파라메터 분석을 통한 차체용 고강도 강판의 스프링백 최적화

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Optimization of High Strength Steel Springback for Autobody through Parametric Analysis

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Key Words : springback, finite element method, orthogonal array, missing value, signal-to-noise

Abstract

최근 자동차 경량화를 위한 부단한 노력이 진행되고 있다. 이 목적에서, HSS (high strength steel)는 전통적인 연강(mild steel)의 대안으로 널리 사용되고 있다. 본 연구의 목적은 판금의 형단조에 있어서의 공구와 공정설계를 위하여 HSS의 스프링백(springback)을 정확히 예측하기 위한 성공적인 방법론을 추구하고자 함이다. 연구를 위하여 먼저 스프링백의 개념과 그의 측정치들을 설명했으며 U-draw bending 시험을 수행하였다. 시험 결과 및 선정된 파라메터들 중심의 수행평가기준에 근거하여, 주어진 파라메터 조합들을 중심으로 유한요소 해석을 수행하였다. 직교배열을 통하여 스프링백에 대한 인자 효과들을 포괄적으로 분석하였으며 최적 인자 조합들을 도출하였다. 이 과정에서 직교배열상의 한 조합 전체의 데이터가 가용하지 않는 문제가 수반되었으며, 반복적으로 signal-to-noise 비(ratio)를 개선해가는 기법을 적용하여 해결하였다.

1. 서 론

With growing efforts to reduce the weight of automobiles, a diversity of new technologies for parts manufacturing have been developed and applied in field exercises. Substituting high strength steel (HSS) for conventional mild steel to reduce the weight-to-strength ratio is recognized as an effective way to achieve this goal and is increasingly being used. Elastic recovery, especially in sheet metal forming process, is an additional deformation of the material to reach a new static equilibrium after compulsorily formed and extracted from a forming die. Elastic recovery after bending is one of the representative phenomena of steel and is called 'springback'. In general, the degree of shape change is proportional to the strength of the material. This requires one or more additional sizing processes to increase the accuracy of dimensions, and thus demands increased effort, time, and cost from design to mass production stages. Since HSS has inferior formability to conventional steels, maintaining the balance to eliminate a local excessive deformation serves as an essential factor in forming processes.

To overcome these problems and thus to produce parts successfully, more accurate and effective design capabilities for both die manufacturing and

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forming process are required. The most widely adopted tool for this purpose is the finite element analysis for forming process and springback diagnosis. Since numerous process variables, or numerical parameters, are involved in determining the results of finite element springback analysis, proper selection of their combinations is a difficult task. Numerous studies have been performed on this matter[1-7]. They are to investigate variable/ factor effects, accuracy in results, or sensitivity of springback based on finite element method.

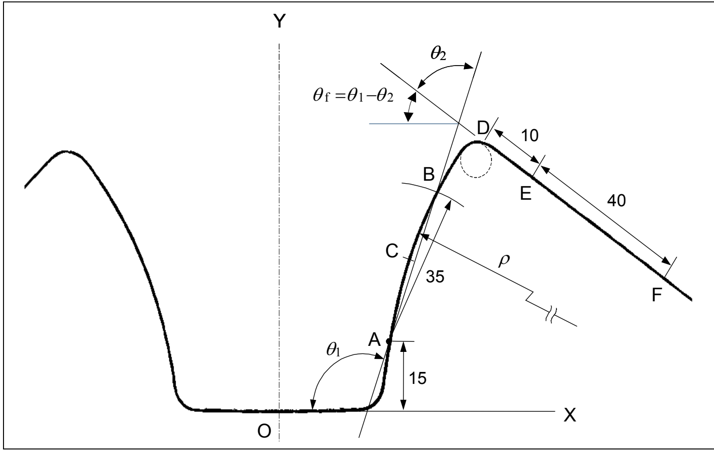
The ultimate goal of this study is to secure a methodology to predict and reduce the springback of HSS through the evaluation of its springback characteristics. Specifically, we want to obtain an approach for finding the optimal combination of input variables or explanatory factors minimizing numerical errors through a systematic and effective parametric study. We first explained the springback measures and performed U-draw bending tests. We drew parameters that might have significant effects on the springback results of finite element analysis. We then evaluated the springback processes using finite element method. Taguchi's parameter design[8,9,10] approach has been applied for quantitative analyses of factor effects to find the best factor combination yielding the closest results to the tests.

II. Springback Measures and U-Draw Bending

Figure 1 defines the geometric factors of springback, i.e. bottom springback angle θ_1, top springback angle θ_2, flange angle $\theta_f(=\theta_1-\theta_2)$, and radius of curvature of side-wall curl ρ. The ideal case with no springback will have $\theta_1=\theta_2=90^\circ$, $\theta_f=0^\circ$, and $\rho=\infty$. The amount of springback is seen to be large when θ_1 and θ_f are large or θ_2 and ρ are small.

The specimen was prepared by cutting a HSS-40 high strength steel sheet of tensile strength 40kgf/mm^2 into a size of 350 mm length and 35 mm width, then burrs were eliminated. A die set with structure and dimensions given in NUMISHEET '93[11] was prepared for our test. It is the most widely used test or analysis model for the evaluation and prediction of sheetmetal springback characteristics. As a plane-strain U-draw bending model, it is simple and generates a close representation of springback characteristics for different structures. Before test a lubricant was coated on the blank surface to form a thin and uniform membrane. Figure 2 shows the die set and the specimens (after springback) formed under different blank holding conditions.

Our test results show precise repetitions of springback angles, θ_1 and θ_2, but large variability in ρ. This may stem from the geometric characteristic

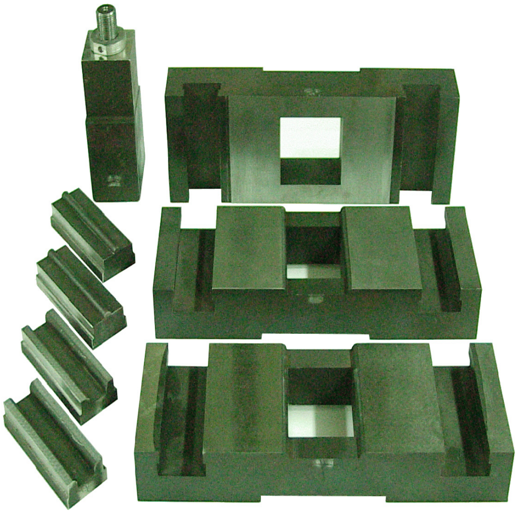


[Springback]
θ_1: angle between OX and AB
θ_2: angle between AB and EF

[Curvature]
ρ: radius of a circle through A, B and C

[Point]
A: 15mm from AB
B: 35mm from A
C: middle point of the straight line AB
D: end of die's curve
E: 10mm from D
F: 40mm from E

Figure 1. Geometric parameters defining springback



a) Tool set

b) Deformed specimens

Figure 2 a) Tool set and b) Deformed specimens

of the radius of curvature. That is, significant errors may be caused by minor errors in the position of points A, B, and C which simultaneously determine the arc ACB in Figure 1.

III. Analysis by Experimental Design

Next we seek the optimal geometric variable levels which yield the value nearest to the value of the experimental results through experimental design analysis.

3.1 Selection of a Measure and Parameters

We may select the geometric parameters, i.e. the springback angles (θ_1, θ_2) and the radius of curvature of side-wall curl (ρ), which simultaneously determine the magnitude of springback, as the candidates for performance measure. The curvature radius (ρ) was eliminated since it is sensitive to minor errors incurred in the parameter values. In this study, we selected the flange angle $\theta_f (= \theta_1 - \theta_2)$ as the major performance measure for analysis. The experimental result for θ_f was 16.11, the average value from U-draw tests, and this value is assumed to the target value (nominal). Since any deviation from this value is seen to be undesirable, θ_f is classified as NTB (nominal the best) quality characteristic.

Five explanatory factors (three modeling and two numerical variables) are considered to be the most significant in forming and springback results and they are as follows:

① BES - blank element size,
② NIP - number of integration points,
③ PV - punch velocity,
④ PP - penalty parameter[12], and
⑤ CDP - contact damping parameter[12].

For each factor above, three levels have been selected within appropriate ranges and they are given in Table 1.

Table 1. Parameters and levels for the experiments

Factor (unit)	Level 1	Level 2	Level 3
BES (mm)	0.5	1.0	1.5
NIP	5	9	13
PV (m/s)	2	5	10
PP	0.01	0.03	0.05
CDP	0.05	0.10	0.20

3.2 Design of Experiments

A total of 243 (=2^5) combinations is required for 5 factors and 3 levels each above. In this study, we consider Taguchi's orthogonal array $L_{18}(2^1 \times 3^7)$[8,9,10] to reduce both the number of treatment combinations and computation time. Five factors, BES, NIP, PP, PV, and CDP are arranged in columns 2, 3, 4, 5 and 7, respectively. With the assumption of negligible interactions between factors, note that three columns in the table are empty.

We are now to perform experiments and analyze the results. For this purpose, we applied finite element method for forming and springback analyses with the commercial code PAM-STAMP[12]. It is generally true that the experimental results vary even for the same experimental condition. Numerical analysis, however, generates the same result for a given factor-level combination. Stress-time curves obtained from the forming analysis reveal an oscillating pattern and this distribution may serve variability. For this reason, we varied the completion time in forming analysis to introduce artificial variability in the stress results. We paused and continued forming analysis and evaluated springback at 8 different times within a wave length of the stress oscillation using the restart function of PAM-STAMP.

3.3 Results and Analysis

We have performed finite element analyses for forming and springback processes with five punch strokes for each of 18 treatment combinations given in the orthogonal array, $L_{18}(2^1 \times 3^7)$. Table 2 summarizes the detailed results about springback parameters. In the table, S/N (signal-to-noise) ratio represents the variability and Sm measures the experimental sensitivity to the target value. Columns 2 through 6 of the table represent factor levels considered in the experiment. Average, standard devia-

Table 2. Experimental results

Run	BES	NIP	PP	PV	CDP	1	2	3	4	5	Average	S/N	Sm
1	1	1	1	1	1	11.54	11.50	11.80	11.74	11.72	11.66	38.93	28.32
2	1	2	2	2	2	18.60	18.67	18.75	18.72	18.75	18.70	49.34	32.43
3	1	3	3	3	3	18.87	18.95	18.93	18.98	19.01	18.95	51.05	32.54
4	2	1	1	2	3	19.40	19.52	19.48	19.52	19.56	19.50	50.14	32.77
5	2	2	2	3	1	17.90	18.00	17.89	17.89	17.88	17.91	51.14	32.05
6	2	3	3	1	2	18.40	18.45	18.57	18.55	18.54	18.50	48.04	32.33
7	3	1	2	1	2	15.43	15.15	15.21	15.30	14.44	15.11	31.83	30.57
8	3	2	3	2	3	16.35	16.29	16.20	16.28	16.24	16.27	49.22	31.22
9	3	3	1	3	1	16.39	16.46	16.62	16.63	16.48	16.52	43.93	31.35
10	1	1	3	3	2	20.31	20.32	20.35	20.36	20.38	20.34	56.98	33.16
11	1	2	1	1	3	-	-	-	-	-			
12	1	3	2	2	1	19.01	19.09	19.15	19.15	19.17	19.11	49.31	32.62
13	2	1	2	3	3	18.97	19.00	19.03	18.99	18.93	18.98	54.17	32.56
14	2	2	3	1	1	18.32	18.43	18.52	18.52	18.46	18.45	46.99	32.31
15	2	3	1	2	2	14.68	16.77	14.74	14.78	14.73	15.14	24.40	30.59
16	3	1	3	2	1	14.63	14.67	12.87	14.72	14.78	14.33	24.84	30.12
17	3	2	1	3	2	16.16	16.30	16.40	16.40	16.27	16.31	44.21	31.24
18	3	3	2	1	3	16.34	16.39	16.63	16.86	16.89	16.62	36.25	31.40

tion, S/N, and Sm are then summarized. The mathematical definitions of them are given in Equations (1) and (2), and units of S/N and Sm are both db (decibel).

$$S/N = 10\log_{10}[\frac{1}{n} \cdot \frac{n(\bar{y})^2 - S^2}{S^2}] \quad (1)$$

and

$$S_m = 10\log_{10}(n\overline{y^2}) \quad (2)$$

where n is the number of data within a treatment combination, and $\bar{y}$ and s^2 are the sample average and the sample variance defined by $\bar{y} = \sum y_i / n$ and $s^2 = \sum (y_i - \bar{y})^2/(n-1)$, respectively.

One problem in the analysis lies in that the whole set of results for treatment combination 11 is missing (or infeasible). The reason for this has not been clarified and estimates for this combination are needed for analysis. An empirical scheme, which iteratively updates the missing values (S/N and Sm) until a specified condition holds, was applied in this study. For the convergence criterion to stop the iteration, the relative error ratio between two successive estimates has been adopted. That is, if the condition

$$\left| \frac{y(k) - y(k+1)}{y(k)} \right| \times 100 < 0.01\% \quad (3)$$

holds for both S/N and Sm at some iteration, then we stop. Current y(k) is optimal, where y(k) represents the approximate value made at iteration k. The magnitude 0.01% is somewhat arbitrarily established but is sufficient for verifying convergence.

We now apply the sequential approximations for analysis. We first evaluate the average values of S/N and Sm from the 17 values in the table and set them to be the initial estimates as follows:

$$S/N_{11}(0) = \frac{38.93 + 49.34 + 51.05 + ... + 36.25}{17} = 44.16$$

and

$$Sm_{11}(0) = \frac{28.32 + 32.43 + 32.54 + ... + 31.40}{17} = 31.62$$

We consider them the experimental results of treatment combination 11 and evaluate ANOVA's (analysis of variance) with 18 values including the S/N and Sm estimates. The results are given in Table 3. Note that each factor has 2 df (degrees of freedom) while df of the error term is 7.

Table 3. ANOVAs for estimated S/N and Sm

$S/N_{11}(0) = 44.16$

Source	SS	df	MS	F
BES	319.35	2	159.68	2.01
NIP	102.09	2	51.05	0.64
PV	333.05	2	166.52	2.10
PP	94.36	2	47.18	0.60
CDP	100.12	2	50.06	0.63
Error	554.99	7	79.28	
Total	1503.96	17		

$Sm_{11}(0) = 31.62$

Source	SS	df	MS	F
BES	4.01	2	2.00	1.52
NIP	1.23	2	0.62	0.47
PV	3.34	2	1.67	1.26
PP	3.66	2	1.83	1.39
CDP	2.48	2	1.24	0.94
Error	9.26	7	1.32	
Total	23.98	17		

The results in the table indicate that BES and PV have relatively large effects while the others have less significant impacts on S/N. For Sm, on the other hand, BES, PV, and PP have more dominant influences than NIP or CDP. These results may lead us to use only significant factors in updating S/N and Sm at an intermediate step. In this study, however, all the five parameters with their levels in combination 11 will be used. This eliminates the efforts to check the significance of the parameter effects at each iteration.

We reestimate S/N and Sm based on the experimental condition given in treatment combination 11 as follows:

$$S/N_{11}(1) = BES_1 + \ni P_2 + PV_1 + PP_1 + CDP_3 - 4\frac{\sum_{i=1}^{18} S/N_i}{18} = 48.30 + 47.51 + 41.04 + 40.96 + 47.50 - 4(44.16) = 48.65$$

and

$$Sm_{11}(1) = 31.78 + 31.81 + 31.09 + 30.99 + 32.02 - 4(31.62) = 31.20$$

BES_1, in the equations represents the average value of S/N (or Sm) evaluated at level 1 of BES. The others are evaluated in the same manner. The relative error ratios (ER) for S/N and Sm are now computed by

$$ER(1)_{S/N} = \left|\frac{44.16 - 48.64}{44.16}\right| \times 100 = 10.16\%$$

and

$$ER(1)_{Sm} = \left|\frac{31.62 - 31.20}{31.62}\right| \times 100 = 1.33\%$$

Both are larger than the tolerance limit set in Equation (3). We decide to proceed to update the estimates. process terminates at iteration 10 and Table 4 shows intermediate results of S/N and Sm estimates with error ratios during iterations. The final estimate for S/N and Sm are 55.56 and 30.55, respectively. ANOVA results obtained with the estimates for S/N and Sm are given in Table 5.

Table 4. Intermediate estimates of S/N and Sm

k	S/N		Sm	
	S/N(k)	ER(k) (%)	Sm(k)	ER(k) (%)
0	44.16	-	31.62	-
1	48.65	10.16	31.20	1.33
2	51.39	5.63	30.94	0.83
3	53.06	3.26	30.79	0.51
4	54.09	1.93	30.69	0.31
5	54.71	1.16	30.63	0.19
6	55.10	0.70	30.59	0.12
7	55.33	0.42	30.57	0.07
8	55.47	0.26	30.56	0.04
9	55.56	0.16	30.55	0.03
10	55.61	0.096	30.55	0.02

Table 5. ANOVA results for a) S/N and b) Sm

a) S/N

Source	SS	df	MS	F
BES	427.95	2	213.97	2.98
NIP	192.81	2	96.40	1.34
PV	276.18	2	138.09	1.92
PP	35.84	2	17.92	0.25
CDP	190.56	2	95.28	1.33
Error	503.27	7	71.90	
Total	1626.61	17		

b) Sm

Source	SS	df	MS	F
BES	3.80	2	1.90	1.51
NIP	0.96	2	0.48	0.38
PV	4.60	2	2.30	1.83
PP	5.16	2	2.58	2.05
CDP	1.75	2	0.88	0.70
Error	8.80	7	1.26	
Total	25.07	17		

From the ANOVA results, the relative impacts on S/N and Sm may be given in descending order BES→PV→NIP/CDP→PP and PP/PV→BES→CDP→NIP, respectively. Even if BES has a dominant effect on S/N results over the others, PV, NIP, and CDP also show significance. PP, however, is observed insignificant. Similarly, PP, PV, and BES show stronger effects, but CDP and NIP seem to have less significant effects on Sm. Table 6 and Figure 3 display the average response results of S/N and Sm in terms of each factor level. (In a strict sense, no factor is considered significant since all the F ratio results in the table fall within 90% confidence interval. Nevertheless, our discussion is made based on their relative magnitudes.)

We may draw some important observations from the results. First, as seen in Figure 3, S/N and Sm show both linear and quadratic trends of the parameters. Sm, for instance, increases linearly as the levels of PV, NIP and CDP increase but also shows quadratic form in terms of BES and PP. This indicates that our original consideration of three levels for each parameter was reasonable. Second, from the comparison of relative significances of all five factors, PP is classified as the adjustment factor whose optimal level may be determined through sequential evaluations of the results by varying its level but maintaining fixed levels of the other factors. This is because it has a strong effect on Sm but an insignificant effect on S/N. Third, BES and PV have significant impacts on both variability and mean of θ_f. For instance, while θ_f is observed most stable at BES level 1 among the levels considered, a significant change in the average value of θ_f may be expected from a minor change in BES. Finally, NIP and CDP have significant impacts only on S/N but not on Sm.

Table 6. Average response tables for a) S/N and b) Sm

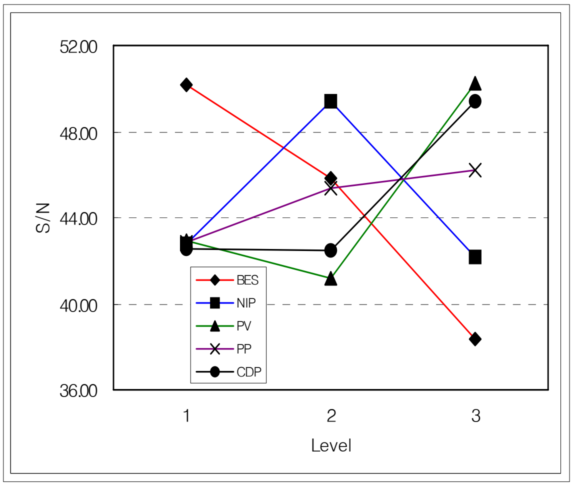
a) S/N

Level	BES	NIP	PV	PP	CDP
1	50.19	42.81	42.93	42.86	42.52
2	45.81	49.41	41.21	45.34	42.47
3	38.38	42.17	50.25	46.19	49.40

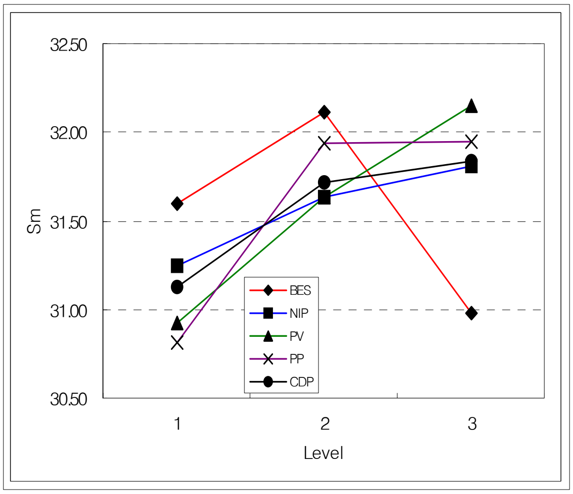
b) Sm

Level	BES	NIP	PV	PP	CDP
1	31.60	31.25	30.92	30.81	31.13
2	32.11	31.63	31.63	31.94	31.72
3	30.98	31.81	32.15	31.95	31.84

We then seek the optimal factor-level combination. Even if some desirable information was drawn, selection of the optimal levels is not easily made. This is due in part to the complicated interactions between parameters as well as linear and quadratic effects of individual parameters. For robust results of θ_f, we first select the level 1 of BES (BES_1) then NIP_2 and CDP_3 which produce a large S/N ratio but not in Sm. Selection of appropriate levels of PV and PP is not clear, since PV has significant impacts on both S/N and Sm, and PP is the adjustment factor. We examined the results for different levels PP and PV and PP_1 and PV_2 are selected as the best. The optimal levels are thus given by BES_1, NIP_2, PV_2, PP_1, and CDP_3 (BES=0.5, NIP=9, PV=5, PP= 0.01, and CDP=0.2).



a) S/N



b) Sm

Figure 3. Average response graphs for a) S/N and b) Sm

Our final consideration is to estimate S/N and average θ_f results at the optimal condition. The latter, unfortunately, is not directly estimated since the whole set of data was missing, and the estimate of the former is computed by

$$
\begin{aligned}
&\widehat{S/N} \\
&= \widehat{BES}_1 + \widehat{\ni P}_2 + \widehat{PV}_1 + \widehat{PP}_1 + \widehat{CDP}_3 - 4\widehat{\mu_{S/N}} \\
&= 50.19 + 49.41 + 41.21 + 42.86 + 49.40 - 4(44.80) \\
&= 53.88
\end{aligned}
$$

We may estimate Sm in a similar manner and the result is given by $\widehat{S_m} = 31.26$. The estimate of the mean of θ_f, from Equation (2), is now obtained by

$$\widehat{\mu_{\theta_f}} = \sqrt{\frac{10^{\widehat{S_m}/10}}{n}} = 16.34$$

The standard deviation of θ_f from Equations (1) and (2) may be estimated by 0.033, or coefficient of variation 0.002 which is small enough for robustness.

To validate the optimal combination obtained from the penalty contact treatment method, we performed confirmation experiments at the optimal condition and the average value of θ_f was 16.50 which is close to the target value. We now conclude that the optimal parameter levels obtained may be freely used to generate robust results.

IV. Conclusion

We have performed extensive analyses on the evaluation of the springback characteristics of automobile high strength steel in this study. Our specific goal was to find the optimal combination of the explanatory factors minimizing numerical errors through a systematic parametric study. We selected $\theta_1 - \theta_2$ as the performance measure and five input parameters for the experimental analysis. Based on the orthogonal array, $L_{18}(2^1 \times 3^7)$, we have performed experiments and extensive analyses of the factor effects on the objective function. We applied the finite element methods for forming and springback analyses. We drew the optimal level combination of the factors and its performance through additional runs was examined. The results from this study not only provide a close estimate of springback, but also serve as a guideline to set optimal numerical parameters for forming and springback analysis.

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