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Research Article

Taguchi based GRA-PCA hybrid optimization for the forming of AL6061 alloy in automotive applications

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ABSTRACT

Current study researches the impact of material and forming factors on punch force and sheet thickness in sheet forming of Aluminum 6061 composites. The particular properties of aluminum make it the most excellent candidate to replace the heavier materials in the vehicles which act as reaction to the mass drop interest inside the car area. As of now, the high-heat treatable composites Al 6000 series alloys are applied to broad applications. The forming tests were directed depending upon L27 orthogonal array (OA) planned by taking into account about temperature, die speed, sheet thickness and type of lubricant as input for process parameters. Multi target improvement was done to decide the individual significance of every reaction through Taguchi based Grey Relational Analysis (GRA) along with Principal Component Analysis. The procedure provide the ideal parameter condition for example sheet thickness of 2mm, die and blank temperature of 300°C, die speed of 0.4 mm/s , with Boric Acid lubrication that results in 25.96% decrease in Punch power and thinning improved by 50.74%. ANOVA is valuable to make out the significance and furthermore the result of each cycle factors on response parameters. Though, considerably all the parameters play important role, the die and blank temperature affects 80.11% of the reaction parameters as that of forming factors whereas die speed turned to be the slightest significant factor. Confirmation test was performed for approving the best blend.

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INTRODUCTION

Rotating Environmental pollution, mostly formed by the fuel emanations of the vehicles, is the major unsafe condition that affects the human race.Though the issues have been subsided by replacing the automobiles with light weight material (20% weight reduction)[1], 6-8% fuel usage[2], it is still a minute progress in that direction. This sort of thinking made to concentrate on the manufacturing methodology, i.e Sheet forming which captured the automobile sector. However, process efficiency has to be improved by selecting appropriate conditions to reduce the forming defects such as fracture, wrinkle, excessive thinning etc.[3],[4],[5].Taguchi strategy is commonly used to choose issues, and enhance the cycle variables [6].

Indeed, even the deep drawing procedure joined with Taguchi technique were examined by padmanabham [7] , Lin kuo [8] and Bor-Tsuen Lin [9]etc.,. Bor-Tsuen in his experimentation on microridged drawing improved the cup height by 60% with 7% expansion in the shaping force while drawing. However, most of the processes are single objective optimization. Taguchi Method is an exceptionally evolved process plan for streamlining the exploratory conditions, however contrast with single reaction issues it faces restriction in multi reaction issues [10], [11]. Though Design of experiment plays an efficient role among the progression parameters, the intricacy in forming process, chooses multi objective optimization for better response. Various methods such as Engineering judgment, regression analysis, six sigma, Swarm Optimization, ANT Colony, Grey Relational Analysis (GRA), and so on applied for multi reaction issues to accomplish most ideal solution. All these techniques spare the production time as well as produce the solid parts at sensible expenses.

Grey Relational Analysis (GRA), extraordinary compared to other multi advancement strategy was presented by Deng in 1989 [12].Taguchi based GRA, applies the averages of normalized multi objectives to estimate the grading factor. Grey relational grade is a factor that converts the multiple recitals to single grade whose performance is improved by replacing the normalized factors with weighting values in each response. Xie Yan-min[13], applied GRA in examining the flanging process parameters to acquire multi reaction esteems through FEA. Yanmin [14], in his other work, see that the positioning acquired from GRA for multi reaction attributes improves the failures in the profound drawing process. Hrairi [15], studied the incremental forming of sheets to decide the ideal parameter for multi target optimization of wall angle, surface harshness and spring back through Taguchi based GRA.As mentioned earlier, the improvement in optimization is attained by taking into account the weighting estimations of the responses rather than averages.

Principal Component Analysis (PCA), first proposed by Pearson [16], was later evolved by Hotelling [17], is the proficient technique for assessing the weighting estimations of the responses. Pandivelan Chinnaiyan[13], utilizing the Taguchi technique (TM) based GRA with PCA for deciding the most ideal arrangement of shaping boundaries in single point incremental forming to acquire the 56.37% improvement in formability and 93.68% upgrade in surface unpleasantness.

Though relevant studies on hybrid GRA-PCA performed by many researchers, the application in sheet forming has been rarer output. Therefore, a novel attempt is made in forming process, for multi response optimization method implementing the Taguchi Method joint with GRA -PCA, would generate the accurate results that enhances the presentation of manufacturing sectors.

Experimental Procedure

In this examination, Al6061-T6 aluminum sheet (Al 97.3%; Si 0.057%; Fe 0.279%; Mn, 0.0678; Mg1.199%; Cr0.179%; Cu 0.181% and Zn, 0.048%) was chosen for the Deep drawing process. Three set of sheets having thickness as 1, 1.5 and 2 mm made roundabout cut of 108mm distance across are considered for experimentation. A grid of circles having 5 mm diameter were laser set apart on a surface of the sheet to facilitate the strain estimation subsequent to forming. Inconel steel die of diameters 52.3mm, 53.3mm, 54.3mm having consistent punch diameter of 49.8mm placed with blank holder, upheld on three cushion pins. The forming test were performed at three temperatures RT, 150°C and 300°C at three different die speeds (0.4, 0.7, 1mm/s) keeping up the consistent blank holder force. The selected input factors for tests were: blank thickness, die

Table 1. Forming parameter and their levels

S. No	Notation	Factor	Levels		
1	A	Blank Thickness (mm)	1	1.5	2
2	B	Die and Blank Temperature	27°C	150°C	300°C
3	C	Die Speed (mm/s)	0.4	0.7	1
4	D	Lubrication (μ)	WOL	BA	G

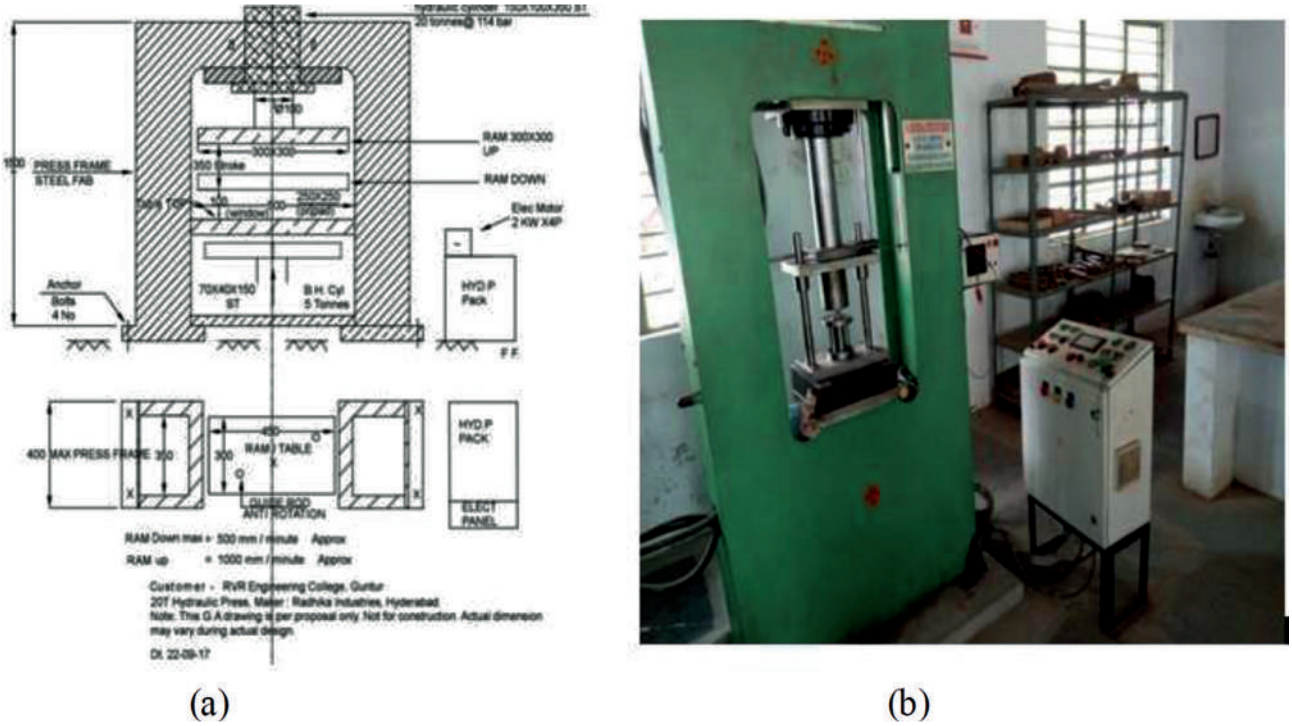

Figure 1. Experimental Setup (a) 2D layout of Equipment (b) Hydraulic Deep Drawing.

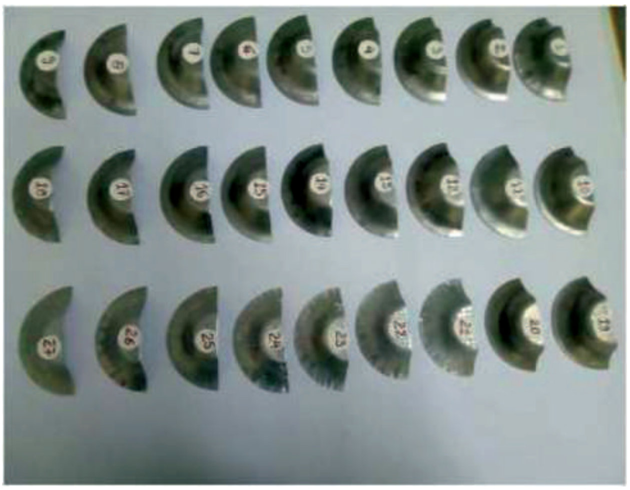

Figure 2. Experimentation Samples.

and blank temperature, die speed and lubricant. Taguchi's L27 OA is utilized for experimentation. The forming factors and their ranges considered in this investigation are given in Table 1. Experimentation is performed on Hydraulic Deep Drawing machine of 13 tons as appeared in Fig. 1 to create the example segments (Figure 2),using the arrangements of boundary level as given in Table 2

ANALYSIS METHOD

Signal-to-noise Ratio

Taguchi Method dependent on the orthogonal array, performs the design of experiments, uses signal –to-noise (S/N) ratio to measure the process performance which, are insensible to noise factor [6]. Noise factors are uncontrolled factors which influence the product or process. The more modest the-better quality trademark is:

$$n_{ij} = -10 log\left(\frac{1}{n}\Sigma_{j=1}^{n} y_{ij}^{2}\right) \tag{1}$$

where y_{ij} is the i^{th} test at the j^{th} trial, n is the overall count of tests, and s is the standard deviation. The experimented standards and calculated S/N ratio values are given in Table 2.

Grey Relational Analysis

Grey Relational Analysis (GRA), is applied for recognizing the most ideal set of input parameters to attain expert characteristics. Generally applied for assessing the presentation of a complex project with inadequate information. In view of weightages to individual responses, the GRA generates optimum condition for multi-objective problems. The procedure followed while using Grey Relation Analysis is:

Table 2. The results of experiments and S/N ratios values

Expt No	Blank Thickness	Die and Blank Temperature	Die Speed	Lubrication	Punch Force, (P)	Thickness Variation, (Th)	S/N ratio for P	S/N ratio for Th
	(mm)	(°C)	(mm/s)	(μ)	(KN)	(mm)	(dB)	(dB)
1	1.5	300	0.7	G	39.4797	0.2125	-31.9275	13.4528
2	2	150	1	BA	66.6358	0.2335	-36.4742	12.6335
3	1.5	27	0.4	G	70.0294	0.1173	-36.9056	18.6084
4	2	300	1	G	73.7564	0.2786	-37.3560	11.1004
5	1	27	0.7	BA	50.2945	0.1016	-34.0304	19.8577
6	1	300	0.4	G	26.8453	0.1459	-28.5774	16.7136
7	1	300	0.7	WOL	25.9053	0.1724	-28.2678	15.2659
8	1.5	150	0.4	WOL	42.0087	0.1757	-32.4668	15.1022
9	1	27	0.4	WOL	54.2636	0.0942	-34.6902	20.5142
10	2	300	0.7	BA	44.8966	0.2680	-33.0443	11.4360
11	2	27	0.7	G	92.4663	0.1926	-39.3197	14.3057
12	1.5	300	0.4	BA	21.8005	0.2012	-26.7693	13.9272
13	1	27	1	G	70.4265	0.1109	-36.9547	19.1003
14	1.5	150	0.7	BA	37.6288	0.2034	-31.5104	13.8318
15	1	150	1	WOL	32.2885	0.1573	-30.1810	16.0627
16	1	300	1	BA	32.8800	0.1487	-30.3386	16.5519
17	2	150	0.4	G	66.2397	0.2248	-36.4224	12.9641
18	1.5	27	0.7	WOL	55.5013	0.13448	-34.8861	17.4268
19	1.5	300	1	WOL	33.8566	0.24308	-30.5929	12.285
20	2	300	0.4	WOL	46.5978	0.2740	-33.3673	11.2431
21	1	150	0.7	G	48.7557	0.1400	-33.7605	17.0732
22	2	150	0.7	WOL	64.3460	0.2360	-36.1704	12.5413
23	1.5	150	1	G	67.7087	0.1916	-36.6129	14.3476
24	2	27	0.4	BA	84.4921	0.1828	-38.5363	14.7586
25	2	27	1	WOL	78.1531	0.1782	-37.8589	14.9782
26	1.5	27	1	BA	62.1216	0.1338	-35.8649	17.4705
27	1	150	0.4	BA	30.1380	0.1272	-29.5823	17.9054

1. Conversion of experimental design into relevant S/N values
2. Normalization of S/N ratios
3. Deviation Sequence
4. Grey Relation Co-efficient calculation
5. Estimation of ranking using PCA
6. Performing ANOVA for statistical analysis of data
7. Choice of ideal degree of forming parameters
8. Performing confirmation experiments.

GRA, is aimed to process the complicated data and transfer into whitening system. Data preprocessing isutilized to distinguish the assessed objective for each impact factor. The linear data pre-processing technique for the S/N proportion is determined as the lower the better rule which can be communicated as,

$$x_i^*(k) = \frac{\max x_i^0(k) - x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \tag{2}$$

where $x_i^*(k)$ is the significance obtained for grey relational generation, min $x_i^0(k)$ is the nominal significance of $x_i^0(k)$ for the kth response and max $x_i^0(k)$ is the prime significance for the kth response where k = 1,2,3,4 …,n and i=1,2,3,……m for the various output responses measured in a sequence.

The deviation sequence of the mentioned series is known by

$$\Delta_{0i}(K) = |x_0^*(k) - x_i^*(k)| \tag{3}$$

$$\Delta_{\max} = \max_{\forall j \in i} \max_{\forall k} |x_0(k) - x_j(k)| \tag{4}$$

$$\Delta_{\min} = \min_{\forall j\in i} \min_{\forall k} |x_0(k) - x_j(k)| \quad (5)$$

The GRC is registered to set up a connection between the best information and the genuine normalize data. The GRC is determined as

$$\zeta_i(k) = \frac{\Delta_{min} + \zeta \cdot \Delta_{max}}{\Delta_{0i}(k) + \zeta \cdot \Delta_{max}} \quad (6)$$

Where $\Delta_{0i}(k) = |x_0(k) - x_i(k)|$, ζ is the distinguishing coefficient lying between $0 \le \zeta \le 1$, Δ_{min} is the least value of Δ_{0i} and Δ_{max} is the highest value of Δ_{0i} . ζ is distinguishing or identification coefficient : $\zeta \in [0,1]$. ζ = 0.5 is generally used.

In view of the weighting values w_k, the GRG is specified as

$$\gamma_i = \frac{1}{n} \sum_{k=1}^{n} w_k \cdot \zeta_i(k) \quad (7)$$

Normally the grey relational ranking speaks to the connection between's the arrangements, yet in addition speaks to the degree of control among comparable and reference sequence. Accordingly, the similarity among sequences generate grade as one or higher than the other grade [7].

Principlal Component Analysis

Principal Component analysis (PCA),enlightens the formation of variance covariance by the linear combinations of all features characteristic. It is explained as:

(i) Developing the original multiple performance characteristic array

$$xi = \begin{bmatrix} x1(1) & x1(2) & x1(3) & \cdots & \cdots & x1(n) \\ x2(1) & x1(2) & x1(3) & \cdots & \cdots & x1(n) \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ xm(1) & xm(2) & xm(3) & \cdots & \cdots & xm(n) \end{bmatrix} \quad (8)$$

Where m, the quantity of experiments and n, the quantity of quality characteristics. Here, x is the coefficient of each quality characteristic.

(ii) The correlation Coefficient Array is evaluated as

$$R_{jl} = \frac{Cov(x_i(j), x_i(l))}{\sigma_{xi}(j)\ X\ \sigma_{xi}(l)} \text{ j =1,2,3,.....,n;} \quad (9)$$

l = 1,2,3,…..n,

Where Cov $(x_i(j), x_i(l))$ are the covariance sequences, $x_i(j)$ and $x_i(l)$ respectively; $\sigma_{xi}(j)$ is the standard deviation of sequence $x_i(j)$; $\sigma_{xi}(l)$ is the standard deviation of sequence $x_i(l)$.

(iii) The eigen standards and eigen vectors are determined from the correspondence coefficient array

$$(R - \lambda_k I_m)V_{ik} = 0 \quad (10)$$

Where λ_k is an eigen value, $\sum_{k=1}^{n} \lambda_k = n$ and k = 1,2,…n; $V_{ik} = [a_{k1}, a_{k2},\ldots\ldots, a_{kn}]$ T correspond to eigen value λ_k.

(iv) The uncorrelated principal component is set as

$$Y_{mk} = \sum_{k=1}^{n} V_{ik} \cdot X_m(\text{i}) \quad (11)$$

Where Y_{m1} and Y_{m2} are the initial and succeeding principal components. The technical aspect of Taguchi/GRA/PCA optimization method for sheet forming is illustrated in Fig.3.

Implementation of The Planned Hybrid Taguchi/GRA/PCA Optimization Procedures for Deep Drawing

In the GRA, the trial results for the Taguchi based experimentation, the S/N proportions of Punch power and uniform thickness variety in Table 2 are first standardized by the small- the-better attribute of the succession by utilizing condition equation (2). The values of punch force and uniform thickness distribution are set as the reference sequence $x_0^{(0)}(k)$, k = 1, 2 and the comparability sequences $x_i^{(0)}(k)$, i = 1, 2, 3, . . . , 27, k = 1, 2. Table 3 lists all the sequences after data preprocessing. According to Deng [8], a bigger estimation of the standardizedoutcomes relates to better execution and the greatest standardized outcomes that are equivalent to one show the best execution.

According to Table 3, the deviation sequences $\Delta_{01}(k)$ can be considered as follows:

$$\Delta_{01}(1) = |x_0^*(1) - x_1^*(1)| = |1.0000–0.589001| = 0.410999$$
$$\Delta_{01}(2) = |x_0^*(2) - x_1^*(2)| = |1.0000–0.750112| = 0.2498888 \quad (12)$$

Therefore, Δ_{01} = (0.410999, 0.2498888).

The same calculating technique is performed for i = 1, . . . , 27, and the outcome of all Δ_{0i} for i = 1, . . . , 27 are given in Table3. On analyzing the statistics shown in Table 3, $\Delta_{max}(k)$ and $\Delta_{min}(k)$ can be given as follows:

$$\Delta_{max} = \Delta_{011}(1) = \Delta_{09}(2) = 1.0000,$$
$$\Delta_{min} = \Delta_{012}(1) = \Delta_{04}(2) = 0.0000 \quad (13)$$

Calculation of The Grey Relational Coefficient

By means of the coefficient ζ = 0.5 in equation (6), the illustration of GRC $\zeta_{1(k)}$is known as:

$$\zeta_{1(1)} = \frac{0.0000 + 0.5(1.0000)}{0.410999 + 0.5(1.0000)} = 0.548848$$
$$\zeta_{1(2)} = \frac{0.0000 + 0.5(1.0000)}{0.2498888+0.5(1.0000)} = 0.666766 \quad (14)$$

Thus, $\zeta_{1(k)}$ = (0.548848, 0.666766), k = 1, 2. A like process is applied for i = 1, . . . , 27. Table 4 lists the coefficient for every trial of the L_{27} OA.

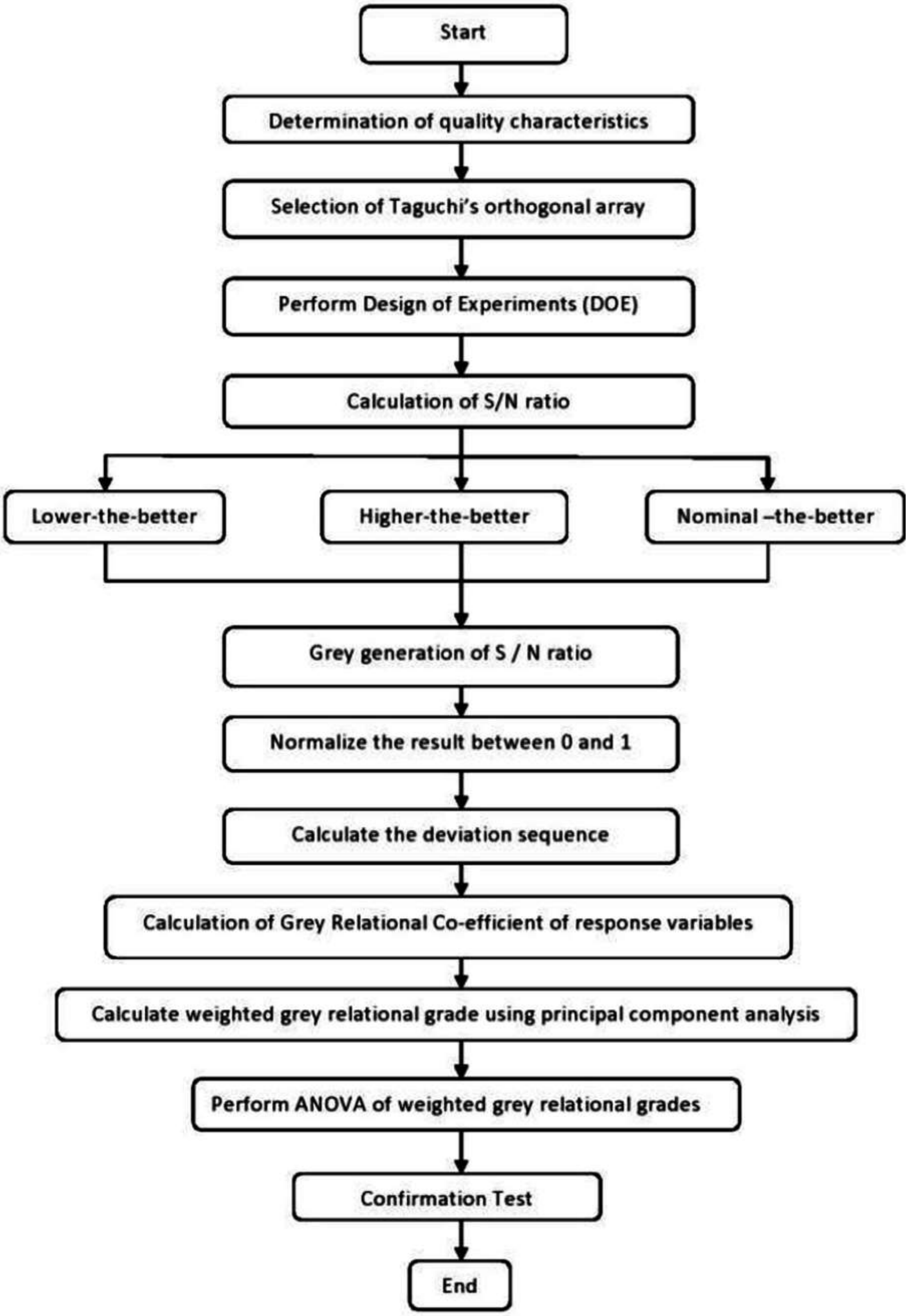

Figure 3. Proposed Optimization technique using hybrid Taguchi/GRA/PCA.

Table 3. Normalized values and deviation sequences for punch force and uniform thickness variation

Expt No	Normalized values		Deviation sequences	
	Punch force	Thickness Variation	Punch force	Thickness Variation
1	0.5890	0.7501	0.4109	0.2498
2	0.2267	0.8371	0.7732	0.1628
3	0.1923	0.2024	0.8076	0.7975
4	0.1564	1	0.8435	0
5	0.4214	0.0697	0.5785	0.9302
6	0.8559	0.4037	0.1440	0.5962
7	0.8806	0.5575	0.1193	0.4424
8	0.5460	0.5749	0.4539	0.4250
9	0.3688	0	0.6311	1
10	0.5000	0.9643	0.4999	0.0356
11	0	0.6595	1	0.3404
12	1	0.6997	0	0.3002
13	0.1884	0.1501	0.8115	0.8498
14	0.6222	0.7098	0.3777	0.2901
15	0.7281	0.4728	0.2718	0.5271
16	0.7156	0.4209	0.2843	0.5790
17	0.2308	0.8020	0.7691	0.1979
18	0.3532	0.3279	0.6467	0.6720
19	0.6955	0.8741	0.3046	0.1258
20	0.4742	0.9848	0.5257	0.0151
21	0.4429	0.3655	0.5570	0.6344
22	0.2509	0.8469	0.7490	0.1530
23	0.2156	0.6550	0.7843	0.3449
24	0.0624	0.6114	0.9375	0.3885
25	0.1163	0.5880	0.8836	0.4119
26	0.2752	0.3233	0.7247	0.6766
27	0.7758	0.2771	0.2241	0.7228

Table 4. Eigen values and explained variation for principal components

Principal Component	Eigen Value	Explained Variations (%)
First	0.9838	51%
Second	0.9421	48.9%

Computation Using PCA for Involvement of Feature Characteristics

In multi objective optimization, rather than adopting traditional trial and error method, the GRA-PCA is introduced to decide the weightage of all worth characteristic, consequently diminishing the uncertainty in decision making. The weighting values for every quality trademark are controlled by utilizing the PCA.

Considering the coefficient data represented in Table 4 for calculating the correlation coefficient matrix and to make out the equivalent eigen values from Equation 10. (Table 4). The eigenvector is appeared in Table 5, and the square of the eigenvector can speak to the association of the comparing quality trademark to the principal component. The contribution are given as 0.4999, 0.4999, respectively. The variance involvement of initial principal component is almost 51% higher among the two quality trademark.

Hence, in this examination, the squares of the respective eigenvectors are picked as the weighting estimations of the concerned quality trademark. Coefficients $w1$, and $w2$ in (7) are set as 0.4999, and 0.4999, respectively.

Table 5. The Eigen vectors for principal components and contribution

Responses	First principal component		Second principal component
	First principal component	Second principal component	
Punch force	0.7071	-0.7071	0.4999
Thickness Variation	0.7071	0.7071	0.4999

Computation Grey Relational Grades

On the basis of equation (7) and the statistics listed in Table 6, the grey relational grades are considered as follows:

$$\gamma_1 = (0.4999^* \ 0.548848) + (0.4999 * 0.666766) = 0.6076 \quad (15)$$

Following similar method, the grade and level of analysis is performed for all $i = 27$ experiments and consolidated in Table 6.Rather than thinking about the various quality attributes for upgrading the forming parameters, the preferred optimizing single factor is grey relational grade (GRG).

RESULTS AND DISCUSSION

More prominent the GRG value, stronger is the relationship to reference sequence, signify the position of the factor [21], [22]. It indicates that, the greater the GRG, the better the presentation [22], [23]. Hence, the most ideal degree of the process parameters is the best GRG value.

In response table, the average of grade rate of corresponding intensity of each forming parameter is taken from the OA. For instance, in the primary column in the OA blank thickness (as shown in Table 2), the test no 5,6,7,9,13,15,16,21 and 27 were the investigational runs at which sheet forming parameter A (blank thickness) was place at level 1.

The associated standards of grey relational grade for A1 are those experimental runs' grey relational grades. Calculations were performed for all forming parameter levels and the response table was constructed as specified in Table 7.

A_1 = (0.406585 + 0.616204 + 0.668872 + 0.387685 + 0.375825+ 0.567298 + 0.550391 + 0.456874 + 0.549675)/9
= 4.579409/9
= 0.5088232

Similarly, the usual grey relational grade for A_2 and A_3 are calculated as follows:

A_2 = (0.607807 + 0.383853 + 0.532304+ 0.81239 + 0.601211 + 0.431314 + 0.710156 + 0.490534 + 0.41659)/9
= 4.986159/9
= 0.554017

Table 6. Grey Relational Co-efficient, GRA and Rank for Punch force and Uniform thickness variation

Expt No	Grey relational coefficient		Grey Relational Grade	Rank
	Punch force	Thickness Variation		
1	0.5488	0.6667	0.6076	8
2	0.3926	0.7543	0.5735	11
3	0.3823	0.3853	0.3838	26
4	0.3721	1	0.6860	5
5	0.4635	0.3495	0.4065	24
6	0.7763	0.4560	0.6162	7
7	0.8072	0.5305	0.6688	6
8	0.5241	0.5404	0.5323	16
9	0.4420	0.3333	0.3876	25
10	0.5000	0.9334	0.7167	3
11	0.3333	0.5948	0.4641	18
12	1	0.6247	0.8123	1
13	0.3812	0.3704	0.3758	27
14	0.5696	0.6327	0.6012	9
15	0.6478	0.4867	0.5672	12
16	0.6374	0.4633	0.5503	14
17	0.3939	0.7163	0.5551	13
18	0.4360	0.4266	0.4313	22
19	0.6213	0.7989	0.7101	4
20	0.4874	0.9705	0.7290	2
21	0.4730	0.4407	0.4568	19
22	0.4002	0.7656	0.5829	10
23	0.3893	0.5917	0.4905	17
24	0.3478	0.5626	0.4552	20
25	0.3613	0.5482	0.4548	21
26	0.4082	0.4249	0.4165	23
27	0.6904	0.4088	0.5496	15

A_3 = (0.5735 + 0.686076+ 0.716727 + 0.464112 + 0.555162 + 0.729019 + 0.582961 + 0.455245+ 0.454832)/9
= 5.217634/9
= 0.579737

Figure 4 represents the GRG graph, where the horizontal line in the representation is the rank of the complete

Table 7. Response table for means of GRG

Factor	Level 1	Level 2	Level 3	Delta	Rank
Blank Thickness	0.5088232	0.554017591	**0.579737042**	0.070913842	2
Die and Blank Temperature	0.419560175	0.545501939	**0.677515718**	0.257955543	1
Die Speed	**0.55795**	0.548496	0.536133	0.021815	4
Lubrication	0.562716	**0.5647**	0.515161	0.049541	3

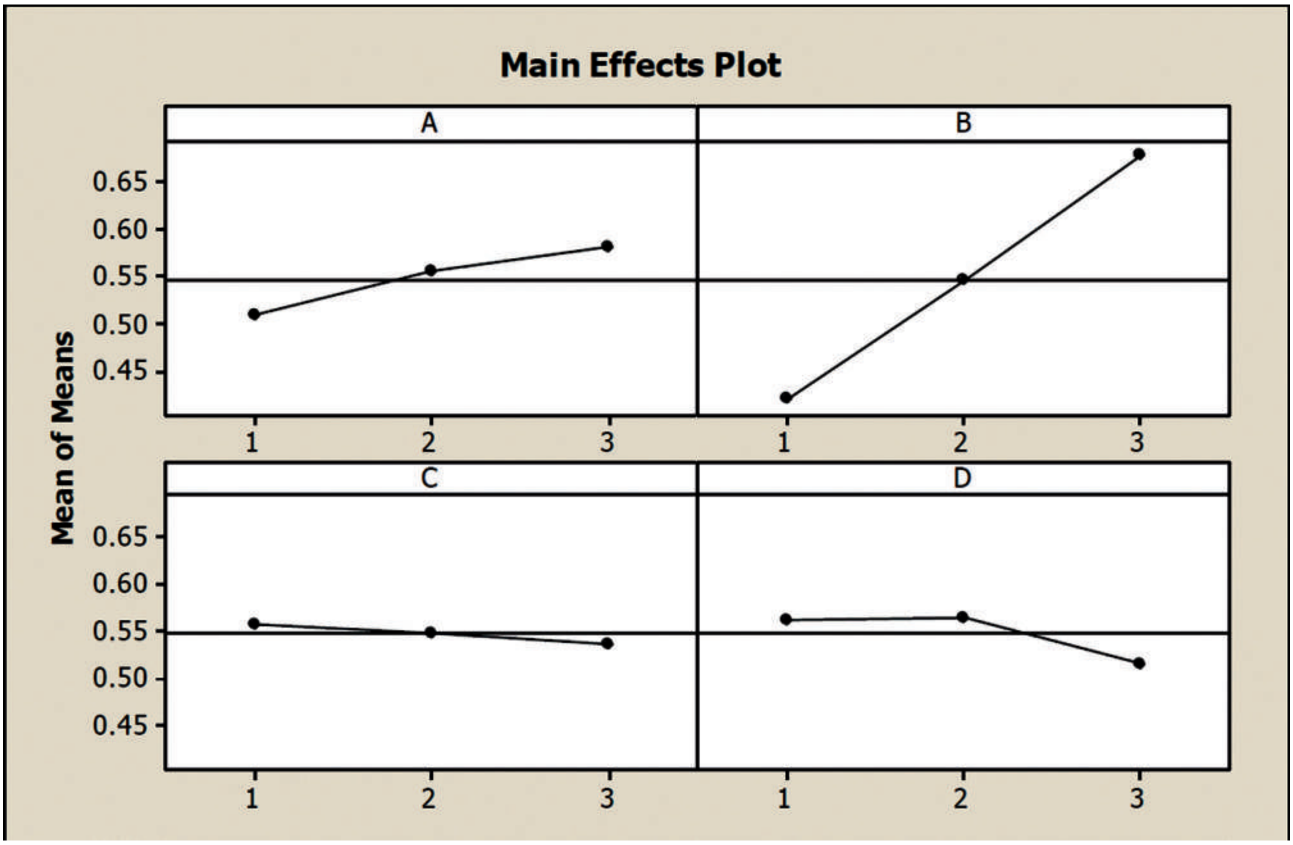

Figure 4. Main Effect plot for means (GRG).

mean of the GRG. Mainly, the bigger the GRG, the better are the various performance characteristics.

Accordingly, we selected the level that gave the significant average response. From the response table for the GRG shown in Table 7, the greatest blend of the forming parameters is the place with A_3 (blank thickness of 2 mm), B_3 (die and blank temperature of 300°C), C_1(die speed of 0.4 mm/s) and D_2 (lubrication type is Boric acid) which gives the least punch force and uniform thickness variation. The GRG significance of 0.729 (A3B3C1D1) got in the trail has a insignificant of 1.61% with respect to the predicted mean value of 0.741. Similarly, while in experimentation, the arrangement of best grade value 0.81239 for (A2B3C1D2) is 9.58% deviation when compared to predicted value.

Analysis of Variance

ANOVA, the measurable procedure is utilized to distinguish the best effective process parameter among the four parameters in the sheet forming process. The consequences of ANOVA for each of the 27 estimations of evaluation are given in Table 8. Percentage involvements for each term affecting GRG are given in Fig 5. It shows that die and blank temperature is the most considerable forming method parameters for affecting the multiple performance qualities due to its highest percentage involvement of 80.11% amongst the process parameters. Table 8 further shows that the forming process parameter, die speed, does not have statistically substantial effect of 1% on the various performance characteristics. It may be noted that die speed might have an effect on some response variables

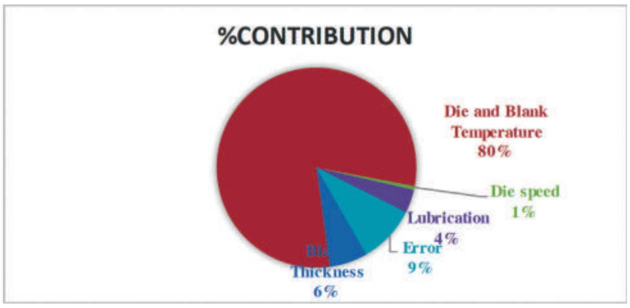

Figure 5. Percentage involvement of process parameters in Forming process.

individually but its effect might be insignificant, when all response variables are considered together with different weightages as it has been observed in the present experimental investigation.

Figure 6 illustrates that the residuals follow an approximately straight line in normal probability plot. Residuals have steady change as they are spread arbitrarily around zero in residuals versus the fitted qualities. Since residuals display no understandable pattern, there is no error due to time or data collection order. The strongest interactions between various parameters are shown in Fig. 7

Table 8. Results of the analysis of variance

Source	DF	SS	AS	AMS	F	P	% Contribution
Blank Thicknesss	2	0.0231	0.0231	0.0115	6.00	0.0100	6.2057
Die and Blank Temperature	2	0.2994	0.2994	0.1497	77.43	0.0000	80.1178
Die Speed	2	0.0021	0.0021	0.0010	0.56	0.5830	0.5762
Lubrication	2	0.0141	0.0141	0.0070	3.66	0.0460	3.7877
Error	18	0.0348	0.0348	0.0019			9.3121
Total	26	0.03738					100
		S=0.0439762 R^2= 90.69% R2(adjusted) = 86.55%					

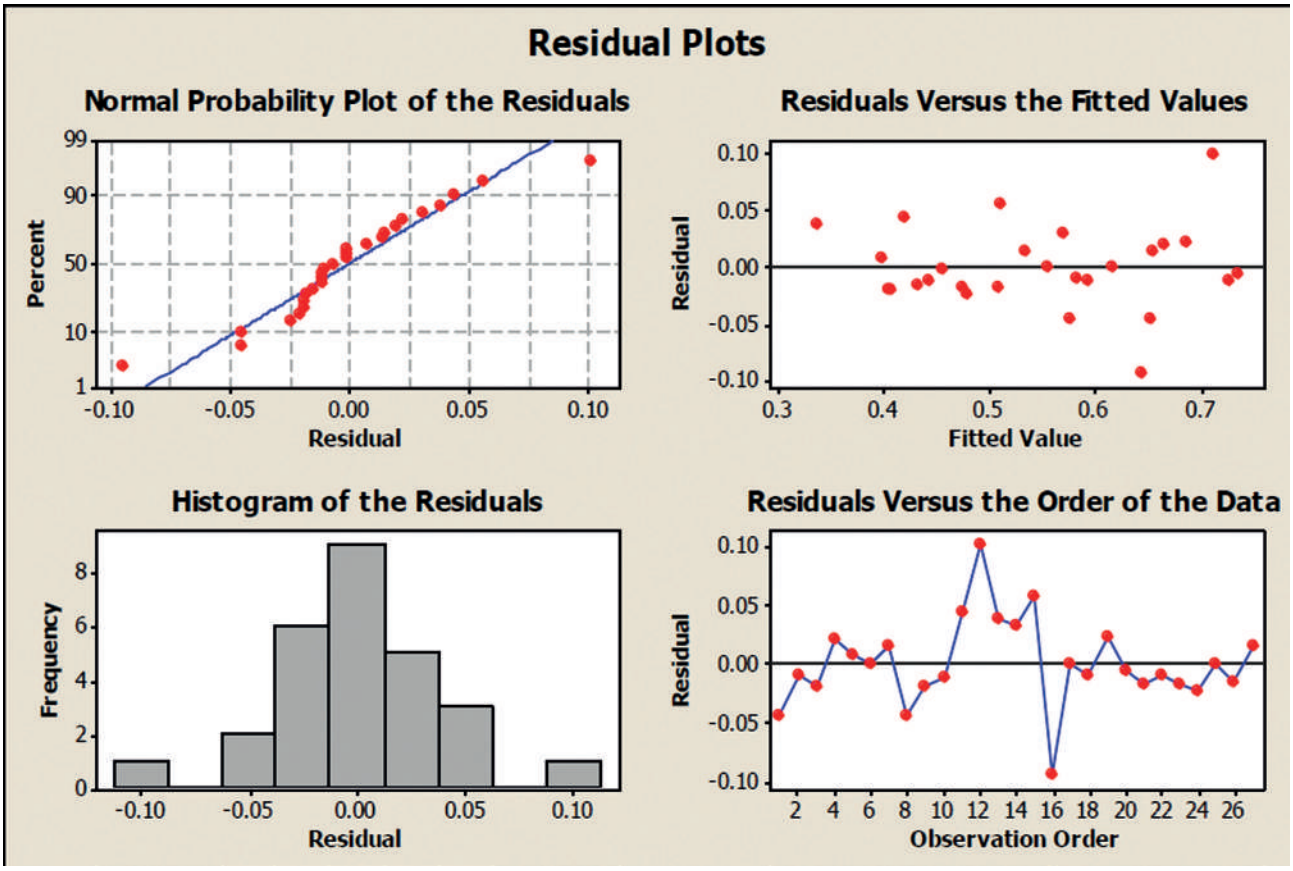

Figure 6. Residual plot for GRG.

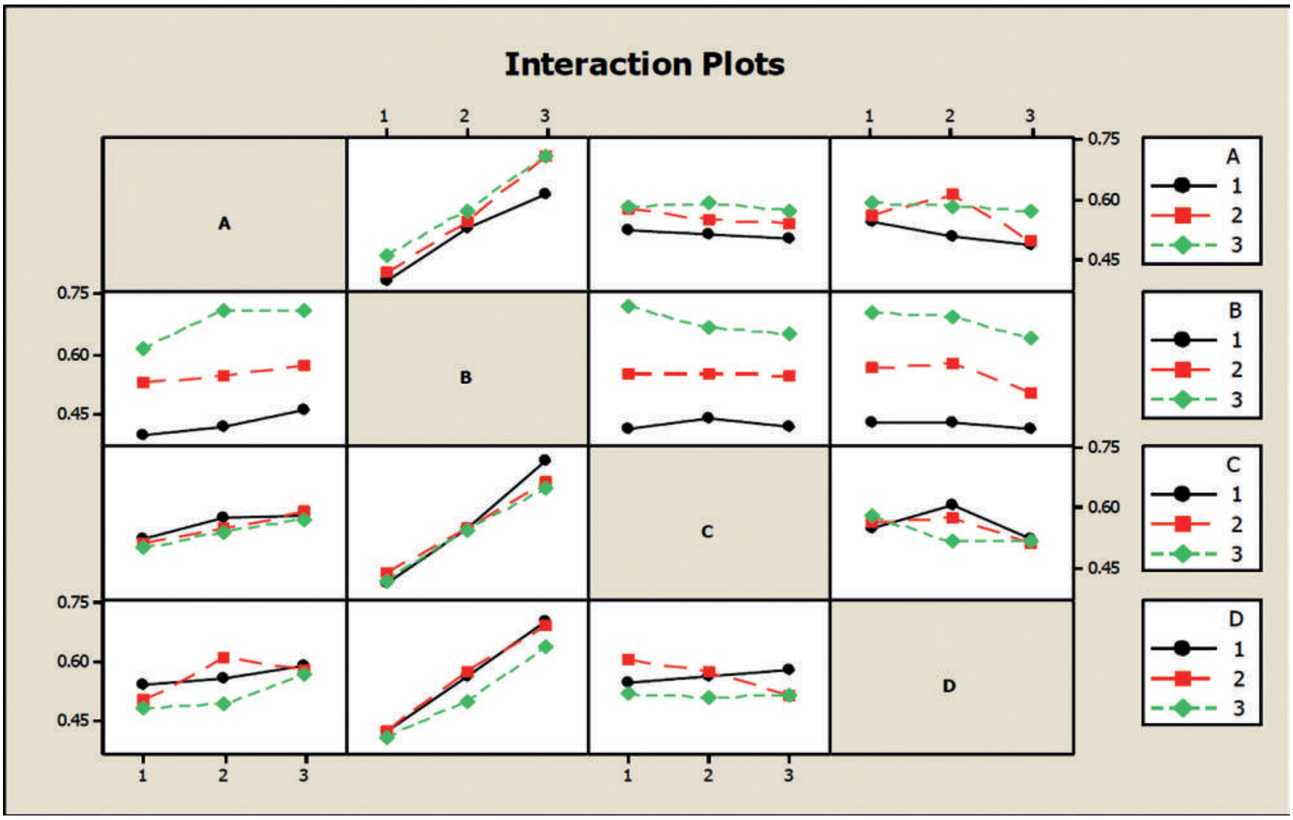

Figure 7. Interaction scheme of mean for GRG.

Table 9. Comparison between Best Experimental and Optimal Conditions

Response Setting level	Best combination A2-B3-C1-D2	Experimental (Nearer to Predicted) A3-B3-C1-D1	Optimal Forming Conditions		% Error = (*Experimental-Predicted*)*100/ *Experimental*
			Predicted A3B3C1D2	Experimental A3B3C1D2	
Punch Force (KN)	21.8005	46.5978	35.23	34.5	2.11%
Uniform Thickness Variation (mm)	0.201206	0.274061	0.1242	0.1111	8%
GRG	0.812	0.729	0.737	0.74	0.539%

Confirmation Test

After obtaining the most ideal level of the sheet forming parameters, the subsequent step is to verify the improvement of the presentation characteristics using this optimal combination. Table 9 compares the outcomes of the confirmation tests utilizing the ideal sheet forming parameters (A3, B3, C1, D2) obtained by the proposed method and with those of the initial forming parameters (A3, B3, C1, D1) whose value is near to optimal grade with 10.26% grade variation. As shown in Table 9, punch force changes from 46.5978 KN to 34.5KN; which says that almost 25.96% of punch force is saved, while the uniform thickness variation from 0.274061 to 0.135 mm, shows 50.74% thinning variation improvement in maintain uniform thinning. By applying optimal forming conditions, as mentioned by [9] the improvement in obtaining minimum punch force and minimum thickness variation is attained.

The best combination (A2-B3-C1-D2) with grade 0.812, obtained from unrefined data shows almost 9.58% variations from the proposed method whose grade is 0.741, indicating the precision of experimentation.

As indicated in Table 9, an experiment is performed to check the optimality for the predicted combination and achieved 2.11% error in punch force, 8% error in uniform thickness variation and 0.53% error in grade value which is in accepting mode.

Consequently, these confirmation tests reveal that the proposed calculation for understanding the ideal combinations of the sheet forming parameters in this work improves Punch force, Uniform thickness variation.

CONCLUSIONS

The utilization of GRA combined with PCA for optimizing the process parameters in sheet forming of Al6061-T6 has summarized the outcome as follows:

1. The general significance of every performance trademark in solving various execution problems have been controlled by comparing weighting values utilizing PCA.
2. Die and blank temperature, with total part of 80.117%, is the major controllable feature influencing the multiple performance qualities.
3. Most ideal combination of the sheet forming parameters acquired from the proposed strategy based on response table is A3, B3, C1 and D2 set. On comparing the proposed method grade value of 0.741 to the experimental unrefined range grade of 0.729 from A3, B3, C1, D1 combination indicates 25.96% decrease in punch force to attain almost 50.74% of enhancement in uniform thinning. Thus, the confirmation tests indicate the performance of proposed method.
4. The A2-B3-C1-D2 combination, showing the highest grade of 0.812 is approximately 9.5% variation with the proposed grade of 0.741 from optimum combination exhibits the accuracy of the performed experimentation.
5. Currently, in this experimentation, not just the best blend of factors are suggested for execution of sheet forming yet additionally proposed the optimization strategy for the sheet forming parameters with various performance attributes**.**

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AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

NOMENCLATURE

A	blank Thickness
B	die and Blank Temperature
C	die Speed
D	lubrication
WOL	without Lubrication
BA	boric acid powder
G	graphite powder
P	punch force
Th	thickness variation
GRA	grey relational analysis
GRC	grey relational coefficient
PCA	principle component analysis
GRG	grey relational grade

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