Quality improvement of food products using taguchi method: a study in a bread product SME

Fakhri Ikhwanul Alifin[1*], Rana Ardila Rahma[1], Ikhwanussafa Sadidan[2], Risma Fitriani[1]

[1] Department of Industrial Engineering, Universitas Singaperbangsa, Karawang
[2] Department of Environmental Engineering, Universitas Singaperbangsa, Karawang

*Corresponding author: fakhri.ikhwanul@ft.unsika.ac.id

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Abstract. *Quality is one of the most crucial factors for manufactured products. Good product quality will increase customer loyalty and hence, higher profit for the company. SR company is a local Small Medium Enterprise (SME) in Bandung that produces bread products. Among various kinds of bread, Kadet is the main product with an average production of approximately 1000 pcs per day. In addition, Kadet bread has numerous defective products with an average of 3%-5% per 1000 pcs. Moreover, Kadet is a product baked at high temperatures, and hence, the timing of the production staff is crucial to prevent defectiveness. In this work, we use the Taguchi method to obtain factors that produce defectiveness and the combination of the optimal production factors. Furthermore, using the Analysis of Variance, the results show the optimal process design for minimum defective Kadet bread products as the process evaluation for better product quality.*

Keywords: quality, design of experiment, taguchi method, defective products

1. Introduction

A business unit moved in food production is one of the long-lasting businesses that fulfill the primary needs of people. In Indonesia, bread product is preferable to rice product as the primary food. According to the Indonesia Central Bureau of Statistics (ICBS) survey, bread product consumption has increased in Indonesia in recent years. The survey revealed that the consumption rate for one person was an ounce per week or at least one bread product purchased in a week. However, the bread manufacturers in Indonesia are 99% formed as Small and Medium Enterprises (SMEs) that still use traditional production equipment. The outdated production equipment leads to an unfavorable position in the marketplace due to the low product quality. Consequently, big companies dominate the market with sophisticated technology use (Arifin, 2018; Ibrahim et al., 2020)

Since production technology requires a big investment, SMEs encounter difficulty in coping with rapid technological development. SMEs rely heavily on external financings, such as bank loans, personal savings, and venture capital, to finance their operations. However, obtaining financing from traditional sources can be difficult, particularly for newer and smaller enterprises (Chen & Lee, 2023). Another study also notes that many SMEs struggle to obtain financing due to the high risk associated with these ventures (Martinez-Cillero et al., 2023). Hence, it is difficult for SMEs with limited financial resources to update the production technology in a short period. Moreover, the rash technology transition also causes a negative before-after gap in SMEs producing organizational problems (Silva et al., 2022). Thus, most SMEs moving into the manufacturing sector tend to choose a conventional production process due to a lack of financial resources.

The production processes that are still performed by workers (i.e., conventional process) will cause some faulty actions (i.e., producing low-quality products) (Schötz et al., 2017). The major workers' involvement also causes many reconfigurations in the production process that lead to high product variability (Colledani et al., 2018). Moreover, SMEs often experience a lack of knowledge regarding product quality and customer satisfaction factors (Rahadi, 2016) . Hence, customers prefer to choose products from big companies due to the high product quality (Lekhanya & Dlamini, 2017). Quality is the feature and characteristic of a service or product that can satisfy customers' requirements. Thus, it is a crucial aspect of a company and becomes one of the customers' main preferences (Heizer & Render, 2011 ; Lagerkvist et al., 2017). Since most SMEs rarely update their business requirements (e.g., quality-oriented products and production innovation) (Wicaksono et al., 2021), SMEs need to update their production method first to increase product quality before updating the process technology.

The study of quality improvement in SME has been conducted by many researchers. However, most studies only focus on the managerial aspect of quality management. There are only a few studies concerning technical aspects, such as the design of production process attributes and production methods. (Abasi et al., 2018) developed a non-destructive method for food quality improvement and monitoring. The study proposed a low-cost and adaptive method for the small-sized company. Whilst Yuniarto et al., (2022) studied a quality improvement on a chicken product focusing on the cutting process. The study proposed a new cutting technology in an SME to comply with the Indonesia National Standard. Moreover, (Soundararajan & Reddy, 2020) used the DMAIC approach to increase product quality in an SME by minimizing product variability. Based on some research above, the design of experiment utilization is still uncommon to improve product quality in SMEs.

Furthermore, this study conducted a quality improvement of bread products in a company (named SR) formed as a Small Medium Enterprise (SME) of bread production. The SR's main product is Kadet, with a production output of approximately 1000 pcs per day. However, Kadet product often produces a high amount of defective products in the company with an average of 4-5%, and thus, become an irreparable waste. This defect formed as charred and cracked on the bread surface. Hence, reducing the taste and aesthetical look of the product. The defective product issue will reduce customer satisfaction, especially from the eight quality dimensions comprising performance, features, reliability, conformance, durability, serviceability, aesthetics, and perceived quality (Garvin, 1984). Table 1 shows the newest annual production data with the defective products information.

Table 1 Production Data of SR Company

Months	Production quantity	Defective products	% Defective products
January	25680	1104	4.3%
February	24872	1008	4.1%
March	25032	1298	5.2%
April	24992	1023	4.1%
May	25704	1123	4.4%
June	32984	1676	5.1%
July	33008	1743	5.3%
August	26208	1198	4.8%
September	25032	1121	4.5%
October	24992	987	3.9%
November	25704	1025	4.0%
December	26592	1101	4.1%

Hence, this study uses the Taguchi method to overcome this quality issue using an experimental approach in the field. This method is a strategy to minimize the number of experiments using orthogonal arrays and create robustness for the product (Moayyedian et al., 2018). Afterward, we examine the robustness of each experiment through the signal-to-noise ratio (SNR) estimation. The SNR analysis also aims to generate the optimal factor design, which can minimize the number of defective product amounts. Then, the analysis of variance (ANOVA) is utilized to show the contribution of each factor considered in the experiment. According to (Chang & Faison III, 2001), the Taguchi method and its experimental design are one of the most suitable methods to optimize the production of manufactured products, especially for reducing the variability of the products. Furthermore, the Taguchi method also reduces the number of experiments, which leads to a reduction in time and cost (Oktem et al., 2007). However, the use of the Taguchi method for food products, especially in SMEs, is quite scarce. Hence, this paper contributes to the utilization of Taguchi experimental design and the optimization of the food production process in reducing defectiveness.

This paper is structured as follows. Section 1 of this work comprises the research background and the problem definition in the research object. Section 2 provides the methodology used in this work consisting of field observation, experiment procedure, and preliminary analysis. In section 3, we provide results consisting of Signal to Noise Ratio analysis and analysis of variance (ANOVA). Furthermore, we provide both the discussion of this work and future research opportunities in section 4.

2. Methodology

This work consists of several steps as follows. First, we observed the actual condition of the production process through site visitation to obtain general data about the company. Furthermore, we conducted a preparation step comprising the determination of production factors and the Design of the Experiment (DOE) through orthogonal arrays. The last step is to process all experiment data using the analysis of variance (ANOVA) to obtain each factor contribution precisely.

Field Observation

The main objective in the observation of SR company is to determine the factors combination for the experimental design. We formulate the factors based on the actual condition that possibly could produce defective products. In general, the actual production process of Kadet products can be seen in Table 2.

Table 2 Production Process

Sequence	Process	Information
1	dough making	The dough ingredients consist of flour (25 kg), sugar (5 kg), water (20 liters), yeast (6 ounces), butter (2.5 kg), salt (6 ounces), and vanilla (2 tablespoons). All ingredients will be mixed for an hour using a big-capacity mixer.
2	cooling 1	Let the dough rise for 15 minutes
3	kneading and cutting	Knead and cut the dough to adjust to the standard product size.
4	cooling 2	Let the dough rise again for 15 minutes
5	baking	The dough will be put in the factory-size oven for 15 minutes at 200 C temperature.
6	cooling 3	The bread then will be cooled off to lower its temperature
7	packaging	The bread then will be packaged in a plastic-sealed wrap

This study found that the defective products formed as the surface charred and cracked emerged after the baking process. Hence, there are possibly improper baking process factors, particularly in the baking duration and temperature. According to the observation, the water volume and yeast amount could also affect the product quality. Furthermore, four factors are chosen as the experimented factors as follows (See Table 3).

Table 3 Experimented Factors

Code	Factor
A	Baking duration (minute)
B	Baking temperature (Celcius)
C	Water volume (liter)
D	Yeast amount (ounce)

Then, we determine three value levels (i.e., level 1 is the actual factor value used in the production process) of each factor as follows (See Table 4).

Table 4 Factor Levels

Code	Factor	Level (*n*)		
		1	2	3
A	Baking duration (minute)	15	14	13
B	Baking temperature (Celcius)	200	220	240
C	Water volume (liter)	20	22	24
D	Yeast amount (ounce)	6	7	8

Design of Experiment (DOE)

In this work, the orthogonal arrays are used to design each factor-level combination. Taguchi methods use the orthogonal arrays to obtain the effect of a factor on the average result. Moreover, the orthogonal arrays could also measure the dominant factor that causes the variance (Sower et al., 1999). According to Table 3 and Table 4, we have determined three value levels of factors, and hence, the three levels of orthogonal arrays will fit with the DOE (See Table 5).

Table 5 Orthogonal Arrays Alternatives

the three levels of orthogonal arrays			
Matrices	$L_9(3^4)$	$L_{27}(3^{13})$	$L_{81}(3^{40})$
V_0	8	26	80

Furthermore, the degree of freedom (V_1) of the experiment (See Table 3) is given by,

$$\begin{aligned} V_1 &= (\text{number of factor}) \text{ x } (\text{number of level - 1}) \\ &= 4 \text{ x } (3 - 1) \\ &= 8 \end{aligned} \tag{1}$$

According to the calculation above, all orthogonal arrays have a greater degree of freedom (V_0) than the V_1 value ($V_0 \geq V_1$). Hence, all orthogonal array options are suitable for the experiment design. However, we choose the $L_9(3^4)$ (i.e., Nine-factor combinations, three levels of each factor, four factors involved) orthogonal arrays to simplify the experiment based on the company's economic perspective. The $L_9(3^4)$ orthogonal arrays are given by (See Table 6).

Table 6 $L_9(3^4)$ Orthogonal Arrays

Experiment Number (*i*)	Factor Level			
	A	B	C	D
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	2
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

Thus, the experiment design is given by (See Table 7).

Table 7 Design of Experiment

Experiment Number (*i*)	Baking duration (minute)	Baking temperature (Celcius)	Water volume (liter)	Yeast amount (ounce)
1	15	200	20	6
2	15	220	22	7
3	15	240	24	8
4	14	200	22	8
5	14	220	24	6
6	14	240	20	7
7	13	200	24	7
8	13	220	20	8
9	13	240	22	6

Preliminary Analysis

The experiment was conducted for nine days in 2021, guided by the experimental design of the chosen orthogonal arrays. The experiment period coincided with the Islamic holy month (Ramadhan), and the product demand was higher than in the other periods. Therefore, the SR company increased the production capacity from 1000 pcs to 3000 pcs per day. We considered that there would be three production batches consisting of 1000 pcs product output, respectively. Hence, we assume that there are three replications of each experiment. This assumption was established to make the experiment more precise. The results are shown in Table 8.

Table 8 Experiment Results

Experiment Number (i)	Baking duration (minute)	Baking temperature (Celcius)	Water volume (liter)	Yeast amount (ounce)	Defective product number per 1000 pcs			$\bar{x}_i$
					x_{i1}	x_{i2}	x_{i3}	
1	15	200	20	6	0.032	0.031	0.037	0.033
2	15	220	22	7	0.031	0.029	0.032	0.031
3	15	240	24	8	0.047	0.045	0.047	0.046
4	14	200	22	8	0.033	0.034	0.036	0.034
5	14	220	24	6	0.028	0.030	0.029	0.029
6	14	240	20	7	0.031	0.032	0.034	0.032
7	13	200	24	7	0.051	0.049	0.045	0.048
8	13	220	20	8	0.051	0.053	0.053	0.052
9	13	240	22	6	0.060	0.062	0.065	0.062
			$\bar{\bar{x}}$					0.041

Let n_l and n_i as the total number of specific levels used for an experiment and the number of experiments, respectively. Hence, we obtain the factor value ($\bar{y}$) from the average defective product using the equation below.

$$\bar{y}_{factor_{level}} = \frac{\sum_i \bar{x}_i}{n_l} \qquad i = 1, 2, 3, 4, ..., 9 \tag{2}$$

Then, we calculate the factor value for each factor level using Equation 2. For example, the value for factor A (baking duration) levels 1, 2, and 3 are given by,

$$\begin{aligned}\bar{y}_{A_1} &= \frac{\bar{x}_1 + \bar{x}_2 + \bar{x}_3}{n_l} \\ &= \frac{0.033 + 0.031 + 0.046}{3} \\ &= \frac{0.110}{3} = 0.037\end{aligned}$$

$$\begin{aligned}\bar{y}_{A_2} &= \frac{\bar{x}_4 + \bar{x}_5 + \bar{x}_6}{n_l} \\ &= \frac{0.034 + 0.029 + 0.032}{3} \\ &= \frac{0.096}{3} = 0.032\end{aligned}$$

$$\begin{aligned}\bar{y}_{A_3} &= \frac{\bar{x}_7 + \bar{x}_8 + \bar{x}_9}{n_l} \\ &= \frac{0.048 + 0.052 + 0.062}{3} \\ &= \frac{0.162}{3} = 0.054\end{aligned}$$

Let $\bar{y}_{A_{\max}}$ and $\bar{y}_{A_{\min}}$ are the maximum and minimum factor values, respectively. The effect of each factor (FE) is the difference between $\bar{y}_{A_{\max}}$ and $\bar{y}_{A_{\min}}$. For example, the factor effect of A (baking duration) is given by,

$$\begin{aligned}FE_A &= \bar{y}_{A_{\max}} - \bar{y}_{A_{\min}} \\ &= 0.054 - 0.032 = 0.022\end{aligned} \tag{3}$$

The summary of all factor effects is shown in Table 9.

Table 9 Preliminary Analysis Results

Factor	Level (l)	$\bar{y}_{factor_{level}}$	Factor Effect	Rank	Suggested Design
A	1	0.037	0.022	1	A_2
	2	0.032			
	3	0.054			
B	1	0.039	0.010	2	B_2
	2	0.037			
	3	0.047			
C	1	0.039	0.003	4	C_1
	2	0.042			
	3	0.041			

Factor	Level (*l*)	$\bar{y}_{factor_{level}}$	Factor Effect	Rank	Suggested Design
D	1	0.042	0.007	3	D_2
	2	0.037			
	3	0.044			

According to Table 9, we sort the effect factor from largest to smallest to show the dominant factor producing defective products. Furthermore, factor A (baking duration) is the most dominant effect, with a value of 0.022. Afterward, since the main objective of this work is to minimize defective products or, in Taguchi's perspective, the smaller is the better, the suggested factor design is based on the minimum effect value of each factor. The design consists of A_2 (baking duration level 2), B_2 (baking temperature level 2), C_1 (water volume level 1), and D_2 (yeast amount level 2). Hence, we predict the number of defective product amount if the company applies this design. Let $\bar{\mu}$ as the prediction of the average defective product that is given by,

$$\begin{aligned}\bar{\mu} &= \bar{\bar{x}} + (\bar{y}_{A_2} - \bar{\bar{x}}) + (\bar{y}_{B_2} - \bar{\bar{x}}) + (\bar{y}_{C_1} - \bar{\bar{x}}) + (\bar{y}_{D_2} - \bar{\bar{x}}) \\ &= 0.041 + (0.032 - 0.041) + (0.037 - 0.041) + (0.039 - 0.041) + (0.037 - 0.041) \\ &= 0.027\end{aligned} \tag{4}$$

The suggested factor design shows that it only produces 2.7% of defective products, smaller than the daily average of defective products (4%-5%). Hence, the suggested design could effectively reduce the number of product defects according to this preliminary study.

3. Results

After the preliminary study, this study conducted the signal-to-noise ratio (SNR) analysis and analysis of variance (ANOVA). This section will confirm the effectiveness of the optimal design produced in the preliminary study and show the contribution of each factor to the defective products (i.e., high variability of the products).

Signal-to-Noise Ratio Analysis

The numerous defective products are affected by the high variability of the product, which shows that the process is not robust enough to some noises. Hence, the signal-to-noise ratio analysis (*SNR*) is conducted to measure the robustness of the experiment through factor combination (Soejanto, 2009). Moreover, this analysis also produces the optimal design that minimizes the defective product number and hence, could be different from the design in the preliminary study. First, the respective SNR ratio in each experiment (*i*) can be obtained by,

$$SNR_i = -10\log_{10}\left(\frac{1}{n_r}\sum_{k=1}^{r} x_{ik}{}^2\right) \qquad i = 1, 2, 3, 4, 5, \ldots, 9 \quad r = 3 \tag{5}$$

Where x_{ik} is the number of defective products for each replication (n_r)? For example, the *SNR* for experiment number one is as follows.

$$\begin{aligned}SNR_1 &= -10\log_{10}\left(\frac{1}{n_r}(x_{11} + x_{12} + x_{13})\right) \\ &= -10\log_{10}\left(\frac{1}{3}(0.032^2 + 0.031^2 + 0.037^2)\right) \\ &= 29.516\end{aligned}$$

The recapitulation of *SNR* for all experiments is shown in Table 10.

Table 10 Signal-to-Noise Ratio Results

Experiment (i)	Defective product number per 1000 pcs			SNR_i
	x_{i1}	x_{i2}	x_{i3}	
1	0.032	0.031	0.037	29.516
2	0.031	0.029	0.032	30.259
3	0.047	0.045	0.047	26.680
4	0.033	0.034	0.036	29.280
5	0.028	0.030	0.029	30.749
6	0.031	0.032	0.034	29.801
7	0.051	0.049	0.045	26.304
8	0.051	0.053	0.053	25.623
9	0.060	0.062	0.065	24.101

Furthermore, we obtain the SNR value for each factor that is given by,

$$\overline{SNR}_{factor_{level}} = \frac{\sum_i SNR_i}{n_l} \qquad i = 1, 2, 3, 4, ..., 9 \tag{6}$$

For example, the SNR for factor A (baking duration) levels 1, 2, and 3 are given by,

$$\begin{aligned}
\overline{SNR}_{A_1} &= \frac{SNR_1 + SNR_2 + SNR_3}{n_l} \\
&= \frac{29.516 + 30.259 + 26.680}{3} = \frac{86.455}{3} = 28.818 \\
\overline{SNR}_{A_2} &= \frac{SNR_4 + SNR_5 + SNR_6}{n_l} \\
&= \frac{29.280 + 30.749 + 29.801}{3} = \frac{89.829}{3} = 29.943 \\
\overline{SNR}_{A_3} &= \frac{SNR_7 + SNR_8 + SNR_9}{n_l} \\
&= \frac{26.304 + 25.623 + 24.101}{3} = \frac{76.027}{3} = 25.342
\end{aligned}$$

Let $\overline{SNR}_{A_{max}}$ and $\overline{SNR}_{A_{min}}$ are the maximum and minimum Signal Noise Ratio of factor A, respectively. The effect of each factor (*FE*) is the difference between both of them. For example, the factor effect of A (baking duration) is given by.

$$\begin{aligned}
FE_A &= \overline{SNR}_{A_{max}} - \overline{SNR}_{A_{min}} \\
&= 29.943 - 25.342 = 4.601
\end{aligned} \tag{7}$$

The summary of all factor effects is shown in Table 11.

Table 11 Signal-to-Noise Ratio Analysis

Factor	Level	$\overline{SNR}_{factor_{level}}$	Factor Effect	Rank	Suggested Design
A	1	28.818	4.601	1	A2
	2	29.943			
	3	25.342			
B	1	28.366	2.016	2	B2
	2	28.877			
	3	26.861			
C	1	28.313	0.433	4	C1
	2	27.880			
	3	27.911			

D	1 2 3	28.122 28.788 27.194	1.593	3	D2

In the SNR analysis, the most dominant factor that affects the product quality is factor A (baking duration) which has the highest factor effect compared to other factors. Furthermore, the optimal design can be obtained by choosing the highest $\overline{SNR}_{factor_{level}}$. The higher $\overline{SNR}_{factor_{level}}$ factor level value indicates that the factor level is robust enough against some uncontrollable noises. From this analysis, we suggest factor A_2 (baking duration level 2), B_2 (baking temperature level 2), C_1 (water volume level 1), and D_2 (yeast amount level 2) as the optimal design. This factor combination is similar to the preliminary study and hence, possibly proved that this design could optimally reduce the number of defective products.

Analysis of Variance (ANOVA)

The ANOVA is used to measure the contribution of each factor in producing defective products (Walpole et al., 2017). We use the table to simplify the result presentment that is shown in Table 12.

Table 12 ANOVA Format in This Study

Factor	Degree of Freedom	Sum of Squares	Mean Sum of Squares	F-ratio	Pure Sum of Squares	Contribution
A	V_A	SS_A	MSS_A	F_A	SS'_A	p_A
B	V_B	SS_B	MSS_B	F_B	SS'_B	p_B
C	V_C	SS_C	MSS_C	F_C	SS'_C	p_C
D	V_D	SS_D	MSS_D	F_D	SS'_D	p_D
Error	V_e	SS_e	MSS_e			p_e
Mean	V_M	SS_m				
Total	V_T	SS_T				

The degree of freedom (V) for ANOVA is given by,

$$\begin{aligned}
&V_A = V_B = V_C = V_D = (\text{number of replication}) - 1 = 3 - 1 = 2 \\
&V_m = 1 \\
&V_T = \text{total number of replication} = 27 \\
&V_e = V_T - (V_A + V_B + V_C + V_D + V_m) = 18
\end{aligned} \tag{8}$$

The Sum of Squares for each factor is given by,

$$SS_{factor} = \left(\frac{[\text{total factor level 1}]^2}{3n_r}\right) + \left(\frac{[\text{total factor level 2}]^2}{3n_r}\right) + \left(\frac{[\text{total factor level 3}]^2}{3n_r}\right) - \left(\frac{[\text{total factor}]^2}{9n_r}\right) \tag{9}$$

For example, the Sum of Squares for factor A (SS_A) is given by,

$$SS_A = \left(\frac{[\text{total } A_1]^2}{9}\right) + \left(\frac{[\text{total } A_2]^2}{9}\right) + \left(\frac{[\text{total } A_3]^2}{9}\right) - \left(\frac{[\text{total A}]^2}{27}\right)$$

$$SS_A = \left(\frac{\left[\sum_i \sum_{k=1}^{m} x_{ik}\right]^2}{9} + \frac{\left[\sum_i \sum_{k=1}^{m} x_{ik}\right]^2}{9} + \frac{\left[\sum_i \sum_{k=1}^{m} x_{ik}\right]^2}{9}\right) - \frac{\left[\sum_{j=1}^{i=9} \sum_{k=1}^{m} x_{jk}\right]^2}{27}$$

$$SS_A = \left(\frac{[0.331]^2}{9} + \frac{[0.287]^2}{9} + \frac{[0.489]^2}{9} \right) - \frac{[1.107]^2}{27}$$
$$= 0.002507556$$

Meanwhile, the SS_m, SS_T, and SS_e are given by,

$$SS_m = \bar{\bar{x}}^2 (i \times m) \qquad (10)$$
$$= 0.041^2 (9 \times 3) = 0.045387$$

$$SS_T = \left[\sum_{j=1}^{i=9} \sum_{k=1}^{r} x_{jk} \right]^2 \qquad (11)$$
$$= 0.048745$$

$$SS_e = SS_T - (SS_A + SS_B + SS_C + SS_D + SS_m) \qquad (12)$$
$$= 0.000073333$$

Furthermore, the Mean Sum of Squares for each factor (MSS_{factor}) and error (SS_e) is given by,

$$MSS_{factor} = \frac{SS_{factor}}{V_{factor}} \qquad (13)$$

Hence, the F-ratio and Pure Sum of Squares can be obtained by,

$$F_{factor} = \frac{MSS_{factor}}{MSS_e} \qquad (14)$$

$$SS'_{factor} = SS_{factor} - (MSS_e \times V_{factor}) \qquad (15)$$

Finally, the contribution of each factor is given by,

$$p_{factor} = \frac{SS'_{factor}}{\sum SS_{factor}} \times 100\% \qquad (16)$$

Afterward, the summary of the results is shown in Table 13.

Table 13 Anova Results

Factor	Degree of Freedom	Sum of Squares	Mean Sum of Squares	F-ratio	Pure Sum of Squares	Contribution
A	2	0.002507556	0.00125378	307.7455	0.00249941	74.4%
B	2	0.000494	0.00024700	60.62727	0.00048585	14.5%
C	2	0.000044222	0.00002211	5.427273	0.00003607	1.1%
D	2	0.000238889	0.00011944	29.31818	0.00023074	6.9%
Error	18	0.000073333	0.00000407	1	0	3.2%
Mean	1	0.045387000				
Total	27	0.048745000				100%

According to the ANOVA results, factor A (baking duration) has the highest contribution to the defective products, with 74.4%. Meanwhile, the other factors have a percentage of less than 50%. This result shows a critical problem in the baking process with a total contribution of 88.9% (Factor A & B). We suspect that this problem emerges from conventional oven use without the automatic timer and temperature control. Hence, the operator should estimate the baking duration and temperature manually. This problem is typical in SMEs, which still use the conventional production process. The best solution to overcome this problem is to purchase a more sophisticated oven. However, it will spend more cost primarily for the company formed as an SME. Thus, the optimal factor combination is the best temporary solution to reduce defective products.

Furthermore, we compare the F-ratio of each factor with the standard F-ratio ($F_{(\alpha,V_m,V_e)}$) to conclude the result inferentially. The hypotheses are given by,

H_0 = The factor does not influence the defective products.
H_1 = The factor influences the defective products.

According to Table 12, the F-ratio of each factor is greater than the standard F-ratio ($F_{(0.05,1,18)} = 4.41$). Hence, it indicates that each factor considered in this work possibly produces defective products (Reject H_0, Accept H_1)

Confirmatory Experiment

The confirmatory experiment's purpose is to signify that the suggested design can reduce defective products optimally. We conducted this experiment for 12 days in 2021 and hence, produced 12 experiments in total. The results are in Table 14.

Table 14 Confirmatory Experiment Result

Experiment (*i*)	**Defective products per 1000 pcs ($\overline{x}_i$)**
1	0.027
2	0.026
3	0.024
4	0.025
5	0.024
6	0.026
7	0.025
8	0.029
9	0.028
10	0.030
11	0.030
12	0.028
$\overline{\overline{x}}$	0.0268

The confidence interval of the confirmatory experiment can be obtained by,

$$C_L = \pm\sqrt{F_{(\alpha=0.05,V_m=1,V_e=18)} \times MSS_e \times \left(\frac{1}{n_{eff}} + \frac{1}{n_i}\right)} \tag{17}$$

Where,

$$F_{(\alpha=0.05,V_m=1,V_e=18)} = 4.41 \quad , \quad MSS_e = 0.00000407$$

$$n_{eff} = \frac{\text{number of experiments}}{1+\text{total number of } V_{factor}} = \frac{27}{1+8}$$
$$= 3$$

Then,

$$C_L = \pm\sqrt{4.41 \times 0.00000407 \times \left(\frac{1}{3} + \frac{1}{12}\right)} = \pm 0.002737$$

Furthermore,

$$\bar{\bar{x}} - C_l \le \bar{\bar{x}} < \bar{\bar{x}} + C_l \qquad (18)$$

$$\bar{\bar{x}} - 0.002737 \le \bar{\bar{x}} < \bar{\bar{x}} + 0.002737$$

$$0.0268 - 0.002737 \le \bar{\bar{x}} < 0.0268 + 0.002737$$

$$0.024096 \le \bar{\bar{x}} < 0.029571$$

The signal-noise ratio (*SNR*) of the confirmatory experiment was obtained using Equation 5. Then, we compare the prediction of defective products and *SNR* value before (Taguchi Method experiment) and after the confirmatory experiment. The results are as follows (See Table 15).

Table 15 Comparison Between Taguchi Method and Confirmatory Experiment

Responses		Prediction	Tolerance
Taguchi Experiment	Average number of defective products	0.02700	± 0.002448
	Signal to Noise Ratio (*SNR*)	31.151	± 0.002448
Confirmatory Experiment	Average number of defective products	0.0268	± 0.002737
	Signal to Noise Ratio (*SNR*)	31.400615	± 0.002737

According to Table 15, the result from both the Taguchi experiment and the confirmatory experiment is relatively similar. This result indicates that the optimal design comprising factor A_2 (baking duration level 2), B_2 (baking temperature level 2), C_1 (water volume level 1), and D_2 (yeast amount level 2) can optimally reduce the defective products and robust enough to some noises.

4. Conclusion And Discussion

In this work, we conducted quality improvement efforts in a company formed as an SME using the Taguchi Method. The main focus of this research is how to improve the bread products quality in SR company. According to the results, this study found that the optimal design consisting of various factor combinations could effectively reduce defective products. This research work also revealed the dominant factor that is influential in product quality. The use of an experimental approach makes this research more relevant to the actual condition. Furthermore, the cost analysis of this quality issue is currently underway as a future research topic. A more comprehensive analysis of the Quality Management System (QMS) comprising the food chain, product-service system, food safety, and sustainability is also an interesting future research opportunity, especially in the company formed as an SME.

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