Analysis of Production Machine Effectiveness in Line A Using OEE and Six Big Losses Method

Muhammad Iqbal Gymnastiar[1], Ridwan Hartono[2*]
[1,2)] Industrial Engineering, Faculty of Engineering, Universitas Dian Nuswantoro
Jl. Nakula 1 No.5-11, Pendrikan Kidul, Semarang Tengah, Semarang City, Central Java 50131
Email: muhammadiqbalgymnastiar50@gmail.com, bj.ridwan@dsn.dinus.ac.id*

ABSTRACT

The operational effectiveness of production machines is crucial in maintaining the smoothness and efficiency of manufacturing processes. This research aims to analyze the effectiveness of the production system on Line A at PT XYZ using the Overall Equipment Effectiveness (OEE) method and the Six Big Losses approach, and identify the dominant factors causing equipment failure losses. Data was collected from January to May 2024, covering quantitative analysis of availability, performance, and quality values. The results show that the average OEE value is 82.58%, which is still below the world-class standard of 85%. Of the total loss time of 20,367 minutes, the highest losses came from equipment failure losses at 38.25%, reduced speed losses (23.58%), and idling and minor stoppage losses (14.36%). These findings indicate that technical machine disruptions are the leading cause of the decline in production effectiveness. Therefore, improvement strategies need to focus on strengthening preventive and predictive maintenance systems, enhancing technician competency, and optimizing the reporting and handling of disruptions to improve the efficiency and reliability of the production system sustainably.

Keywords: *Equipment Failure Losses; Overall Equipment Effectiveness; Six Big Losses.*

Introduction

Operational efficiency and the reliability of production systems are two main pillars for maintaining competitiveness in the manufacturing industry, especially in the automotive sector, which demands timeliness, high precision, and consistent product quality. [1]. In an increasingly fierce global competition, companies must optimize all aspects of the production process to produce output that meets market demand in quantity and quality. Companies must have an accurate and comprehensive system for measuring production effectiveness to achieve this goal.

One of the most widely used methods for evaluating the effectiveness of a production system is Overall Equipment Effectiveness (OEE). This method assesses machine effectiveness through three main components: availability, which measures the proportion of time a machine is running compared to its scheduled operating time; performance, which compares actual production speed to the ideal speed; and quality, which evaluates the percentage of good-quality products out of the total produced. [2]–[4]. These three indicators comprehensively show how effectively machines operate in a production line. [5].

However, despite its usefulness, the OEE method alone often falls short in identifying specific sources of inefficiencies, especially when the losses are complex or hidden in daily operations. [6], [7]. To address this limitation, the Six Big Losses approach is commonly used to complement OEE analysis. This approach classifies the primary sources of productivity losses in manufacturing into six categories: equipment failure, setup and adjustment, idling and minor stoppages, reduced speed, startup rejects, and production rejects [8], [9]. This combined approach enables a more detailed diagnosis of performance gaps and supports identifying priority areas for improvement. [9]–[11].

These methods are highly relevant in a continuous production system, such as in PT XYZ, a manufacturing company specializing in automotive and heavy equipment components. One of its key production lines, Line A, operates in a serial machine configuration where the output of one machine becomes the direct input for the next. This interdependency makes Line A extremely sensitive to disruptions, where even minor issues such as delayed component changes or undetected machine wear can cause process bottlenecks and halt the entire production flow. [12].

Equipment failure losses are considered the most critical among the various production losses due to the significant downtime they cause. Additionally, many of these losses are not visible in routine reports, making them more challenging to resolve without a structured analysis approach. Based on these considerations, this research is focused on analyzing the effectiveness of machines on Production Line A that has a serial configuration, where a disruption on one machine can cause a significant chain effect on the entire production flow. Many previous studies have not found an evaluation approach using the Overall Equipment Effectiveness (OEE) and Six Big Losses methods in a serial production line like this. Therefore, this study presents a new and more in-depth perspective in understanding the effectiveness of machine performance in a structurally interdependent production line system, and opens up opportunities for more targeted evaluation applications in managing and improving production process performance in the manufacturing sector.

Research Method

This research uses a quantitative approach to evaluate the operational effectiveness of Line A's production machines at PT XYZ using the Overall Equipment Effectiveness (OEE) method. It also identifies production loss categories based on the Six Big Losses concept.

The study was conducted at PT XYZ, a manufacturing company in the automotive industry located in an industrial area in Central Java. Line A, the object of this study, is responsible for the final machining process of automotive components. This line consists of several machines that operate sequentially in a continuous process flow, with each machine having a specific role in the production stages. All production and work time data were recorded at the line level, not per machine, so the effectiveness analysis was based on the line's overall performance.

Data Collection

Data collection for this study was conducted from January to May 2024 to support the analysis of Line A's operational effectiveness based on the Overall Equipment Effectiveness (OEE) method and the Six Big Losses classification. The data used included:

1) Documentation
   Data was collected by accessing monthly production records, machine breakdown logs, reports on total production and defective products, line operating time, and the ideal cycle time used as a benchmark. All this data was obtained from the company's production and maintenance departments, which record information in an aggregate format for all activities on Line A.
2) Field Observation
   Observations were conducted directly to understand the continuous production workflow on Production Line A, including observing material flow patterns, times of disruption, and conditions when production speed decreased. These observations were also used to match documented data with actual conditions in the field, especially regarding working time, operating cycles, and potential production losses. To ensure data validity, the observation results were systematically compared with production records and downtime reports to identify possible discrepancies between recorded data and actual conditions in the field. With this approach, the data used in the OEE and Six Big Losses analysis is ensured to reflect actual operational performance.
3) Interviews
   Interviews were conducted with operators and technicians working on Line A. The goal was to obtain qualitative information regarding the causes of downtime, reasons for defective products, and work habits that might affect the speed and stability of the production process. The interview results were also used to classify losses into the six categories of the Six Big Losses.

Data Analysis

Data analysis in this study aims to measure the operational effectiveness of Production Line A using the Overall Equipment Effectiveness (OEE) approach and to identify the sources of production losses based on the Six Big Losses concept. The evaluation is carried out by calculating the three main components of OEE: Availability, Performance Rate, and Quality Rate. These calculations are based on production data, including line operating time, total output, the number of defective products, and the line cycle time. The formula used is presented in Equations (1)-(4).

$$Avaibilty\ rate(\%) = \frac{Operation\ Time}{Loading\ time} \tag{1}$$

$$Performance\ rate(\%) = \frac{Total\ Production \times Ideal\ Cycle\ time}{Operation\ Time} \tag{2}$$

$$Quality\ rate(\%) = \frac{Total\ Production - Defect\ Product}{Total\ Production} \tag{3}$$

$$OEE(\%) = Availability \times Performance \times Quality \tag{4}$$

Next, an analysis was conducted on the types of losses that occur during the production process. The losses were grouped into six categories of Six Big Losses, with explanations as follows:

1) Equipment failure losses
   Losses due to machine breakdowns occur when a machine suddenly fails or completely stops because of a technical issue. This loss significantly impacts the production flow by halting the entire line in a continuous production process.
2) Setup and adjustment losses

Losses due to setup and adjustment time, which are lost during product changeovers, cutting tool replacements, or process parameter adjustments. Although this happens regularly, it can lower the line's availability if not managed.

3) Idling and minor stop-losses
Minor stoppages are small, recurring losses caused by minor issues like faulty sensors, material flow jams, or temporary machine stops without a major breakdown. These losses often occur in continuous-running lines but are difficult to detect without proper recording.
4) Reduce speed losses
Even without any breakdowns, a machine operating below its ideal speed (ideal cycle time) reduces speed losses. The causes include suboptimal operator performance, difficult-to-process materials, or aging machinery. This is one of a continuous production line's most frequently overlooked losses.
5) Rework losses
Rework losses happen when a product fails to meet quality standards during production but can still be repaired to meet specifications.
6) Scrap losses
Scrap losses occur when a product cannot be repaired or adjusted and must be permanently discarded. These products do not meet the technical specifications or quality standards and are unfit for customer use, repair, or delivery.

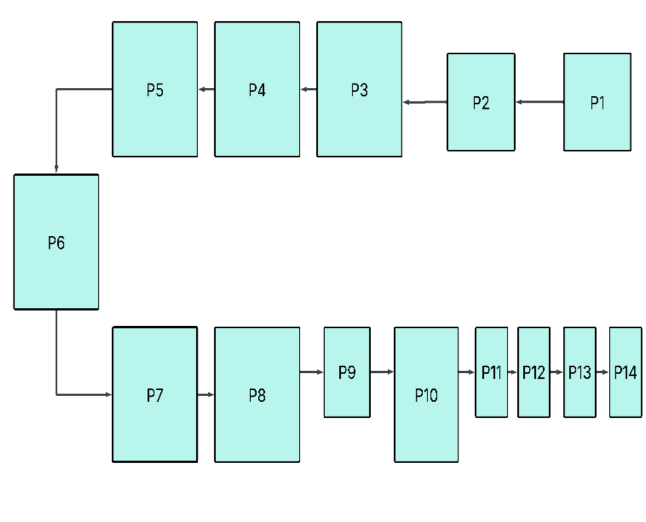
Each category was analyzed based on the total loss time or the number of occurrences during the observation period. The data was then organized into a Pareto Chart to identify the type of loss with the largest contribution. The dominant category was further analyzed using a Fishbone Diagram (Ishikawa) to trace its root causes. The results of this analysis were used as a basis for developing improvement recommendations to continuously enhance the work effectiveness of Production Line A.

Result and Discussion

A continuous production system supports the finishing machining process for automotive components in Line A, where a disruption in one machine can hinder the entire production flow. The OEE (Overall Equipment Effectiveness) and Six Big Losses methods were utilized to evaluate its performance comprehensively to identify the primary sources of production losses.

Table ***1*** Show the production line's configuration, which consists of 15 sequential processes in a continuous series-type system. Each product unit moves continuously from one workstation to the next, with a different process type at each stage. The processes are closely linked, so a disruption at one point can affect the smooth flow of the entire line, especially when the buffer capacity between processes can no longer compensate for the disruption. The flow stability and the balance of processing time between machines are crucial factors in maintaining production continuity. Therefore, a performance evaluation approach like Overall Equipment Effectiveness (OEE) is highly relevant to apply at the line level to view overall production effectiveness. Additionally, analyzing the Six Big Losses is important for identifying the main waste sources affecting the line's integrated performance and efficiency.

Table 1. Production process layout of line A



Machine	Process
P1	Milling surface bottom
P2	Milling surface Hopper
P3	Drill tap Hopper & Bottom
P4	Center Drill GC & MBC
P5	Saluran Oil group
P6	Tap GC & MBC
P7	FM Finish GC & MBC
P8	Boring Finish CL & MBC
P9	Check Quality
P10	Washing Airblow
P11	Pasang Plug
P12	Leak Body & Water Jacket
P13	Visual Check
P14	Noxrust

In Table 2The available time is derived from the company's official data, representing the net time available for Line A to perform production activities, excluding downtime and planned downtime. Next, the loading time is calculated by subtracting planned downtime from available time. Operating time is obtained by subtracting downtime from loading time. The company's Planned downtime is a fixed 60 minutes per month, which is set due to a reactive maintenance strategy. This involves a one-time monthly machine check at a scheduled time.

Table 2. Line A operational data for the period January-May 2024

Month	January	February	March	April	May
Available Time (Minute)	21.220	18,760	19,580	17,965	19,555
Operational time (minutes)	19,047	16,665	17,870	16,297	17,340
Loading time (minutes)	21,160	18,700	19,520	17,905	19,495
Planned downtime (minutes)	60	60	60	60	60
Set up time (minutes)	390	345	360	330	360
Breakdown (Minute)	1,723	1,690	1,320	1,248	1,810
Downtime(Minute)	2,113	2,035	1,650	1,608	2,155
Production Total (pcs)	2566	2253	2391	2258	2303
Good Production (pcs)	2486	2188	2312	2216	2210
Reject (pcs)	80	65	79	42	93

In this study, downtime is defined as when the production line does not produce any output due to a halt in the production process. Downtime consists of two main categories: breakdowns and setup time. Breakdowns are when a machine is stopped due to a malfunction, preventing the process flow from continuing. However, a malfunction is only categorized as a breakdown if it causes all subsequent processes on the next machine to stop, specifically when the buffer is no longer sufficient. Meanwhile, setup time includes the time required to make adjustments or reconfigure a machine, such as changing tools, programs, or calibration, before production can resume. By limiting the definition of downtime to conditions where the production flow is completely halted, this approach ensures that the collected data reflects the real disruptions to the final output of the production line.

Availability Ratio

The availability ratio is the ratio of operating time to loading time, reflecting the machine's availability level for operation. This ratio shows the proportion of working time used for production, after deducting downtime. Table 3 shows the results of the availability ratio calculation for Line A for the period of January to May 2024

Table 3. Results of the availability ratio calculation for production line A for the period January-May 2024

Month	Operation Time (Minute)	Loading Time (Minute)	Availability Rate (%)	Standard World Class (%)
January	19,047	21,160	90,01%	90%
February	16,665	18,700	89,11%	90%
March	17,870	19,520	91,54%	90%
April	16,297	17,905	91,01%	90%
May	17,340	19,495	88,94%	90%
Average	**17,4438**	**19,356**	**90,12%**	**90%**

While the average availability rate has surpassed the world-class standard, the monthly fluctuations indicate unstable machine performance. This suggests ongoing issues with downtime control, in both technician response and maintenance effectiveness. A drop in availability doesn't always reflect a high frequency of breakdowns; it can also be caused by slow recovery times. With the rate close to the 90% threshold, the system is highly sensitive to even minor downtime. Therefore, a root cause analysis of the Six Big Losses is essential to determine the right improvement strategy.

Performance Rate

Performance rate is calculated to determine a machine's effectiveness level during production. This indicator shows how fast a machine runs compared to its ideal speed. Data on the actual number of products and ideal cycle time is required to calculate the performance rate. The data used to calculate the performance rate includes the actual number of products and the operating time during the process. The closer the result is to 100%, the more the machine operates at its ideal speed. Table 4 Below presents the results of the performance rate calculation for Line A from January to May 2024.

Table 4. Calculation of performance rate for production line A for the period January-May 2024

Month	Production Total (Minute)	Ideal Cycle Time (Minute)	Operation Time (Minute)	Performance Rate (%)	Standard World-Class (%)
January	2566	7	19047	94,30 %	95%

February	2253	7	16665	94,63%	95%
March	2391	7	17870	93,65%	95%
April	2258	7	16297	96,98%	95%
May	2303	7	17340	92,97%	95%
Average	**2354,2**	**7**	**17443,8**	**94,51%**	**95%**

This study's calculation of the performance rate refers to the overall operating speed of the entire line, using the machine's Ideal Cycle Time (ICT) with the longest process as the primary reference. This is because the slowest machine on the line controls the flow in a continuous production system. Therefore, performance is not calculated based on the average cycle time per machine but rather on the line's ability to produce final output during its operating time.

The ideal time cycle for a continuous production line system is determined by the workstations' longest cycle time. Although some machines have faster processing times, the slowest point limits production capacity. In this study, workstation P7 had a cycle time of 7 minutes, so the ICT was set at 7 minutes per unit.

This approach is used to avoid analytical bias if the ICT of the fastest machine was used, potentially resulting in a performance rate that doesn't reflect real-world conditions. Using the machine with the longest cycle time as the benchmark makes the performance analysis more representative of the system's reality.

The five-month performance rate measurement results show that most achievements were close to the 95% industry standard. The highest value was recorded in April, while the most significant drop in performance was seen in May. Although the differences between months weren't extreme, they were enough to show that actual efficiency isn't fully optimal or consistent. This can be influenced by several factors, such as variations in machine operating speed, slow operator response to minor obstacles, or differences in operator discipline in maintaining the work rhythm.

Quality Rate

Quality rate is a ratio that compares the number of good products to the total production output. This calculation shows the proportion of products that meet quality standards compared to the total output, including defective products. Table 5 Presents the results of the quality rate calculation for Line A from January to May 2024.

Table 5. Calculation of quality rate for production line A for the period January-May 2024

Month	Production Quantity (Pcs)	Defective Products (Pcs)	*Quality Rate* (%)	*Standard World Class* (%)
January	2566	80	96,88%	99%
February	2253	65	97,11%	99%
March	2391	79	96,69%	99%
April	2258	42	98,13%	99%
May	2303	93	95,96%	99%
Average	**2354,2**	**72,2**	**96,95%**	**99%**

In a continuous production system, final product quality heavily depends on consistent performance across all stages, as each unit passes through every machine sequentially. Defects can emerge at the process's beginning, middle, or end. For this reason, the quality rate calculation in this study was focused on the final output to reflect overall quality performance. Based on data from January to May 2024, the quality rate ranged from 95,96% to 98,13%, with an average of 96,95%, still below the world-class standard of 99%. Interestingly, the month with the lowest production volume, April (2,258 units), showed the highest quality rate (98,13%), while May, despite not having the highest production (2,303 units), recorded the most defects (93 units) and the lowest quality rate (95,96%). This phenomenon shows that production volume is not directly proportional to quality. The drop in quality is more heavily influenced by external factors such as raw material quality, machine performance, and operator precision.

Overall Equipment Effectiveness

Overall Equipment Effectiveness (OEE) is based on three main ratios: availability ratio, performance rate, and quality rate.[13]–[16]. These three ratios represent the aspects of machine time availability, machine performance effectiveness during production, and the quality of production output. Table 6 Shows the results of the OEE calculation for Line A from January to May 2024.

Table 6. OEE calculation for production line A for the period January-May 2024

Month	Availability Rate (%)	Performance Rate (%)	Quality Rate (%)	OEE (%)	Standard World Class (%)
January	90,01%	94,30 %	96,88%	82,23%	85%
February	89,11%	94,63%	97,11%	81,88%	85%
March	91,54%	93,65%	96,69%	82,88%	85%
April	91,01%	96,98%	98,13%	86,61%	85%
May	88,94%	92,97%	95,96%	79,34%	85%
Average	**90,12%**	**94,51%**	**96,95%**	**82,58%**	85%

The average OEE for Line A from January to May 2024 was 82,58%, which is close to but has not yet met the world-class standard of 85%. Generally, this value indicates quite good performance, but a closer look at each component reveals several signs of unbalanced performance. The availability rate component is the weakest, with an average of 90,12%, indicating that production-halting downtime occurs frequently. This confirms that production time lost due to operational disruptions remains significant.

On the other hand, the performance rate recorded the highest value, with an average of 94.51%, showing that production speed is close to ideal. This is because the calculation is based on the longest process time, so the line's work rhythm realistically reflects the performance of the slowest machine. However, the quality rate is the main concern. With an average of 96,95%, this value is still well below the world-class standard of 99%. This proves that Line A's quality level is not fully stable, and final product quality is still vulnerable to defects from various points in the process. The failure to meet this quality standard is exacerbated by significant month-to-month fluctuations, as seen in May, which recorded the most defects (93 units) even though its total production was not the highest.

These findings indicate that non-technical factors such as raw material quality and operator work consistency influence product quality, not just machine performance. [17]. Therefore, despite the OEE value being near the world-class threshold, the quality and availability components remain critical points that require serious attention in a continuous improvement strategy. The future focus should be on stabilizing quality through material inspection, operator training, and improved process control while minimizing downtime that genuinely impacts the overall line output.

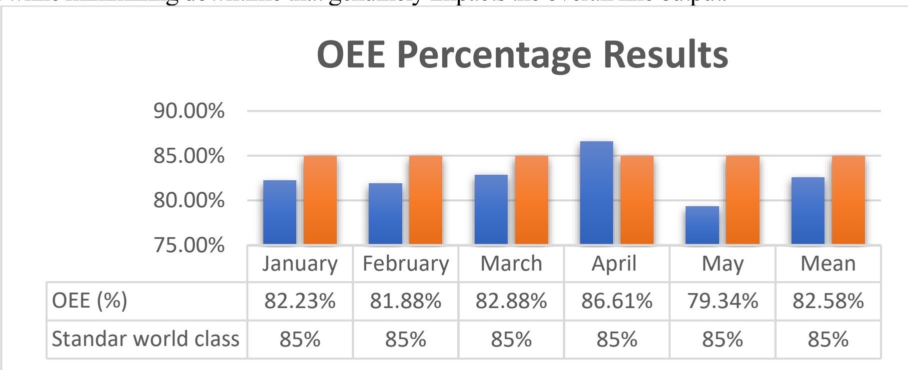


Figure 1. Overall equipment effectiveness graphic

Six Big Losses

This analysis aims to identify and measure the various significant losses that affect the effectiveness of production equipment and to provide a deeper understanding of the sources of inefficiency, whether they originate from downtime, reduced production speed, or product defects. Table 7 Presents the results of the Six Big Losses recapitulation for Line A. The data is then visualized as a Pareto diagram in Figure 2. This diagram presents the losses from largest to smallest, making it easy to identify priority areas that need immediate action to improve the production system effectively.

Table 7. Total losses of production line A for the period January-May 2024

Six big losses	Total losses (minutes)	Percentage (%)	Cumulative (%)
Equipment failure losses	7791	38,25%	38,25%
Reduce speed losses	4802	23,58%	61,83%
Idling and minor stoppage losses	2924	14,36%	76,19%
Scrap losses	2503	12,29%	88,48%
Set up and adjustment losses	1785	8,76%	97,24%
Rework losses	562	2,76%	**100,00%**
Total	**20367**	**100%**	

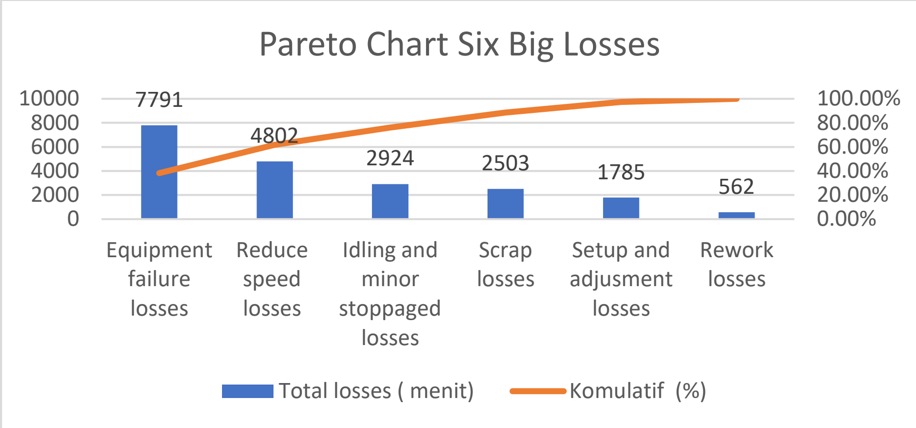


Figure 2. Pareto six big losses line A diagram.

The analysis of the Six Big Losses shows that equipment failure losses are the largest source of loss, contributing nearly 39% of the total lost time. This finding is particularly concerning because it contrasts with the relatively high availability rate. It indicates that while overall machine uptime appears optimal, there is still a high frequency of short-duration breakdowns. This doesn't significantly lower availability but still results in a large cumulative time loss.

Reducing speed and idling losses also contributes significantly to the total losses, indicating imperfections in machine speed settings and daily operational stability. Scrap and rework losses still occur in smaller proportions, impacting product quality and efficiency. Therefore, the improvement approach must focus on strengthening early detection systems and responses to technical failures, real-time monitoring of variations in production speed, and enhancing process quality to reduce waste from defects and rework.

A focused root cause analysis was conducted on the largest loss category: Equipment Failure Losses, to better understand the main sources of loss in the production process. This analysis used a Fishbone Diagram (Ishikawa) approach, which groups various causal factors into five main categories: Man, Machine, Method, Material, and Environment. This approach provided a systematic overview of the dominant factors causing machine breakdowns, allowing for developing more targeted improvement strategies.

Equipment Failure Losses

Equipment failure losses are one of the most significant sources of loss in the production system. This loss is related to machine downtime caused by equipment malfunctions, such as hydraulic system failures, non-functional sensors, or wear on mechanical components. The impact is critical because it can disrupt the smooth flow of the production process. The factors contributing to these high losses include the suboptimal implementation of preventive maintenance programs and the lack of an integrated predictive system. Additionally, minimal record-keeping of breakdown history increases the potential for recurring disruptions. To systematically identify the root causes, an analysis was conducted and presented in Figure 3, using a Fishbone Diagram to map the various technical and organizational factors contributing to equipment failure losses.[18]–[21].

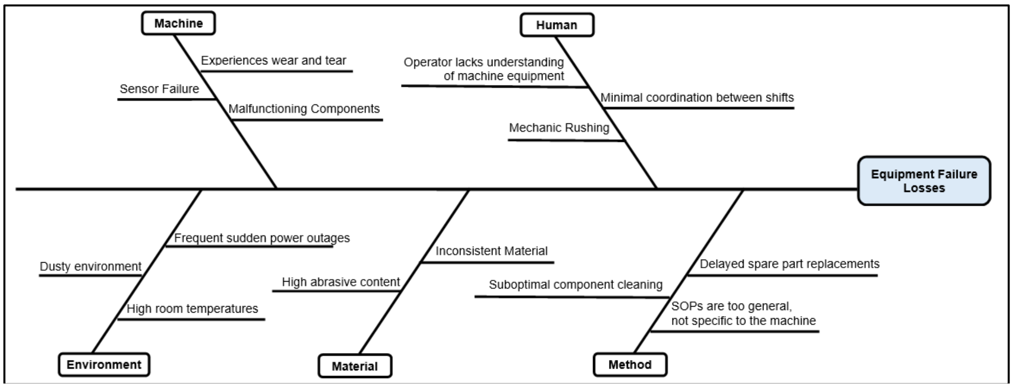


Figure 3. Fishbone diagram equipment failure losses

Figure 3 Displays the results of the root cause identification for equipment failure losses, classified into five main aspects: Man, Machine, Method, Material, and Environment. Each aspect has a specific impact on the operational stability of Line A's machines. The following analysis discusses the contribution of each aspect and provides recommendations for improvement to prevent recurring equipment breakdowns.

1. Human Factors

Human factors play a significant role in increasing equipment failure losses. One of the main causes is technicians' habit of rushing, especially when handling urgent repairs or during high workloads. This hurried approach often leads to incomplete inspections, meaning the root problem isn't fully resolved and triggers a recurring breakdown. Additionally, operators' low levels of early reporting about initial signs of damage, such as abnormal sounds, excessive vibration, or a slow machine response, prevent small issues from being addressed until they develop into serious breakdowns. The lack of coordination between shifts also worsens the situation, as information about a machine's latest condition isn't communicated well to the next team. The accumulation of these factors leads to many preventable machine breakdowns being overlooked, directly contributing to the high equipment failure losses on the production line.

2. Machine Factors

In the machine aspect, equipment failure losses are often triggered by technical issues that could have been anticipated earlier. One of the main causes is malfunctioning sensors or inaccurate calibration. A faulty sensor provides incorrect data or no signal, allowing a machine to continue operating in an abnormal state without being detected. This worsens the damage and increases the risk of sudden functional failure.

3. Method Factors

From the method side, several significant weaknesses also contribute to low maintenance effectiveness. SOPs that are too generic and not adapted to each machine's specific characteristics lead to inconsistent maintenance and a risk of not following necessary technical procedures. Furthermore, delays in replacing spare parts are a crucial factor. When a machine component is worn or nearing the end of its lifespan and isn't replaced immediately due to procurement delays, the machine is forced to operate in non-ideal conditions. This increases the likelihood of a sudden breakdown, resulting in a halt in the production process. If not addressed properly, these factors will continue to increase the number of equipment failure losses.

Inadequate cleaning of components also directly impacts machine lifespan and performance, especially in sensitive areas prone to dust, oil, or abrasive particles. This combination of methodological weaknesses shows that current maintenance standards do not fully support a precise, responsive, data-driven work system.

4. Material Aspects

From the material aspect, inconsistent raw material quality is a critical factor affecting machine performance. Inconsistencies in the mechanical properties or dimensions of the material can cause fluctuating machine workloads, triggering premature wear on vital components such as cutting tools, spindles, or bearings. Additionally, using highly abrasive materials, like grey cast iron or hard metal alloys, accelerates the wear of cutting tools and machine contact surfaces. [22]. This condition increases the frequency of component changes and impacts the consistency of the production quality. When abrasive materials are not balanced with adjusted machining parameters and adequate protective systems, the rate of component damage will increase significantly, shortening the overall machine lifespan.

5. Environmental Factors

An unconducive work environment is one of the triggers for increased equipment failure losses, especially in a continuous production setting. One of the main problems is frequent, sudden power outages. These outages can cause machines to stop abruptly mid-process, risking damage to internal components like motors, control systems, or actuators. A sudden outage also has the potential to cause a loss of process data and disrupt automation systems.

Based on the analysis of the five causal aspects of Equipment Failure Losses, several improvement recommendations have been compiled for each factor and are presented concisely in Table 8.

Table 8. Casual factors and recommendations for repairing equipment failure losses

Factor	Specific problems	Improvement recommendations
Human	Lack of coordination between shifts	● Implement a daily shift log system to document completed and pending tasks. This ensures the next shift can continue the work based on clear directions, which is crucial for the repair process and minimizes errors.
	Operators lack understanding of machine conditions	● Operators should be trained to recognize early signs of abnormal sounds, unusual vibrations, rising temperatures, unstable hydraulic pressure, or changes in spindle speed.
	Mechanics Rushing	● Install a quality assessment system for mechanics' work. This quality-based evaluation will encourage mechanics to work more carefully and professionally, as they'll know their work will be thoroughly inspected. This approach helps create a work culture that prioritizes the reliability of repairs, not just speed.
Machine	Experiencing wear and tear	● Use additional sensors to monitor key components' temperature, vibration, pressure, or electrical current. This allows for early detection before a component completely fails.
	Malfunctioning Components	● Enhance preventative inspection and maintenance programs and add problematic components to the priority list for regular checks to prevent similar breakdowns from recurring.
	Sensor Failure	● Install additional sensors in critical areas as a backup, so the

		system can continue to function without interruption if the main sensor fails.
Method	Delayed spare parts replacement	● Create a visual alarm on the machine panel for replacement reminders. For example, after 500 hours of operation, an indicator light turns on to remind technicians that a specific part needs to be checked or replaced.
	SOPs are too general, not specific to each machine	● Develop specific SOPs for each type of machine, based on its technical specifications and characteristics, to ensure operators can work accurately and safely.
	Suboptimal component cleaning	● Establish a more frequent cleaning schedule for critical areas prone to dust or dirt, to prevent accumulation that can accelerate machine damage.
Material	Unstable material quality	● Perform routine evaluations of vendor performance based on defect data found in the field. Conduct site visits to ensure the casting process meets the required quality standards if necessary.
	High abrasive content	● Regular inspection of machine movement systems—like linear rails, ball screws, and spindle bearings—is important when processing abrasive materials. Fine particles can accumulate in movement pathways, causing excess friction that reduces accuracy and accelerates component wear in the long run.
Environment	Sudden power outages	● Develop emergency SOPs that are clear and easy for operators and technicians to understand. These SOPs should cover machine safety measures, salvaging semi-finished products, and restart procedures after power returns to normal, all to minimize the risk of equipment damage and production disruption.
	Dusty environment	● To facilitate machine inspections and prevent damage from dust buildup, it's recommended to routinely clean the area around the machines, including hard-to-reach parts. A clean environment makes it easier for technicians to detect leaks, wear, or early signs of damage.
	High room temperature	● Installing a room thermosensor helps monitor temperature in real-time, so cooling measures can be taken immediately when the temperature exceeds safe limits. This step is important for maintaining stable machine performance and preventing work fatigue caused by excessive heat.

Discussion

The findings in this study are not only relevant for Line A at PT XYZ. Still, they can also be generalized to other production lines with continuous-type production systems and serial configurations. Key characteristics such as machine-to-machine dependency, dominance of equipment failure, and the accumulative impact of downtime are similar in the automotive industry and other precision manufacturing using serial systems. The OEE-based approach, which is commonly used to evaluate performance on a per-machine basis, proved to be adaptable in this context to assess the overall effectiveness of continuous production lines. Therefore, the OEE and Six Big Losses methods remain relevant at the machine unit level and in evaluating performance across interconnected machines in a single production process flow.

Practically, this research provides a basis for companies to develop more proactive maintenance strategies, such as predictive maintenance based on historical downtime data. The implementation of a digital reporting system and real-time monitoring can also accelerate the process of damage handling. In this context, integrating Internet of Things (IoT) technology is a potential solution to facilitate automatic operational data acquisition, detect machine performance anomalies early, and provide immediate notifications when deviations occur. In addition, technical training focused on early identification of malfunction symptoms is essential to reduce the frequency of equipment failure and improve the overall reliability of the production system. n

Conclusion

Based on the analysis of Line A's production system effectiveness using the Overall Equipment Effectiveness (OEE) method and the Six Big Losses approach, the average OEE value was 82,58%, which has not yet reached the world-class standard of 85%. The availability rate component showed an average of 90,12%, which meets the industry standard. In comparison, the performance rate of 94,51% and quality rate of 96,95% have not met their world-class standards of 95% and 99%, respectively. The Six Big Losses analysis revealed that the most significant loss came from equipment failure losses, which contributed 38,25% to the total lost time, followed by reduced speed losses (23,58%) and idling and minor stoppage losses (14,36%). These findings indicate that machine breakdowns are the dominant factor reducing overall production effectiveness. Therefore, the primary improvement focus should be addressing the root causes of equipment failure by implementing more targeted and sustainable maintenance strategies to increase machine reliability and overall operational efficiency.

As a follow-up to these findings, it is recommended that the company develop a maintenance system based on historical downtime data, such as predictive maintenance, to anticipate potential breakdowns before they occur. Regular evaluations of critical component conditions, increased technician competency through systematic training, and improved damage reporting procedures are necessary to ensure handling disruptions more quickly and effectively.

For future work, integrating Internet of Things (IoT) technology is highly recommended to enhance the real-time monitoring of machine performance. The company can build a more responsive and data-driven maintenance system by deploying sensors to track temperature, vibration, and cycle time deviations. This would enable early detection of anomalies and facilitate automated alerts, reducing unplanned downtime and improving overall equipment reliability.

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