HEURISTIC
Vol. 23, No. 2, October 2026
ISSN(p) 1693-8232
ISSN(e) 2723-1585

Interaction Effects of Temperature, Pressure, and Palm Oil Mill Location on Crude Palm Oil (CPO) Losses Using the Additive Main Effects and Multiplicative Interaction (AMMI) Model

Nurul Aflah Br Sembiring Pandia[1]*, Fatimah[2], Yohana Dian Putri[3]
[1,2,3]Industrial Engineering Study Program, Faculty of Engineering, Universitas Malikussaleh, Aceh Utara, Indonesia

***Corresponding Author**: nurul.220130033@mhs.unimal.ac.id

Article history:
Received: 3 August 2026
Accepted: 13 August 2026
Published: 1 October 2026

Keywords:
Additive Main Effects and Multiplicative Interaction (AMMI);
Crude Palm Oil (CPO);
Digester Temperature;
Oil Losses;
Screw Press Pressure

ABSTRACT

Oil losses during Crude Palm Oil (CPO) processing are a key indicator of production efficiency in palm oil mills. They are influenced by operating conditions, particularly digester temperature and screw press pressure, as well as differences in mill operational characteristics. This study aimed to evaluate the interaction effects of treatment combinations (digester temperature × screw press pressure) and mill location on CPO oil losses and to identify the most effective operating conditions for minimizing oil losses. Operational data were collected from three palm oil mills and analyzed using two-way Analysis of Variance (ANOVA), followed by the Additive Main Effects and Multiplicative Interaction (AMMI) model to evaluate interaction patterns and treatment stability across mill locations. The results showed that treatment combinations, mill location, and their interaction significantly affected CPO oil losses. The S2T2 treatment combination produced the lowest average oil loss (3.58%) and exhibited stable performance across the three mills. This study demonstrates the applicability of the AMMI model for evaluating treatment stability and interaction patterns under different mill Mill Locations, providing practical guidance for selecting operating conditions that consistently minimize CPO oil losses. These findings indicate that optimizing digester temperature and screw press pressure can improve the efficiency of CPO processing in palm oil mills.

INTRODUCTION

Indonesia is the world's largest producer and exporter of crude palm oil (CPO), making the palm oil industry one of the country's most strategic agro-industrial sectors. In addition to contributing significantly to national export earnings, the industry generates employment opportunities, supports rural economic development, and supplies raw materials for the food, oleochemical, cosmetic, and renewable energy industries. As global demand for palm oil continues to increase, improving production efficiency has become a major priority for palm oil mills. Consequently, maintaining optimal processing conditions throughout the production chain is essential to maximize oil recovery while ensuring product quality and operational sustainability.

One of the most important indicators used to evaluate the performance of a palm oil mill is oil losses, which refer to the amount of oil that remains unrecovered during the extraction process and is discharged together with processing by-products such as press fiber, empty fruit bunches (EFB), decanter solids, sludge, and palm oil mill effluent

(POME). Excessive oil losses reduce the Oil Extraction Rate (OER), decrease production efficiency, increase operational costs, and ultimately reduce mill profitability. Therefore, minimizing oil losses has become one of the primary objectives of process optimization in the palm oil industry (Supriatna, 2024).

The magnitude of oil losses is influenced by several operational factors throughout the extraction process. Among these, digester operating temperature and screw press hydraulic pressure play crucial roles because they directly affect oil release from the mesocarp tissue. Appropriate digester temperature reduces oil viscosity and facilitates cell disruption, whereas optimum screw press pressure improves mechanical extraction efficiency without causing excessive kernel breakage. However, operational parameters alone do not fully explain variations in oil losses. Palm oil mills differ in processing capacity, machine specifications, equipment conditions, maintenance practices, raw material quality, operator experience, and production management systems. These differences create distinct processing Mill Locations in which identical operating conditions may produce different extraction performances. Therefore, mill location in this study represents differences in operational Mill Locations rather than merely geographical location.

The interaction between operational parameters and mill Mill Locations has become increasingly important in industrial process optimization. A temperature–pressure combination that performs efficiently in one mill may not necessarily produce the same performance in another because each mill operates under different Mill Locational and operational conditions. Consequently, identifying operational conditions that are not only effective but also stable across different mills is essential for developing practical recommendations applicable to a wider range of industrial settings.

Numerous studies have investigated factors affecting crude palm oil losses, including processing temperature, screw press pressure, fruit maturity, machine performance, and operational efficiency. Most studies reported that these factors individually influence oil recovery and production performance. However, previous studies have primarily focused on evaluating the main effects of individual operational variables or have been conducted within a single palm oil mill using conventional statistical approaches. As a result, limited attention has been given to evaluating the interaction between operational parameter combinations and different mill Mill Locations, particularly regarding the stability and adaptability of treatment combinations across mills with different operational characteristics. This limitation represents an important research gap because operational recommendations derived from a single production Mill Location may not be directly applicable to other palm oil mills.

Analysis of Variance (ANOVA) is widely used to determine the significance of treatment effects and their interactions. Nevertheless, although ANOVA can identify statistically significant interactions, it provides limited information regarding the stability and adaptability of treatment combinations across different Mill Locations (Bueraheng et al., 2021). Therefore, complementary analytical approaches are required to further interpret interaction patterns and identify operational conditions that consistently perform well under different Mill Locational conditions.

The Additive Main Effects and Multiplicative Interaction (AMMI) model addresses this limitation by integrating the strengths of Analysis of Variance (ANOVA) and Principal Component Analysis (PCA). ANOVA estimates the additive effects of treatments and Mill Locations, whereas PCA decomposes treatment × Mill Location interactions into Interaction Principal Component Axes (IPCA). Consequently, AMMI not only evaluates the statistical significance of treatments and Mill Locations but also

reveals interaction patterns, treatment stability, Mill Locational adaptability, and the associations between treatments and Mill Locations through AMMI biplot visualization.

This study contributes to the application of the AMMI model in industrial engineering by evaluating the interaction between operational parameter combinations and different mill Mill Locations in crude palm oil processing. Unlike previous studies that mainly emphasized individual operational factors, this research evaluates the stability and adaptability of treatment combinations across multiple palm oil mills. The findings are expected to provide both scientific and practical contributions by expanding the application of the AMMI model in industrial process optimization and by providing operational guidance for selecting temperature and pressure combinations that consistently minimize CPO oil losses under different mill characteristics.

Therefore, this study aims to analyze the interaction effects of digester operating temperature, screw press hydraulic pressure, and mill location on crude palm oil losses using the Additive Main Effects and Multiplicative Interaction (AMMI) model. Specifically, the study seeks to identify the most effective and stable combination of operational parameters for minimizing oil losses across different palm oil mills. The outcomes are expected to support data-driven decision-making for process optimization and improve operational efficiency in the palm oil processing industry.

MATERIALS AND METHODS

Research Design

This study employed a quantitative explanatory approach using a factorial treatment structure combined with the Additive Main Effects and Multiplicative Interaction (AMMI) model to evaluate the interaction effects of digester operating temperature, screw press hydraulic pressure, and factory location on crude palm oil (CPO) losses. The research was designed to investigate not only the individual influence of each operational factor but also the interaction between treatment combinations and different factory Mill Locations. The analytical framework consisted of two sequential stages. First, a combined Analysis of Variance (ANOVA) was performed to determine the significance of the main effects and interaction effects among factors. Second, the significant interaction component was further analyzed using the AMMI model through Singular Value Decomposition (SVD) to identify treatment stability and interaction patterns across different factory locations.

Location and Time of Research

The study was conducted at three palm oil mills, hereinafter referred to as Mill A (L1), Mill B (L2), and Mill C (L3). These mills were selected to represent different operational characteristics in the crude palm oil processing system, enabling the evaluation of treatment–Mill Location interactions using the AMMI model. Operational data were collected directly during the production process at each mill.

Experimental Factors

The experiment involved three research factors. The first factor was digester operating temperature, which was classified into two levels based on class interval analysis of field observations. The second factor was screw press hydraulic pressure, which was also classified into two operational levels using the same procedure. The third factor consisted of three factory locations representing different processing Mill Locations. The

combination of temperature and pressure levels produced several treatment combinations, which were subsequently evaluated across all factory locations.

Treatment Combination

Initially, four treatment combinations were generated from the factorial arrangement of temperature and pressure levels. However, only treatment combinations that were consistently available in all three factories were included in the AMMI analysis to maintain a balanced data structure. Consequently, three treatment combinations were analyzed, namely S1T2, S2T1, and S2T2. Each treatment was represented by three replications at every factory, resulting in a balanced treatment-by-Mill Location matrix suitable for AMMI analysis.

Data collection

Primary data were collected directly from three commercial palm oil mills, namely (L1), (L2), and Jaya (L3). The observations were conducted during the crude palm oil extraction process at the Digester and Screw Press stations. Data collection focused on three main variables, namely digester operating temperature, screw press hydraulic pressure, and crude palm oil losses.

Measurements were conducted for seven consecutive production days. During each observation day, data were recorded three times at two-hour intervals corresponding to active processing periods. Consequently, the initial dataset consisted of 63 observations representing variations in operating conditions encountered during normal factory operations.

To facilitate factorial analysis, the observed temperature and pressure values were classified into two operational levels using class interval analysis. The classified levels were then combined to generate treatment combinations used in the AMMI analysis. Only treatment combinations that were available in all three factories were retained to ensure a balanced treatment-by-Mill Location dataset. As a result, three treatment combinations (S1T2, S2T1, and S2T2) with three replications at each factory were included in the final analysis.

Research Variables

The response variable analyzed in this study was crude palm oil losses expressed as a percentage (%). Three explanatory factors were considered. The first factor was digester operating temperature (Factor S), the second factor was screw press hydraulic pressure (Factor T), and the third factor was factory location (Factor L). Temperature and pressure represented controllable operational variables, whereas factory location represented Mill Locational variation reflecting differences in operational characteristics among palm oil mills.

Data Analysis Procedure

The research procedure began with direct field observations at each factory to record operating temperature, hydraulic pressure, and crude palm oil losses. The collected operational data were subsequently grouped into predefined treatment levels according to class interval analysis. Average oil losses were then calculated for every treatment combination within each factory.

The resulting treatment-by-Mill Location matrix was analyzed using a combined Analysis of Variance (ANOVA) to evaluate the significance of treatment effects, factory effects, and treatment-by-factory interactions. When significant interactions were detected, the

interaction matrix was decomposed using Singular Value Decomposition (SVD) within the AMMI framework to obtain Interaction Principal Component Axes (IPCA). Finally, AMMI biplots were constructed to visualize treatment stability, Mill Locational adaptability, and interaction patterns.

Analysis of Variance (ANOVA)

The statistical analysis was conducted in two sequential stages. The first stage involved a combined Analysis of Variance (ANOVA) to evaluate the significance of the main effects of treatment and factory location, as well as their interaction effect on crude palm oil losses. The second stage employed the Additive Main Effects and Multiplicative Interaction (AMMI) model to further investigate the interaction structure between treatment combinations and factory Mill Locations.

The ANOVA results were first examined to determine whether significant interaction effects existed between treatments and Mill Locations. If the interaction effect was statistically significant, the interaction matrix was subsequently decomposed using Singular Value Decomposition (SVD) to obtain the Interaction Principal Component Axes (IPCA). The resulting IPCA scores were then used to evaluate treatment stability, Mill Locational adaptability, and interaction patterns through AMMI biplot visualization.

$$Y_{ij} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \varepsilon_{ij} \quad \ldots\ldots(1)$$

Y_{ij} = oil loss value for the *i*-th treatment at the *j*-th mill location
μ = overall mean
α_i = treatment effect
β_j = mill location effect
$(\alpha\beta)_{ij}$ = interaction effect between treatment and mill location
ε_{ij} = experimental error

If the interaction effect was found to be statistically significant ($p < 0.05$), the analysis was continued using the Additive Main Effects and Multiplicative Interaction (AMMI) method.

Construction of the Interaction Matrix

The AMMI analysis was initiated by constructing a treatment-by-Mill Location interaction matrix from the mean oil loss values obtained for each treatment combination in every factory. Before decomposition, the additive effects of treatments and factory Mill Locations were removed from the observed data so that the remaining values represented only the interaction effects.

$$I_{ij} = Y_{ij} - \bar{Y} - Y_i - \bar{Y}_j \quad \ldots\ldots(2)$$

This step aims to construct the pure interaction matrix by eliminating the main effects of treatments and locations. The resulting matrix is essential for the subsequent Principal Component Analysis (PCA), which is used to identify the interaction patterns between treatments and locations.

I_{ij} = interaction value
Y_{ij} = observed value
$\bar{Y}$ = overall mean
Y_i = treatment effect

$\bar{Y}_j$ = mill location effect

The resulting interaction matrix was subsequently used as the basis for the AMMI analysis.

AMMI Analysis

After identifying significant treatment-by-Mill Location interactions, the interaction matrix was analyzed using the Additive Main Effects and Multiplicative Interaction (AMMI) model. The mathematical representation of the AMMI model is given as follows:

$$Y_{ij} = \mu + \alpha_i + \beta_j + \sum_{k=1}^{n} \lambda_k \gamma_{ik} \delta_{jk} + \varepsilon_{ij} \quad \text{.....(3)}$$

Y_{ij} = observed value for the *i*-th treatment at the *j*-th mill location
μ = overall mean
α_i = treatment effect
β_j = mill location effect
λ_k = singular value of the *k*-th principal component
γ_{ik} = IPCA score for the *i*-th treatment
δ_{jk} = IPCA score for the *j*-th mill location
n = experimental error

The significant principal components were used to describe the interaction pattern between the treatment combinations and palm oil mill locations.

The AMMI model provides a comprehensive mathematical representation in which the additive part describes the main effects, while the multiplicative PCA component explains the treatment × Mill Location interaction.

a. Treatment Combination (Pi)
   Represents the main effect of the temperature and pressure treatment combinations on the observed response variable.
b. Mill Location (Lj)
   Represents the main effect of the Mill Location or testing location on the observed response variable.
c. Treatment × Mill Location Interaction (P × L)
   Represents the interaction between the temperature–pressure treatment combinations and the Mill Locations. A significant interaction indicates that the response of a treatment varies across different Mill Locations.
d. IPCA1 (Interaction Principal Component Analysis 1)
   Represents the first principal component obtained from the decomposition of the treatment × Mill Location interaction. IPCA1 explains the largest proportion of the interaction variation and is used to evaluate treatment stability across different Mill Locations.
e. IPCA2 (Interaction Principal Component Analysis 2)
   Represents the second principal component, which explains the remaining interaction variation after IPCA1. This component provides additional information regarding the interaction patterns between treatments and Mill Locations.
f. Residual
   Represents the portion of the interaction that cannot be explained by the retained IPCA components. The residual value indicates the amount of unexplained variation remaining after the interaction has been decomposed into principal components.

g. Error (Residual Error)
   Represents the random variation arising from uncontrolled factors during the experiment. The error term serves as the denominator in the F-test to determine the statistical significance of the other sources of variation.
h. Total
   Represents the total variation in the observed data, which is equal to the sum of all sources of variation included in the model.

Singular Value Decomposition (SVD)

The treatment-by-Mill Location interaction matrix was decomposed using Singular Value Decomposition (SVD). This procedure separates the interaction matrix into several orthogonal principal components, each explaining a certain proportion of the interaction variation.

$$Z = ULA^T \quad \text{.....(4)}$$

Z = interaction matrix
U = left singular vector matrix
L = diagonal matrix of singular values
A^T = transpose of the right singular vector matrix

The resulting singular values were used to calculate the eigenvalues, the proportion of variance, and the IPCA scores, which served as the basis for constructing the AMMI biplot.

Interaction Principal Component Axis (IPCA)

The interaction principal component axes (IPCA) were calculated from the SVD results. Each principal component explains a specific proportion of the interaction sum of squares. Components with significant contributions were retained for interpretation, whereas components explaining only a negligible proportion of the interaction variance were considered residual noise. The first interaction principal component (IPCA1) generally explains the largest proportion of the interaction variation and therefore provides the primary basis for evaluating treatment stability. The second component (IPCA2) complements the interpretation by describing additional interaction variability not explained by IPCA1.

AMMI Biplot Interpretation

The interaction patterns between treatment combinations and factory Mill Locations were visualized using an AMMI biplot constructed from the IPCA scores. In the biplot, treatments and Mill Locations located near the origin indicate relatively stable performance because they exhibit minimal interaction effects across Mill Locations. Conversely, points located farther from the origin indicate stronger interaction effects and greater Mill Locational specificity.

Furthermore, treatments positioned close to a particular Mill Location suggest positive adaptation to that Mill Location, whereas treatments located in the opposite direction indicate negative interaction. Therefore, the AMMI biplot provides a graphical interpretation of treatment stability, Mill Locational adaptability, and the association between treatment combinations and factory locations.

The objective of this stage is to identify the actual relationships between treatments and Mill Locations and to determine the stability and adaptability of each treatment across different locations.

a. Points located close to the origin indicate stable treatments.
b. Points located farther from the origin indicate strong interaction effects.
c. The proximity between the treatment and mill location points indicates a tendency for the treatment to be associated with or adapted to a particular mill location.

Through this analysis, the temperature and pressure combination that produces the lowest CPO oil losses while maintaining stability across different palm oil mill locations can be identified.

Flow diagram

The research flowchart is presented in Figure 1.

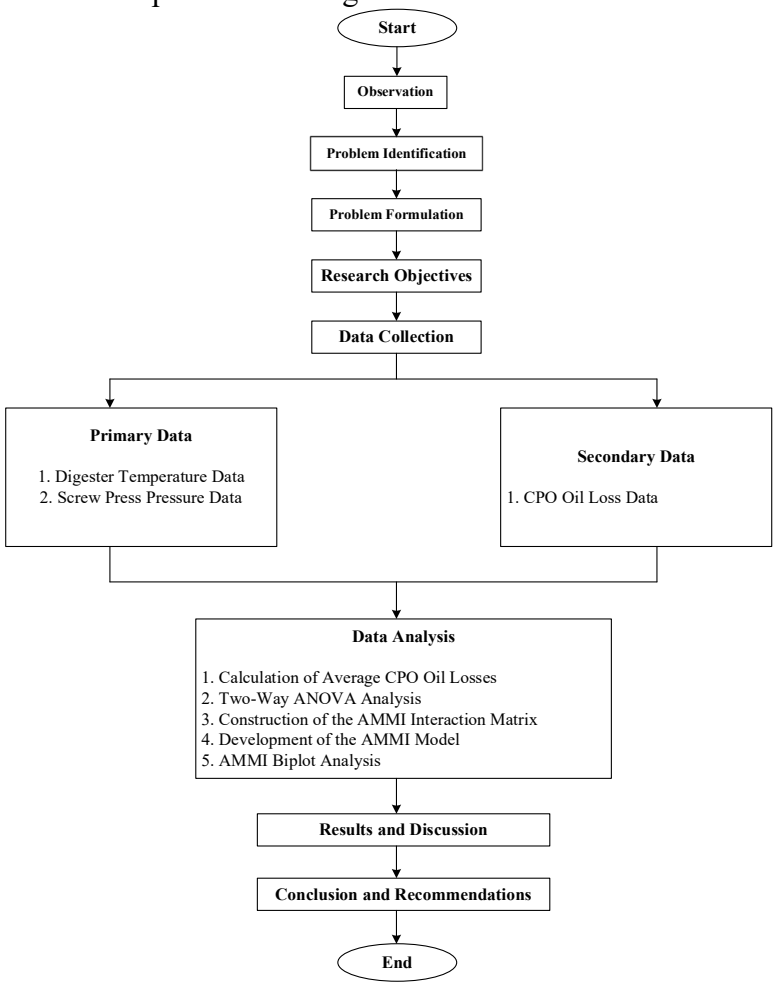


Figure 1. Flowchart

RESULTS AND DISCUSSIONS

Classification of Temperature and Pressure

The research data were collected from three palm oil mills, hereinafter referred to as Mill A (L1), Mill B (L2), and Mill C (L3). Operational data included digester temperature, screw press pressure, and crude palm oil (CPO) oil losses. The digester temperature and screw press pressure were classified into two levels based on class interval analysis to generate the treatment combinations used in the AMMI analysis.

The resulting treatment combinations consisted of S1T2, S2T1, and S2T2. The S1T1 combination was excluded from the analysis because it was not completely available across all research locations, and therefore did not meet the requirements for AMMI analysis. Consequently, only the treatment combinations that were present at all three mill locations were included to ensure a balanced.

Average CPO Oil Losses

The average CPO oil losses for each treatment combination and mill location showed variations in response among the different mill locations. The average values are presented in Table 1.

Table 1. Average Crude Palm Oil (CPO) Losses (%)

FACTOR A	FACTOR B			Treatment Mean (%)
	L1	L2	L3	
S2T2	3,93	3,84	2,98	3,58
S2T1	4,19	4,11	4,28	4,19
S1T2	4,09	4,33	3,3	3,91
Location Mean (%)	**4,07**	**4,09**	**3,52**	**3,89**

Table 1 shows that treatment S2T2 produced the lowest mean CPO oil loss, with an average value of 3.58%, whereas treatment S2T1 resulted in the highest mean oil loss of 4.19%. In terms of location, L3 exhibited the lowest average oil loss (3.52%), while L1 and L2 recorded average losses of 4.07% and 4.09%, respectively. These mean values were subsequently used to estimate the main effects of treatments and locations in the following stage of the analysis. In addition, they served as the basis for constructing the AMMI interaction matrix. The lower oil loss observed under the S2T2 treatment indicates that the selected combination of digester temperature and screw press pressure provided more favorable operating conditions for oil extraction. Appropriate digester temperature reduces oil viscosity and facilitates the rupture of mesocarp cells, while optimum screw press pressure improves oil recovery without causing excessive kernel breakage. These findings suggest that maintaining balanced operating conditions contributes to higher extraction efficiency.

Analysis of Variance (ANOVA)

Analysis of Variance (ANOVA) was performed to determine the effects of mill location, treatment combinations, and their interaction on CPO oil losses

Table 2. Results of the Two-Way Analysis of Variance (ANOVA)

Source	DF	Adj ss	Adj MS	F Value	p-value
Treatment	2	2,718	1,359	7,24	0,002
Location	2	2,33	1,166	6,21	0,004
Treatment*Location	4	1,986	0,496	2,64	0,047
Error	42	7,888	0,187		
Total	50	17,373			

Table 2 The results of the analysis showed that mill location had a significant effect on CPO oil losses (p = 0.004). This finding indicates that differences in the operational

characteristics of each palm oil mill resulted in variations in the level of oil losses during the production process.

The combination of digester temperature and screw press pressure also had a significant effect on CPO oil losses (p = 0.002). This result indicates that variations in digester temperature and screw press pressure directly influenced the efficiency of the oil extraction process.

In addition, the interaction between mill location and treatment combinations was also statistically significant (p = 0.047). This finding indicates that the response of each temperature and pressure combination varied across the different mill locations, thereby requiring further analysis using the Additive Main Effects and Multiplicative Interaction (AMMI) method.

The significant effect of mill location indicates that operational differences among mills, including machine condition, maintenance systems, raw material quality, and production management, contributed to variations in CPO oil losses. This finding confirms that Mill Locational conditions should be considered when optimizing operating parameters.

AMMI Analysis

The combined analysis of variance (ANOVA) revealed a significant treatment × Mill Location interaction, indicating that treatment responses differed across Mill Locations. Consequently, the interaction effect was further analyzed using the Additive Main Effects and Multiplicative Interaction (AMMI) model. Bilinear decomposition was performed to partition the treatment × Mill Location interaction sum of squares into the sums of squares of the Interaction Principal Component Axes (IPCAs), which capture the major patterns of the treatment × Mill Location interaction [18]

Eigenvalues and Proportion of Variance

The AMMI decomposition produced the eigenvalues presented in Table 3.

Table 3. Eigenvalues and Proportion of Variance

Component	*Eigenvalue*	Proportion (%)	Cumulative (%)
IPCA1	0,18999	94,1	94,1
IPCA2	0,01188	5,9	

Table 3 The first principal component (IPCA1) explained 94.1% of the interaction variance between the treatment combinations and mill locations, whereas IPCA2 explained only 5.9%. These results indicate that most of the interaction pattern was explained by IPCA1, indicating that this component was sufficiently representative for describing the relationship between the treatment combinations and mill locations.

Treatment IPCA Scores

The IPCA scores for each treatment are presented in Table 4.

Table 4. IPCA Scores of Treatments Combinations

Treatments	IPCA1	IPCA2
S2T2	0,275680	-0,096955
S2T1	-0,465275	0,017873
S1T2	0,302962	0,12

Table 4 The IPCA scores indicate the magnitude of each treatment's contribution to the interaction effect. Treatments with IPCA scores close to zero tended to be more stable across different mill locations than those with larger IPCA scores.

The S2T2 treatment had a relatively small IPCA score, indicating a high level of stability across the different research locations. In contrast, the S2T1 treatment had the largest IPCA score, indicating that it was more strongly influenced by Mill Locational conditions.

The high proportion of interaction variance explained by IPCA1 indicates that the first interaction principal component adequately represented the treatment × Mill Location interaction. Therefore, the AMMI biplot based on IPCA1 provides a reliable basis for evaluating treatment stability and adaptability across different mill Mill Locations.

Mill Location IPCA Scores

The IPCA scores for each mill location are presented in Table 5

Table 5. IPCA Scores of Locations

Locations	IPCA1	IPCA2
L1	0,359	-0,733
L2	0,456	0,677
L3	-0,815	0,056

As presented in table 5 The mill location IPCA scores indicate that each palm oil mill had different Mill Locational characteristics, resulting in different responses to the temperature and pressure treatment combinations.

AMMI Analysis of Variance

The decomposition of the interaction effect into principal components resulted in the AMMI analysis of variance, as presented in Table 6.

Table 6. AMMI Analysis of Variance for the ammi model

Source of Variation	Df	SS	MS	F Value	P Value
Treatment	2	2,718	1,359	7,24	3,22
Locations	2	2,333	1,1664	6,21	3,22
Interaction	4	1,986	0,4964	2,64	2,59
IPCA1	3	1,869	0,623	3,31	3,22
IPCA2	1	0,117	0,117	0,62	4,07
Error	42	7,888	0,1878		
Total	50	14,373			

Based on table 6 These results indicate that only IPCA1 made a significant contribution to explaining the interaction effect, whereas IPCA2 did not provide any additional meaningful information. Therefore, the interpretation of the interaction pattern was primarily based on the first principal component.

Biplot

The AMMI biplot was used to illustrate the interaction pattern between the treatment combinations and the mill locations. The proximity between the treatment and mill location points indicates a tendency for the treatments to be associated with or adapted to specific mill locations.

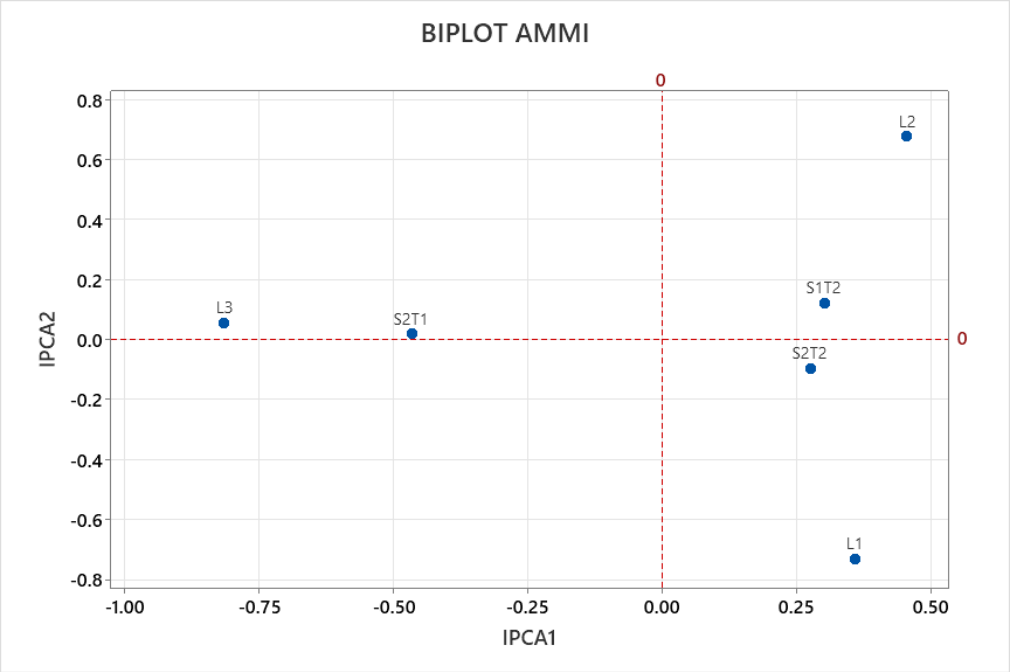


Figure 2. Biplot

Based on the AMMI biplot, the stability of the treatment combinations and mill locations was determined according to their proximity to the origin (0,0) of the biplot. The results showed that the S2T2 treatment combination was the most stable because it was located closest to the origin, followed by the S1T2 treatment combination, whereas the S2T1 treatment combination was the least stable.

AMMI Biplot Interpretation

The AMMI biplot was used to illustrate the relationship between the treatment combinations and the mill locations based on the IPCA1 and IPCA2 scores.

The biplot results showed that the S2T2 treatment combination was located relatively close to the origin, indicating a high level of stability across different mill locations. In addition, S2T2 was positioned in the same quadrant as L1, indicating a tendency for this treatment combination to be associated with L1.

The S1T2 treatment combination was located close to L2, whereas the S2T1 treatment combination was located closer to L3. This proximity indicates that each treatment combination exhibited the best response at a specific mill location. Conversely, the farther a point is located from the origin, the stronger its interaction effect.

Overall, the S2T2 treatment combination can be recommended as the optimal treatment combination because it produced the lowest average CPO oil loss (3.58%) while maintaining good stability across different mill locations. These findings indicate that the temperature and pressure settings represented by the S2T2 treatment combination improved the efficiency of the oil extraction process, thereby minimizing potential oil losses during palm oil processing.

CONCLUSION

Based on the AMMI analysis, a significant treatment × Mill Location interaction was observed, indicating that the effects of temperature and pressure combinations on CPO oil losses varied across mill locations. Among the evaluated treatments, S2T2 produced

the lowest mean CPO oil loss (3.58%) and exhibited good stability under the operational conditions of the three study locations. The AMMI results also revealed specific adaptation patterns, with S2T2 associated with L1, S1T2 with L2, and S2T1 with L3. These findings suggest that the effectiveness of temperature and pressure combinations is influenced by the operational characteristics of each location. Therefore, the S2T2 combination may serve as a reference for evaluating operating parameters under conditions similar to those investigated in this study. However, the results should not be considered a universal standard for temperature and pressure settings, as their effectiveness may vary depending on fresh fruit bunch (FFB) characteristics and the operating conditions of individual palm oil mills.

REFERENCES

[1] J. Supriatna, "Evaluation of the Oil Extraction Rate (OER) Study as a Standard for Oil Palm Harvest," vol. 12, no. 1, pp. 19–28, 2024.

[2] N. Bueraheng, S. Sdoodee, J. Anothai, and T. Eksomtramage, "Stability of oil palm (Elaeis guineensis Jacq.) progenies on yield and yield components across mill locations using AMMI analysis," vol. 12, no. 08, pp. 1259–1264, 2021, doi: 10.21475/ajcs.18.12.08.PNE964.

[3] G. Muslih, Iswarini, and Harniatun, "Agribusiness Production Management Margin of an Oil Palm Factory," pp. 50–59, 2022.

[4] D. Kurnia and S. Lumbantoruan, "Calculation of Oil Losses in Press Cake during the Screw Press Unit Extraction Process at PT. XYZ," pp. 0–4, 2024.

[5] G. S. Dian Bayu and Priyambada, "Analysis of Crude Palm Oil (CPO) Yield Based on Fruit Maturity Level at PT. Bumitama Gunajaya Agro," vol. 1, no. September, pp. 2051–2060, 2023.

[6] L. Masruroh and H. Mardesci, "Oil Palm Fresh Fruit Bunch (FFB) Sterilization Process (Case Study at PT. Tri Bakti Sarimas PKS 2 Ibul, Riau)," J. Teknol. Pertan., vol. 10, no. 1, pp. 43–48, 2021, doi: 10.32520/jtp.v10i1.1282.

[7] O. Hikmawan et al., "Performance Determination of a Palm Oil Mill Digester (Capacity: 10 Tons FFB/Hour) in the Sterilizer Unit," pp. 43–50, 2021.

[8] M. Hutagalung, "Pressure Values and Hydraulic Efficiency of the Automated System in the Process of Pressing Loose Fruits into Crude Palm Oil at the Screw Press Unit of PT XY," 2023.

[9] M. A. Saukani et al., "Analysis of Oil Losses in the Production Process at a Palm Oil Mill," vol. 7, no. 1, 2025.

[10] J. Brigjen, H. H. Basri, H. B. R. V, K. Alalak, K. B. Kuala, and P. K. Selatan, "Oil Losses at the Press Station of PT Palmina Utama," vol. 6, no. June, pp. 37–41, 2021.

[11] T. Ningsih, I. L. Sibuea, and M. Siddiq Dongoran, "AGRO FABRICA: Journal of Palm Oil and Rubber Processing Technology," vol. 2, no. 2, pp. 66–76, 2020.

[12] M. Taufik Siregar, Z. Effendi, B. Mulyara, F. A. Lubis, T. Pengolahan, and H. Perkebunan, "Analysis of Palm Oil Loss Percentage in Press Waste at PTPN VI Solok Selatan Business Unit," Agro Fabr., vol. 5, no. 1, pp. 14–21, 2023.

[13] A. Nurrahman, E. Permana, and A. Musdalifah, "Analysis of Oil Losses in the Production Process at PT X," J. Daur Lingkung., vol. 4, no. 2, p. 59, 2021, doi: 10.33087/daurling.v4i2.89.

[14] J. Yardani, A. Ulimaz, and P. W. Astuti, "Keywords: Crude Palm Oil (CPO); Oil Losses; Empty Bunch; Bunch Press; Control Chart."

[15] A. P. Ranika, S. Meutia, and D. Irwansyah, "Analysis of Oil Loss Control in Crude Palm Oil (CPO) Using the Six Sigma Method," vol. 12, no. 2, pp. 68–74, 2023.
[16] A. Aldi and H. P. Giyanto, "Effect of Moisture Content, Temperature, and Storage Duration on Free Fatty Acid Increase in Crude Palm Oil (CPO)," vol. 6, no. 2, 2024.
[17] T. Firmansyah, Sri Adi Kadarsih, "Use of AMMI Biplot Analysis Technique to Identify Salinity-Tolerant Sesame Accessions," vol. 12, no. July 2012, pp. 86–93, 2020, doi: 10.21082/btsm.v12n2.2020.86-93.
[18] A. Zaki, T. Wuryandari, and Suparti, "Analysis of Variance for a Two-Factor Factorial Experiment in a Randomized Complete Block Design (RCBD) using the Fixed Additive Main Effects and Multiplicative Interaction Method," vol. 3, pp. 529–536, 2024.
[19] I. Widiastuti, "Additive Main Effects and Multiplicative Interaction (AMMI)," 2021.
[20] M. & Sumertajaya, *Experimental Design with SAS and Minitab Applications*. PT. Penerbit IPB Press, 2013.
[21] G. R. Raihanah, "Increasing Shallot Plant Productivity Using the SEM-AMMI Method," vol. 15, no. 1, pp. 115–126, 2021.
[22] J. Tadris, M. Fakultas, I. Keguruan, and I. Batusangkar, "Development of Elementary Statistics Teaching Materials Using the Minitab Application," vol. 10, no. 2, pp. 63–67, 2018.
[23] C. Ma, C. Liu, and Z. Ye, "Effect of Genotype × Environment Interaction on Maize Hybrid Yield Stability Using AMMI and GGE Biplot Models," 2024.
[24] A. Atanasio et al., "Analysis of Genotype × Environment Interaction in Bread Wheat Using AMMI and GGE Biplot Methods," vol. 9, no. 4, pp. 316–325, 2025.
[25] D. N. Tiwari, M. P. Pandey, H. K. Manandhar, and T. N. Bhusal, "Genotype by Mill Location Interaction Using AMMI , GGE Biplot and Multivariate Analysis of Nepalese Aromatic Rice Landraces," vol. 8, no. 1, pp. 34–51, 2024.
[26] S. Haque, S. Khanam, A. S. Hasibuzzaman, and M. Ali, "Analisis Interaksi Genotipe dan Lingkungan pada Kacang Tanah Menggunakan Metode AMMI," vol. 11, no. 3, pp. 389–400, 2024.