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Process Mining-Based Capacity Utilization Analysis in a Manufacturing Company

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Abstract
Purpose: This study provides a strategic analysis of capacity utilization in a manufacturing company by examining workload distribution and transition loss through process mining to facilitate effective decision-making.
Research Methodology: The study was conducted at PT XYZ, a cosmetic manufacturing company in Indonesia that operates a 24-hour, three-shift system. A descriptive quantitative approach was applied using historical event log data from the daily production reports. Event log data from 24,553 production activities (Jan 2020-Mar 2021) were analyzed using Disco (Fluxicon) to visualize production flows, measure transition loss, and evaluate capacity utilization across three shifts.
Results: The results indicated a notable disparity in capacity utilization across shifts, with Shift 1 (50.56%) and Shift 2 (45.15%) overutilized and Shift 3 (4.29%) significantly underutilized. Consequently, the effective production capacity decreased, and the overall operational performance was reduced.
Conclusions: The findings indicate that uneven workload allocation leads to inefficient capacity use, resulting in opportunity and transition loss. Both overuse and underuse during shifts lower the overall production effectiveness. These findings support strategic decisions regarding capacity planning, resource allocation, and performance improvement.
Limitations: This study was limited to a single manufacturing company and relied on manually recorded event log data, which may limit the generalizability of the findings.
Contributions: This study builds on the fields of strategic management and operations management by demonstrating how process mining can be useful in strategic capacity planning and resource allocation decisions.

Keywords: *Capacity Utilization, Operational Management, Process Mining, Production Management, Strategic Management*

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1. Introduction

The cosmetic manufacturing industry is highly competitive, requiring companies to continuously improve their operational efficiency to meet the increasing market demand. In Indonesia, the beauty and personal care market has shown consistent growth and is projected to continue expanding in the coming years, reflecting rising consumer demand and intensifying competition (Statista 2025). This trend is illustrated in Figure 1, which shows the increasing revenue of the beauty and personal care market between 2019 and 2028.

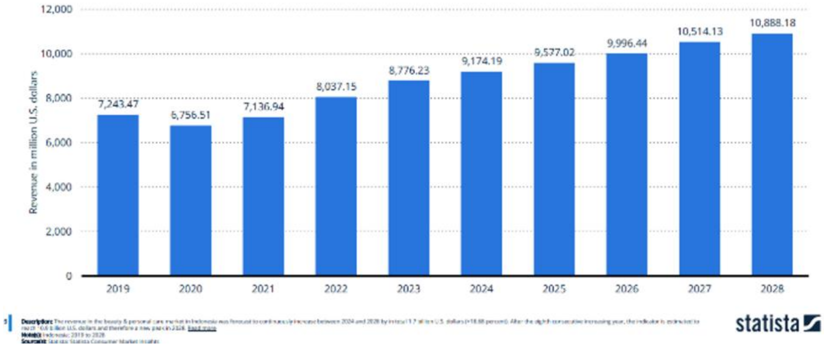

Figure 1. Revenue of the beauty & personal care market in Indonesia

Furthermore, Indonesia's cosmetics sector showed a sustained increasing trend, as shown in Figure 2. The steady increase in revenue indicates that manufacturing companies must continuously improve their production capacity while at the same time maintaining efficiency and quality standards to remain competitive.

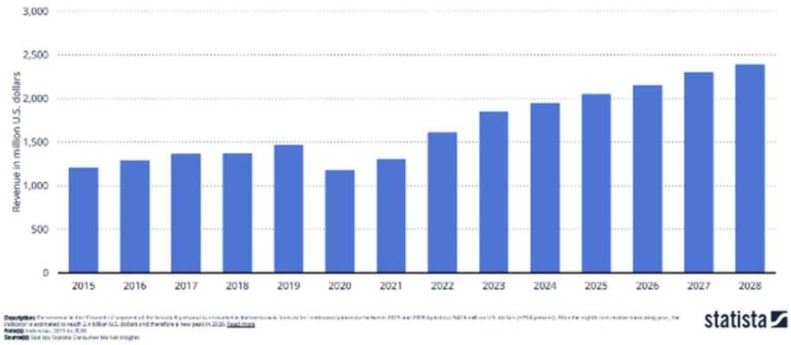

Figure 2. Revenue of the cosmetic industry in Indonesia from 2015 to 2028

However, the workload is not always evenly distributed. This causes inefficient capacity utilization. Consequently, performance decreases and costs increase (Lu, Du, & Peng, 2022). In this context, capacity utilization becomes a critical indicator of how effectively resources are used to support organizational performance (Odei et al., 2024). Employee performance is commonly evaluated based on work quality, quantity of output, and timeliness in completing assigned tasks according to organizational targets (Perwitasari, Pahrudin, Wahyuni, Lermatan, & Sugiyanto, 2025).

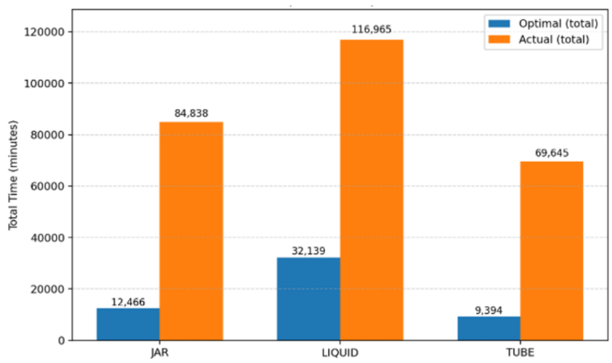

Figure 3. The total actual production time and optimal production time at PT. XYZ

Figure 3 illustrates the enormous gap between the ideal and actual production times in all production areas at PT XYZ. There are substantial inefficiencies in the production process because the actual production time is much longer than the ideal time. The accumulation of ineffective actions that cause the processing time to exceed expectations is shown in this gap (Fuad, 2022). Production inefficiencies in manufacturing environments are often caused by non-value-added activities, such as waiting time, unbalanced workload, and inefficient start-up processes, which reduce equipment effectiveness and operational performance (Khisbulloh & Yudoko, 2024). Variations in operational performance may occur when employee capabilities and work discipline are not fully aligned with task requirements, resulting in inefficiencies and inconsistent productivity levels (Wiyono, Wahyuningsih, Rohayati, & Wulandari, 2026).

From a strategic perspective, this indicates that the company's ability to meet the growing market demand is constrained. The inefficient use of existing production capacity reduces overall operational effectiveness (Battaïa, 2018; Wu & Luo, 2025). Manufacturing organizations continuously seek to streamline processes, reduce waste, and improve operational efficiency to maintain productivity and competitiveness (Ichdan 2024). Furthermore, transition losses can be observed across production activities, as shown in Figure 4. The visualization highlights the difference between the optimal production time and transition loss, indicating that a substantial portion of the production time is spent on non-productive activities.

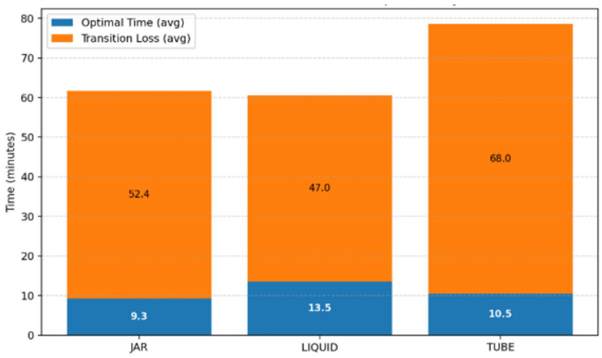

Figure 4. Transition loss visualization at the PT. XYZ

Previous studies have shown that reducing production losses and improving workload balance can significantly enhance the manufacturing performance. (Achmadi, Harsanto, & Yunani, 2023). In recent years, process mining has emerged as an advanced analytical approach for analyzing and improving business processes based on event log data. Although earlier research has applied process mining in manufacturing settings for operational analysis and processes, its application to strategic capacity planning and shift-level workload imbalance in multi-shift production systems has received limited attention. (Er, Arsad, Astuti, Kusumawardani, & Utami, 2018; Lorenz, Senoner, Sihn, & Netland, 2021). Workload distribution across shifts is often uneven in production settings, which can result in underutilization in certain shifts and overutilization in others, eventually decreasing the operational efficiency (Lu et al., 2022).

Although process mining has been increasingly used to examine operational workflows and identify inefficiencies in manufacturing processes, the majority of current research focuses on operational process analysis and productivity enhancement. Organizational performance is closely associated with the effectiveness of task execution and the efficient utilization of resources within operational systems (Subiha, Ruliana, & Permana, 2026). Production losses, bottlenecks, and workflow optimization utilizing event log data have been studied in the past. Nevertheless, few studies have combined capacity utilization assessment with transition loss analysis in multi-shift production systems, especially in manufacturing settings where several production areas run concurrently.

Process mining can assist organizations in visualizing actual process flows, identifying inefficiencies, and supporting decision-making based on actual data. (Alnahas 2023). Despite its potential, there is still limited research that integrates process mining with capacity utilization analysis to support strategic decision-making in manufacturing systems, particularly in identifying transition losses and workload imbalances across shifts (Dreher, Reimann, & Gröger, 2021). Therefore, this study aimed to address this gap by integrating process mining with capacity utilization analysis to examine workload distribution and transition loss in a multi-shift manufacturing environment. Specifically, the objectives of this study are as follows:

1. To analyze workload distribution across shifts using process mining.
2. To quantify the transition loss at both the activity and production area levels.
3. This study aims to provide strategic insights and recommendations for capacity planning and resource allocation.

By integrating process mining with capacity utilization analysis, this study provides empirical insights into how production data can support more effective operational and strategic decision-making in multi-shift manufacturing systems. This study contributes to the literature in three main ways. First, process mining is applied to analyze workload distribution and capacity utilization at the shift level in a multi-shift production setting. To better understand how transition losses affect effective production capacity, it also measures them across production areas. Third, this study presents actual data from the Indonesian cosmetics manufacturing sector, which has yet to receive much attention in operations management studies.

2. Literature Review and Research Framework

2.1 Theoretical Foundation

This section reviews the theoretical foundations relevant to this study, including operations and production management, capacity utilization, and process mining in manufacturing systems. These perspectives provide a theoretical foundation for examining capacity utilization, transition loss, and workload distribution in multi-shift manufacturing environments.

2.1.1 Operational and Production Management

By integrating resources, including labor, machinery, materials, and information, operations management plays a crucial role in effectively converting input into output. It involves key activities, including capacity planning, scheduling, and process design, to ensure optimal performance in terms of cost, quality, and time (Ceylan, Başkurt, Erkan, & Uğur, 2023). Previous studies have also highlighted that operational inefficiencies during production start-up and transition activities significantly impact overall equipment effectiveness and productivity. Reducing non-value-added activities and improving task coordination can enhance operational performance and production efficiency (Khisbulloh Yudoko, 2024). In manufacturing contexts, production management focuses on managing resources to create value through efficient and coordinated production processes. (Basak, Baumers, Holweg, Hague, & Tuck, 2022).

Prior research highlights that optimizing production processes using methodical techniques, such as workflow enhancement and process optimization, can drastically cut delays and inefficiencies (Bähner & Huusom, 2019; Kuhnle, Jakubik, & Lanza, 2019). Furthermore, it has been shown how integrating digital and modern manufacturing technology improves operational performance and provides improved coordination among production processes (Gillani, Chatha, Jajja, & Farooq, 2020). From a strategic management perspective, operations management is concerned with efficiency and how production systems are designed and managed to support long-term competitiveness. Therefore, effective management of production processes is essential for achieving sustainable organizational performance (Fernando & Wulansari, 2020).

2.1.2 Capacity Utilization Theory

Capacity utilization represents the extent to which available production capacity is effectively used to generate output and support organizational objectives (Song, Yao, & Jiang, 2016). Achieving optimal capacity utilization requires a balanced workload distribution, efficient scheduling, and proper coordination of production resources (Horita, 2025). In multi-shift production systems, an imbalance in workload distribution can result in overutilization in certain shifts and underutilization in others, leading to inefficiencies in the overall system performance (Walter, Brückner, & Schumann, 2024). Production losses arise from non-value-adding activities that reduce system efficiency and increase production time. One critical form of loss is transition loss, which includes activities such as setup, cleaning, waiting, and idle time that occur between the production processes (Fuad, 2022). These activities contribute to longer processing times and reduce the effectiveness of capacity utilization (CU). In addition, inefficiencies in production processes may result from equipment-related losses and operational disruptions (Basak et al., 2022).

Furthermore, inefficient capacity utilization leads to opportunity loss, where available production capacity is not fully utilized to generate output (Kusmono, Bangun, & Sushandoyo, 2024). Studies have shown that reducing production losses and improving workload balance are essential for enhancing manufacturing performance and achieving operational excellence (Yoo & Park, 2019). Thus, the efficient control of production losses and capacity utilization is essential for both strategic performance improvement and operational efficiency. Efficient resource utilization and disciplined operational practices enable organizations to achieve higher performance levels and improved productivity (Subiha et al., 2026).

2.1.3 Process Mining in Manufacturing Systems

Process mining is a data-driven analytical approach that integrates process and data science to analyze and improve business processes using event log data (van der Aalst, Reijers, & Maruster, 2024). It facilitates companies in gaining an objective picture of actual process behavior by evaluating the sequences of operations, timestamps, and resource interactions (Kurniati & Wisudiawan, 2021). Process mining has been widely used in production systems to optimize performance, uncover bottlenecks, and increase process transparency (Stefanovic, Dakic, Stevanov, Lolic, & Marjanovic, 2021). It presents a thorough picture of production flows, enabling companies to identify inefficiencies and deviations from planned operations (Er et al., 2018).

Additionally, process mining can be combined with other analytical approaches, such as statistical process control and simulation modeling, to further improve process performance and decision-making (Dogan & Hiziroglu, 2024). Despite its advantages, the successful implementation of process mining depends on data quality, system integration, and organizational readiness (Kusuma, Kurniati, Hafidz, & Johnson, 2023; Rinderle-Ma & Mangler, 2021). Furthermore, although process mining has been extensively used for operational analysis, its application in supporting the strategic evaluation of capacity utilization and production losses remains limited.

2.2 Synthesis and Research Gap

The significance of integrating operations management, capacity utilization, and statistical analytical techniques in manufacturing systems is highlighted by the three theoretical stances discussed above. Although capacity utilization theory explains how available production capacity is utilized to generate output, especially in multi-shift production situations, operations and production management value efficient resource allocation to achieve optimal production performance. Process mining, on the other hand, offers the use of data to examine real operational processes using information from event logs. Few studies have examined how process mining can be used to support the strategic evaluation of capacity utilization and workload distribution across shifts, even though earlier research has used it to analyze operational processes and increase productivity (Er et al., 2018; Lorenz et al., 2021).

Most of these studies prioritize operational process optimization over the strategic assessment of production capacity. Furthermore, studies on capacity utilization and output losses frequently consider these factors independently. Because workload imbalance may substantially impact the efficient use of production resources in multi-shift manufacturing systems, limited studies have integrated transition loss analysis with capacity utilization evaluation. To support strategic capacity planning and resource allocation decisions, empirical insight into how process mining may be used to concurrently examine transition loss, workload distribution, and capacity utilization is lacking. To close this gap, the current study evaluates transition loss and workload imbalance across shifts in a manufacturing setting by integrating process mining with capacity utilization analysis.

2.3 Conceptual Framework and Research Questions

Building on the conceptual framework previously described, this study integrates capacity utilization analysis and process mining to analyze production inefficiencies in multishift manufacturing systems. Process mining is an analytical technique used to depict the actual flow of production activities and construct insights from production event log data. This study allows for the identification and quantification of the transition losses that occur between industrial operations.

Transition losses are non-value-added time that reduces the effective use of industrial capacities. Frequent occurrences of these losses may cause production flow disruptions and workload imbalances between shifts. A production system's overall capacity utilization may be impacted by this imbalance, resulting in some shifts being overutilized while others are underutilized. Consequently, examining transition loss and task distribution offers a crucial foundation for assessing capacity usage and locating operational inefficiencies. From this perspective, process mining enables the identification of transition loss and workload imbalance using real production data, providing a more thorough assessment of capacity usage and offering insights for resource allocation and strategic capacity planning.

The conceptual framework illustrating these relationships is shown in Figure 5.

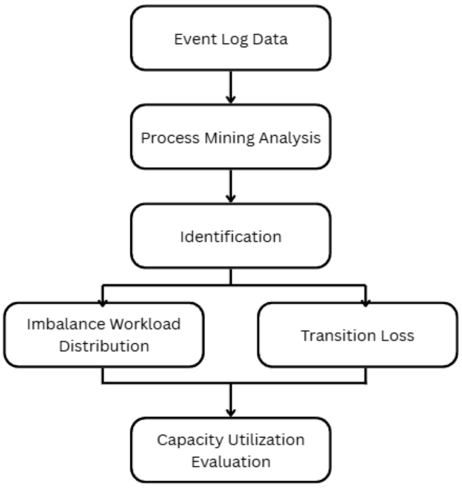

Figure 5. Conceptual framework

Based on the conceptual framework, this study was guided by the following research questions:

- *RQ_1*: How is the production workload distributed across shifts in the manufacturing system of PT XYZ?
- *RQ_2*: How significant is the transition loss across production activities and production areas?
- *RQ_3*: What insights can be derived from the analysis of workload distribution and transition loss to evaluate capacity utilization in manufacturing systems?

3. Methodology

3.1 Research Design

This study applied a descriptive quantitative research design to investigate capacity utilization and transition loss in a manufacturing system. This approach supports a systematic analysis of operational performance using numerical production data to identify patterns and inefficiencies in the manufacturing processes (Brzychczy, Gackowiec, & Liebetrau, 2020). In this study, the approach was applied to evaluate workload distribution, capacity utilization, and transition loss across shifts using historical production data. This study focuses primarily on process-oriented analysis, which uses process mining techniques to visually represent production workflows and assess operational inefficiencies using event-log data. Consequently, this approach prioritizes descriptive and exploratory evaluations of production processes, workload distribution, and transition loss over inferential statistical models. This methodology is compatible with many process mining research studies that seek to find process behavior and operational patterns in event logs before applying predictive or statistical techniques.

3.2 Data and Research Object

The study was conducted at PT XYZ, a cosmetic manufacturing company in Indonesia that operates a 24-hour production system using three shifts. The production system consists of multiple production areas that utilize similar machines and operational resources. The data used in this study were historical production event log data obtained from daily production reports recorded by team leaders during each shift. These event logs contain information such as activity names, timestamps, production durations, and sequences of operations. In the event log structure used for process mining, each recorded activity is associated with a case identifier (Case ID) that represents a single production instance.

In this study, the Case ID corresponds to a production batch processed within a specific production area, and the sequence of activities related to each batch is traced chronologically. Therefore, each event log record contains three key attributes required for process mining analysis: (1) Case ID representing the production batch, (2) activity name describing the production operation performed, and (3) timestamps indicating the start and completion times of each activity. The reconstruction of real production workflows is made possible by this framework, which also facilitates the analysis of activity sequences and processing times. The dataset represents actual production operations and provides a basis for analyzing production behavior, activity sequences, and time utilization patterns based on recorded event log data (Lorenz et al., 2021).

3.3 Data Preprocessing and Preparation

To guarantee data consistency and reliability, the raw production data were pre-processed before process mining analysis. Python was applied during the preparation phase to clean and prepare the event log data obtained from daily production reports. Correcting inconsistent shift labels, standardizing time formats for production activities, and choosing pertinent features required for process mining analysis were all part of the data cleansing procedure. Preprocessing indicated several irregularities, including missing timestamps, formatting mistakes, and incomplete records, because the production data were manually recorded by operators and shift leaders. As the production data were manually recorded by operators and shift leaders, several steps were taken to ensure data reliability.

During the preprocessing stage, the dataset was carefully reviewed to identify inconsistencies, such as missing timestamps, formatting errors, and incomplete records. These issues were addressed through data-cleaning procedures and cross-validation with the original production reports provided by the company. Records with incomplete or inconsistent information were excluded from the analysis to ensure the integrity of the event log dataset used for the process mining. To confirm that the cleaned dataset appropriately reflected actual production activities, these problems were resolved by validating and amending the data in cooperation with the data provider. From the raw dataset, only data relevant to shift-based production activities were retained for analysis.

3.4 Process Mining Approach

This study applies process mining as the primary analytical method to evaluate production processes. Process mining enables the analysis of actual process behavior based on event log data by examining the activity sequences, timestamps, and resource interactions. (van der Aalst et al., 2024). The research was carried out using Disco (Fluxicon), a process mining software tool that visualizes and explores process flows using discovery maps. Disco is used to visualize actual production workflows, detect bottlenecks and inefficiencies, and view workload distribution mapping. Compared to traditional manual analysis, process mining provides a more analytical and objective procedure, thereby making it possible to identify hidden inefficiencies in industrial processes with greater precision (Thiede, Fuerstenau, & Bezerra Barquet, 2018). In this study, no additional filtering was applied during the process mining analysis in the Disco software.

3.5 Measurement of Capacity Utilization and Transition Loss
Capacity utilization is measured based on the distribution of production activities across shifts, relative to the expected balanced workload. In a three-shift system with equal working hours and resources, the expected capacity distribution is assumed to be evenly allocated across shifts (Martha, Yunani, Setiabudi, & Harsanto, 2024; Olaitan, Alfnes, Vatn, & Strandhagen, 2018). Transition loss is defined as the time gap between the actual and optimal production times. It represents non-productive activities, such as setup, cleaning, waiting, and idle time, that occur during production processes (Sunation, Kurniati, & Fuad, 2025).

Inefficiencies in operational processes can arise when task execution lacks consistency or when employee competencies are not optimally matched with job requirements, leading to reduced productivity and performance instability (Wiyono et al., 2026). The measurement method is consistent with prior studies on production loss and time-based performance evaluation in manufacturing systems, which highlights the need to compare actual and ideal production times to detect inefficiencies (Sunation et al., 2025). This approach aligns with prior studies that examined workload distribution in multi-shift manufacturing systems (Song et al., 2016).

3.6 Process Mining Parameters
Process mining analysis was conducted using Disco (Fluxicon), which provides visualization and exploration of process flows based on event log data. To ensure comprehensive process discovery, Disco was configured using the following parameters:

a) Frequency threshold: All recorded actions and transitions may be included in the discovery map because the frequency threshold was set to 0% for both absolute and relative values. The setup guarantees that the analysis includes all the structures of the production process without discarding less frequent tasks that could still cause transition loss.
b) Performance metric: To assess the time taken for each activity and transition, the performance metric was set up using the overall duration. This statistic helps identify time-related inefficiencies in the production process and makes it possible to identify activities that contribute significantly to the overall production time.
c) Path analysis: Variant-based path analysis was applied to examine the sequence of activities within each production case. This method identifies typical workflow patterns and detects differences in the execution of production procedures among various production batches.

These parameter settings enable process mining analysis to capture the structural and temporal aspects of the production workflow, resulting in the discovery of bottlenecks, transition losses, and task distribution patterns.

3.7 Research Presumptions and Conditions
This study is based on various expectations to ensure that the analysis is consistent and comparable. First, each shift is considered to have identical working hours, resources, and production capability, which permits the workload allocation to be assessed proportionally. Second, production processes are believed to follow standard protocols in all production regions. Third, the event log data recorded in the daily production reports has been regarded as accurately reflect the actual production operations. Finally, the optimal production time was defined based on the standard processing duration under normal operating conditions. These presumptions are required to simplify research and provide a consistent evaluation of capacity usage and transition loss across shifts.

Although this analysis assumes that all shifts have the same production capacity, the actual operating conditions may differ because of variations in worker skill levels, machine conditions, maintenance schedules, and operational disturbances. The actual production performance and task distribution among shifts may be affected by these factors. Consequently, these presumptions should be considered when interpreting the study's findings. To provide a more thorough assessment of capacity utilization in industrial systems, future research should include more operational variables.

4. Results and Discussion

4.1 Data Characteristics

The data used in this study consisted of secondary production event log data obtained from the production system of PT XYZ. The dataset records production activities chronologically, including the Case ID, activity name, production area, timestamps (start and end times), production quantity, target achievement, and shift classification. The data analyzed covered the period from January 2020 to March 2021 and represented actual production conditions. The analyzed dataset consisted of 16,069 cleaned activity records derived from an initial raw dataset of 24,553 production entries, representing the validated event log used for process mining analysis.

Before the analysis, the data were standardized and classified into three shifts based on the company's operational working hours to ensure accurate workload mapping. As the data were manually recorded by shift leaders and operators, they reflect real operational conditions, although some informal non-productive activities may not be fully captured in the data. Nevertheless, event log data provide sufficient information to analyze production behavior, time utilization, and process inefficiencies (Er et al., 2018; Lorenz et al., 2021).

4.2 Transition Loss at Activity Level

To illustrate how transition loss occurs at the micro-level, a production batch record was analyzed. Table 1 presents an example of production activity data, including the preparation time, production time, and recorded timestamps.

Table 1. Illustration of production activity record at PT XYZ

Item Code	Total Item	Preparation Time	Production Time	Time Start	Time End
A01	1000pcs	00:10:00	00:20:00	10:00	10:45

Ideally, the production process should be completed within 30 min (10 min preparation + 20 min production). However, the recorded duration was 45 min, indicating a 15-minute gap. This gap represents transition loss, which consists of non-value-added time that is not directly associated with productive activities. Such hidden time losses accumulate across production batches and significantly reduce the effective production capacity (Fuad, 2022). Note that the illustrative data are based on typical production batch records.

4.3 Total Transition Loss by Production Area

Comparing the actual and ideal production times across production locations resulted in a more thorough analysis of transition loss. Figure 6 shows a comparison of the total optimal and actual production times for the Jar, Liquid, and Tube production areas. The results show a substantial gap between the optimal and actual production times in all production areas, indicating the presence of significant transition losses within the manufacturing process. Among the three areas, the liquid production area exhibited the largest transition loss, followed by the Jar and Tube areas.

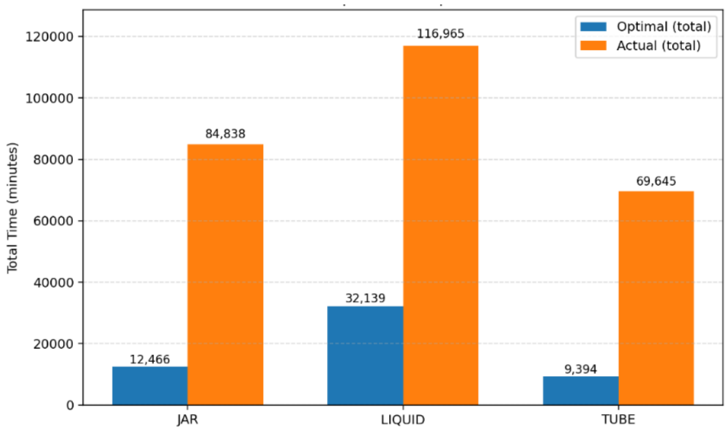

Figure 6. Total actual production time and optimal production time by production area

The large differences between the optimal and actual production times imply that activities such as material preparation, machine setup, cleaning, and waiting periods frequently occur between production batches. These transition-related activities extend the total processing time and reduce the effective utilization of the available production capacity. These inefficiencies align with earlier research highlighting how transition activities affect production performance (Fuad, 2022; Sunation et al., 2025).

4.3.1 Production Efficiency Ratio

To further quantify the production performance, a production efficiency ratio (PER) was calculated by comparing the optimal production time to the actual production time. In this study, the optimal production time represents the expected processing time under ideal operational conditions, whereas the actual production time reflects the total time consumed during real production activities. Therefore, the production efficiency ratio is defined as the proportion of the optimal processing time relative to the total actual production time:

$$PER = \frac{Optimal\ Production\ Time}{Actual\ Production\ Time} \quad (1)$$

A higher PER indicates that the production process operates closer to its optimal processing conditions, which means that a larger proportion of the production time contributes directly to value-adding activities. Conversely, a lower PER indicates that a significant share of the production time is consumed by non-productive or transition activities such as machine setup, cleaning operations, waiting periods, or coordination delays between production batches.

Table 2. Production efficiency ratio by production area

Production Area	Optimal Time (Minutes)	Actual Time (Minutes)	Production Efficiency Ratio
Jar	12,466	84,838	0.147
Liquid	32,139	116,965	0.275
Tube	9,349	69,645	0.135

To interpret the calculated Production Efficiency Ratio (PER), the results can be compared with common efficiency benchmarks used in manufacturing performance evaluation. In industrial engineering, production efficiency is frequently assessed using metrics such as Overall Equipment Effectiveness (OEE), which measures the proportion of productive manufacturing time relative to the theoretical maximum. OEE integrates several operational factors, such as availability, performance, and quality, to evaluate the effectiveness of manufacturing processes and machine utilization (Klimecka-Tatar and Ingaldi, 2022). In practical manufacturing environments, OEE values above 0.85 are generally considered world-class performance, values between 0.60 and 0.85 represent acceptable operational performance, and values below 0.60 indicate relatively low production efficiency. These benchmarks are widely used to evaluate the effectiveness of production systems and identify operational inefficiencies in manufacturing processes.

The production efficiency resulting from the PER calculation varied across the three production areas. The Liquid production area had the highest efficiency ratio (0.275), indicating that a relatively large proportion of its production time contributed to effective processing activities. In contrast, the Jar and Tube production areas show lower efficiency ratios of 0.147 and 0.135, respectively, indicating that transition-related activities occupy a larger share of their total production time. In manufacturing environments, process performance is commonly evaluated using key performance indicators (KPIs), which provide measurable metrics for assessing whether operational processes achieve their expected efficiency. KPIs support organizations in evaluating how effectively production processes utilize resources (Sujová, Vysloužilová, Koleda, & Gajdzik, 2023). When efficiency indicators show relatively small ratios between effective production output and total process resources, it typically indicates operational inefficiencies or non-value-added activities within the process.

Compared with common manufacturing efficiency benchmarks, where acceptable operational performance typically exceeds 0.60, the PER values obtained in this study (0.147, 0.275, and 0.135) are substantially lower. This indicates that only a small proportion of the total production time corresponds to effective processing activities, whereas a large share of time is consumed by transition-related operations. The results suggest that a significant share of production time is consumed by non-productive activities, such as machine setup, cleaning operations, waiting periods, and coordination delays between production batches. Overall, the relatively low efficiency ratios across all production areas confirm substantial transition losses within the production system. These findings support the earlier results obtained from process mining analysis, which revealed frequent setup, cleaning, and preparation activities between production batches. From an operational perspective, reducing the duration and frequency of these transition activities can significantly improve production efficiency and increase the effective utilization of manufacturing capacity.

4.4 Process Mining Analysis

Disco (Fluxicon) was used to conduct process mining analysis and visualize the actual production workflow based on event log data. Figure 7 illustrates the discovery map of the production process, based on activity frequency. In the visualization, nodes represent production activities, and the thickness of the connecting arrows indicates the frequency of transitions between activities. The results show that machine cleaning and setup are among the most frequently occurring activities in the production workflow. The high frequency of transitions between setup and cleaning activities suggests that the production processes involve frequent interruptions between consecutive production batches. These repeated transitions indicate that preparation and changeover activities occupy a significant portion of the production workflow. From an operational perspective, this pattern reflects the presence of frequent transition cycles, which may reduce production continuity and contribute to transition losses within the manufacturing system. These frequent changes indicate that the production process has redundancies and counterproductive cycles (van der Aalst et al., 2024).

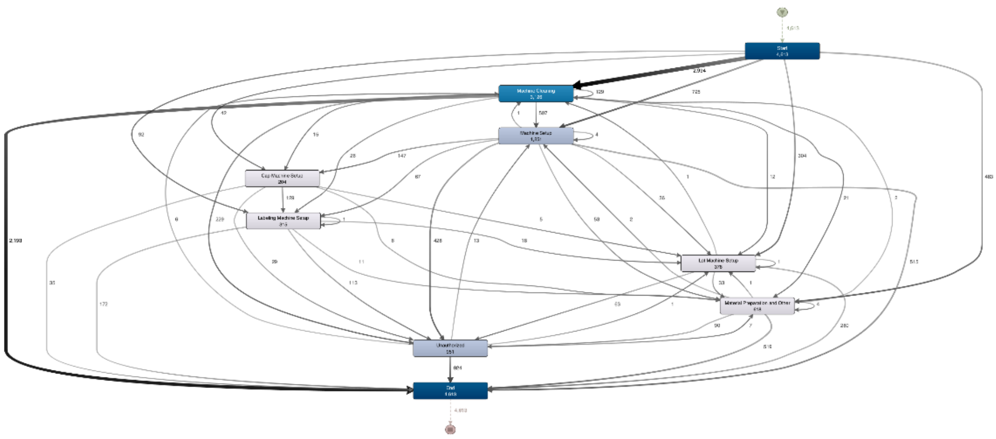

Figure 7. Discovery map based on frequency

The discovery map highlights several activities that frequently occur in the production process. The most common activities include machine cleaning, machine setup, unauthorized activities, material preparation, and lot machine setups. The high frequency of these activities indicates repeated transitions between the preparation and operational stages within the production workflow.

1. Machine Cleaning (3,126 occurrences)
2. Machine Setup (1,251 occurrences)
3. Unauthorized activities (951 occurrences)
4. Material Preparation (618 occurrences)
5. Lot Machine Setup (378 occurrences)

Figure 7 presents the discovery map from a performance perspective, where the visualization emphasizes the duration associated with each activity and the transition. The analysis revealed that machine cleaning and setup consumed the largest proportion of the total production time. Although some activities may occur less frequently, their longer duration significantly affects the overall production cycle.

Based on the performance analysis, the activities with the highest time consumption included:
1. Machine Cleaning (13.2 weeks)
2. Machine Setup (40.8 days)
3. Unauthorized activities (17 days)
4. Material Preparation and Other (12.7 days)
5. Lot Machine Setup (6.7 days)

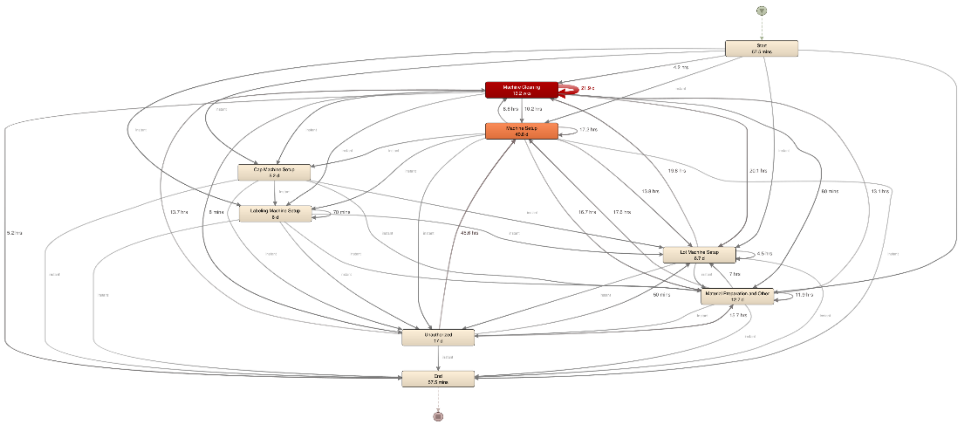

Figure 8. Discovery map based on performance

These findings indicate that non-value-added and transition-related activities consume a substantial portion of the total production time. In particular, the dominance of cleaning and setup activities suggests inefficiencies in transition management, which directly contribute to transition losses. Compared to the frequency-based analysis in Figure 7, this performance-based perspective reveals that even activities with lower occurrences can have a significant impact if they require a long processing time. From a strategic perspective, the company struggles to meet the increasing demand. This is caused by the inefficient use of production capacity (Bähner & Huusom, 2019; Dzakiy, Sushandoyo, Simatupang, Prasetio, & Mirzanti, 2025). Process mining visualization revealed that several non-value-added activities occurred frequently within the production process. Activities such as machine cleaning and setup dominate both frequency and performance perspectives, indicating repeated transition cycles within the workflow.

4.5 Capacity Utilization Across Shifts

Production activities were analyzed across shifts to evaluate the capacity utilization. Figure 9 illustrates the distribution of production activities across the three operational shifts in the plant. Ideally, the production workload should be evenly distributed across shifts, with each shift contributing approximately one-third of the total production activities. However, the results showed a significant imbalance in the workload distribution. Shift 1 accounts for more than half of the total production activities, whereas Shift 3 contributes only a small proportion.

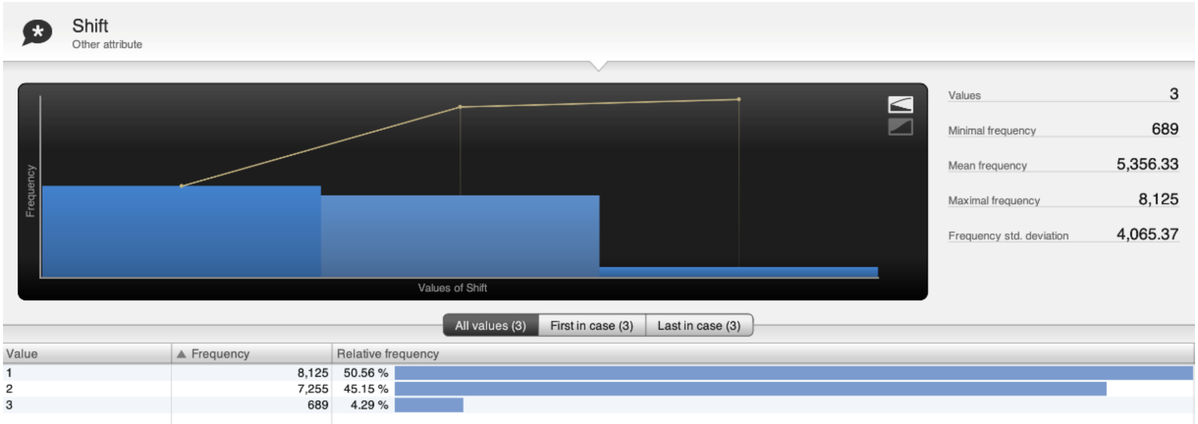

Figure 9. Distribution of production activities by shift

The distribution of the 16,069 analyzed activities is as follows:
1. Shift 1: 50.56%
2. Shift 2: 45.15%
3. Shift 3: 4.29%

The results showed a significant imbalance in the workload distribution. Shifts 1 and 2 are heavily utilized, whereas Shift 3 is significantly underutilized. In a balanced system, each shift should contribute approximately 33.33% of the total activities, assuming equal working hours and resource allocation across shifts, reflecting proportional capacity allocation in multishift manufacturing systems (Song et al., 2016; Walter et al., 2024). This imbalance indicates inefficient capacity allocation and suboptimal utilization of available production resources, which can negatively affect overall system performance (Aldianto, Tjakraatmadja, Larso, Primiana, & Anggadwita, 2021).

The results in Table 3 confirm that capacity utilization is not evenly distributed across the shifts. Overutilization in Shifts 1 and 2 indicates excessive workload concentration, whereas underutilization in Shift 3 reflects unused production capacity, limiting operational effectiveness and production performance (Alamsyah, Ramadhani, Kristanti, & Khairunnisa, 2022).

Table 3. Capacity Utilization Result

Shift	Frequency	Activity	Threshold	Result
1	50.56%	8,125	33.33%	Overutilized
2	45.15%	7,255	33.33%	Slightly Overutilized
3	4.29%	689	33.33%	Underutilized

Disproportionate capacity utilization across shifts, where some resources are overworked while others are idle, decreases overall system efficiency and eventually limits production performance and the organization's capacity to rapidly adapt to market demand (Madiawati & Wijaksana, 2023). The severe underutilization of Shift 3 (4.29% of total activities) indicates that the production capacity during the night shift is largely unused by the workers. This imbalance suggests that production activities are primarily concentrated during daytime operations.

Several operational factors may contribute to this condition, including limited workforce availability during night shifts, operational preferences for daytime production, and the absence of scheduled production planning for late shifts. From a strategic perspective, this imbalance represents a potential opportunity loss because operational resources, such as machines, facilities, and utilities, remain available but are not fully utilized to generate production output. This additional efficiency metric complements the process mining analysis by providing a quantitative indicator of production inefficiency across different production areas.

4.6 Analysis of Transition Loss and Production Time

Further analysis was conducted to compare the optimal production time and transition loss across shifts and production areas. Figure 10 compares the average optimal production times across shifts. The relatively consistent optimal processing time indicates that the production standards and processing requirements remain similar regardless of the shift. This suggests that the production process design is relatively stable across operational periods. Therefore, the variations observed in the actual production time are more likely to be caused by execution-related factors rather than differences in process standards. These factors may include operational delays, transition activities, and coordination inefficiencies during production execution.

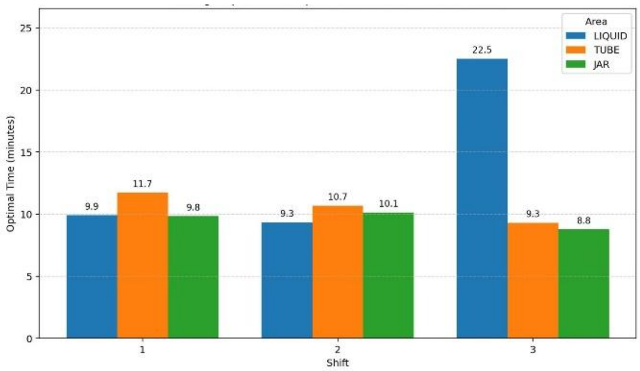

Figure 10. Average optimal production time per shift

The results show that the ideal production time is largely constant during shifts, indicating that the process standards are consistent. However, actual time variations point to executional inefficiencies rather than flaws in the process design. Figure 11 presents the average transition loss observed across the shifts and production areas. The results indicate that the tube production area experiences the highest transition loss, followed by the Jar and Liquid areas. Interestingly, although Shift 3 records the lowest number of production activities, it exhibits a relatively high transition loss.

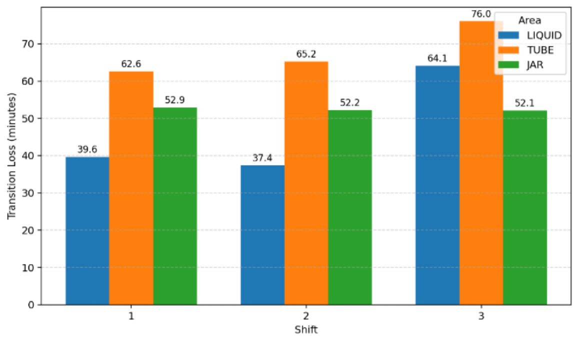

Figure 11. Average transition loss per shift

Across all shifts, the tube production area experienced the most significant transition loss, followed by the jar and liquid areas. Despite having a low activity volume, shift 3 showed a larger transition loss, implying inefficiency even under inadequate utilization. This finding suggests that inefficiencies may occur, regardless of production volume. In other words, even when production activity is limited, transition-related interruptions can significantly affect the processing time. This indicates that operational coordination and transition management remain important factors influencing production efficiency across all the shifts.

Figure 12 shows the distribution of the total actual production time across shifts. The results indicate that the majority of the production time is concentrated in Shifts 1 and 2, whereas Shift 3 contributes only a small portion of the total processing time. The imbalance observed in the activity distribution indicates that the manufacturing system experiences simultaneous overutilization and underutilization of production capacity. Although daytime shifts operate under heavier workloads, the available capacity during the night shift remains largely unused. From a strategic perspective, this imbalance represents an opportunity loss, as existing production resources could be utilized more effectively through improved workload allocation across shifts.

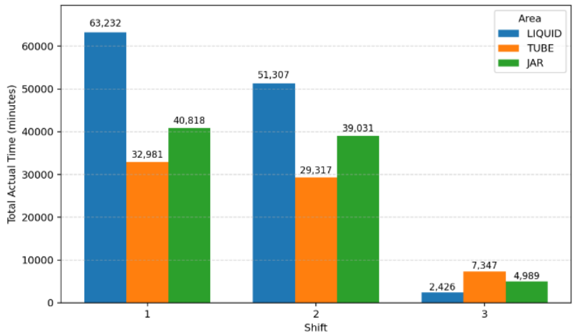

Figure 12. Total actual time per shift

Shifts 1 and 2 occupy the majority of the production time, with Shift 3 contributing a small percentage. This indicates that the system is experiencing both overutilization and underutilization because of the disparate distribution of capacity utilization. The results indicate that although Shift 3 has the lowest number of production activities, it still experiences a relatively high transition loss. This finding suggests that inefficiencies occur not only due to excessive workload but also due to operational interruptions and transition-related activities in the ED. Therefore, improving transition management and optimizing activity scheduling can help reduce unnecessary delays and improve overall production efficiency.

4.7 Synthesis of Results

The results demonstrate two key findings. First, capacity utilization was ineffective because of the highly uneven workload distribution across shifts. Certain shifts were overutilized, whereas others were underutilized. This reduces the efficient utilization of the available capacity and lowers the overall production efficiency. Second, high transition losses contribute to opportunity losses. Non-value-added operations consume a large amount of production time, especially in the Tube and Liquid sections. Owing to the underutilization of available capacity, these inefficiencies reduce the effective production time and directly result in opportunity loss (Fuad, 2022). The transition loss ratio was calculated as the proportion of non-productive time to the total production time, adding an indicator of production inefficiency across production areas. Through process mining, actual manufacturing processes can be thoroughly and impartially analyzed, presenting insights that are useful in strategic decision-making regarding workload distribution, capacity planning, and process development (Dogan & Hiziroglu, 2024).

5. Conclusions

5.1 Conclusion

This study analyzed the capacity utilization and transition loss in a multi-shift manufacturing system using process mining. The results revealed a significant imbalance in workload distribution across shifts at PT XYZ. Shift 1 (50.56%) and Shift 2 (45.15%) are overutilized, while Shift 3 (4.29%) is severely underutilized, indicating inefficient allocation of production capacity. In addition, substantial transition losses were identified across production areas, particularly in the Tube and Liquid processes, where non-value-added activities consume a significant portion of the production time. These inefficiencies reduce the effective production capacity and limit the overall operational performance. The results show that by offering statistical insights into workload distribution and transition losses, process mining can effectively reveal hidden inefficiencies in production systems. From a strategic standpoint, these insights support better decision-making in capacity planning, resource allocation, and production process improvements.

5.2 Research Limitations

This study had several limitations that should be considered when interpreting the results. First, the study was limited to a single manufacturing company, which may affect the generalizability of the findings across different industries. Future studies should include multiple case studies to improve external validity. Second, the analysis relies on manually recorded event log data, which may not fully capture all non-productive activities that occur during production processes. This limitation may affect the accuracy of the transition loss measurement and overall performance evaluation. Previous research suggests that integrating digital systems and advanced data analytics can improve data accuracy and operational monitoring. Third, the study assumes equal working hours and production capacity across shifts, which may not fully reflect the actual operational conditions. Variations in workforce capability, machine reliability, and operational disruptions may influence the actual production performance. Therefore, future studies should incorporate these factors to provide a more comprehensive analysis of capacity utilization.

This study contributes to the operations management literature by demonstrating how process mining can bridge the gap between operational data analysis and strategic decision-making in manufacturing systems. By applying process mining to analyze workload distribution and transition losses, this study extends previous research that primarily focused on operational process improvement. The findings validate the applicability of process mining for shift-level capacity utilization analysis, supporting recent calls for more strategic applications of process mining in manufacturing.

5.3 Suggestions and Directions for Future Research

Future research could extend this study by incorporating additional quantitative and statistical techniques, such as correlation analysis, regression modeling, and predictive analytics, to further examine the relationships between transition loss, workload distribution, and production performance. From an academic perspective, future research could extend this study by integrating process mining with advanced analytical techniques, such as machine learning, to predict transition loss patterns and identify potential production bottlenecks. Comparative studies involving multiple manufacturing companies or different industries could provide broader insights into capacity utilization patterns and improve the generalizability of the findings.

In addition, integrating process mining with simulation modelling and intelligent manufacturing systems may further enhance decision-making and process optimization in manufacturing environments. Future studies should explore the integration of process mining with real-time production monitoring systems to support more dynamic capacity planning. Moreover, investigating the role of innovation capability and digital transformation in improving manufacturing performance and strategic competitiveness can provide deeper insights into how operational analytics contribute to long-term organizational performance.

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Author Contributions

CF conceptualized the study, designed the research methodology, and was responsible for the data collection, analysis, and interpretation. BP contributed to the development of the research framework, assisted with data analysis, and participated in the manuscript revisions. GPK provided key input on process mining techniques, contributed to the analysis and interpretation of the results, and revised the manuscript. AMF contributed to the research design, refined the theoretical framework, and provided critical feedback during manuscript revision. All authors have reviewed and approved the final manuscript for publication.

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