JABA
Journal of Applied Business Administration
https://jurnal.polibatam.ac.id/index.php/JABA

Optimizing Powertrain Disassembly Efficiency via Machine Learning -Based Lean Six Sigma at PT.TU Surabaya Branch

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Abstract
Operational efficiency is vital in mining and construction, were equipment availability drives productivity. This study assesses reconditioning effectiveness for Powertrain components at PT. TU Surabaya, focusing on the Disassembly stage the primary bottleneck in the maintenance cycle. Lean Six Sigma is applied using the DMAIC (Define, Measure, Analyze, Improve, Control) framework to identify, measure, and regulate service duration factors. Machine Learning, via Decision Tree Regression in KNIME, analyzes historical data to predict optimal Disassembly timeframes. Efficiency improvement is implemented using the 5S method, while a Decision Matrix prioritizes solutions to enhance overall system performance. Results from initial implementation show a reduction in average process duration from 26.37 days to 15.33 days. Predictive analysis also reflects an increase in Process Cycle Efficiency (PCE) from 46.49% to 53.20%. These findings affirm the effectiveness of a structured, data-driven operational strategy that combines Lean Six Sigma and predictive analytics to resolve service bottlenecks and improve industrial process outcomes.

Keywords: Decision Tree Regression, DMAIC, Lean Six Sigma, Operational Efficiency, Process Cycle Efficiency

Article History:
Received: July 13, 2025; Accepted: September 1, 2025; Published: September 26, 2025

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DOI:
https://doi.org/10.30871/jaba.10209

JEL Code:
L72, M11, D24

INTRODUCTION

Indonesia abundant natural resources have positioned the mining sector as one of the key pillars of its national economy. According to data from (Badan Pusat Statistik (BPS), 2024.), mining and quarrying contributed Rp2,198,018.10 to the national GDP in 2023. In parallel, Indonesia's infrastructure expansion, propelled by National Strategic Projects (PSN), has significantly stimulated the construction sector, contributing Rp2,072,384.80 to GDP and reinforcing the structural underpinnings of national economic development.

Table 1. GDP on the basis of prices in business sector

Description	Amount
Manufacturing Industry	Rp3,900,061.70
Large and Retail	Rp2,702,445.60
Agriculture, Forestry and Fisheries	Rp2,617,670.00
Mining and quarrying	Rp2,198,018.10
Construction	Rp2,072,384.80

Source: (Badan Pusat Statistik (BPS), 2024.)

As both mining and construction activities intensify, the demand for high-performance heavy equipment such as excavators, dump trucks, and bulldozers continues to rise. These machines operate in harsh environments and play a vital role in ensuring operational continuity. Their efficiency is not only determined by acquisition cost and lifespan but also by the speed and reliability of maintenance services. Timely reconditioning and reduced downtime are essential to minimize operational disruptions and cost overruns (Saputra et al., 2023).

Given the strategic importance of reconditioning in sustaining heavy equipment performance, attention turns to key industry players that provide such services in Indonesia. In this context, PT. TU, the official distributor of Caterpillar equipment since 1971, plays a pivotal role in supporting industrial operations through its after-sales services. Among these, the System Component Reconditioning Service is particularly crucial for maintaining equipment reliability. One of PT.TU's key branches located in Surabaya serves the East Java region, including major clients in the mining sector.

However, PT.TU Surabaya has recently faced challenges in delivering timely reconditioning services, particularly for MMG a prominent mining company operating in Banyuwangi. MMG has reported prolonged service durations for Powertrain components, which are critical systems responsible for transmitting engine power to the drivetrain, including the transmission, torque converter, and final drive. These delays have resulted in extended equipment downtime and increased operational costs. This study aimed to analyze historical reconditioning data at PT.TU Surabaya to identify bottlenecks and propose improvements for service efficiency.

To better understand the scope and impact of this issue, an analysis was conducted on 344 reconditioning jobs performed for MMG between January 2023 and May 2024. The data revealed that 42% of these jobs involved Powertrain systems, making them the most frequently serviced component (PT.TU Surabaya, 2024). Historical records indicate that the average reconditioning duration reached 84–85 days, spanning five main stages: Disassembly, Prepare Quotation, Customer Approval, Part Order, and Assembly. In the context of this research, Turnaround Time was established collaboratively between the client and the service provider, aiming for job completion within 30–45 days, typically based on the complexity of the maintenance and the anticipated readiness of required parts. Nevertheless, empirical observations reveal that actual execution frequently surpasses this threshold, extending up to 84–85 working days. Such deviations from the agreed timeline not only compromise service reliability but also pose substantial risks of stakeholder dissatisfaction and economic setbacks for the clients, with calculations estimated that 84-85 days of downtime could result in losses of ±$2.94 million for a CAT 773E unit and ±$2.18 million for a CAT 745 unit (PT.TU Surabaya, 2024). This underscores the urgent need for a systematic approach to enhance the efficiency of the reconditioning process.

A closer examination of the workflow reveals that, within the five stages of the reconditioning process, the Disassembly stage represents the most time-consuming phase, with an average duration of 26.37 days, thereby warranting particular attention in efforts to improve overall efficiency (PT.TU Surabaya, 2024). As the primary bottleneck, this stage not only extends the overall maintenance cycle but also delays the redeployment of equipment to operational sites, which in turn disrupts MMG's productivity and project timelines.

In order to address these inefficiencies in a systematic and data-driven manner, Lean Six Sigma (LSS), guided by the DMAIC framework (Define, Measure, Analyze, Improve, Control), was selected as the core methodology to identify and reduce waste and process variation within the reconditioning workflow. Its effectiveness has been demonstrated across various industries, including railcar bogie assembly (Daniyan et al., 2022) and sustainable maintenance in manufacturing (Antosz et al., 2022), making it a robust foundation for process improvement in this study. However, given the complexity of operational data and the need for more accurate time predictions to determine the optimal scheduling of each stage in the Disassembly process present challenges that cannot be fully addressed by LSS alone. To overcome this limitation, this research integrates Machine Learning (ML) into the LSS framework. Specifically, the open-source KNIME Analytics Platform is employed to implement the Decision Tree Regression algorithm, enabling predictive modeling of Disassembly duration based on historical job records. This hybrid approach aligns with the findings of (Pongboonchai-Empl, 2023), who advocates for the incorporation of Industry 4.0 technologies such as ML into the DMAIC 4.0 framework to support data-driven decision-making.

This integration reinforces the relevance of LSS in the digital era. (Acito, 2023) emphasized the usefulness of Decision Tree Regression for prediction, market segmentation, and interaction detection in operational contexts. Furthermore, (Shivaramu, 2025) demonstrated the potential of combining ML algorithms with the LSS DMAIC framework to optimize predictive strategies. His study achieved a significant reduction in machine failure rates and improved process capability, validating the role of data-driven methodologies in enhancing operational reliability. Therefore, this study not only introduces an innovative approach to improving Disassembly efficiency but also contributes to the advancement of LSS 4.0 methodology in the context of data-driven operations.

The integration of ML into the LSS framework is projected to significantly enhance operational efficiency. Specifically, it is expected to reduce the average disassembly duration from 26.37 days to fewer than 20, and compress the overall powertrain reconditioning turnaround time from 84-85 days to within the contractual range of 30-45 days. These improvements are anticipated to minimize equipment downtime and better align actual performance with service-level agreements. Such alignment not only reinforces service reliability but also elevates customer satisfaction, fully in line with contemporary operational management principles that prioritize efficiency, predictability, and sustainability (Heizer et al., 2020).

RESEARCH METHOD

The researcher employed a Mixed-Method research design to examine the Disassembly process of Powertrain components at PT. TU, Surabaya branch. The study population consisted of individuals directly involved in the System Component Reconditioning process, identified based on their functional roles, level of involvement, and technical responsibilities. From this population, respondents were selected to include a project leader, supervisor, foreman, technicians, and one individual certified with a Green Belt in Six Sigma. Selection prioritized personnel actively engaged in planning, execution, supervision, and quality control, ensuring that the data captured both operational practices and managerial perspectives. The inclusion of Six Sigma-certified personnel further enriched the analysis by introducing insights into structured problem-solving and process improvement methodologies.

This research integrates both qualitative and quantitative data. Qualitative data were obtained through observations, interviews, and brainstorming sessions, aimed at capturing experiential insights, operational challenges, and improvement opportunities. Quantitative data were derived from historical records of disassembly process durations, spanning January 2023 to May 2024, which enabled performance benchmarking and identification of timeline deviations.

Primary data were collected through direct observation and discussions with stakeholders, while secondary data included standard operating procedures (SOPs), academic literature, and internal company archives. Data analysis was conducted using the LSS framework with a DMAIC approach, integrated with ML, LSS is defined by (Jiménez-Delgado et al., 2023) as a fusion of Lean aimed at reducing non-value-added activities and Six Sigma, which targets process variation. (Tarantino, 2022) emphasizes that this synergy fosters a sustainable improvement culture through continuous refinement beyond project completion. ML complements this framework by enabling predictive analytics based on historical data. As classified by (Çinar et al., 2020).

Describe ML as a subfield of Artificial Intelligence (AI) that enables systems to learn from data and improve performance autonomously, ML techniques include Supervised, Unsupervised, and Reinforcement Learning (Janiesch et al., 2021). Platforms such as KNIME allow users to execute ML workflows visually and without coding, making advanced analytics accessible and impactful (Acito, 2023), (Bansal et al., 2022) define Decision Tree as a supervised learning algorithm used for both classification and regression. In process prediction contexts,

Decision Tree Regression divides datasets into meaningful subsets based on relevant attributes to estimate continuous values, specifically the Decision Tree Regression algorithm via the KNIME Analytics Platform. Model performance was assessed through validation and reliability testing using MAE, RMSE, and MAPE metrics (Acito, 2023). To sustain improvements, a Decision Matrix prioritized solutions based on financial impact, customer satisfaction, efficiency, and implementation ease. As noted by (S. Ariantini et al., 2023) the method involves selecting criteria, weighting them, scoring alternatives, and choosing the best option. (Triantaphyllou, 2000) adds that techniques such as the Analytic Hierarchy Process (AHP) can be applied to rationalize the weighting of criteria objectively., ensuring structured and outcome-focused decision-making within the reconditioning process at PT. TU Surabaya

The conceptual framework integrates LSS methodology with ML technologies to improve the efficiency of the Disassembly process in Powertrain component reconditioning. This approach is grounded in the principles of Total Quality Management (TQM), which emphasize continuous improvement and customer satisfaction. LSS serves as the foundation for identifying and reducing process inefficiencies through the DMAIC structure, while ML supports data-driven prediction to guide informed decision making.

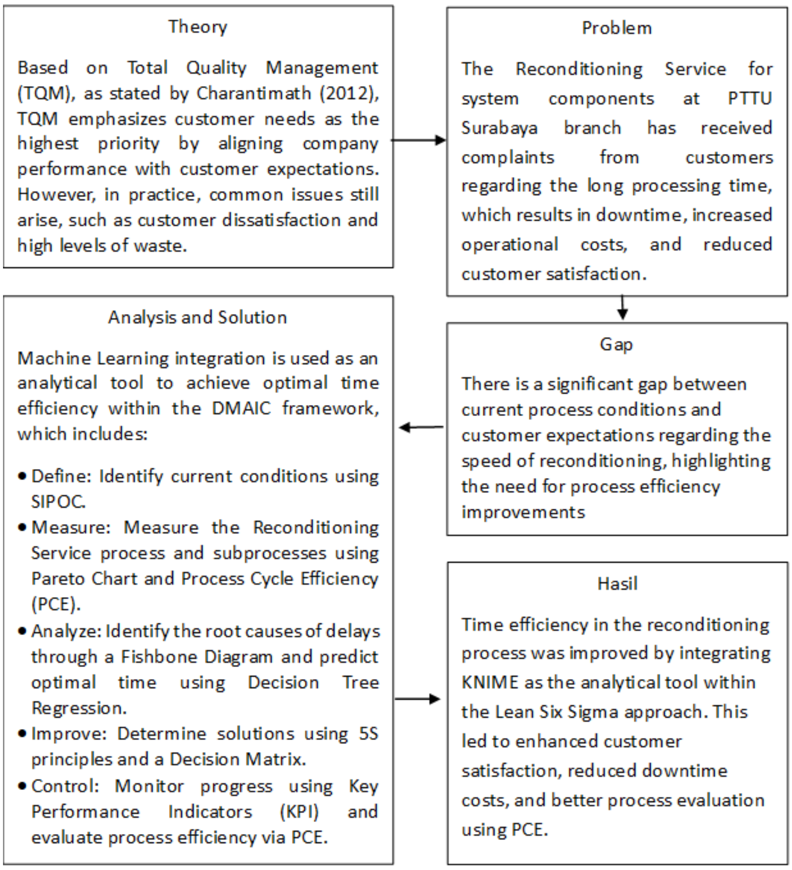

Figure 1. Conceptual Framework

Equations

Process Cycle Efficiency (PCE) is defined as the ratio of Value Added Time to Total Process Time, as stated by Ying (2011) in (Adeodu et al., 2021).Value Added Time refers to the productive time that contributes additional value to the product being processed, while Total Process Time encompasses the entire duration required to complete the process

$$PCE = \frac{VDT}{TT} 100\%$$

Note :

PCE = Process Cycle Time
VDT = Value Added Time
TT = Total Time = Value Added Time + Non Value Added Time

RESULTS AND DISCUSSION

Result

The DMAIC methodology was used to systematically identify, analyze, and improve the efficiency of the Disassembly process in Powertrain component reconditioning. Each step Define, Measure, Analyze, Improve, and Control was executed to minimize time waste, enhance prediction accuracy, and ensure sustainable improvements.

Define

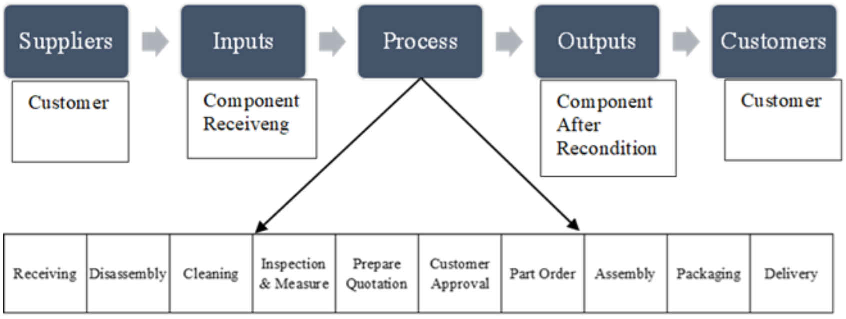

Figure 2. SIPOC Diagram
Source: Data Processing (2025)

The Disassembly process was identified as the most time-consuming subprocess in the Powertrain reconditioning service at PT. TU, Surabaya. Historical data showed that Disassembly accounted for an average of 26.37 days out of a total Lead Time of 84.16 days, contributing significantly to customer downtime and operational costs. Using SIPOC, the workflow was mapped from Open Ticket to Start Disassembly, Disassembly, and then to Component Condition Report (CCR), allowing for clear identification of critical points and problem boundaries.

Mesure

The Measure phase aimed to assess actual process conditions and pinpoint inefficiency hotspots. A dataset of 132 historical records (Jan 2023–May 2024) was evaluated, distinguishing between Lead Time, Cycle Time, Value-Added Time (VAT), and Non-Value Added Time (NVAT) to calculate Process Cycle Efficiency (PCE).

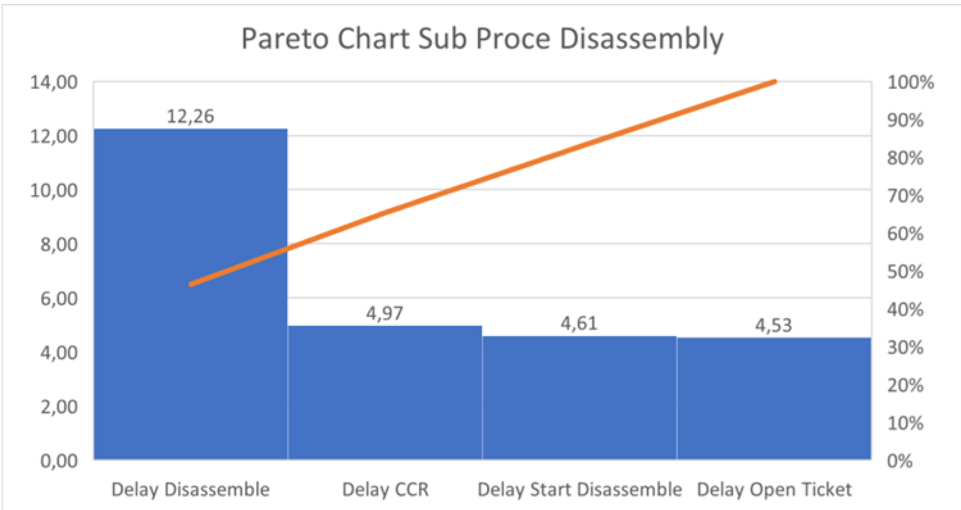

Figure 3. Pareto Chart
Source: Data Processing (2025)

Based on Figure 3, the Disassembly subprocess has the highest average Cycle Time, reaching 12.26 days, followed by the Component Condition Report (CCR) at 4.97 days, Start Disassembly at 4.61 days, and Open Ticket at 4.53 days. The total time required for the Disassembly process amounted to 26.37 days. By applying the Process Cycle Efficiency (PCE) method, the initial efficiency was calculated at 46.49%, indicating that more than half of the total process time was spent on activities that do not directly add value. This measurement revealed that the actual value-added time comprised only around 12.26 days out of the full 26.37 days, highlighting a significant opportunity for improvement. The findings offer a solid quantitative foundation for establishing performance benchmarks and guide the improvement efforts toward activities that have the greatest impact on process efficiency.

Analyze

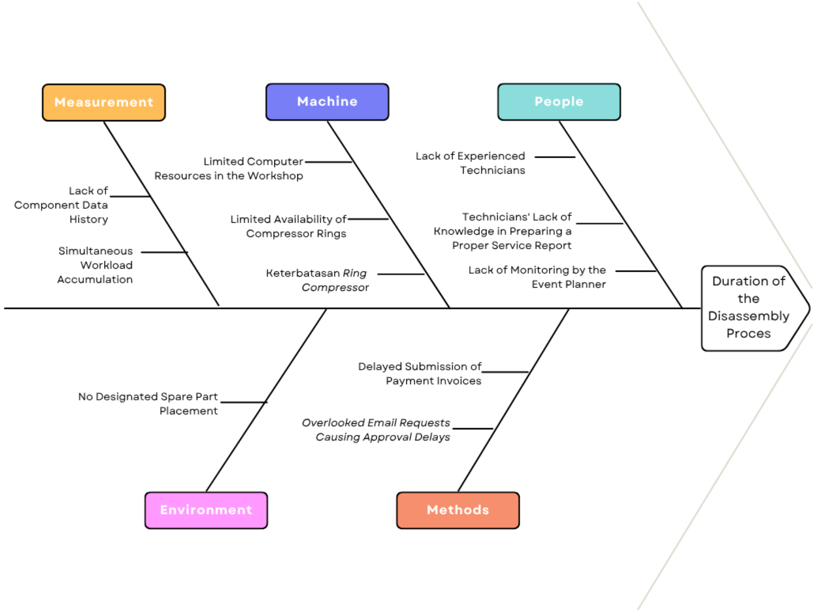

Figure 4. Fishbone Diagram
Source: Data Processing (2025)

The Analyze phase aims to identify the root causes behind the prolonged duration of the Disassembly process. A Fishbone Diagram, shown in Figure 4, was used to categorize these causes into five main groups: Man, Method, Machine, Material, and Environment. Several key factors were identified, including a lack of experienced technicians, limited supporting tools such as ring compressors and computers, and delays in the submission of invoices and approval of quotations. Additionally, the accumulation of jobs occurring simultaneously also contributed significantly to the delays.

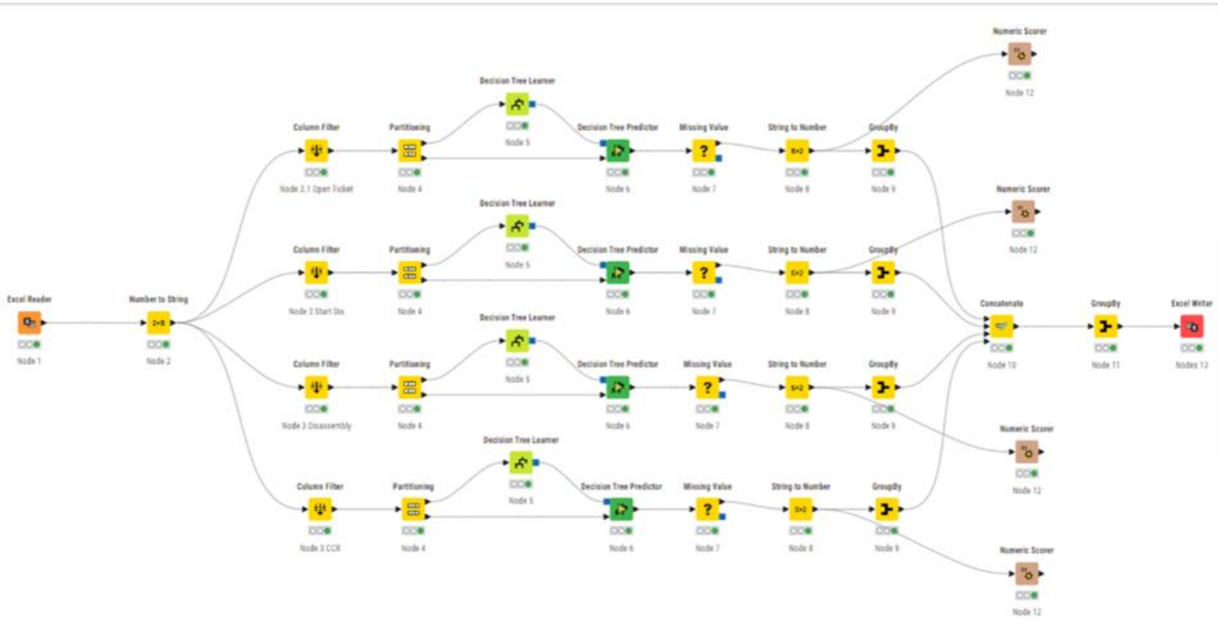

Figure 5. Knime Workflow
Source: Knime Analytics Platform (Version 5.4.4)

Quantitative analysis in this research was conducted using the Decision Tree Regression algorithm through the KNIME Analytics Platform (Version 5.4.4). The workflow illustrated in Figure 5 includes stages such as data reading, preprocessing, model training, and prediction evaluation. This approach enables systematic and structured modeling for each subprocess within the Disassembly phase.

Table 2. Prediction Result of the Decicion Tree Regression

Prediction (Open Ticket)	Prediction (Start Disassembly)	Prediction (Disassembly)	Prediction (CCR)
2,00	1,22	5,70	1,78

Source: Data Processing (2025)

This model predicted the optimal duration based on historical data patterns for each subprocess. According to Table 2, the total ideal time for the Disassembly process can be reduced to 10.70 days, with the following breakdown: Open Ticket (2.00 days), Start Disassembly (1.22 days), Disassembly (5.70 days), and Component Condition Report (CCR) (1.78 days). These results serve as a realistic benchmark for setting achievable process efficiency targets.

Table 3. Numeric Scorer Result of the Prediction

Proses	MAE	RMSE	MAPE
Open Ticket	5.37	10.851	1.226
Start Disassembly	3.889	9.09	0.324
Disassembly	15.333	40.562	0.828
CCR	2.296	6.76	0.16

Source: Data Processing (2025)

Model evaluation using MAE, RMSE, and MAPE (Table 3) confirmed the prediction accuracy of the Decision Tree Regression. At PT.TU Surabaya, MAE reflects the average deviation between predicted and actual Disassembly time, while RMSE highlights outliers that signal potential inefficiencies. MAPE, expressed as a percentage, enables comparison across sub-processes and time periods. These results demonstrate the model's reliability in supporting strategic decisions, optimizing resources, and minimizing downtime. Integrating ML in the Analyze phase replaces intuition-based estimates with data-driven precision, aligning with LSS 4.0 principles for continuous improvement.

Compared to conventional methods that rely heavily on technician intuition and manual estimation, the predictive model demonstrates superior consistency and objectivity. Traditional approaches often lack historical benchmarking and are prone to subjective bias, resulting in fluctuating service timelines and reduced customer satisfaction. In contrast, the ML model trained on 132 historical records delivers quantifiable insights that align with LSS 4.0 principles, emphasizing precision, repeatability, and continuous improvement.

Improvement

The Improvement phase focused on formulating and implementing solutions that address the root causes identified earlier. These solutions were developed based on the 5S principles: Sort, Set in Order, Shine, Standardize, and Sustain. The solutions aligned with each 5S category are detailed in Table 4 below.

Table 4. Solutions Based on 5S Principles

5S	Issue	Solution
Sort	- Simultaneous workload accumulation - Ignored Quotation Requests from originating branch	- Knowledge sharing among technicians on selecting the correct spare parts and avoiding unnecessary tasks

5S	Issue	Solution
		- Approving Disassembly Quotations within two days
Set in Order	- No dedicated area for disassembled spare parts	- Organizing spare parts using racks/boxes categorized by type and size (Bearings, Shafts, Clutches, Driveshafts)
Shine	- Lack of spray tools for cleaning disassembled spare parts	- Adding spray tools for component cleaning
Standardize	- Poor detail in technicians service report documentation - Limited availability of Compressor Rings - Limited computers in the workshop	- Standardizing guidelines for proper service report writing - Submitting budget requests for equipment - Adding more computers
Sustain	- 60% of technicians have under three years of experience - Delayed submission of payment invoices - Lack of monitoring from Event Planner	- Conduct regular training and knowledge-sharing sessions - Rotate technician roles every six months - Recruit technicians from other branches - Hire experienced technicians - Initiate training programs for Event Planner

Source: Data Processing (2025)

The structured application of 5S principles directly contributed to operational efficiency by eliminating root causes of delay and disorganization. Sort and Set in Order reduced non-value-added activities and improved spare part accessibility, while shine accelerated component readiness. Standardize minimized documentation errors and resource gaps, and sustain enhanced workforce capability through targeted interventions. These integrated actions fostered a more responsive and streamlined workflow, validating 5S as a catalyst for Lean-driven performance improvement.

Table 5. Decision Matrix

Order	Solution	Criterion														Total
		Financial Stability		**Internal/External Satisfaction**		**Increase Efficiency**		**Possible Success**		**Ease of Implementation**		**Ease of Implementation**		**Implementation Time**		
	Weight	**20%**		**15%**		**15%**		**15%**		**10%**		**15%**		**10%**		**100%**
1	Expedite the delivery of invoice documents to customers up to three days after the date of the Invoice.	9	1,8	7	1,05	7	1,05	7	1,05	5	0,5	9	1,35	5	0,5	7,3
2	Standardize how to create a good repair report.	1	0,2	9	1,35	9	1,35	7	1,05	9	0,9	9	1,35	5	0,5	6,7
3	Rotation of technician roles every six months	9	1,8	9	1,35	9	1,35	9	1,35	3	0,3	1	0,15	1	0,1	6,4
4	Share knowledge between technicians in sorting and choosing the right spare parts.	1	0,2	1	0,15	9	1,35	9	1,35	9	0,9	9	1,35	9	0,9	6,2
5	Periodic training and Knowledge Sharing.	1	0,2	1	0,15	9	1,35	9	1,35	9	0,9	9	1,35	9	0,9	6,2

Order	Solution	Criterion														
		Financial Stability		Internal/External Satisfaction		Increase Efficiency		Possible Success		Ease of Implementation		Ease of Implementation		Implementation Time		Total
	Weight	20%		15%		15%		15%		10%		15%		10%		100%
6	Approve Quotation Disassembly within two days.	1	0,2	1	0,15	9	1,35	9	1,35	9	0,9	9	1,35	9	0,9	6,2
7	Training program for Event Planners	1	0,2	1	0,15	3	0,45	5	0,75	7	0,7	9	1,35	1	0,1	3,7
8	Recruit technicians from other branches	1	0,2	1	0,15	5	0,75	5	0,75	3	0,3	5	0,75	1	0,1	3
9	The addition of a sprayer to clean the components.	1	0,2	1	0,15	9	1,35	5	0,75	1	0,1	1	0,15	1	0,1	2,8
10	Budget submission for tools	1	0,2	1	0,15	7	1,05	3	0,45	1	0,1	1	0,15	1	0,1	2,2
11	Adding computers to the Workshop	1	0,2	1	0,15	5	0,75	3	0,45	3	0,3	1	0,15	1	0,1	2,1
12	Hire experienced technicians	1	0,2	1	0,15	1	0,15	1	0,15	1	0,1	1	0,15	1	0,1	1

Source: Data Processing (2025)

The solutions were prioritized using a Decision Matrix presented in Table 5, based on seven criteria: financial benefits, customer satisfaction, efficiency improvement, success probability, ease of implementation, cost, and execution time. The results identified six solutions for initial implementation, which include:

1. Accelerating the delivery of invoice documents to customers maximum three days after the invoice date, with a score of 7.3
2. Standardizing the format for creating thorough repair reports, with a score of 6.7
3. Rotating technician roles every six months, with a score of 6.4
4. Sharing knowledge among technicians to correctly sort and select the right spare parts, with a score of 6.2
5. Conducting regular training and knowledge-sharing sessions, with a score of 6.2
6. Approving Disassembly quotations within 2 days, with a score of 6.2

Table 6. Cycle Time After Early Process Improvement

Period	Open Ticket	Start Disassembly	Disassembly	CCR	Total Disassembly
Average	4,67	3,00	5,00	2,67	15,33
8500326156	2	1	2	1	6
8600790356	6	4	6	4	20
8600790384	6	4	7	3	20

Source: Data Processing (2025)

After implementing the initial solutions, observations were conducted on three reconditioning jobs to evaluate the impact of the improvements. As shown in Table 6, the average Disassembly process time decreased to 15.33 days, reflecting an efficiency gain of 11.04 days compared to the initial condition. This reduction indicates not only enhanced task execution but also improved coordination among subprocesses.
Process optimization was observed across nearly all subprocesses, with the most substantial improvement occurring in the Disassembly stage, which had previously been identified as the primary bottleneck. Furthermore, the actual outcomes closely aligned with the ML predictions, reinforcing the validity of this data-driven approach in designing measurable and realistic process enhancements.

Control

Table 7. Key Performance Indicator

Improve Cycle Time Recondition Process Powertrain						
Performance Evaluation (1-5)	**KPI**	**Performance Standard**	**Checking Item**	**Frequency**	**Responsibility**	**Alternative Plan**
	Compliance with Component Acceptance Standards	the date of component receipt	1. Surrounding photo documentation	Daily	Event Planner	Strict Oversight
	Cycle Time for Reconditioning Ticket Creation	Ticket created on the same day as component receipt	1. Date of Ticket creation, 2. Component history	Daily	Sending Branch	Follow up to Sending Branch
	Cycle Time Disassembly component	Component disassembly max 6-7 days	1. Tools, 2. Available technicians and capabilities,	Daily	Foreman Workshop	Initial info from Sending Branch

Improve Cycle Time Recondition Process Powertrain						
Performance Evaluation (1-5)	**KPI**	**Performance Standard**	**Checking Item**	**Frequency**	**Responsibility**	**Alternative Plan**
			3. SOP Disassembly			
	Cycle Time Cleaning, inspection and measurement	Creation of CCR max 1 day	1. Standard report templates	Daily	Workshop Technician	Strict Oversight
	Cycle Time validasi laporan CCR	Cycle Time of CCR report validation	1. CCR Report	Daily	Foreman and Supervisor	Strict Oversight

Source: Data Processing (2025)

The Control phase is intended to ensure that the improvements made can be sustained over time and do not revert to their initial conditions. To achieve this, Key Performance Indicators (KPIs) were established, as shown in Table 7, covering all subprocesses within Disassembly from component receipt, ticket creation, and the disassembly execution to validation of the CCR report. Each KPI includes performance standards, daily monitoring frequency, assigned responsibilities, and contingency plans in case of deviations. This framework establishes a systematic and structured control mechanism.

Following the implementation of improvements, the Process Cycle Efficiency (PCE) increased to 53.20%, marking a rise of 6.71% from the baseline. This improvement indicates that the process has moved toward greater efficiency, with a higher proportion of value-added time. Furthermore, the daily monitoring system carried out by the Event Planner, Foreman, and Supervisor ensures that any deviations are promptly identified and addressed. With stringent controls and well-defined performance indicators, the company can maintain process stability and embed these enhancements as a lasting part of its operational culture.

Discussion

The implementation of ML-based LSS in the reconditioning process of Powertrain components at PT. TU Surabaya branch has proven to enhance operational efficiency and service quality. This approach replaces conventional methods that rely on technician intuition, focusing instead on the Disassembly process as the critical point of delay. The transformation aligns with the LSS concept presented by (Daniyan et al., 2022), which emphasizes reducing waste and process variation through the DMAIC framework. In the Define phase, the process flow was mapped using a SIPOC diagram. The Measure phase identified the most impactful subprocesses through a Pareto Chart and metrics such as Lead Time, Cycle Time, Value Added Time, and Non-Value added Time (Irahman & Rayhan, 2024) These steps provided a quantitative foundation for setting priorities in a systematic improvement strategy (Stern, 2024).

During the Analyze phase, ML integration via the KNIME platform enabled predictive analysis using the Decision Tree Regression algorithm. The model produced more accurate optimal time predictions compared to manual approaches, evaluated through MAE, RMSE, and MAPE metrics (Acito, 2023). This aligns with the principles of LSS 4.0, as described by (Pongboonchai-Empl, 2023). which emphasize the use of data-driven technologies to enhance process efficiency. In the Improve phase, solutions were developed based on the 5S principles and then prioritized using a Decision Matrix to align with efficiency and success criteria. This approach reinforces the principle of Continuous Improvement in LSS and resulted in a significant reduction in Disassembly time

To ensure the sustainability of the improvements achieved, the Control phase emphasized institutionalizing performance monitoring mechanisms and embedding continuous feedback loops into daily operations. This was accomplished through the strategic use of Key Performance Indicators (KPIs) and Process Cycle Efficiency (PCE), which serve not only as evaluative tools but also as drivers of long-term behavioral and process discipline. As noted by Kerzner in (Villazón et al., 2020), KPIs must be aligned with strategic objectives and reviewed periodically to maintain relevance and effectiveness. Meanwhile, PCE, as discussed by (Stern, 2024), quantifies the proportion of value-added time, offering a dynamic lens for assessing operational efficiency. The integration of these metrics supports a data-driven framework that reinforces sustained service quality improvements at PT. TU Surabaya. The increase in Maintenance Process Efficiency and stronger control over Planned Maintenance indicate that the process has become more stable and standardized (Gomaa, 2023). These outcomes support operational management principles outlined by (Heizer et al., 2020).

The enhanced Disassembly process reflects improved operational consistency and contributes to better overall service quality at PT. TU Surabaya. This advancement aligns with the five core pillars of Total Quality Management, including management commitment, organizational culture, continuous improvement, customer orientation, and process control according to (Luthra et al., 2020.). By integrating LSS and ML, offers dual value: theoretically, it extends the Lean Six Sigma framework by embedding predictive analytics into the Analyze and Improve phases for sharper diagnostics and agile decision-making; practically, it validates ML as a tool for real-time control and resource optimization. This synergy strengthens LSS 4.0's capacity to manage complex service operations in dynamic industrial settings. The organization demonstrates a strategic, data-driven approach to service excellence, supporting more predictable lead times, streamlined workflows, and increased customer satisfaction showing that the Disassembly process is now better controlled and capable of improving overall service quality, This approach can be extended to other operational areas such as assembly, part ordering, and customer approval, where predictive analytics and structured workflow enhancements can drive measurable improvements. It offers a replicable model for efficiency gains across industries with complex, service-oriented operations

CONCLUSION

This study aims to optimize the Disassembly process of Powertrain components at PT. TU Surabaya branch through the application of LSS integrated with ML. The DMAIC framework successfully identified inefficiencies in each subprocess, with the Disassembly stage contributing most significantly to delays. Root cause analysis using a Fishbone Diagram revealed challenges such as limited technician experience, insufficient technical reporting skills, and inadequate support facilities. Time predicted using the Decision Tree Regression algorithm via KNIME provided realistic and accurate efficiency targets.

Improvements were carried out using the 5S method and prioritized through a Decision Matrix, resulting in reduced Disassembly time, lower downtime, and improved service quality. Monitoring through Key Performance Indicators (KPIs) and Process Cycle Efficiency (PCE) demonstrated that the improvements could be sustained over time. These findings confirm that integrating LSS with ML is effective in holistically optimizing operational processes.

Based on the research findings, several recommendations can be applied both in the short term and long term to support continuous improvement in process efficiency.

In the short term, PT. TU Surabaya branch is advised to conduct regular technician training and implement role rotation to enhance technical competence and understanding of operational standards. Performance evaluation using Key Performance Indicators (KPIs) should be carried out routinely to ensure optimal time targets are met and improvement consistency is maintained. Additionally, improving the accuracy and consistency of historical data recording is essential to support the quality of ML predictions and facilitate more precise decision-making.

For the long term, the company is encouraged to expand the implementation of ML-based LSS to other process stages such as Prepare Quotation, Part Order, and Assembly, in order to achieve holistic efficiency in reconditioning services. Considering the challenges related to data quality, future research should focus on enhancing data integrity and exploring alternative ML algorithms. This aims to increase prediction accuracy and broaden the impact of improvements on overall process efficiency

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