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SELECTING OPTIMAL PROCESS PARAMETERS OF Al_2O_3/C COMPOSITE USING GRA WITH PCA AND TAGUCHI'S QLF APPROACH

Idrus Syahzaqi[1], Hani Brilianti Rochmanto[2], and Muhammad Ahsan[3*]

[1,2,3] Department of Statistics, Institut Teknologi Sepuluh Nopember Surabaya, 60111, Indonesia

Corresponding author e-mail: [3] muh.ahsan@its.ac.id*

Abstract. *The aim of this study is to find the controlled factors affecting the mass density of the combined Al_2O_3/Cu. All experiments were carried out using powder metallurgy. Experiments were carried out with four controllable powder processing parameters, namely milling time, compaction pressure, sintering temperature, and holding time. The L_{18} mixed-level Taguchi Orthogonal Array was used for experimental because it is the basis for the analysis of the Taguchi method. In this research, statistical analysis is carried out using GRA with PCA and Quality Loss Function. The result was the best model based on the Quality Loss Function, because the method has the biggest determination coefficient value is 99,97% where the results is better than GRA with PCA. From the main effect table study, the optimal combination of parameters for response: mass density and hardness are $A_2B_3C_3D_2$ powder metallurgical process parameters, namely milling time of 360 minutes, compacting powder of 200 MPa, sintering of 700^{0}C, and holding time of 20 minutes. The ANOVA results show that the compaction pressure has the most influential parameter that affects the response. The percentage contribution of compaction pressure is 87.09%. Based on ANOVA, the R-squared value is 99.97%, which means the tested factor variables can explain the density of the Al_2O_3/Cu composite by 99.70%. Therefore, only 18 experimental trials are needed to discover the reality of what will happen in the process.*

Keywords: *Analysis of Variance, Composite, Taguchi Method, GRA with PCA, Quality Loss Function*

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1. INTRODUCTION

Composite materials are multiphase materials created by artificially combining different materials to achieve properties that the individual components cannot achieve on their own. Composite materials should be distinguished from alloys, which may include two additional components but form naturally through processes such as casting. Composite materials can be tailored to different properties by suitable selection of their composition, proportions, distribution, morphology, degree of crystallinity, crystal texture, and structure and components of the interface between components. Because of this strong adaptability, composite materials can be engineered to meet the needs of aerospace, automotive, electronics, construction, energy, biomedical, and industrial sectors. Therefore, composite materials make up most of the commercial engineering materials [1]

In general, composites are classified according to their matrix material. The main classes of composites are polymer-matrix, cement-matrix, metal-matrix, carbon-matrix, and ceramic-matrix composites. Copper (Cu) metal is ductile, having poor mechanical and tribological properties, but very high thermal and electrical properties. Remarkable improvements in mechanical and physical properties of Cu matrix reinforced composites can be achieved by adding alumina (Al_2O_3) ceramic particles [2].The development of a high-performance Cu composite for advanced materials requires the ability to tailor multi-functional properties. The successful implementation of such composites depends on the development of novel fabrication techniques.

There are have been researched the process of making Al_2O_3/Cu composites with the Powder Metallurgy Technique [2]. Powder metallurgy is a popular and cost-effective technique used to manufacture composite materials. This technique is a complex process for the manufacture of composite parts because it involves many parameters. Therefore, parameter optimization is very important to meet good spare parts properties. The optimal powder metallurgical process parameters depend on the type of lubrication during mixing, the ball-to-powder weight ratio, mixing time, filler particle size, compaction pressure, sintering temperature, holding time, etc. Identification of optimal effective parameters is prerequisite for their successful implementation. Therefore, it is very important to improve the efficiency and quality of the powder metallurgical process by determining the optimal conditions of the powder metallurgical process parameters.

To determine the optimal effective parameters for meeting the characteristics of good spare parts, it is necessary to conduct research as an evaluation of the composition of raw materials and then make improvements to the manufacturing process by applying the Taguchi experimental design statistical method. The Grey Relational Analysis (GRA) based on grey system theory can be used for solving the complicated interrelationships among the multi responses [3]. To determine the optimal effective parameters for meeting the characteristics of good spare parts, it is necessary to conduct research as an evaluation of raw material composition and then make improvements to the manufacturing process using the Taguchi experimental design statistical method. Grey Relational Analysis (GRA) based on grey system theory can be used to solve complex interrelationships among multiple responses [4].

Aside from these methods, the following can be used for multi-response optimization: Quality Loss Function of Taguchi (QLF). Taguchi's quality loss function methodology has proven to be an appealing and efficient optimization tool for a variety of performance characteristics [5]. The weighting factors in the total loss function are used in the multi-response signal to noise (S/N) ratio optimization using Taguchi's quality loss function. Then the two methods are compared based on the highest coefficient of determination. The best method will be used to determine the process parameters in the manufacture of Al_2O_3/Cu composites.

Experiments were carried out to find the controlled factors affecting the Mass Density and Rockwell Hardness of the combined Al_2O_3/Cu. All experiments were carried out using powder metallurgy based on the publication of Hussain [6]. Experiments were carried out with four controllable powder processing parameters, namely milling time, compaction pressure, sintering temperature, and holding time. Other processing parameters, such as percent by mass of Al_2O_3, particle size, and spindle speed, were kept constant throughout the experiment. A mix of parameter level designs was used for the experimental trials, as shown in Fig. The appropriate range for powder processing parameters was determined by varying the milling time in the range of 180–360 minutes, the compaction pressure in the range of 100–200 MPa, the sintering temperature in the range of 600–700^{0}C, and holding time in the range of 20–60 minutes. The steps and methods of analysis are described in chapter 2. The results of the analysis and discussion will be discussed in chapter 3.

2. RESEARCH METHODS

2.1 Literature Review

Dr. Genichi Taguchi invented the Taguchi technique in 1949 intending to improve quality and reduce variability [7]. Taguchi's approach to reducing variation entails two steps: first, determining the best performance of a product or process over the longest period so that deviation from the target is minimal; and second, determining the best performance of a product or process over the longest period so that deviation from the target is minimal. Furthermore, it aims to make the products as similar as possible so that product variance is minimal [8]. Taguchi's method of enhancing quality during the design phase is to optimize a product or process design and make it insensitive to uncontrollable circumstances.

1. Orthogonal Array

To identify the combination of components and levels to utilize in an effective experiment and analyze the trial findings, the Taguchi technique employs a special set of matrices known as orthogonal arrays [9]. Taguchi Orthogonal Arrays ensure that in studies, all controlled variables are equally considered. The total degrees of freedom must be greater than or equal to the minimum number of trial runs. Each row of the Orthogonal Array represents a different level parameter combination.

2. GRA with PCA

Step 1 Signal-to-noise ratio (S/N Ratio)

The terms 'signal' and 'noise' in the Taguchi technique refer to the desired value (mean) for the output characteristic and the unwanted value (standard deviation) for the output characteristic, respectively [10]. As a result, the S/N Ratio is defined as the ratio of mean to standard deviation. The S/N Ratio is used by Taguchi to determine how far a quality feature deviates from the ideal value. The cause of quality fluctuations is uncontrollable elements known as noise factors, which can be classed as external causes, manufacturing flaws, and product deterioration. There are three quality qualities depending on the design objective: "nominal-is-best," "the smaller the better," and "the larger the better" [11]. The following are their mathematical expressions:

Case 1: ‘‘The smaller the better: aiming to minimize the performance [12].

$$SN_{ij} = -10\log_{10}\left(\frac{\sum_{i=1}^{N} y_i^2}{N}\right) \quad (1)$$

where the y denotes the performance indicator, subscript i experiment number, N number of replicates of experiment ‘i’

Case 2: ‘‘The larger the better’’: aiming to maximize the performance [13].

$$SN_{ij} = -10\log_{10}\left(\frac{\sum_{i=1}^{N} 1/y_i^2}{N}\right) \quad (2)$$

Case 3: ‘‘Nominal-is-best’’: aiming to target the predetermined nominal value [14].

$$\begin{cases} SN_{ij} = 10\log_{10}\left[\left(\frac{\bar{y}}{s}\right)^2\right] \\ \bar{y} = \frac{y_1+y_2+y_3\cdots+y_n}{N} \\ s = \frac{\sum_{i=1}^{N}(y_1-\bar{y})^2}{N-1} \end{cases} \quad (3)$$

Step 2 Calculating S/N Ratio Normalization Value

The value of the S/N ratio that has been obtained previously will be normalized, which is changed to a value ranging from 0 to 1 according to the characteristics of each response as follows.

$$Z_{ij} = \frac{max_{\forall j} SN_{ij} - SN_{ij}}{max_{\forall j} SN_{ij} - min_{\forall} SN_{ij}} \quad (4)$$

(for smaller the better quality characteristics)

$$Z_{ij} = \frac{SN_{ij} - min_{\forall j} SN_{ij}}{max_{\forall j} SN_{ij} - min_{\forall} SN_{ij}} \tag{5}$$

(for larger the better quality characteristics)
where

Z_{ij} : normalized value of S/N ratio oni-th experiment and j-th response
SN_{ij} : the value of the S/N ratio in the th experiment i and j response
$max_{\forall j} SN_j$: value of S/N ratio maximum response to-j
$min_{\forall j} SN_{ij}$: value of S/N ratio minimum response to-j

Step 3 Calculating Deviation Sequence

Deviation Sequence is the absolute difference between the maximum value of the normalized result and the normalized data. The formula for determining the deviation sequence is as follows.

$$\Delta_{0ij} = \left| Z_{0j} - Z_{ij} \right| \tag{6}$$

where

Δ_{0ij} : value deviation sequence in the i-th experiment and j . response
Z_{0j} : maximum value of normalized S/N ratio (value 1)
Z_{ij} :the normalized value of the S/N ratio in the i-th experiment and the j . response

Step 4 Calculating the Gray Relational Coefficient

The Gray Relational Coefficient (GRC) shows the relationship between the ideal (best) conditions and the actual conditions of the normalized response [15]. GRC is obtained from the following equation.

$$\gamma_{ij} = \frac{\Delta_{min} + \zeta \Delta_{max}}{\Delta_{0ij} + \zeta \Delta_{max}} \tag{7}$$

Δ_{max} : minimum valuefrom deviation sequence
Δ_{min} : maximum value of deviation sequence
ζ : distinguishing coefficient (usually 0.5) [15]

Step 5 Determine the Eigen Value and Eigen Vector

Eigen value can be obtained by using the following formula.

$$|\boldsymbol{R} - \lambda_k \boldsymbol{I}| = 0 \quad ; k = 1, 2, \dots, m \tag{8}$$

While the eigenvectors are obtained from the following equation.

$$(\boldsymbol{R} - \lambda_k \boldsymbol{I}) \boldsymbol{V}_k \tag{9}$$

where

$\boldsymbol{R}$: correlation matrix
λ_k : eigen value for the kth principal component
$\boldsymbol{I}$: identity matrix

$\boldsymbol{V}_k{}^T = [v_{1k}, \quad v_{2k}, \quad \cdots, \quad v_{jk}, \quad \cdots \quad v_{mk}]$are the eigenvectors corresponding to and are the values of the eigenvector components which are the coefficients of the principal components.$\lambda_k v_{1k}, \quad v_{2k}, \quad \cdots, \quad v_{jk}, \quad \cdots \quad v_{mk}$

Step 6 Define Principal Component

Principal component is a linear combination of observed variables that are not correlated with each other. Principal components can be written with the following equation.

$$PC_k = v_{1k} Y_1 + v_{2k} Y_2 + \cdots + v_{mk} Y_m \tag{10}$$

where Y is the response totaling m, and PC1 is the first principal component, PC2 is the second principal component, and PCk is the k-th principal component.

Step 7 Calculating Weight Value

Principal component which has the highest proportion of variance will be used as weighting. The value of the coefficients is none other than the value of the eigenvector component of the selected principal component and then squared, so that the weight value is obtained as follows.

$$\omega_j = v_{jk}^2 \qquad j,k = 1,2,\dots,m \tag{11}$$

where

ω_j : weight value for j . response
v_{jk} : the value of the eigenvector component or the coefficients of the principal component the chosen

Step 8 Calculating the Gray Relational Grade

The Gray Relational Grade value will be used as a performance index to determine the combination of factor levels that produces an optimal response. To calculate the value of the Gray Relational Grade, the following equation is used [16].

$$G_i = \sum_{j=1}^{m} \omega_j \gamma_{ij} \qquad ; i,j = 1,2,\dots,m \tag{12}$$

where:

G_i : the value of Gray Relational Grade in the i-th experiment
ω_j : weight value for j . response
γ_{ij} : the value of the Gray Relational Coefficient of the j-th response in the i-th experiment

3. Taguchi Quality Loss Function Analysis

Step 1 Calculate the Loss Function value for each response with the following equation.

$$L_{ij} = \frac{k}{n}\sum_{p=1}^{n} y_{ijp}^2 \tag{13}$$

(for smaller the better quality characteristics)

$$L_{ij} = \frac{k}{n}\sum_{p=1}^{n} \frac{1}{y_{ijp}^2} \tag{14}$$

(for larger the better quality characteristics)

where

L_{ij} :the value of the loss function in the i-th experiment and the j response
n : number of replications
y_{ijp} : the value of the i-th experiment, j-th response and p-th replication
k : cost coefficient

Step 2 Normalization of the quality loss function in the equation below is used to normalize the value of k.

$$N_{ij} = \frac{L_{ij}}{\bar{L}_{ij}} \tag{15}$$

where

$\bar{L}_{ij}$: the average loss function in the i-th experiment and the j-th response.
L_{ij} : loss function in the i-th experiment and j-th response.

Step 3 Calculate the Total Loss Function with a predetermined weight with the following equation.

$$TL_i = \sum_{j=1}^{m} w_j N_{ij} \tag{16}$$

where
TL_i : total loss function in the i-th experiment
m : number of observed performance characteristics
w_j : weighting factor for j . response
N_{ij} : loss function in experiment-th and j-th responses that have been normalized

Step 4 Transform the Total Loss Function value into S/N Ratio with the following equation.

$$\eta_i = -10 log(TL_i) \tag{17}$$

4. Analysis of Variance (ANOVA)

The general linear model (GLM) is often used for factorial designs, and analysis of variance (ANOVA) is an example of the GLM. A factorial design is one in which the experimental settings are divided into groups based on one or more factors, each of which has two or more levels. ANOVA is commonly used to calculate confidence levels. The technique determines the variability (variance) of the data rather than simply analyzing it. The variance is used to calculate confidence. The variance of controlled and noise components is determined by analysis. Robust operating conditions can be predicted by understanding the source and magnitude of variance. This is the methodology's second advantage. Many parameters, such as degrees of freedom, sums of squares, mean square, and so on, are computed and grouped in a standard tabular manner in the analysis of variance [17].

5. Measurement of the response variable

Mass Density of Al_2O_3/Cu composite can be evaluated by Archimedes principle. Initially, the composite sample was weighed in air (w1), then suspended in distilled water and weighed (w2) from the sample [18]. The actual density is calculated according to Equation (4).

$$\rho_A = \frac{w_1}{w_1 - w_2} \times \rho_W \tag{18}$$

with ρ_A= actual density of Al_2O_3/Cu, w_1= wight of Al_2O_3/Cu samples in air, w_2= weight of the sample in distilled water, and ρ_W= mass density of distilled water in 25^0C = 997,044 kg/m^3.

2.2 Research Methods

In this paper, a study was conducted to find the controlled factors that affect the density of Al_2O_3/Cu composites. All experimental trials were carried out via the powder metallurgical route. Experiments were carried out with four controllable powder processing parameters, namely milling time, compaction pressure, sintering temperature, and holding time. Other processing parameters, such as percentage by weight of Al_2O_3/Cu, particle size, and spindle speed were kept constant throughout the experiment. The mix parameter rate design was used for the experimental trials as shown in Table 1. The feasible range for the powder processing parameters was determined by varying the milling time in the range of 180 – 360 min, the compaction pressure in the range of 100 – 200 MPa, the sintering temperature in the range of 600 – 700^0C, and holding times in the range of 20 – 60 minutes.

Table 1. Factor parameters and their levels

Symbol	Parameters	Unit	Level-1	Level-2	Level-3
A	Milling time	Min	180	360	-
B	Compaction pressure	MPa	100	150	200
C	Sintering temperature	^{0}C	600	650	700
D	Holding time	Min	20	40	60

The L_{18} mixed-level Taguchi Orthogonal Array was used for experimental because it is the basis for the analysis of the Taguchi method. The Taguchi Orthogonal Arrays state that all controlled variables are equally considered in the experiment. The minimum number of trials must be greater than or equal to the total degrees of freedom. Each row of the Orthogonal Array represents a different combination of level parameters. The steps for using GRA and QLF to resolve multi-response problems is presented below.

3. RESULTS AND DISCUSSION

Data from the results of experiments that have been carried out can be seen in Table 2.

3.1 Optimization using GRA with PCA

Principal Component Analysis is a dimension reduction tool that can be used in multi variable analysis problem. The initial step for PCA analysis is to calculate the value of the S/N ratio and normalize the S/N ratio, which is presented in Table 3 below:

Table 2. Data Result

Run	Milling Time (Min)	Compaction Pressure (MPa)	Sintering Temperature (^0C)	Holding Time (Min)	Mass density (gm/cm^3)	Rockwell Hardness (B scale)
1	180	100	600	20	7.6197	15.3173
2	180	100	650	40	7.6605	15.5150
3	180	100	700	60	7.6493	15.7910
4	180	150	600	20	7.7905	16.4945
5	180	150	650	40	7.8115	16.9725
6	180	150	700	60	7.8374	17.0554
7	180	200	600	40	7.8733	18.0926
8	180	200	650	60	7.9351	18.4054
9	180	200	700	20	7.9918	18.8273
10	360	100	600	60	7.7257	15.4552
11	360	100	650	20	7.7695	15.7394
12	360	100	700	40	7.7973	15.9392
13	360	150	600	40	7.8695	17.0544
14	360	150	650	60	7.8905	17.1595
15	360	150	700	20	8.0183	17.2743
16	360	200	600	60	8.0476	17.5673
17	360	200	650	20	8.0675	17.9901
18	360	200	700	40	8.0798	19.0167

Table 3. S/N ratio and normalize the S/N ratio

Run	S/N Ratio		Normalize S/N Ratio	
	Mass Density	Rockwell Hardness	Mass Density	Rockwell Hardness
1	17.6388	23.7036	0	0
2	17.6851	23.8150	0.0911	0.0593
3	17.6724	23.9682	0.0661	0.1408
4	17.8313	24.3468	0.3781	0.3423
5	17.8547	24.5949	0.4240	0.4743
6	17.8834	24.6372	0.4805	0.4968
7	17.9231	25.1500	0.5584	0.7697
8	17.9910	25.2989	0.6918	0.8490
9	18.0529	25.4958	0.8132	0.9537
10	17.7588	23.7815	0.2356	0.0414
11	17.8079	23.9398	0.3321	0.1257
12	17.8389	24.0493	0.3930	0.1840
13	17.9189	24.6367	0.5502	0.4966
14	17.9421	24.6901	0.5956	0.5250
15	18.0816	24.7480	0.8697	0.5558
16	18.1133	24.8941	0.9319	0.6335
17	18.1348	25.1007	0.9740	0.7435
18	18.1480	25.5827	1	1

Then in the next stage, deviation sequence and GRC values are calculated. Then by using the value of the PC1 eigenvector component, it will be used for the calculation of the GRG with the results presented in Table 4. With the larger is the better criterion, the experimental results for the appropriate density S/N ratio are tabulated in Table 5.

Table 4. Deviation sequence, GRC and GRG

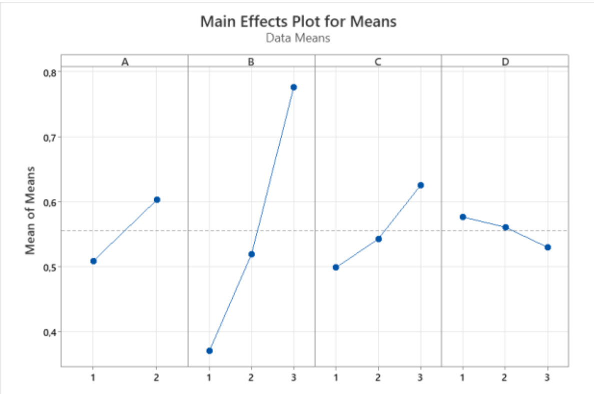
Run	Deviation Sequence		Grey Relational Coefficient		Grey Relational Grade
	Mass Density	Rockwell Hardness	Mass Density	Rockwell Hardness	
1	0.017224	0.004262	1.062368	0.262897	0.3332
2	0.017041	0.004154	1.051082	0.25624	0.3509
3	0.017091	0.00401	1.054162	0.247361	0.3582
4	0.016477	0.003676	1.016295	0.226711	0.4386
5	0.016388	0.003471	1.010838	0.214121	0.4759

Run	Deviation Sequence		Grey Relational Coefficient		Grey Relational Grade
	Mass Density	Rockwell Hardness	Mass Density	Rockwell Hardness	
6	0.01628	0.003438	1.004169	0.212044	0.4943
7	0.016132	0.003055	0.995032	0.188429	0.6077
8	0.015882	0.002952	0.979593	0.182079	0.6931
9	0.015657	0.002821	0.965743	0.17401	0.8214
10	0.016754	0.004186	1.033415	0.258227	0.3690
11	0.016566	0.004037	1.021797	0.248986	0.3958
12	0.016448	0.003936	1.014524	0.242783	0.4157
13	0.016148	0.003438	0.995993	0.212069	0.5122
14	0.016062	0.003396	0.990699	0.209479	0.5327
15	0.015554	0.003351	0.95937	0.206704	0.6612
16	0.015441	0.00324	0.952397	0.199867	0.7284
17	0.015365	0.00309	0.947704	0.190583	0.8055
18	0.015318	0.002765	0.944821	0.170561	0.9997

Table 5. Signal Noise and Rank from GRA with PCA

Factors Parameter	Signal Noise Rates for Levels			Delta	Rank
	Level 1	Level 2	Level 3		
Milling time	-6.279	-4.871		1.407	3
Compaction pressure	-8.649	-5.767	-2.309	6.340	1
Sintering temperature	-6.375	-5.688	-4.661	1.714	2
Holding time	-5.322	-5.552	-5.851	0.529	4

Based on Table 5 it is found that the compaction pressure variable has the highest influence with a value of rank 1, followed by the sintering temperature, milling time, and holding time variables. It can be seen that main effect plot for mean and main effect plot for S/N ratios have equivalent forms. On the effect of each factor, it appears that at the milling time the S/N ratio is higher at the 360 min level. Likewise, the compaction pressure at 200MPa gives a higher S/N ratio than the compaction pressure at other levels. The sintering temperature and waiting time are relatively stable at different levels.



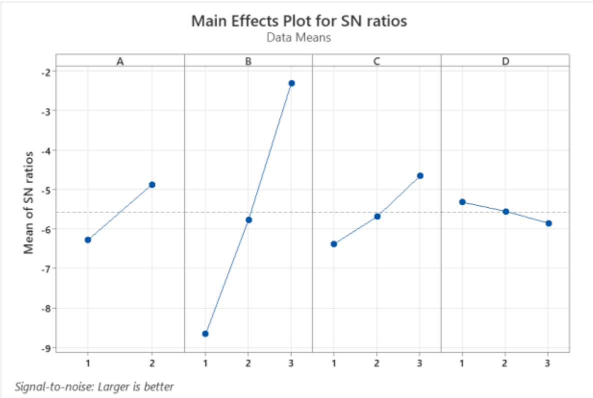


Figure 1. Main Effects Plot for Means and SN Ratios

In order to investigate the effects of drilling process parameters quantitatively the analysis of variance (ANOVA) is performed. The ANOVA is accomplished by separating total variability of multi response S/N ratio, which is measured by sum of squared deviations from total mean of multi-response S/N ratio into percent contribution (PC) by each of the parameters and the error.

Table 6. ANOVA from GRA with PCA

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
A	1	0.039842	6.33%	0.039842	0.039842	88.32	0.011
B	2	0.504975	80.23%	0.504975	0.252487	559.72	0.002
C	2	0.049789	7.91%	0.049789	0.024895	55.19	0.018
D	2	0.006781	1.08%	0.000381	0.000191	0.42	0.703
A*B	2	0.006272	1.00%	0.006272	0.003136	6.95	0.126
A*C	2	0.003745	0.59%	0.002684	0.001342	2.98	0.252
B*C	4	0.017104	2.72%	0.017104	0.004276	9.48	0.098
Error	2	0.000902	0.14%	0.000902	0.000451		
Total	17	0.629410	100.00%				

Based on the table above, it can be seen that there are factors that have a significant effect. These factors include Milling time, Compaction pressure, and Sintering Temperature. The Compaction Pressure factor gave the largest contribution with a value of 80.23%. Then the results of the GRA with PCA analysis obtained the following R-square values:

Table 7. R-square from GRA with PCA

Method	R-square
GRA with PCA	99.86%

By using the GRA with PCA method, the R-square value of 99.86% is obtained, which means that the factor can explain the multi response variable of 99.86% and the remaining 0.14% is explained by other factors outside this study.

Table 8. Computed values of multi-response S/N ratio

Run	Loss Function		Normalized Loss Function		Total loss function (Tli)	Multi-response S/N ratio (ηi)
	Mass Density	Rockwell Hardness	Mass Density	Rockwell Hardness		
1	0.017224	0.004262	1.062368	0.262897	0.662633	1.787272
2	0.017041	0.004154	1.051082	0.25624	0.653661	1.846476
3	0.017091	0.00401	1.054162	0.247361	0.650761	1.865782
4	0.016477	0.003676	1.016295	0.226711	0.621503	2.065567
5	0.016388	0.003471	1.010838	0.214121	0.61248	2.129083
6	0.01628	0.003438	1.004169	0.212044	0.608106	2.160204
7	0.016132	0.003055	0.995032	0.188429	0.591731	2.278759
8	0.015882	0.002952	0.979593	0.182079	0.580836	2.359463
9	0.015657	0.002821	0.965743	0.17401	0.569876	2.442193
10	0.016754	0.004186	1.033415	0.258227	0.645821	1.898877
11	0.016566	0.004037	1.021797	0.248986	0.635391	1.969588
12	0.016448	0.003936	1.014524	0.242783	0.628653	2.015889
13	0.016148	0.003438	0.995993	0.212069	0.604031	2.189406
14	0.016062	0.003396	0.990699	0.209479	0.600089	2.217843
15	0.015554	0.003351	0.95937	0.206704	0.583037	2.343038
16	0.015441	0.00324	0.952397	0.199867	0.576132	2.394782
17	0.015365	0.00309	0.947704	0.190583	0.569143	2.447784
18	0.015318	0.002765	0.944821	0.170561	0.557691	2.536064

3.2 Optimization using Quality Loss Function

Taguchi's quality loss function concept was used in the current study to optimize the multiple performance characteristics, Mass Density and Rockwell Hardness. The loss functions, normalized loss functions for each response, total loss function, and corresponding multi-response S/N ratios for each trial of the L18 orthogonal array were calculated using Eqs. (16) - (19), and are shown in Tables 3 below. In this study, the total loss function was computed with a weighting factor of 0.5, which gives equal weight to Mass Density and Rockwell Hardness.

With the larger is the better criterion, the experimental results for the appropriate density S/N ratio are tabulated in Table 9.

Table 9. Signal Noise and Rank

Factors Parameter	Signal Noise Rates for Levels			Delta	Rank
	Level 1	Level 2	Level 3		
Milling time	6.412	6.901		0.489	3
Compaction pressure	5.556	6.779	7.635	2.079	1
Sintering temperature	6.41	6.655	6.905	0.495	2
Holding time	6.693	6.671	6.606	0.087	4

Based on Table 9 it is found that the compaction pressure variable has the highest influence with a value of rank 1, followed by the sintering temperature, milling time, and holding time variables.

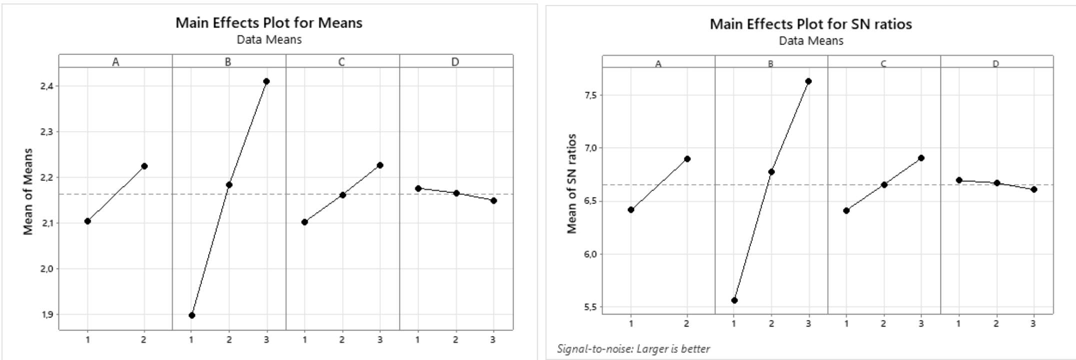


Figure 2. Main Effects Plot for Means and SN Ratios

It can be seen that the main effect plot for mean and main effect plot for S/N ratios have equivalent forms. On the effect of each factor, it appears that at the milling time the S/N ratio is higher at the 360 min level. Likewise, the compaction pressure at 200MPa gives a higher S/N ratio than the compaction pressure at other levels. The sintering temperature and waiting time are relatively stable at different levels.

In order to investigate the effects of drilling process parameters quantitatively the analysis of variance (ANOVA) is performed. The ANOVA is accomplished by separating total variability of multi response S/N ratio, which is measured by sum of squared deviations from total mean of multi-response S/N ratio into percent contribution (PC) by each of the parameters and the error.

Table 10. ANOVA from Quality Loss Function

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	P-Value
A	1	0.064617	7.11%	0.064617	0.064617	3786.91	0.000
B	2	0.791799	87.09%	0.791799	0.3959	23201.92	0.000
C	2	0.046727	5.14%	0.046727	0.023364	1369.24	0.001
D	2	0.002135	0.23%	0.001479	0.00074	43.35	0.023
A*B	2	0.000948	0.10%	0.000948	0.000474	27.78	0.035
A*C	2	0.002367	0.26%	0.001898	0.000949	55.6	0.018
B*C	4	0.000587	0.06%	0.000587	0.000147	8.6	0.107
Error	2	0.000034	0.00%	0.000034	0.000017		
Total	17	0.909215	100.00%				

Based on the Table 10 above, it can be seen that there are factors that have a significant effect. These factors include Milling time, Compaction pressure, Sintering Temperature, Holding Time, Interaction of Milling Time with Compaction Pressure, and Interaction of Milling Time with Sintering Temperature. Then the results of the Quality Loss Function analysis obtained the following R-square values:

Table 11. R-square from Quality Loss Function

Method	R-square
Quality Loss Function	99.97%

By using the Quality Loss Function method, an R-square value of 99.97% is obtained, which means that the factor can explain the multi-response variable of 99.97% and the remaining 0.03% is explained by other factors outside of this study.

The following were resulted of GRA with PCA and Quality Loss Function. Table 5 showed the results of comparing R-square values based on parametric and nonparametric approaches.

Table 12. Comparison based on R-square

Estimation	R-square
GRA with PCA	99.86%
Quality Loss Function	99.97%

Based on Table 12, it showed that R^2 values in the Quality Loss Function were better than GRA with PCA with R^2 is 99.97%. It means that Quality Loss Function is very suitable to be used in this research.

4. CONCLUSIONS

This paper investigated the effect of powder metallurgical processing parameters on the characteristics of Al_2O_3/Cu composites based on the Taguchi method. From the main effect table study, the optimal combination of parameters for response mass density are $A_2B_3C_3D_2$ powder metallurgical process parameters, namely milling time of 360 minutes, compacting powder of 200 MPa, sintering of 700^0C, and holding time of 20 minutes. The result, we choose Quality Loss Function, because the method has the biggest determination coefficient value is 99.97% where the results is better than GRA with PCA. The ANOVA results show that the compaction pressure has the most influential parameter that affects the response. The percentage contribution of compaction pressure is 87.09%. Based on ANOVA, the R-squared value is 99.97%, which means the tested factor variables can explain the density of the Al_2O_3/Cu composite by 99.97%. Therefore, only 18 experimental trials are needed to discover the reality of what will happen in the process.

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