



Taguchi grey relational analysis for parametric optimization of severe plastic deformation process

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Abstract

In this paper, a new effective approach, Taguchi grey relational analysis has been applied to experimental results in order to optimize the severe plastic deformation process parameters with consideration to multiple performance measures. The approach combines the orthogonal array design of L27 experiments with grey relational analysis. Grey relational analysis is adopted to determine the best process parameters that give ultrafine grain structure leading to enhanced mechanical properties. The response table and the grey relational grade for each level of the process parameters has been established. The parameters that were considered were the specimen thickness of 3 mm, 4 mm and 5 mm; the displacement rates of 1.0 mm/min, 1.5 mm/min and 2.0 mm/min; and the number of passes which were 1, 3 and 5. A total of 27 experiments were conducted. The optimum parameter values producing the highest value of grey relational grade was allotted rank one which pertained to the factors setup for experiment number 17 having 1.5 mm/min as the displacement rate, with 5 numbers of pass and thickness of specimen being 4 mm.

Keywords Al 6061 · SPD process · Mechanical properties · Optimization · Grey relational analysis

1 Introduction

The process of severe plastic deformation (SPD) is gaining great interest in the field of material science and engineering in view of its usefulness in refining the microstructure to nanometer levels. In Al-based alloys, it is generally difficult to reduce the grain size below 10 μm through the conventional recrystallization process following thermos-mechanical treatments. This difficulty arises from the inherent nature of Al alloys that the stacking fault energy is relatively large so that it is easy for the recovery of dislocation to occur. One of the advantages is the capability of producing large samples that are free from any residual porosity and readily amenable to mechanical testing and forming operations. In terms of using severe plastic deformation to produce nanostructure sheets [1–3], two major severe plastic deformation

techniques, which are mostly employed, are accumulative roll bonding [4] and constrained groove pressing [5]. The constrained groove pressing process, introduced by Shin et al. [6], involves repetitive corrugating and flattening stages. During constrained groove pressing, the work piece is subjected to cyclic shear deformation by utilizing asymmetrically grooved dies and flat dies. In this technique, the gap between the upper die and lower die is identical to the sample thickness and therefore the inclined part of the sample, located in the groove, is subjected to pure shear deformation [7]. By imposing more constrained groove pressing passes, higher strains are introduced to the work piece. The work piece subjected to severe plastic deformation by applying three passes of constrained groove pressing resulted in a total strain of 3.48. This led to ultrafine grain low carbon steel having the grains of 260–270 nm. Recently, many

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SN Applied Sciences (2019) 1:937 | <https://doi.org/10.1007/s42452-019-0982-6>

Received: 25 May 2019 / Accepted: 24 July 2019 / Published online: 30 July 2019

works are carried out to study the mechanical properties and microstructural evolutions of different materials such as low carbon steel, aluminium and copper alloys subjected to constrained groove pressing. According to these studies [8–12], the constrained groove pressing process can effectively enhance the mechanical properties of sheet metals.

The material used in the present study was aluminium alloy (Al) 6061. It contains magnesium and silicon as its major alloying elements. The chemical composition of the alloy is presented in Table 1. Al 6061 has good mechanical properties, exhibits good weldability and can be conveniently extruded, forged, or rolled to a variety of shapes and sizes. It can be easily brazed and has very good corrosion resistance, good machinability and workability. It is a medium to high strength alloy which is widely used in aircraft structures such as fuselages and wings.

It is important to develop an optimal manufacturing method in severe plastic deformation process. The advantage of grey multiple attributes decision is that it has been clearly observed that the number of passes (B) has the highest amount of contribution and the displacement rate (A) has the second highest contribution on the response values. The specimen thickness (C) and interaction factors show a very less amount of contribution. The results in terms of the change in mechanical properties are discussed.

The objectives of the research paper is to establish a relationship between the various process parameter like displacement rate, thickness of the plate and number of passes and the microstructure of the specimen obtained and the effect of the process parameters on the mechanical properties of Al 6061 alloy. The results in terms of micro structural characteristics and the change in mechanical properties are discussed in this paper.

2 Design of experiments

The design of experiments (DOE) approach using Taguchi technique has been successfully applied by several researchers in various studies relating to aluminum-based alloys and composites. Taguchi technique significantly reduces the number of experiments that are required to model the response function compared to the full factorial design of experiments. A major advantage of this technique is to find the possible interaction between the various parameters [13, 14]. Design of experiments is one of the many problem-solving quality tools that can be used for various investigations such as finding the significant factors in a process, the effect of each factor on the outcome, the variance in the process,

troubleshooting the machine problems, screening the parameters, and modeling the processes. Many industries use this tool to stay competitive worldwide by designing robust products as well as improving quality and reliability of a product. By using strategically designed and statistically performed experiments, it is possible to study the effect of several variables at one time, and to study inter-relationships and interactions [15, 16].

In the present study, the parameters considered in the experiments are the displacement rate, thickness of the test specimen, and the number of passes for various compressive displacement rates in order to study the grain refinement and its effect on mechanical properties. Taguchi Orthogonal Array (OA) was employed to develop the experimental layout. Table 2 shows the three parameters and their levels considered in the experiment.

2.1 Taguchi orthogonal array (OA) design

A matrix experiment consists of a set of experiments where the settings of the various product or process parameters in consideration are changed from one experiment to another. After conducting a matrix experiment, the data from all the experiments in the set are taken together and analyzed to determine the effects of the various parameters. Conducting matrix experiments using special matrices, called orthogonal arrays, allows the effects of several parameters to be determined efficiently.

Taguchi orthogonal array designs are repeatedly used in design experiments with multiple level factors. Taguchi orthogonal array can be thought of as a general fractional factorial design process. However, before constructing an orthogonal array, the following requirements must be defined.

1. Number of factors to be studied: In the present study the numbers of factors to be studied are 3. They are strain rate of specimen compression in mm/min, number of passes assigned for compression, and the thickness of the test specimen in mm.

Table 2 Experimental parameters and their levels

Factor	Name	Unit	Levels		
A	Displacement rate	mm/min	1	1.5	2
B	Number of pass	–	1	3	5
C	Thickness	mm	3	4	5

Table 1 Chemical composition of Al 6061 alloy in wt%

Mg	Si	Cu	Cr	Zn	Mn	Ti	Al
0.8–1.2	0.4–0.8	0.15–0.4	0.04–0.35	0.0–0.25	0.0–0.15	0.0–0.15	Balance

2. Number of levels for each factor: The number of levels considered for each factor is also 3.
3. Response values of the experiment: The response values considered are micro-hardness, tensile strength and grain size.

Three main effects are considered as follows.

1. Strain rate of specimen compression in mm/min (A)
2. Number of passes assigned for compression (B)
3. Thickness of the test specimen in mm (C)

Three interaction effects are considered as follows.

1. Strain rate and number of passes (AB and AC)
2. Strain rate and Thickness (BA and BC)
3. Number of passes and thickness (CA and CB)

2.2 Linear graph and interaction assignment

Linear graph represents the interactions graphically and makes it easy to assign with factors and interactions to the various columns of an orthogonal array. In a linear graph, the columns of an orthogonal array are represented by dots and lines. The interaction of the two columns represented by the dots is confounded with the column represented by the line. In a linear graph, each column and each line has a distinct column numbers associated with it. Further, every column of the array is represented in its linear graph once only. In the present experiment the linear graph is constructed as shown in Fig. 1

Taguchi orthogonal array designs are repeatedly used in design of experiments with multiple level factors. The

notation for matrix experiments $L_{27}(3^{13})$ shows the calculations for total number of experiments to be conducted which is 27 in this case and the number of factors being represented by 3^{13} .

A total of 27 experiments were designed using Taguchi orthogonal array. The experiment's log, where different factors and their levels used in each experiment are as shown in Table 3.

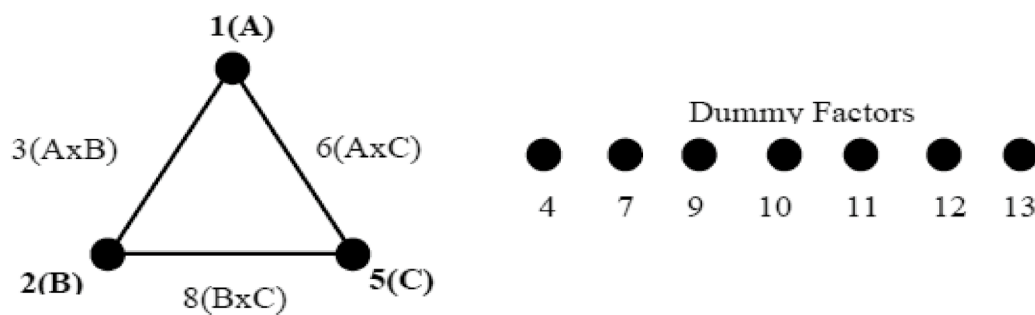
The experimental conditions for the 27 experiments are as presented in Table 4. A total of 27 experiments were designed using Taguchi orthogonal array. Taguchi orthogonal array designs are repeatedly used in design of experiments with multiple level factors.

After setting the experimental parameters for each experiment, the responses are characterized as grain size, micro-hardness and tensile strength. The responses obtained according to each experiment conducted are shown in Table 5.

3 Results and discussions

3.1 Grey relational analysis

Grey relational analysis is widely used for measuring the degree of relationship between sequences by grey relational grade. Grey relational analysis has been applied by several researchers [17, 18] to optimize the control parameters having multi-responses through grey relational grade. The Grey relational analysis is widely used to combine all the considered performance characteristics into a single value that can be used as the single characteristic in optimization problems.



Experimental parameters and their levels

Main Effect

- 1(A) Displacement rate
- 2(B) number of passes
- 5(C) thickness

Interaction Effect

- 3(AxB)
- 6(AxC)
- 8(BxC)

Dummy factors

- 4, 7, 9, 10, 11, 12 and 13

Fig. 1 Linear graph

Table 3 Experiment’s log, where different factors and their levels used in each experiment are shown

Expt. no.	Column number and factor assignment						Expt. no.	Column number and factor assignment					
	1	2	3	5	6	8		1	2	3	5	6	8
	A	B	AB	C	AC	BC		A	B	AB	C	AC	BC
1	1	1	1	1	1	1	15	2	2	3	3	1	1
2	1	1	1	2	2	2	16	2	3	1	1	2	3
3	1	1	1	3	3	3	17	2	3	1	2	3	1
4	1	2	2	1	1	2	18	2	3	1	3	1	2
5	1	2	2	2	2	3	19	3	1	3	1	3	1
6	1	2	2	3	3	1	20	3	1	3	2	1	2
7	1	3	3	1	1	3	21	3	1	3	3	2	3
8	1	3	3	2	2	1	22	3	2	1	1	3	2
9	1	3	3	3	3	2	23	3	2	1	2	1	3
10	2	1	2	1	2	1	24	3	2	1	3	2	1
11	2	1	2	2	3	2	25	3	3	2	1	3	3
12	2	1	2	3	1	3	26	3	3	2	2	1	1
13	2	2	3	1	2	2	27	3	3	2	3	2	2
14	2	3	2	2	3	3							

Table 4 Experiment’s log, where different factors and their levels used in each experiment

Expt. no.	Experimental condition			Expt. no.	Experimental condition		
	Displacement rate (mm/min)	No. of passes	Thickness (mm)		Displacement rate (mm/min)	No. of passes	Thickness (mm)
1	1	1	3	15	1.5	3	5
2	1	1	4	16	1.5	5	3
3	1	1	5	17	1.5	5	4
4	1	3	3	18	1.5	5	5
5	1	3	4	19	2	1	3
6	1	3	5	20	2	1	4
7	1	5	3	21	2	1	5
8	1	5	4	22	2	3	3
9	1	5	5	23	2	3	4
10	1.5	1	3	24	2	3	5
11	1.5	1	4	25	2	5	3
12	1.5	1	5	26	2	5	4
13	1.5	3	3	27	2	5	5
14	1.5	3	4				

3.2 Normalization of response values

Normalization of response values are divided into three types according to expected nature of the response values. The first normalization is ‘the smaller the better’ values where the lowest values of the objective function are expected. Second is ‘nominal the better’ where the objective function has average values. The third one is ‘higher the better’ where highest values of the results are expected.

In the present study, the values for micro-hardness and tensile strength should increase with the grain refinement. Hence, ‘higher the better’ normalization criteria is considered for micro-hardness and tensile strength. The formula for ‘higher the better’ normalization criteria considered is as follows:

$$x_i(k) = \frac{y_i(k) - \min y_i(k)}{\max y_i(k) - \min y_i(k)} \tag{1.1}$$

Table 5 Data summary by experiments

Expt. no.	Experimental condition matrix			Micro hardness (HV)	Tensile strength (MPa)	Grain size (µm)
	Displacement rate (mm/min)	No. of passes	Thickness (mm)			
01	1	1	3	44.48	94.82	7.7
02	1	1	4	43.27	97.31	7.9
03	1	1	5	43.02	76.38	8.0
04	1	3	3	46.17	105.96	6.5
05	1	3	4	45.50	109.81	6.4
06	1	3	5	45.70	89.29	5.6
07	1	5	3	49.20	113.00	3.8
08	1	5	4	48.65	120.00	3.1
09	1	5	5	47.98	96.00	4.0
10	1.5	1	3	46.01	97.70	8.0
11	1.5	1	4	44.38	96.92	7.2
12	1.5	1	5	42.79	79.07	6.7
13	1.5	3	3	47.62	104.95	6.7
14	1.5	3	4	46.19	109.58	5.8
15	1.5	3	5	45.45	91.10	5.0
16	1.5	5	3	52.78	114.7	4.2
17	1.5	5	4	52.73	119.01	3.5
18	1.5	5	5	50.08	96.25	4.7
19	2	1	3	46.33	95.92	8.0
20	2	1	4	44.82	96.09	7.6
21	2	1	5	42.33	78.69	6.4
22	2	3	3	47.91	104.51	6.3
23	2	3	4	46.02	112.10	5.6
24	2	3	5	44.18	88.44	5.1
25	2	5	3	52.13	115.13	4.2
26	2	5	4	52.23	121.94	3.8
27	2	5	5	49.63	97.10	4.6

where,

$x_i(k)$ = value after the grey relational generation
 $\min y_i(k)$ = smallest value of $y_i(k)$ for the k th response
 $\max y_i(k)$ = largest value of the $y_i(k)$ for the k th response

In the present work, it is observed that as value of grain size is decreased, the micro-hardness and tensile strength increases. Hence, the normalization criteria considered for grain size is that lower value is the better value. The analytical formula for 'lower the better' criteria considered is as follows:

$$x_i(k) = \frac{\max y_i(k) - y_i(k)}{\max y_i(k) - \min y_i(k)} \tag{1.2}$$

where,

$x_i(k)$ = value after the grey relational generation
 $\min y_i(k)$ = smallest value of $y_i(k)$ for the k th response

$\max y_i(k)$ = largest value of the $y_i(k)$ for the k th response

Accordingly, the normalized values of the responses are calculated and presented in Table 6 below.

Specimen calculation for Normalized value of micro hardness

$$x_i(k) = \frac{y_i(k) - \min y_i(k)}{\max y_i(k) - \min y_i(k)}$$

Accordingly, the normalized values of the responses are calculated and presented in Table 6 below.

$\min y_i(k)$ = smallest value of $y_i(k)$ for the k th response = 42.33
 $\max y_i(k)$ = largest value of the $y_i(k)$ for the k th response = 52.78

$$x_i(k) = \frac{44.48 - 42.33}{52.78 - 42.33} = 0.206$$

Specimen calculation for Normalized value of Tensile strength

Table 6 Normalized values for the responses

Expt. no.	Micro hardness (HV)	Normalized value	Tensile strength (MPa)	Normalized value	Grain size (µm)	Normalized value
1	44.48	0.206	94.82	0.405	7.7	0.061
2	43.27	0.090	97.31	0.459	7.9	0.020
3	43.02	0.066	76.38	0.000	8.0	0.000
4	46.17	0.367	105.96	0.649	6.5	0.306
5	45.50	0.303	109.81	0.734	6.4	0.327
6	45.70	0.322	89.29	0.283	5.6	0.490
7	49.20	0.657	113.00	0.804	3.8	0.857
8	48.65	0.605	120.00	0.957	3.1	1.000
9	47.98	0.541	96.00	0.431	4.0	0.816
10	46.01	0.352	97.70	0.468	8.0	0.000
11	44.38	0.196	96.92	0.451	7.2	0.163
12	42.79	0.044	79.07	0.059	6.7	0.265
13	47.62	0.506	104.95	0.627	6.7	0.265
14	46.19	0.369	109.58	0.729	5.8	0.449
15	45.45	0.299	91.10	0.323	5.0	0.612
16	52.78	1.000	114.7	0.841	4.2	0.776
17	52.73	0.995	119.01	0.936	3.5	0.918
18	50.08	0.742	96.25	0.436	4.7	0.673
19	46.33	0.383	95.92	0.429	8.0	0.000
20	44.82	0.238	96.09	0.433	7.6	0.082
21	42.33	0.000	78.69	0.051	6.4	0.327
22	47.91	0.534	104.51	0.617	6.3	0.347
23	46.02	0.353	112.10	0.784	5.6	0.490
24	44.18	0.177	88.44	0.265	5.1	0.592
25	52.13	0.938	115.13	0.851	4.2	0.776
26	52.23	0.947	121.94	1.000	3.8	0.857
27	49.63	0.699	97.10	0.455	4.6	0.694

$$x_i(k) = \frac{y_i(k) - \min y_i(k)}{\max y_i(k) - \min y_i(k)}$$

Accordingly, the normalized values of the responses are calculated and presented in Table 6 below.

$\min y_i(k)$ = smallest value of $y_i(k)$ for the k th response = 76.38
 $\max y_i(k)$ = largest value of the $y_i(k)$ for the k th response = 121.94

$$x_i(k) = \frac{94.82 - 76.38}{121.94 - 76.38} = 0.405$$

Specimen calculation for Normalized value of Grain size

$$x_i(k) = \frac{\max y_i(k) - y_i(k)}{\max y_i(k) - \min y_i(k)}$$

Accordingly, the normalized values of the responses are calculated and presented in Table 6 below.

$\min y_i(k)$ = smallest value of $y_i(k)$ for the k th response = 3.1
 $\max y_i(k)$ = largest value of the $y_i(k)$ for the k th response = 8.0

$$x_i(k) = \frac{8.0 - 7.7}{8.0 - 3.1} = 0.061$$

3.3 Determining grey relational grades

The grey relational degree is used to measure the correlation between the measurement spaces factor and the target sequence after a grey relational generation of the discrete sequence.

The grey relation coefficient $\xi_i(k)$ can be calculated using the below given equation.

$$\xi_i(k) = \frac{\Delta_{\min} + \xi \Delta_{\min}}{\Delta_{0i}(k) + \xi \Delta_{\max}} \tag{1.3}$$

where,

$$\Delta_{0i} = ||x_0(k) - x_i(k)||$$

Δ_{0i} : difference of the absolute value between the target sequence $x_0(k)$ and the comparison sequence $x_i(k)$;
 ξ = distinguishing coefficient in between 0 and 1.
 $x_0(k)$ = ideal sequence or the target sequence;
 $x_i(k)$ = given sequence or the comparison sequence;
 $\Delta_{\min} = \forall j \min \epsilon_i \forall_k \min ||x_0(k) - x_j(k)||$ = smallest value of Δ_{0i}
 Δ_{\min} : The absolute value of the minimum difference of the comparison sequence and the target sequence.
 $\Delta_{\max} = \forall j \max \epsilon_i \forall_k \max ||x_0(k) - x_j(k)||$ = largest value of Δ_{0i} .
 Δ_{\max} : The absolute value of the maximum difference of the comparison sequence and the target sequence.

The grey relational coefficient results for the experimental data are shown in Table 7.

After averaging the grey relational coefficients, the grey relational grade γ_i can be calculated using the below given equation.

$$\gamma_i = \frac{1}{n} \sum_{k=1}^n \xi_i(k) \tag{1.4}$$

where n = number of process responses.

The grey relation coefficient $\xi_i(k)$ can be calculated using the below given equation.

$$\xi_i(k) = \frac{\Delta_{\min} + \xi \Delta_{\max}}{\Delta_{0i}(k) + \xi \Delta_{\max}} \tag{1.5}$$

where,

$\Delta_{0i} = ||x_0(k) - x_i(k)||$ = difference of the absolute value between $x_0(k)$ and $x_i(k)$;
 ξ = distinguishing coefficient in between zero and one.
 $\Delta_{\min} = \forall j \min \epsilon_i \forall_k \min ||x_0(k) - x_j(k)||$ = smallest value of Δ_{0i}
 $\Delta_{\max} = \forall j \max \epsilon_i \forall_k \max ||x_0(k) - x_j(k)||$ = largest value of Δ_{0i} . The grey relational coefficient results for the experimental data are shown in the Table 6.

After averaging the grey relational coefficients, the grey relational grade γ_i can be calculated using the below given equation.

$$\gamma_i = \frac{1}{n} \sum_{k=1}^n \xi_i(k) \tag{1.6}$$

$\xi = 0.1$ $x_0(k) = 1$ $x_j(k) = x_{27}(k)$
 $\Delta_{\min} = ||x_0(k) - x_{27}(k)|| = (1 - 0.699) = 0.301$
 $\Delta_{\max} = ||x_0(k) - x_1(k)|| = (1 - 0.206) = 0.794$
 $\Delta_{0i}(k) = ||x_0(k) - x_2(k)|| = (1 - 0.090) = 0.91$

$$\xi_i(k) = \frac{\Delta_{\min} + \xi \Delta_{\max}}{\Delta_{0i}(k) + \xi \Delta_{\max}} \tag{1.7}$$

$$\xi_i(k) = \frac{0.301 + 0.1(0.794)}{0.91 + 0.1(0.794)} = \mathbf{0.386}$$

$\xi_i(k) = 0.386$ (specimen calculations of grey relational value for micro hardness) similarly
 $\xi_i(k) = 0.457$ (specimen calculations of grey relational value for Tensile strength)

Table 7 Grey relational coefficient of each performance characteristics

Expt. no.	Grey relational values			Expt. no.	Grey relational values		
	Micro hardness (HV)	Tensile strength (MPa)	Grain size (µm)		Micro hardness (HV)	Tensile strength (MPa)	Grain size (µm)
1	0.386	0.457	0.348	15	0.416	0.425	0.563
2	0.355	0.480	0.338	16	1.000	0.759	0.690
3	0.349	0.333	0.333	17	0.991	0.886	0.860
4	0.441	0.588	0.419	18	0.659	0.470	0.605
5	0.418	0.653	0.426	19	0.448	0.467	0.333
6	0.425	0.411	0.495	20	0.396	0.468	0.353
7	0.593	0.718	0.778	21	0.333	0.345	0.426
8	0.559	0.922	1.000	22	0.518	0.567	0.434
9	0.521	0.468	0.731	23	0.436	0.698	0.495
10	0.436	0.484	0.333	24	0.378	0.405	0.551
11	0.383	0.477	0.374	25	0.889	0.770	0.690
12	0.343	0.347	0.405	26	0.905	1.000	0.778
13	0.503	0.573	0.405	27	0.624	0.478	0.620
14	0.442	0.648	0.476				

$\xi_i(k) = 0.348$ (specimen calculations of grey relational value for Grain size)

The higher the value of grey relational grade considered, the stronger is the relational degree between the ideal sequence $x_0(k)$ and the given sequence $x_i(k)$. Earlier it has been mentioned that the ideal sequence $x_0(k)$ is the best process response in the experimental layout. Here, it may be concluded that the higher relational grade means that the corresponding parameter combination is closer to the optimal.

Grey relational grade is calculated from the Table 7 based on the higher grey relational grade upon which its order or rank will be fixed.

Specimen calculations

Grey relation Grade = average of grey relational values

$$\text{Grey relation Grade} = \frac{0.386 + 0.457 + 0.348}{3} = 0.397$$

Grey relational grade was calculated using grey relational analysis and the rank was allotted according to the grey relational grades. The highest value of the grey relational was considered as first rank experiment and further ranking was sorted from larger to smaller. The experimental setup which yielded first rank response values will be considered as an ideal experimental setup to obtain superior values of response. Table 8 shows the grey relational values along with the rank or order.

Table 8 The experimental results for the grey relational grade and its rank

Expt. no.	Grey relational grade	Rank	Expt. no.	Grey relational grade	Rank
1	0.397	23	15	0.468	16
2	0.391	24	16	0.816	4
3	0.338	27	17	0.912	1
4	0.483	15	18	0.578	7
5	0.499	13	19	0.416	20
6	0.444	18	20	0.406	22
7	0.696	6	21	0.368	25
8	0.827	3	22	0.506	12
9	0.573	9	23	0.543	10
10	0.418	19	24	0.445	17
11	0.411	21	25	0.783	5
12	0.365	26	26	0.894	2
13	0.494	14	27	0.574	8
14	0.522	11			

3.4 Grey relational analysis from Taguchi technique

Using the Taguchi Orthogonal Array (OA) technique, the designed experimental layout yielded the following response values of grain size, micro-hardness and tensile strength which are presented in Table 8.

Experiment 17 has the highest value of grey relational grade and it was allotted as rank one. The factors setup for experiment number 17 has 1.5 mm/min as its displacement rate, 5 being the numbers of pass and thickness of specimen was 4 mm. Table 9 shows the response values obtained from the experiment number 17. As per Table 9, gives highest values on all the responses i.e., for 4 mm thickness Al 6061 sheet compressed by 1.5 mm/min displacement rate up to 5 passes gives the lowest grain size of 3.5 μm with micro-hardness value of 52.73 HV and tensile strength 119.01 N/mm².

3.5 ANOVA analysis

The ANOVA analysis has been performed to predict the statistical significance of the process parameters. It helps to determine the effect of individual input parameter on output parameters. The results of ANOVA presented for CCGP in Table 10 provided below indicate the percentage contribution (P) of each factor on the total variation with their degree of influence on the results obtained. The Table 10 shows the influence of Displacement Rate (A = 12.1%), number of passes (B = 77.8%), and thickness of the plate (C = 0.9%). It is observed that the pooled error is 0.009%. Based on the results presented in Table 10, the number of passes is found to be the most influencing process parameter, followed by Displacement Rate and plate thickness as shown in Fig. 2. Table 10 also shows the ranking of process parameters generated by the conduct of Taguchi method.

3.6 Response features

The Response features are as follows:

1. Grain size (μm)
2. Micro hardness (HV)
3. Tensile strength (MPa)

Effect of number of passes on grain size

After each pass of corrugation and straightening, a high density of dislocations in the grains is achieved. The obtained grain boundaries are wavy and ill defined. The dislocation density decreases with increasing number of passes and the high angle grain boundaries are generated after five passes. The grain size after 1, 3, and 5 passes are measured. After five pass of corrugation and straightening,

Table 9 Taguchi OA layout and response values

Expt. no.	Experimental condition			Response		
	Displacement rate (mm/min)	No. of passes	Thickness (mm)	Grain size (μm)	Micro hardness (HV)	Tensile strength (MPa)
1	1	1	3	7.7	44.48	94.82
2	1	1	4	7.9	43.27	97.31
3	1	1	5	8.0	43.02	76.38
4	1	3	3	6.5	46.17	105.96
5	1	3	4	6.4	45.5	109.81
6	1	3	5	5.6	45.7	89.29
7	1	5	3	3.8	49.2	113.00
8	1	5	4	3.1	48.65	120.00
9	1	5	5	4.0	47.98	96.00
10	1.5	1	3	8.0	46.01	97.70
11	1.5	1	4	7.2	44.38	96.92
12	1.5	1	5	6.7	42.79	79.07
13	1.5	3	3	6.7	47.62	104.95
14	1.5	3	4	5.8	46.19	109.58
15	1.5	3	5	5.0	45.45	91.10
16	1.5	5	3	4.2	52.78	114.70
17	1.5	5	4	3.5	52.73	119.01
18	1.5	5	5	4.7	50.08	96.25
19	2	1	3	8.0	46.33	95.92
20	2	1	4	7.6	44.82	96.09
21	2	1	5	6.4	42.33	78.69
22	2	3	3	6.3	47.91	104.51
23	2	3	4	5.6	46.02	112.10
24	2	3	5	5.1	44.18	88.44
25	2	5	3	4.2	52.13	115.13
26	2	5	4	3.8	52.23	121.94
27	2	5	5	4.6	49.63	97.10

Table 10 ANOVA for multiple performance characteristics

Source	Degrees of freedom	Sum of squares (SS)	Mean squares variance (MS)	F_{cal}	F_{tab}	%P
A	2	0.091	0.046	12.439	8.65	12.1
B	2	0.584	0.292	79.693	8.65	77.8
C	2	0.007	0.004	0.999	8.65	0.9
A×B	4	0.001	0.000	0.096	7.01	0.2
A×C	4	0.000	0.000	0.029	7.01	0.12
B×C	4	0.037	0.009	2.520	7.01	4.9
Error	8	0.029	0.004			
Total	26	0.750	–			

a total of 58% to 69% was achieved in all the three different thickness test specimens. These changes in the grain sizes is due to the extension of pre-existing boundaries in proportion to the strain and also due to the formation of new high angle grain boundaries formed by grain sub division.

Effect of number of passes on microhardness

After every pass of CCGP, the hardness of the specimen shows increasing trend with an average increase in hardness of all the specimens. Hall–Petch equation can be used to obtain the strength of any material which is inversely proportional to its grain size. By decreasing the average

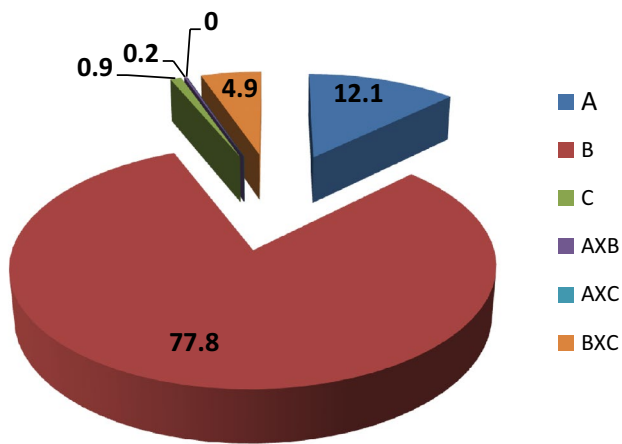


Fig. 2 Contribution of the most influencing parameters for physical properties of CCGP in percentage

grain size as in any SPD method, the yield strength of any material can be increased.

Effect of number of passes on tensile strength

The distribution of tensile strength values after each pass of the specimens was evaluated and the overall increase in tensile strength for all displacement rates was found to be 21% for 3 mm, 35% for 4 mm and 15% for 5 mm. It can be concluded that on the basis of the results obtained, that the highest stress is observed for specimens with five passes of corrugation and straightening.

4 Conclusions

The objective of the research paper was to establish a relationship between pressing parameter like displacement rate, thickness of the plate and number of passes. The effect of these parameters on the microstructure and the mechanical properties of Al 6061 alloy were also studied in detail. It is important to develop an optimal severe plastic deformation process which has several utilities in practice. Due to the advantages of grey multiple attributes decision, it is clear that the number of passes (B) has the highest amount of contribution and the displacement rate (A) has the second highest contribution on the response values. The thickness (C) and interaction factors have a very less amount of contribution. The results in terms of the change in mechanical properties are discussed.

The Taguchi Orthogonal Array (OA) technique which was used to design the experimental layout yielded the response values of grain size, micro-hardness and tensile strength which are elaborately discussed. It was found that the experiment 17 has the highest value of grey relational grade and it was designated as rank one. The factors

setup for experiment number 17 has 1.5 mm/min as the displacement rate, 5 being the numbers of pass and thickness of specimen being 4 mm.

In order to seek a proper manufacturing process which also meets the requirements of the industry, it is important to develop an accurate evaluation method. In the backdrop of the advantages of grey multiple attributes decision, this paper tries to propose an evaluation method to determine the overall performance for each of the factors considered.

Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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