The 2013 World Congress on
Advances in Structural Engineering and Mechanics (ASEM13)
Jeju, Korea, September 8-12, 2013

Shape design of a sheet contour against concurrent criteria

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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 initial blank shape with innovative methods.

The aim of this paper is to prevent and predict these two phenomena. For this purposed, the simulation of the stamping of an industrial workpiece is investigated to estimate the springback and the failure. To optimize these two criteria, a global approach was chosen. It's the Simulated Annealing algorithm hybridized with the Simultaneous Perturbation Stochastic Approximation in order to gain in time and in precision. Although, the optimization of stamping problem is multi-objective and accurately springback and failure are two conflicting criteria. 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. Performing test problems with comparison of Non-dominated Sorting Genetic Algorithm II results, the accuracy of presented algorithms is investigated. The results show that the proposed approaches are efficient and accurate in most cases.

Keywords: Sheet metal forming. Initial blank shape. Springback. Failure. Multi-objective optimization.

1. INTRODUCTION

The processing of sheet metal forming is of vital importance to a large range of industries as production of car bodies, cans, appliances, etc. It generates complex and precise parts. Although, it is an involved technology combining elastic-plastic bending and stretch deformation of the workpiece. These deformations can lead to undesirable problems in the desired shape and performance of the stamped. To perform a successful stamping process and avoid shape deviations such as springback and failure defects, process variables should be optimized.

One of the most important issue in stamping process concerns initial blank shape optimization that can reduce if not eliminate design problems of the obtained product (Chen 1992, Tsi 1997, Kim 1998, Lee 1998, Kleinermann 2003).

In general practice, techniques that are used in this optimization process were based on experiments and trial and error method which induce very high costs. Nowadays, growth and advances in computer science technologies are proved and numerical simulation tools became an efficient alternative principally the finite element method (FEM). This method is recently widely used, in research and in industry, for predicting problems and defects in sheet metal forming process.

In this context, several studies had been done to optimize forming parameters such as punch speed, blank holder force, friction coefficient, etc (Kleinermann 2003, Jansson 2005, Liu 2008). Others investigated the optimization of geometrical parameters such as the radii of the punch and the die, the binder surface, etc (Hamdaoui 2013, Azaouzi 2008). More recently, some studies have presented in optimization design procedures for tools in order to reduce the design time but without considering the quality of the desired workpiece (Tsuen 2008).

It will be advantageous to have a numerical tool for initial blank shape optimization that can reduce springback and risk of failure. The goal of this article is to optimize the initial blank shape used in the stamping of an industrial workpiece stamped with a cross punch presented in section 4. The stamping process is performed using the commercial FEA code LS-DYNA (LS-DYNA 2007). The aim is the prediction and the prevention of, especially, springback and failure. These two phenomena are the most common problems in the stamping process that present much difficulties in optimization since they are two conflicting objectives. To solve each single objective optimization problem, the approach chosen in section 5.1 was based on the hybridization of an heuristic algorithm, The Simulated Annealing (SA) (Kirkpatrick 1983), and a direct descent method, the Simultaneous Perturbation Stochastic Approximation (SPSA) (Spall 1998). 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 in section 5.2 which are the Normal Boundary Intersection (NBI) (Das 1998) and The Normalized Normal Constraint Method (NNCM) (Messac 2003). These methods have the capability to capture the Pareto front and have the advantage of generating a set of Pareto-optimal solutions uniformly spaced. The last 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 to single-objective sub-problems and only with few points, these two methods can form a uniform distribution of Pareto-optimal solutions, which can help designer and decision maker to easily choose a Pareto solution in the design space.

It's important to notice the utility of solving the single-objective sub-problems 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 check the effectiveness of this multi-objective approaches, numerical examples were used to compare the obtained results with those obtained with a notable technique in multi-objective optimization called Non-dominated Sorting Genetic Algorithm II (NSGAII) (Deb 1999). The results of initial blank shape optimization of the investigated test case, in order to reduce the springback and the risk of failure, were done in the end of this section. Finally, a conclusion and perspective views are provided in Section 6.

2. Finite element modeling

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 FEA code, LS-DYNA, was used to simulate the stamping of an industrial workpiece. LS-DYNA is an explicit and implicit Finite Element program to simulate and analyze highly non-linear physical phenomena.

The aim was to study the influence of the initial blank shape on the stamping process of a part with a cross punch (Fig. 1). The blank was made of high-strength low-alloy steel (HSLA260) and was modeled using Belytschko-Tsay shell elements, with full integration points.

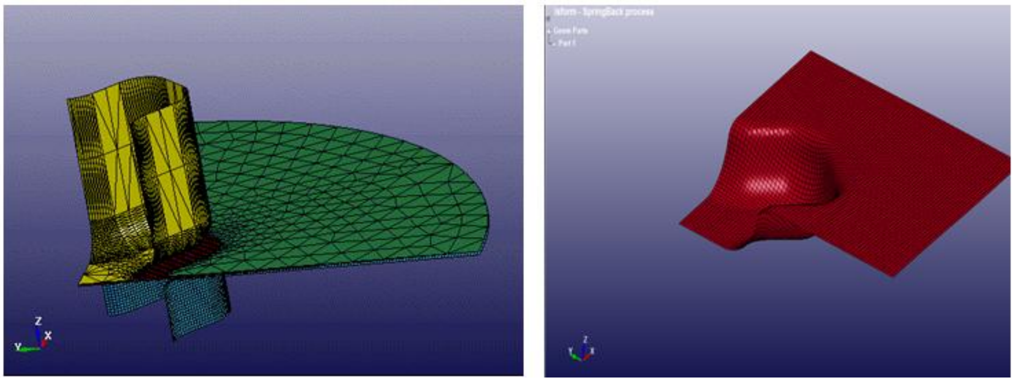

Fig. 1: Simulation of stamping process (LS-DYNA)

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 2: Process parameters used in simulation

Material	HSLA260
Young's modulus	196GPa
Poisson's ratio	0.307
Density	7750Kg=m^{3}
Hardening coe cient	0.957
Punch speed	5m=s
Punch stroke	30mm
Blanck holder e ort	79250N
Friction coe cient	0.125
Number of elements	5775

3. Problem description

A sensitivity analysis done using FEA demonstrated that the overall dimensional quality is highly influenced by the initial dimensions of the blank. The initial blank design is a critical step in stamping design procedure therefore it should be correctly designed.

This study aim to find the optimal initial blank shape that satisfy the design specifications during the forming process which help to eliminate or at least minimize springback and risk of failure problems.

For this study, the geometry of the blank contour is described by parametric spline curves (Fig. 2). Seven control points (P1,...,P7) are used to define the spline curves in order to have a wide variety of geometries. Some investigated shapes are described in Fig. 3.

The maximum displacement of each control point is equal to 15mm in both axes in order to avoid distorted meshes.

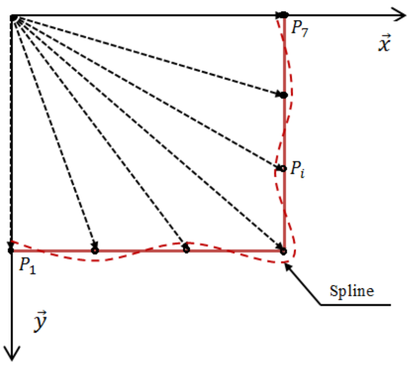

Fig. 2: Blank contour parametrization

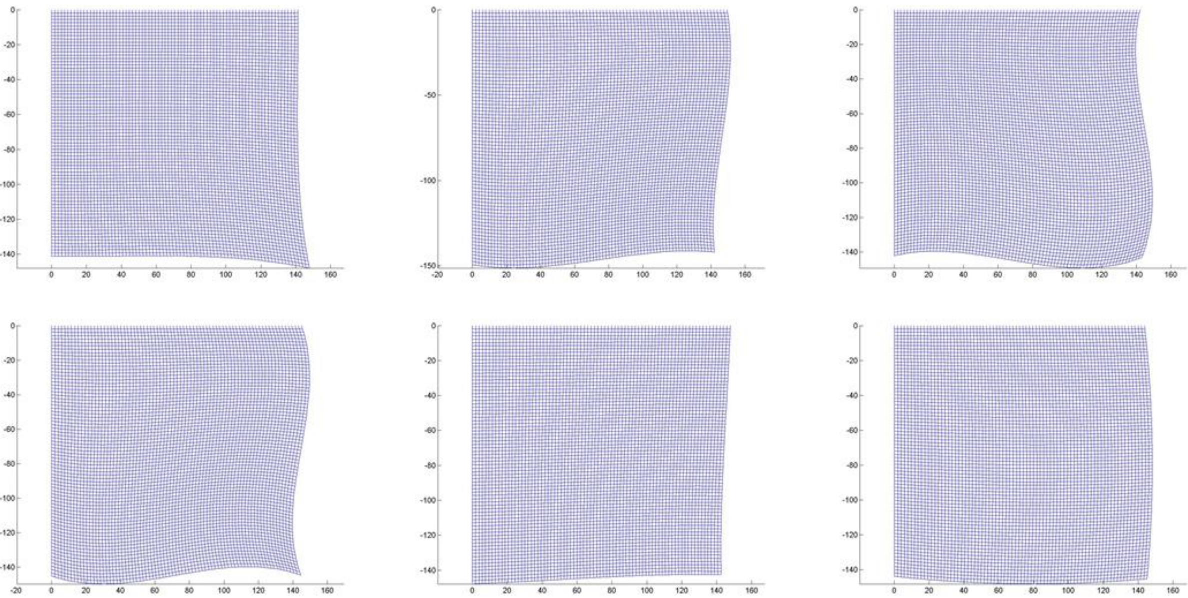

Fig. 3: Exemples of initial blank shapes using Spline curves

Due to storage requirements and computational complexity, the cost of computing in sheet metal forming processes and representing an approximation with good accuracy is very expensive. Therefore, the construction of the metamodel is done using the sparse grid interpolation. Optimization process based on sparse grid interpolation is an optimal alternative in which criteria can be approximated with a suitable interpolation formula that needs significantly less points than the full grid.

It's important to notice the potential of sparse grids method especially for highly dimensional problems. This potential was illustrated in several studies (Achatz 2003b, Blader 1994, Bungartz 2003, Bungartz 1995, Garcke 2002). The basis of all sparse grids is the famous Smolyak's method (Smolyak 1963) which provides a construction of interpolation functions with a minimum number of points in multi-dimensional space and extends adequately the univariate interpolation formulas to the multivariate case. The related interpolation algorithms are performed in a MATLAB Toolbox based on piecewise multilinear and polynomial basis functions. Additional tasks involving the interpolant is used in order to reduce the computational effort for function evaluations.

This Toolbox was developed by Andreas Klimke at the institute of Applied Analysis and Numerical Simulation in Stuttgart during his Phd studies (Klimke 2005, Klimke 2006).

4. Calculation of criteria

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. After the stamping simulation of the investigated workpiece, LS-DYNA generates an output file that contains all informations about stresses and strains upon unloading. Based on these informations, LS-DYNA can simulate the springback by an implicit integration scheme. Fig. 4 shows a small deflection in the corner of the part that represents the springback phenomenon.

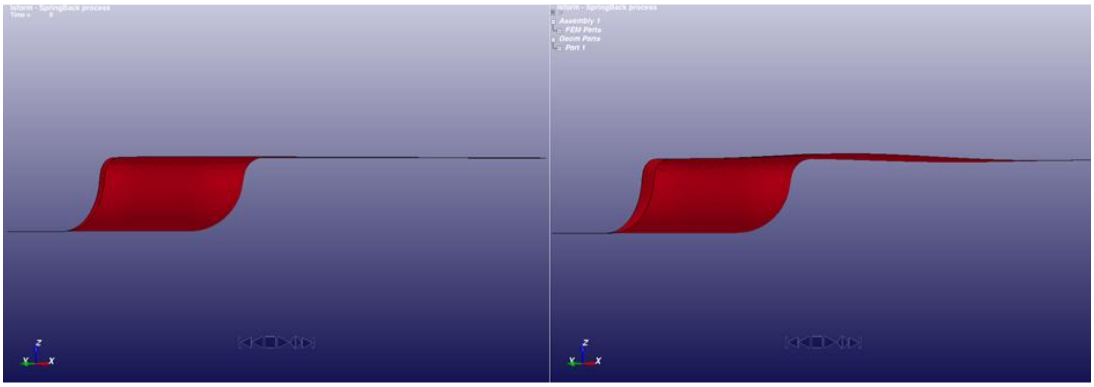

Fig. 4: Simulation of the springback (LS-DYNA)

To assess the springback, first the displacement in the z direction of each node is calculated by LS-DYNA after the springback simulation and then we extract the maximum value of this component for all nodes. Thus, the first objective function, namely the springback criterion, can be formulated as in Eq.(1).

$$f_1(\Phi) = max_{1 \le i \le m} \, (UZ)_i$$

Where Φ is the vector of design parameters, m the total number of nodes, i the node number and $(UZ)_i$ is the displacement in the z direction of the node i.

During sheet metal forming, localized deformations lead to local defect that appears in the stamped as sheet failure. To better characterize this sheet 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 (Marciniak 2002, Marsden 1998). It is determined by experimental tests in order to separate spaces representing homogeneous and localized strains (Fig. 5).

For more reliability, we have considered a security margin estimated to 10%, which allow us to consider the curve below the FLC where cracking can start beyond this curve. So, this curve describes the transition from the safe material behavior to material failure. One of the aims of this study is to determine if the material can sustain the strains underneath the forming limit curve without failure.

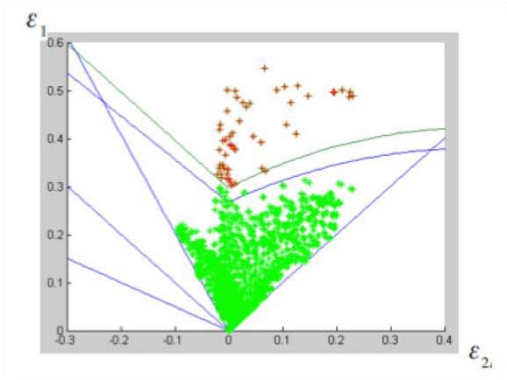

Fig. 5: Forming limit diagram for HSLA260 steel sheet

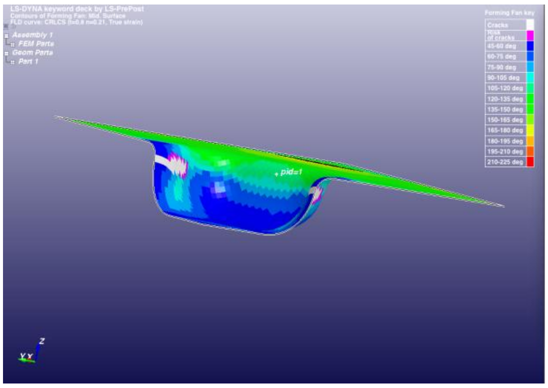

Fig. 6: Simulation of the failure (LS-DYNA)

To quantify the safness of the stamped, We formulated the second objective function, namely the failure criterion, as Eq. (2).

$$f_2(\Phi) = max_{1\leq i\leq m}((\varepsilon_1)_i - 0.9 * \left(\varepsilon_f\right)_i)$$

This is the value of the distance between the strain of the most critical element $(\varepsilon_1)_i$ and the corresponding strain value in the limit curve $\left(\varepsilon_f\right)_i$ taking into account the margin of safety that we have considered.

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.

6. The SA hybridized with the SPSA method

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 this section to present a hybrid method that has shown good results. This is the simulated annealing (SA) method (Kirkpatrick 1983) hybridized with simultaneous perturbation stochastic approximation (SPSA) method (Spall 1998).

The SA algorithm was established by Kirkpatrick (Kirkpatrick 1983) and Cerny (Cerny 1985). It simulates the evolution of the system towards the optimal configuration, and the algorithm of Metropolis (Metropolis 1953) aims to start from an initial configuration and submit the system to a disturbance for each range of the control 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, in 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.

One of the methods which joins this approach and which answers this requirement is the method named *simultaneous perturbation stochastic approximation* (SPSA) (Spall 1998).

It is a method based on gradient approximation from the 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 (x) , where x is a m-dimensional vector. The SPSA has the same general recursive stochastic approximation form as in Eq.(3).

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

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).

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

Where c_k is a small positive number that gets smaller as k gets larger and $\Delta_k = (\Delta_{k_1}, \dots, \Delta_{k_m})^t$ a m dimensional random perturbation vector; a simple and valid 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 condition is that a_k and c_k both go to 0 at rates neither too fast nor too slow, that the cost function is sufficiently smooth near the optimum. In this way, convergence is faster when we approach an optimum than the random moves of the SA algorithm.

To increase the accuracy of the simulated annealing, we need to implement the SPSA after each move minimizing the objective function and the Metropolis criterion always gives us the possibility to escape from local optima.

7. Multi-objective optimization

According to the principle established by Pareto, the solution of a multi-objective function is not unique; it is a set of solutions called "Pareto-optimal". Based on the Pareto's concept, a solution is Pareto-optimal if it is impossible to improve a component without degrading at least another one. The best choice to solve this kind of problem is to generate an optimal Pareto front, very practical and easy to use by engineers, which requires first the capture of the Pareto front and second a good visualization of the front's points. This is the aim of these two methods: Normal Boundary Intersection (NBI) method (Das 1998) and Normalized Normal Constrained Method (NNCM) (Messac 2003).

The proposed approaches were compared with the NSGAII algorithm, 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.

8. Results of optimization of Springback and Failure

It is important to notice that the prediction of our criteria, springback and failure, is very expensive. The FE model request around 45 min to predict these two criteria. However, the obtained metamodel using sparse grid interpolation needs less than 1s to predict springback and failure on the same computation machine. To find the optimal initial blank shape, it was decided to perform the optimization process using the obtained metamodel. The construction of the sparse grid interpolant was based on the Chebyshev Gauss-Lobatto grid type and using the polynomial basis functions (Klimke 2005, Klimke 2006). This technique achieves a good accuracy with a competitive number of grid points.

The SA hybridized with SPSA has been applied to minimize the corresponding 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 are coupled with the SA hybridized with SPSA to obtain global solutions in each step of the two approaches. Fig. 7 shows the Pareto frontier obtained with these two approaches. The same comparison was made with the NSGAII and the Pareto-optimal solutions are shown in the same Figure.

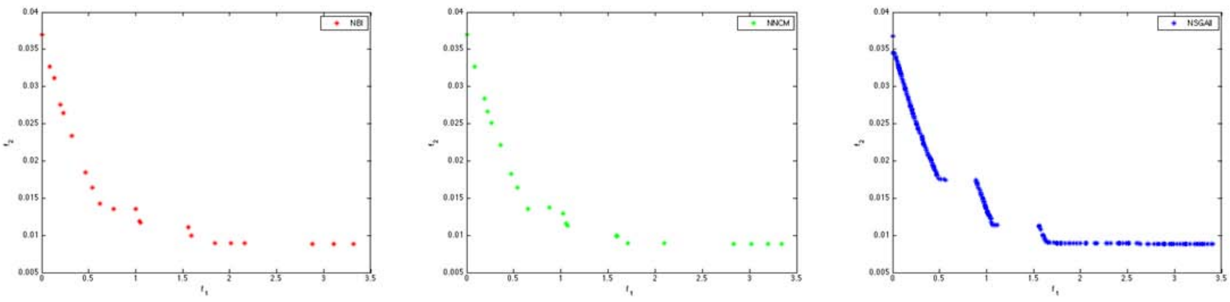

Fig. 7: Simulation of the failure (LS-DYNA)

This Pareto curves confirm that the trade-off between the springback and the failure criterion exists and can help the engineers to best understand it. It's noted also that we can eliminate sprinback and reduce the impact of failure by optimizing the initial blank shape. The comparison of the obtained fronts shows that we can capture Pareto solutions by NBI and NNCM with few points than NSGAII which requires a large number of populations and several generations to obtain the Pareto front.

9. Conclusion and perspectives

In the present paper, an estimation of the springback and the failure of a workpiece is achieved. Considering the complexity of finite element models of sheet metal forming finite element models of large scale, non-linear…, the simulation and the estimation of these two criteria are very expensive.

To optimize these criteria, a Hybrid approach is investigated to optimize each single-objective problem. This approach is based on hybridization of SA algorithm, which belong to meta-heuristic methods, and SPSA method, which is one of deterministic methods. The advantage of this approach was to find the global minimum in few steps.

Unfortunately, the optimization problem in our study, is multi-objective and criteria are antagonistic, whence the benefit of the NBI and the NNCM methods. These two methods have the power of generating a set of Pareto-optimal solutions uniformly spaced. This advantage was tested and validated against many mathematical well-known benchmarks and successfully compared to the results of NSGAII method. Based on an accurate approximation of the two criteria using Sparse grid interpolation method, the obtained Pareto Front of springback and failure criteria considering the initial blank shape were compared with the results of NSGAII. The main advantage of our approach was the possibility to obtain a Pareto front with few function evaluations compared with NSGAII method. In further works, we will try, first, to improve the current algorithms and extend the study to innovative approximation methods based on enrichment of metamodels in order to improve the Pareto front in each enrichment step and second apply these approaches in shape optimization of more complicated workpiece considering other criteria as wrinkling criterion.

Aknowledgement.

The present work was achieved within the framework of the OASIS Consortium, funded by the French FUI grant id. 1004009Z.

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