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New approaches for springback-based offline dimensional control in sheet metal forming

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The springback reduction is a difficult task and the subject of numerous research studies in the field of sheet metal forming. In this paper, we develop a new integrated-optimal dimensional offline control approach for springback and a new approach for springback reduction. The key idea is to build a reduced-order model of the entire blank-process-tooling system and, by using it, to find the optimal values of the system parameters for which the part accuracy and precision are the highest using a searching algorithm. The integrated-optimal dimensional offline control of springback consists in three modules simulation, reduced-order modelling and optimization. FEM is used for simulation. NN modelling is used for building the reduced-order modelling. For optimization, the searching algorithm is used. Using the exhaustive search the part accuracy and precision are evaluated by considering the system parameters values as belonging to their tolerated domains of variation. The approach implementation is applied to sheet multipoint forming with interpolators. Finally, the results come to validate the integrated-optimal dimensional offline control of springback approach and for the new optimized springback reduction, the obtained accuracies and precisions are presented.

Keywords: Accuracy, Precision, Multiforming forming, Sheet metal forming, Simulation, Reduced order modeling

In sheet metal forming, the springback percentage in dimensional error is much higher than the percentage of other sources of errors[1,2]. Reduction of the error springback-caused component means drastically reduction of the entire dimensional error. Moreover, the idea to control the dimensional error through proper handling the springback-caused component appears as feasible[3,4]. In other words, the springback control could be equivalent with the control of entire dimensional error. Therefore, in thin sheet metal forming we can accept the term springback-based dimensional control.

On the other hand, the thin sheet metal forming is often a high-speed process, done with high frequency mechanical presses. Therefore, the real time control of springback is extremely difficult to achieve.

This is why the offline control of springback, i.e., the control in preparatory stages, such as tooling development and press work-cycle programming, appears to be a more realistic solution.

Regarding the springback-based dimensional control approach, nowadays, we discuss about springback reduction or springback compensation[5,6]. During a batch processing, the values of springback varies because the real values of the blank, process, and even the tooling parameters vary randomly, close to their nominal values[7,8]. In applying of these traditional approaches, this fact is not taken into account. Moreover, in traditional application of the two approaches, instead of systemic identification of the causal relations on which the application of one or other of the two approaches could be based, intuition is used to find such relations. Therefore, the solutions not always it is the best.

To reduce the aforementioned shortcomings of the conventional springback-based offline dimensional control, in this paper we are proposing an overall approach of the springback-based offline dimensional control, namely integrated-optimal approach, which is based on a new strategy and new algorithm for the reduction traditional control approach, which we call optimized springback reduction approach.

New Optimized Springback Reduction Approach Formulation

Lets consider an hypothetical example, Fig. 1, there is only one controlled variable, i.e., the L dimension. Reference is presented in Fig. 1a, where $L_{min}^{accepted}$ =50.1 mm and $L_{max}^{accepted}$ =50.7 mm are the limits and $\Delta L^{accepted}$ = 0.6 mm is the range of tolerance domain of

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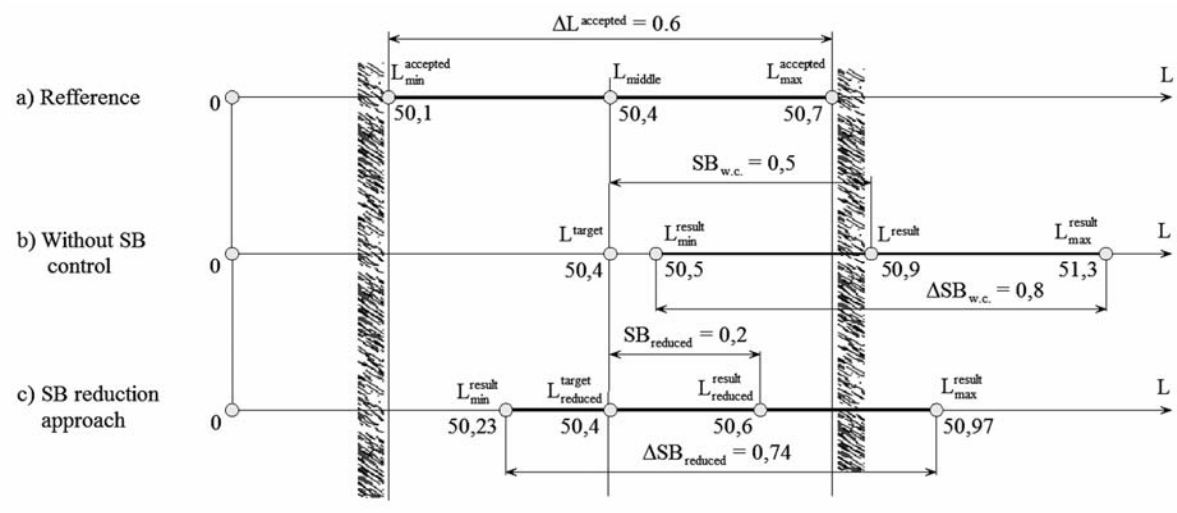

Fig. 1—Springback-based dimensional control - reduction approach

L. The value L_{middle} = 50.4 mm corresponds to the middle of this domain and is considered as desired value of dimension.

In the following, we will characterize the springback by the springback parameter *SB*, defined as springback-caused error and computed as difference between the real value L^{result} of dimension *L*, which is affected by springback phenomenon, and its desired value L_{middle}. In addition, to define the reference, let us consider the case in which the batch of products are processed without any offline control, the target dimension, L^{target}, is equal with L_{middle}, and the values of all other variables are in the middle of their domains of variation.

Also, let us consider that the real value of the dimension *L* is L^{result} =50.9 mm. In this case the value of springback parameter is $SB_{w.c.}$=0.5 mm. As a consequence that, at different samples of the batch, the perturbed variables fluctuate, then the springback varies as well, with $\Delta SB_{w.c.}$=0.8 mm, between L^{result}_{min} =50.5 mm and L^{result}_{max} =51.3 mm. If the tolerance limits of *L* are exceeded, as is the case shown in Fig. 1b, then the springback control is required.

We propose that if the control is offline and optimal, then this problem should be addressed as below.

In optimized springback reduction approach, the control consists in the following:

The first step is to set the geometry of contact surfaces between part and tooling, giving to each geometric parameter of these surfaces the value that corresponds to the situation in which the values of parameters that describe the blank, process, and part are in the middle of their domain of variation.

In the second step, the group of manipulated variables is made up by selecting from the variables that describe the blank-process-tooling behaviour, those that both are in causal relationship with the springback parameters and could be manipulated. For each such variable, a manipulation domain is established.

In the third step, the manipulated variables are assigned to those values that are considered optimal, since for these values, the objective function *F*, defined by the relation:

$$F = L^{result}_{reduced} - L_{middle} + \frac{1}{2}\Delta SB_{reduced} \qquad \dots (1)$$

become minimum, and all restrictions are met.

In the example shown in Fig. 1c, the target value of the dimension *L* is $L^{target}_{reduced}$ (equal with L^{target} from the case where there is no control, i.e., 50.4 mm), the real value of the dimension *L* is $L^{result}_{reduced}$ =50.6 mm, and the springback parameter has the value $SB_{reduced}$ = 0.2mm, which is smaller than $SB_{w.c.}$= 0.5 mm. Also the variation of the springback parameter, which now has the value $\Delta SB_{reduced}$ = 0.74 mm is lower, in comparison with 0.8 mm in without control case.

In the fourth step, the condition that the minimum value of function *F*, denoted F_{minim}, is less than $\frac{1}{2}\Delta L^{accepted}$ is checked. If this condition is not met, then springback reduction approach is not effective. This is the case shown in Fig. 1c, where F_{minim}=50.6–50.4+0.37=0.57 mm is greater than 0.3 mm.

Method for the New Integrated Offline Dimensional Approach Implementation

Integrated offline dimensional springback-based control consists in to applying the optimized springback reduction approach, proposed in this paper. It has three main stages, namely simulation, reduced-order modelling, and optimization.

Simulation stage

Firstly, the structure of the full dimensional model of blank-process-tooling system is established along with their input/output parameters establishing. Based on this model, a full dimensional mathematical model of the system is built, often using the FE technique.

Secondly, the domain of perturbation/manipulation for each such input variables of the FE model is established. For each input variable we should define a domain to which the variable belongs. The fact that input variables can take any value in the respective interval made to identify the domain of perturbation with tolerance or uncertainty domain.

The manipulation domain is established on the base of tooling and process restrictions. Be they perturbated or manipulated, the project engineer defines and establishes these domains, according with the current application. As regards the output variables, they are controlled type and can be a simulation, basic, or synthetic one.

Simulation output variables are those specific for the output of the full dimensional model, springback is one of them.

Basic output variables are the definite features of the product and process, for example the width B, radius R, height H (Fig. 2). Theirs values should be computed starting from the simulation output variables values. Synthetic output variables refer to specific requirements of the control approach, for example the part dimensional deviations. Their values should be obtained by processing the values of input and basic output variables.

Thirdly, a numerical simulation should be made in order to describe the system behavior at different levels of disturbance/manipulation of the input variables. Finally, the output basic variables are computed, by processing the simulation variables values. As a result, the basic dataset, describing the system behavior in a number of cases is obtained.

Reduced-order modelling stage

On the basis of previous obtained dataset, in this stage we will identify the causal relations between each basic output variable, and the perturbed and manipulated variables. For this, the best neural network model was applied. After that, each causal relation should be modelled. The model obtained make up the reduced-order model of blank-process-tooling system. The reduced-order model addresses the problem of obtaining an approximate model that is computationally tractable and capture the essential physics, but neglect details that are not critical for the problem at hand[9-11].

Optimization stage

For optimized springback reduction approach, the springback caused modifications of the part tolerated dimensions as well as the variation domains of these dimensions, corresponding to perturbed variables changing.

The reduced-order model will be used for assessment the control approach.

Firstly, the output synthetic variables and the performance indicators, the dimension accuracy and precision, should be defined.

Secondly, the optimal values of manipulated variables along with the corresponding most appropriate levels of performance indicators are established using an appropriate search technique. The deviation corresponding to the optimal point is considered the dimension accuracy.

Then the dimension precision is evaluated. For this, is discretized another search space, which refers to the perturbed variables and theirs domains of perturbation. Difference between the extreme values of the dimension deviation, evaluated in the points defined in this space, is considered the dimension precision.

Finally, for each dimension of part, the variation domain resulted by implementing the control approach is compared with its admissible domain of

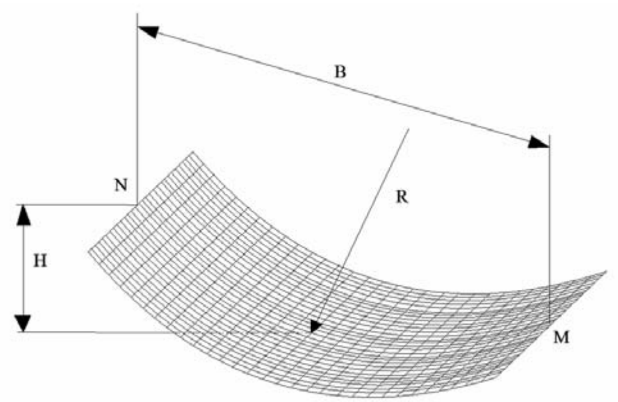

Fig. 2—Product definitely features (example)

variation, and in this way the best choice is highlighted.

Variables Defining the Process-Tooling-Blank System in Multipoint Forming

The multipoint forming is based on the concept of discrete approximation of a die continuous surface. It consists of a number of closely spaced multiple rigid surface tool elements, known as pins, each of which is a surface element of an expected contour[12,13]. The heights of the pins can be adjusted to approximate the desired surface shapes either manually or using a computer control. The main advantage of such a tooling is that it is reconfigurable. A variety of surface shapes can be realized by properly adjusting the heights of surface tool elements[14,15]. The total time involved in the tool set up is considerably less than that involved in the development of a hard tool[16,17]. The discrete nature of the tool can be overcome by placing a rubber interpolator between the pins and the blank.

To apply for the proposed approach a simulation model was developed using Dynaform finite element software. The model was constructed considering the obtaining of plate with single curvature (Fig. 2). Figure 3 shows the simulation model, in different deformations stages. The model includes two rigid discretized active elements and the two interpolators (upper and down rubber) between these and the blank. No blankholder has used so the ends of the rubbers are free to expand.

The figure shows the complexity of the deformation process which is developing during the forming considering both the deformation of the rubber interpolator and the blank. The rubber and the sheet are deforming gradually, from the initial step (a) until the last step (b). In the first steps of the deformation process, the rubber interpolator bends, the upper rubber in a higher degree then the down rubber. In the area of contact between the rubber and the pins, the rubber material fills the gaps between the pins, the higher degree of fillings appearing at the end of the deformation process.

The variables defining the process-tooling-blank system are: The target values dimensions are: length B_i = 120 mm, depth H_i = 21.345 mm, (radius R_i = 95 mm) (Fig. 2). The width is 130 mm.

The blank lenght is 129.883 mm and width is 130 mm.

Perturbed variables

Each perturbed variable has a domain of disturbance that is either tolerated according to the standards or is determined by the designer. To study the influence of the perturbed variables upon the springback minimization we will consider their variations. So, (i) thickness of blank material, t, varies between 0.8 and 1.2 mm, (ii) material characteristics, K. The material characteristics results from the power law of material yielding:

$$\sigma = K\,\varepsilon^{n} \quad \dots (2)$$

where: K is the above parameter; n is hardening exponent. Material characteristic, K, varies between 616 and 680 MP; and (iii) friction coefficient, μ, varies between 0.1 and 0.15.

Manipulated variables

Manipulated variables are those whose values can be changed in a controlled manner by the process and equipment designer. Each variable has a domain in which the variable value can be manipulated by the designer. For springback reduction, next manipulated variables are used: (i) pins stroke or the punch stroke, s, varies between 17 and 29 mm, according to interpolator thickness; (ii) rubber thickness, t_R, varies between 2 and 10 mm; (iii) rubber elastic modulus, E_R, varies between 14 and 44 MPa.

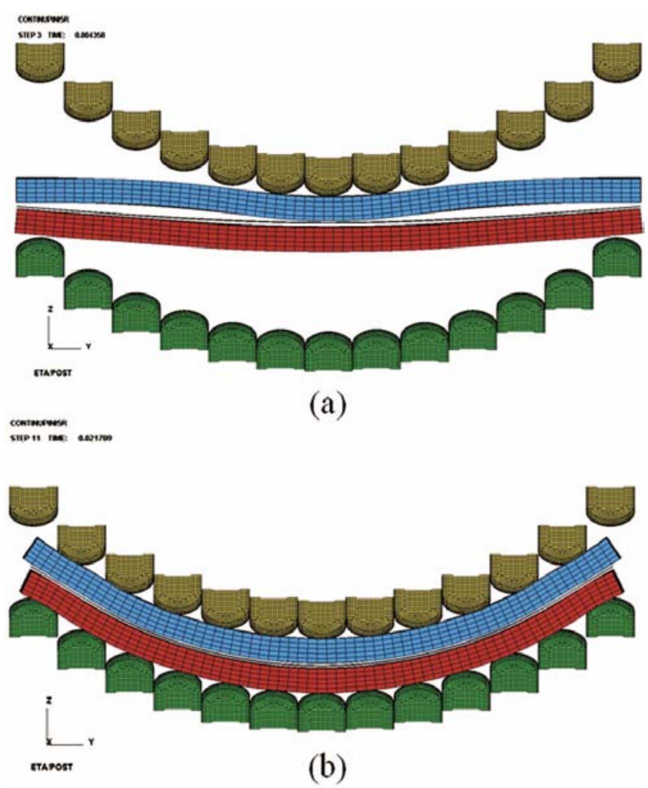

Fig. 3—Simulation model (a) initial step and (b) final step

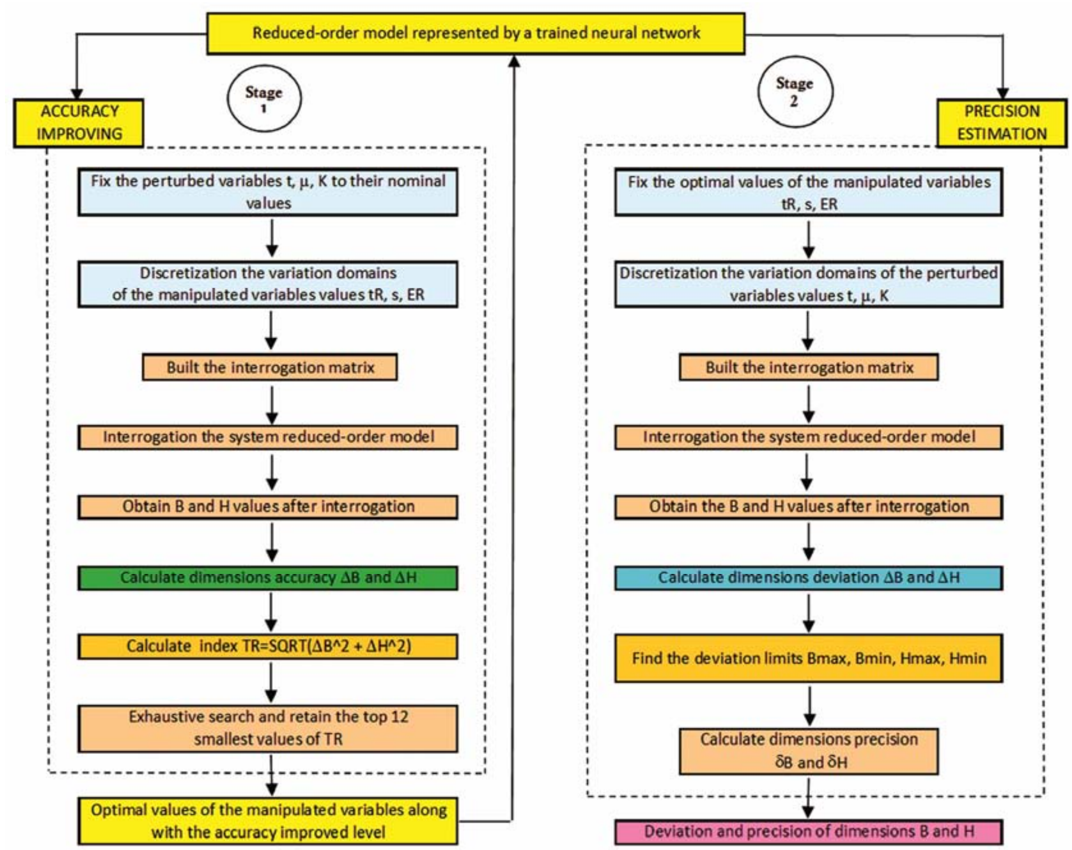

Fig. 4—Optimization algoritm optimized springback reduction approach

Fixed variables

These variables didn't change neither during material processing stage nor during process preparation stage. In the present case, the fixed variables are:

(i) Dimensions desired values. The part is a sheet with single curvature with a width of B_{tp} = 120 mm, a maximum depth H_{tp} = 21.345 mm (radius of 95 mm), and a length of 130 mm;
(ii) The material hardening exponent n was 0.22. The R anisotropy coefficients values were set to: R_{00} – 1.87; R_{45} – 1.27; R_{90} – 2.17.
(iii) The FE blank mesh consists of 4-node Belytschko-Lin-Tsay shell elements, with five integration points through the thickness of the sheet[4].
(iv) The punch speed was 100 mm/s.
(v) The tool is model as rigid surfaces. The geometrical model of die-punch tool is composed from two working arrays with 100 pins for each array, 10 rows on x-direction and 10 rows on y-direction. The pins are disposed face to face, both on x and y-direction.
(vi) For rubber interpolator was chosen a material type Elvax 460. The material data were: density, ρ=0.946 g/cm^3; hardness Shore ASTM D2240 scale B – 40 and scale A – 80; tensile strength, R_m=18 MPa; elongation 750%; stiffness, k=43 MPa; Poisson ratio, ν=0.499. Solid elements were use for the rubber interpolator mesh. The interpolator was modeled as Mooney Rivlin Rubber material.

Controlled variables

The controlled variables are those product dimensions, which are important for its function, and for this reason are restricted to a small interval called the tolerance domain: (i) dimensions accuracy, ΔB and ΔH; (ii) dimensions errors E_{psB} and E_{psH}, are those errors that remain uncompensated, considering the variation of dimensions target values; and (ii) overall part accuracy index, T_R. This criterion refers to the error minimization due to springback values, ΔB and ΔH.

Application of Optimized Springback Reduction to Multipoint Forming

Figure 4 presents the method flowchart. The start point is the reduced-order model of the blank-process-tooling system, while the end is the optimal values of system parameters for which the accuracy and precision of the part tolerated dimensions have their best values. Finally, by comparing the domain of tolerance with the real domains of variation, for each tolerated dimension of the part, the errors are estimated at batch and part level. The best result is chosen as problem solution. The two steps are:

Accuracy improving

In this stage for optimized springback reduction the variation domains of the manipulated variables are divided in small increments. The perturbed variables, t, μ and K are fixed to their nominal values (1; 0.125; 648 respectively).

For dimensions error estimation an interrogation matrix is built. The system reduced-order model represented by the trained network will be interrogated using this matrix (Fig. 4, left). Table 1 shows the first 12 values of the manipulated variables which were used in interrogation. The interrogation results will be the dimensions values of B_1 and H_1, as the basic output variables, presented in Table 2.

The dimensions accuracy, ΔB and ΔH, as the synthetic variables, are obtained as:

$$\Delta B = B_1 - B_{tp} \quad \text{... (3)}$$

$$\Delta H = H_1 - H_{tp} \quad \text{... (4)}$$

where B_1 and H_1 are the real values of the dimensions after springback; B_{tp} and H_{tp} – dimensions desired values.

Table 1—Values of manipulated variables used in interrogation matrix (partial)

No.	Manipulated variables Interpolator and process parameters		
	Rubber Thickness, t_R, (mm)	Pins stroke, s, (mm)	Rubber elastic modulus, E_R, (MPa)
1	7	27.5	44
2	7	27.5	42
3	7	27.5	40
4	7	27.5	38
5	4	23.5	44
6	7.5	27.5	44
7	7	27.5	36
8	5.5	25.0	44
9	7.5	27.5	42
10	7	27.5	34
11	4	23.5	42
12	7.5	27.5	40

Overall part accuracy index is given by:

$$TR = \sqrt{\Delta B^2 + \Delta H^2} \quad \text{... (5)}$$

The optimal values of the manipulated variables are finding using exhaustive search technique.

According to TR index, using the exhaustive search, Table 3 presents the top 12 smallest resulted interrogation values, in ascending order.

It is considering that the optimal values of the manipulated variables along with the accuracy improved level are the triplet (7; 27.5; 44). The deviation corresponding to this optimal triplet of manipulated variables is the dimension accuracy.

Precision estimation

In this stage the discretized search space refers to the perturbed variables and their domains of

Table 2—Values of basic output after reduced order model interogation (partial)

No.	Basic output variables	
	B_1	H_1
1	120.7781	21.42676
2	120.8532	21.34187
3	120.9294	21.25418
4	121.0071	21.16334
5	120.9907	20.91263
6	121.0827	21.09209
7	121.0867	21.06891
8	121.1156	20.92315
9	121.162	20.99941
10	121.1685	20.97039
11	121.1006	20.78136
12	121.2427	20.90378

Table 3—The error level obtained by applying the optimized springback redcution approach (partial)

No.	Synthetic variables: dimensions error and overall part error for the top 12 best sets of manipulated variables values		
	ΔB	ΔH	TR
1	0.77809	0.08176	0.782374
2	0.85317	-0.00313	0.853176
3	0.92941	-0.09082	0.933837
4	1.00711	-0.18166	1.023363
5	0.99066	-0.43237	1.080903
6	1.0827	-0.25291	1.111847
7	1.08666	-0.27609	1.121185
8	1.11559	-0.42185	1.192685
9	1.16204	-0.34559	1.21234
10	1.16849	-0.37461	1.22707
11	1.10064	-0.56364	1.236567
12	1.24267	-0.44122	1.318675

perturbation. For this, the system reduced-order model represented by the trained network will be interrogated with the above triplet of optimal values (7; 27.5; 44), (Fig. 4, right).

The tool geometry will remain constant at his desired values of the part dimensions (120; 21.345). The perturbed variables domains will be divided in small increments. An interrogation matrix will be built.

Table 4 presents the input variables values, used in network interrogation. The result of the interrogation will be the dimensions values of *B* and *H*, as the basic output variables (Table 5).

The dimensions deviations, ΔB and ΔH, as the synthetic variables, are given by:

$$\Delta B = B_2 - B_{tp} \quad \ldots (6)$$

$$\Delta H = H_2 - H_{tp} \quad \ldots (7)$$

Table 4—Values of perturbed variables used in interrogation matrix (partial)

No.	Perturbed variables		
	Material thickness, *t*, (mm)	Friction coefficient, μ	Material characteristic *K*, (MPa)
1	0.9	0.1	647
2	0.9	0.1	647.5
3	0.9	0.1	648
4	0.9	0.1	648.5
5	0.9	0.1	649
6	0.9	0.1125	647
7	0.9	0.1125	647.5
8	0.9	0.1125	648
9	0.9	0.1125	648.5
10	0.9	0.1125	649
11	0.9	0.125	647
12	0.9	0.125	647.5

Table 5—Values of basic output after reduced order model interogation (partial)

No.	Basic output variables	
	B	*H*
1	121.9753	19.9327
2	121.993	19.90987
3	122.0108	19.88696
4	122.0286	19.86398
5	122.0465	19.84095
6	121.4091	20.59794
7	121.4225	20.5816
8	121.4362	20.56487
9	121.4502	20.54777
10	121.4645	20.53028
11	121.1507	20.86448
12	121.1571	20.85716

where B_2 and H_2 are the dimensions after springback; B_{tp} and H_{tp} – dimensions desired values.

The dimensions precision, defined as the difference between the extreme values of the dimension deviation, evaluated in the points defined in this space, δB and δH, are given by:

$$\delta B = \Delta B_{max} - \Delta B_{min} \quad \ldots (8)$$

$$\delta H = \Delta H_{max} - \Delta H_{min} \quad \ldots (9)$$

where ΔB_{max}, ΔB_{min} and ΔH_{max}, ΔH_{min} –extreme dimensions deviation.

Table 6 presents the corresponding resulted output values of the variables according to Table 5, after network interrogation.

In the two columns of the synthetic variables ΔB and ΔH from Table 6, we will search for the maximum values respective the minimum values of them. These extreme values represent the deviation limits.

Using the relations (8) and (9) it results the dimension precisions, δB and δH, which are presented in Table 7.

The maximum errors for the optimized springback reduction approach is $\varepsilon B_{max}^{opt} = 2.046$ mm.

Table 6—Dimension deviations obtained by applying the optimized springback reduction approach (partial)

No.	ΔB	ΔH
1	0.77809	0.08176
2	0.85317	-0.00313
3	0.92941	-0.09082
4	1.00711	-0.18166
5	0.99066	-0.43237
6	1.0827	-0.25291
7	1.08666	-0.27609
8	1.11559	-0.42185
9	1.16204	-0.34559
10	1.16849	-0.37461
11	1.10064	-0.56364
12	1.24267	-0.44122

Table 7—Precision level in optimized springback reduction approach

Deviation limits for dimension *B*:	Deviation limits for dimension *H:*
ΔB_{max} =2.04652 ΔB_{min} =0.59698	ΔH_{max} = 0.2664 ΔH_{min} = -1.50405
Precision of dimension *B*	Precision of dimension *H*
δB = 1.44954 mm	δH = 1.77045 mm

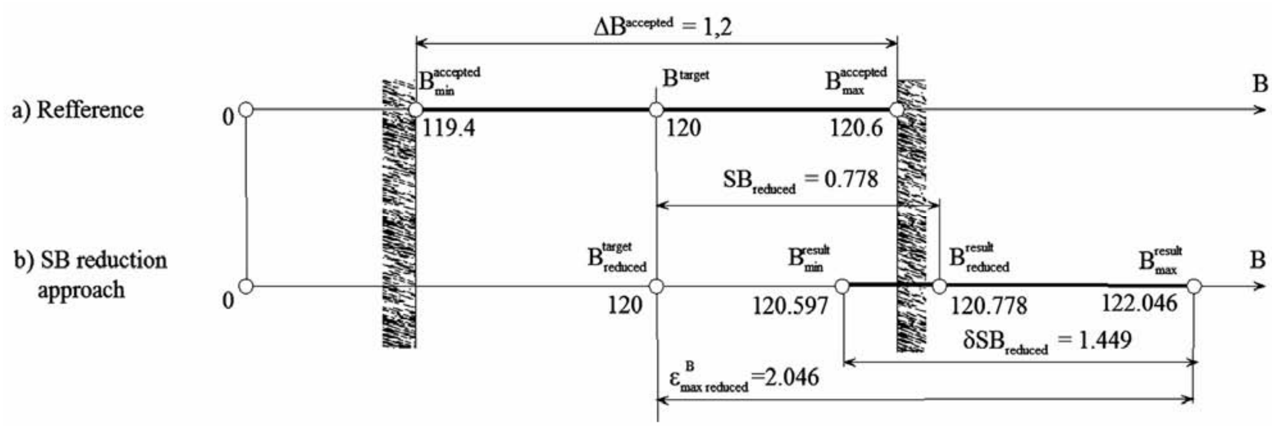

Fig. 5—The result of the optimized springback reduction approach

Table 8—The approach results for the optimized springback reduction approach

	Accuracy		Precision	
	EpsB	*EpsH*	*δB*	*δH*
Optimized springback reduction	0.778	0.081	1.449	1.770

Table 8 and Fig. 5 show the approach result.

According to Eq. (1) and based on the obtained results, the function F_{minim} has in this case the value of 1.5525. This function is not less then $\frac{1}{2}\Delta B^{accepted}$ which is equal with 0.6 mm in this case.

It results that for the used data set, the springback reduction approach is not effective. Another method must be used.

On the other hand, the range of tolerance value for a normal operation in sheet metal forming is 2 mm. That is way the obtained results could be considered as acceptable.

Conclusions

In the paper, an integrated-optimal approach is developed for offline control of springback applied in sheet multipoint forming with interpolators and included the three main stages, e.g., simulation, reduced-order modelling and optimization. The strategy of the integrated-optimal approach is applied to a new control approach, e.g., optimized springback reduction. The application of the new approach for optimal springback-based dimensional control to reconfigurable multipoint forming is presented.

A series of FEM simulation were performed. Based on this a reduced-order model of the blank-process-tooling system at whole was designed. For optimization, the designed reduced order model was used. Different values of the variables were used for reduced order model interrogation. Using the exhaustive search the part accuracy and precision were evaluated by considering the system parameters values as belonging to their tolerated domains of variation. The application of the integrated-optimal approach shows the dimension precision importance and the fact that untill now this output parameter was not considered. The obtained results could be considered acceptable for a part with a normal precision.

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