

Spring back optimization in metal forming using cohort intelligence

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ABSTRACT

Deep drawing process is a sheet metal forming process in which the blank of sheet metal is radially drawn into a forming die by the mechanical punch. It is a shape transformation process. The process is considered "deep" drawing when the depth of the drawn part exceeds its diameter. Springback can be defined as an elastically-driven change of shape of a deformed product which takes place during removal of external loads. It is a very complex physical phenomenon which is mainly governed by the stress state obtained at the end of a deformation. The main reason for Spring Back is that as the material is bent the inner region of the bend is compressed while the outer region is stretched hence Springback occurs. Nature inspired optimization algorithms or bio – inspired algorithms have been performing very well in the field of mechanical optimization problems. Cohort intelligence is a new bio – inspired algorithm which was developed by Anand Kulkarni in 2013. It is based on the self-supervised learning behavior of cohort. Cohort refers to a group of candidates interacting and competing with one another to achieve some individual goal which is inherently common to all the candidates. The learning refers to a cohort candidate's effort to self supervise its behavior and further adapt to the behavior of other candidate which it intends to follow. This makes every candidate to improve/evolve its own and eventually the entire cohort behaviour. In this paper Springback optimization in sheet metal forming is done using Cohort intelligence.

Keywords— Metal Forming, Optimization, Springback, Cohort intelligence.

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I. INTRODUCTION

Metal forming process are classified into bulk forming processes and sheet metal forming processes .In both types of process, the surface of the deforming metal and tools in contact, and friction between them may have a major influences on material flow.Deep drawing is a sheet metal forming process in which a sheet metal blank is radially drawn into a forming die by the mechanical action of a punch. One of the important sheet metal forming process is deep drawing which has been used in a wide range of industrial applications for converting the sheet into the

~~work piece. Deep drawing of metal sheet is used to form~~ containers by a process in which a flat blank is constrained while the central portion of the sheet is pressed into a die opening to draw the metal into the desired shape without folding of the corners. This generally requires the use of presses having a double action for hold down force and punch force. The process is capable of forming circular shapes, such as cooking pans, box shapes, or shell-like containers. The term deep drawing implies that some drawing – in of the flange metal occurs and that the formed parts are deeper than could be obtained by simply

stretching the metal over a die. Clearance between the male punch and the female die is closely controlled to minimize the free spam so that there is no wrinkling of the side wall. This clearance is sufficient to prevent ironing of the metal

being drawn into the sidewalls is to be part of the process; it is done in operations subsequent to deep drawing. Suitable radii in the punch bottom to side edge, as well as the approach to the die opening, are necessary to allow the metal sheet to be formed without tearing. In most deep drawing operations, the part has a solid bottom to form a container and a retained flange that is trimmed later in the processing. In some cases, the cup shape is fully drawn into the female die cavity, and a straight-wall cup shape is ejected through the die opening. To control the flange area and to prevent wrinkling, a hold-down force is applied to the blank to keep it contact with the upper surface of the die. A suitable sub press or a double-action press is required. Presses can be either hydraulic or mechanical devices, but hydraulic presses are preferred because of better control of the rate of punch travel. [1, 2]

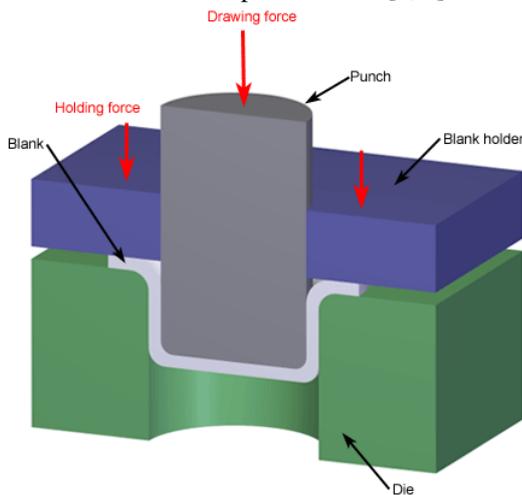


Fig 1 Deep Drawing Process

II. SPRING BACK IN DEEP DRAWING

Springback represents a challenge for manufacturers who desire to meet specific dimensions. The accurate and reliable assembly of components in the automotive or aircraft industry necessitates that the parts meet certain tolerances. Controlling and/or minimizing springback would enable designers to achieve better process control and reduce rejects. Springback is the geometric change made to a part at the end of the forming process when the part has been released from the forces of the forming tool. Upon completion of sheet metal forming, deep-drawn and stretch-drawn parts spring back and thereby affect the dimensional accuracy of a finished part. The final form of a part is changed by springback, which makes it difficult to produce the part. [3, 4, 5, 6]

A. Blank Holder Force:

Blank holder force is important parameter in drawing process and mainly because of wrinkle prevention. When complex parts are drawn the special case can occur – there is no way to produce the product by using constant blank holder force. In this case is necessary to use variable blank holder force. This contribution deals with influence of variable blank holder force on hemispherical product in drawing process. [7]

V. COHORT INTELLIGENCE

B. Coefficient of friction:

Friction is another important factor that influences deep drawing process. Surface quality of finished product, tool life and drawability of sheet are well dependent on presence of good lubricating film between contact surfaces. In metal forming processes friction influences the strain distribution at tool blank interface and drawability of metal sheet. Also drawability of metal sheet affects wear of tool. [8]

C. Die and Punch Radius

The radius on die and punch too has an effect on wrinkling. Hence properly designing of the punch and die is very important in avoiding wrinkling.

III. PROBLEM FORMULATION

The optimization problem was formulated by linear regression analysis and the linear equations obtained were as follows:

$$SDM = 0.0488 - 0.000133 * BHF - 0.0167 * \mu + 0.00150 * R_p$$

Subject to

$$2.5 < R_D < 8$$

$$3 * R_D > R_p > 6 * R_D$$

Where –

$$BHF = \frac{\pi}{4} (d_0^2 + 2r^2) * P, \text{ Where } P = 2.5 \text{ N/mm}^2.$$

And

$$R_D = 0.035 [50 + (d_0 - d_1) \sqrt{S_0}]$$

Where S_0 is the sheet thickness.

$$R_p = (3 \text{ to } 6) R_D$$

The problem is solved using Cohort Intelligence Algorithm and the results were obtained. [9]

IV. COMPONENT DESCRIPTION

The component selected for Springback optimization is Punch Plate. The thickness of the sheet was selected as 0.8 mm. The material used was SPCC.

The springback in the component occurs at various regions is obtained and is optimized by the equation and optimized result is obtained.

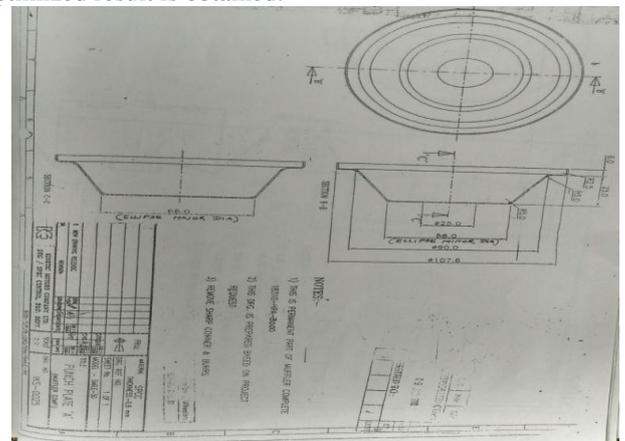


Fig 2 Production Drawing of the Component.

An emerging technique, inspired from the natural and social tendency of individuals to learn from each other referred to

as Cohort Intelligence (CI). Learning here refers to a cohort candidate's effort to self supervise its own behavior and further adapt to the behavior of the other candidate which it intends to follow. This makes every candidate improve/evolve its behavior and eventually the entire cohort behavior. [10]

Considered a cohort with number of candidates C, every individual candidate c (c = 1... C) Belongs a set of characteristics/attributes/qualities $x^c = (x_1^c, x_2^c, \dots, x_N^c)$. Which makes the overall quality of its behavior $f(x^c)$. The individual behavior of each candidate c is generally being observed by itself and every other candidate (c) in the cohort. This naturally urges every candidate c to follow the behavior better than its current behavior. More specifically, candidate c may follow $f^*(x^c)$ if it is better than $f(x^c)$, i.e. $f^*(x^c) < f(x^c)$. Importantly, following a behavior f(x) refers to following associated qualities $x = (x_1 \dots, x_i \dots x_N)$ with certain variations t associated with them. However, following better behavior and associated qualities is highly uncertain. This is because; there is certain probability involved by which it selects certain behavior to follow. In addition, a stage may come where the cohort behavior could become saturated. In other words, at a certain stage, there could be no improvement in the behavior of every individual candidate for a considerable number of learning attempts. Such situation is referred to as saturation stage. This makes every candidate to expand its search around the qualities associated with the current behavior being followed. The mathematical formulation of the CI methodology is explained below in detail with the algorithm flowchart. [11]

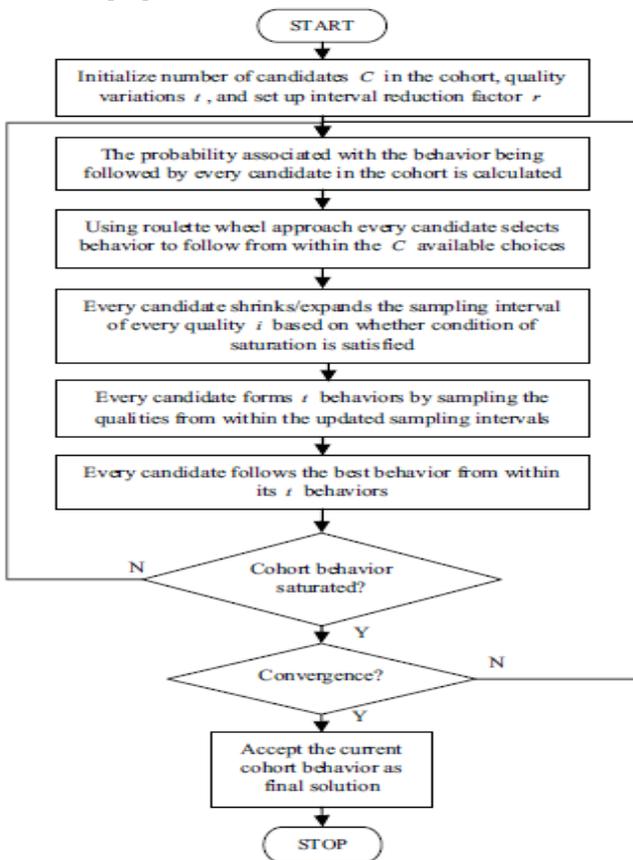


Fig 3. Flowchart of CI.

Step 1: The probability of selecting the behavior $f^*(x_c)$ of every associated candidate c (c =1,...,C) is calculated as follows:

$$P^c = \frac{1}{\sum_{c=1}^C \frac{f^*(x^c)}{f^*(x^c)}} , (c = 1, \dots, C)$$

Step 2 Every candidate c (c =1,...,C) generates a random number $\text{rand} \in [0,1]$ and using a roulette wheel approach decides to follow corresponding behavior $f^*(x^{c[?]})$ and associated qualities $x^{c[?]} = (x_1^{c[?]}, \dots, x_i^{c[?]}, \dots, x_N^{c[?]})$. The superscript indicates that the behavior is selected by candidate c and not known in advance. The roulette wheel approach could be most appropriate as it provides chance to every behavior in the cohort to get selected purely based on its quality. In addition, it also may increase the chances of any candidate to select the better behavior as the associated probability stake p_c (c =1... C) Presented in the interval [0, 1] is directly proportional to the quality of the behavior $f^*(x_c)$. In other words, better the solution, higher is the probability of being followed by the candidates in the cohort.

Step 3: Every candidate c (c =1... C) Shrinks the sampling interval $\Psi_i^{c[?]}$, $I = 1, \dots, N$ associated with every variable $x_i^{c[?]}$, $i = 1, \dots, N$ to its local neighbourhood. This is done as Follows:

$$\Psi_i^{c[?]} \in [x_i^{c[?]} - (\|\Psi_i\|/2), x_i^{c[?]} + (\|\Psi_i\|/2)]$$

Where $\Psi_i = (\|\Psi_i\|) \times r$.

Step 4 Each candidate c (c =1... C) samples t qualities from within the updated sampling interval $\Psi_i^{c[?]}$, $i = 1, \dots, N$ associated with every quality $x_i^{c[?]}$, $i = 1, \dots, N$ and computes a set of associated t behaviors, i.e.

$F_c = \{f(x^c), \dots, f(x^c), \dots, f(x^c)\}$ and selects the best behavior $f^*(x^c)$ from within. This makes the cohort available with C updated behaviors represented as $F^C = \{f^*(x^1), \dots, f^*(x^c), \dots, f^*(x^C)\}$.

Step 5 The cohort behavior could be considered saturated, if there is no significant improvement in the behavior $f^*(x_c)$ of every candidate c (c =1,...,C) in the cohort, and the difference between the individual behaviors is not very significant for successive considerable number of learning attempts, i.e. if

$$1 - \|\max(F^c)^n - \max(F^c)^{n-1}\| \leq \epsilon$$

Step 6 If either of the two criteria listed below is valid, accept any of the C behaviors from current set of behaviors in the cohort as the final objective function value $f^*(x)$ as the final solution and stop, else continue to Step 1.

- (a) If maximum number of attempts exceeded.
- (b) If cohort saturates to the same behavior (satisfying the conditions in Step (5) for max τ times.

VI. OPTIMIZATION RESULTS

The formulated optimization problem is solved by Cohort Intelligence and the results were obtained as follows

Springback	0.06698697 mm
Radius on Die	2.863417 mm
Blank Holder Force	17.5058 KN
Radius on Punch	11.82510 mm
Coefficient of Friction	0.1449

The results of the formability analysis on the original component is performed and the springback results are plotted.

FTI_Forming_Suite_2014_SP1_build_1956_SSQ software is used for formability analysis and analysis results of original component are displayed below.

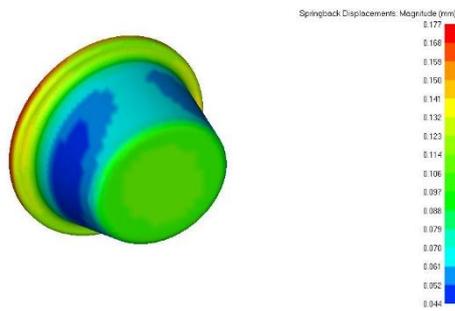


Fig 4. Springback Displacements

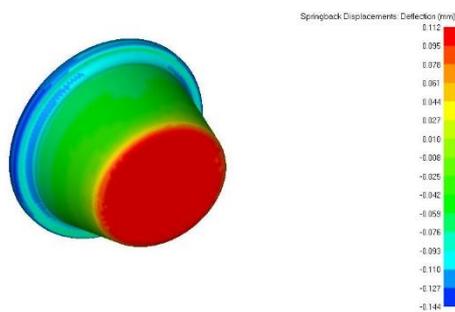


Fig 5. Springback displacement deflection

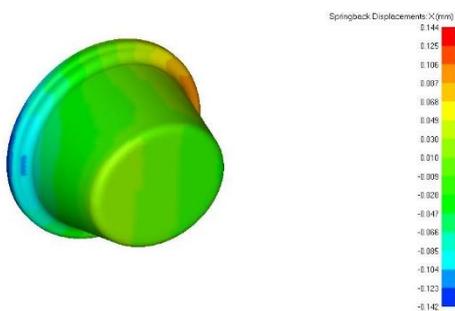


Fig 6. Springback displacement x (mm)

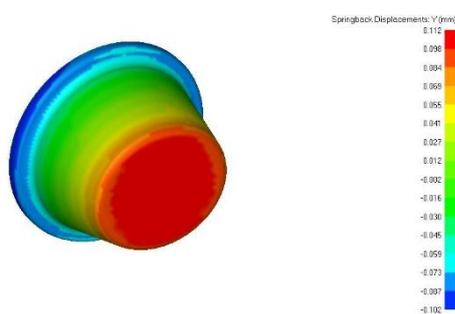


Fig 7. Springback displacement y (mm)

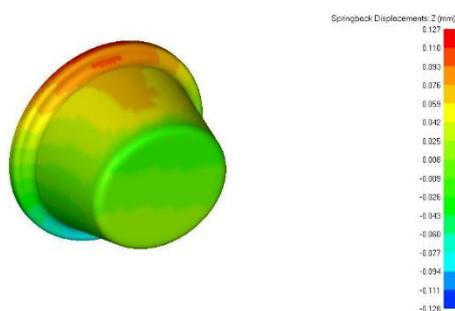


Fig 8. Springback displacement z (mm)

Future work is in progress and the result are in validation.

VII.CONCLUSIONS

Springback in Deep Drawing is an important criteria which needs to be optimized in order to maintain the functional requirements of the component. The Springback is dependent on various parameters related to deep drawing like Blank Holder Force (BHF), coefficient of friction (μ), Die radius (R_d) and punch radius (R_p). These four parameters need to be optimized in order to minimize Springback in component after the process and enhance the quality of the finished part. Cohort Intelligence is used to reduce the springback, which is a very efficient and fast algorithm inspired by a group of cohort and their self-supervising ability. The formability analysis of the original component

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