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Optimization of steam utilization in palm oil refinery processes using Kaizen and design of experiment

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ABSTRACT
This research investigates the optimization of steam consumption in the refinery process of palm oil production. Excessive steam usage during the drying stage of Spent Bleaching Earth (SBE) has resulted in higher production costs and oil content levels that do not meet company targets. To address this issue, Kaizen's continuous improvement cycle and the Design of Experiment (DOE) method were applied. Data collection involved field observation, operator interviews, and documentation, which were analyzed using Pareto diagrams and checksheets. The improvement focused on adjusting the SBE drying time as a key parameter influencing both steam usage and oil content. Prior to improvement, the drying process required 850 seconds per cycle, consuming 6,824 kg of steam per day, while producing an average oil content of 18.91%. After implementing DOE-based adjustments, the drying time was reduced to 700 seconds, decreasing steam consumption to 5,600 kg per day, a reduction of 1,224 kg/day (17.9%), and achieving an oil content of 21.03% within the company's target range of 20–22%. The study demonstrates that combining Kaizen and DOE provides an effective strategy for reducing energy usage while maintaining product quality.

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1. INTRODUCTION

The palm oil industry stands as one of the most strategically significant sectors, exerting wide-ranging economic and social impacts both globally and regionally. Global palm oil production in 2022-2023 reached approximately 77.6 million tons, with Indonesia contributing around 46.5 million tons (about 59%) and Malaysia about 18.4 million tons (roughly 24%) [1]. Together, these two countries account for nearly 80-85% of global palm oil production and exports [2]. The crop's remarkable productivity is evident in its land-use efficiency, around 19 million hectares of oil palm plantations yield roughly 81 million tons of oil, representing about 39% of total global vegetable oil output [3]. In Indonesia, the industry contributes approximately 3.3% to the national GDP in 2019, with export values reaching USD 25.38 billion, making palm oil the country's leading export commodity [4]. It also supports livelihoods for millions in rural areas, with an estimated eight million Indonesians directly dependent on the palm oil sector, and nearly 40% of plantations managed by smallholders [5]. The export value of palm-based products has grown significantly, rising from USD 0.372 billion in 2002 to USD 4.7 billion in 2021 [6]. However, the rapid expansion of palm oil plantations has been linked to large-scale deforestation across Southeast Asia's tropical forests [1]. Despite sustainability challenges, palm oil remains central to Indonesia's economy, requiring systematic management and responsible industry practices, such as sustainable palm oil certification schemes [8], to balance economic benefits with environmental stewardship [7].

In process industries such as chemical, food, and palm oil refining, steam systems account for a substantial portion of total energy consumption. Steam functions as both a heating medium and a power source for various production processes. Studies indicate that in refinery and processing operations, approximately 23% of total energy use is allocated to steam generation and distribution [9]. Poorly maintained systems often result in significant energy losses, leaking steam traps alone can cause up to 20% of steam to be lost before utilization [9]. Within palm oil refineries, boiler efficiency remains a major concern. A case study in Malaysia reported that boiler efficiency in a palm oil mill averaged only 68.6%, largely due to condensate losses and steam leakage during oil extraction [10]. Through systematic optimization measures, such as installing economizers, improving blowdown control, and optimizing condensate recovery, boiler efficiency improved to 77%, reducing steam consumption by approximately 75,000 GJ per year, equivalent to annual cost savings exceeding USD 100,000 [10].

Lean-based methods such as Kaizen have been widely implemented to enhance energy performance and cost efficiency across industrial sectors. Applying Kaizen principles in manufacturing has been shown to reduce overall energy consumption by up to 7.5% while simultaneously improving process stability [11]. Similarly, in Vietnam's wood-processing industry, integrating Kaizen with energy management practices helped identify non-value-added activities, such as idle machines, unnecessary motion, and redundant processing, resulting in substantial energy savings and lower production costs [12]. In broader manufacturing contexts, energy costs may account for 15-30% of total production costs, and lean implementation can reduce this share by nearly one-third [13]. For palm oil refineries, advanced experimental design tools such as the Design of Experiments (DOE) and Response Surface Methodology (RSM) have proven highly effective. Using Aspen Plus simulation coupled with RSM, optimization of the sterilization process in crude palm oil (CPO) production achieved a 33.6% reduction in heat losses compared with conventional operations [14]. Collectively, these findings indicate that addressing steam losses and integrating systematic improvement methods, particularly Kaizen and DOE, can significantly enhance energy efficiency, minimize waste, and lower production costs in palm oil refining industries.

The integration of Kaizen and DOE has gained prominence across agro-industrial and manufacturing systems. In palm oil processing, implementing Kaizen's continuous improvement cycle with quality-control tools has been effective in identifying defect sources, improving oil clarity, and reducing impurities [15]. DOE-based optimization approaches, such as D-optimal design applied to palm fatty acid distillate (PFAD) esterification, have optimized reaction parameters, increased conversion efficiency and reducing chemical waste [16]. The application of RSM in CPO esterification using natural zeolite catalysts successfully minimized free fatty acid levels while maintaining high yield [17]. Additional research has confirmed that DOE and RSM approaches improve process precision and energy utilization across palm oil and derivative production systems [18], [19]. In food and manufacturing industries, combining statistical process control, Pareto analysis, and lean principles has lowered defect rates and improved product consistency [20]. The application of Pareto and Ishikawa analyses in coffee packaging operations effectively identified key sources of defects, reducing waste and machine downtime [21]. These studies confirm that structured improvement frameworks improve process precision, energy utilization, and product quality across diverse industrial applications.

Integrating continuous improvement frameworks with statistical design has become a cornerstone of industrial optimization in process industries. Studies show that coupling Kaizen-based continuous improvement with DOE yields measurable gains in process reliability and resource utilization [24], [25]. The integration of full-factorial DOE with statistical process control (SPC) within a PDCA framework has significantly minimized energy consumption in industrial processes without compromising product integrity [26]. Similarly, structured implementation of DOE (often integrated with SPC) systematically identifies optimal process parameters, improving productivity and reducing operational variability [27]. Factory-scale audits and boiler system enhancements in food production facilities have successfully reduced energy consumption by nearly 18% per year [28], while similar steam system optimizations in North African food industries achieved over 50% reductions in thermal energy losses [29]. These examples demonstrate how data-driven continuous improvement initiatives can produce substantial and measurable sustainability outcomes.

Despite the proven effectiveness of Kaizen and DOE in individual applications, several critical gaps remain in the literature. Recent research has revealed that aggressive energy-reduction efforts can sometimes compromise product quality. Studies on cassava roasting, for example, demonstrated that excessive reductions in process temperature and residence time led to undesirable changes in texture and expansion properties [22]. Comparable results from broader manufacturing analyses emphasize the need for balanced optimization strategies that preserve product quality while advancing sustainability goals [23]. Moreover, many prior studies have focused primarily on energy reduction or cost savings, with limited attention to maintaining product quality. In oil refining, the consistency of critical parameters such as oil content and free fatty acid (FFA) levels remains essential to meeting regulatory standards [30]. Research on valorization and regeneration of spent bleaching earth (SBE) highlights that excessive oil residue elevates waste management costs and may classify the material as hazardous [31]. Previous optimization efforts have explored DOE applications to improve oil recovery and regeneration from SBE [32], but few have combined continuous improvement frameworks with statistical design to jointly control energy efficiency and oil quality in real refinery settings. Specifically, there remains limited empirical evidence on the integrated use of Kaizen and DOE for optimizing steam utilization in the SBE drying phase of palm oil refinery operations. This represents a significant research gap, as SBE drying is a critical, energy-intensive process that directly impacts both operational costs and product quality. The novelty of the present study lies in its integrated approach: combining Kaizen's PDCA cycle with DOE-based statistical optimization to achieve simultaneous improvements in energy efficiency and product quality within an industrial-scale palm oil refinery setting. Unlike previous studies that address either energy reduction or quality control separately, this research systematically balances both objectives through a structured, data-driven framework applicable to real production environments.

This study seeks to address that gap by integrating Kaizen's PDCA cycle with DOE-based process optimization to achieve balanced operational performance. Specifically, it aims to experimentally assess the effect of drying-time variations on both steam consumption and SBE oil content in a palm oil refinery process. The objective is to determine the optimal drying duration that minimizes steam utilization while maintaining product quality within target specifications. The findings show that setting the drying time at 700 seconds reduces daily steam consumption by 1,224 kg/day (17.9%), while maintaining the SBE oil content at 21.03% within the target range of 20-22%. These results demonstrate that systematic, statistically guided continuous improvement can deliver substantial energy savings and quality assurance simultaneously, offering a practical and scalable framework for sustainable process optimization in the palm oil refining industry.

2. MATERIALS AND METHODS

The methodology applied in this research is illustrated in Figure 1, which presents a comprehensive framework combining the Kaizen continuous improvement cycle (PDCA) and the Design of Experiment (DOE) method to optimize steam utilization in the refining process. The research flow begins with problem identification, focusing on excessive steam consumption and suboptimal oil content during the drying of Spent Bleaching Earth (SBE).

This study was conducted at a palm oil refinery facility over two phases: baseline data collection from January to December 2024, and experimental trials from January to February 2025. Data collection involved multiple approaches to ensure comprehensive process understanding. Production records for 2024 were analyzed to extract monthly steam consumption and oil content data. Steam usage was measured using condensate flow meters installed at three main utilization points (Steam Drying, Steam PHE, and Steam Hot Water). Oil content was determined daily by the quality control department using Soxhlet extraction (AOCS Method Ba 3-38), with daily measurements averaged to monthly values for baseline analysis. Field observations were conducted during normal production operations across three shifts to capture process variability and operator practices. Semi-structured interviews with eight operators and two shift supervisors provided insights into operational challenges, typical parameter adjustments, and factors affecting steam consumption. Pareto diagrams and check sheets were employed to systematically record and analyze process data.

Subsequently, the Kaizen "Plan" and "Do" stages were implemented through structured experimentation. The baseline SBE drying process operated at 850 seconds per cycle with an average steam consumption of

6,824 kg/day and oil content of 18.91%, below the target range of 20-22%. During the baseline period (2024), process parameters exhibited natural variability, with bleaching earth (BE) dosage ranging from 0.9% to 1.2% and oil flow rate varying between 54 and 65 tons per hour depending on production demands. Based on preliminary analysis identifying drying time as the primary controllable parameter, four experimental levels were selected: 650, 700, 750, and 800 seconds. To isolate the effect of drying time during experimental trials (January-February 2025), other process parameters were held constant. Steam pressure was maintained at 3.5 bar through automated boiler control, bleaching earth dosage was fixed at 1.0% of oil throughput, and oil flow rate was held constant at 60 tons per hour. This single-factor approach was selected because Pareto analysis indicated drying time as the dominant factor affecting steam consumption, and maintaining constant conditions for other parameters ensured experimental validity while facilitating rapid implementation of findings.

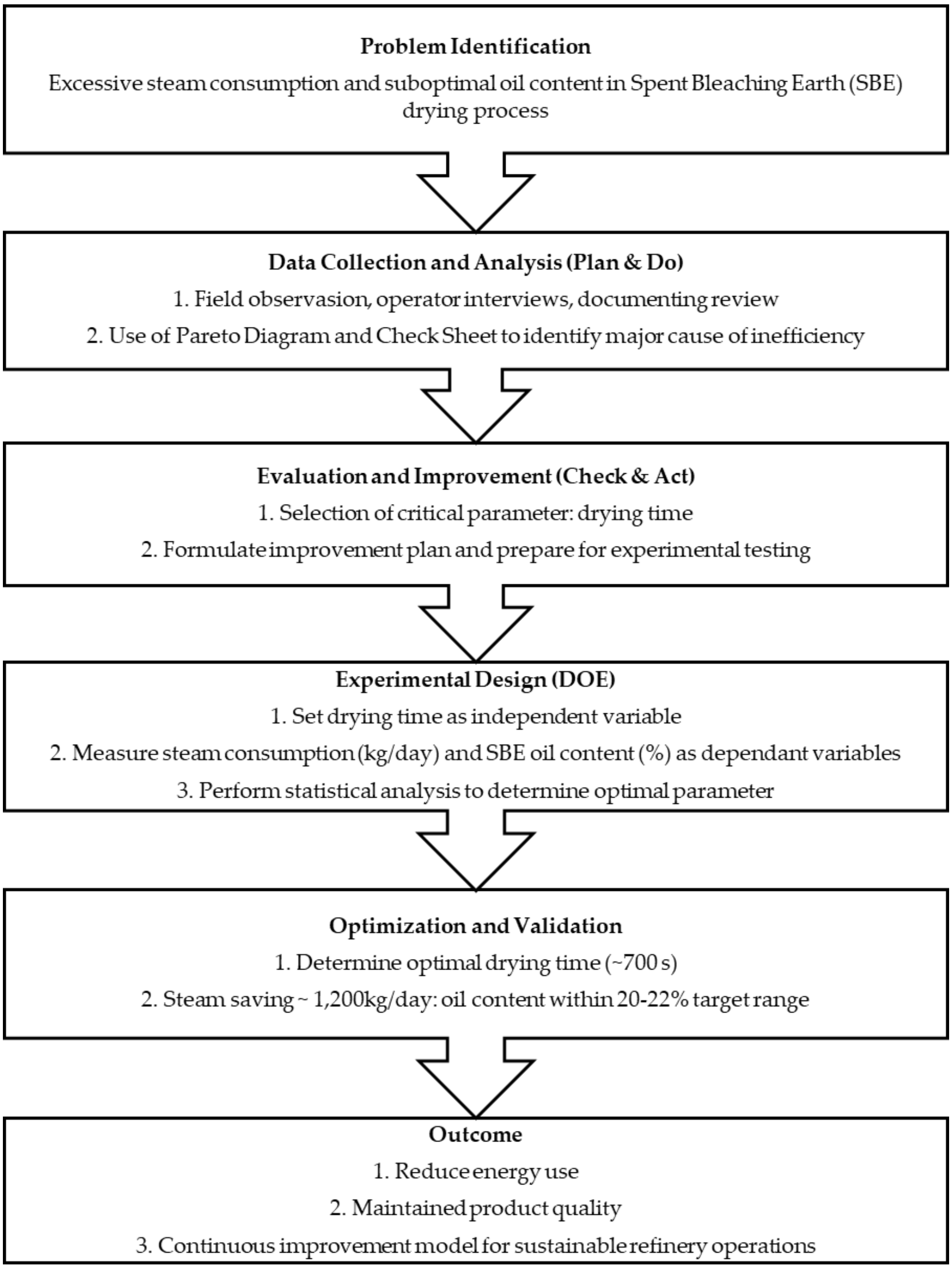

Figure 1. Research Flowchart

The next stage, representing Kaizen's "Check" and "Act" phases, involved evaluating potential improvement opportunities through systematic experimentation. A Completely Randomized Design (CRD) was employed with four drying time levels, each replicated four times, resulting in 16 experimental runs. Randomization of run order minimized the influence of time-based trends or systematic bias. For each experimental run, steam consumption was measured via calibrated flow meters per drying cycle and converted to daily rates by multiplying by the standard number of cycles per day (typically 12 cycles), while SBE oil content was determined through Soxhlet extraction of samples collected from three points per batch and averaged.

In the DOE stage, drying time was treated as independent variable, while steam consumption (kg/day) and SBE oil content (%) served as dependent variables. Statistical analysis was performed using Analysis of Variance (ANOVA) to test whether drying time significantly affected oil content. The ANOVA model examined differences among treatment means using the F-test, with the null hypothesis stating no effect of drying time and the alternative hypothesis indicating significant treatment effects. The calculated F-value was compared against the critical value at $\alpha = 0.05$ significance level. To validate ANOVA assumptions, normality of residuals was assessed using the Shapiro-Wilk test, homogeneity of variance was verified through Levene's test, and residual plots were examined for patterns or outliers. Additionally, simple linear regression was performed to develop a predictive model relating drying time to oil content, with model fit evaluated using the coefficient of determination (R^2).

The final stage involved optimization and validation, where the best parameter setting, identified as a drying time of 700 seconds, resulted in a reduction of steam consumption by 1,224 kg/day (17.9%) while maintaining oil content at 21.03% within the company's target range of 20-22%. This integrated Kaizen-DOE framework establishes a data-driven improvement model that enhances energy efficiency and maintains product quality in palm oil refinery operations.

3. RESULTS

3.1. Identification of the Problem and Current Condition

3.1.1. Steam Consumption Analysis

Data collection on steam usage was conducted across twelve months to capture fluctuations and determine areas of high consumption. The total annual steam utilization reached 2,646,316 kg, distributed among three main processes: Steam Drying, Steam PHE, and Steam Hot Water. As summarized in Table 1, Steam Drying accounted for 82.97% of total steam use, making it the most energy-intensive process in the refinery.

Table 1. Annual steam utilization (2024)

Steam Application	Steam Usage (kg)	Percentage (%)	Cumulative (%)
Steam Drying	2,195,575	82.97	83
Steam PHE	286,453	10.82	94
Steam Hot Water	164,288	6.21	100
Total	2,646,316	100.00	—

The Pareto analysis as shown in Figure 2 demonstrates that the Steam Drying operation dominates total steam consumption, accounting for approximately 83% of annual usage. This distribution validates the selection of the SBE drying process as the primary target for process improvement.

3.1.2. Product Quality (SBE Oil Content) Evaluation

Parallel to steam usage analysis, the oil content of SBE was monitored to evaluate the consistency and quality of the drying process. Monthly data collected through check sheets revealed oil content fluctuations between 16.53% and 19.96%, with an annual average of 18.91%, as shown in Table 2. The recorded average remained below the company's target range of 20-22%, indicating that the drying process consumed substantial steam without achieving the desired product quality.

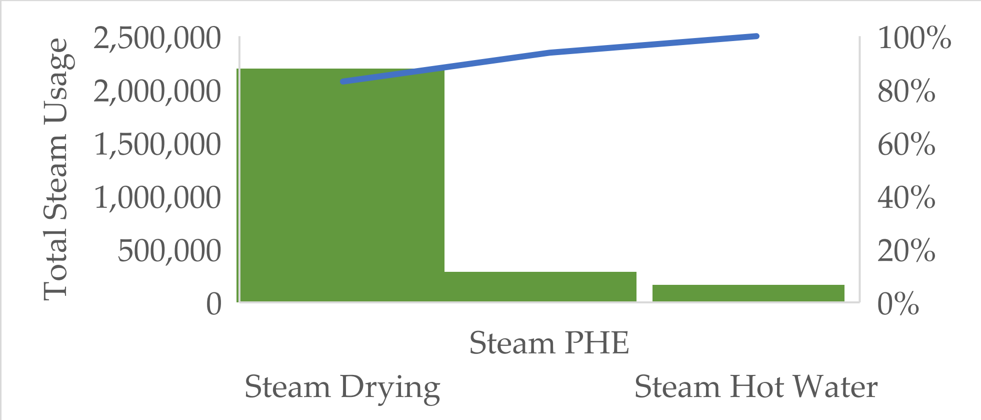

Figure 2. Pareto Diagram of Steam Utilization

Table 2. Average Monthly SBE Oil Content (2024)

Month	Oil Content (%)
January	19.20
February	19.68
March	19.96
April	16.69
May	19.76
June	16.53
July	19.49
August	17.43
September	19.63
October	19.48
November	19.63
December	19.34
Average	18.91

3.1.3. Operating Parameters and Baseline Condition

Observation of the operating parameters as shown in Table 3 revealed that the SBE drying process was conducted under nearly constant conditions, with a drying time of 850 seconds per cycle, an average steam consumption of 6,824 kg/day, and an average oil content of 18.91%.

From this baseline analysis, the SBE drying process was characterized by high steam consumption (approximately 6,824 kg/day, representing 83% of total refinery steam), fixed drying duration (850 seconds per cycle), and average oil content below target specifications (18.91% versus the 20-22% target). These findings defined the operational inefficiencies to be addressed through the Kaizen-DOE methodology.

3.2. Application of Kaizen for Process Improvement

3.2.1. Plan Stage (Problem Identification and Planning)

The planning phase aimed to determine the improvement target and define the experimental strategy. Analysis of operational records for January-December 2024 revealed excessive steam consumption (approximately 6,824 kg/day) and oil content below the desired range (average 18.91%). The Kaizen team established a specific target of reducing steam consumption below 6,824 kg/day while increasing SBE oil content to within 20-22%. Four drying-time variations were selected for experimentation: 650 s, 700 s, 750 s, and 800 s, under controlled conditions of 1% bleaching earth dosage and oil flow rate of 60 tons per hour, as summarized in Table 4.

Table 3. Baseline Operating Parameters of the SBE Drying Process

Month	Oil Content (%)	BE Dosage (%)	Steam (kg/day)	Oil Flow (ton/hour)	Drying Time (s)
January	19.20	1.0	6,801	60	850
February	19.68	1.1	6,814	65	850
March	19.96	1.2	6,804	65	850
April	16.69	1.1	6,825	54	850
May	19.76	1.1	6,827	64	850
June	16.53	0.9	6,809	55	850
July	19.49	1.1	6,834	64	850
August	17.43	1.0	6,853	56	850
September	19.63	1.1	6,820	65	850
October	19.48	1.0	6,837	63	850
November	19.63	1.1	6,820	64	850
December	19.34	1.0	6,847	61	850
Average	18.91	1.06	6,824	61.33	850

Table 4. Kaizen Planning Summary

Category	Description
Problem	Excessive steam consumption and SBE oil content below target (January–December 2024)
Target	Steam consumption < 6,800 kg/day; Oil content 20–22%
Improvement Plan	Experimental adjustment of drying time (800, 750, 700, 650 s)
Controlled Parameters	BE dosage: 1%; Oil flow: 60 tons/hour
Department	Refinery
Implementation Period	January–February 2025

3.2.2. Do Stage (Experimental Execution)

During the Do phase, experimental trials were performed according to the DOE protocol. The four drying time levels were tested with four replications each. The experimental data are presented in Table 5, demonstrating a clear inverse relationship between drying time and oil content: as drying time decreased, oil content increased while steam consumption decreased.

Table 5. Experimental Data of Drying Time Variation and SBE Oil Content

Drying Time (s)	Steam Usage (ton/day)	Oil Content (%)
800	6.4	19.28, 18.97, 19.38, 19.18
750	6.0	19.92, 19.72, 19.84, 19.98
700	5.6	20.95, 21.30, 21.07, 20.80
650	5.2	21.85, 22.07, 22.30, 22.02

3.2.3. Check Stage (Evaluation of Improvement Results)

Statistical analysis using ANOVA as shown in Table 6 confirmed that the variation in drying time had a significant effect on oil content, with an F-value of 208.95, exceeding the F-table value (3.49) at a significance level of $\alpha = 0.05$. This result indicates that changes in drying duration significantly influence oil content and steam efficiency.

Table 6. ANOVA Results for Drying Time Variation

Source of Variation	SS	df	MS	F-Value
Between Groups	18.9682	3	6.3227	208.95
Within Groups	0.3694	12	0.0308	—
Total	19.3376	15	—	—

To validate the statistical analysis, ANOVA assumptions were tested and results are presented in Table 7. The Shapiro-Wilk normality test yielded W = 0.9597 with p-value = 0.6567, confirming that residuals follow a normal distribution ($p > 0.05$). Levene's test for homogeneity of variance produced F = 0.3293 with p-value = 0.8043, indicating equal variances across treatment groups ($p > 0.05$). Visual inspection of residual plots confirmed random distribution around zero with no discernible patterns, outliers, or violations of model assumptions.

Table 7. Statistical Assumption Tests for ANOVA Validity

Test	Statistic	Value	p-value	Conclusion
Shapiro-Wilk (Normality)	W	0.9597	0.6567	Residuals are normally distributed (p > 0.05)
Levene's Test (Homogeneity of Variance)	F	0.3293	0.8043	Variances are equal across groups (p > 0.05)

Note: Both tests satisfy ANOVA assumptions, validating the statistical conclusions.

3.2.4. Act Stage (Implementation and Standardization)

Based on the experimental findings, analysis revealed that the 700-second treatment produced the optimal balance between energy efficiency and product quality. This condition achieved an average oil content of 21.03%, falling within the target range (20-22%), while reducing steam consumption to 5,600 kg/day, a reduction of 1,224 kg/day (17.9%) compared to baseline operations.

3.3. DOE Statistical Analysis and Optimization Results

3.3.1. ANOVA Analysis and Significance Test

The ANOVA results presented in Table 6 showed a calculated F-value of 208.95, substantially higher than the critical F-table value of 3.49 at the 95% confidence level ($\alpha = 0.05$). This result indicates that drying time variation had a statistically significant effect on SBE oil content. The small within-group variance (MS = 0.0306) compared to the between-group variance (MS = 6.3934) suggests that observed differences in oil content were primarily due to treatment effects rather than random fluctuations.

3.3.2. Mean Comparison and Optimization Trend

Mean oil content for each drying time variation is presented in Table 8. The results demonstrate a steady increase in oil content as drying time decreases from 800 to 650 seconds. The plotted response curve between drying time and oil content as shown in Figure 3 indicates a near-linear relationship, where oil content increases as drying time decreases.

From a process stability perspective, the 700-second setting provides the best balance between energy savings and quality control. At this condition, steam consumption averaged 5,600 kg/day, representing a reduction of 1,224 kg/day (17.9%) from baseline operations, while maintaining oil content within the target range of 20-22%. The 650-second treatment, while achieving lower steam consumption (5,200 kg/day), produced oil content exceeding the upper target limit (22.06%), indicating potential under-drying.

Table 8. Average Oil Content and Steam Consumption by Drying Time

Drying Time (s)	Steam Usage (kg/day)	Mean Oil Content (%)
800	6,400	19.20
750	6,000	19.87
700	5,600	21.03
650	5,200	22.06

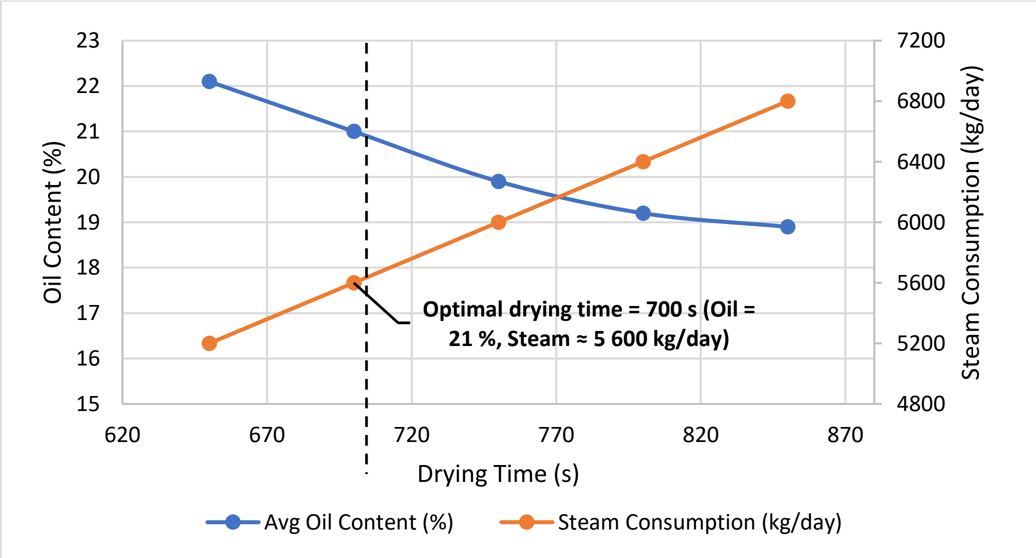

Figure 3. Relationship between Drying Time and SBE Oil Content showing optimal point at 700 seconds

3.3.3 Statistical Validation and Model Implications

A linear regression model was developed to describe the functional relationship between drying time (X) and oil content (Y):

$$Y = 34.66 - 0.0195X \quad (1)$$

Where,

Y = SBE oil content (%)

X = drying time (seconds)

This regression equation exhibits a high coefficient of determination ($R^2 = 0.97$), confirming that 97% of the oil content variation can be explained by changes in drying time. The model predicts that at 700 seconds, the oil content reaches 21.03%, matching the experimental observation and the company's target specification. The negative slope (-0.0195) indicates that each 10-second reduction in drying time increases oil content by approximately 0.20 percentage points.

3.4. Summary of Findings

The experimental and statistical analyses established the following outcomes. Drying time variation significantly influences both steam consumption and oil content ($F = 208.95$ exceeds F-table = 3.49, $p < 0.05$). The optimal drying time is 700 seconds, yielding a mean oil content of 21.03% with steam consumption of 5,600 kg/day, representing a 17.9% reduction from baseline (1,224 kg/day reduction). The developed regression model ($R^2 = 0.97$) accurately predicts oil content behavior relative to drying duration. Statistical assumption tests confirmed the validity of ANOVA results through satisfied normality (Shapiro-Wilk, $p = 0.6567$) and homogeneity of variance (Levene's test, $p = 0.8043$) requirements. These findings confirm that systematic process optimization guided by the integrated Kaizen-DOE approach can deliver measurable improvements in refinery efficiency.

4. DISCUSSION

This study aimed to optimize steam utilization in a palm oil refinery process while maintaining oil-content quality within the target range of 20-22%. The experimental findings revealed that integrating Kaizen's continuous improvement cycle with the Design of Experiment (DOE) method provided a structured and statistically grounded approach to achieving this objective. The outcomes are discussed here in relation to previous research, the initial hypotheses, and their broader industrial implications.

4.1. Interpretation of Results in Relation to Initial Hypotheses

The initial hypothesis of this study proposed that drying time significantly affects both steam consumption and SBE oil content, and that its optimization could reduce energy usage without lowering product quality. The ANOVA results confirmed this hypothesis, showing a highly significant F-value (208.95) compared to the F-table (3.49, $\alpha = 0.05$), indicating that drying-time variation had a measurable and substantial impact on process performance.

The results demonstrated that a shorter drying time improved oil recovery efficiency and reduced daily steam demand. The optimal condition was achieved at 700 seconds, corresponding to 5,600 kg/day of steam consumption and an average oil content of 21.03%, both of which meet the company's operational targets. The observed inverse relationship between drying time and oil content can be explained through two primary mechanisms. First, extended drying periods allow progressively dried SBE particles to re-adsorb volatilized oil components into their porous structure, effectively reducing extractable oil content. At 140°C (the saturated steam temperature at 3.5 bar), residual oil can partially vaporize and subsequently be trapped in the dried clay matrix when drying extends beyond optimal moisture removal. Second, prolonged thermal exposure increases the risk of oil degradation and oxidative polymerization, which chemically binds oil molecules to the bleaching earth surface, rendering them less extractable. These mechanisms explain why excessive drying durations (850 seconds baseline) not only waste energy but also degrade oil retention, while the optimized 700-second condition terminates the cycle before significant re-adsorption or degradation occurs.

However, the experimental data also reveal operational trade-offs that must be considered. The 650-second treatment, while achieving the lowest steam consumption (5,200 kg/day), produced oil content exceeding the upper target limit (22.06%), suggesting potential under-drying that could compromise product moisture balance and long-term storage stability. The selected 700-second setting provides a safety margin against feed variability while achieving substantial steam savings, representing a pragmatic balance between energy efficiency, product quality, and process robustness.

These findings are consistent with prior studies reporting that process-parameter optimization, particularly time-temperature control, has a dominant influence on energy efficiency in agro-industrial operations [14], [24], [27]. For instance, DOE-based refinements in crude palm oil (CPO) sterilization and bleaching systems achieved heat-loss reductions of up to 30% while maintaining output quality [18]. The present study aligns with these outcomes and further extends them by demonstrating the same principle in the SBE drying process, which has been less explored in existing literature.

4.2. Kaizen–DOE Synergy and Its Analytical Significance

The success of this optimization lies not only in the statistical validation but also in the integration of Kaizen's PDCA (Plan-Do-Check-Act) cycle with DOE methodology. The PDCA framework provided a systematic structure for iterative testing and evaluation, while DOE enabled quantitative analysis of treatment effects. The "Plan" and "Do" stages established the experimental parameters, and the "Check" and "Act" stages ensured evaluation and standardization of the best-performing condition.

This synergy between continuous improvement and experimental design confirms what has been suggested by previous authors, that combining lean methodologies with statistical tools leads to more robust and data-driven decision-making [11], [13], [20]. In particular, Kaizen emphasizes gradual, cumulative change rather than isolated intervention, and DOE complements it by validating those changes statistically. The result is a closed-loop improvement process that minimizes trial-and-error and promotes sustained performance enhancement.

While this study employed a single-factor Completely Randomized Design, alternative optimization methodologies exist. Taguchi robust parameter design focuses on minimizing process variability through orthogonal arrays but requires more complex experimental structures. Response Surface Methodology (RSM) enables modeling of non-linear relationships and multi-factor optimization but typically requires 13-20 experimental runs, which was impractical given operational constraints. Machine learning algorithms can identify optimal conditions from large datasets but require extensive historical data not available at the studied facility and produce less interpretable results than mechanistic models. The selected Kaizen-CRD integration represents a pragmatic balance between methodological rigor and industrial feasibility, suitable for the single-factor optimization required in this context.

Such integrated frameworks have been successfully implemented in other process-intensive sectors. In the wood-processing and beverage industries, similar Kaizen-DOE combinations achieved notable efficiency gains by reducing process variability and stabilizing product quality [12], [26]. The present study reinforces this evidence within the context of palm-oil refining, highlighting that operational excellence can be achieved through structured, data-based problem solving rather than reactive maintenance or intuitive adjustments.

4.3. Broader Context: Energy Efficiency and Industrial Sustainability

From a broader sustainability perspective, optimizing the SBE drying process contributes directly to reducing the refinery's overall energy footprint. Steam systems represent one of the largest energy consumers in palm-oil processing, accounting for over 70% of total energy expenditure in certain operations [9], [10]. The 1,224 kg/day steam reduction achieved in this study translates to measurable economic and environmental benefits. Assuming continuous operation for 350 days per year, the annual steam reduction is approximately 428,400 kg. With typical industrial steam generation costs of $25-30 per ton, estimated annual savings range from $10,700 to $12,900. Additionally, the increase in oil content from 18.91% to 21.03% enhances SBE byproduct value, contributing approximately $54,000 per year in increased recoverable oil. Combined, these improvements represent an estimated annual economic benefit of $65,000-67,000 achieved with zero capital investment.

From an environmental perspective, the steam reduction corresponds to decreased boiler fuel consumption. Assuming typical palm oil refinery boilers operate on natural gas with 85% thermal efficiency and an emission factor of 2.75 kg CO_2 per kg of fuel, the estimated greenhouse gas reduction is approximately 66 tons CO_2 per year. While modest in absolute terms, this represents a 17.9% improvement in the steam-related carbon footprint of the refinery. These improvements align with global sustainability objectives emphasizing energy intensity reduction and resource efficiency across agro-industrial supply chains [1], [8]. Moreover, the results confirm that energy optimization need not compromise product quality, an important consideration given that prior attempts to reduce process energy have sometimes led to inferior oil quality or inconsistent moisture levels [22], [23]. The balance achieved here between energy reduction and quality assurance positions Kaizen-DOE integration as a pragmatic model for sustainable palm-oil refining.

4.4. Industrial and Operational Implications

The outcomes of this study offer several actionable insights for industrial practitioners. First, establishing an optimal drying-time standard (700 seconds) provides a benchmark for Standard Operating Procedures (SOPs) within refinery operations. Second, the continuous monitoring mechanisms embedded in the Kaizen cycle ensure that deviations are promptly identified and corrected, thus promoting process reliability and long-term efficiency. Third, this framework is adaptable and can be replicated for other steam-dependent processes, such as deodorization or fractionation.

This research supports the growing industrial movement toward lean energy management, which integrates productivity improvement with sustainability objectives [12], [29]. For companies aiming to meet international sustainability certification standards, such as ISPO or RSPO, systematic energy optimization supported by statistical validation enhances both environmental compliance and economic competitiveness.

4.5. Limitations and Future Research Directions

Although this study produced statistically and operationally significant results, several limitations warrant consideration. The experimental design focused solely on drying-time variation, assuming other factors such as steam pressure, condensate return efficiency, and SBE feed moisture to be constant. This single-variable approach was deliberately chosen because Pareto analysis indicated drying time as the dominant controllable factor, and holding other parameters constant simplified implementation while minimizing confounding effects. However, this constrains the comprehensiveness of optimization. Future studies should expand the experimental design to include additional variables using factorial or response surface methods for multidimensional optimization, as interactions among steam pressure, bleaching earth dosage, and oil flow rate may reveal further improvement opportunities.

Additionally, this study was conducted at a single refinery with specific equipment characteristics and operational practices. The optimal drying time of 700 seconds is specific to the steam-jacketed rotary dryer used at this facility and may differ for other dryer designs or scales. Feedstock variability, climate conditions, and process integration configurations at different refineries may require adjusted parameters. While the general principle that excessive drying degrades oil recovery and wastes energy likely applies broadly, refineries seeking to replicate this work should conduct site-specific DOE studies rather than directly adopting the 700-second standard.

Further research should also examine economic and environmental impacts more comprehensively, including direct metering of boiler fuel consumption before and after optimization, life-cycle assessment (LCA) to quantify full environmental footprint, and detailed cost-benefit analysis incorporating capital, labor, and opportunity costs. Additionally, integrating digital sensors, real-time process monitoring, and machine-learning algorithms could enhance predictive control and automate continuous improvement cycles. Such hybrid systems represent the next evolution of Industry 4.0-ready Kaizen frameworks, capable of sustaining gains beyond manual implementation [27].

5. CONCLUSION

This research demonstrated that integrating the Kaizen continuous improvement cycle with the Design of Experiment (DOE) method is an effective strategy for optimizing steam utilization in palm-oil refinery operations, particularly in the Spent Bleaching Earth (SBE) drying process. Through this combined framework, the study systematically identified, analyzed, and optimized key process parameters, producing measurable improvements in both energy efficiency and product quality.

Experimental results confirmed that drying time significantly influences steam consumption and SBE oil content. The ANOVA test produced an F-value of 208.95, exceeding the F-table value of 3.49 (α = 0.05), validating the research hypothesis. The optimum condition was obtained at a drying time of 700 seconds, reducing steam usage from 6,824 kg/day to 5,600 kg/day (a reduction of 1,224 kg/day or 17.9%) while maintaining an average oil content of 21.03%, fully within the company's target range of 20-22%.

These findings highlight the effectiveness of data-driven continuous improvement in achieving operational efficiency. Kaizen's PDCA (Plan-Do-Check-Act) cycle provided a structured path for planning and implementing change, while DOE supplied the statistical rigor to validate and quantify results. Together, they created a robust, repeatable framework linking management strategy with quantitative optimization.

From an industrial standpoint, the outcomes confirm that systematic process optimization yields tangible benefits in both cost savings and sustainability performance. Lower steam demand reduces fuel consumption and emissions, supporting cleaner production and alignment with national and global sustainability goals. The estimated annual economic benefit of $65,000-67,000 and CO_2 reduction of approximately 66 tons per year demonstrate the practical value of this approach. The Kaizen-DOE framework developed here can also serve as a reference for other refinery units, such as bleaching, deodorization, or steam systems, where efficiency and product quality are equally critical.

While the study achieved its intended objectives, its scope was limited to the effect of drying-time variation under fixed operating conditions. Future investigations are encouraged to incorporate additional parameters, such as steam pressure, feed-moisture content, and condensate-recovery efficiency, through multifactorial DOE approaches. Expanding the analysis to include economic evaluation, life-cycle assessment, and real-time process monitoring will provide deeper insight into the long-term sustainability and adaptability of this improvement model.

In summary, this research provides clear evidence that combining Kaizen's structured improvement principles with DOE-based statistical analysis offers a practical and scalable model for enhancing energy performance and product quality in palm-oil refining. The integration of continuous improvement and quantitative optimization represents a significant step toward more sustainable, efficient, and data-informed industrial operations.

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DECLARATION OF AI-TOOL USAGE

AI-assisted tools were used only to improve the clarity, grammar, and readability of the manuscript. The research design, data collection, analysis, interpretation of results, and conclusions were carried out entirely by the authors. The authors take full responsibility for all content presented in this manuscript.