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Multi-Response Quality Optimization of Gluten-Free Noodles Through the Integration of Taguchi, GRA and PCA Method

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ABSTRACT

The demand for gluten-free products is rising due to health awareness and celiac disease requirements. A major challenge in gluten-free noodle formulation is replicating gluten's viscoelastic properties to achieve desired elasticity and chewiness. This study aims to optimize a gluten-free noodle formulation based on modified cassava flour (Mocaf) and rice flour using an integrated quality engineering approach: Taguchi method, Grey Relational Analysis (GRA), and Principal Component Analysis (PCA).Using an $L^9(3^2)$ orthogonal array, the experiment evaluated two factors—Mocaf and rice flour—at three levels, focusing on elongation and water absorption responses. GRA aggregated these into a Grey Relational Grade (GRG), while PCA determined objective response weights based on eigenvalues. Results identified the optimal formulation as 150g Mocaf and 50g rice flour (A2B2), with Mocaf contributing 71.27% to product quality. This integrated methodology effectively identifies optimal parameters without repetitive trial-and-error, ensuring consistent quality and robust ANOVA reliability. This research enhances gluten-free food quality and promotes local ingredients like Mocaf, providing manufacturers with a systematic approach to meet modern market preferences for high-quality non-gluten alternatives

1. Introduction

Gluten is the primary protein found in grains such as wheat, barley, and rye [1]. This protein plays a crucial role in forming the elastic structure and texture of various processed food products, including bread, pasta, and noodles. The combination of gliadin and glutenin generates viscoelastic properties capable of retaining gas, providing the characteristic chewiness and elasticity in dough. However, gluten consumption is not safe for all individuals, particularly those suffering from celiac disease, non-celiac gluten sensitivity, or those adopting a gluten-free lifestyle for health reasons [2].

Celiac disease is a chronic autoimmune disorder triggered by gluten ingestion, leading to damage in the small intestinal villi and subsequent nutrient malabsorption [3]. On the other hand, non-celiac gluten sensitivity causes distressing gastrointestinal symptoms even without intestinal mucosal damage. These conditions have driven an increasing global demand for gluten-free products [4], including in Indonesia.

Indonesia exhibits exceptionally high instant noodle consumption [5]. Data from the World Instant Noodles Association (WINA) and the Indonesian Central Bureau of Statistics (BPS) indicate that Indonesia ranks second globally, with consumption reaching 12.6 billion packets annually, or approximately 47 packets per capita. Additionally, bread consumption shows an upward trend, averaging 3.01 kg per capita per year. This consumption pattern demonstrates a strong public preference for wheat-based products, which typically contain gluten.

The high consumption of wheat-based products presents both a challenge and an opportunity for developing non-gluten alternative food products. Gluten-free noodles are a potential candidate for development, serving not only those with gluten intolerance but also contributing to functional food diversification. However, the development of gluten-free noodles faces major hurdles regarding textural quality. The absence of gluten often results in products that are brittle, inelastic, and sensorially less appealing to consumers [6].

The utilization of local raw materials such as Modified Cassava Flour (Mocaf) and rice flour is a strategic alternative for developing high-value gluten-free noodles. Mocaf, produced through the fermentative modification of cassava, possesses functional characteristics similar to gluten due to its superior adhesiveness and elasticity. As one of the world's largest cassava producers with abundant availability, Indonesia can produce Mocaf sustainably and at a relatively lower cost compared to imported wheat flour (BPS, 2024). Meanwhile, rice flour is widely available across Indonesia, serving as a staple commodity with a broad supply chain and stable pricing.

The combination of these two ingredients offers functional potential to produce noodle textures comparable to conventional products while providing economic value to small and medium enterprises. Utilizing local materials reduces dependence on wheat imports, strengthens national food security, and opens commercialization opportunities for domestic-based gluten-free products. Thus, the selection of Mocaf and rice flour is based on functional considerations, availability, competitive production costs, and growing market prospects. Nevertheless, precise and optimal formulation is required to achieve superior product quality, making a systematic optimization approach essential in this study.

Determining the optimal proportion of raw materials is a critical aspect of food product development. Therefore, a quality engineering-based approach is necessary to evaluate and optimize these factors efficiently. The Taguchi method is widely used in formulation research to identify the optimal combination of factors affecting product quality with a minimal number of experiments [7]. Taguchi employs an orthogonal array design to evaluate the influence of each factor on the observed responses, considering process variation and robustness against environmental conditions [8].

This study offers novelty in two main aspects: contextual and methodological. Contextually, the application of multi-response optimization for gluten-free noodles based on Mocaf and rice flour remains very limited, especially concerning the utilization of high-potential Indonesian local raw materials. Previous studies have generally focused on partial wheat substitution or single-parameter optimization, failing to provide a holistic approach to the interaction between process parameters and final product quality.

Methodologically, this research synergistically integrates the Taguchi method, Grey Relational Analysis (GRA), and Principal Component Analysis (PCA) to produce a more comprehensive optimization model. This combination has seldom been applied to Mocaf-based food systems and offers advantages in experimental efficiency, objective multi-response decision-making, and increased accuracy in identifying dominant factors. GRA enables the conversion of multiple response values into a single aggregate value known as the Grey Relational Grade (GRG), reflecting the overall quality of the factor combination [9].

Furthermore, to provide objective weighting for each response variable, Principal Component Analysis (PCA) is employed. PCA identifies primary variables based on data variance contributions, preventing subjectivity in weight determination. The integration of these three methods—Taguchi, GRA, and PCA—provides a comprehensive and efficient approach for optimizing food formulations, particularly for products with multiple quality characteristics [10].

The primary contribution of this research is providing a high-quality gluten-free noodle formulation based on local ingredients while offering a replicable analytical approach for developing other functional food products. Additionally, this study supports the utilization of cassava-based Mocaf as a wheat substitute and bolsters national food diversification programs.

2. Method

To improve the quality of gluten-free noodles based on mocaf and rice flour, a structured experiment is required, as the material formulation significantly influences several quality characteristics, such as elasticity, chewiness, and structure. Furthermore, texture measurements of gluten-free noodles must be conducted quantitatively to ensure consistency of results.

The Taguchi experimental design method, developed by Genichi Taguchi in 1985, is applied in this study as a systematic statistical approach to determine the most effective combination of variables and factor levels in the gluten-free noodle production process to achieve optimal product quality. The primary focus of this method is to optimize product quality by considering critical variables, namely the ratio of mocaf to rice flour, water content, and processing temperature. By implementing the Taguchi method, a robust gluten-free noodle formulation (resistant to condition variations) can be designed to ensure optimal product quality.

In this study, the Taguchi method is applied to generate an Orthogonal Array (OA) matrix to test the combinations of factors and levels in the production process. However, the Taguchi method is inherently limited to optimizing a single response. To address the challenge of multi-response optimization—such as elasticity, chewiness, and structure—an integrated approach combining Grey Relational Analysis (GRA) and Principal Component Analysis (PCA) is employed [11][12].

The GRA approach allows the conversion of multiple responses into a single value, known as the Grey Relational Grade (GRG), thereby facilitating overall quality evaluation. Meanwhile, PCA is used to determine objective weights for each response based on eigenvalues, ensuring that the most critical characteristics in the production process are accurately identified [13].

Table 1. Research Factor Variables

Code	Factor (g)
A	Mocaf Flour
B	Rice Flour

The research stages are illustrated in Figure 1 (Research Flowchart). The steps include:

a. Constructing the Orthogonal Array (OA) Matrix $\boldsymbol{L_n}(\iota^f)$: Where f is the number of factors (columns), l is the number of levels, n is the number of observations (rows), and L represents the Latin Square design.

b. Conducting Experiments with Replications to obtain quantitative data for each response.

c. Determining the S/N Ratio for quality characteristics (Larger-is-better and Smaller-is-better) using the following equations:

$$T = \sum_{i=1}^{n} y_i\,, \quad Sm = \frac{T^2}{n} \tag{1}$$

$$Ve = \sum_{i=1}^{n} \frac{(y_i - y)^2}{n-1} = \frac{y_1^2 + y_2^2 + \cdots + y_n^2 - Sm}{n-1} \tag{2}$$

$$S/N\ Ratio = 10\ \log\left[\frac{1}{n} \cdot \frac{(Sm - Ve)}{Ve}\right] \tag{3}$$

d. Data Normalization :

$$x_i^*(j) = \frac{|x_i(j) - T| - \min(|x_i(j) - T|)}{\max(|x_i(j) - T|) - \min(|x_i(j) - T|)} \tag{4}$$

Where T is the target value, $x*(j)$ is the S/N ratio value, and i & j represent the number of experiments and responses.

e. The calculation of the delta value or deviation sequence, $\Delta 0(j)$, is performed as follows:

$$\Delta_{oi}(J) = |x_0^*(j) - x_i^*(j)| \tag{6}$$

Where: $x_0^*(j)$= = 1 is the maximum value of the normalized Signal-to-Noise (S/N) Ratio, serving as the ideal reference sequence.

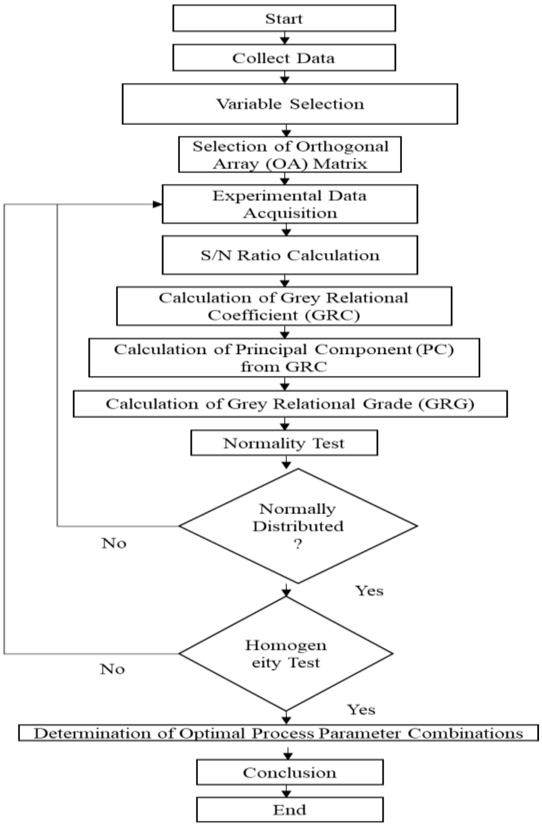

Fig. 1. Research procedures

f. The next step is to calculate the Grey Relational Coefficient (GRC), denoted as gamma $\gamma 0(j)$:

$$\gamma_{0i}(j) = \frac{\Delta_{min}+\zeta\Delta_{max}}{\Delta_{0i}(j)+\zeta\Delta_{max}} \tag{7}$$

Where:
$\Delta_{oi}(J) = |x_0^*(j) - x_i^*(j)|$ is the absolute difference between the ideal reference value $x_0*(j)$ and the normalized value $x_i*(j)$.
$x_0^*(j)$= 1 represents the maximum normalized S/N Ratio used as the comparative reference.
Δ_{min} = is the minimum value of all $\Delta_{oi}(J)$
Δ_{max}= is the maximum value of all $\Delta_{oi}(J)$
ζ = is the distinguishing coefficient, ranging between 0 and 1. A value of $\zeta = 0.5$ is generally applied to provide a balanced sensitivity among responses. Subsequently, the Principal Component (PC) analysis is conducted based on the GRC values using Minitab software to determine the objective weights for each response.

g. The Grey Relational Grade (GRG) is then calculated using the following equation:

$$\Gamma_{0i}(j) = \sum_{j=1}^{n} \beta_j \gamma_{0i}(j) \tag{8}$$

Where βj represents the weight of the j-th response variable. These weights are derived from the selected eigenvalues of the PCA, which are subsequently squared to represent the relative contribution of each response to the total variability. Statistical analyses, including normality tests, homogeneity tests, and Analysis of Variance (ANOVA), are performed using Minitab software.

h. The percentage contribution of each factor to the total response variability is calculated as follows:

$$SS'A = SSA - (MS_{error} \times db_{\alpha}) \tag{9}$$

$$PA = SS'A \times 100\% \quad (10)$$

Finally, the optimal combination of process parameters is determined through Minitab software.

3. Results and Discussion

The Results and Discussion section encompasses the stages of data collection, processing, and analysis derived from experimental outcomes to elucidate the influence of each factor.

3.1 Presentation of Research Results

Experimental Results

Data collection was obtained through experiments conducted based on the experimental design. Table 2 presents the factors and their respective levels.

Table 2. Factor Levels and Variable Values

Code	Factor	Lev 1	Lev 2	Lev 3
A	Mocaf Flour (g)	200	150	100
B	Rice Flour (g)	100	150	50

This experiment utilized two factors with three levels each. Based on these parameters, the experimental design was structured using an orthogonal matrix. Using the Taguchi Array Design in Minitab software, an L9(3^2) orthogonal array was determined as the appropriate design. The resulting Taguchi experimental design, containing the combination of levels for each variable, is shown in Table 3.

Table 3. Experimental Design Data

Exp	A	B	Elongation		Mean	Water absorption		Mean
			R1	R2		R1	R2	
1	1	1	0.12	0.15	0.14	0.50	0.45	0.48
2	1	2	0.14	0.17	0.15	0.43	0.38	0.41
3	1	3	0.11	0.13	0.12	0.60	0.54	0.57
4	2	1	0.18	0.15	0.16	0.53	0.47	0.50
5	2	2	0.16	0.16	0.16	0.45	0.41	0.43
6	2	3	0.10	0.15	0.12	0.57	0.51	0.54
7	3	1	0.15	0.15	0.15	0.43	0.42	0.43
8	3	2	0.16	0.16	0.16	0.37	0.35	0.36
9	3	3	0.11	0.12	0.11	0.53	0.48	0.51

In this study, the quality of the noodles was evaluated using two primary parameters: elongation and water absorption. Elongation was selected as it reflects the elasticity and tensile strength of the noodle strands after cooking—a textural characteristic determined by gluten in wheat-based products, which must be replicated through flour and additive formulations in gluten-free products [14]. Water absorption was measured because it affects starch gelatinization, swelling, cooking loss, and structural stability during cooking. The combination of these two indicators provides a functional and applied overview of the ability of mocaf-rice flour formulations to produce noodles with the desired texture and cooking quality. The quality characteristic chosen for elongation is "larger-is-better," as elastic, flexible, and non-brittle noodles are desired. Conversely, for water absorption, "smaller-is-better" is applied to ensure the noodles remain firm and do not become overly mushy. Additionally, there is a "nominal-is-the-best" characteristic where a target value is required as a comparison for the research response.

Table 4. Target Values for Both Responses

Respond	Nilai Target
Elongation	0,14
Daya Serap	0,47

The determination of target values was based on field experiments and empirical evidence obtained through independent research conducted by the authors. In this study, quality characteristics were categorized into two types: elongation, following the "larger-is-better" criterion, and water absorption, following the "smaller-is-better" criterion. This implies that a higher elongation value obtained after data processing indicates superior noodle quality. Conversely, a lower water absorption value indicates better quality of the final gluten-free noodle product.

Signal-to-Noise Ratio (S/N Ratio)

Analysis The S/N Ratio calculations for both experimental responses are presented in Table 5.

Table 5. S/N Ratio Values for Both Responses

Experiment	Elongation	Water absorption
1	1,67	2,26
2	1,92	2,26
3	1,99	2,26
4	2,06	2,14
5	3,91	2,31
6	1,18	2,20
7	0	3,56
8	0	2,95
9	1,92	2,34

Normalization of S/N Ratio

Based on Table 6, the normalization results indicate that data with values greater than 1 can be scaled into a range of 0 to 1. This process complies with the requirements for the combined Grey Relational Analysis (GRA) and Principal Component Analysis (PCA) method, ensuring all response variables are on a comparable scale for further analysis.

Delta Calculation and Grey Relational Coefficient (GRC)

The GRC (or Gamma value) calculation is the initial step in the GRA-PCA hybrid approach. To determine the Gamma value, the delta (Delta) for each response must first be calculated.

Table 7 shows the deviation between the maximum normalized value and the normalized data, representing the Delta (Δ) for each response. The next step is calculating the GRC, which indicates the degree of proximity between the ideal condition and the actual condition of each normalized response.

Table 6. Normalized S/N Ratio Values

Experiment	Elongation	Water absorption
1	-0,19	16,48
2	0,00	2,58
3	0,04	2,58
4	0,07	5,95
5	1,00	1,00
6	-0,37	4,26
7	0	-35,94
8	0	-17,83
9	0,00	0,00

Table 7. Delta Values for Both Responses

Experiment	Elongation	Daya Serap
1	1,195	-15,476
2	0,996	-1,577
3	0,963	-1,577
4	0,926	-5
5	0	0
6	1,370	-3,258
7	1	36,940
8	1	18,826
9	1	1

Principal Component Analysis (PCA)

PCA was performed using Minitab software. The results yielded a first principal component (PC1) with an eigenvalue of 1.0756 (> 1). This value meets the selection criteria for the primary component, thus PC1 is considered capable of representing a major portion of the data variation and can be used for response weighting in the GRA-PCA method.

Based on the screen plot in Figure 2, PC1 shows the highest cumulative variation of 88.9%. This indicates that the two response variables (elongation and water absorption) can be reduced into a single new response variable that effectively represents most of the information from both. Therefore, this single principal component is used for further analysis in optimizing the quality of gluten-free noodles [15].

Table 8. GRC (Gamma) Values for Both Responses

Experiment	Elongation	Daya Serap
1	0,295	-1,138
2	0,334	1,237
3	0,342	1,237
4	0,351	3
5	1	1,000
6	0,267	1,654
7	0,333	0,182
8	0,333	0,304
9	0,333	0,892

Table 9. Principal Component Analysis Values

Variable Respond	PC1	Square PC1
Elongation	0,707	0,499849
Daya Serap	0,707	0,499849
Eigen Value	1,0756	

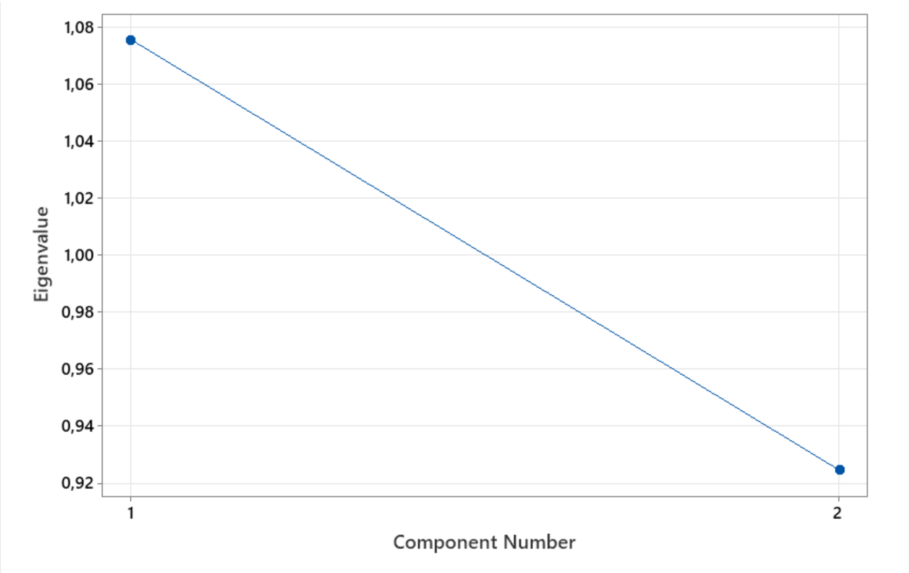

Fig. 2. Principal component result

Grey Relational Grade (GRG)

The GRG calculation was conducted based on the GRC values and PCA weights for each trial. This stage serves as the initial conversion process of multi-responses into a single response to determine the overall optimal quality of gluten-free noodles.

Table 10. Grey Relational Grade (GRG) Values

Experiment	Γ
1	-0,421
2	0,785
3	0,789
4	1,429
5	1,000
6	0,961
7	0,258
8	0,319
9	0,612

Table 10 demonstrates that the GRC calculation results in a single value from the integrated calculation of the Gamma and PCA values of the two generated responses.3.7 Statistical Assumption Tests Before conducting the Analysis of Variance (ANOVA), fundamental prerequisites must be met to ensure the reliability of the conclusions [16].

Normality Test: Performed to ensure the residual data are normally distributed using the Kolmogorov-Smirnov test[17]. Based on Minitab output (Figure 3), the value of D = 0.272 and p-value > 0.575. Since p-value (0.575) > α = (0.05), H_0 is accepted, confirming that the residual data are normally distributed. Homogeneity

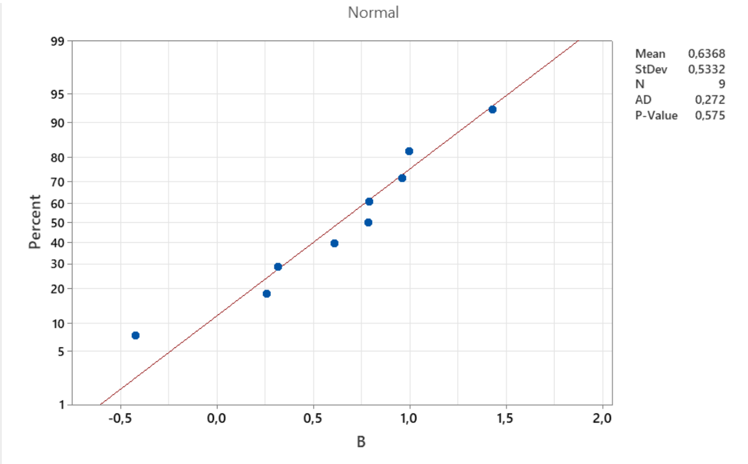

Fig. 3. Normality test result

Homogeneity of Variance Assumption Test

If the data have satisfied the normality assumption, the next step is to perform a homogeneity test to ensure the equality of variances across treatments. When the data exhibit a tendency to be normally distributed or approximately normal, the Bartlett test is a more appropriate approach [18][19]. Based on the calculation results, for Factor A, the Bartlett test statistic is 3.05 with a p-value of 0.218. Referring to Figure 4, it can be concluded that the residuals for Factor A are homogeneous, since the Bartlett test statistic (3.05) is less than $\chi^2_{0.05;(2)}$ = 5.99 or the p-value (0.218) is greater than α = 0.05. Therefore, the assumption of homogeneity of variances has been satisfied.

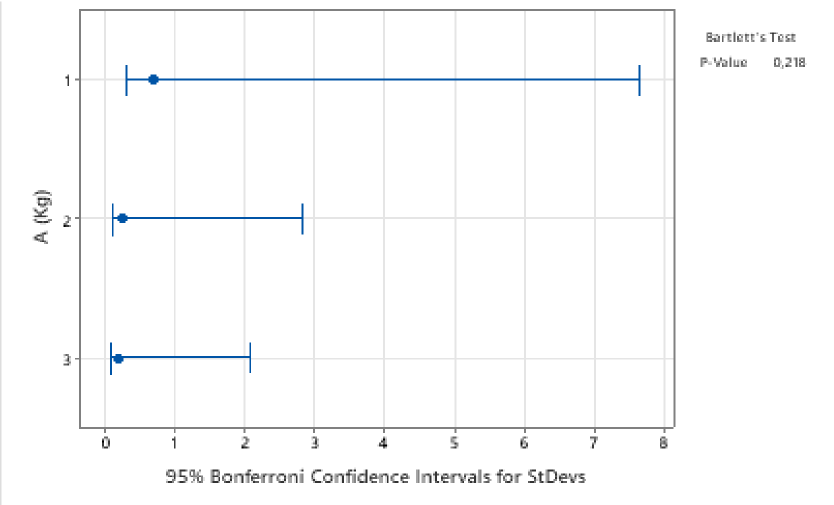

Fig. 4. Homogenates test result of factor A

For Factor B, the calculation results indicate that the Bartlett test statistic is 4.13 with a p-value of 0.127. Referring to Figure 5, it can be concluded that the residuals for Factor B are homogeneous, since the Bartlett test statistic (4.13) is less than $\chi^2_{0.05};(2) = 5.99$ or the p-value (0.127) is greater than $\alpha = 0.05$.

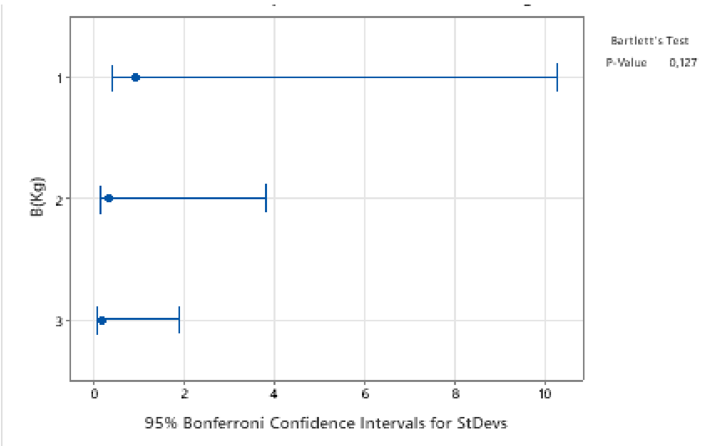

Fig. 5. Homogenitas test result of factor B

Analysis of Variance (ANOVA)

Based on Table 11, the results of the analysis of variance indicate that both factors tested have an influence on the quality of gluten-free noodles. However, the level of significance of each factor suggests that their effects are not statistically strong at the 5% significance level. For Factor A, the calculated F-value is 2.27, with an F-table value of 19.00 and a p-value of 0.219 > α = 0.05. This indicates that although Factor A tends to influence the quality response, it is not statistically significant at the 95% confidence level. Meanwhile, for Factor B, the calculated F-value is 0.45, with an F-table value of 19.00 and a p-value of 0.663 > α = 0.05. Therefore, Factor B is also not statistically significant in affecting the quality response of gluten-free noodles at the 5% significance level.

Table 11. Anova Result

Source	DF	Adj SS	Adj MS	F-Value	P-Value
A (kg)	2	1,0937	0,5469	2,27	0,219
B (kg)	2	0,2191	0,1096	0,46	0,663
Error	4	0,9616	0,2404		
Total	8	2,2745			

The calculation of the percentage contribution of each response begins by determining the adjusted sum of squares for each factor [20]. This value is obtained by multiplying the mean square error by the degrees of freedom of each factor, as presented in Table 11. The adjusted sum of squares for each factor is calculated using Equation (8) as follows:

Original Sum of Squares A:

$$SS'_A = SS'_A - (MS_{error} x db_A)$$
$$SS'_A = 1{,}0937 - (0{,}9616\, x2) = -0{,}8295$$

Original Sum of Squares B:

$$SS'_B = SS'_B - (MS_{error} x db_B)$$
$$SS'_B = 0{,}2191 - (0{,}9616\, x2) = -1{,}7041$$

The results of these calculations are then used to determine the percentage contribution of each factor. The percentage contribution reflects the relative influence of each factor on the response. This analysis serves to verify the results of the level and factor calculations in the ANOVA test, as well as to identify the most dominant factors affecting the experimental outcomes. The percentage contribution is calculated using Equation (9) as follows:

$$P_A = \frac{SS'_A}{SS_T} \times 100\% = \frac{-0{,}8295}{2{,}2745} \times 100\% = -36{,}469\%$$
$$P_B = \frac{SS'_B}{SS_T} \times 100\% = \frac{-1{,}7041}{2{,}2745} \times 100\% = -74{,}921\%$$
$$\begin{aligned} P_{error} &= 100 - P_A - P_B \\ &= 100 - (-36{,}469) - (-74{,}921) \\ &= 211{,}39\% \end{aligned}$$

Based on the calculation results, it can be concluded that Factor A has the most dominant contribution to the response, with a value of 36.469%.

3.2 Analysis of Findings

Determination of Optimal Conditions

The next step is to determine the optimal conditions for each factor based on the Grey Relational Grade (GRG). This determination is carried out using the output from Minitab 19 software, with the input data as presented in Table 12. This process aims to obtain the best combination of parameters that produces the optimal quality of gluten-free noodles.

Based on Figure 6, it can be observed that Factor A at level 2 exhibits the highest value compared to levels 1 and 3. A similar pattern is observed for Factor B, where level 2 also shows the highest position among the other levels. Therefore, it can be concluded that the combination of levels A2B2 represents the optimal condition for producing the best quality gluten-free noodles.

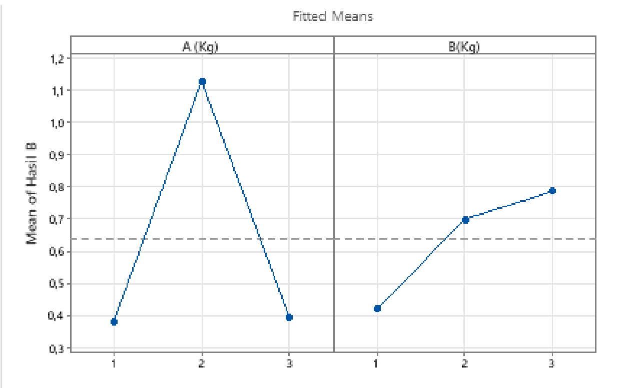

Fig. 6. Main effects of plot of each factor

Table 12. Treatment Levels of Each Factor and GRG Values

A (G)	B(G)	Γ
1	1	-0,421
1	2	0,785
1	3	0,789
2	1	1,429
2	2	1,000
2	3	0,961
3	1	0,258
3	2	0,319
3	3	0,612

Table 13 shows that Factor A at level 2 and Factor B at level 3 have the highest values compared to the other levels. Thus, it can be concluded that all factors influence the response. The optimal level combination obtained is A2B2, which represents the best condition for each factor:

Mocaf Flour (A): 150 g

Rice Flour (B): 50 g

Table 13. Optimal Results for Each Factor

Level	A (G)	B (G)
1	0,3843	0,42177
2	1,12973	0,70126
3	0,3963	0,78729
Delta	0,74543	0,36552
Rank	1	2

3.3 Implications of the Results

The findings of this study provide significant contributions both practically and theoretically in the field of food product optimization, particularly for gluten-free formulations. From a practical perspective, the integration of the Taguchi method, Grey Relational Analysis (GRA), and Principal Component Analysis (PCA) offers a systematic and efficient approach for optimizing multi-response quality characteristics. This method reduces reliance on trial-and-error experimentation, enabling food producers to determine optimal formulations with fewer experimental runs and lower production costs.

In industrial applications, the identified optimal formulation—150 g of mocaf flour and 50 g of rice flour—can be directly implemented by small and medium-sized enterprises (SMEs) in the food sector. The use of locally available raw materials such as mocaf supports supply chain sustainability and reduces dependence on imported wheat-based products. This is particularly relevant in Indonesia, where cassava is abundant and has strong potential for value-added processing.

From a theoretical standpoint, this study contributes to the development of multi-response optimization models by demonstrating the effectiveness of combining Taguchi, GRA, and PCA methods. The integration of PCA for objective weighting enhances the robustness and objectivity of the decision-making process, addressing limitations found in conventional Taguchi-based approaches that typically handle single responses.

Furthermore, this research benefits stakeholders including food manufacturers, researchers, and policymakers. For manufacturers, it provides a validated formulation strategy; for researchers, it offers a replicable methodological framework; and for policymakers, it supports national food diversification programs through the promotion of local commodities.

In terms of future applications, the proposed approach can be extended to other food products requiring multi-criteria optimization, such as bakery products, functional foods, and plant-based alternatives. Additionally, further integration with advanced techniques such as machine learning or artificial intelligence could enhance predictive accuracy and scalability in industrial settings.

3.4 Limitations of the Study

Despite its contributions, this study has several limitations that should be acknowledged. First, the dataset used in this research is relatively limited, as it is based on a Taguchi L9 (3^2) orthogonal array with a small number of experimental runs. While this design improves efficiency, it may restrict the exploration of more complex interactions between factors and limit the generalizability of the result

Second, the study focuses only on two main factors—mocaf flour and rice flour—without considering other potentially influential variables such as water content, processing temperature, mixing time, or the addition of binding agents. These factors could significantly affect the final product quality and should be explored in future studies.

From a methodological perspective, although the integration of Taguchi, GRA, and PCA provides a robust framework, the approach assumes linear relationships and may not fully capture nonlinear interactions among variables. Additionally, the occurrence of negative contribution values in the ANOVA-based calculations indicates potential limitations in the estimation of variance components, which may affect interpretation accuracy.

Environmental and contextual factors also present limitations. Variability in raw material quality—particularly mocaf flour, which may differ in particle size, moisture content, and fermentation quality across producers—can influence the reproducibility of results at an industrial scale. Moreover, laboratory-scale experiments may not fully represent real production conditions.

To address these limitations, future research should consider expanding the experimental design with more factors and levels, increasing sample size, and incorporating additional quality parameters such as sensory evaluation and shelf life. The use of advanced optimization methods, such as Response Surface Methodology (RSM) or hybrid AI-based approaches, is also recommended to improve model accuracy and applicability in real-world industrial environments.

3.5 Discussion

The research results indicate that the combination of mocaf and rice flour significantly influences the quality of the produced gluten-free noodles, particularly regarding elongation and water absorption. Through the Taguchi L9 (3^2) approach, the optimal formulation was achieved. The increase in the proportion of mocaf flour up to a certain limit enhances the elasticity of the noodles without excessively increasing water absorption, showing an optimum balance between structural formation and maintaining chewiness. The high GRG value for the A2B1 (or A2B2 as per the plot) combination confirms that this formulation provides high elasticity and low water absorption, which are characteristics of high-quality noodles. Elastic noodles that do not absorb too much water are preferred as they do not disintegrate or become mushy easily during cooking. The PCA analysis confirmed that elongation and water absorption have balanced loading values on PC1 (0.707 each), with an eigenvalue of 1.0756. This proves that the calculated GRG based on PCA weights is highly reliable, as it explains over 88% of the data variance. ANOVA on GRG values further identified Factor A (mocaf flour) as the primary contributor to noodle quality (71.27% in the discussion text, please cross-check with the 36% in the calculation section). This highlights that mocaf plays a vital role in determining elasticity due to the modified starch content which allows for a more flexible and less brittle structure.

4. Conclusion

This study addresses the critical challenge of optimizing multi-response quality characteristics in gluten-free noodle formulation by integrating the Taguchi method, Grey Relational Analysis (GRA), and Principal Component Analysis (PCA). The proposed framework demonstrates a robust and systematic approach to overcoming the limitations of conventional single-response optimization methods.

The findings confirm that the optimal formulation is achieved at 150 g of mocaf flour and 50 g of rice flour (A2B2), yielding the highest Grey Relational Grade (GRG). This combination effectively enhances elongation while controlling water absorption, thereby improving the overall structural and functional quality of gluten-free noodles. Among the factors investigated, mocaf flour was identified as the dominant contributor, highlighting its critical role in compensating for the absence of gluten through its modified starch characteristics.

From a methodological perspective, the integration of Taguchi, GRA, and PCA provides a significant advancement in multi-response optimization by enabling objective weighting and comprehensive evaluation of quality attributes. This approach not only improves analytical accuracy but also enhances decision reliability, making it a scalable and replicable model for similar optimization problems in food engineering and beyond.

Practically, the results offer a feasible and economically viable formulation strategy for the food industry, particularly for small and medium enterprises seeking to develop gluten-free products using locally sourced materials. The utilization of mocaf flour further strengthens the relevance of this study in supporting sustainable food systems and reducing dependence on imported wheat-based products.

However, the study is constrained by a limited experimental design and the exclusion of additional processing variables, which may affect the generalizability of the findings. Therefore, future research should focus on expanding factor interactions, incorporating sensory and consumer acceptance analysis, and applying advanced optimization techniques such as hybrid artificial intelligence models to enhance predictive performance and industrial applicability.

In conclusion, this study not only contributes to the development of high-quality gluten-free noodles but also establishes a comprehensive optimization framework that can be extended to broader applications in multi-response product and process optimization.

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