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Product Quality Improvement of Lanting Kebumen Using Quality Function Deployment and Taguchi Method

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ABSTRACT: Lanting is a traditional snack from Kebumen, which is made from cassava. Based on interviews with business owners, some lanting products are often returned by consumers. Therefore, improving the quality of Lanting is necessary to satisfy consumer needs. Meet consumer needs, it can be done with the House of Quality (HOQ), which will be developed with Taguchi's experimental design to get the best combination of parameters to meet consumer needs and make the product robust. This study aims to determine the priority attributes of consumers for lanting products, to know the factors that affect consumer needs, and to determine the most optimal combination of parameters that can meet the priorities of consumer needs. The results of distributing questionnaires show that the priority of consumer needs for lanting products is the crispness of lanting. The HOQ shows that the technical responses that have a strong relationship with consumer needs are the amount of frying (A), frying time (B), and frying temperature (C). These technical responses will be used as factors in experiments using the Taguchi method to determine the best combination of parameters that can improve the crispness of lanting. The results of the ANOVA analysis found that the factors that had a strong effect were factors A and C. In the SNR analysis, factor A contributes 96.1%, B 1.2%, and C 2.7%. The most optimal combination of parameters that can provide crispy lanting is the number of frying as much as twice, a frying time of 3 minutes, and a frying temperature of 170℃.

KEYWORDS: HoQ, Lanting Kebumen, QFD, Taguchi Method.

INTRODUCTION

Snack production is an essential sector in the food industry (1). Globally, in 2022, the total production of snacks is valued at $584.58 billion (2). Snacks have increased in popularity because they can provide a satisfactory taste, increase consumer appetite, are conveniently ready to eat, and are easy to handle (3).

The global population has also increased the demand for quality and affordable food products (4). It is a challenge for the food industry to provide high-quality food at an affordable cost to compete in the global market. Competition in the food industry forces companies to continue being innovative and supporting the quality of their products (5). Companies must understand what consumers need and want and how consumer priorities can be met on product attributes (6). Food quality is the most significant factor that food companies must consider because product quality is related to the suitability of the product to be used, where a food product must be able to meet customer needs and expectations (7). In addition, the food industry requires statistical approaches, experiments, and other operational advantages to overcome the increasing challenges in food production.

According to the Kebumen Central Statistics Agency (BPS) research (8), the number of industries in Kebumen Regency is 56,402 business units, where the largest small industry is the food industry. One of the famous foods in Kebumen Regency is lanting (8). Lanting is a traditional snack from Kebumen Regency made from cassava shaped into a figure eight with several flavor variations (9). Many small industries or MSMEs produce lanting, including Tuti's MSME. Mrs. Tuti MSME is one of the small industries producing authentic lanting from Kebumen. Currently, Mrs. Tuti's MSME is trying to improve the quality of lanting products so that they can compete with other lanting products.

Based on interviews with business owners, some lanting products are often returned by consumers. This is known because lanting products do not suit customers' needs, such as the color of the lanting that is not bright enough, the taste that is not savory enough, and the crispness of the product that does not follow the needs and wants of consumers. From this, MSMEs need to improve the quality of their products according to the needs and wants of consumers. The challenge in improving product quality is that the developed product must be able to meet the needs and wants of consumers (10). Product quality is seen as the product's ability to satisfy consumer wants (10). The effect of product quality is essential because it can improve consumer satisfaction with the product and consumer loyalty to the products used (11). Therefore, it is important to improve product quality by consumer wants so that the products produced can compete and be accepted by the market.

According to Armand V. Feigenbaum, quality must begin with identifying consumer needs and finish with the product or service that can satisfy consumers. Consumer needs and wants are determined to identify critical issues in the design of food processes and products (12). To maximize consumer needs and wants, the Quality Function Deployment (QFD) method has been widely applied to many companies (7). According to (13), QFD is a particular way to create consumer needs and wants as an integral part of the design and production of a product or service. The central part of QFD is the House of Quality, a tool to interpret the consumer's voice into technical product responses (14). HOQ consists of six matrixes, including the voice of customers, technical Response, relationship, benchmarks, correlations, and technical assessment (15). QFD can be used as a first step to improve product quality according to consumer needs and wants.

Quality improvement can be done with several methods, including the Taguchi Method. The Taguchi method is a new method in engineering that aims to improve product and process quality simultaneously and to reduce costs and resources (16). The advantages of this method are its effectiveness, simplicity, ease of analysis, and speed up the experimentation process (8). This method can make the product insensitive to various factors and make the product or process robust to noise factors (17). The Taguchi method seeks to find the optimal level for the control factor by minimizing the response variance towards the optimal Response, and it significantly reduces the time required to conduct experiments (18). From this, the Taguchi method seeks to obtain the best combination of levels and factors to improve product quality.

Previous studies that used the Taguchi method to improve the quality of food products were conducted by (18) related to fermented chickpea flour, related to enhancing the taste quality of fish crackers. The results obtained the best combination of factors and levels in improving the taste of fish crackers, and the most influential factor is the fish broth. (19) Using Taguchi Grey Analysis, related to Djulis Sourdough Bread, obtained the optimal formula to produce Djulis Sourdough with good texture, color, and quality.

This research focuses on improving the quality of Lanting Kebumen products by designing experiments using the Taguchi method. The first step is to get the voice of the customer to find out the needs and wants of consumers for lanting products. The results of the customer's voice will be developed to obtain technical responses that can meet customer needs. The results of the relationship between technical responses and customer needs will be used as a control factor in the design of experiments. Taguchi experiments combine existing factors and levels to maximize experimental results. So, it is expected to produce the best combination of factors and levels to improve the quality of Lanting Kebumen products.

METHOD

Quality Function Deployment

Quality Function Deployment (QFD) is a structured approach to finding consumers, understanding consumer needs, and ensuring that consumer needs can be met with product specifications provided by the company (20). QFD is a method used to determine consumers' needs and wants, interpreted into technical requirements, manufacturing systems, and production planning precisely and accurately (21). QFD can be applied to various fields, such as food products, agriculture, services, fruit, organic products, olive oil, and meat products (21). In the food industry, QFD can be helpful in product development's planning and design stages by making modifications and adjustments according to food industry specifications (22).

QFD has four phases for product development, but the primary key in QFD is in phase 1, product planning, commonly known as making a House of Quality (HOQ) (23). HOQ has six graphical matrix components: customer needs and wants, technical Response, technical Correlation, relationship, technical matrix, and planning matrix (16). The HOQ matrix can be seen in Figure 1.

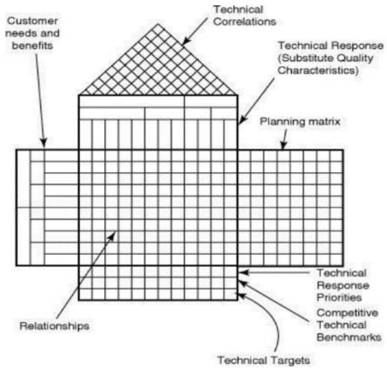

Figure 1. House of Quality

These matrixes can clearly illustrate the relationship between technical requirements and product technical responses and identify comparisons with competitors who have similar businesses (16). The primary key in making HOQ is to focus on customer needs so that the development design suits consumers' needs. A questionnaire was distributed to get consumer needs.

The questionnaire determined consumers' needs and wants for lanting products. The needs and wants of consumers that have been obtained are then developed into technical responses that can meet consumer needs. The prioritization of consumer needs and wants and technical responses that have a strong influence will be created with Taguchi's experimental design to meet consumer needs.

Experimental Design

Experimental design is a technique that describes and investigates various experimental situations and allows many factors to be manipulated to determine their effect on the intended output response (24). In experimental design, three principles must be considered: replication, randomization, and local control (25). The use of experimental design in developing products can create products that are robust to environmental factors and other sources of variability (26). One of the experimental designs that can be used is the Taguchi experimental design.

Using Taguchi's experimental design allows for the evaluation of multiple variables affecting a product or process at various levels using several experiments (27). Taguchi's methods improve product and process quality by identifying factors affecting product quality and efficiently optimizing experimental conditions (27). The Taguchi method seeks to find the optimal level of control factors by minimizing the variance towards the optimal Response and significantly reducing the time required to conduct experiments (23).

Orthogonal Array

Using orthogonal arrays can reduce the number of experiments conducted, reducing the cost and time of experimentation [28]. Orthogonal Arrays deal with equation calculation and evaluate functional reproducibility [29]. The orthogonal array table consists of rows and columns. The number of rows indicates the number of experiments to be conducted, while the number of columns indicates the number of factors to be observed [30]. The orthogonal array matrix used in the Taguchi method can be seen in Table 1.

Table 1. Orthogonal array

2 level	3 level	4 level	5 level	Combined Level
$L_4(2^3)$	$L_9(3^4)$	$L_{16}(4^5)$	$L_{25}(5^6)$	$L_{18}(2^1x3^7)$
$L_8(2^7)$	$L_{27}(3^{13})$	$L_{64}(4^{21})$	-	$L_{32}(2^1x4^9)$
$L_{12}(2^{11})$	$L_{81}(3^{40})$	-	-	$L_{36}(2^{11}x3^{12})$
$L_{16}(2^{15})$	-	-	-	$L_{36}(2^3x3^{13})$
$L_{32}(2^{31})$	-	-	-	$L_{54}(2^1x3^{25})$
$L_{64}(2^{63})$	-	-	-	$L_{50}(2^1x5^{11})$

The orthogonal array is denoted by La(bc), where L is the Latin square, notation a represents the number of experiments, b is the number of levels for each factor, and c is the number of factors used (16).

Signal-to-Noise Ratio

Signal to Noise Ratio (SNR) can be defined as the ratio of sensitivity to variability (18). In SNR, signal relates to the actual expected value, while noise relates to the unwanted factors in the measurement. The S/N ratio can be understood as the inverse of variance. Maximizing the S/N ratio reduces process variability against unwanted changes in the surrounding environment or noise factors (20). To minimize the variability, the factor level that produces the most significant S/N ratio value must be selected. This is because variability is inverse to the S/N ratio (28).

The Taguchi method describes three types of optimization criteria for response variables: Larger The Better (LTB), Nominal The Best (NTB), and Smaller The Better (STB). The more significant the result, the better the result will be in maximizing the result with the ideal target at a higher value (29). The smaller, the better, the type where it is desired to minimize the result with the perfect target at a smaller or minimum value. Nominal, the better is the kind with a finite target point to be achieved (23).

The S/N ratio for STB characteristics can be calculated using formula 1.

$$S/N = -10 \times \log \frac{\sum Y^2}{n} \quad (1)$$

The S/N ratio for NTB characteristics can be calculated using formula 2.

$$S/N = 10 \log(\frac{y^2}{s^2}) \quad (2)$$

The S/N ratio for LTB characteristics can be calculated using formula 3.

$$S/N = -\log \frac{\sum Y^2}{n} \quad (3)$$

Whereas,

y: the Response of a particular factor level combination

n: the number of responses from a particular combination of factor levels.

Analysis of Variance

In the design of experiments, Analysis of Variance (ANOVA) is applied with mean values and S/N ratios to determine the parameters and effect values that affect the product. S/N Ratio analysis provides data on the significance of a parameter compared to other parameters in terms of the effect of the response variable. Meanwhile, ANOVA provides data on the significance of parameters on the response variable. ANOVA is a method that helps understand the contribution of influencing factors to the response variable (30).

RESULT AND DISCUSSION

Customer needs identification is conducted to determine consumer needs for lanting products. Identification is performed by distributing questionnaires containing six attributes to 30 consumers. The questionnaire comprises consumer perceptions and consumer expectations of lanting products. The attributes used in the questionnaire can be seen in Table 2.

Consumers will fill in the level of suitability and importance of lanting products with a scale range of 1-5, where the most significant scale indicates the level of suitability and importance that best suits consumer needs. The data that has been collected is then tested for validity and reliability. The validity test uses a 5% significance value with a rtable value of 0.361. Data is valid if the rcount is greater than the rtable. The validity test results can be seen in Table 2.

Table 2. Validity Test

No	Attribute	Validity Test		r_{table}	Desc
		Perception	Expectation		
1	Q1	0,592	0,624	0,361	*Valid*
2	*Q2*	0,595	0,570	0,361	*Valid*
3	Q3	0,720	0,660	0,361	*Valid*
4	Q4	0,407	0,448	0,361	*Valid*
5	Q5	0,461	0,701	0,361	*Valid*
6	Q6	0,710	0,665	0,361	*Valid*

The reliability test is conducted using the Cronbach's Alpha value, where the data can be said to be reliable if the Cronbach's Alpha value is 0.6.

Table 3. Reliability Test

Attribute	Reliability	*Cronbach's Alpha*	Desc
Consumer Perception	0,625	0,6	R
Consumer Expectation	0,646	0,6	R

Technical Response, Correlation of Technical Response and Relationship

The Technical Response contains those technical responses that can fulfill customer needs. Ten technical responses can fulfill all consumer needs. These technical responses consist of cassava type, amount of milling, pressing time, steaming time, kneading time, amount of frying, frying time, frying temperature, and draining time.

Technical Correlation contains the relationship between technical responses. The relationship between technical responses has a positive and negative relationship. A positive relationship indicates that the relationship between technical responses is directly proportional, while a negative relationship indicates that the relationship between them is opposite. Technical Correlation consists of strong positive (++), positive (+), unrelated, negative (-), and strong negative (--).

The relationship is made by connecting consumer needs with technical responses. A relationship has a relationship that can be seen in the following table.

Table 4. *Relationship*

relation	Symbol	Value
strong	●	9
moderate	O	3
weak	Δ	1
no relation		0

Value of Satisfaction, Importance, Overall Importance, and Relative Importance

The value of satisfaction and importance are calculated using the following formula.

$$T = \frac{CRSV_1 + CRSV_2 + \cdots + CRSV_k}{k} \quad (4)$$

Overall Importance and Relative Importance are calculated using the following formula.

$$Overall\ Importance = Tpenting - \left(Tpuas \times \frac{Tpenting}{\max value}\right) \quad (5)$$

$$Relative\ Importance = \frac{Overall\ Importance}{\sum Overall\ Importance} \times 100\% \quad (6)$$

The calculation of relative importance is conducted by determining the weight as a consideration for selecting prioritized technical responses. The calculation uses the following formula.

$$a_j = \sum_{i=1}^{n} R_{ij}\, c_i \quad (7)$$

Whereas,

R_{ij} : *relationship matrix*

C_i : *customer importance*

House of Quality

House of Quality (HOQ) is composed of several matrixes: customer needs and benefits, technical Response, planning matrix, relationship, technical correlation matrix, and technical priorities. Combining these matrixes will produce the HOQ form, which can be seen in Figure 2.

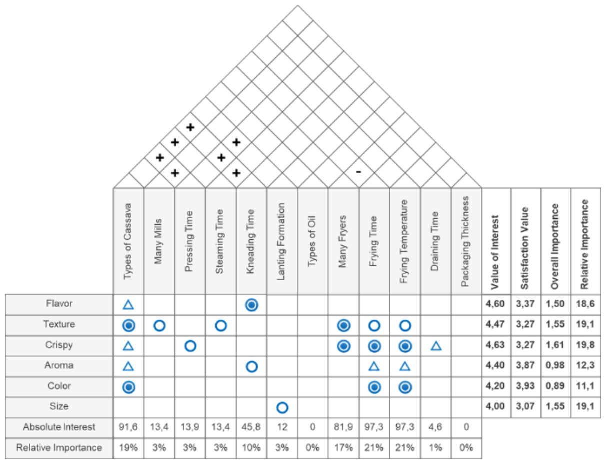

Figure 2. HOQ of *Lanting*

Taguchi Experimental Design

The Taguchi method was conducted to obtain factors and levels that affect the crispness of lanting. The factors used in the experiment are technical responses in HOQ that have a strong relationship with lanting crispness, which are the amount of frying, frying time, and frying temperature. This experiment uses three factors, and each factor has two levels. The factors and levels utilized can be seen in Table X. Orthogonal Array is selected based on the factors and levels used in the experiment. This experiment used three factors and two levels, so L4(23) was chosen. The Orthogonal Array matrix used can be seen in Table 5.

Table 5. Factors and Levels

Code	Factors	Levels	
		1	2
A	The amount of frying	1x	2x
B	Frying time	3mnts	5mnts
C	Frying Temperature	150°C	170°C

Table 6. Factors Combination and Levels

Experiments	Factors		
	A	**B**	**C**
1	1	1	1
2	1	2	2
3	2	1	2
4	2	2	1

The experimental results were then tested for hardness using a Texture Analyzer (TA TX-Plus). The test results are shown in Table 7.

Table 7. Test Results

Experiments	Factors			Replica 1	Replica 2
	A	**B**	**C**		
1	1	1	1	7834,877	8889,177
2	1	2	2	5541,637	6722,517
3	2	1	2	3457,772	3582,789
4	2	2	1	4957,122	4797,767

ANOVA Mean Value

The analysis stage is conducted by calculating the Analysis of Variance (ANOVA) and Signal to Noise Ratio (SNR) on experimental results. ANOVA calculations are conducted to test the initial hypothesis of the data. The initial hypothesis relates to whether or not the treatment affects the response variable. This analysis aimed to determine the optimal combination of parameters (6).

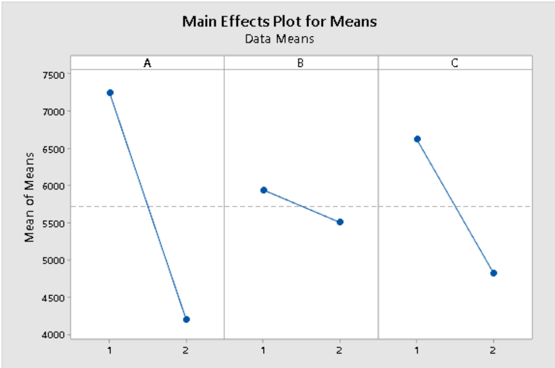

Figure 3. Main effects Plot for Means

The level effect can be seen from the mean value, close to the *lanting* crispness value of 3969.344 gf. Based on the mean value response, a combination of factors and levels is obtained: factor A level 2, factor C level 2, and factor B level 2.

Table 8. ANOVA Mean Value

Sources	SS	DF	MS	Fratio	SS'	Ratio %	F Table	Desc
A	18582918,456	1	18582918,456	58,367	18264537,289	68%	7,71	Reject H_0
B	380877,701	1	380877,701	1,196	62496,535	0%	7,71	Accept H_0
C	6433693,424	1	6433693,424	20,208	6115312,258	23%	7,71	Reject H_0
e	1273524,665	4	318381,166		2228668,164	8%		
SSt	26671014,2466	7	3810144,892		26671014,247	100%		
Mean	262017917,5	1						
Sstotal	288688932	8						

The decision to hypothesis is made by comparing the Fratio value with Ftable. If Fratio>Ftable, then H0 is rejected, which means there are factors that influence the crispness of lanting. From the calculation results, factors A and C have an influence on the response variable, while factor B does not affect the response variable. Factors that do not influence the response variable are then pooled up. In pooling up, factor B will be included in the error factor. The results of the pooling up calculation can be seen in Table 9

Table 9. **Polling up Mean Value**

Sources	**Pooled**	**SS**	**DF**	**MS**	**F ratio**	**SS'**	**Ratio %**	**F Table**
A		18582918,456	1	18582918,456	56,162	18252037,983	68%	6,608
B	**V**	380877,701	-					
C		6433693,424	1	6433693,424	19,444	6102812,951	23%	6,608
e	**V**	1273524,665	-					
Polled		1654402,366	5	330880,473	1,000	2316163,313	9%	
SSt		26671014,247	7	3810144,892		26671014,247	100%	
Mean		262017917,483	1					
Sstotal		288688931,729	8					

The results of ANOVA calculation after pooling up obtained factors A and C influence the response variable, with the contribution of factor A by 68% and factor B by 23%. After obtaining the influential factors, the prediction of optimum conditions and the average value is calculated. The confidence interval and prediction of optimum conditions are performed to determine whether the confirmation experiment is acceptable. Experiments are accepted if confirmation experiment results intersect or fall within the confidence interval value of the optimum condition prediction. The calculation of optimal condition prediction and confidence interval is as follows.

a. Estimated optimal state of all data

$$\bar{y} = \frac{\sum y}{n} \quad (8)$$

$$\bar{y} = \frac{7834{,}877 + 8889{,}177 + \cdots + 4797{,}767}{8}$$

$$\bar{y} = 5722{,}957$$

b. Predictions of optimal conditions

$$\mu_{predicted} = \bar{y} + (\overline{A_2} - \bar{y}) + (\overline{C_2} - \bar{y}) \quad (9)$$

$$\mu_{predicted} = 3302{,}084$$

c. Mean value confidence interval

$$CI_{mean} = \pm\sqrt{F_{\alpha;v1;v2} \times MS_{pooled\ e} \times \frac{1}{neff}} \quad (10)$$

$$CI_{mean} = \pm\sqrt{6{,}608 \times 330880{,}473 \times \frac{1}{2{,}667}}$$

$$CI_{mean} = \pm 905{,}495$$

Then, the confidence interval for the mean value is :

$$\mu_{predicted} - CI_{mean} \leq \mu_{predicted} \leq \mu_{predicted} + CI_{mean}$$

$$2396{,}589 \leq 3302{,}084 \leq 4207{,}579$$

ANOVA SNR

The Signal to Noise used is Nominal The Best (NTB). NTB SNR calculation uses the following formula.

$$SNR_{NTB} = -10 \log \frac{\bar{y}^2}{s^2}$$

Recapitulation of SNR calculation in table 10.

Table 10. SNR Value

Exp.	A	B	C	R1	R2	SNR
1	1	1	1	7834,877	8889,177	20,997
2	1	2	2	5541,637	6722,517	17,318
3	2	1	2	3457,772	3582,789	32,003
4	2	2	1	4957,122	4797,767	32,727

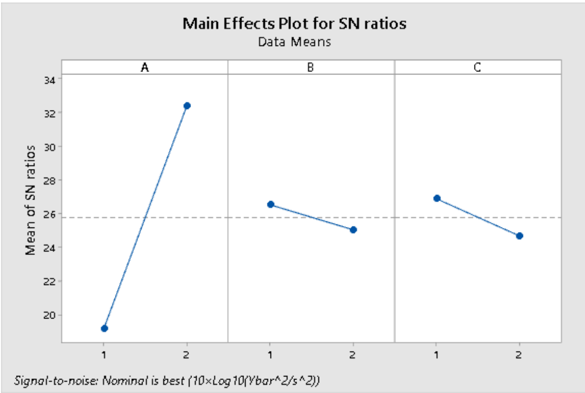

Figure 4. SNR Effect Response

Based on Figure 4, the order of the influence of factors and levels on the response variable is obtained based on the SNR response value. To minimize the variance value, select the highest SNR value. This is because the SNR value is the opposite of the variance itself, so the highest SNR value can minimize the noise and make it smaller. Therefore, we get a combination of factors and levels based on the mean value response: factor A level 2, factor C level 1, and factor B level 1. The ANOVA SNR calculation is in the following table.

Table 11. ANOVA SNR

Sources	**SS**	**DF**	**MS**	**%**
A	174,422	1	174,422	96,1%
B	2,182	1	2,182	1,2%
C	4,847	1	4,847	2,7%
SSt	181,4517	3	60,484	
Mean	2654,558	1		
Sstotal	2836	4		

The contribution percentage shows how much influence the control factor has on the response variable under research (31). The calculation also shows that the factor with the most significant contribution is factor A (the amount of frying) at 96.1%. This indicates that factor A greatly influences and contributes to reducing the variance in the response variable. After obtaining the influential factors, the calculation of optimal condition predictions and SNR value confidence intervals is then carried out. The calculation of predictions and confidence intervals is as follows.

a. Estimated optimal state of all data

$$\bar{\eta} = \frac{\sum y}{n}$$

$$\bar{\eta} = \frac{20{,}997 + 17{,}318 + \cdots + 32{,}727}{4}$$

$$\bar{\eta} = 25{,}761$$

b. Predictions of optimal conditions

$$\mu_{predicted} = \bar{\eta} + (\overline{A_2} - \bar{\eta})$$

$$\mu_{predicted} = 25{,}761 + (19{,}158 - 25{,}761)$$

$$\mu_{predicted} = 3302{,}084$$

c. Mean value confidence interval

$$CI_{mean} = \pm\sqrt{F_{\alpha;v1;v2} \times MS_{pooled\ e} \times \frac{1}{neff}}$$

$$CI_{mean} = \pm\sqrt{18{,}513 \times 3{,}515 \times \frac{1}{2}}$$

$$CI_{mean} = \pm 5{,}704$$

Then, the confidence interval for the mean value is

$$\mu_{predicted} - CI_{mean} \leq \mu_{predicted} \leq \mu_{predicted} + CI_{mean}$$

$$26{,}661 \leq 32{,}365 \leq 38{,}069$$

CONFIRMATION EXPERIMENT

Confirmation experiments were conducted to validate the optimal level settings obtained. Based on ANOVA and SNR calculations, confirmation experiments are conducted with the best combination of factors and levels that influence the response variable. Table 12 shows the combination of factors and levels used in confirmation experiments.

Table 12. Confirmation of Factors and Levels

Factors	Levels	Level Value
The amount of Frying	2	2x
Frying Time	1	3minutes
Frying Temperature	2	170

The results of the confirmation experiment using the optimal level setting were then tested for hardness using a Texture Analyzer to obtain the level of crispness of the lanting product. Texture Analyzer results can be seen in Table 13.

Table 13. Confirmation Experiment Results

Experiments	Results
1	4034,252
2	3917,143

The confirmation experiment confidence interval calculation is conducted as follows.

a. Mean Value of Confirmation Experiment

$$\mu_{confirmation} = \frac{\sum y}{n}$$

$$\mu_{confirmation} = \frac{4034{,}252 + 3917{,}143}{2}$$

$$\mu_{confirmation} = 3975{,}698$$

b. Mean Value of Confirmation Experiment Confidence Interval

$$CI_{confirmation} = \pm\sqrt{F_{\alpha;v1;v2} \times MS_{pooled\ e} \times (\frac{1}{neff} + \frac{1}{r})}$$

$$CI_{confirmation} = \pm\sqrt{18{,}513 \times 3{,}515 \times (\frac{1}{2} + \frac{1}{2})}$$

$$CI_{confirmation} = \pm 8{,}066$$

Thus, the confidence interval of the confirmation experiment is

$$\mu_{confir} - CI_{confir} \leq \mu_{confir} \leq \mu_{confir} + CI_{confir}$$

$$2592{,}531 \leq 3975{,}698 \leq 5358{,}864$$

The results of the confidence interval for the confirmation experiment were then compared with the confidence interval of the optimum condition prediction. The following figure compares the confidence intervals of the optimum condition prediction and the confirmation experiment for the mean value.

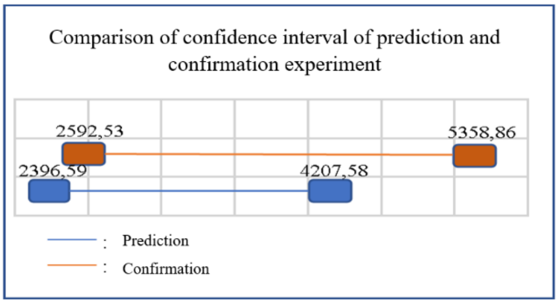

Figure 5. Mean Value of Confidence Interval

The confirmation experiment using the optimal level setting can be said to be successful or accepted because its confirmation value is within the prediction interval. From Figure 5.1, it can be seen that the mean value confidence interval of the confirmation experiment results overlaps with the confidence interval of the optimal condition prediction results. Therefore, the confirmation experiment in the mean value is acceptable.

The confirmation experiment confidence interval calculation for the SNR value is as follows.

a. SNR Value of Nominal The Better

$$\eta = 10\log\frac{\bar{y}^2}{s^2}$$
$$\eta = 10\log\frac{3975{,}7^2}{82{,}8^2}$$
$$\eta = 33{,}627$$

b. Confirmation experiment confidence interval

$$CI_{confirmation} = \pm\sqrt{F_{\alpha;v1;v2} \times MS_{pooled\ e} \times (\frac{1}{neff} + \frac{1}{r})}$$
$$CI_{confirmation} = \pm\sqrt{18{,}513 \times 3{,}515 \times (\frac{1}{2} + \frac{1}{2})}$$
$$CI_{confirmation} = \pm 8{,}066$$

Therefore, the confidence interval of the confirmation experiment for the SNR value is

$$\mu_{confir} - CI_{confir} \le \mu_{confir} \le \mu_{confir} + CI_{confir}$$

$$33{,}627 - 8{,}066 \le 33{,}627 \le 33{,}627 + 8{,}066$$
$$25{,}560 \le 33{,}627 \le 41{,}693$$

The following figure compares the confidence intervals of the optimum condition prediction and the SNR confirmation experiment.

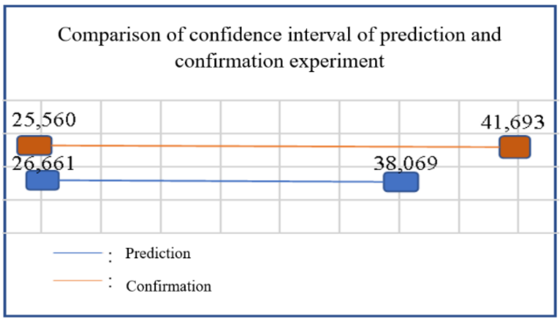

Figure 6. Comparison of SNR Value

Figure 6 shows that the mean value confidence interval of the confirmation experiment results overlaps with the confidence interval of the optimal condition prediction results. Therefore, the SNR confirmation experiment is acceptable.

CONCLUSION

Based on the distribution of questionnaires, it was found that consumer needs prioritized the crispness of lanting. Technical responses that have a strong relationship with consumer needs include the amount of frying, frying temperature, and draining time. These technical responses are then used as factors in Taguchi experiments, where each factor consists of two levels. The results of calculations using ANOVA averaged the factors influencing lanting crispness: factor A (The amount of frying) and factor C (freezing temperature). In contrast, factor B (freezing time) has no influence. SNR calculation obtained the contribution of factors to lanting crispness. Factor A has a contribution of 96.1%, while factor B contributes 1.2%, and factor C has a contribution of 2.7%. The most optimal combination of factors and levels to get the level of crispiness of lanting is factor A (The Amount of Frying) level 2 for 2x frying, factor B (Frying Time) level 1 for 3 minutes and factor C (Frying Temperature) level 2 for 170^{O}c.

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REFERENCES

1. Erliana CI, Hasanuddin I, Away Y, Ariffin R, Ghazilla R. Good Manufacturing Practice (GMP) in Tofu MSMEs in North Aceh. 2023;27(3):443–50.
2. Ginting R, Suwandira B, Malik AF. Determination of Technical Requirements and Priority of The Critical Part In The Quality Function Deployment Phase I and Quality Function Deployment Phase II Methods In Product Development: A Literatur Review. IOP Conf Ser Mater IOP Publ. :1–9.
3. Ishak A, Ginting R, Suwandira B, Malik AF. Integration of Kano Model and Quality Function Deployment (QFD) to Improve Product Quality: A Literature Review. IOP Conf Ser Mater Sci Eng IOP Publ. 2020;
4. Lawal A, Olatoye K, Babalola K. Beta-carotene retention, physical, phytochemical and storage characteristics of value added snacks from pigeon pea and yellow-fleshed cassava. Food Humanit. 2024;1–10.
5. Chung PL, Liaw ET, Gavahian M, Chen HH. Development and Optimization of Djulis Sourdough Bread Using Taguchi Grey Relational Analysis. 2020;9:2–19.
6. Anggraeni P, Handayani SM, Barokah U. Analisis Industri Kecil Lanting di Kecamatan Kuwarasan Kabupaten Kebumen. Agrista. 2021;9(4):103–13.
7. Andayani A, Sukardi, Suryani A. Desain Produk Makanan Ringan Untuk Ibu Hamil Dengan Menggunakan Quality Function Deployment (QFD). E-Jurnal Agroindustri Indones. 2015;4(1):244–51.
8. Andriani DP, Setyanto NW, Kusuma LTWN. Desain dan Analisis Eksperimen Untuk Rekayasa Kualitas. Malang UB Press 1. 2017;
9. Krishnaiah K, Shahabudeen P. Applied Design of Experiments And Taguchi Methods. 1 ed New Delhi PHI Learn Priv Ltd. 2012;
10. Taguchi G, Chowdhury S, Wu Y. Taguchi Quality Engineering Handbook. 1 ed New Jersey John Wiley Sons. 2015;
11. Francis D V, Aiswarya T, Gokhale T. Optimization

of the incubation parameters for the biogenic synthesis of WO3 nanoparticles using the Taguchi method. Heliyon. 2022;8:1–11.

12. Neder-Suarez D, Mel´endez-Pizarro CO, Murowaniecki-Otero D. Effect of using alternative flours on the development and characteristics of a third-generation snacks. Foof Chem Adv. 2024;1–9.
13. Santoso JB. Pengaruh Kualitas Produk, Kualitas Pelayanan, dan Harga Terhadap Kepuasan dan Loyalitas Konsumen (Studi Pada Konsumen Geprek Bensu Rawamangun). J Akunt dan Manaj. 2019;127–47.
14. Jaqin C, Rozak A, Purba HH. Quality Function Deployment for Quality Performance Analysis in Indonesian Automotive Company for Engine Manufacturing. ComTech. 2020;11(1):11–8.
15. Sanggup SDYP, Dahda SS. Peningkatan Kualitas Bunga Telang Melalui Perbaikan Proses Pengeringan Menggunakan Metode Taguchi. J Optim. 2022;8(2).
16. Abdul Muid. Penerapan Metode Taguchi Untuk Meningkatkan Kualitas Produk Ukm Makanan Khas Sidayu Bonggolan. 2021;
17. Priyanga R, Muthadhi A. Optimization of compressive strength of cementitious matrix composition of Textile Reinforced Concrete-Taguchi approach. Result Control Optim. 2023;10:1–12.
18. Chakraborty S, Shrivastava. Comparison between multiresponse-robust process design and numerical optimization: A case study on baking of fermented chickpea flour-based wheat bread. Food Process Eng. 2019;13008:1–13.
19. Ronaldi SG, Andesta D, Ismiyah E. Pendekatan Metode Taguchi Pada Perbaikan Kualitas Rasa Kerupuk (Studi Kasus : UKM Kerupuk Ikan Ibu Chalim). J Sist dan Tek Ind. 2020;1(1):69–74.
20. Jugulum R. Robust Quality; Powerful Integration of Data Science and Process Engineering. Florida CRC Press. 2018;
21. Wahyuono BA, Suef M, Karningsih PD, Marwanta E, Fikri NA. Production System by Considering Hazard Analysis and Critical Control Points. Proc Int Conf Multidiscip Res Sustain. 2024;522–9.
22. Başataç R, Yalçın ZG, Dağ M, Aydoğmuş E. Optimization of Parameters Affecting Noodle Drying by Taguchi Method Erişte Kurutmasını Etkileyen Parametrelerin Taguchi Metodu ile Optimizasyonu. 2022;(34):34–41.
23. Sefudin A. Meningkatkan Motivasi Dalam Berwirausaha Pada Para Pengrajin Dan Pengusaha Lanting Di Kebumen. 2023;2:111–4.
24. Vanany I, Maarif GA, Soon JM. Application of multi-based quality function deployment (QFD) model to improve halal meat industry. J Islam Mark. 2019;1–29.
25. Montgomery DC. Design and Analysis of Experiments. New Jersey Wiley Publ. 2020;
26. Wungguli D. Implementation of The Taguchi Method With Trapezoidal Fuzzy Number In The Tofu Production Process. J Math Its Appl. 2023;17(3):1313–24.
27. Navidad-murrieta MS, Alejandro P, Alberto J, Arturo J, Luna-b G, Sonia GS. Use of a Taguchi Design in Hibiscus sabdari ff a Extracts Encapsulated by Spray-Drying. 2020;(Md):1–13.
28. Chudy S, Makowska A, Piatek M, Krzywdzinska-Bartkowiak M. Application of microwave vacuum drying for snack production: Characteristics of pure cheese puffs. Soc Dairy Technol. 2019;82–8.
29. Dian TM. Quality Improvement of Honey Product Using Quality Function Deployment (QFD) Method. 2021;10(3):260–73.
30. Antony J, Bhat S, Mittal A, Jayaraman R, Gijo E, Cudney E. Application of Taguchi design of experiments in the food industry: a systematic literature review. Total Qual Manag Bus Excell. :1–27.
31. Access O. Product Development with Quality Function Deployment (QFD) : A Literature Review. 2020;0–6.