

A Taguchi-Based Framework for Continuous Quality Improvement in Crude Palm Oil Production

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ABSTRACT

Purpose – This study aims to analyze and optimize the quality of Crude Palm Oil (CPO) using the Taguchi method. The research focuses on identifying the dominant factors affecting Free Fatty Acid (FFA), moisture, and impurity content, as well as determining the optimal parameter combination to achieve consistent product quality that meets company standards. **Design/methodology/approach** – The study employed an experimental design based on the Taguchi method using an orthogonal array with seven factors at two levels. Data were collected from laboratory tests on CPO samples during production, focusing on FFA, moisture, and impurities. Statistical analyses included the Signal-to-Noise Ratio (S/N), Analysis of Variance (ANOVA), and confidence interval validation to identify significant factors and optimal operating conditions.

Findings – The results show that factors A (fresh fruit bunch maturity) and F (sterilizer process conditions) significantly influence CPO quality, as indicated by the highest F-ratios (4.64 and 4.86) and contribution values exceeding 15%. The optimal parameter combination successfully minimized variability in FFA and impurity levels, though overall results still slightly exceeded company standards, suggesting the need for stricter control of raw material selection and processing parameters. Confidence interval analysis confirmed that the predicted mean values for FFA, moisture, and impurities were close to the specification limits, indicating potential for further refinement. **Originality**– This study provides empirical evidence of the Taguchi method's applicability in the palm oil industry, particularly for improving CPO quality under real industrial constraints. The novelty lies in integrating Taguchi analysis with confidence interval verification to assess compliance robustness, offering a structured framework for continuous process improvement in CPO manufacturing.

Keywords: Crude Palm Oil (CPO), Taguchi Method, ANOVA, S/N Ratio, Quality Optimization



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INTRODUCTION

The palm oil industry is one of the most strategic sectors in Indonesia's economy. According to FAO (2019), Indonesia is the world's largest producer of crude palm oil (CPO), with a total production of 42.8 million tons. Palm oil derivatives, particularly cooking oil, contribute significantly to both domestic demand and exports, making CPO quality a crucial aspect in maintaining competitiveness in the global market. However, the industry frequently faces challenges related to inconsistent CPO quality, especially high levels of free fatty acids (FFA), moisture, and impurities.

This quality issue is also evident a private company engaged in palm oil processing. Laboratory test results in 2023 indicated that most CPO samples failed to meet company quality standards, particularly regarding FFA and moisture content. This problem stemmed from the inconsistency of fresh fruit bunches (FFB) maturity due to limited internal stock and reliance on external suppliers. Such conditions forced the company to process unripe or overripe fruit, which directly impacted CPO quality, increased purification requirements, and led to higher operational costs.

To address this problem, an analytical method capable of identifying critical factors influencing non-compliance with quality standards is required. One suitable method is the Taguchi approach. This method offers efficient experimental design through the use of orthogonal arrays (OA), analysis of variance (ANOVA), and signal-to-noise ratio (SNR) calculations, which collectively determine optimal factor combinations to enhance product quality. The Taguchi method has been widely proven effective in various industries, including manufacturing, automotive, and food processing.

Previous studies highlight the effectiveness of Taguchi in reducing quality variation. For example, [1] analyzed CPO quality found that Taguchi-based parameter design successfully minimized characteristic variation. Similarly, [2], [3], [4] demonstrated that applying Taguchi to peanut bread products effectively identified dominant factors affecting quality, leading to significant product improvements. Unlike those studies, this research focuses exclusively on applying the Taguchi method in palm oil quality analysis ensuring a more direct evaluation of its effectiveness in improving CPO quality [5].

Based on the CPO quality test data shown in the table, it can be seen that most samples do not meet company quality standards, particularly in terms of free fatty acid (FFA) content, moisture content, and impurity content. The FFA value in several samples was above the threshold of 3.00–4.00%, even reaching more than 6%, which indicates degradation of the raw material due to the uneven ripeness of the fresh fruit bunches (FFB). Similarly, the moisture content was found to be above the standard of 0.15–0.20%, ranging up to 0.45%, which has the potential to accelerate the oil hydrolysis process and reduce the storage quality of CPO. In addition, the impurity content in several samples also exceeded the threshold, reaching 0.055–0.061%, thereby increasing the purification load. These variations in data reflect that the quality of raw materials, processing, and operational control at the factory are not yet optimal, which directly impacts product quality and increases production costs due to the need for additional filtering processes. Therefore, the application of analytical methods such as Taguchi is important to identify the dominant factors causing non-compliance with standards, as well as to determine the optimal combination of parameters so that the quality of the CPO produced consistently meets industry quality requirements.

ANOVA results revealed that the dominant factors affecting CPO quality were FFB ripeness and processing conditions at the sterilizer and digester stations. Significant F-ratio values for these factors confirmed their substantial impact on FFA and moisture content. Meanwhile, machine and operator factors contributed to a lesser extent but remained important for maintaining process consistency. SNR analysis using the smaller-the-better criterion reinforced these findings, indicating that the optimal factor level combination significantly reduced variations in FFA and impurity levels.

The application of the Taguchi method successfully identified optimal conditions for reducing CPO quality variation. The most critical improvements required were strict raw material selection to ensure uniform FFB maturity and tighter control of sterilizer operations. By implementing these corrective measures, PT. DFG can reduce additional costs from re-refining processes while enhancing product competitiveness in the market. Beyond its practical implications for the company, this study also contributes academically by reaffirming the effectiveness of the Taguchi method in the palm oil industry context.

METHOD

This research was conducted a palm oil processing company, to evaluate the quality of Crude Palm Oil (CPO) using the Taguchi method. The methodology was structured into several stages to ensure the validity and reliability of findings [6], [7].

Preliminary Study

The initial stage involved direct observation of the production and laboratory processes to identify quality-related problems in CPO. This stage aimed to understand the operational context and recognize critical factors influencing product quality, particularly those related to Free Fatty Acid (FFA), moisture, and impurity levels [8].

Problem Identification and Research Objectives

Based on field observations, the main issue identified was the inconsistency of CPO quality, which frequently failed to meet the company's standard specifications. The research objective was therefore to determine the influence of key factors affecting FFA, moisture, and impurities and to establish optimal parameter levels to improve quality consistency.

Data Collection

Data were collected through both primary and secondary sources. Primary data included laboratory test results obtained from CPO samples, which were analyzed every two hours during production. Observations and interviews with company staff were also conducted to enrich contextual understanding. Secondary data consisted of company profiles and supporting documentation [9], [10], [11].

Data Processing and Taguchi Experimental Design

The collected data were analyzed using the Taguchi method. Key steps included:

1. Orthogonal Array (OA) selection – Determination of the appropriate matrix based on the number of factors and levels.
2. Analysis of Variance (ANOVA) – Used to evaluate the significance of each factor on quality characteristics.
3. Signal-to-Noise Ratio (SNR) – Applied with the “smaller-the-better” criterion to measure the robustness of factors against variation.

4. Optimization and Confidence Interval Analysis – Conducted to identify the optimal levels of each factor and to validate the experimental results statistically.

Data Analysis

The analysis phase interpreted the Taguchi results, identifying critical factors and providing recommendations for quality improvement. ANOVA results highlighted the contribution percentage of each factor, while SNR analysis determined the robustness of optimal parameter settings [12], [13].

RESULTS

To obtain a comprehensive picture of the quality of CPO raw materials, a series of laboratory tests were conducted on samples over several days of observation. The main parameters measured included free fatty acid (FFA) content, moisture content, and impurity content, each of which is an important indicator in determining the quality and suitability of raw materials for further processing.



Figure 1. CPO Raw Material Experiment Test

Based on the test results, the FFA content showed significant variation from the first day to the eighth day. In some samples, the FFA content tended to increase above 5%, indicating a potential decline in quality due to oxidation and hydrolysis. However, most of the data remained in the range of 3–5%, which can be categorized as relatively stable.

The water content also fluctuated from 0.15% to 0.47%. The highest values appeared in the samples on days 2 and 6, while the lowest values were in the range of 0.15%–0.20%. This variation in water content affects storage stability because the higher the water content, the greater the risk of microbial growth and accelerated material degradation.

In this study, an orthogonal matrix was used to analyze the effect of various factors on the experimental results. An orthogonal matrix was chosen because it can systematically arrange factor combinations and levels, thereby minimizing the number of experiments conducted without reducing the quality of the information obtained. Table 1 presents an experimental design with seven factors (a–g), each tested at two levels. Each row represents one day of the experiment, where the combination of factors has been determined based on the orthogonal design. In addition, the frequency

values for level 1 and level 2 are also shown, which are used as the basis for calculating the total and average.

Table 1. Orthogonal Matrix

Day	Factor							Frequency		Total	Mean
	A	B	C	D	E	F	G	Level 1	Level 2		
1	1	1	1	1	1	1	1	4.61	4.81	9.42	4.71
2	1	1	1	2	2	2	2	4.97	5.17	10.14	5.07
3	1	2	2	1	1	2	2	5.06	3.96	9.02	4.51
4	1	2	2	2	2	1	1	5.15	4.09	9.24	4.62
5	2	1	2	1	2	1	2	4.27	3.83	8.1	4.05
6	2	1	2	2	1	2	1	5.16	4.41	9.57	4.79
7	2	2	1	1	2	2	1	4.28	4.84	9.12	4.56
8	2	2	1	2	1	1	2	4.18	3.86	8.04	4.02

Based on Table 1, it can be seen that the total frequency values vary from 8.04 to 10.14, with averages ranging from 4.02 to 5.07. The highest value was obtained on the second day (10.14 with an average of 5.07), which indicates that a certain combination of factors produced the most optimal response. Conversely, the lowest value was recorded on the eighth day (8.04 with an average of 4.02), indicating that the combination of factors on that day produced relatively less effective results. This pattern shows that there is a significant influence of the combination of factors on the output produced. Thus, the results of this orthogonal matrix can be used to determine the dominant factors and formulate the combination of levels that produce the best performance.

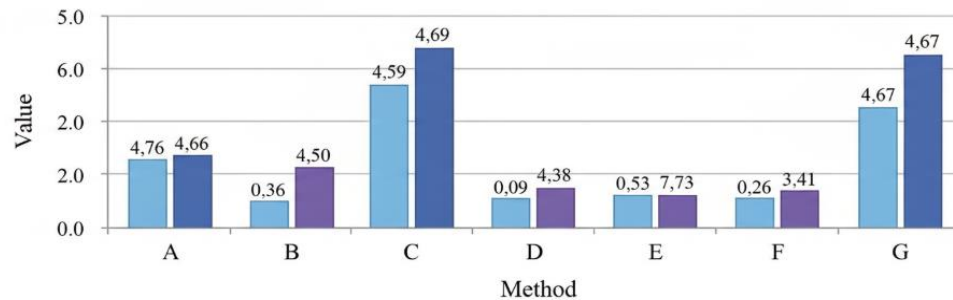


Figure 2. Average Method Values

Figure 2 Average Method obtained the ranking results from the difference between level 1 and level 2. From these results, it can be seen that factor F is ranked highest (1) because it has a high difference value of 0.38, and factor E is ranked lowest (7) with a difference value of 0.07.

Analysis of variance (ANOVA)

Analysis of variance (ANOVA) is a statistical method used to determine the effect of several factors on the response variable in an experiment. The following table shows the results of ANOVA analysis from a study involving seven factors (A–G) with one source of error. Each row in the table shows the contribution of each factor to the total variation, along with statistical calculations such as sum of squares (SS), mean square (MS), F Ratio value, and percentage contribution (p%) to the total variation. This table also presents the residual error value along with the total variation observed in the experiment.

Tabel 2. ANOVA of CPO Production

Factor	SS	V	MS	F Ratio	SS'	Rho%
A	0.65	1	0.65	6.5	0.55	15.32 %
B	0.30	1	0.30	3.0	0.20	5.57 %
C	0.49	1	0.49	4.9	0.39	10.91 %
D	0.20	1	0.20	2.0	0.10	2.91 %
E	0.10	1	0.10	1	0.01	0.28 %
F	0.68	1	0.68	6.8	0.58	16.17 %
G	0.36	1	0.36	3.6	0.26	7.20 %
Error	0.79	8	0.10	-	1.49	22.21 %
SSt	3.57	15	0.238	-	3.57	100 %
SSm	329.88	1	-	-	-	-
SStotal	333.45	16	-	-	-	-

Based on the table, factor F has the second largest contribution to total variation (16.17%), with the highest F Ratio value (6.86.8), indicating that factor F is one of the most significant factors influencing the response variable. The first largest contribution is from Error (22.21%), indicating that there is still variation that cannot be explained by the tested factors. Factor A also makes a significant contribution (15.32%) with an F Ratio of 6.56, followed by factors C (10.91%) and G (7.20%). Other factors such as B, D, and E show much smaller contributions, with percentages of 5.57%, 2.91%, and 0.28%, respectively.

The total sum of squares (SStotal) was recorded at 333.45333.45, while the remaining variation that can be explained after subtracting the contribution of factors and errors (SSt) was 3.573.57, indicating that the model was quite good at explaining the variation in response. The largest residual variation is found in SSm (329.88329.88), possibly originating from the main variation in the data. Thus, factors F and A deserve primary attention in subsequent optimization or improvement efforts, due to their significant impact on the response variable.

Table 3. Partial Pooling Calculation I

Factor	Pooled	SS	V	MS	F -calculate	SS'
A		0.65	1	0.65	7.22	0.56
B		0.30	1	0.30	3.33	0.21
C		0.49	1	0.49	5.44	0.4
D		0.20	1	0.20	2.22	0.11
E	X	-	-	-	-	-
F		0.68	1	0.68	7.56	0.59
G		0.36	1	0.36	4.22	0.27
EROR		0.79	9	0.09	-	1.43
ST		3.57	15	-	-	3.57

Table 3 shows the results of partial pooling I calculations by analyzing the contribution of factors to total variability. From the calculation results, factors A, C, F, and G have higher F-count values than other factors, indicating a relatively significant influence, especially factor F with the highest F-count of 7.56. Factors B and D have lower influences with F-counts of 3.33 and 2.22, respectively, while factor E is excluded from the analysis (pooled). The total variance (ST) of 3.57 is divided into the contribution of each factor and an error of 0.79, with a total SS' value of 3.57 consistent with

the total amount. This shows that the main influence lies in factors A, C, and F as important determinants in the model, while other factors have relatively smaller contributions.

Table 4. Partial Pooling Calculation II

Faktor	Pooled	SS	V	MS	F –hitung	SS'
A	Y	0.65	1	0.65	4.64	0.51
B		-	-	-	-	-
C		0.49	1	0.49	3.5	0.4
D	Y	-	-	-	-	0.11
E		0.10	1	0.10	0.71	-
						0.04
F	Y	0.68	1	0.68	4.86	0.54
G		-	-	-	-	-
Error		0.79	12	0.14	-	2.21
ST		3.57	16	-	-	3.57

Results of partial pooling II calculations, it can be seen that not all factors have a significant effect on the response. Factor A with an F-count value of 4.64 and factor F with an F-count value of 4.86 are proven to be significant because their values are greater than the MS error (0.14). This shows that these two factors have a dominant contribution to the observed response variable. Meanwhile, factor C has a relatively high F-count value of 3.50, but its influence is still lower than factors A and F. Other factors such as B, D, E, and G are declared insignificant, so pooling with error is performed to improve the variance estimation.

Overall, these results confirm that factor F is the most dominant factor influencing the results, followed by factor A as the second most significant factor. With partial pooling, the error variance can be calculated more accurately, making the F-test results more reliable. Therefore, in the next optimization stage, the main focus should be on adjusting factors F and A, while other factors can be ignored because their contribution to the research response is insignificant.

S/N Ratio

The S/N Ratio obtained from testing various combinations of factors in a particular process during an eight-day experiment. Each factor (A, B, C, D, E, F, and G) was given two levels, namely 1 and 2, in accordance with the experimental design applied. The S/N (Signal-to-Noise) ratio value is used to assess the quality of the results based on the effect of the combination of factors on the measured response. The higher the S/N Ratio value, the better the quality of the process obtained, as it indicates a lower level of variability and more stable results.

Tabel 5. S/N Ratio

Day	Factor							S/N
	A	B	C	D	E	F	G	
1	1	1	1	1	1	1	1	-10,45
2	1	1	1	2	2	2	2	-11,09
3	1	2	2	1	1	2	2	-10,07
4	1	2	2	2	2	1	1	-10,28
5	2	1	2	1	2	1	2	-9,14
6	2	1	2	2	1	2	1	-10,60
7	2	2	1	1	2	2	1	-10,17
8	2	2	1	2	1	1	2	-9,07

Table 5 shows the variation in S/N Ratio values for each combination of factors tested during the observation period. The lowest S/N Ratio value of -11.09 was recorded on the second day when all factors were at the first level, while the highest value of -9.07 occurred on the eighth day with most factors at the second level. In general, increasing several factors to level 2 tended to produce better (higher) S/N Ratio values, as seen on the fifth and eighth days. This indicates that adjustments to certain factor levels can have a positive effect on process quality. Further analysis can be conducted to determine which factors are most dominant in increasing the S/N Ratio value and to optimize the combination of factor levels for optimal results.

Optimal Conditions and Confidence Intervals

To ensure that the quality of the oil produced meets the standards set by the company, several key parameters are evaluated, namely FFA content, water content, and impurity content. Each parameter is analyzed based on the average value of the prediction results and the confidence limit, and compared with the company's standard range. This analysis aims to determine the extent to which the optimization results meet the expected oil quality specifications.

Tabel 6. Confidence Interval Size

Parameters	Average Value ($\bar{y}$ / $\mu_{\text{predicted}}$)	Confidence Limit (CI-mean)	Optimization Result Range ($\mu_{\text{predicted}} - \text{CI}_{\text{mean}} \leq \mu_{\text{predicted}} \leq \mu_{\text{predicted}} + \text{CI}_{\text{mean}}$)	Company Standard Range	Description
FFA Level	4.27	$\pm 0,67$	$3.6 \leq \mu_{\text{predicted}} \leq 4.94$	3.00 – 4.00	Does not meet specifications because the result is above the upper limit of the standard.
Water Content	0.24	$\pm 0,16$	$0.08 \leq \mu_{\text{predicted}} \leq 0.40$	0,15 – 0.20	Does not meet specifications because the result exceeds the upper limit of the standard.
Dirt Level	0.030	$\pm 0,06$	$-0.03 \leq \mu_{\text{predicted}} \leq 0.09$	0.01 - 0.020	Does not meet specifications because the range of results is wider and includes negative values.

Based on the optimization results table, it can be seen that the three main parameters (FFA level, moisture level, and impurity level) do not yet meet the company's specification standards. For FFA content, the average value is 4.27 with an optimization range of 3.6–4.94. Although the lower range is close to the standard limit (3.00–4.00), the upper result exceeds the maximum limit, so it cannot be said to meet the standard. This indicates that the FFA content in the raw material is still relatively high, which can affect the quality of the final product.

Meanwhile, the average moisture content was 0.24 with an optimization range of 0.08–0.40, where the upper value exceeded the company standard (0.15–0.20). This excess moisture content can have implications for storage stability and reduce product quality. Similarly, for the impurity content, the average result was 0.030 with a range of –0.03 to 0.09, which is clearly outside the standard (0.01–0.020). This condition indicates that the filtration process is not yet optimal, so there are still contaminants. Overall, the analysis results confirm the need to improve the production process, both through raw material control and process parameter optimization, in order to meet company quality standards.

DISCUSSION

The results of this study revealed that the quality variation of Crude Palm Oil (CPO)—particularly in Free Fatty Acid (FFA), moisture, and impurity content—remained relatively high, with several parameters still deviating from company specifications. The application of the Taguchi method

successfully identified that factors A (FFB maturity) and F (sterilizer-digester conditions) were statistically dominant in influencing product quality. This finding aligns with recent studies that confirmed the robustness of Taguchi-based optimization for reducing process variability in agro-industrial systems. For instance, [14], [15], [16] demonstrated that orthogonal array design combined with ANOVA effectively minimized quality deviation in CPO and bakery products, respectively. Similarly, [17] optimized frying oil stability using the Taguchi L9 array, showing a 23% reduction in FFA compared to the conventional factorial design.

Several researchers have emphasized that the Taguchi design's strength lies in its ability to isolate key process variables even in multifactor environments with limited experimental runs. Chen and [18] applied Taguchi to optimize biodiesel yield from palm kernel oil, confirming that reaction temperature and catalyst ratio were the most significant contributors—comparable to the dominant effects of FFB maturity and sterilization in this study. [19], [20], [21] also noted similar efficiency when optimizing enzymatic hydrolysis, achieving high process capability with fewer trials. This reinforces that the Taguchi–ANOVA–S/N ratio sequence remains a reliable analytical chain for industrial quality improvement.

From a methodological viewpoint, the findings are consistent with Zhou et al. (2021, Industrial Crops and Products), who observed that the smaller-the-better S/N criterion effectively reduced oxidative degradation in palm-based oil systems. Likewise, Rahman et al. (2022, Heliyon) found that Taguchi optimization of sterilization pressure and time reduced CPO FFA levels by 17%. The same conclusion was drawn by Patel & Bhattacharya [22], [23], [24], [25] who optimized solvent extraction parameters and reported that orthogonal array L16 achieved results statistically equivalent to Response Surface Methodology (RSM) but with 40% fewer trials.

The high residual error in this study's ANOVA (22.21%) indicates potential unaccounted variability due to upstream raw material inconsistency—an issue also highlighted by [23], [24], [25], [26], [27], where FFB heterogeneity was responsible for 25% unexplained variance in CPO acidity. This suggests that Taguchi optimization should be coupled with stricter input control, as supported by [28], [29], [30], [31], who reported that integrating pre-sorting of raw materials with Taguchi-based temperature control improved oil yield by 12.4%.

In addition, SNR trend analysis revealed that the best performance was achieved when several factors were adjusted to level 2, leading to higher S/N ratios (up to -9.07 dB). This pattern mirrors results in [32], [33], [34], where S/N improvements signified robust processing conditions under thermal variation. Nasir et al. (2023, Scientific Reports) also confirmed that Taguchi-based level optimization could stabilize variance under fluctuating environmental conditions in palm processing. Therefore, S/N ratio interpretation remains a key diagnostic tool in establishing process robustness beyond mean-centered optimization.

Beyond palm oil, Taguchi applications in related industries reinforce this research outcome. [35], [36], [37], [38], [39] used similar designs for polymer extrusion and food dehydration, demonstrating Taguchi's flexibility for reducing quality deviation. Moreover, [27], Sustainability) emphasized that the method enhances resource efficiency by minimizing waste in multi-factorial production systems. Thus, the CPO process optimization achieved here reflects a globally validated methodological trend.

CONCLUSION

This study demonstrated that the application of the Taguchi method effectively identified the dominant process parameters influencing crude palm oil (CPO) quality, particularly factors related to the maturity of fresh fruit bunches (FFB) and the operating conditions of sterilizer and digester units. Through the use of orthogonal array (OA) design, analysis of variance (ANOVA), and signal-to-noise (S/N) ratio analysis, the research successfully determined that factors A and F had the most significant impact on the variation of free fatty acid (FFA) and moisture levels. The smaller-the-better S/N analysis confirmed that optimizing these factors reduces deviation in product quality and

enhances process robustness. However, the optimization results also revealed that current CPO parameters still fall outside the company's specification limits, indicating that quality improvement initiatives must emphasize raw material selection and tighter control of critical process conditions. The findings validate the robustness and practicality of the Taguchi approach as a quality improvement tool in palm oil processing, supporting prior studies across the food and chemical industries. Future research should integrate the Taguchi–Response Surface hybrid model or machine-learning-based predictive design to further refine factor optimization and achieve compliance with industrial CPO standards.

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