MULTI OBJECTIVE OPTIMIZATION OF DEEP DRAWING OF AA 6061 SHEET MATERIAL

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ABSTRACT

The performance of a manufactured product is often characterized by a group of responses. These responses in general are correlated and measured via a different measurement scale. This problem is regarded as a multi-response optimization problem, subject to different response requirements. The dimensionality reduction strategy is one of the numerical techniques for the optimization of multiple responses. It aggregates multiple responses into a single dimensionless measure called desirability function. In this study, the results of the three research articles, each considering three different single responses, namely springback, thickness variation and punch force, published by the same author have been taken for multi-objective optimization using desirability function approach for the three responses namely springback, Signal to noise ratio representing the thickness variation and punch force. The results were then compared.

KEYWORDS: Deep Drawing, AA 6061 Sheet Material & Multi Objective Optimization

1. INTRODUCTION

Most industrial processes and products have more than one quality characteristic. To select the best design, it is necessary to take into account all characteristics of quality simultaneously which is known as multi-objective optimization. In solving a multi-objective optimization problem, the optimum design parameters' settings are searched for a product or a process in such a manner that the product characteristic or response attains its desired target with minimum variation. A wide range of multi-objective optimization techniques, also sometimes called multi-criteria decision making (MCDM) techniques, can be found in the literature [1]. Sheet metal forming by deep drawing is a common manufacturing process used in many industries, especially the automotive industry. Despite the broad application, the design of the drawing tools, selection of sheet materials, lubricants, etc., is still based on trial and error which is very expensive [2]. It is, therefore, essential to determine the optimum value of the parameters influencing the quality of the drawn parts considering various desirable quality characteristics.

In this study, the results of the research articles [3-4], each considering three different single responses, namely springback, thickness variation and punch force, published by the same author were taken for multi-objective optimization. The articles [3-4] suggest that the deep drawing parameters namely, the punch nose radius (PR), die shoulder radius (DR) and blank holder force (BHF) are important parameters in the deep drawing of AA 6061 sheet material. The selection and influences of the parameters have been discussed sufficiently in the articles. The parameters selected were varied with three levels. Table 1 exhibits the different levels of the chosen parameters. Therefore, the scope of this study is limited to only the multi objective optimization using desirability approach and comparing the results with that of the single objective optimization.

Table 1: Parameters and their Levels

Parameter	Symbol	Levels		
		-1	0	1
Punch nose radius, mm	PR	3	5.5	8
Die shoulder radius, mm	DR	3	5.5	8
Blank holder force, kN	BHF	4	7	10

Central Composite Face Centered Design, a method of response surface methodology, which is the most popular class of second-order design, was used to generate the experimental design. Table 2 shows the design matrix in coded and actual values.

Table 2: Design Matrix in Actual and Coded Values

Exp. Run	Coded value			Actual value		
	PR	DR	BHF	PR	DR	BHF
1	-1	1	1	3	8	10
2	0	0	0	5.5	5.5	7
3	0	-1	0	5.5	3	7
4	0	1	0	5.5	8	7
5	0	0	1	5.5	5.5	10
6	0	0	0	5.5	5.5	7
7	0	0	0	5.5	5.5	7
8	1	1	1	8	8	10
9	1	1	-1	8	8	4
10	1	-1	-1	8	3	4
11	1	-1	1	8	3	10
12	0	0	0	5.5	5.5	7
13	-1	-1	1	3	3	10
14	-1	0	0	3	5.5	7
15	-1	1	-1	3	8	4
16	0	0	0	5.5	5.5	7
17	0	0	-1	5.5	5.5	4
18	-1	-1	-1	3	3	4
19	1	0	0	8	5.5	7
20	0	0	0	5.5	5.5	7

2. MULTI OBJECTIVE OPTIMIZATION

The performance of a manufactured product often characterize by a group of responses. These responses in general are correlated and measured via a different measurement scale. Consequently, a decision-maker must resolve the parameter selection problem to optimize each response. This problem is regarded as a multi-response optimization problem, subject to different response requirements [5].

2.1 Objective Functions

The quality characteristics chosen for the experiment should reflect as accurately as possible the design parameters under study. Often it is not possible to improve one of them without deteriorating one or more of the others. For example, in deep drawing, forming with larger plastic deformation results in lower springback, but increases the risk of

thinning. In this study, three responses were selected namely springback (SPBK), Signal to noise ratio (SNR) which represent the thickness variation of and punch force (PF).

The quality characteristics chosen for the experiment should reflect as accurately as possible the design parameters under study. Though the choice of these responses were discussed in detail vide articles [3-4], a modest discussion of the responses is given here for clear understanding of this study.

2.2 Springback

The elastic energy stored in the metal sheet during forming is subsequently released after the forming pressure is removed. This release of energy is the driving force for spring-back of sheet metal forming. Springback may introduce surface distortions and unexpected out of shape tolerances that may cause not only deviations from the designed target shape but also can lead to the assembly problems [6]. Therefore it is essential to achieve minimum springback.

2.3 Punch Force

The punch force (PF) needed for deep drawing is one of the important factors as this force is a resultant of the forces needed to overcome the following stresses. A smaller punch force would predict drawing success. The lowest punch force is desired because the higher is the punch force the greater is the amount of wear on the tooling, which is critical in industry where expensive tooling for complicated components cannot be replaced on a regular basis [7].

2.4 Thickness Variation

Existence of thickness variation from the production stage may cause stress concentration in the part leading to acceleration of damage mechanism. And also the load carrying capability of the material decreases with decreasing thickness. Consequently, preventing failure during the forming process becomes more difficult with decreasing thickness. A statistical approach based on Taguchi's Signal to Noise Ratio (SNR) was adopted to determine the optimum combination of the three parameters such as die shoulder radius, punch nose radius and the blank holder force on the thickness distribution, for which the Signal to Noise Ratio (SNR) is to be maximized. The values of the three responses for the twenty experiments are given in the Table 3.

Table 3: Value of the Three Responses

Exp. No.	Coded value			Actual value			Springback D (mm)	Punch Force PF (kN)	Signal to Noise Ratio SNR
	PR	DR	BHF	PR	DR	BHF			
1	-1	1	1	3	8	10	35.66	26	54.14072
2	0	0	0	5.5	5.5	7	35.56	20	48.79514
3	0	-1	0	5.5	3	7	30.95	23	46.80108
4	0	1	0	5.5	8	7	36.94	21	53.71212
5	0	0	1	5.5	5.5	10	37.78	23	49.09927
6	0	0	0	5.5	5.5	7	34.36	21	48.61033
7	0	0	0	5.5	5.5	7	35.86	21	47.64231
8	1	1	1	8	8	10	36.12	24	52.80685
9	1	1	-1	8	8	4	41.52	17	54.03997
10	1	-1	-1	8	3	4	33.00	20	49.78324
11	1	-1	1	8	3	10	32.08	25	44.96143
12	0	0	0	5.5	5.5	7	34.74	21	49.13805
13	-1	-1	1	3	3	10	35.34	29	45.84594
14	-1	0	0	3	5.5	7	33.24	22	48.07837
15	-1	1	-1	3	8	4	38.62	16	54.15072
16	0	0	0	5.5	5.5	7	34.79	20	47.65868

17	0	0	-1	5.5	5.5	4	38.02	15	50.43498
18	-1	-1	-1	3	3	4	31.22	22	53.42095
19	1	0	0	8	5.5	7	34.4	23	48.30490
20	0	0	0	5.5	5.5	7	34.64	21	48.25210

2.5 Desirability Approach

In multi objective decision making environments, a problem of interest is to select a set of input conditions (or independent variables), which results in a product with a desirable set of outputs (or response variables). In fact, this problem is about simultaneous optimization of the response variables, each of which depends upon a set of independent variables. Here, it is desirable to select the levels of the independent variables such that all the response variables are optimized [8]. One of the most popular approaches to multi- responses decision making problems is to aggregate the multiple performance characteristics into a dimensionless measure of performance called overall desirability function [9-10]. The desirability approach involve transforming each estimated response Y_i into a unit less utility bounded by $0 < d_i < 1$, where a higher d_i value indicates that response value Y_i is more desirable. If $d_i = 0$ this means a completely undesirable response. The most commonly adopted forms for d_i were proposed by Derringer and Suich, 1980 [11]. There are two cases for transformation to consider: one-sided and two-sided transformations. One-sided transformations are used when the goal is to either maximize the response or minimize the response. Two-sided transformations are used when the goal is for the response to achieve some specified target value. For a goal of smaller the better type, where it is ideal to have the outcome value as small as possible, the individual desirability function is defined as

$$d_i = \begin{cases} 1 & \text{for } y_i < L_i \\ \left(\frac{U_i - y_i}{U_i - L_i} \right)^{r_i} & \text{for } L_i \leq y_i \leq U_i \\ 0 & \text{for } y_i > U_i \end{cases} \quad (1)$$

There is a lower bound L_i and upper bound U_i for the i th outcome y_i such that it is unacceptable when $y_i > U_i$ and it is described as perfect or most desirable when $y_i < L_i$. Where r_i is the user-selected shape parameter called weights. The choice of weight r_i is subjective and this quantity results in different desirability shapes.

Another one-side problem is the larger-the better type, where it is desirable to have the outcome value as large as possible. It is unacceptable when $y_i < L_i$ and it is nearly perfect or most desirable when $y_i < U_i$. Then the individual desirability is defined as

$$d_i = \begin{cases} 0 & \text{for } y_i < L_i \\ \left(\frac{y_i - L_i}{U_i - L_i} \right)^{r_i} & \text{for } L_i \leq y_i \leq U_i \\ 1 & \text{for } y_i > U_i \end{cases} \quad (2)$$

If there is a target value for the outcome, a two-sided problem for the nominal-the-best type is employed. In this case, it is ideal to have the y_i value as close as possible to the target value. It is unacceptable if $y_i < L_i$ or $y_i > U_i$. The individual desirability function can be modified by combining the smaller-the-better and larger-the-better types of

desirability functions. For goal as target, the desirability is defined as

$$d_i = \begin{cases} \left(\frac{y_i - L_i}{T_i - L_i} \right)^{wt_{2i}} & \text{Low}_i < y_i < T_i \\ \left(\frac{y_i - U_i}{T_i - U_i} \right)^{wt_{2i}} & T_i < y_i < \text{High}_i \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

For goal within the range, the desirability is defined as

$$d_i = \begin{cases} 1 & , L_i < y_i < U_i \\ 0 & , \text{otherwise} \end{cases} \quad (4)$$

The weight defines the shape of the desirability function for each response. Weights give added emphasis to upper or lower bounds or emphasize target values. For each response, you can select a weight (from 0.1 to 10) to emphasize or de-emphasize the target. A weight less than 1 (minimum is 0.1) places less emphasis on the target, a weight equal to 1 places equal importance on the target and the bounds and a weight greater than 1 (maximum is 10) places more emphasis on the target. The illustrations below show how the shape of the desirability function changes depending on the weight (Table 4)

Table 4: Shape of the Desirability Function

<p>Minimize the response Below the target, the response desirability is 1; above the upper bound, it is 0.</p>	
<p>Maximize the response Below the lower bound, the response desirability is 0; above the target, it is 1.</p>	
<p>Target the response Below the lower bound, the response desirability is 0; at the target, it is 1; above the upper bound, it is 0.</p>	

Once the desirable function for each outcome is determine the individual desirability functions can be combined into an overall desirability score D using the geometric mean proposed by [45], where

$$D = (d_1 d_2 \dots d_m)^{\frac{1}{m}} \quad (5)$$

where m is the number of responses. The value of D is between 0 and 1. A higher value of D denotes better

achievement of the responses. Clearly, high values of d_i result in a high value of D . If all the outcomes are not equally important [71] proposed the weighted overall desirability function as

$$D = d_1^{w_1} d_2^{w_2} \dots \dots d_m^{w_m} \quad (6)$$

Where the weights are user-selected to reflect the level of importance of the difference outcomes and satisfy $0 < w_i < 1$ and $\sum w_i = 1$.

RESULTS AND DISCUSSIONS

In this work, the multi objective optimization is carried out using Minitab (V16) software package. This package helps us to determine the "best" settings to simultaneously optimize multiple responses. Once the mathematical models have been developed and checked for adequacy, the optimization criteria can be set to find out the optimum setting of the selected parameters.

In this investigation, four criteria were implemented by choosing the desired goals. The first criterion is to reach minimum springback with no limitation on the other two responses (punch force and signal to noise ratio). The second criterion is to achieve minimum punch force with no limitation on the springback and signal to noise ratio. The third criterion is to reach maximum signal to noise ratio with no limitation on springback and punch force. The fourth criterion is to achieve minimum springback, minimum punch force and maximum signal to noise ratio. All the responses can be considered equally important. Table 5 summarizes these criteria and optimal solution.

Table 5: Optimization Criteria and Optimal Solutions

#	Criterion	PR (mm)	DR (mm)	BHF (kN)	SPBK (mm)	SNR	PF (kN)
1	Minimum Springback	3	3	6	30.0099	-	-
2	Maximum SNR	3	8	4	-	54.1507	-
3	Minimum Punch force	5.17	6	4	-	-	14.51
4	Minimum Springback, Maximum SNR, Minimum Punch force	3.91	3	4	32.27	52.1656	33.0345

From Table 5, it is observed that the optimum combination of the three selected parameters such as die shoulder radius, punch nose radius and the blank holder force varies depending on the criterion selected. For achieving minimum springback, comparatively a higher blank holding force (6 kN) is required. For optimum values of the selected parameters, the level that gives the highest S/N ratio was chosen. Accordingly, the optimum levels for the three significant factors, for the most even wall thickness distribution are Punch nose radius, 3 mm; Die shoulder radius, 8 mm; and Blank holder force 4 kN which are the parameter level settings for the experimental run No.15. However for minimum punch force requirement, moderately higher values of punch nose radius and die shoulder radius are required while keeping the blank holder force minimum i. e. Punch nose radius, 5.17 mm; Die shoulder radius, 6 mm; and Blank holder force 4 kN. The composite desirability values are around 0.7, which is reasonably good.

CONCLUSIONS

It was observed that the optimum values of the parameters with single objective function vary considerably with that of the values for achieving all the three objectives. For instance, if the criterion is only to achieve the springback, the achievable springback is 30.0099 mm only. But attempting to achieve all the three objectives increases it to 32.27 mm.

That is, when the desired response changes, a significant compromise is required on the other responses and parameter settings which should be carefully handled during the die design.

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