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A NEW COMPUTATIONAL DESIGN OF EXPERIMENT FOR PROCESS OPTIMIZATION
APPLICATION FOR BENDING PROCESS

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The aim of this paper is to propose an original optimization approach using the concept of computational design of experiments and response surface methodology to check the curvature in numerical experiments. Generally, for the study of the strongly nonlinear phenomena, it is recommended to use a second-order model. This paper proposes a new technique to estimate a quadratic effect for a model based on finite element simulations and the Design of Experiments. Therefore, it is very important that the proposed technique (adding center points) controls other properties of the design matrix, especially orthogonality for the response surface methodology and brings more information for the quality of the proposed model. The computational design of experiments is considered an advantage in comparison with design of physical experiments because generally computer solutions cost less than physical testing. The bending process optimization is used to improve the performances of this approach.

1. Introduction

Sheet metal L-bending processes are widely used for mass production. The design of bending processes is connected with time consuming and costly experiments. Therefore, the finite element simulation of the process could be a helpful tool for the designer and quality assurance of the products. After bending, springback occurs upon the removal of the tool (Fig. 1) [8], [12], [21], [30].

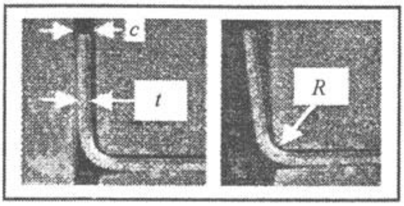

Fig. 1.– Processes sequence during L-bending and springback [Int.1].

As lead times are shortened and materials of higher strength are used in manufacturing, the simulation of springback following sheet forming is essential for optimal designing of tooling and processes. Traditional trial-and-error methods are time consuming and expensive, while empirical rule-based adjustments for springback [13] are not usually applicable to complex geometries or materials without a large database of experience.

The leading L-bending parameters that affect the process [31] are the die corner radius (R_d), punch-die clearance (c), punch radius (R_p), pad force ($F_{\mathbf{pad}}$) and sheet metal thickness (t) (Fig. 2). In this study among the L-bending parameters, only the effect of the die radius, clearance and sheet metal thickness are investigated.

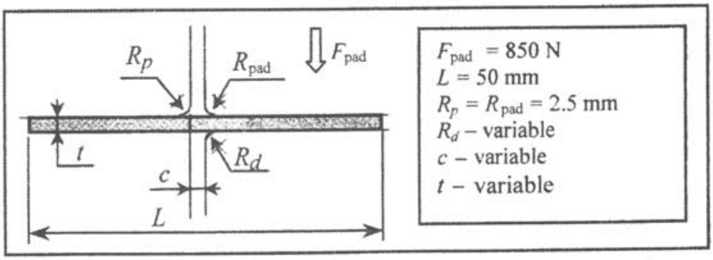

Fig. 2.- Model of L-bending operation.

Optimization of the process by the classical method involves changing one independent variable (radius, clearance, sheet metal thickness, etc.) while fixing all others at a fixed level [10], [26], [29]. If it is used the classical method (one at the time) for each independent variable, that is extremely time consuming and expensive for a large number of variables. To overcome this difficulty, experimental factorial design and response methodology can be employed to optimize medium components [3], [5], [18], [24], [25]. The response to be optimized (springback) [4], [11], [17], [20], [23], [30] constitutes the principal difficulty to control during the bending process, and involves a dimensional variation of the manufactured pieces. The aim of this work is to include the optimization of the L-bending process. The use of computational experimental design [4], [7], [9], [27] and Response Surface Methodology (RSM) [2], [3], [24] has been successfully applied to optimize metal bending processes. A new technique to estimate the curvature of the quadratic model for the numerical simulations is proposed in this paper. ABAQUS finite element code is used to realize the numerical simulations. Computational Design Of Experiments (CDOE) and RSM were used to optimize the value of three factors (die corner radius, punch-die clearance and sheet metal thickness). In section two we present the behavior of the sheet modeling and, thereafter, in section three, we study the numerical simulation of L-bending process. The fourth section makes an introduction to RSM for passing afterwards in the section five to explain the new technique to check the curvature of the CDOE. The paper finishes with the conclusions.

2. Modelling of the Sheet Behavior

The algorithms generally implemented in the finite element codes for integration of nonlinear constitutive equations are the so-called radial return algorithms (ABAQUS), and they are used to solve the equations in an incremental form. The integration methods of the nonlinear constitutive equations are based on the use of a special algorithm, which solves the equations in incremental form. For this purpose, during a small time interval, $[t_n, t_{n+1}]$, it is assumed that the whole increment is purely elastic, then an elastic prediction is defined as

$$\sigma_{n+1}^{T} = \sigma_n + \Delta\sigma, \tag{1}$$

where σ_n is a stress tensor at increment n, σ_{n+1} – a stress tensor at increment $n+1$ and $\Delta\sigma$ – the stress increment. The superscript refers to Trial test. The equation (1) can be written as

$$\sigma_{n+1}^{T} = C_{\mathrm{el}}(\varepsilon_{n+1}^{\mathrm{tot}} - \varepsilon_{n}^{\mathrm{pl}}), \tag{2}$$

where: C_{el} is the elastic modulus tensor, $\varepsilon_{n+1}^{\mathrm{tot}}$ – the total strain tensor at increment $n+1$ and $\varepsilon_{n}^{\mathrm{pl}}$ – the plastic strain tensor at increment n.

The yield criterion defining the plastic flow is given by the von Mises stress function

$$f = \sigma_{\mathrm{eq}} - (\sigma_y + \sigma_0), \tag{3}$$

where: σ_{eq} is the von Mises stress, σ_y – the yield stress and σ_0 – the strain hardening law. If this elastic prediction satisfies the yield condition $f < 0$, the prediction is true and the local procedure is completed. Then it can be stated that

$$\sigma_{n+1} = \sigma_{n+1}^{T}. \tag{4}$$

Otherwise, this state must be corrected by means of a plastic correction. For this purpose, the variables at increment $n+1$ must satisfy the system (ABAQUS)

$$\begin{cases} f = 0, \\ \sigma_{n+1} - C_{\mathrm{el}}(\varepsilon_{n}^{\mathrm{tot}} + \Delta\varepsilon - \varepsilon_{n}^{\mathrm{pl}} - \Delta\varepsilon^{\mathrm{pl}}) = 0, \end{cases} \tag{5}$$

where: $\varepsilon_{n}^{\mathrm{tot}}$ is the total strain tensor at increment n, $\Delta\varepsilon$ – the total strain increment, $\varepsilon_{n}^{\mathrm{pl}}$ – the plastic strain tensor at increment n, and $\Delta\varepsilon^{\mathrm{pl}}$ – the plastic strain increment.

3. Simulation of L-bending Operation

The problem studied here considers bending of 4 mm thick sheet metal. The geometry of the process with all dimensions is shown in Fig. 2.

The meshing of the model is carried out by means of 420 quadrangular four node continuum elements (Fig. 3). Four layers of finite element have been assigned in the thickness. The plastic properties of the sheet metal part are assumed to be isotropic, described by the von Mises yield function with the corresponding strain hardening law given by (ABAQUS)

$$\sigma_0 = \sigma_y + K(\varepsilon_{\mathrm{eq}})^n, \tag{6}$$

where: $\varepsilon_{\mathrm{eq}}$ is equivalent plastic strain, n – the dimensionless strain hardening exponent and K – the bulk modulus.

The mechanical characteristics (where E is the Young's modulus and ν – the Poisson's ratio) of the material obtained by a tensile test, are given in Table 1.

Table 1
Material Characteristics

Material	E, [MPa]	ν	σ_y, [MPa]	K, [MPa]	n
Steel X6CrNiTi18 10	210,000	0.3	250	1,045	0.2

Contact at the interfaces between the sheet and the tool is modeled by adopting a rigid body hypothesis using contact surface laws defined by a Coulomb friction model. Typical values of the friction coefficient are given in [16], [19] for a combination of contacting materials. For steel/steel contact, typical value of the friction coefficient is equal to 0.1 The computation results corresponding to different displacement steps of the punch penetration are presented in Fig. 3. It can be seen that the springback takes place when the punch is removed from the simulation.

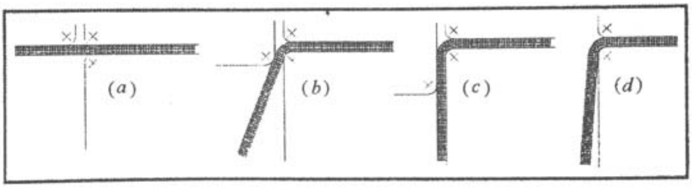

Fig. 3.– Deformed configuration at different steps: (*d*) springback.

4. Concept of Response Surface Methodology

RSM consists of a group of empirical techniques [2], [3], [24] devoted to the evaluation of relations existing between a cluster of controlled experimental factors and the measured responses, according to one or more selected criteria [5], [18]. *Prior* knowledge and understanding of the process and the process variables under investigation are necessary for achieving a realistic model.

RSM provides an approximate relationship between a true response, y, and k design variables, which is based on the observed data from the process or system. The response is generally obtained from real experiments or computer simulations, and the true response, y, is the expected response. Thus, computer simulations are performed in this paper. It is supposed that the true response, y, can be written as

$$y = F(x_1, x_2, ..., x_k), \tag{7}$$

where the variables $x_1, x_2, ..., x_k$ are expressed in natural units of a measurement, so they are called "natural variables". Usually, the approximating function, F, of the true response, y, is chosen to be either a first-order or a second-order polynomial model, which is based on a Taylor series expansion. In this study, the second-order model given by

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{ii} x_i^2 + \sum_{\substack{i=1 \\ i<j}}^{k} \sum_{j=1}^{k} \beta_{ij} x_i x_j + e, \tag{8}$$

is retained to describe the springback response and to verify the nonlinearity of the process, where: β_0, β_i, β_{ii} and β_{ij}, are called regression coefficients, and e represent the noise or the error observed in the response y [24].

For a given material to be manufactured and a given geometry, a cause and effect analysis was done to identify primary and secondary causes resulting in springback of the workpiece. Out of the number of factors identified, the following factors were considered to be most important and necessary to control (Fig. 2):

1. Die corner radius (R_d).
2. Punch-die clearance (c).
3. Sheet metal thickness (t).
4. Type of material.
5. Force to be applied to the blankholder (F_{pad}).

Among those leading factors, the die corner radius, the clearance and the sheet metal thickness have been retained, after the screening study, to reduce the springback.

5. A New Technique to Check the Curvature of the CDOE

This paper proposes to use an CDOE, which is based on a new technique to check the curvature, combined with a Finite-Element Analysis (FEA) code to generate the numerical simulated data. This technique consists of adding center points *small shifted*, reported at the center point (Fig. 4), obtained by numerical simulations, too. Several numerical simulations were performed in order to determine with more accuracy the maximum distance to the shifted points ($d_1 = 0.046d$ – Fig. 4). This technique is used where the studied problem is a very complex phenomenon and the response function is not adequately modeled by the first-order model. In such cases, a logical model to consider is given by Eq. (8).

One important reason for adding the replicate runs at the design center is that center points do not affect the usual effect estimates in a 2^k design and this permits to check the curvature for the second-order response surface model (Eq. (8)). Therefore, the use of higher-order terms increased the precision of the prediction and was important for the optimization of the variable levels. The number of center points controls other properties of the design matrix and many information are added for the proposed model.

For a single degree of freedom is associated a non-null hypothesis

$$H_1 : \sum_{j=1}^{k} \beta_{ij} \neq 0; \tag{9}$$

the sum of the squares for quadratic curvature is given by [24]

$$\mathrm{SS}_{\text{pure-quadratic}} = \frac{n_F n_C (\overline{y}_F - \overline{y}_C)^2}{n_F + n_C}, \tag{10}$$

where: $\mathrm{SS}_{\text{pure-quadratic}}$ is the sum of squares for quadratic curvature, n_F – the number of factorial design points 2^k, k – the number of the study's factors, n_C – the number of runs in the center points, $\overline{y}_F$ – the average for the runs in the factorial design, $\overline{y}_C$ – the average for the runs in the center points.

The mean square error is calculated from the center point with relation

$$\mathrm{MS}_E = \frac{\mathrm{SS}_E}{n_C - 1} = \frac{\sum_{i=1}^{n_c} (y_i - \overline{y})^2}{n_C - 1}, \tag{11}$$

where: SS_E is the sum of square error for the center points, y_i – the i value for the center points and $\overline{y}$ – the average for all center points.

Comparing $\mathrm{SS}_{\text{pure-quadratic}}$ to MS_E (F_{ratio}) gives a lack-of-fit statistic. If this value (F_{ratio}) is greater than the critical value (F_{test} – Fisher test), there is an indication of a pure quadratic effect. This F_{test} procedure provides an objective method for determining whether or not the model has a pure quadratic effect *i.e.*

$$F_{\text{ratio}} = \frac{\mathrm{SS}_{\text{pure-quadratique}}}{\mathrm{MS}_E}, \tag{12}$$

$$F_{\text{test}} = F(\alpha, \nu_1, \nu_2), \tag{13}$$

where: α – alpha risk is defined as the risk of rejecting the non-null hypothesis when in fact it is true, and ν_1, ν_2 – the degrees of freedom for the numerator and the denominator, respectively.

After the screening study, the important variables for the springback in the bending process are shown in Table 2.

Table 2
Order of Importance of the Variables

	Variables	Worked variables	Importance order
1	Die corner radius	A	1
2	Clearance	B	3
3	Sheet metal thickness	C	2

For this study it is assumed that the three factors are quantitative. The design space of the three design variables in both coded and original format is listed in Table 3.

Table 3
Design Variables and their Coded Value

Design variables	Star point	Lower bound	Middle point	Upper bound	Star point
Coded value	$-\delta$	-1	0	1	$+\delta$
Die corner radius	3.32	4	5	6	6.68
Sheet metal thickness	2.66	3	3.50	4	4.34
Clearance	0.318	1	2	3	3.68

In order to check the curvature the center points (Table 4), situated at the same distance reported for the center, are added (Fig. 4).

Table 4
Factorial Design with Multiple Center Points for Checking the Curvature

	A	B	C	Y
1	−1	−1	−1	2.7433
2	1	−1	−1	3.1858
3	−1	1	−1	2.5727
4	1	1	−1	2.8683
5	−1	−1	1	3.0503
6	1	−1	1	3.4928
7	−1	1	1	2.8797
8	1	1	1	3.1753
9	0	0	0	2.9625
10	0	0	0	2.9676
11	0	0	0	2.9712
12	0	0	0	2.9835
13	0	0	0	2.9878
14	0	0	0	2.9551
15	0	0	0	2.9699

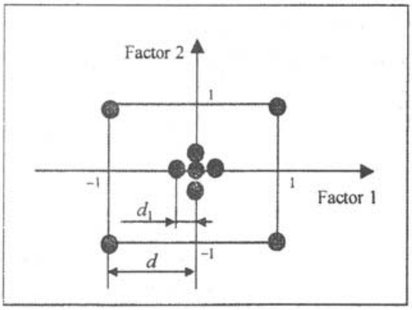

Fig. 4.– Adding center points for checking the curvature.

Using relations (10),...,(12) the following results are obtained:

$$\text{SS}_{\text{pure-quadratic}} = \frac{8 \times 7(2.996 - 2.971)^2}{8+7} = 2.322 \times 10^{-3}, \tag{14}$$

$$\text{MS}_E = \frac{8.068 \times 10^{-4}}{6} = 1.3446 \times 10^{-4}. \tag{15}$$

If

$$F_{\text{ratio}} \geq F_{\text{test}}, \tag{16}$$

H_1 is accepted.

In the studied case

$$F_{\text{ratio}} = 17.268 \geq F_{(0.05,1,6)} = 5.99. \tag{17}$$

The analysis presented here indicates that there is evidence of second-order curvature in the response in the region of exploration. That is, the non-null hypothesis

$$H_1 : \beta_{11} + \beta_{22} + \beta_{33} \neq 0 \tag{18}$$

is accepted.

To illustrate the non-null hypothesis, it is considered in the following two cases using Central Composite Design (CCD) with a single center point and CCD with the new purpose technique (multiple center points).

5.1. Central Composite Design with a Single Center

The first case in the study consisted of a classical CCD (Table 5) with a single center point (for the computational experiments). The inclusion of the axial and the center points enabled the determination of curvature in the mathematical model (Eq. (8)).

Table 5

CCD with a Single Center Point

	A	B	C	Y
1	−1	−1	−1	2.7433
2	1	−1	−1	3.1858
3	−1	1	−1	2.5727
4	1	1	−1	2.8683
5	−1	−1	1	3.0503
6	1	−1	1	3.4928
7	−1	1	1	2.8797
8	1	1	1	3.1753
9	−1.682	0	0	2.682
10	1.682	0	0	3.3064
11	0	−1.682	0	3.2629
12	0	1.682	0	2.8272
13	0	0	−1.682	2.6059
14	0	0	1.682	3.1741
15	0	0	0	2.9625

The Pareto diagram (Fig. 5) shows a significant quadratic effect (Q) for the variable B (clearance). The same results are obtained by ANalysis Of VAriance (ANOVA) (Table 6).

Table 6
Analysis of Variance

ANOVA – Variable Y $R^2 = 0.9983$; $Aj = 0.9966$					
Variables	SS	dl	MS	F	p
A (Linear)	0.467330	1	0.467330	1,117.435	0.000000
A (Quadratic)	0.001585	1	0.001585	3.791	0.109094
B (Linear)	0.213852	1	0.213852	511.343	0.000003
B (Quadratic)	0.007063	1	0.007063	16.888	0.009269
C (Linear)	0.349137	1	0.349137	834.824	0.000001
C (Quadratic)	0.002581	1	0.002581	6.172	0.055540
$A(L)$ *$B(L)$	0.010790	1	0.010790	25.800	0.003837
$A(L)$ *$C(L)$	0.000000	1	0.000000	0.000	1.000000
$B(L)$ *$C(L)$	0.000000	1	0.000000	0.000	1.000000
Error	0.002091	5	0.000418		
Total SS	1.068981	14			

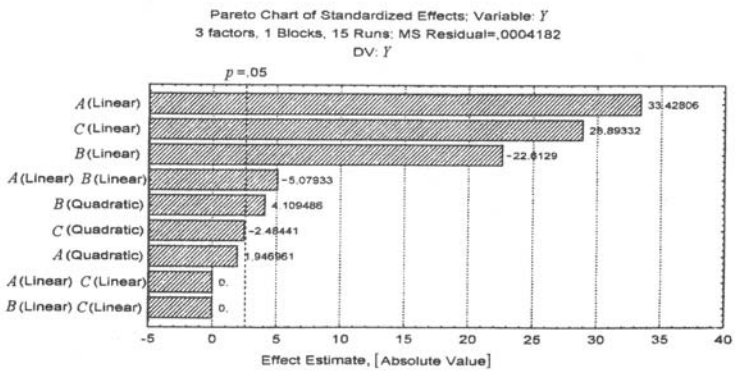

Fig. 5.– Pareto diagram in case of central composite design with a single center.

The response surface equation obtained by regression analysis for the proposed model (with a single center point) is given by

$$Y = 2.992 + 0.185\,A - 0.125\,B + 0.16\,C + 0.0241\,B^2 - 0.037\,AB, \tag{19}$$

where : A is the die corner radius, B – the clearance and C – the sheet metal

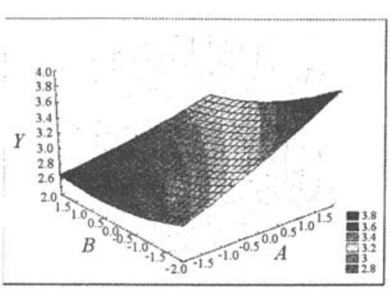

Fig. 6.– Response surface for the interaction AB.

thickness. Fig. 6 shows the response surface for the interaction between variables A and B.

5.2. Central Composite Design with the New Technique (Multiple Center Points)

The second case in the study consisted of a CCD with the new technique (multiple center points – replicate points for the real experiments). For the classical CCD six points *small shifted* reported off the center points are added (Table 7 – runs 16,...,21). The response function (springback) is obtained by numerical simulations, too.

Table 7

CCD with a Multiple Center Points

	A	B	C	Y
1	−1	−1	−1	2.7433
2	1	−1	−1	3.1858
3	−1	1	−1	2.5727
4	1	1	−1	2.8683
5	−1	−1	1	3.0503
6	1	−1	1	3.4928
7	−1	1	1	2.8797
8	1	1	1	3.1753
9	−1.682	0	0	2.682
10	1.682	0	0	3.3064
11	0	−1.682	0	3.2629
12	0	1.682	0	2.8272
13	0	0	−1.682	2.6059
14	0	0	1.682	3.1741
15	0	0	0	2.9625
16	0	0	0	2.9676
17	0	0	0	2.9712
18	0	0	0	2.9835
19	0	0	0	2.9878
20	0	0	0	2.9551
21	0	0	0	2.9699

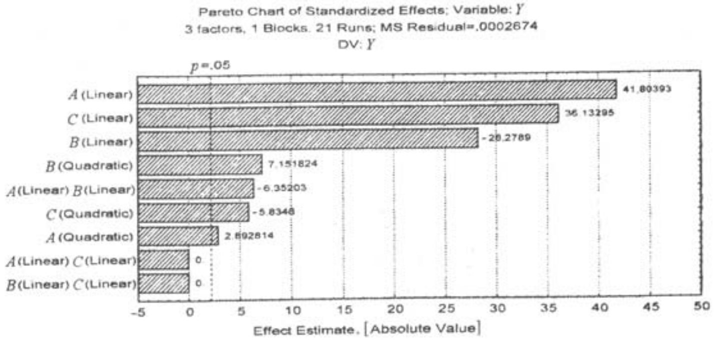

Fig. 7.– Pareto diagram in case of central composite design with the new proposed technique.

The Pareto diagram of Fig. 7 shows a significant quadratic effect (Q) for the variables C (sheet metal thickness) and A (die corner radius) additionally to the existing variable B (clearance). The observation is in accordance with the analysis of variance (Table 8). This observation proves that adding the center points for the numerical design of experiments controls other properties of the design matrix (uniform precision) and gives additional information (quadratic effect, Q, for the variables C and A) for the performance of the proposed model and a better quality for the working model. For this reason the center points are called *control runs*.

Table 8
Analysis of Variance for the Second Case

ANOVA – Variable Y $R^2 = 0.9983$; $Aj = 0.9966$					
Variables	SS	dl	MS	F	p
A (Linear)	0.467330	1	0.467330	1,117.435	0.000000
A (Quadratic)	0.001585	1	0.001585	3.791	0.109094
B (Linear)	0.213852	1	0.213852	511.343	0.000003
B (Quadratic)	0.007063	1	0.007063	16.888	0.009269
C (Linear)	0.349137	1	0.349137	834.824	0.000001
C (Quadratic)	0.002581	1	0.002581	6.172	0.055540
$A(L)*B(L)$	0.010790	1	0.010790	25.800	0.003837
$A(L)*C(L)$	0.000000	1	0.000000	0.000	1.000000
$B(L)*C(L)$	0.000000	1	0.000000	0.000	1.000000
Error	0.002091	5	0.000418		
Total SS	1.068981	14			

5.3. Backward Stepwise Regression Method

Stepwise regression is a technique for choosing the variables, that is, terms, to include in a multiple regression model [22]. Forward stepwise regression starts with no model terms. At each step, it adds the most statistically significant term (the one with the highest F statistic or lowest p-value) until there is none left. Backward stepwise regression starts with all the terms in the model and removes the least significant terms until all the remaining terms are statistically significant. It is also possible to start with a subset of all the terms and then add significant terms or remove insignificant terms.

Backward stepwise regression analysis gives the following fitted model (with multiple center points) expressed in coded values

$$(20)\quad Y = 2.971 + 0.185\,A - 0.125\,B + 0.16\,C + 0.0122\,A^2 + 0.03\,B^2 - 0.025\,C^2 - 0.037\,AB.$$

The $R^2 = 0.9986$ value shows the best quality of the fitted model. One of the advantages of using the stepwise regression analysis procedure is that it can take care of the multicollinearity problem, which could be present in the data as some variables may be highly correlated.

6. Conclusions

In this paper a sheet metal bending process optimization method for springback minimization is proposed that combines Finite Element Analysis, Response Surface Method and Computational Design Of Experiments.

This work proposed a new technique to check the curvature using RSM in computational experiments. By this technique a center points runs to provide a check for both process stability and possible curvature were added.

In RSM, the number of center points controls other properties of the design matrix. The number of center points can make the design orthogonal or have "uniform precision" which offers more protection against bias in the regression coefficients than does an orthogonal design because of the presence of the higher terms in the true response surface.

This method is especially dedicated for Computational Design of Experiments and it will help to:

a) obtain an information for process variability;

b) test the quadratic effect or possibly curvature;

c) test the model validity;

d) increase the model quality.

The numerical simulations in this work were obtained using the ABAQUS. A Python script program has been developed to automatically parameterize the ABAQUS computations, which result from different configurations of the designs of experiments used.

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UN NOU PLAN DE EXPERIENŢE NUMERICE PENTRU OPTIMIZAREA PROCESELOR
Aplicaţie pentru procesul de pliere

(Rezumat)

Se propune o metodă originală de optimizare utilizând conceptul de planuri de experienţe numerice şi metodologia suprafeţelor de răspuns pentru verificarea curburii unor modele obţinute prin simulare numerică. In general pentru studiul fenomenelor neliniare se recomandă utilizarea modelelor de ordinul doi. Prin consecinţă este foarte important de precizat faptul că această metodă (adăugarea de puncte centrale) controlează alte proprietăţi ale matricei de experienţe în special ortogonalitatea, în particular pentru metodologia suprafeţelor de răspuns şi aduce mai multe informaţii asupra calităţii modelului propus. Planurile de experienţă numerice sunt considerate mai avantajoase în raport cu experienţele fizice din cauza faptului că simulările numerice au un cost mult mai redus. Optimizarea procesului de pliere este utilizată pentru a arăta performanţele metodei.