena. Our aim is to study the influence of process parameters on the stamping process of a blank with a cross punch (Figure 1). The blank is made of high-strength low-alloy steel (HSLA260) and is modeled using Belytschko-Tsay shell elements, with full integration points.

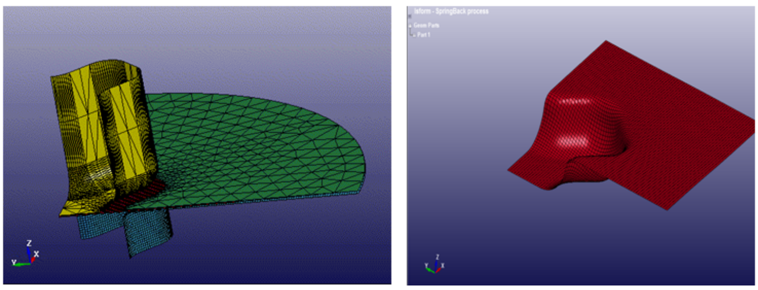

Figure 1: Initial and final steps of the stamping process (LS-DYNA)

Due to symmetry, only the quarter of the blank, the die, the punch and the blank holder were modeled and symmetric boundary conditions were applied along the boundary planes. Mechanical properties of materials and process characteristics are shown in Table 1.

Table 1: Rheological and process parameters for the case-study

Material	HSLA260
Young's modulus	$196GPa$
Poisson's ratio	0.307
Density	$7750Kg/m^3$
Hardening coefficient	0.957
Punch speed	$5m/s$
Punch stroke	$30mm$
Blanck holder effort	$79250N$
Friction coefficient	0.125

4.2. Calculation of the springback cost

In sheet metal forming, first the deformation is elastic and reversible; then, this property is no longer possible, so the deformation is plastic. During this operation, the sheet metal is normally deformed to conform to the shape of the tools, except that upon unloading, the sheet looks for finding its original geometry due to the elastic component of deformation work previously stored as potential energy in the sheet. This phenomenon is called "Springback ". Simulation of springback involves two steps: loading (stamping) and unloading. Thus, after the sheet metal stamping simulation of the investigated workpiece, LS-DYNA generates an output file that contains all informations about stresses and strains upon unloading. Based on this informations, LS-DYNA can simulate the springback by an implicit integration scheme. Figure 2 shows a small deflection in the corner of the part that represent the springback phenomenon.

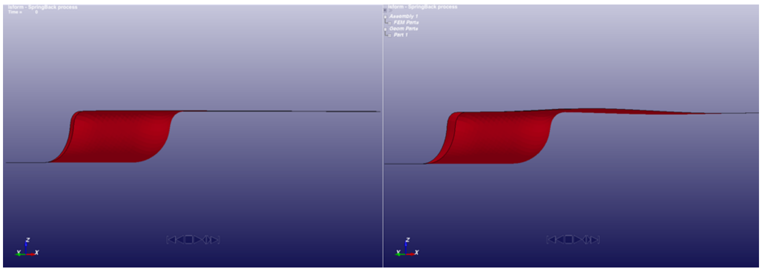

Figure 2: Simulation of the springback (LS-DYNA)

To estimate the springback, we first average the residual strains for each element, then we extract the maximum value of this component for all elements. Thus, the first objective function, namely the springback criterion, can be formulated as in Eq.(1).

$$f_1(\Phi) = \max_{1 \leq i \leq m} (\varepsilon_{avg})_i \quad (1)$$

where Φ is the vector of design parameters, m the total number of elements, i the element number and ε_{avg} is the average residual strain where $\varepsilon_{avg} = \frac{1}{n}\sum_{j=1}^{n}(\varepsilon_{\text{residu}})_j$, n the total number of integration points, j the integration point number.

4.3. Calculation of the failure cost

The failure in sheet metal forming poses for metallurgists a big challenge that limits the formability of the steel sheet. It is a local defect that appears, in general, in a localized region of the stamped. To better characterize the failure, it is first necessary to fully understand the formability of the sheet. In this sense, the concept of forming limit curve (FLC) was introduced [6][9]. It is determined by experimental tests which allow to determine the boundary space in the principal strain space that separate homogeneous and localized strains (Figure 3).For more reliability, we have considered a safety margin estimated to 10%, which allows us to consider the curve 10% below the FLC. So, this curve describes the transition from the safe material behavior to material failure (cracking may initiate if there exist strain values beyond this curve). Our study aims at determining if the material can sustain the strains underneath the forming limit curve without failure. First, from the strain tensor of each element, we calculated the principal strains in the blank midsurface. By placing these values of principal strains on the FLC diagram, we see that indeed, the elements whose principal strains are placed above the forming limit curve failed, we have corroborated this failure with the simulation by LS-DYNA in Figure 4.

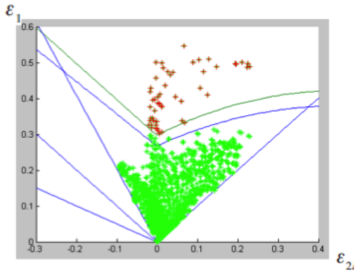

Figure 3: Forming limit diagram for HSLA260 steel sheet

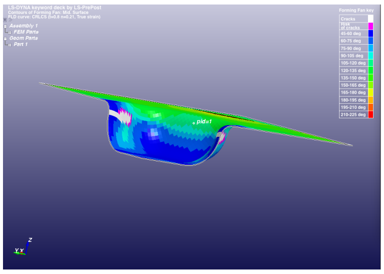

Figure 4: Simulation of the failure (LS-DYNA)

It is very important to mention the principal values must be calculated in the **local** system and not with the tensor which is defined in the **global** cartesian system. We formulated the second objective function as Eq.(2).

$$f_2(\Phi) = \max_{1 \leq i \leq m} ((\varepsilon_1)_i - 0.9(\varepsilon_f)_i) \quad (2)$$

The cost f_2 measures the distance between the strain of the most critical element $(\varepsilon_1)_i$ and the corresponding strain value in the limit curve $(\varepsilon_f)_i$ taking into account the prescribed safety margin.

5. Optimization process

The optimization problem of the two criteria, springback and failure, is a multi-objective optimization problem. Indeed, these objective functions are expensive, in most cases antagonistic, sensitive to several variables and can present several optima. To solve these problems, we had recourse to new approaches in global optimization as methods based on hybridization and methods for identifying Pareto front, in order to take advantage from the robustness of global optimization methods to have a Pareto front easily exploited by engineers with Pareto points uniformly distributed.

5.1. Single-objective optimization

Currently, approaches from the hybrid meta-heuristics present promising prospects in optimization, in order to have a high rate of quality and also precision. We propose in the present work a hybrid method that has shown good results. The main optimization algorithm is the simulated annealing (SA) method [1], which is hybridized with simultaneous perturbation stochastic approximation (SPSA) method [2][10][11].

5.1.1. The SA method

The algorithm was established by Kirkpatrick [1] and Cerny [12]. It simulates the evolution of the system towards the optimal configuration, roughly speaking, by mimicking the evolution of a thermodynamical system towards equilibrium. The algorithm of Metropolis [13] aims to start from an initial configuration and submit the system to a disturbance for each range of the control (temperature) parameter T. If this disturbance generates a solution optimizing the objective function f, we accept it ; if it has the opposite

effect, we draw a random number between 0 and 1, if this number is less than or equal to $e^{\frac{-\Delta f}{T}}$, we accept the configuration. Thus, at high T, the majority of moves in the space of configurations are accepted. By reducing progressively T, the algorithm allows less solutions optimizing the objective function; therefore, to very low T, $e^{\frac{-\Delta f}{T}}$ is close to 0 and the algorithm rejects the moves which increase the cost function.
SA has many advantages that distinguish it from other optimization algorithms. First, it is a global optimization method, easy to program and applicable in several areas. On the other hand, it has some inconvenient such as the empirical regulation of parameters, the excessive calculation time and at low T, the acceptance's rate of the algorithm becomes too weak, so that the method becomes ineffective, hence the idea of coupling the algorithm with a descent method in order to reduce the number of objective function evaluations.

5.1.1. The SA hybridized with the SPSA method
One of the methods which follow this approach and which answers this requirement is the method named *simultaneous perturbation stochastic approximation* (SPSA) [2]. It is a method based on gradient approximation from a stochastic perturbation of the objective function that requires only two evaluations of the objective function regardless of optimization problem dimension, which accounts for its power and relative ease of implementation. For the problem of minimizing a loss function $f(x)$ where x is a m-dimensional vector, the SPSA has the same general recursive stochastic approximation form as in Eq.(3).

$$\hat{x}_{k+1} = \hat{x}_k - a_k \hat{g}_k(\hat{x}_k) \tag{3}$$

where $\hat{g}_k(\hat{x}_k)$ is the estimate of the gradient $g(x) = \frac{\partial f}{\partial x}$ at the iterate $\hat{x}_k$. This stochastic gradient approximation is calculated by a finite difference approximation and a simultaneous perturbation, so that for all $\hat{x}_k$ randomly perturbed together we obtain two evaluations of $f(\hat{x}_k \pm \xi)$. Then, each component of $\hat{g}_k(\hat{x}_k)$ is a ratio of the difference between the two corresponding evaluations divided by a difference interval as in Eq.(4).

$$\hat{g}_{k_i}(\hat{x}_k) = \frac{f(\hat{x}_k + c_k\Delta_k) - f(\hat{x}_k - c_k\Delta_k)}{2c_k\Delta_{k_i}} \tag{4}$$

where c_k is a small positive number that gets smaller as k gets larger and $\Delta_k = (\Delta_{k_1}, \ldots, \Delta_{k_m})^t$ a m dimensional random perturbation vector; a simple and proved choice for each component of Δ_k is to use a Bernoulli ± 1 distribution with probability of $\frac{1}{2}$ for each ± 1 outcome. The convergence requirement is that a_k and c_k both go to 0 at rates neither too fast nor too slow, as well as that the cost function should be sufficiently smooth near the optimum. In this way, convergence is faster when we approach an optimum than the random moves of the simulated annealing. To increase the accuracy of the simulated annealing, we need to implement the SPSA after every moves minimizing the objective function. The Metropolis criterion always gives us the possibility to escape from local optima.

5.2. Multi-objective optimization
Based on the Pareto's concept, a solution is Pareto-optimal or non-dominated if it is impossible to improve a (cost) component without degrading at least another one. Taken in the space of objective functions, the set of all non-dominated solutions is called the Pareto front or the efficiency set. It is commonly admitted among design engineers that any finally implemented design has to be non-dominated, that is, the knowledge of the Pareto Front is a necessary phase. In our case, we implemented two well known methods : Normal Boundary Intersection (NBI) method [3] and Normalized Normal Constrained Method (NNCM) [4].

5.2.1. Normal Boundary Intersection method
Let x_1^* and x_2^* be two individual global minimizers of the two objective functions, respectively, $f_1(x)$ and $f_2(x)$, the components of the vector $F = [f_1(x) \;\; f_2(x)]^t$. To compute them, we use the hybrid method previously described. The utopia point, F^*, is the vector containing the individual global minima, $f_i^* = f_i(x_i^*)$, of the objectives, i.e. $F^* = [f_1^* \;\; f_2^*]^t$.
Let $F_i^* = [f_1(x_i^*) \;\; f_2(x_i^*)]^t$. The Convex Hull of Individual Minima (CHIM) can be expressed as a set of points $\phi\beta_j$ such as in Eq.(5).

$$CHIM = \{\phi\beta_j : \beta_j = [\beta_{1j}\beta_{2j}]^t \in \mathbb{R}^2; \sum_{i=1,2} \beta_{ij} = 1, \beta_{ij} \geq 0, \forall j = 1, \ldots, N_j\} \tag{5}$$

where $\phi = [F_i^* - F^*]$, called "Pay-off matrix", is a $m \times m$ matrix, $\beta = \{(b_1, b_2, \cdots, b_m)^T | \sum_{i=1}^m b_i = 1\}$ and N_j is the total number of points $\phi\beta_j$.

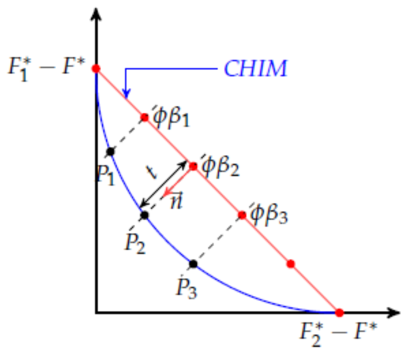

Figure 5: Normal Boundry Intersection method

The main idea of NBI is to find a uniform spread of the set of efficient points forming intersection between feasible space's boundary and the normal $\vec{n}$ to the CHIM in each point $\phi\beta_j$ and pointing toward the origin. This principle was algebraically formulated by Das and Denis [3] as follows: It consists to solve the single objective problem in Eq.(6) on each point $\phi\beta_j$.

$$\begin{cases} \max t \\ \phi\beta_j + tn = F(x) - F^* \\ x \in \boldsymbol{C} \end{cases} \tag{6}$$

where t represents the set of points belonging to the normal. So the NBI method takes a point on the CHIM and searches for the maximum distance along the normal pointing toward the origin by solving each NBI sub-problem always with our hybrid method.

5.2.2. The Normalized Normal Constrained Method

NNCM is also a method for generating Pareto front and it has the same aim as NBI. First, we find the individual global minima of both objectives independently, called "anchor points", with our hybrid method. The line joining the two anchor points is called "Utopia line". To avoid scaling dependences, the optimization takes place in the normalized design objective space which can be obtained by the normalized form of f as in Eq.(7).

$$\bar{f}(x) = \left(\frac{f_1(x) - f_1(x_1^*)}{l_1} \quad \frac{f_2(x) - f_2(x_2^*)}{l_2}\right)^t \tag{7}$$

where $l_1 = f_1(x_2^*) - f_1(x_1^*)$ and $l_2 = f_2(x_1^*) - f_2(x_2^*)$. After, we define the vector directed from $\bar{f}(x_1^*)$ to $\bar{f}(x_2^*)$, called "utopia line vector" as $\bar{N} = \bar{f}(x_2^*) - \bar{f}(x_1^*)$. For each point generated on the utopia line, $x_p = \alpha_1 \bar{f}(x_1^*) + \alpha_2 \bar{f}(x_2^*)$, where $\alpha_1 + \alpha_2 = 1$, $0 \leq \alpha_1 \leq 1$ and $0 \leq \alpha_2 \leq 1$, we solve the NNCM sub-problem formulated as in Eq.(8).

$$\begin{cases} \min f_2(x) \\ \bar{N}^t(\bar{f}(x) - x_p) \leq 0 \\ x \in \boldsymbol{C} \end{cases} \tag{8}$$

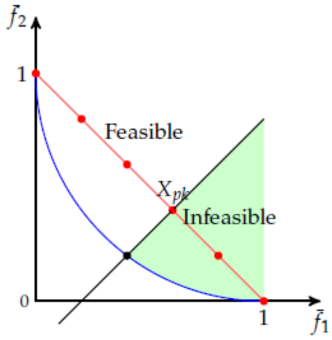

Figure 6: Normalized Normal Constrained Method

Finally, the design solution corresponding to each Pareto solution can be evaluated by the inverse transformation by the relation in Eq.(9).

$$f(x_k) = (l_1\bar{f}_1(x_k) + f_1(x_1^*) \quad l_2\bar{f}_2(x_k) + f_2(x_2^*))^t \tag{9}$$

The proposed approaches were compared with the NSGAII algorithm [14], universally considered as representative of the state of the art and a reference algorithm in multi-objective optimization in various studies. The obtained results prove that the proposed approaches have also good performances compared with those obtained with NSGAII.

5.3. Concurrent springback and failure reduction

The general optimization problem of the sheet metal forming process rises several difficulties. A classical one in structural design, is that criteria (springback and failure) are not explicit functions with respect to the design parameters. Additionally, the computation of the elasto-plastic response underlying the two criteria is very expensive. As a result, each optimization step mobilizes important computational resources. A classical solution is to use surrogates. In our case, we used a cubic spline interpolation to approximate both springback and failure. This approximation was assessed by leading a comparison with meta-models obtained by Kriging and RBF methods. An a posteriori validation of the surrogate results is performed by comparing them to the exact evaluation done by the LS-DYNA code. This study was led in a first time with the blank thickness e and the punch speed Vp as optimization variables. The SA hybridized with SPSA was applied to minimize the springback and failure criteria. According to the obtained results, the two multi-objective optimization approaches, NBI and NNCM, are used to find the set of Pareto optimal solutions in the criterion space i.e. springback criteria versus failure criteria. The NBI and the NNCM approaches were coupled with the SA hybridized with SPSA to obtain global solutions in each sub-optimization step of the two methods. Figure 7 shows the Pareto frontier obtained with this two approaches, as well as a comparison with the NSGAII results.

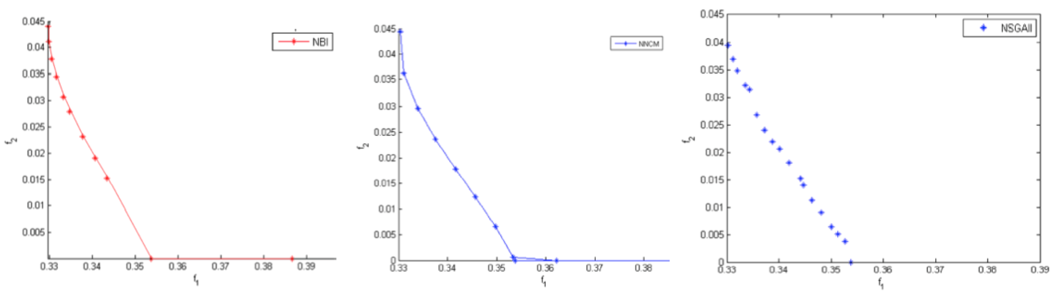

Figure 7: Springback/Failure Pareto Front, from left to right : NBI - NNCM - NSGA II.

In a second step, we have followed the same procedure to test the sensitivity of the springback and the failure for two additional parameters that are the blank holder force (BHF) and the friction coefficient. It is well known that the impact of this two parameters on springback and failure is not negligible. The Pareto front obtained with our approach is compared with the one obtained with NSGAII in Figure 8.

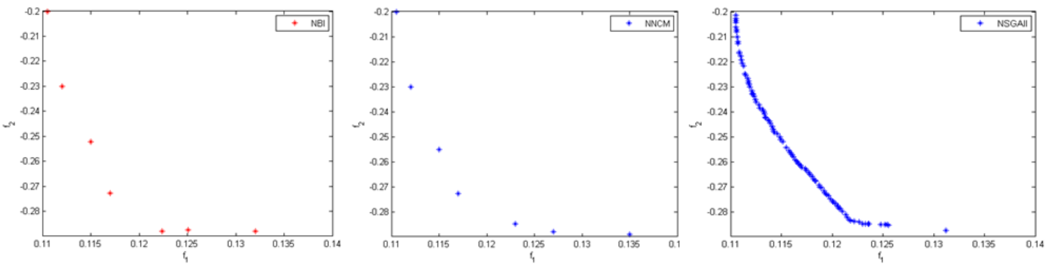

Figure 8: Pareto front of Springback and Failure for four parameters

The Pareto fronts confirm that the springback and the failure criteria are strongly concurrent for both two and four parameters cases.

By comparing the Pareto fronts in figures 7 and 8, we remark that by considering four optimization parameters, we identified a better Pareto Front for both springback and failure criteria than when considering only thickness and punch speed.

Although the approximation of our criteria in the second case was not obvious (using four dimensional cubic splines), it was possible to capture Pareto solutions by NBI and NNCM methods with fewer points than NSGAII which required a large number of populations and several generations to obtain the Pareto front.

6. Conclusion

We implemented two well known methods, Normal Boundary Intersection -NBI- and Normal Normalized Constraint -NNCM-, dedicated to efficient identification of the Pareto Fronts associated to multiobjective optimization problems. Our original contribution was to couple NBI and NNCM to a global hybrid optimizer, the SASP method. The SASP algorithm uses Simulated Annealing to lead the global optimization, and uses the Simultaneous Perturbation Stochastic Approximation -SPSA- which is a "stochastic gradient", to perform local optimization. The method was successfully applied to the process parameter optimization of a stamping case study. The criteria under consideration were the springback and the failure of the workpiece. These criteria are known to be conflicting. As the simulation of the elasto-plastic response in stamping is too computationally expensive, we used cubic spline surrogates of the involved costs. We then performed the Pareto front identification (of the surrogate costs) for the case of two and four process parameters. The obtained Pareto fronts were similar to the ones yielded by the NSGA-II method, while they needed much less cost evaluations. They not only proved the concurrent character of the considered costs, but also illustrated the ability of the approach NBI/NNCM with SASP and with cubic 4-dimension surrogates to handle the capture of Pareto fronts associated to the multiobjective optimization of complex process parameters.

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