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Overall Equipment Effectiveness (OEE) Analysis as a Framework for Mapping the Root Causes of Production Inefficiencies in Cream Filling Processes

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Abstract: This study aims to utilize Overall Equipment Effectiveness (OEE) analysis as a diagnostic framework to identify and map the root causes of performance losses in critical cream filling machinery within a cosmetics manufacturing company in East Java, recognizing that fragmented or piecemeal approaches to evaluating machine performance often fail to capture the interrelated sources of production inefficiency. The research was conducted over a three-month period using a descriptive quantitative method through direct observation of filling machine operations. The collected data included machine operating time, downtime, production output, and defective units. In this study, OEE was applied not merely as a performance indicator but as a loss-based diagnostic tool capable of systematically revealing hidden inefficiencies affecting equipment effectiveness. The results show that OEE values fluctuated significantly between 20.31% and 90.51%, with monthly averages of 71.12%, 80.62%, and 61.29%, respectively. While the quality component remained relatively stable at above 98%, substantial variations were observed in availability and performance due to machine downtime and reduced operating speeds. Further analysis using the Six Big Losses framework identified setup and adjustment time and idling or minor stoppages as the dominant contributors to decreased machine effectiveness, confirming that the filling machine functions as a critical production bottleneck whose instability directly influences production continuity. These losses collectively accounted for the majority of production interruptions and performance deterioration throughout the observation period. The findings underscore the importance of systematically reducing the Six Big Losses to stabilize and improve OEE. Implementing preventive maintenance, minimizing setup time variability, and strengthening operational discipline are therefore essential steps for achieving sustainable improvements in machine effectiveness and overall production efficiency.

Keywords: Availability; Filling machine; Manufacturing efficiency; Overall equipment effectiveness (OEE); Performance; Quality; Six big losses

Introduction

In modern cream manufacturing industries, production efficiency and equipment reliability play a decisive role in ensuring consistent output and maintaining product quality. Industrial competitiveness increasingly depends on the ability of production systems to operate with minimal downtime, optimal speed, and consistent quality standards. Equipment performance therefore becomes a central factor in achieving operational excellence, reducing waste, and sustaining customer satisfaction in highly competitive manufacturing environments (Alfadhlani et al., 2025).

One of the most widely recognized tools for evaluating equipment effectiveness is Overall Equipment Effectiveness (OEE), a comprehensive metric that integrates availability, performance, and quality to

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measure how efficiently production assets are utilized. OEE provides a systematic framework for quantifying productivity losses and identifying performance gaps in manufacturing systems (Corrales et al., 2020). Its interpretation is closely related to the Six Big Losses concept in Total Productive Maintenance (TPM), which classifies the primary sources of inefficiency—equipment failures, setup and adjustment losses, idling and minor stops, reduced speed, process defects, and reduced yield. These loss categories directly affect the three core components of OEE and serve as a structured diagnostic tool for analyzing production performance (Yermia Tobe et al., 2017).

Despite the availability of structured evaluation frameworks such as OEE and the Six Big Losses, many manufacturers still encounter difficulties in identifying the root causes of reduced equipment performance, particularly in critical production assets like filling machines. In cream filling operations, inefficiencies often appear as intermittent breakdowns, inaccurate fill volumes, nozzle clogging, slow operating speeds, and increased reject rates (Alda et al., 2024). These problems are frequently associated with inconsistent preventive maintenance, inadequate operator training, variations in cream viscosity, and improper machine calibration. Without systematic root cause analysis, such issues accumulate over time, leading to reduced productivity, higher operational costs, and unstable production performance (Stefana et al., 2022).

Previous studies have largely focused on measuring OEE values or identifying general loss factors, but limited research integrates OEE measurement with detailed root cause analysis specifically for cream filling machinery. This study therefore offers a more comprehensive approach by combining OEE evaluation with a systematic investigation of dominant losses affecting filling machine performance. The purpose of this research is to analyze the root causes of inefficiencies in cream filling operations and to develop targeted improvement strategies that enhance equipment reliability, minimize downtime, and stabilize production output. The urgency of this research lies in the critical role of filling machines as key production assets whose performance directly determines packaging accuracy, product uniformity, and overall manufacturing efficiency. To provide a technical foundation for this analysis, it is important to understand the structure and operating mechanism of the equipment being evaluated.

The semi-automatic pneumatic filling machine is a widely utilized piece of equipment in cream, paste, and viscous-product manufacturing due to its simplicity, accuracy, and suitability for small to medium-scale production environments. Anatomically, the machine consists of several key components that work cohesively to ensure precise volumetric dispensing. At the top of the system, a stainless-steel hopper serves as the primary reservoir that holds the cream or viscous material prior to filling. Its conical design ensures continuous and uniform feeding of the product into the filling chamber through gravity-assisted flow.

Beneath the hopper lies the central volumetric filling mechanism, which is based on a piston–cylinder assembly. This mechanism is driven entirely by compressed air supplied through a pneumatic control system equipped with air regulators, solenoid valves, and flow control valves. These pneumatic components govern the motion of the piston during both the suction and dispensing phases. When compressed air actuates the pneumatic cylinder, the piston retracts to create negative pressure within the filling chamber, thereby drawing product from the hopper into the cylinder. In the subsequent phase, the pneumatic system reverses the airflow direction, pushing the piston forward to discharge the product through the filling nozzle. The nozzle itself is designed with an anti-drip system that ensures clean, controlled material transfer into the container.

The machine's operation is semi-automatic, typically activated by a foot pedal that triggers each filling cycle. This allows the operator to maintain control over the timing of the filling process while ensuring consistent dispensing volume determined by the adjustable piston stroke. The stainless-steel frame provides structural stability and supports hygienic operation, making the equipment compliant with food-grade and pharmaceutical manufacturing requirements.

From a performance standpoint, the pneumatic filling machine offers several advantages. Its volumetric piston mechanism ensures high accuracy and repeatability, while the pneumatic actuation provides smooth and reliable operation even for high-viscosity products. Additionally, the machine requires minimal energy consumption, as it operates without electric motors for the filling motion. Maintenance procedures are relatively simple because the filling components are easy to disassemble for cleaning, and the system has few wear-prone parts.

Overall, the anatomical structure and operating principles of the semi-automatic pneumatic filling machine make it an efficient, flexible, and economically viable solution for industries requiring consistent cream-filling performance. Its straightforward mechanism not only supports accurate and repeatable filling but also enables seamless integration with performance improvement tools such as Overall Equipment Effectiveness (OEE) analysis and root cause diagnostic methods within a continuous improvement framework. Furthermore, the machine has undergone formal qualification activities—including Installation

Qualification (IQ) and Operational Qualification (OQ)—which confirm that the equipment operates in accordance with predefined specifications. The completion of these qualification stages establishes the machine's technical reliability and regulatory compliance, thereby ensuring that subsequent OEE evaluation is based on a validated and properly functioning production asset.

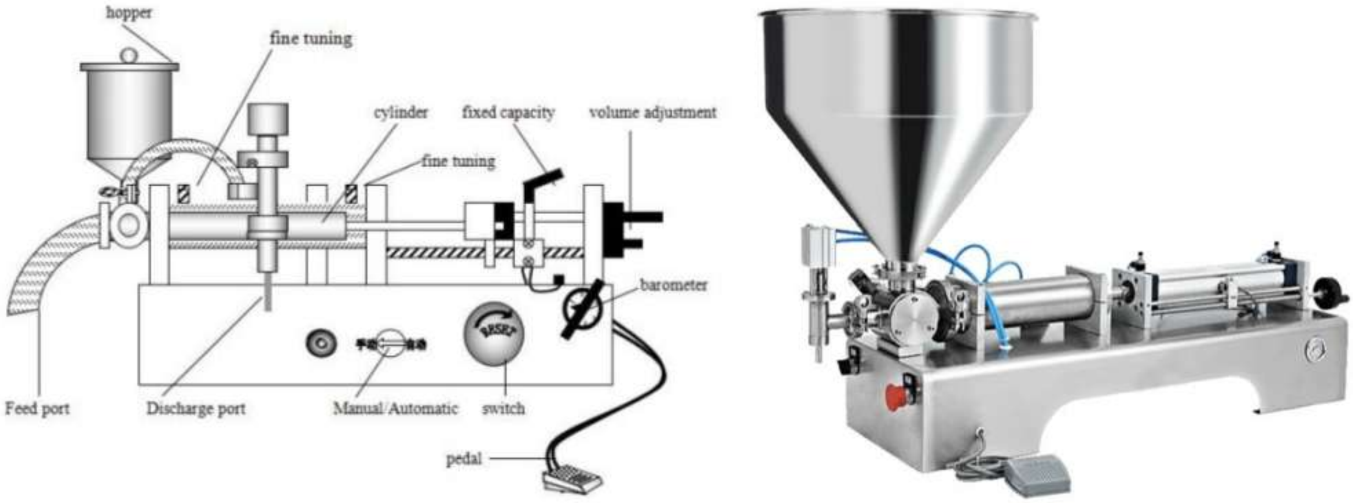

Figure 1. Semi- automatic pneumatic filling machine & anatomy

Method

This study was conducted over a three-month observation period at a cosmetics manufacturing company located in East Java, Indonesia, where a semi-automatic pneumatic filling machine is used as a primary production asset in cream packaging operations.

This research employed a descriptive quantitative design aimed at evaluating production efficiency using the Overall Equipment Effectiveness (OEE) method. The population consisted of all production activities involving the filling machine during the observation period, while the sample comprised operational data recorded over 13 consecutive production weeks (Muchiri & Pintelon, 2008a). A total sampling technique was applied, in which all available operational records within the study period were included as research data, following the principle that total sampling is appropriate when the population size is limited and fully accessible. The research variables included Availability, Performance, and Quality as dependent variables representing equipment effectiveness, and operational parameters such as Total Working Time, Planned Production Time, Operating Time, downtime duration, total output, good units, and defective units as independent measurement variables. Data collection was conducted through direct observation, documentation review, and production log analysis. The tools and materials used in this study included production reports, machine operation logs, downtime records, and standard production documentation provided by the company.

The research was conducted through several systematic stages. First, preliminary observation was performed to understand the filling machine's operating system and production workflow. Second, production data were recorded daily for three months, including working time, downtime, production quantity, and defect quantity. Third, the collected data were validated and organized into weekly datasets. Fourth, OEE values were calculated using standard formulas for Availability, Performance, and Quality. Fifth, downtime events were classified according to their causes, such as waiting for materials, setup and adjustment, mechanical failure, administrative delays, and other operational factors. Finally, dominant loss factors were identified to determine priority improvement areas.

Data analysis was carried out quantitatively to evaluate equipment effectiveness and identify the primary causes of production losses. Availability was calculated by comparing actual operating time with planned production time. Performance was determined by comparing actual output with theoretical output based on ideal cycle time, while Quality was calculated as the ratio of good units to total units produced. To identify dominant loss factors, downtime data were categorized and analyzed using a Pareto diagram, which highlights the most significant contributors to efficiency reduction. The results of these analyses were then interpreted to determine root causes of inefficiency and to formulate targeted improvement recommendations for enhancing machine reliability and production stability.

The OEE calculation was conducted based on its three main components: availability, performance, and quality. Each component was computed using the following formulas:

$$\text{Availability} = \frac{\text{Effective Working Time}}{\text{Total Working Time}} \times 100\% \quad (1)$$

Planned Production Time = Total scheduled production time – planned downtime.
Operating Time = Planned Production Time – unplanned downtime

$$\text{Performance} = \frac{\text{Actual Output}}{\text{Theoretical Output}} \times 100\% \quad (2)$$

Theoretical Output = Planned Production Time × Ideal Cycle Rate

$$\text{Quality} = \frac{\text{Good Units}}{\text{Total Units Produced}} \times 100\% \quad (3)$$

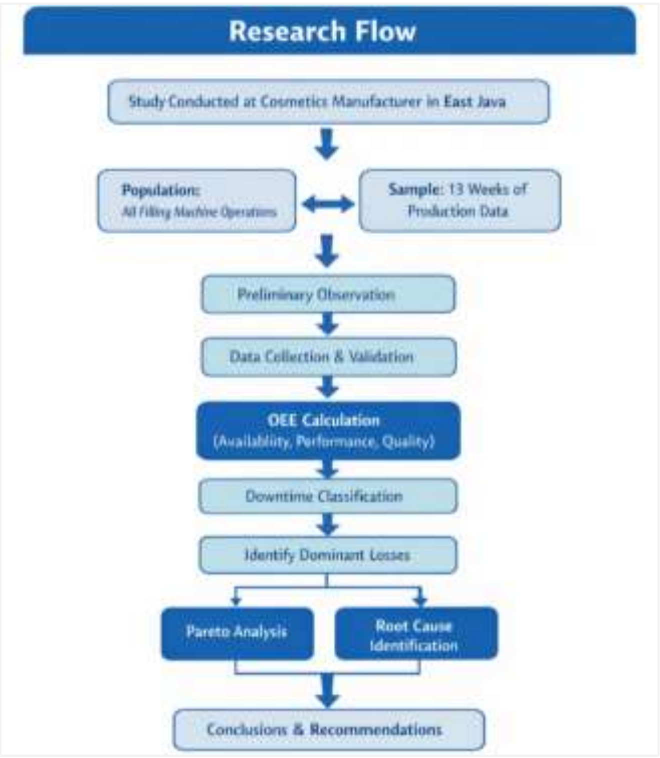

Figure 2. Research flow diagram of OEE-based filling machine performance analysis

Results and Discussion

The calculation of Overall Equipment Effectiveness (OEE) in this study was based on three main components: (1) availability, which represents the proportion of effective operating time to the planned production time; (2) performance, which measures the ratio between the actual output and the machine's theoretical capacity; and (3) quality, which is determined by the percentage of good products relative to the total output. The values of availability, performance, and quality were calculated using the formulas proposed by (Yazdi et al., 2018).

In the context of this study, the company employed an internal calculation approach that incorporates the terms Effective Working Time and Production Idle Time to reflect the actual production conditions. Production Idle Time includes all periods when the machine is not operating and not producing output, encompassing both planned downtime (e.g., routine maintenance activities) and unplanned downtime (e.g., technical failures or unexpected breakdowns). Therefore, in this study, Production Idle Time is treated as a combined representation of both planned and unplanned downtimes. This clarification is intended to ensure consistency between the company's operational terminology and the standard OEE components used in the analysis (Aleš et al., 2019).

Ideally, the achievement of Overall Equipment Effectiveness (OEE) is realized after the implementation of Total Productive Maintenance (TPM). Under such conditions, machine performance is expected to reach an availability rate above 90%, performance efficiency exceeding 95%, and a quality rate greater than 99%. When all three indicators are achieved, the overall OEE value can surpass the ideal benchmark of 85%, which is widely recognized as the global standard for production equipment effectiveness (Muchiri & Pintelon, 2008).

At PT X, located in East Java, OEE was used as a method to measure the effectiveness of machine performance by considering the three main indicators: availability, performance, and quality. The availability calculation was based on Effective Working Time and Production Idle Time, distinguishing the total machine hours into these two operational categories. Effective Working Time represents the machine's actual production time within one month, calculated as the total machine working hours minus Production Idle Time. Meanwhile, Production Idle Time includes the time spent on setup, shutdown, maintenance, repair, handling of defective products, and process adjustments. This distinction enables the company to accurately assess machine utilization levels and identify sources of production time losses. The data on Effective Working Time and Production Idle Time collected during the period of January to March 2025 served as the basis for the OEE calculation. The results of the availability calculation are presented in Table 1.

Based on the calculation of availability for the production process over a 13-week period, a significant variation was observed from week to week. The highest availability value reached 97.50% in Weeks 8 and 9, indicating that the machine was almost fully utilized according to the planned working schedule, with very minimal idle time (only 60 minutes out of a total of 2400 minutes). This condition reflects effective scheduling and minimal operational disturbances.

Table 1. Calculation of Availability Values

Week	Total Working Time (Minutes)	Production Idle Time (Minutes)	Effective Working Time (Minutes)	Availability (%)
1	1140	420	720	63.16
2	2400	240	2160	90
3	2400	420	1980	82.50
4	2400	180	2520	93.33
5	1560	120	1440	92.31
6	2400	420	1980	82.50
7	2400	600	1800	75
8	2400	60	2340	97.50
9	2400	60	2340	97.50
10	2400	1680	720	30
11	2400	240	2160	90
12	2400	600	1800	75
13	2070	270	1800	86.96

Conversely, the lowest availability value occurred in Week 10, at only 30%, due to an extensive idle time of 1680 minutes out of a total of 2400 minutes. This result indicates that the machine was idle for most of the production period, leading to a drastic decline in production capacity.

Based on the analysis of downtime data collected during the observation period, a Pareto Diagram was constructed, as shown in Figure 3 & Table 2. This diagram illustrates the proportional distribution of machine downtime according to its main causes, which include setup and adjustment, mechanical failures, production administration, and other minor factors.

Based on the analysis presented in the Pareto Diagram, the primary contributor to downtime in the cream filling process was setup and adjustment activities, with a total duration of 3,631 minutes, accounting for 68% of the total downtime. This was followed by mechanical failures, amounting to 720 minutes or 14%, and production administration-related delays, which contributed 507 minutes or 10% of total downtime. The remaining 452 minutes (9%) were categorized as other minor disturbances. Collectively, setup & adjustment and mechanical failure accounted for more than 80% of total downtime, indicating that the decline in machine availability and OEE performance was primarily driven by process-related and technical factors that disrupted operational continuity.

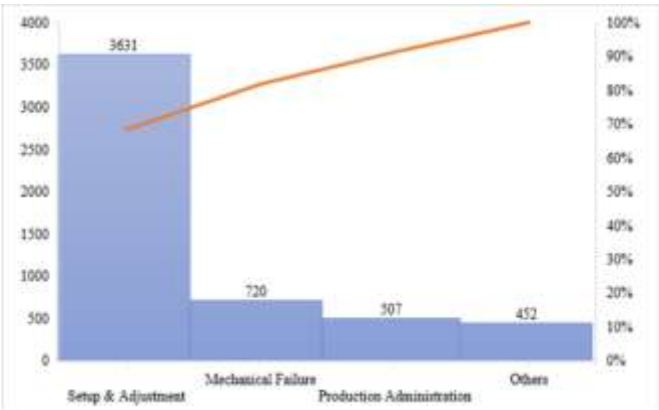

Figure 3. Pareto diagram of machine downtime causes

Table 2. Distribution of Downtime Causes, Duration, and Contribution Percentage

Downtime Cause	Duration (minutes)	Percentage (%)	Cumulative (%)
Setup & Adjustment	3,631	68%	68%
Mechanical Failure	720	14%	82%
Production Administration	507	10%	91%
Others	452	9%	100%
Total	5,310	100%	–

These findings are consistent with the Pareto 80/20 principle, which states that the majority of production losses typically stem from a small number of dominant factors. Therefore, improvement efforts should prioritize reducing setup and adjustment duration—particularly through better standardization, operator training, and streamlined changeover procedures—and addressing recurring mechanical issues through enhanced preventive and predictive maintenance. This observation aligns with the perspective of Yazdi et al. (2018), who identified setup time and mechanical disturbances as common root causes of low machine effectiveness in batch-based manufacturing environments. By implementing focused improvements in these areas, the company can significantly enhance Overall Equipment Effectiveness (OEE) and ensure more stable production performance (Chidiebube et al., 2025).

Table 3. Calculation of Performance Values

Week	Effective Working Time (Minutes)	Ideal Cycle Rate (unit/ minutes)	Theoretical Output (unit)	Actual Output (unit)	Performance (%)
1	720	4	2880	2115	73.44
2	2160	4	8640	7803	90.31
3	1980	4	7920	7412	93.59
4	2520	4	10080	7506	74.46
5	1440	4	5760	5203	90.33
6	1980	4	7920	7211	91.05
7	1800	4	7200	6705	93.13
8	2340	4	9360	8503	90.84
9	2340	4	9360	8711	93.07
10	720	4	2880	2051	71.22
11	2160	4	8640	7908	91.53
12	1800	4	7200	6603	91.71
13	1800	4	7200	6804	94.50

In general, most weeks exhibited availability values ranging between 75% and 93%, which can be considered satisfactory. For instance, Week 2 (90%), Week 4 (93.33%), and Week 5 (92.31%) showed stable performance with relatively low idle time. However, several weeks experienced notable declines, such as Week 1 (63.16%) and Week 6 (82.50%), indicating potential areas for improvement in material planning, setup scheduling, maintenance practices, and production problem handling. This suggests that consistency remains a key challenge in maintaining stable production performance.

Significant fluctuations in availability require close attention, as this instability directly affects production throughput and cost efficiency. Overall, the analysis shows that while the production process can achieve high availability under certain conditions, there were also critical weeks with substantial idle time (Cordova et al., 2023). Improvement efforts should therefore focus on reducing unplanned downtime, optimizing setup duration, and enhancing machine reliability through preventive and predictive maintenance programs. Addressing these aspects is expected to improve availability stability, thereby contributing to higher overall OEE and lower production costs (COGS) (Panigrahi et al., 2023).

The performance analysis of the production process over the 13-week observation period revealed variations ranging from 71.22% to 94.50%. The highest performance value was achieved in Week 13, reaching 94.50%, where the machine produced 6,804 units out of a theoretical output of 7,200 units. This indicates that the production rate was operating very close to its ideal cycle speed. Conversely, the lowest performance values were recorded in Week 10 (71.22%) and Week 1 (73.44%), reflecting a significant reduction in production speed compared to the ideal standard. Such decreases are likely attributable to technical factors, such as equipment wear or operational issues that caused the machine to run below its optimal capacity (Tang, 2019).

Overall, most weeks showed performance values within the 90%–94% range, which can be classified as good according to OEE standards. However, the fluctuations observed in several weeks indicate inconsistency in production speed performance. These variations are closely associated with the dominant downtime contributors identified in the analysis, particularly setup and adjustment activities (68%), which often require operators to recalibrate machine settings, causing delays in achieving stable operating speeds. Additionally, mechanical failures (14%) may lead to temporary reductions in machine speed as operators attempt to maintain safe operation, while production administration delays (10%) and other minor disturbances disrupt workflow continuity and affect machine rhythm (Alda et al., 2024).

To improve performance stability, the company should ensure consistent implementation of scheduled maintenance, optimize process parameter settings during setup, and strengthen operator competency to maintain machine speed close to the ideal cycle rate (Annamalai & Suresh, 2019). These measures will help reduce speed-related losses, stabilize machine performance, and ultimately contribute to higher and more consistent Overall Equipment Effectiveness (OEE).

The quality values of the production process throughout the 13-week observation period remained relatively high, ranging from 92.67% to 99.94%. Most weeks recorded quality rates above 99%, indicating that the pneumatic filling machine generally produced low levels of defective products. The highest quality value occurred in Week 2 (99.94%), with only five defective units out of 7,803 units produced, while the lowest was found in Week 13 (92.67%) due to a substantial increase of 499 defective units out of 6,804 units. Several other weeks—such as Week 10 (95.08%) and Week 12 (97.27%)—also showed noticeable quality declines, primarily due to a rise in defective outputs.

Table 4. Calculation of Quality Values

Week	Total Output (unit)	Good Units (unit)	Defect Units (unit)	Quality (%)
1	2115	2105	10	99.53
2	7803	7798	5	99.94
3	7412	7402	10	99.87
4	7506	7490	16	99.79
5	5203	5100	103	98.02
6	7211	7100	111	98.46
7	6705	6685	20	99.70
8	8503	8483	20	99.76
9	8711	8688	23	99.74
10	2051	1950	101	95.08
11	7908	7853	55	99.30
12	6603	6423	180	97.27
13	6804	6305	499	92.67

To understand the underlying causes that contributed to these quality deviations, an Ishikawa (Fishbone) Diagram was used as shown in Figure 4. The fishbone model systematically categorizes potential sources of problems into Materials, Methods, Machine, Man, and Environment, enabling a structured evaluation of factors that may influence machine downtime and product defects (Clements et al., 2018).

Based on the analysis using the Fishbone Diagram (cause-and-effect diagram), several key factors were identified as potential contributors to the decline in product quality during the filling process. These factors include Man, Machine, Material, Method, Measurement, and Environment (Rachman & Nugraha, 2018).

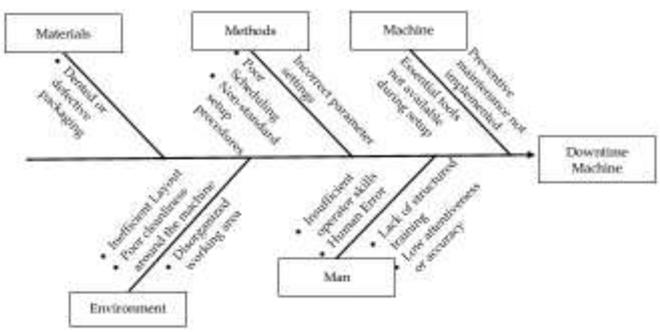

Figure 34 Fishbone diagram

From the human (Man) aspect, human-related issues were among the prominent contributors to downtime and quality variation. Insufficient operator skills, human error, and a lack of structured training were frequently observed. Operators with limited experience may struggle to adjust pneumatic pressure, filling volume settings, or sealing parameters accurately, which can lead to inconsistent filling results or temporary machine stoppages. Low attentiveness or accuracy, particularly during long production cycles, may also increase the likelihood of improper tube alignment and misfeeds (Luozzo et al., 2023).

Machine-related causes played a critical role in downtime events. The most significant issues included the absence of preventive maintenance, leading to gradual performance degradation. In addition, essential tools that were unavailable during setup caused prolonged adjustment time. Mechanical wear, misalignment of the filling cylinder, and leakage in pneumatic connections also contributed to unstable machine operation. These problems directly affect fill accuracy, sealing consistency, and machine cycle time, thereby influencing both performance and quality (Abdullah et al., 2025).

The fishbone analysis identified material conditions as a direct contributor to downtime. Dented or defective packaging frequently caused interruptions as the machine was unable to process deformities, forcing operators to stop production and manually replace units (Pitoyo et al., 2024). Variability in packaging quality also increased the risk of misfeeds and product spillage. An inefficient layout of supporting materials—leading to longer searching and handling times— further contributed to minor stoppages (Dobra & Jósvai, 2022).

Several downtime events were associated with method-related factors, especially poor scheduling and non-standard setup procedures. Inconsistent setup practices led to repeated adjustments during production, reducing machine availability. Incorrect parameter settings—identified as a major root cause—resulted in unstable filling volume, improper sealing, and the need for rework. These inconsistencies emphasize the lack of standardized operating procedures for machine setup and calibration (Yuik & Puvanasvaran, 2020).

Environmental factors also contributed to downtime. An inefficient layout around the machine, poor cleanliness, and a disorganized working area increased the time required for movement, inspection, or troubleshooting. Accumulated dust or spilled product residues could interfere with pneumatic components, increasing the likelihood of minor stoppages and reduced filling speed (Alda et al., 2024).

Overall, the Fishbone Diagram analysis indicates that downtime in the pneumatic filling machine is not caused by a single factor but by the interaction among human error, inadequate machine maintenance, substandard packaging materials, non-standardized methods, and a poorly organized working environment. Although the quality rate remained relatively high across most weeks, the identified issues highlight the need for improvements in operator training, standardization of setup procedures, and preventive maintenance practices to minimize downtime-related losses (Singh et al., 2022).

Ensuring consistency in raw material quality, maintaining a clean production environment, and implementing structured work arrangements are also crucial to stabilizing machine operations. Enhancing these factors is expected to further improve the reliability of the pneumatic filling process, reduce the rate of defective products, and ultimately strengthen overall production effectiveness (Durga Prasad & Radhakrishna, 2019).

Table 5. Calculation of OEE Values

Week	Availability (%)	Performance (%)	Quality (%)	OEE (%)	OEE / Month
1	63.16	73.44	99.53	46.17	
2	90	90.31	99.94	81.23	
3	82.5	93.59	99.87	77.11	Month 1 71.12%
4	93.33	74.46	99.79	69.35	
5	92.31	90.33	98.02	81.73	
6	82.5	91.05	98.46	73.96	
7	75	93.13	99.7	69.64	Month 2 80.62 %
8	97.5	90.84	99.76	88.36	
9	97.5	93.07	99.74	90.51	
10	30	71.22	95.08	20.31	
11	90	91.53	99.3	81.80	Month 3 61.29 %
12	75	91.71	97.27	66.90	
13	86.96	94.5	92.67	76.15	

The calculation results of Overall Equipment Effectiveness (OEE) for the 13-week production period showed a wide variation, ranging from 20.31% to 90.51%. This fluctuation was influenced by changes in the three OEE components: availability, performance, and quality. During the first month (Weeks 1–5), the average OEE was 71.12%, with the highest value achieved in Week 5 (81.73%) and the lowest in Week 1 (46.17%), primarily due to low availability (63.16%). In the second month (Weeks 6–9), the average OEE improved to 80.62%, reaching its peak in Week 9 (90.51%). This improvement was supported by high availability (97.5%) and consistently strong performance levels above 90%. However, in the third month (Weeks 10–13), the average OEE declined significantly to 61.29%. The sharp drop in Week 10 (20.31%) was the most notable, driven by a steep decrease in availability (30%) and a slight decline in quality (95.08%).

To better understand the causes behind these OEE fluctuations, the Six Big Losses framework was utilized to analyze performance losses across the observation period. Among the loss categories, equipment failure (breakdown losses) emerged as the most dominant factor affecting availability. This was evident in Weeks 1 and 10, where extended mechanical failures—including agitator motor malfunction and valve leakage—resulted in prolonged downtime and consequently low OEE values. These failures highlight the critical need for more structured preventive maintenance and periodic equipment inspection.

Setup and adjustment losses also played a significant role in reducing availability, particularly during production transitions such as material changeovers and sanitation procedures. Weeks 3, 6, and 11 showed noticeable increases in setup duration, indicating potential inconsistencies in preparation activities. Standardizing these processes through SMED-based improvements may help reduce variability and enhance production readiness (Bangun et al., 2023).

In addition to major downtime events, idling and minor stops contributed to hidden performance losses, particularly in weeks where OEE fell below 70%. Short but frequent interruptions—such as raw material delays and operator coordination issues—accumulated to reduce effective machine utilization, suggesting the need for better material flow control and workflow synchronization (Purba et al., 2018).

While performance remained relatively high throughout most weeks, reduced speed losses were observed during the third month due to variations in product viscosity, forcing operators to lower machine speed to maintain accuracy. This indicates the importance of raw material consistency and may warrant the implementation of viscosity monitoring or pre-processing adjustments (Yermia Tobe et al., 2017).

Regarding quality losses, process defects and reduced yield had a smaller but still noticeable impact. Weeks 10 and 12 showed slight declines in quality due to inconsistent homogenization, contamination risks, and temperature deviations, resulting in defective outputs and start-up rejects. Although average quality performance remained above 95%, these deviations still contributed to weekly OEE instability (Tasya Kirana & Widiasih, 2024).

Overall, the OEE performance can be categorized as fairly good but inconsistent, as it did not consistently achieve the world-class standard of 85%. Only in Weeks 8 and 9 did the machine surpass this benchmark. The integrated Six Big Losses analysis confirms that breakdown losses, setup and adjustment losses, and reduced speed losses were the most influential contributors to efficiency variation throughout the 13-week observation period (Tonny et al., 2023). Therefore, improvement efforts should focus on minimizing unplanned downtime through enhanced maintenance routines, optimizing setup procedures, reducing minor stops through better operational coordination, and strengthening process controls to minimize defects. Addressing these areas is essential for achieving stable and improved OEE performance across future production cycles (Kamble et al., 2018).

Conclusion

The analysis revealed that the Overall Equipment Effectiveness (OEE) of the filling machine fluctuated significantly during the 13-week observation period, ranging from 20.31% to 90.51%, with monthly averages of 71.12%, 80.62%, and 61.29%, indicating inconsistent machine effectiveness that did not reach the world-class benchmark of 85%. Although the quality component remained stable at above 98%, performance limitations were primarily associated with the availability and performance components, which were affected by frequent downtime and reduced operating speeds. Evaluation using the Six Big Losses framework showed that breakdown losses, setup and adjustment losses, and idling or minor stoppages were the dominant contributors to reduced effectiveness, with waiting for raw materials and prolonged setup activities accounting for nearly 70% of total downtime, confirming that operational and material-flow disruptions were the main barriers to stable performance. Reduced speed losses were also evident during weeks with lower productivity, often caused by variations in material characteristics that required operators to decrease machine speed to maintain process stability. These findings indicate that improving OEE requires a targeted reduction of dominant losses through strengthened preventive and predictive maintenance, reduced setup variability, improved production-material readiness, consistent raw-material properties, and enhanced operator responsiveness. Overall, the study demonstrates that systematic mitigation of the Six Big Losses is essential to stabilize and increase OEE values, thereby improving machine reliability, minimizing downtime, and supporting sustainable production efficiency in cosmetics manufacturing.

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Author Contributions

A.F. contributed to data collection and manuscript writing. E.W.F. & A.N.W. provided critical review and final approval of the manuscript.

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Conflicts of Interest

Authors declare that no conflict of interest in this publication.

References

Abdullah, J., Al Hossain Rifat, M., & Deb Ray, A. (2025). Enhancing Overall Equipment Effectiveness (OEE) Of A Selected Machine In A Light Manufacturing Factory In Bangladesh. *Journal of Engineering and Technology for Industrial Applications ITEGAM-JETIA Manaus*, *52*, 179–185. https://doi.org/10.5935/jetia

Alda, T., Ramadhan, M., Revadi, C. E., Shalihin, A., Ramadhani, F., & Nasution, P. (2024). Analysis of Overall Equipment Effectiveness (OEE) as an Effort to Increase The Productivity Filling Line of Lithos Packaging Lubricant. *Simetrikal Journal of Engineering and Technology*, *03*(01), 1–08. https://doi.org/10.62375/jmrib.v2i2.284

Aleš, Z., Pavlů, J., Legát, V., Mošna, F., & Jurča, V. (2019). Methodology of overall equipment effectiveness calculation in the context of industry 4.0 environment. *Eksploatacja i Niezawodnosc*, *21*(3), 411–418. https://doi.org/10.17531/ein.2019.3.7

Alfadhlani, A., Zuhair, A., & Fithri, P. (2025). Reliability-Based Preventive Maintenance Scheduling for Raw

Mill Equipment to Minimize Downtime at PT X. *METAL: Jurnal Sistem Mekanik Dan Termal*, *9*(2), 146–157. https://doi.org/10.25077/metal.9.2.146-157.2025

Annamalai, S., & Suresh, D. (2019). Implementation of total productive maintenance for overall equipment effectiveness improvement in machine shop. *International Journal of Recent Technology and Engineering*, *8*(3), 7686–7691. https://doi.org/10.35940/ijrte.C6212.098319

Bangun, C. S., Purnama, D., & Suwandi, A. (2023). Using the Single Minute Exchange of Die (SMED) Method to Minimize Machine Setup Time: A Case Study. *International Journal of Research and Review*, *10*(12), 429–434. https://doi.org/10.52403/ijrr.20231247

Chidiebube, I. N., Nwamekwe, C. O., Chukwuemeka, G. H., & Wilfred, M. (2025). Optimization of overall equipment effectiveness factors in a food manufacturing small and medium enterprise. *Journal of Research in Engineering and Applied Sciences, 10*(1), 836-845. Retrieved from https://hal.science/hal-04999684/

Clements, E. J., Sonwaney, V., & Singh, R. K. (2018). Measurement of overall equipment effectiveness to improve operational efficiency. *International Journal of Process Management and Benchmarking*, *8*(2), 246. https://doi.org/10.1504/ijpmb.2018.10010267

Cordova, A. C. Q., Damiano, V. B. A., & Quiroz-Flores, J. C. (2023). Improving availability by Lean Manufacturing and TPM tools in an SME in the plastics sector. *International Conference on Innovation and Trends in Engineering*. https://doi.org/10.1109/CONIITI61170.2023.10324215

Corrales, L. del C. N., Lambán, M. P., Hernandez Korner, M. E., & Royo, J. (2020). Overall equipment effectiveness: Systematic literature review and overview of different approaches. In *Applied Sciences (Switzerland)* (Vol. 10, Number 18). MDPI AG. https://doi.org/10.3390/APP10186469

Dobra, P., & Jósvai, J. (2022). Assembly Line Overall Equipment Effectiveness (OEE) Prediction from Human Estimation to Supervised Machine Learning. *Journal of Manufacturing and Materials Processing*, *6*(3). https://doi.org/10.3390/jmmp6030059

Durga Prasad, N. V. P. R., & Radhakrishna, C. (2019). Key performance index for overall substation performance. *International Journal of Recent Technology and Engineering*, *8*(2), 6067–6071. https://doi.org/10.35940/ijrte.B3797.078219

Kamble, S. S., Gunasekaran, A., & Gawankar, S. A. (2018). Sustainable Industry 4.0 framework: A systematic literature review identifying the current trends and future perspectives. *Process Safety and Environmental Protection*, *117*, 408–425. https://doi.org/10.1016/j.psep.2018.05.009

Kirana, A. T., & Widiasih, W. (2024). Analisis Perhitungan Overall Equipment Effectiveness (OEE) untuk Meningkatkan Efisiensi Mesin Haloong (Studi Kasus: PT Benteng Api Technic, Gresik). *Jurnal Tekstil: Jurnal Keilmuan dan Aplikasi Bidang Tekstil dan Manajemen Industri, 7*(1), 59-68. https://doi.org/10.59432/jute.v7i1.89

Luozzo, S. Di, Starnoni, F., & Schiraldi, M. M. (2023). On the relationship between human factor and overall equipment effectiveness (OEE): An analysis through the adoption of analytic hierarchy process and ISO 22400. *International Journal of Engineering Business Management*, *15*. https://doi.org/10.1177/18479790231188548

Muchiri, P., & Pintelon, L. (2008). Performance measurement using overall equipment effectiveness (OEE): Literature review and practical application discussion. *International Journal of Production Research*, *46*(13), 3517–3535. https://doi.org/10.1080/00207540601142645

Panigrahi, S., Al Ghafri, K. K., Al Alyani, W. R., Ali Khan, M. W., Al Madhagy, T., & Khan, A. (2023). Lean manufacturing practices for operational and business performance: A PLS-SEM modeling analysis. *International Journal of Engineering Business Management*, *15*. https://doi.org/10.1177/18479790221147864

Pitoyo, D., Azwar, A. G., & Aprilia, A. (2024). Optimizing Operations: Evaluating Overall Equipment Effectiveness (OEE) And Failure Mode Effect Analysis (FMEA) For Muratec Qpro Ex Winding Machines at PT XYZ. *Journal of Physics: Conference Series*, *2928*(1). https://doi.org/10.1088/1742-6596/2928/1/012013

Purba, H. H., Wijayanto, E., & Aristiara, N. (2018). Analysis of Overall Equipment Effectiveness (OEE) with Total Productive Maintenance Method on Jig Cutting: A Case Study in Manufacturing Industry. *Journal of Scientific and Engineering Research*, *5*(7), 397–406. Retrieved from https://shorturl.at/LnLo8

Rachman, T., & Nugraha, A. W. (2018). *Pengukuran Overall Equipment Effectiveness(OEE) untuk Perbaikan Proses Manufaktur Mesin Bead Grommet Jurnal Inovisi*, *14*(1). Retrieved from https://digilib.esaunggul.ac.id/public/UEU-Journal-19369-11_0984.pdf

Singh, S., Agrawal, A., Sharma, D., Saini, V., Kumar, A., & Praveenkumar, S. (2022). Implementation of Total Productive Maintenance Approach:

Improving Overall Equipment Efficiency of a Metal Industry. *Inventions*, *7*(4). https://doi.org/10.3390/inventions7040119

Stefana, E., Cocca, P., Fantori, F., Marciano, F., & Marini, A. (2022). Resource Overall Equipment Cost Loss indicator to assess equipment performance and product cost. *International Journal of Productivity and Performance Management*, *73*(11), 20–45. https://doi.org/10.1108/IJPPM-10-2021-0615

Tang, H. (2019). A new method of bottleneck analysis for manufacturing systems. *Manufacturing Letters*, *19*, 21–24. https://doi.org/10.1016/j.mfglet.2019.01.003

Tonny, F. A., Maliha, A., Chayan, M. I., & Xames, M. D. (2023). Optimization of overall equipment effectiveness (OEE) factors: Case study of a vegetable oil manufacturing company. *Management Science Letters*, *13*(2), 124–135. https://doi.org/10.5267/j.msl.2022.12.002

Yazdi, P. G., Azizi, A., & Hashemipour, M. (2018). An empirical investigation of the relationship between overall equipment efficiency (OEE) and manufacturing sustainability in industry 4.0 with time study approach. *Sustainability (Switzerland)*, *10*(9). https://doi.org/10.3390/su10093031

Yermia Tobe, A., Widhiyanuriyawan, D., & Yuliati, L. (2017). The Integration Of Overall Equipment Effectiveness (OEE) Method And Lean Manufacturing Concept To Improve Production Performance (Case Study: Fertilizer Producer). *Journal Of Engineering And Management Industrial System*, *5*(2). https://doi.org/10.21776

Yuik, C. J., & Puvanasvaran, P. (2020). Development of Lean Manufacturing Implementation Framework in Machinery and Equipment SMEs. *International Journal of Industrial Engineering and Management*, *11*(3), 157–169. https://doi.org/10.24867/IJIEM-2020-3-261