Optimization of Incremental Sheet Metal Forming Process using Grey Relational Analysis

Meftah Hrairi, Jamal I. Daoud, Faiz Zakaria

Abstract--- ***The incremental sheet forming (ISF) process has features that are adaptable to a great variety of applications and demands without relying on dies and punches. However, some features of incremental sheet forming part quality can be unsatisfactory if the forming process parameters are not adequately chosen. In this paper, a Taguchi-based Grey optimization of the incremental sheet forming process is presented for the purpose of determining a combination of optimal process parameters that will result in a high part quality with many favorable characteristics, such as the wall angle, the surface roughness, and the springback. Signal-to-noise ratio (S/N) and Taguchi's L18 orthogonal array design were the basis for obtaining the objective function. The impact of individual factors on the final output was determined with Analysis of variance (ANOVA). The study supplied the optimal process parameters. Indeed, the vertical step depth with contribution value of 68.5% followed by the tool diameter with 9.7% contribution, and number of sheets with 6.1% contribution were found to be the most influential parameters on the three responses taken together. Consequently, the other two parameters (spindle speed and feed rate) were deemed non-significant with contribution of 2.9% and 1%, respectively. In addition, the graphs and response tables that resulted from ANOVA and Taguchi analysis together form an efficient and effective method of finding optimal levels for each design parameter. With optimized parameters, the ideal value of wall angle and the minimum values of springback and surface roughness are produced. Finally, confirmation testing, using suggested optimal conditions, showed a GRG value with 27.4% improvement. It can thus be concluded that the use of the multi objective optimization of wall angle, surface roughness and springback in the proposed Grey-Taguchi method is suitable for optimizing the ISF process and is additionally effective for use in other metal forming processes.***

Keywords: ***Grey-relational; Incremental sheet forming; Optimization; Metal forming; Multi-objective; Taguchi***

1. INTRODUCTION

Incremental sheet forming (ISF) is used to manufacture parts out of sheet metal. The process is suitable for low volume production as well as the creation of prototypes [1, 2]. ISF can yield complex sheet parts without dedicated dies because it employs a moving single point tool fixed to a standard 3-axis CNC machine. Incremental sheet forming is a more useful process for small and medium production quantities, including those necessary for rapid prototyping. This is due to the process' key advantages of eliminating conventional dies and molds, using existing CNC machines, having low costs of production, accommodating rapid design alterations, interlinking with CAD files, and resulting in parts with lower induced stresses, excellent surface finish, dimensional versatility, and high material formability [3]. Single stage single point incremental forming (SPIF) can support greater strains than other traditional sheet forming processes. When single-stage SPIF is performed, the process is limited by deformation types that are near the strain plane. Multistage forming is a strategy that is frequently employed in parts with near-straight angled walls in order to avoid excessive thinning for parts having almost straight wall angles (angles > 60°), to combat thinning within the part walls [4].

In ISF, the forming tool's path greatly influences the distribution of the sheet thickness. It also goes a long way towards determining the part's formability, surface finish, and dimensional accuracy. Other factors, such as tool radius, spindle speed, step down unit, and lubrication system also play a role in determining the surface quality [5].

Various methods have been used for the optimization of multi-response problems, including regression analysis, grey relational analysis (GRA), fuzzy logic, response surface methodology (RSM), principal component analysis (PCA), data envelopment analysis, artificial neural networks (ANN), and goal programming [6]. When GRA is employed, the grey relational grade is used to indicate performance and its values are maximized regardless of the nature of the quality characteristics [7].

The Taguchi L_{18} orthogonal array is not applied as often to the field of incremental sheet metal forming, but it has been used to optimize response parameters and to determine input variable levels by way of the Taguchi grey relational analysis methodology (TGRA). In this research, TGRA [8-10] was used for response parameter optimization, such as optimization of the wall angle, the surface roughness, and the spring back.

2. INCREMENTAL SHEET FORMING PROCESS

The ISF process is somewhat new and can be used to produce complex parts out of sheet metal by the moving a single point tool mounted on a standard 3-axis CNC machine, without using dedicated dies. Multi-stage forming strategies are required to avoid part thinning where part walls are almost straight angles (> 60°) [4]. SPIF also tolerates higher strains in comparison to other sheet forming processes. For single stage formations, SPIF is

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Meftah Hrairi, Department of Mechanical Engineering, International Islamic University Malaysia, PO Box 10, 50728 Kuala Lumpur, Malaysia (meftah@iium.edu.my)

Jamal I. Daoud, Department of Science in Engineering, International Islamic University Malaysia, PO Box 10, 50728 Kuala Lumpur, Malaysia

Faiz Zakaria, Department of Mechanical Engineering, International Islamic University Malaysia, PO Box 10, 50728 Kuala Lumpur, Malaysia

limited by deformation types that are near the strain plane.

Fig. 1 illustrates the SPIF process, where a blank and fixture are affixed with a clamp. The tool is free to move in three dimensions and is also programmable for spindle rotation. A completely stationary form-giving tool can be used to help lend the required shape to the end product. The forming tool creates a path around the form-giver, moving from top to bottom in increments and incrementally forming the blank at each level in order to obtain the desired shape.

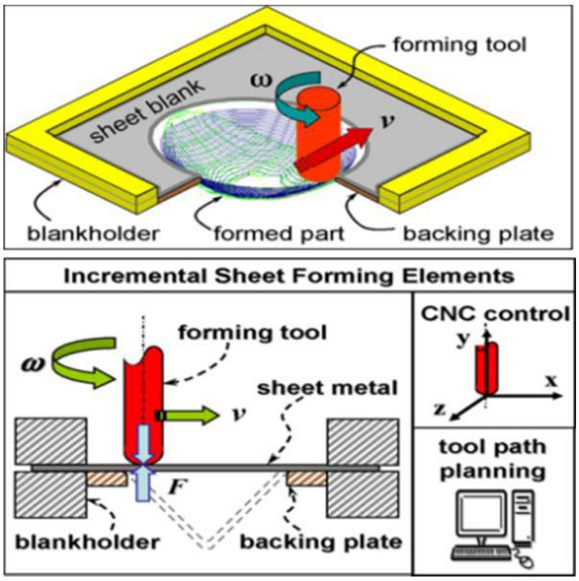

Fig. 1: The working principle of SPIF [5].

This innovative technology is under consideration for use in many industries, from the manufacture of medical products and automobiles, to the calibration of the void nucleation models. The ability to deform the metal in a localized manner is a principal enhancement of sheet metal formability. A forming limit still exists for incremental forming, and it can be graphed as a straight line in the stretching region, with a negative slope [11].

3. MATERIALS AND METHODS

3.1. Taguchi method

The Taguchi method is a powerful design tool for testing a large number of parameter combinations for the purpose of optimizing a process and identifying those parameters that have the greatest influence on the outcome. A set of standard Taguchi orthogonal arrays determines the minimum number of experiments required to fully quantify the effect of each parameter. The performance characteristic and its deviation from the targeted value are measured by the signal-to-noise ratio (S/N). S/N ratio analysis is typically undertaken in one of three performance characteristic categories: the smaller-the better, the nominal-the better, or the larger-the better.

The primary advantage of Taguchi design experiment is the significant decrease in cost. The Taguchi method keeps the number of experiments low through the use of unique orthogonal arrays to study the entire parameter space. In this study, the L_{18} orthogonal array (OA) was nominated because it offers five control factors, each with three levels to investigate (The full factorial design usually requires an unrealistic 5^3 = 125 experimental iterations which would have too high a cost and require too much effort) [12]. Due to the use of the OA L_{18}, only 18 experiments needed to be conducted to fully assess the five control parameters.

In this work, the study of the process parameters' impact on part quality was performed focusing on three performance characteristics: the wall angle, the surface roughness, and the springback. Table 1 contains the information on the 5 selected control parameters in the ISF process, their symbol, the units they are measured in, and three possible levels.

The three main response parameters considered herein are: surface roughness, wall angle, and springback. According to the L_{18} orthogonal array, wall angle targeted a maximum value, and surface roughness and springback targeted minimum vales under the influence of five ISF process parameters: number of sheets (A), tool diameter (B), feed rate (mm/min) (C), speed (rpm) (D) and vertical step depth (E), each having three levels as shown in Table 1. Table 2 shows Taguchi's L_{18} orthogonal array consisting of 18 experiments.

Table 1: Levels of selected control parameters

Parameters	Symbols	Units	Levels		
			1	2	3
No of sheets	A	-	2	3	4
Tool diameter	B	mm	8	10	12
Feed rate	C	mm/min	300	600	900
Speed	D	rpm	300	450	600
Vertical Step depth	E	mm	0.5	1.0	1.5

Table 2: Layout of L_{18} orthogonal array

Run	Coded values					Original values				
	A	B	C	D	E	A	B	C	D	E
1	1	1	1	1	1	2	8	300	300	0.5
2	1	2	2	2	2	2	10	600	450	1.0
3	1	3	3	3	3	2	12	900	600	1.5
4	2	1	1	2	2	3	8	300	450	1.0
5	2	2	2	3	3	3	10	600	600	1.5
6	2	3	3	1	1	3	12	900	300	0.5
7	3	1	2	1	3	4	8	600	300	1.5
8	3	2	3	2	1	4	10	900	450	0.5
9	3	3	1	3	2	4	12	300	600	1.0
10	1	1	3	3	2	2	8	900	600	1.0
11	1	2	1	1	3	2	10	300	300	1.5
12	1	3	2	2	1	2	12	600	450	0.5
13	2	1	2	3	1	3	8	600	600	0.5
14	2	2	3	1	2	3	10	900	300	1.0
15	2	3	1	2	3	3	12	300	450	1.5
16	3	1	3	2	3	4	8	900	450	1.5
17	3	2	1	3	1	4	10	300	600	0.5
18	3	3	2	1	2	4	12	600	300	1.0

Additionally to the Taguchi method, a statistical analysis of variance (ANOVA) became a tool to identify the process parameters with statistical significance.

As a final step, result accuracy is ensured with a confirmationexperiment for the validation of numerical results using the DOE's optimum process parameters.

3.2. Analysis of variance (ANOVA)

This study focuses on three main response parameters: the wall angle, the surface roughness and the springback, denoted as "WA", "SR", and "SB", respectively. At each run of the L_{18} array, the response parameters were evaluated [3] and these results are shown in Table 3. The optimization was performed by grey-based Taguchi relation with ANOVA analysis in order to accommodate multiple performance characteristics. The effect of the process' three response factors was studied in order to find an optimized set of parameters for the forming process.

Table 3: Orthogonal array L_{18} of the experiments runs and results [3]

Exp. no.	WA	SR	SB
1	41.700	0.46	0.500
2	49.700	1.13	0.555
3	55.015	1.03	0.785
4	43.573	1.18	0.060
5	53.037	0.91	0.560
6	41.800	0.81	0.150
7	53.148	0.65	0.668
8	35.245	0.30	0.430
9	41.113	0.78	0.835
10	44.500	0.97	0.300
11	52.250	1.30	0.775
12	36.050	1.11	0.025
13	36.167	0.76	0.317
14	51.033	1.29	0.710
15	50.133	1.00	0.704
16	52.058	1.28	0.200
17	31.950	0.95	0.345
18	48.888	0.84	0.315

The S/N ratio measures the data against a standard deviation. For this study, wall angle was a response of the type: larger-the-better. Consequently, the S/N ratio calculation was as shown in Eq. (1). However, the surface roughness and springback were smaller–the-better type responses. Consequently, the S/N ratio for these two reponses was calculate with Eq. (2).

$$S/N = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{{y_i}^2}\right) \tag{1}$$

$$S/N = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n}{y_i}^2\right) \tag{2}$$

where n is the number of replications for each experiment and y_i is the response value.

The reason behind the use of the analysis of variance (ANOVA) is the determination of ISF process parameters that have the greatest effect on performance characteristics or the response. This is typically performed through a separation of the total response variability into the contributions made by individual process parameters and error; the total response being measured by the sum of squared deviations from the total mean of the response factors [13]. So,

$$SS_T = SS_F + SS_e \tag{3}$$

where

$$SS_T = \sum_{j=1}^{p}\left(\bar{\gamma}_j - \gamma_m\right)^2 \tag{4}$$

SS_T – Total summation of the squared deviations about the mean

γ_m – Grand mean of the response

γ_j – Mean response for the j^{th} experiment

p – Number of experiments in the orthogonal array

SS_F _ Sum of square deviation due to each factor

SS_e - error of the sum of the squared deviation

Furthermore, the *F-test* served as an indication of the ISF forming parameters with effective influence on the performance characteristic. Typically, the larger the *F-test* value, the greater the influence of any variation in the process parameter on the overall performance characteristic.

3.3. Grey relational analysis

A common way of converting multiple response optimization problems into a single response optimization case is to use grey relational analysis. The objective function, a combination of performance factors, is called the grey relational grade (GRG) [14]. The parametric conditions conforming to the greatest GRG generate the smallest values of surface roughness and springback and the largest value of wall angle.

This is achieved in steps, beginning with determining the signal to noise S/N ratio that will to optimize the experiment characteristics as either 'larger the better' or 'smaller the better' S/N ratios.

The next step was normalizing the *S/N* ratio. To maximize and minimize the performance characteristics, Eq. (5), for higher-the-better S/N ratio, and Eq. (6), for smaller-the-better S/N ratio, were used, respectively, to calculate the normalized values.

$$x_{ij} = \frac{y_{ij} - \min(y_{ij})}{\max(y_{ij}) - \min(y_{ij})} \tag{5}$$

$$x_{ij} = \frac{\max(y_{ij}) - y_{ij}}{\max(y_{ij}) - \min(y_{ij})} \tag{6}$$

where, x_{ij} is the magnitude after the normalization, $\max(y_{ij})$ is the largest value of y_{ij} for the j^{th} response and the $\min(y_{ij})$ is the smallest value of y_{ij} for the j^{th} response.

The grey relational coefficient (GRC) and the grey relational grade (GRG) are based on a normalized S/N

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ratio. The relationship between normalized and ideal values is expressed by the grey relational coefficient. The GRC for the i^{th} response variable in j^{th} experiment is expressed as:

$$GRC_{ij} = \frac{\Delta_{\min} + \xi\Delta_{\max}}{\Delta_{ij} + \xi\Delta_{\max}} \quad (7)$$

where Δ_{ij} is the absolute value of the difference between x_{0j} and x_{ij} (Eq. 8). The minimum (smallest) value of Δ_{ij} is denoted by $\Delta_{\min}$ (Eq. 9) whereas the maximum (largest) value is denoted by $\Delta_{\max}$ (Eq. 10). ξ is the weight scale factor that ranges between 0 and 1 and distinguishes between the effects of each factor. Here, ξ is assumed to be 0.5 because some response characteristics are larger-the-better whereas others are smaller-the-better.

$$\Delta_{ij} = \left|x_{0j} - x_{ij}\right| \quad (8)$$

$$\Delta_{\min} = \min_i \min_j \left|x_{0j} - x_{ij}\right| \quad (9)$$

$$\Delta_{\max} = \max_i \max_j \left|x_{0j} - x_{ij}\right| \quad (10)$$

The final step consists of calculating the grey average for the different responses of the ISF process, namely, wall angle, surface roughness and springback. The average calculation is done with Eq. (11), where γ_i is the grey relational grade

$$\gamma_i = \frac{1}{m}\sum_{j=1}^{m}\xi_{ij} \quad (11)$$

where m is the total count of process responses. The larger the Grey relational grade represents an intense relational degree between the given sequence x_{ij} and the reference sequence x_{0j} [15].

The GRG is then converted to *S/N* ratio using larger-the-better criterion (Eq. 1).

4. RESULTS AND DISCUSSION

4.1. Multi-response optimization analysis

In order to maintain a high wall angle and low surface roughness and springback, a 'larger the better' *S/N* ratio is selected for wall angle and 'smaller the better' is selected for surface roughness and springback. Table 4 illustrates the S/N ratio variation for the three characteristic responses of the process.

Table 4: Signal to noise S/N ratio values for the three responses

Exp. no.	WA	SR	SB
1	32.40	6.74	6.02
2	33.92	-1.06	5.11
3	34.80	-0.25	2.10
4	32.78	-1.43	24.43
5	34.49	0.81	5.03
6	32.42	1.83	16.47
7	34.50	3.74	3.50
8	30.94	10.45	7.33
9	32.27	2.15	1.56
10	32.96	0.26	10.45
11	34.36	-2.27	2.21
12	31.13	-0.90	32.04
13	31.16	2.38	9.97
14	34.15	-2.21	2.97
15	34.00	0.00	3.04
16	34.32	-2.14	13.97
17	30.08	0.44	9.24
18	33.78	1.51	10.03

Table 4 shows that the largest values of S/N ratio in wall angle, surface roughness and springback are 34.80, 10.45 and 32.04 respectively. Similarly, the lowest values of S/N ratio are 30.08, -2.27 and 1.56 respectively. Because of the scatter range of the values and the trend difference, pre-processing of data was carried out and the normalization of S/N ratio is tabulated in Table 5.

Table 5: Normalized S/N ratio values.

Exp. no.	WA	SR	SB
1	0.4901	0.2915	0.8538
2	0.8130	0.9044	0.8836
3	1.0000	0.8412	0.9824
4	0.5709	0.9340	0.2495
5	0.9326	0.7568	0.8861
6	0.4945	0.6774	0.5107
7	0.9365	0.5273	0.9364
8	0.1806	0.0000	0.8108
9	0.4640	0.6516	1.0000
10	0.6097	0.8003	0.7082
11	0.9051	1.0000	0.9787
12	0.2222	1.0000	0.0000
13	0.2281	0.6339	0.7240
14	0.8617	0.9947	0.9538
15	0.8290	0.8215	0.9514
16	0.8983	0.9894	0.5927
17	0.0000	0.7861	0.7481
18	0.7827	0.7022	0.7221

Table 6 shows the values of the GRC for each response and the GRG for the combination of three responses. The GRC of the responses describes the interaction between the normalized S/N ratio and ideal data. The grey relational grade is the basis for all of the multi-objective characteristics assessment. Greater value of the latter means greater influence.

Table 6: Grey relational coefficient and grey relational grade for wall angle, surface roughness and springback

Exp. no.	GRC			GRG
	WA	SR	SB	
1	0.4951	0.4137	0.7738	0.5609
2	0.7278	0.8395	0.811	0.7928
3	1.0000	0.7590	0.9660	0.9083
4	0.5382	0.8833	0.3998	0.6071
5	0.8812	0.6727	0.8145	0.7895

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6	0.4973	0.6078	0.5054	0.5368
7	0.8873	0.5140	0.8872	0.7628
8	0.3790	0.3333	0.7255	0.4793
9	0.4826	0.5894	1.0000	0.6907
10	0.5616	0.7146	0.6315	0.6359
11	0.8405	1.0000	0.9592	0.9332
12	0.3913	1.0000	0.3333	0.5749
13	0.3931	0.5773	0.6443	0.5382
14	0.7834	0.9896	0.9154	0.8961
15	0.7452	0.7365	0.9113	0.7977
16	0.8310	0.9793	0.5511	0.7871
17	0.3333	0.7004	0.6650	0.5662
18	0.6971	0.6267	0.6428	0.6555

The grey grade values vary with respect to the experiment number found in Fig. 2. Experiment number 11 resulted in the highest grey grade value.

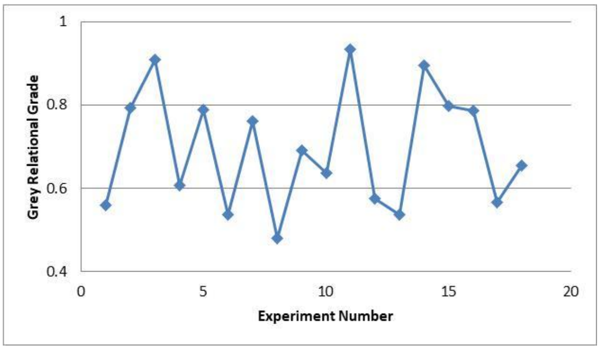

Fig. 2: Grey relational grade for each experimental run

In order to make a behavior prediction of independent input variables and grey relational grades associated with each test result, regression models can be employed. A regression model was created with MINITAB software that was based on the GRA data given in Table 6. The model in Eq. 12 contains the following independent variables: number of sheets (A), tool diameter (B), feed rate (C), speed (D) and vertical step depth (E).

$$GRG = -1.9 + 0.094A + 0.471B + 0.000023C - 0.000165D + 0.177E$$
$$+ 0.0131A^2 - 0.0216B^2 - 0.251E^2 + 0.0239A \times B + 0.0398A \times E + 0.0468B \times E \quad (12)$$

ANOVA of the GRG results was used to investigate the significance of each of the five input process variables: number of sheets, tool diameter, speed (rpm), feed rate (mm/min), and vertical step depth. Table 7 shows the grey relation mean values for process parameter and level. Mean values are used for optimal process parameter selection and evaluation with respect to the three response factors (WA, SR and SB). The ranking show the relative importance of the parameters to the final result. Vertical step depth has the most impact on the result while feed rate has the least.

Table 7: Normalized S/N ratio values.

Level	A	B	C	D	E
1	-2.869	-3.850	-3.346	-3.000	-5.324
2	-3.348	-2.825	-3.380	-3.859	-3.020
3	-3.774	-3.316	-3.265	-3.393	-1.647
Delta	0.905	1.025	0.115	0.859	3.677
Rank	3	2	5	4	1

The optimal parameters could also be identified graphically, using the main effects plot for *S/N* ratio in Fig. 3. As seen in Fig. 3, the vertical step depth has a large positive effect on the wall angle, surface roughness and springback of the part produced by ISF.

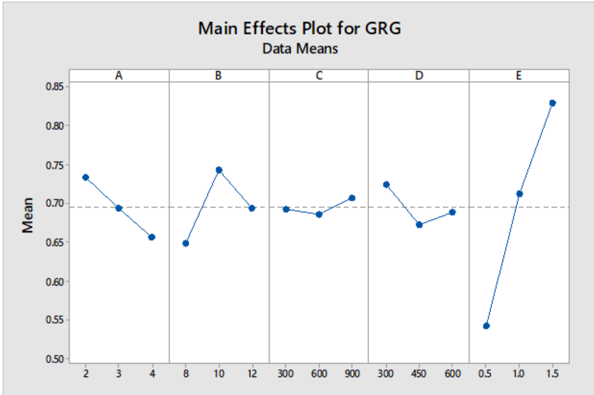

Fig. 3: Main effect plots of the grey grade values

The interaction plots of the GRG values are shown in Fig. 4. These plots show the vertical step depth and all the other parameters are minimally related while greater interaction between the tool diameter and the speed was observed.

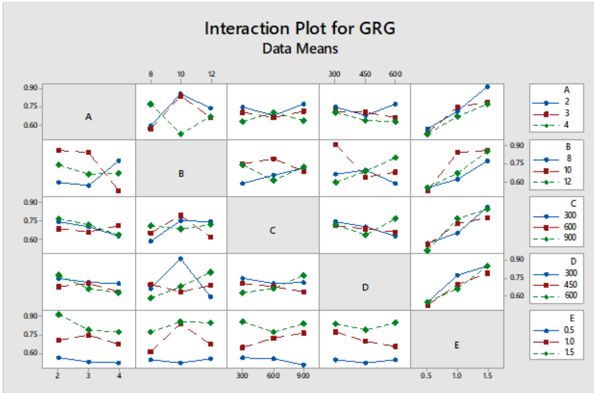

Fig. 4: Interaction plots of the grey grade values

Visible in both Table 7 and Fig. 3, the optimal factors are $A_1B_2C_3D_1E_3$. Furthermore, ANOVA helped determine which variables had the greatest effect on the resulting grey grade. ANOVA acts as a cutoff method that sorts significant and not-significant factors ones, using the F-test as its cut-off criterion where P<0.05 determines the significance of a factor at 95% confidence level. Table 8 presents the ANOVA data and demonstrates that the most significant parameters in the ISF process, based on the grey relational grade are for wall angle, surface roughness and springback, is the vertical step depth (E) with contribution value of 68.5% followed by the tool diameter (B) with 9.7 % contribution, number of sheets (A) with 6.1% contribution. Consequently, the other two parameters (speed (D) and feed rate (C)) were deemed non-significant with contribution of 2.9% and 1% respectively.

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Table 8: ANOVA test results

Source	DF	Seq. SS	Adj. SS	Adj. MS	F	P	Contribution (%)
A	2	0.042	0.0426	0.0213	1.81	0.233	6.1
B	2	0.067	0.0673	0.0336	2.85	0.124	9.7
C	2	0.007	0.0070	0.0035	0.30	0.752	1.0
D	2	0.020	0.0202	0.0101	0.86	0.456	2.9
E	2	0.475	0.4759	0.2379	20.17	0.001	68.5
Error	7	0.082	0.0826	0.0118			11.8
Total	17	0.693	0.6956				

4.2. Comparison with single optimization

Table 9 displays the optimal process parameter settings for the single optimization as well as the multi-objective optimization of the three quality characteristics: wall angle, surface roughness and springback. It can be seen that wall angles seems to be the quality that dominates as four out of the five process parameters that optimize wall angle also optimize the combination of the three characteristics.

Table 9: Optimum settings for all objective functions

Process parameters	Single objective optimization			Multi-objective optimization
	WA	SR	SB	
No of sheets	A_1	A_3	A_2	A_1
Tool diameter	B_3	B_1	B_1	B_2
Feed rate	C_3	C_3	C_2	C_3
Speed	D_1	D_1	D_2	D_1
Vertical step depth	E_3	E_1	E_1	E_3

4.3. Confirmation test

After obtaining the optimal level of input parameters, the final phase is the prediction and analysis of the efficiency of the performance characteristics, with the use of optimum ISF process condition levels. Eq. (13) describes how the estimated GRG is determined from the optimum level of the input parameters.

$$\gamma = \gamma_m + \sum_{j=1}^{q} \left(\gamma_j - \gamma_m\right) \tag{13}$$

where γ_m is the total mean of the GRG, γ_j is the mean of the GRG at the optimal level and q is the number of forming conditions, that significantly influence the performance characteristics.

Table 10 shows the results obtained from the confirmations tests compared to the maximum value of the performance factor (experiment 11 from Table 6). In summary, the result of the confirmation test for the three characteristic factors is better than the experiments in Table 6. There is an improvement of 0.0246 in the GRG.

Table 10: Results of the confirmation tests

	Maximum Initial parameters combination	Optimal parameters combination	
		Regression	Prediction
Levels	$A_1B_2C_1D_1E_3$	$A_1B_2C_3D_1E_3$	$A_1B_2C_3D_1E_3$
GRG	0.9332	0.9057	0.9578

The grey relational grade of 0.9577 is found to correspond with the optimal settings. Hence, the Taguchi-based grey analysis is a very useful tool for optimisation of multiple performance characteristics in incremental forming process.

5. CONCLUSION

In this research, the goal was understand the significant input factors for the performance characteristics (wall angle, surface roughness and springback taken together) in ISF process. Input factors such as number of sheets to be formed, tool feed rate, tool diameter, vertical step down, and spindle speed play a significant role in forming. Taguchi's L_{18} orthogonal array, grey relational analyses and ANOVA were used to achieve the optimum parameters for maximizing the wall angle and minimizing the surface roughness and the springback.

The optimum process parameters for all three responses taken together are 1.5 mm vertical step down, 10 mm tool diameter, 2 metal sheets, 300 rpm spindle speed and 900 mm/min feed rate.

Vertical step down has been identified as the parameter with the most influence with a contribution of 68.5%. Tool diameter and number of sheets were found to be the second and third contributing parameters. The least influencing parameter was the feed rate as this parameter only speeds the process.

Prediction of the grey relational grade is carried out by the empirical model that was developed and can be used in further experimentations using the same processing technique.

The confirmation experiment GRG shows a 27.4% improvement from the mean grade value.

Finally, using the multi objective optimization of wall angle, surface roughness and springback, the Grey-Taguchi method is found to be appropriate for optimizing the ISF process and can be effectively applied to other metal forming processes.

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