SELECTING OPTIMAL PROCESS PARAMETERS OF Al₂O₃/C COMPOSITE USING GRA WITH PCA AND TAGUCHI’S QLF APPROACH

Idrus Syahzaqi¹, Hani Brilianti Rochmanto², and Muhammad Ahsan³*

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 Al₂O₃/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 L₁₈ 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 A₂B₃C₃D₂ powder metallurgical process parameters, namely milling time of 360 minutes, compacting powder of 200 MPa, sintering of 700°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 Al₂O₃/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

How to cite this article:
I. Syahzaqi, H. B. Rochmanto and M. Ahsan, “SELECTING OPTIMAL PROCESS PARAMETERS OF Al₂O₃/C COMPOSITE USING GRA WITH PCA AND TAGUCHI’S QLF APPROACH”, BAREKENG: J. Math. & App., vol. 16, iss. 3, pp. 1039-1050, September, 2022.
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 (Al₂O₃) 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 Al₂O₃/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 Al₂O₃/Cu composites.

Experiments were carried out to find the controlled factors affecting the Mass Density and Rockwell Hardness of the combined Al₂O₃/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 Al₂O₃, 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°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].

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

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].

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

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

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

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.

\[ Z_{ij} = \frac{\max_y SN_{ij} - SN_{ij}}{\max_y SN_{ij} - \min_y SN_{ij}} \]  

(for smaller the better quality characteristics)
Selecting Optimal Process Parameters of Al₂O₃/C Composite Using Grey Relational Analysis

\[ Z_{ij} = \frac{SN_{ij} - \min_{j} SN_{ij}}{\max_{j} SN_{ij} - \min_{j} SN_{ij}} \]  

(for larger the better quality characteristics)

where

\[ Z_{ij} \]: normalized value of S/N ratio on i-th experiment and j-th response
\[ SN_{ij} \]: the value of the S/N ratio in the i-th experiment and j-th response
\[ \max_{j} SN_{ij} \]: value of S/N ratio maximum response to-j
\[ \min_{j} SN_{ij} \]: 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.

\[ \Delta_{0ij} = |Z_{0j} - Z_{ij}| \]  

where

\[ \Delta_{0ij} \]: value deviation sequence in the i-th experiment and j-th 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-th 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.

\[ \gamma_{ij} = \frac{\Delta_{\text{min}} + \zeta \Delta_{\text{max}}}{\Delta_{0ij} + \zeta \Delta_{\text{max}}} \]  

\[ \Delta_{\text{max}} \]: minimum value from deviation sequence
\[ \Delta_{\text{min}} \]: maximum value of deviation sequence
\[ \zeta \]: 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.

\[ |R \lambda_k - I| = 0 ; k = 1, 2, \ldots, m \]  

While the eigenvectors are obtained from the following equation.

\[ (R - \lambda_k I)V_k \]  

where

\[ R \]: correlation matrix
\[ \lambda_k \]: eigen value for the kth principal component
\[ I \]: identity matrix
\[ V_k^T = [v_{1k}, v_{2k}, \ldots, v_{jk}, \ldots, v_{mk}] \] are the eigenvectors corresponding to and are the values of the eigenvector components which are the coefficients of the principal components. \( \lambda_k v_{1k}, v_{2k}, \ldots, v_{jk}, \ldots, v_{mk} \)

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.

\[ PC_k = v_{1k}Y_1 + v_{2k}Y_2 + \cdots + v_{mk}Y_m \]  

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.
\[
\omega_j = v_{jk}^2 \quad j, k = 1, 2, ..., m
\]  

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].

\[
G_i = \sum_{j=1}^{m} \omega_j \gamma_{ij} \quad ; i, j = 1, 2, ..., m
\]

where:
- \( G_i \): the value of Gray Relational Grade in the \( i \)-th experiment
- \( \omega_j \): weight value for \( j \) response
- \( \gamma_{ij} \): 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.

\[
L_{ij} = \frac{k}{n} \sum_{p=1}^{n} y_{ijp}^2
\]

(for smaller the better quality characteristics)

\[
L_{ij} = \frac{k}{n} \sum_{p=1}^{n} \frac{1}{y_{ijp}^2}
\]

(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, \( j \)-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 \( k \).

\[
N_{ij} = \frac{L_{ij}}{\bar{L}_{ij}}
\]

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

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

\[
TL_i = \sum_{j=1}^{m} w_j N_{ij}
\]

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-\( i \)-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.

\[
\eta_i = -10\log(TL_i)
\]
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 Al2O3/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).

\[ \rho_A = \frac{w_1}{w_1 - w_2} \times \rho_W \]  

with \( \rho_A \) = actual density of Al2O3/Cu, \( w_1 \) = wight of Al2O3/Cu samples in air, \( w_2 \) = weight of the sample in distilled water, and \( \rho_W \) = mass density of distilled water in 25°C = 997.044 kg/m³.

2.2 Research Methods

In this paper, a study was conducted to find the controlled factors that affect the density of Al2O3/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 Al2O3/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°C, and holding times in the range of 20 – 60 minutes.

| 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  | °C   | 600     | 650     | 700     |
| D      | Holding time           | Min  | 20      | 40      | 60      |

The L18 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:
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.

| Run | Milling Time (Min) | Compaction Pressure (MPa) | Sintering Temperature (°C) | Holding Time (Min) | Mass density (gm/cm³) | 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                      | 60                | 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                      | 60                | 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 2. Data Result

| Run | Milling Time (Min) | Compaction Pressure (MPa) | Sintering Temperature (°C) | Holding Time (Min) | Mass density (gm/cm³) | 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                      | 60                | 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                      | 60                | 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 |
|-----|-----------|---------------------|
| 1   | 17.638    | 23.7036             |
| 2   | 17.685    | 23.8150             |
| 3   | 17.6724   | 23.9682             |
| 4   | 17.8313   | 24.3468             |
| 5   | 17.8547   | 24.5949             |
| 6   | 17.8834   | 24.6372             |
| 7   | 17.9231   | 25.1500             |
| 8   | 17.9910   | 25.2989             |
| 9   | 18.0529   | 25.4958             |
| 10  | 17.7588   | 23.7815             |
| 11  | 17.8079   | 23.9398             |
| 12  | 17.8389   | 24.0493             |
| 13  | 17.9189   | 24.6367             |
| 14  | 17.9421   | 24.6901             |
| 15  | 18.0816   | 24.7480             |
| 16  | 18.1133   | 24.8941             |
| 17  | 18.1348   | 25.1007             |
| 18  | 18.1480   | 25.5827             |

Table 4. Deviation sequence, GRC and GRG

| Run | Deviation Sequence | Grey Relational Coefficient | Grey Relational Grade |
|-----|--------------------|-----------------------------|-----------------------|
| 1   | 0.017224           | 0.004262                    | 0.062368              | 0.262897             | 0.3332                     |
| 2   | 0.017041           | 0.004154                    | 0.105082              | 0.25624              | 0.3509                     |
| 3   | 0.017091           | 0.00401                     | 0.1054162             | 0.247361             | 0.3582                     |
| 4   | 0.016477           | 0.003676                    | 0.1016295             | 0.226711             | 0.4386                     |
| 5   | 0.016388           | 0.003471                    | 0.1010838             | 0.214121             | 0.4759                     |
Syahzaqi, et al. Selecting Optimal Process Parameters Of Al₂O₃/C Composite Using……

| 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                   | 1.034315              | 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   | -2.309   | 1.407 | 3    |
| Compaction pressure | -8.649  | -5.767   | -4.661   | 6.340 | 1    |
| Sintering temperature | -6.375  | -5.688   | -5.851   | 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.
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 (TL) | Multi-response S/N ratio (qi) |
|-----|---------------|--------------------------|--------------------------|-------------------------------|
|     | 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                 | 0.959376     | 0.206704          | 0.583073            | 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   | 7.635   | 0.489 | 3    |
| Compaction pressure     | 5.556   | 6.779   | 7.095   | 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.

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 into percent contribution (PC) by each of the parameter and the error.

| 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:
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 11. R-square from Quality Loss Function |
|-----------------------------------------------|
| Method | R-square |
|--------|----------|
| 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 $A_2B_3C_2$ powder metallurgical process parameters, namely milling time of 360 minutes, compacting powder of 200 MPa, sintering of 700°C, 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.

### REFERENCES

[1] D. D. L. Chung, *Composite materials: science and applications*. Springer Science & Business Media, 2010.
[2] M. Z. Hussain, S. Khan, R. Nagarajan, U. Khan, and V. Vats, “Fabrication and microhardness analysis of MWCNT/MnO2 nanocomposite,” *J. Mater.*, vol. 2016, p. 6070468, 2016.
[3] P. B. Zaman, M. N. Sultana, and N. R. Dhar, “Multi-variant hybrid techniques coupled with Taguchi in multi-response parameter optimisation for better machinability of turning alloy steel,” Adv. Mater. Process. Technol., pp. 1–21, 2021.
[4] N. M. Mehat, S. Kamaruddin, A. R. Othman, N. M. Mehat, S. Kamaruddin, and A. R. Othman, “Hybrid integration of taguchi parametric design, grey relational analysis, and principal component analysis optimization for plastic gear production,” Chinese J. Eng., vol. 351206, no. 1–11, p. 2014, 2014.
[5] V. N. Gaitonde and S. R. Karnik, “Selection of optimal process parameters for minimizing burr size in drilling using Taguchi’s quality loss function approach,” J. Brazilian Soc. Mech. Sci. Eng., vol. 34, pp. 238–245, 2012.
[6] M. Z. Hussain, S. Khan, and P. Sarmah, “Optimization of powder metallurgy processing parameters of $Al_2O_3/Cu$ composite through Taguchi method with Grey relational analysis,” J. King Saud Univ. Sci., vol. 32, no. 4, pp. 274–286, 2020.
[7] B. Hsueh, W. Lin, C. Huang, and B. Wu, “Application of Fuzzy-Taguchi theory in the optimization of teaching method and process design,” in *Journal of Physics: Conference Series*, 2021, vol. 1976, no. 1, p. 12073.
[8] R. K. Roy, *A primer on the Taguchi method*. Society of Manufacturing Engineers, 2010.
[9] I. O. Fagbolagun and S. A. Oke, “The optimization of packaging system process parameters using Taguchi method,” Int. J. Ind. Eng. Eng. Manag., vol. 2, no. 1, pp. 1–14, 2020.
[10] B. Varghese and N. Philip, “A Review: Taguchi Experiment Design for Investigation of Properties of Concrete,” Int. J. Civ. Eng., vol. 5, no. 6, pp. 11–16, 2016.
[11] G. Sun, J. Fang, X. Tian, G. Li, and Q. Li, “Discrete robust optimization algorithm based on Taguchi method for structural crushworthiness design,” Expert Syst. Appl., vol. 42, no. 9, pp. 4482–4492, 2015.
[12] M. Zaid, “Taguchi Optimization Method for Identifying Surface Roughness,” *MECHANICAL*, vol. 2, no. 1, 2011.
[13] E. Ginting and M. M. Tambunan, “Selection of Optimal Factor Level From Process Parameters in Palm Oil Industry,” in IOP Conference Series: Materials Science and Engineering, 2018, vol. 288, no. 1, p. 12056.

[14] S. K. Jha, “Parametric optimization of turning process using Taguchi method and ANOVA analysis,” Int. J. Adv. Eng. Technol., vol. 9, no. 3, p. 289, 2016.

[15] S. Raghuraman, K. Thiruppathi, T. Panneerselvam, and S. Santosh, “Optimization of EDM parameters using Taguchi method and grey relational analysis for mild steel IS 2026,” Int. J. Innov. Res. Sci. Eng. Technol., vol. 2, no. 7, pp. 3095–3104, 2013.

[16] L. Singh, R. A. Khan, and M. L. Aggarwal, “Multi performance characteristic optimization of shot peening process for AISI 304 austenitic stainless steel using grey relational analysis with principal component analysis and Taguchi method,” Am. J. Eng. Res., vol. 2, no. 10, pp. 160–172, 2013.

[17] R. N. Henson, “Analysis of variance (ANOVA),” Brain Mapp. an Encycl. Ref. Elsevier, pp. 477–481, 2015.

[18] H. Y. Wang, Q. C. Jiang, Y. Wang, B. X. Ma, and F. Zhao, “Fabrication of TiB₂ particulate reinforced magnesium matrix composites by powder metallurgy,” Mater. Lett., vol. 58, no. 27–28, pp. 3509–3513, 2004.