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Seasonality and Operational Delays in Palm Kernel Trucking: Evidence from Central Kalimantan (2022–2024)

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ABSTRACT

Timely distribution of Palm Kernel (PK) is critical for maintaining Free Fatty Acid (FFA) levels and supply chain stability, yet logistical inefficiencies persist in the Indonesian palm oil sector. This study empirically investigates the determinants of shipment delays within the trucking logistics framework of a major Palm Oil Mill in Central Kalimantan from 2022 to 2024. Utilizing a mixed-methods approach, the research integrates historical shipment data (N=119), field observations, and linear regression analysis to evaluate six potential delay factors. The findings reveal a 23.5% delay rate over the three-year period, with 'Long Holidays' (religious festivals) and 'Weather/Road Conditions' identified as the most significant predictors of lateness, particularly in 2024 where holidays showed a dominant regression coefficient (β=0.962). Unlike previous studies focusing solely on infrastructure, this research highlights a shift toward seasonal operational constraints and transporter performance. The study implies that technical fleet upgrades are insufficient without adaptive scheduling strategies. Consequently, implementing predictive logistics planning around seasonal events and real-time infrastructure monitoring is recommended to mitigate delays, offering a practical framework for enhancing supply chain resilience in the tropical agricultural industry.

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INTRODUCTION

The global vegetable oil market is heavily reliant on the productivity of the oil palm (*Elaeis guineensis*), with Indonesia contributing approximately 59% of the world's total production [1]. Within this industry, Palm Kernel (PK) constitutes a critical secondary commodity, serving as the raw material for Palm Kernel Oil (PKO), which is essential for the food, cosmetic, and oleochemical sectors [2]. The economic value of PK is intrinsically linked to its quality, specifically the maintenance of low Free Fatty Acid (FFA) levels, which degrades rapidly if the interval between harvest, processing, and delivery is prolonged. Consequently, the efficiency of the logistics supply chain—spanning from the Palm Oil Mill (PKS) to the refinery or buyer—is not merely an operational concern but a determinant of market competitiveness and product integrity. However, logistics in developing regions such as Central Kalimantan faces unique challenges, ranging from infrastructural deficits to complex socio-environmental variables [3], often exacerbated by significant supply chain risks distinct to the Indonesian archipelago [4]. A study [5] further emphasize that transportation inefficiencies in the Indonesian CPO industry significantly inflate production costs, necessitating rigorous performance measurement and improvement strategies.

Despite the critical nature of logistics, existing literature often focuses on macro-level supply chain management or agronomic productivity. For instance, a research [6] highlights general logistical management in plantations, while recent studies [7] discuss the implementation of Industry 4.0 and circular economy concepts in the sector. Similarly, Thoben et al. [8] argue that "Smart Logistics" and IoT integration are the future of manufacturing supply chains. While theoretically valid, these high-level technological perspectives often overlook the foundational "last-mile" transportation bottlenecks in peatland-dominated regions, where terrestrial distribution via trucks remains highly susceptible to physical and social disruptions rather than digital ones. Furthermore, Manning et al. [9] argue that in tropical food supply chains, physical logistics performance is the primary determinant for minimizing food loss and waste. Yet, few studies quantify the specific impact of temporal delays on this efficiency in the specific context of palm kernel distribution. Previous studies [10] have analyzed waiting times at factories but often overlook the interaction between technical fleet conditions and temporal socio-cultural factors. This study addresses this gap by isolating specific delay determinants—ranging from mechanical readiness to seasonal phenomena—within a specific B2B distribution route from PT X to PT Y over a longitudinal period (2022–2024).

The primary objective of this research is to empirically analyze the factors causing shipment delays in PK distribution using a mixed-methods approach. By integrating historical shipment data (N=119) with qualitative field insights, this study evaluates six potential delay variables: truck condition, production fluctuation, weather/road infrastructure, administrative processes, transporter performance, and seasonal holidays. The logistical framework in Central Kalimantan is characterized by distinct constraints, including unpaved plantation roads that deteriorate during the monsoon season and significant labor fluctuations during religious festivals such as *Idul Fitri*. This focus aligns with the "House of Risk" framework proposed by Pujawan and Geraldin [11], which classifies operational interruptions and socio-cultural events as critical supply chain risks requiring proactive rather than reactive mitigation strategies. Understanding these dynamics is crucial for developing resilient supply chain strategies in tropical agrarian economies.

This article proposes a novel perspective by quantifying the impact of socio-cultural calendar events alongside physical infrastructure variables. While conventional wisdom posits that physical infrastructure (roads and weather) is the primary driver of delays [3] [12] this study demonstrates that temporal operational pauses during major holidays exert a statistically dominant influence on delivery schedules, particularly in the post-pandemic recovery period of 2024.

Recent logistics literature increasingly recognizes public holidays and festive seasons as structural logistics shocks rather than incidental disturbances. Obermair et al. [13] show that holiday periods simultaneously generate higher demand pressure while reducing effective working days, creating a systematic capacity squeeze in transportation and warehousing that leads to congestion, longer lead times, and reduced operational flexibility. Complementing this view, Bao et al. [14] demonstrate that public holidays significantly alter traffic flow patterns and intensify congestion risks in road-based transportation networks, resulting in measurable delays and reliability degradation. Taken together, these findings indicate that festive seasons represent predictable, high-impact disruptions driven by the convergence of demand surges, labor and time constraints, and infrastructure congestion, thereby justifying explicit analytical treatment of holiday effects in last-mile logistics delay models.

By utilizing linear regression analysis to calculate the precise coefficient of these disruptions, this research offers a new value proposition: a shift from reactive infrastructure maintenance to predictive, calendar-based logistics planning. This innovation provides actionable insights for stakeholders to mitigate quality loss due to delayed processing.

The remainder of this paper is organized as follows: Section 2 describes the research methodology, including data collection and the mixed-methods design; Section 3 presents the empirical results and discussion regarding the regression analysis and root cause identification; and Section 4 concludes with policy implications for improving supply chain resilience in the palm oil sector.

RESEARCH METHOD

Research Design and Rationale

To achieve a comprehensive understanding of the logistics bottlenecks, this study employs a Sequential Explanatory Mixed-Methods Design [15]. This approach is selected to ensure both statistical generalizability and contextual depth. The first phase involves a quantitative analysis of historical shipment data to identify statistical correlations between delay factors and shipment duration. The second phase utilizes qualitative inquiry through semi-structured interviews to explain the "why" behind the statistical anomalies, particularly regarding seasonal disruptions. This methodological triangulation ensures the validity and reliability of the findings by cross-verifying empirical data with operational realities [16].

Time and Place of Study

The research was conducted at the operational headquarters of PT X and its associated Palm Oil Mill (PKS) in Central Kalimantan, Indonesia.
The observation period spans six months (February to August 2025), while the dataset analyzed covers a longitudinal period of three years (January 2022 – December 2024). This specific location was selected due to its representative nature of peatland-based logistics, characterized by high susceptibility to distinct tropical weather patterns and infrastructural challenges.

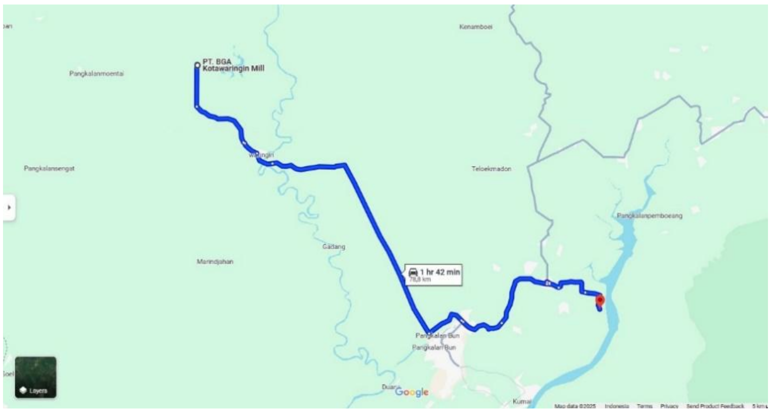

Figure 1. Geographical scope of the logistics route in Central Kalimantan

Data Acquisition and Materials

The data acquisition process involved two distinct streams:

1. Secondary Data (N=119): Historical shipment logs were extracted from the company's Enterprise Resource Planning (ERP) system. The dataset includes dates of *Start Delivery*, *Finish Delivery*, volume (kg), and transporter details. A delivery is classified as "delayed" if the duration (T) exceeds the standard lead time of 14 days ($T > 14$).
2. Primary Data: Qualitative data were gathered through semi-structured interviews with four key stakeholders: the Palm Ground Shipping Section Head, Shipping Officer, Logistics Admin, and Operational Foreman (*Mandor*). These subjects were selected using purposive sampling based on their direct involvement in the decision-making process.

Research Procedure

The research procedure follows a systematic algorithm depicted in Figure 2.

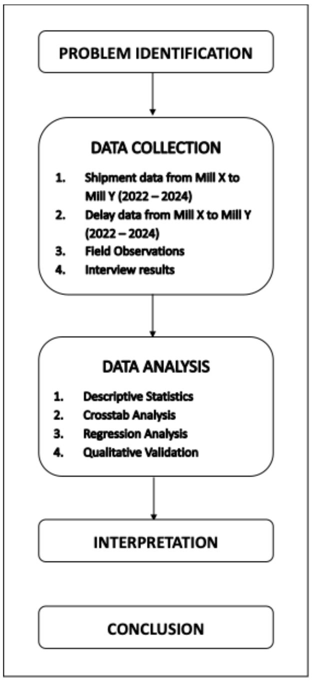

Figure 2. Sequential Explanatory Mixed-Methods Research Flowchart

The systematic procedure is defined as follows:

1. Data Pre-processing: Raw data is cleaned to remove incomplete entries. The dependent variable, Delay Frequency (*Y*), is calculated based on the threshold:
2. Variable Operationalization: The independent variables (*X*) are categorized based on field observations as shown in Table 1.

Table 1. Variable Operationalization

Variable Operationalization			
Variable	**Code**	**Indicator**	**Scale**
Truck Condition	X1	Breakdown frequency, maintenance schedule	Ordinal
Production	X2	Mill output fluctuation vs. quota	Ratio
Weather/ Roads	X3	Rainfall intensity, road deterioration	Nominal
Administration	X4	Document issuance (SIPB) latency	Interval
Transporter	X5	Fleet availability, driver performance	Nominal
Holidays	X6	Idul Fitri, Christmas, New Year periods	Nominal

3. Statistical Modeling: The relationship between the independent variables and delay frequency is analyzed using Multiple Linear Regression. The mathematical model is expressed as [17]:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_3 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \varepsilon$$

Where β represents the regression coefficient indicating the weight of influence for each factor, and ε is the error term.

4. Hypothesis Testing: The significance of the model is tested using the F-test (simultaneous) and t-test (partial) with a confidence interval of 95% ($\alpha = 0.05$).
5. Qualitative Validation: Significant predictors identified in Step 3 are cross-referenced with interview transcripts using Thematic Analysis to derive root causes. Interview transcripts were analyzed using open coding, followed by theme categorization (e.g., labor shortage, road impassability, fleet inflexibility), which were then mapped against statistical outliers.

This study applies Multiple Linear Regression as an exploratory analytical tool to quantify the relative influence of operational, environmental, and socio-cultural factors on shipment delay duration. The dependent variable is defined as delay duration (in days), calculated as the difference between actual delivery time and the company's standard lead time (14 days). As such, the dependent variable is continuous and suitable for regression-based analysis.

Although several independent variables originate from categorical operational records (e.g., holidays, weather disruptions, transporter constraints), these variables were transformed into binary dummy variables to meet regression requirements. The purpose of the regression model is not causal inference or population-level prediction, but applied diagnostics, identifying dominant delay drivers within a specific logistics corridor.

This approach is consistent with applied logistics and supply chain studies where operational datasets are analyzed to support managerial decision-making rather than theory testing. Regression results are therefore interpreted as indicative relationships that support prioritization of mitigation strategies rather than deterministic causality.

Variable Coding and Transformation

All independent variables were derived from operational shipment logs and field validation. To enable quantitative modeling, categorical delay factors were transformed into dummy variables, indicating the presence (1) or absence (0) of each factor for a given shipment record. The operational definitions are summarized as follows:

- Truck Condition (X1): coded as 1 if shipment delay was associated with truck breakdown or maintenance issues; 0 otherwise.
- Production Fluctuation (X2): measured as deviation between planned and realized production volume (ratio scale).
- Weather and Road Condition (X3): coded as 1 if delay coincided with heavy rainfall, flooding, or road impassability; 0 otherwise.
- Administrative Process (X4): coded as 1 if delay was associated with delayed issuance of shipping documents (SIPB); 0 otherwise.
- Transporter Performance (X5): coded as 1 if delay was associated with limited fleet availability or driver readiness; 0 otherwise.
- Seasonal Holidays (X6): coded as 1 if shipment overlapped with major public or religious holidays (Idul Fitri, Christmas, New Year); 0 otherwise.

This transformation ensures consistency between operational records and statistical modeling requirements, while preserving the empirical meaning of each delay factor.

Beyond isolated holiday events, logistics performance is strongly influenced by recurring seasonal demand and supply patterns. Borucka et al. [18] show that explicitly modeling seasonality, such as through time-based dummy variables, reduces estimation bias and improves the explanatory power of logistics performance models in environments subject to cyclical shocks. In tropical agricultural supply chains, seasonality arises not only from production and weather cycles but also from socio-cultural calendars affecting labor availability and transport capacity. Therefore, the inclusion of seasonal and holiday dummy variables in this study is methodologically justified to isolate systematic temporal effects and support more targeted, calendar-aware logistics planning.

RESULTS AND DISCUSSION

Statistical Overview of Shipment Delays

The empirical assessment of 119 shipment logs from 2022–2024 identified 28 validated delay events (100% usable data), resulting in an overall delay rate of 23.5%. Although the absolute number of delays shows a declining trajectory—from 12 cases in 2022 to 7 cases in 2024—the pattern of disruption reveals a substantive shift in the underlying risk structure.

Across the three-year period, Weather & Road Damage and Public Holidays (Eid, Christmas, and New Year) consistently emerged as the dominant contributors, each accounting for 10 delay incidents (35.7%). In 2022, delays were distributed across a wider range of operational and administrative causes, with holiday-related congestion contributing five cases and weather-related issues three cases. The year 2023, however, was marked by a sharp increase in weather-induced delays (n=6), indicating heightened infrastructure vulnerability during the monsoon season. By 2024, holiday-related disruptions once again became the leading source of delays (n=3), reflecting the recurring and predictable influence of major seasonal events.

Secondary factors such as administrative latency, truck condition, transporter constraints, and production-related fluctuations collectively contributed only a small proportion of delays. Their limited impact suggests that internal operational failures have become less influential, reflecting improvements in routine SOPs and day-to-day logistics management.

As depicted in Figure 3, although the overall frequency of delays declined, the severity and concentration of disruptions intensified. By 2024, delays were no longer dispersed but instead clustered around a few high-impact, externally driven events. This pattern indicates that systemic vulnerabilities, particularly those linked to environmental conditions and socio-cultural cycles remain insufficiently mitigated by existing operational controls. Consequently, the data suggests that the core logistics challenge has shifted from internal inefficiencies to external, non-controllable risks that require anticipatory and adaptive management strategies.

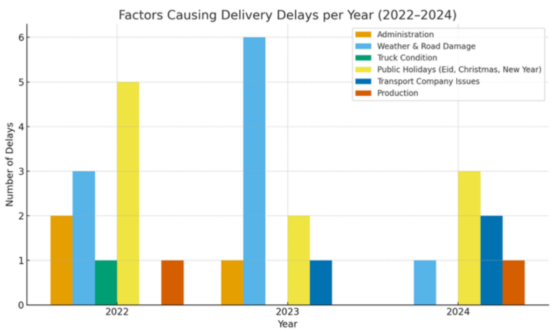

Figure 3. Year-on-Year Comparison of Delay Factors (2022–2024)

This reduction in total delay events aligns with the findings of study [6] suggesting that logistical maturity tends to improve over time as Standard Operating Procedures (SOPs) stabilize. Nevertheless, the persistence of delays in 2024 suggests that certain systemic risks remain unmitigated by standard operational improvements.

Determinants of Delay: Regression Analysis

To quantify the influence of the identified variables, Multiple Linear Regression analysis was conducted for each operational year. The resulting mathematical models describe the probability and weight of delays (Y) as a function of the independent variables (X).

For the most recent operational period (2024), the regression yielded the following equation:

$$Y_{2024} = 0.962X_6 + 0.432X_5 + 0.321X_3 + 0.321X_2 \quad (1)$$

Where:
X_6: Seasonal Holidays
X_5: Transporter Performance
X_3: Weather/Road Condition
X_2: Production Volume

The coefficients (β) indicate the standardized impact of each variable. The results for the entire longitudinal study are summarized in Table 2.

Table 2. Summary of Standardized Regression Coefficients (β)

Factor	Var	β (2022)	β (2023)	β (2024)
Holidays	X6	0.359	0.264	**0.962**
Weather	X3	0.230	**0.541**	0.321
Transporter	X5	0.000	0.196	0.432
Administration	X4	0.180	0.000	0.000
Condition	X1	0.115	0.000	0.000

The regression analysis is conducted on a dataset comprising 119 shipment records, representing the full population of Palm Kernel shipments along the studied route during 2022–2024. As the data are population-based operational logs rather than survey samples, statistical inference is interpreted cautiously.

To capture temporal dynamics, regression models were estimated separately for each operational year. While this segmentation enhances interpretability of evolving risk patterns, it also reduces effective sample size per model. Consequently, the regression results should be interpreted as exploratory indicators of dominant delay factors, not as predictive or generalizable coefficients.

Despite these limitations, the consistency of key variables—particularly seasonal holidays and weather-related disruptions—across multiple years strengthens the robustness of the observed patterns and supports their relevance for applied logistics planning.

Discussion of Key Phenomena

The Dominance of Socio-Cultural Disruptions (X6)

The most significant finding of this study is the drastic escalation of the "Holiday" factor (X6) in 2024, where it reached a dominant coefficient of β= 0.962. This contradicts earlier studies [19] which primarily attributed delays to technical queuing mechanisms at the mill.

The phenomenon observed here is deeply rooted in the socio-cultural fabric of Indonesia. The "Holiday" variable primarily correlates with Idul Fitri, a period characterized by the mass exodus of labor (*Mudik*). During this window, transporter availability drops to near zero as drivers return to their hometowns. A classifies such events as "supply chain risks," but they are often treated as force majeure rather than predictable variables. Our data suggests that as technical efficiency improved (evidenced by β=0 for Truck Condition X1 in 2024), the human resource constraint became the single point of failure. This implies that supply chain resilience in this region is less about mechanical reliability and more about workforce planning during cultural peak periods.

Infrastructural Vulnerability and Weather (X3)
Weather and road conditions (*X3)* remained a consistent predictor of delays throughout the study, peaking in 2023 β=0.541). This aligns with a study [5] which argue that infrastructure quality is the primary cost driver in the Indonesian CPO supply chain.
The PKS–buyer route in Central Kalimantan relies heavily on unpaved peatland roads, which deteriorate rapidly in heavy rainfall.

Figure 4. Condition of unpaved peatland infrastructure during the monsoon season

High rainfall intensity (X3) directly correlates with road impassability, forcing trucks to reduce speed or halt operations entirely to prevent accidents. Unlike the holiday factor, which is temporal, this is a spatial constraint. The persistence of this factor in 2024 (β=0.321) despite lower rainfall indicates that the road infrastructure has suffered cumulative deterioration that maintenance schedules have failed to address.

Transporter Performance vs. Industry 4.0 (X5)
Interestingly, the influence of Transporter Performance (*X5*) rose significantly from non-existent in 2022 to a major factor in 2024 (β=0.432). A study [7] suggests that Industry 4.0 technologies can mitigate such issues through real-time tracking. However, our qualitative validation reveals that the issue is not a lack of data, but a lack of fleet capacity relative to production surges.

In 2024, Production Volume (X2) again exerted influence (β = 0.321), suggesting variability in mill output. However, the transporter fleet lacked the flexibility to scale up in response. This supports the argument by Manning et al. [9] regarding the fragility of tropical food supply chains; when production peaks coincide with logistical rigidity, food loss (quality degradation of PK) becomes inevitable. The gap here is not technological, but contractual and operational, rooted in reliance on a fixed number of trucks incapable of adapting to dynamic logistics demands.
Overall, the evidence indicates a fundamental realignment in the nature of logistical risk: (1) Internal operational issues have declined in significance due to improvements in SOP

implementation and technical reliability; (2) External systemic risks, including socio-cultural cycles, weather fluctuations, and infrastructure degradation, now dominate the logistics environment; (3) Disruptions in 2024 were highly concentrated around predictable events, highlighting the need for anticipatory planning.
Thus, enhancing PK logistics resilience in Central Kalimantan requires moving beyond reactive infrastructure maintenance and toward predictive socio-cultural logistics planning, climate-adaptive routing, and dynamic transporter capacity strategies.

Although the study spans a three-year observation period (2022–2024), the analysis does not constitute a panel model tracking identical shipment units over time. Instead, the research employs a time-segmented longitudinal approach, comparing annual operational patterns within the same logistics corridor.

This approach enables identification of structural shifts in delay determinants, such as the increasing dominance of socio-cultural disruptions in 2024, while remaining appropriate for the structure of the available operational data.

CONCLUSION

This time-segmented longitudinal study has empirically deconstructed the logistical bottlenecks within the Palm Kernel (PK) supply chain in Central Kalimantan. While the overall delay frequency decreased by 41.6% from 2022 to 2024, indicating an improvement in general operational maturity, the nature of supply chain disruptions has evolved from technical to socio-cultural constraints. The multiple linear regression analysis provides compelling evidence that Seasonal Holidays (X6), specifically the *Idul Fitri* period, have become the single most critical determinant of logistics failure in the post-pandemic era (β2024 = 0.962). This refutes the initial hypothesis that physical infrastructure (Weather/Roads X3) is the sole dominant barrier in peatland logistics. While weather remains a constant variable (β2024} = 0.321), its impact is predictable and manageable compared to the systemic paralysis caused by the seasonal labor exodus. Furthermore, the emergence of Transporter Performance (X5) as a significant factor in 2024 (β=0.432) highlights a contractual rigidity in the current logistics model, where fleet capacity fails to scale dynamically with production surges.
Based on these findings, this study proposes a paradigm shift from reactive maintenance to Predictive Socio-Cultural Logistics Planning. Industry practitioners are advised to implement a "Dynamic Holiday-Buffer Protocol," where companies integrate a "Holiday Factor" into their Enterprise Resource Planning (ERP) systems. Shipments scheduled for the $T - 14$ day window prior to major religious festivals should be accelerated or buffered, and contracts with transporters must include "Peak Season Availability" clauses or incentives to retain drivers during holiday periods. Additionally, given the persistence of weather-related delays, logistics managers should utilize real-time rainfall data to dynamically adjust lead times using a "Red-Yellow-Green" dispatch system to prevent truck breakdowns on peatland tracks.
Theoretically, this research extends the House of Risk framework [11] by validating that in tropical developing economies, socio-cultural events function as high-impact supply chain risks comparable to natural disasters. It challenges the techno-centric view of "Smart Logistics" [11] by demonstrating that in "last-mile" agrarian contexts, human resource availability remains the primary constraint over digital connectivity. However, this study is limited to a single B2B distribution route in Central Kalimantan, which may restrict the generalizability of the regression coefficients to regions with different soil types or cultural demographics. Future research should expand this model to a multi-site comparison across Sumatra and Kalimantan to develop a generalized "Tropical Logistics Risk Index" and explore the cost-benefit analysis of investing in private paved roads versus increasing transporter incentives.

This study is subject to several limitations. First, regression analysis is applied as an exploratory diagnostic tool based on operational data from a single B2B distribution route, which limits generalizability to other regions or commodities. Second, categorical delay factors were transformed into dummy variables, which simplifies complex operational realities. Third, year-based regression segmentation reduces statistical power and warrants cautious interpretation of coefficient magnitude.

Nevertheless, these limitations do not undermine the study's primary contribution: identifying dominant and predictable logistics risks that can be proactively managed through calendar-based planning, adaptive fleet contracting, and climate-aware dispatch strategies.

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Please attach clear photo (3x4 cm) and vita. Example of biographies of authors:

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Complementary Subtitles:

NOMENCLATUR (if any) (12 pt, bold)

CPO = Crude Palm Oil
ERP = Enterprise Resource Planning
FFA = Free Fatty Acid
IoT = Internet of Things
PK = Palm Kernel
PKO = Palm Kernel Oil
PKS = Palm Oil Mill (Pabrik Kelapa Sawit)
SIPB = Goods Dispatch Permit (Surat Ijin Pengiriman Barang)
SOP = Standard Operating Procedure
T = Duration of delivery (days)
X_1 = Truck Condition Variable
X_2 = Production Fluctuation Variable
X_3 = Weather and Road Condition Variable
X_4 = Administrative Process Variable
X_5 = Transporter Performance Variable
X_6 = Seasonal Holidays Variable

Y = Delay Frequency/Duration *KD* = *Design Coefficient*

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APPENDIX (if any) (12 pt, bold)

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