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Evaluation of overall equipment effectiveness in the bottling line packaging process: A case study of the beverage company

Jusra Tampubolon *
Department of Industrial Engineering, Faculty of Science and Technology, Universitas Prima Indonesia, Sumatera Utara, Indonesia

*__Corresponding Author__: jusratampubolon@unprimdn.ac.id

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ABSTRACT
The effectiveness of equipment on the bottling packaging line greatly determines throughput and quality in the high-capacity beverage company. Overall Equipment Effectiveness (OEE) is commonly used to assess performance and map sources of loss. This study evaluates beverage company bottling line using OEE and six big losses based on weekly data from weeks 14–26, including production output (good, reject, total), available time, planned downtime, and unplanned downtime. OEE components were calculated (Availability–Performance–Quality) and decomposed into breakdown, setup & adjustment, idling & minor stoppages, reduced speed, and defect. The results showed an average OEE of 69.35% (68.03–70.79%) with availability at 97.9%, performance at 70.9%, and quality at 99.9%. The dominant loss was reduced speed (≈28.48% of loading time), while setup & adjustment was 0.95%, breakdown 0.89%, idling & minor 0.24%, and defect 0.0895%, which were relatively small. The findings confirm performance as the main constraint; improvements are directed at stabilizing the Filler speed (pacemaker), line balancing & buffering, controlling micro-stops, and predictive maintenance of critical points. Improving performance is projected to be the most effective way to bring OEE closer to the 85% benchmark without compromising quality.

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1. INTRODUCTION

For the manufacturing and Fast-Moving Consumer Goods (FMCG) sectors to remain competitive and productive, equipment effectiveness is essential. Machine availability, performance rate, and quality rate are all measured by Overall Equipment Effectiveness (OEE), a crucial performance parameter. According to Setiawan et al. [1], performance rate is the main cause of effectiveness inadequacies. Since the FMCG industry uses a lot of materials and needs constant throughput improvement for sustainability, ongoing performance evaluation and efficiency analysis are crucial for process improvement and market responsiveness [2]. The effectiveness of equipment is significantly impacted by Total Preventive Maintenance (TPM) implementation; one confectionery plant's OEE increased from 54.31% to 68.39% following TPM implementation [3]. However, with an average OEE of 55.30%, many food production enterprises fall short of international requirements, highlighting the urgent need for better maintenance procedures and strategies to keep things running [4].

The three main components of OEE, a complete performance measuring method, are availability, performance, and quality [5], [6]. By assessing various production losses and pinpointing areas for process improvement, OEE offers a comprehensive perspective of operational performance [7]. The metric provides a straightforward means of monitoring production performance and lean initiatives, making it especially useful in the present competitive manufacturing climate [8]. According to research, OEE is a comprehensive metric that links process availability to productivity and quality, and it can be used to any activity that involves plant and machinery [6]. Cross-functional teams working to increase company competitiveness are involved in the most successful OEE implementations [6]. Plant Operating Time is the starting point for OEE analysis, which assists businesses in identifying hidden losses, cutting downtime, and promoting quality enhancements, all of which eventually boost output and profitability [5], [8].

Significant operational difficulties that affect efficiency and output are faced by bottling operations. Micro downtime (less than 15 minutes) accounts for 57% of automated flow line inefficiencies, making downtime a significant issue in bottling operations [9]. Equipment failures in vital parts like inkjet printers and fillers [10] and problems with the production and labeling of PET containers [11] are frequent causes of downtime. According to maintenance analysis, different machines display distinct patterns of downtime; some show random failures, while others indicate wear-out failures brought on by aged parts [12]. OEE, a crucial performance indicator that gauges bottling line efficiency across availability, performance, and quality dimensions, is strongly impacted by these outages [13], [14]. In order to solve these problems and enhance production processes, a methodical analysis of techniques such as queuing theory, Weibull modeling, and statistical methods is necessary.

Beverage company was chosen as the object of this study because it is one of the largest and oldest beverage companies in Indonesia, widely known for its bottled and carton tea products. The company has a high-volume production system and strict quality standards, making the effectiveness of production equipment, especially on the packaging bottling line, a critical factor in ensuring supply continuity and product quality.

In addition, packaging lines in the beverage company tend to face significant challenges, such as machine downtime, unstable operating speeds, and potential product defects due to equipment limitations. This makes OEE measurement highly relevant for assessing actual performance against world-class OEE standards.

The selection of beverage company was also based on the availability of relatively complete production data and management support in efforts to improve efficiency and implement Total Productive Maintenance (TPM) principles. Thus, this case study is expected to not only contribute academically, but also produce practical recommendations that can be directly implemented to improve equipment effectiveness and the company's competitiveness in the national and international beverage markets.

The research questions in this study focus on two main points. First, what is the OEE value in the packaging process at the bottling line of beverage company. Second, what are the dominant factors that affect the OEE value in this process. Based on these research questions, this study aims to measure the OEE value in the bottling line packaging process, identify the dominant factors that cause a decline in equipment effectiveness through Six Big Losses analysis, and provide an evaluation and recommendations for improvements that can increase the effectiveness of the packaging process.

This study is expected to provide practical and academic benefits. From a practical perspective, the results of this study can provide a comprehensive picture of the actual condition of equipment effectiveness on the bottling line at beverage company, thereby providing a basis for management decision-making in maintenance planning, productivity improvement, and quality control. Thus, the company can move towards achieving world-class OEE standards while increasing its competitiveness in the beverage company. From an academic perspective, this research contributes to the development of studies on the application of the OEE method in the beverage company, particularly on packaging lines, and can serve as a reference for further research focusing on equipment effectiveness evaluation and the application of TPM.

2. LITERATURE REVIEW

OEE is a key indicator used to assess the effectiveness of machine usage in a production process. This concept was introduced by Nakajima [15] within the framework of TPM and measures equipment performance based on three main dimensions, namely availability, performance, and quality. The OEE value is calculated by multiplying these three factors, thereby providing a comprehensive picture of operational effectiveness. In general, the globally recognized OEE benchmark is 85% for the world class category, with details of 90% Availability, 95% Performance, and 99% Quality [7].

In its implementation, OEE is also closely related to the concept of Six Big Losses, which are the six main sources of loss that affect equipment effectiveness, including: breakdown losses, setup and adjustment losses, idling and minor stoppages, reduced speed losses, defect losses, and startup losses. Identifying these losses helps companies understand the dominant factors that reduce equipment performance so that targeted improvement efforts can be made [16].

Many people use production machine effectiveness calculations, such as OEE and Six Big Losses Analysis. Putra and Rahmawati [17] stated that OEE can provide a comprehensive picture of machine condition through three main elements: availability, performance, and quality. This is then linked to six sources of time loss on the production line. Thus, Musyafa'ah and Sofiana [18] stated that mapping the Six Big Losses is very important for finding the root cause of operational problems, especially those related to breakdowns, setup & adjustment, idling, and abnormal speed reductions. By using the quantitative approach of OEE and Six Big Losses to analyze the effectiveness of the bottling line, these two studies strengthen the methodological basis of this research.

Previous studies have proven the importance of implementing OEE in various industrial sectors. Muchiri and Pintelon [19] emphasized that OEE is not only a measurement tool, but also a strategy for increasing productivity through a maintenance approach. Research by Ojeda et al. [20], in the automotive industry showed that the application of OEE can reduce downtime by up to 15% with preventive improvements. Meanwhile, Das et al. [21] in their study of the Nigerian manufacturing industry showed that OEE is effective as an indicator of the successful implementation of TPM. In Indonesia, several studies have also been conducted, such as research in the food and beverage company, which showed that OEE values on packaging lines are often still below world-class standards, mainly due to high downtime and product defects [22], [23].

Several studies show that, in addition to the theoretical basis of OEE, improvement measures such as TPM and Kaizen are very important for reducing production losses and improving equipment reliability. Wiyatno and Kurnia [24] showed that the systematic application of TPM together with loss analysis can significantly reduce losses caused by damage and setup, which increases machine availability in CNC-based manufacturing systems. Furthermore, Wiyatno et al. [25] emphasized that combining Kaizen with a design-based improvement approach consistently reduces losses caused by minor stoppages and speed losses, which are consequences of stoppages.

Furthermore, Shumaesi et al. [26] found that the use of TPM and OEE monitoring improves operational efficiency and enhances sustainability performance by reducing energy waste and stabilizing process variability. This study shows that improvement-oriented maintenance approaches are crucial for measuring OEE, as they enable companies to address the root causes of the six big losses more effectively and achieve sustainable performance improvements.

The ability of businesses to utilize Industry 4.0 technologies, particularly predictive maintenance, greatly influences the improvement of machine effectiveness in contemporary industrial development. Prawatya et al. [27] showed that the use of machine learning to predict possible machine damage can reduce unplanned downtime and improve equipment reliability. This method complements traditional TPM methods with data-based early detection capabilities, enabling maintenance before failure occurs. Therefore, the beverage company, including beverage company, has a strategic opportunity to reduce breakdown losses and increase component availability in OEE calculations through the implementation of Industry 4.0-based predictive maintenance.

Thus, the literature review shows that OEE is a relevant approach to assess the effectiveness of equipment on high-capacity production lines, such as the bottled beverage company. The application of OEE at beverage company is important because the bottling line plays a strategic role in determining the smooth distribution of products. Through OEE and six big losses analysis, this study aims to identify the dominant factors affecting equipment performance while providing practical recommendations for improving operational effectiveness.

3. MATERIALS AND METHODS

3.1 Research Design

This study uses a quantitative descriptive approach with a case study method at beverage company. The analysis was conducted through the calculation of OEE using available machine operational data, including production data, available time, planned downtime, and unplanned downtime.

3.2 Research Location and Object

The research was conducted on the bottling line at beverage company. The main focus was on the machines and equipment involved in the process of filling and packaging beverages in bottles.

The sequence of machines on the bottling line is shown in Figure 1, including Depalletizer → Decrater → Bottle Washer → Inspection → Filler → Crater → Palletizer. This diagram also serves as the boundary for OEE analysis, where planned production time, downtime (planned and unplanned), actual output, defects, and ideal cycle time (particularly at the filler as the line speed control machine) are taken. the conveyors between machines are treated as part of the line; minor disruptions to the conveyors are recorded as idling & minor stoppages. This mapping ensures the traceability of each oee component and six big losses per workstation.

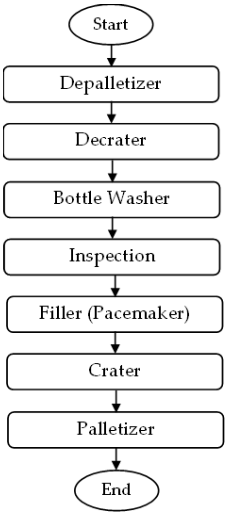

Figure 1. Standardized flowchart of the machine sequence on the bottling line
Source: Beverage company

3.3. Research Data

The data used in this study are:

1. Production data for the bottling Line, which is the number of products produced per specific time period.
2. Available time data, which is the machine operating time provided for production activities.
3. Planned downtime data, which is scheduled downtime, such as routine maintenance or changeovers.
4. Downtime data, which is unplanned downtime due to machine damage or technical disruptions.

3.4. Planned Downtime

In this study, planned downtime includes scheduled activities such as changeover and cleaning-in-place (CIP), which are excluded from effective production time. Unplanned downtime consists of machine breakdowns and line stops that occur during production. Accordingly, the time variables used in the OEE calculation are defined as follows:

$$AT - PD = LT \tag{1}$$

$$LT - UD = OT \tag{2}$$

where:

LT = Loading Time, the effective available time after planned downtime
AT = Available Time, the total scheduled production time
PD = Planned Downtime, includes scheduled changeover and CIP activities
UD = Unplanned Downtime consists of breakdowns and line stops
OT = Operating Time represents the actual time during which the equipment operates effectively

3.5. Research Period

Data collection was conducted during a specific observation period (April-June) so that the results would be representative of the company's operational conditions.

3.6. Analytical Framework

In summary, the research flow can be seen in **Figure 2**.

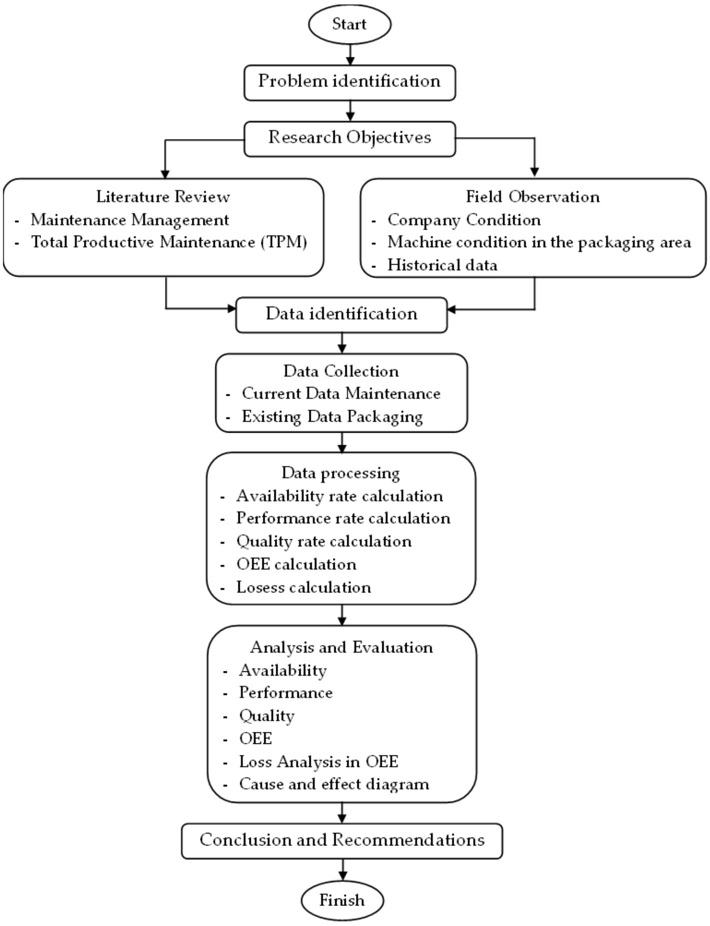

Figure 2. Research flow chart

The research flowchart used in this study is illustrated in Figure 2. After the problem was identified, the research continued by setting objectives to determine the scope and focus of the analysis. Field observations were conducted to study the company's conditions, machine performance in the packaging area, and the availability of old production data. In addition, literature was reviewed to build a theoretical foundation for maintenance management and TPM.

Next, relevant information was identified and collected, including maintenance records and current packaging process data. This data was then processed to calculate availability, performance, quality, OEE, and production losses. In the next stage, analysis and evaluation were conducted. Here, OEE components and loss categories were thoroughly evaluated, using cause-and-effect diagrams and loss analysis, to find the main factors affecting equipment effectiveness. Before the study ended, results and practical recommendations were made to improve operational performance.

4. RESULT AND DISCUSSION

4.1. Operational Description of the Packaging Line

Based on the configuration in Figure 1, the line's performance is mainly determined by three critical points. (i) The Bottle Washer affects Availability due to washing cycles and planned downtime (heating/CIP); unplanned downtime on pumps/heaters is a major contributor to breakdown losses. (ii) Inspection plays a direct role in quality; false rejects and short stops add to idling & minor Stoppages and increase defect losses. (iii) The Filler acts as a pacemaker; the difference between rated speed and actual speed results in reduced speed losses that suppress performance. Downstream, the Crater–Palletizer affects conveyor back-pressure; stoppages at the palletizer trigger a ripple effect all the way to the Filler (decreased throughput). This pattern is consistent with the availability, performance, quality, OEE recap and six big losses decomposition in the following Table/Section, so priority interventions are directed at reducing unplanned downtime in the Washer, stabilizing inspection logic, and controlling process parameters in the Filler so that the actual speed approaches the rated speed.

4.2. Production Data Profile (April–June)

The weekly production summary in Table 1, shows a relatively stable bottling line output volume in the range of ≈0.72–0.76 million bottles/week (lowest total in week 24: 724,954 bottles; highest in week 25: 762,495 bottles). The number of rejects ranged from 432 to 2,034 bottles per week, reflecting a defect rate of ≈0.06%–0.27%. Since rework = 0, the quality component can be calculated directly as Good/Total, with values ranging from ≈99.73%–99.94%. Although quality data are recorded in units (good and reject products), within the six big losses framework these values are converted into lost time using the ideal cycle time (ICT). Each rejected unit represents time that was consumed by the machine but did not result in a good product; therefore, total defect losses = reject units × ICT. This conversion ensures that defect-related losses are comparable with other time-based losses such as breakdown, setup & adjustment, idling & minor stoppages, and reduced speed.

In this study, the quality component (≈99.73–99.94%) yields relatively small defect losses (≈0.041–0.190% of loading time). However, even small variations in weekly reject counts contribute to measurable time losses that interact with other loss categories. For example, unstable filler settings or inspection false-rejects not only increase defect losses but also tend to cause micro-stoppages, which are captured in idling & minor stoppages and partially in reduced speed. Thus, the integration of quality data with time-based metrics enables a complete mapping of the Six Big Losses and shows how product quality variations can influence the Performance component of OEE through additional time losses.

Table 1. Data production for bottling line

Month	Week	Good Product (bottle/unit)	Reject Product (bottle/unit)	Rework	Total Product (bottle/unit)
April	14	749,212	1,005	-	750,217
	15	752,321	908	-	753,229
	16	754,215	974	-	755,189
	17	749,251	899	-	750,150
	18	732,521	765	-	733,286
May	19	735,023	704	-	735,727
	20	755,021	565	-	755,586
	21	749,231	1,560	-	750,791
	22	739,231	2,034	-	741,265
June	23	745,231	1,143	-	746,374
	24	724,522	432	-	724,954
	25	761,523	932	-	762,455
	26	739,515	584	-	740,099

Table 2 shows that available time per week is constant at 8,640 minutes (144 hours) during weeks 14–26. this consistency indicates a stable production schedule, so that variations in availability in the next section are mainly influenced by changes in planned down time and unplanned down time, rather than by changes in planned hours. Thus, operating time is calculated as 8,640 − planned downtime − downtime, and becomes the basis for calculating availability and integration with the performance and quality components.

Table 2. Data available time

Month	Week	Total Available Time (min/unit)	Total Available Time (hour/unit)
April	14	8,640	144
	15	8,640	144
	16	8,640	144
	17	8,640	144
May	18	8,640	144
	19	8,640	144
	20	8,640	144
	21	8,640	144
June	22	8,640	144
	23	8,640	144
	24	8,640	144
	25	8,640	144
	26	8,640	144

Table 3 shows that planned downtime per week ranges from 5 to 120 minutes (0.08 to 2.00 hours) with an average of ≈44.2 minutes/week (median 35 minutes). The highest value occurred in week 24 (120 minutes), followed by week 18 (75 minutes) and week 20 (85 minutes), which are likely related to setup/changeover/CIP activities. With available time = 8,640 minutes, the contribution of planned downtime to the planned time is relatively small (average ≈0.51%, minimum ≈0.06%, maximum ≈1.39%), so the variation in availability in the next section is more influenced by unplanned downtime. The Operating Time value is then calculated as 8,640 − planned downtime − downtime (unplanned) and used as the basis for calculating availability, then integrated with production data for performance, quality, and finally OEE.

Table 3. Data planned down time

Month	Week	Planned Downtime (min/unit)	Planned Downtime (hour/unit)
Aprl	14	10	0.17
	15	15	0.25
	16	5	0.08
	17	5	0.08
May	18	75	1.25
	19	39	0.65
	20	85	1.42
	21	35	0.58
June	22	55	0.92
	23	60	1.00
	24	120	2.00
	25	35	0.58
	26	35	0.58

During weeks 14–26. total weekly downtime ranged from 97 to 300 minutes. with an average of approximately 178.8 minutes per week. The main contributors were change over at 45.6% (1.060 minutes). followed by Breakdown at 42.8% (995 minutes) and Stop Line at 11.6% (269 minutes). The highest spike occurred in week 21 = 300 minutes (150 + 120 + 30). while the lowest was in week 24 = 97 minutes (25 + 61 + 11). On a monthly basis. the cumulative downtime contribution was 979 minutes (42.1%) in April. 722 minutes (31.1%) in May. and 623 minutes (26.8%) in June. These findings indicate that availability is most sensitive to controlling the duration of changeover/CIP and reducing the frequency/duration of breakdowns; while line stops are relatively small but have the potential to trigger micro-stops and back-pressure upstream. The operating time value in the following section is calculated as 8.640 − planned Downtime − downtime (Table 4) for each week of analysis.

Table 4. Data down time

Month	Week	Change Over (min/unit)	Break down (min/unit)	Stop Line (min/unit)	Down time (min/unit)
April	14	122	70	21	213
	15	65	100	20	185
	16	130	75	15	220
	17	80	102	13	195
	18	65	76	25	166
May	19	60	35	13	108
	20	60	66	12	138
	21	150	120	30	300
	22	75	75	26	176
June	23	43	80	50	173
	24	25	61	11	97
	25	105	65	23	193
	26	80	70	10	160

4.3. OEE Component Calculation (Availability, Performance, Quality)

In this study, the OEE components were calculated on a weekly basis for the packaging process at the bottling line to capture operational variations over the observation period. The calculation of each component follows standard OEE formulations and is based on actual data.

4.3.1. Calculation of Availability

Based on Table 5, the weekly availability value ranges from 96.51% to 98.86%. with an average of 97.92%. The lowest value occurred in week 21 (96.51%). which correlated with a surge in downtime of 300 minutes (see Table 4). while the highest value occurred in week 24 (98.86%) when downtime was at its minimum (97 minutes) and planned downtime was relatively small (120 minutes). In general. the stable loading time ≈ 8.630 minutes/week indicates a consistent production schedule; thus. the variation in Availability is primarily influenced by fluctuations in unplanned downtime. These results confirm that controlling breakdowns and line stops is key to improving the availability component of OEE.

Table 5. Availability calculation

Month	Week	Total Available Time (min/unit)	Planned Downtime (min/unit)	Loading Time (min/unit)	Down time (min/unit)	Operating Time (min/unit)	Availability Rate (min/unit)
April	14	8,640	10	8,630	213	8,417	97.53
	15	8,640	15	8,625	185	8,440	97.86
	16	8,640	5	8,635	220	8,415	97.45
	17	8,640	5	8,635	195	8,440	97.74

Month	Week	Total Available Time (min/unit)	Planned Downtime (min/unit)	Loading Time (min/unit)	Down time (min/unit)	Operating Time (min/unit)	Availability Rate (min/unit)
	18	8,640	75	8,565	166	8,399	98.06
May	19	8,640	39	8,601	108	8,493	98.74
	20	8,640	85	8,555	138	8,417	98.39
	21	8,640	35	8,605	300	8,305	96.51
	22	8,640	55	8,585	176	8,409	97.95
June	23	8,640	60	8,580	173	8,407	97.98
	24	8,640	120	8,520	97	8,423	98.86
	25	8,640	35	8,605	193	8,412	97.76
	26	8,640	35	8,605	160	8,445	98.14
Total		112.320	1,797	129,243	2,324	114,829	97.92

4.3.2. Calculation of Performance

As shown in Table 6, the performance value ranged from 68.85% to 72.51%. with an average of 70.92%. The lowest achievement occurred in week 24 (68.85%)—despite the smallest weekly downtime (97 minutes)—indicating the dominance of reduced speed losses (actual speed below the rated 125 bpm) or micro-stops that are not recorded as long downtime. The highest value appeared in week 25 (72.51%). This pattern indicates that OEE components are most sensitive to filler speed control (pacemaker). inter-machine balance (avoid starved/blocked). and process parameter stability (foaming. nozzle. back-pressure). These findings form the basis for improvement priorities in the Six Big Losses section (particularly reduced speed and idling & minor stoppages).

Table 6. Performance calculation

Month	Week	Total Product (bottle/unit)	Standar Speed (bottle/unit)	Loading Time (min/unit)	Downtime (min/unit)	Performance Rate (%)
April	14	750,217	125	8,630	213	71.30
	15	753,229	125	8,625	185	71.40
	16	755,189	125	8,635	220	71.79
	17	750,150	125	8,635	195	71.10
	18	733,286	125	8,565	166	69.85
May	19	735,727	125	8,601	108	69.30
	20	755,586	125	8,555	138	71.82
	21	750,791	125	8,605	300	72.32
	22	741,265	125	8,585	176	70.52
June	23	746,374	125	8,580	173	71.02
	24	724,954	125	8,520	97	68.85
	25	762,455	125	8,605	193	72.51
	26	740,099	125	8,605	160	70.11
Total		36,060,500	125	129,243	12,214	70.92

4.3.3. Calculation of Quality

Table 7 shows consistently high Quality in the range of ≈99.73%–99.94%, with an average of ≈99.90% (total good 36,024,364 out of total production of 36,060,500 units). The lowest value appeared in week 22 (≈99.73%), while the highest was in week 24 (≈99.94%), This quality stability indicates that the Quality component is not the main constraint on OEE; line performance variations are more influenced by actual speed and downtime.

Table 7. Quality calculation

Month	Week	Good Product (bottle/unit)	Total Product (bottle/unit)	Quality Rate (%)
April	14	749,212	750,217	99.87
	15	752,321	753,229	99.88
	16	754,215	755,189	99.87
	17	749,251	750,150	99.88
	18	732,521	733,286	99.90
May	19	735,023	735,727	99.90
	20	755,021	755,586	99.93
	21	749,231	750,791	99.79
	22	739,231	741,265	99.73
June	23	745,231	746,374	99.85
	24	724,522	724,954	99.94
	25	761,523	762,455	99.88
	26	739,515	740,099	99.92
Total		36,024,364	36,060,500	99.90

4.3.4. Calculation of OEE

Based on Table 8, the weekly OEE value ranges from 68.03% to 70.79%, with an average of ≈ 69,35% in the period of weeks 14–26. The lowest value occurred in week 24 (68.03%), while the highest was in week 25 (70.79%). The main limiting component of OEE is performance (≈68.85–72.51%), while availability is relatively high (≈96.51–98.86%) and quality is consistently very high (≈99.73–99.94%). This pattern confirms that the most effective way to improve OEE is by reducing reduced speed losses (the gap between actual and rated speed on the Filler) and idling & minor stoppages that are not recorded as long downtime, along with controlling breakdowns at critical points (Washer, Filler).

Table 8. OEE Calculation

Month	Week	Availibility Rate (%)	Performance Rate (%)	Quality Rate (%)	OEE (%)
April	14	97.53	71.30	99.87	69.45
	15	97.86	71.40	99.88	69.78
	16	97.45	71.79	99.87	69.87
	17	97.74	71.10	99.88	69.41
	18	98.06	69.85	99.90	68.41
May	19	98.74	69.30	99.90	68.36
	20	98.39	71.82	99.93	70.6
	21	96.51	72.32	99.79	69.65
	22	97.95	70.52	99.73	68.88
June	23	97.98	71.02	99.85	69.48
	24	98.86	68.85	99.94	68.03
	25	97.76	72.51	99.88	70.79
	26	98.14	70.11	99.92	68.75
Total		88.85	78.51	99.90	69.34

4.3.5. Breakdown (Equipment Failure) Losses

Based on Table 9, breakdown losses ranged from ≈0.41%–1.39% of loading time per week. with an average of ≈0.89%. The peak loss occurred in week 21 (≈1.3945%). which contributed to a decrease in weekly availability (see

Table 5), while the lowest value was seen in week 19 (≈0.4069%). For the total period. the accumulated breakdown was ~995 minutes (≈0.89% of total loading time). so controlling the frequency and duration of breakdowns especially at critical stations such as the Bottle Washer and Filler became a priority for stabilizing availability.

Table 9. Breakdown losses calculation

Month	Week	Breakdown (min/unit)	Loading Time (min/unit)	Equipment Failure Losses (min/unit)
	14	70	8,630	0.8111%
	15	100	8,625	1.1594%
	16	75	8,635	0.8686%
April	17	102	8,635	1.1812%
	18	76	8,565	0.8873%
	19	35	8,601	0.4069%
	20	66	8,555	0.7715%
May	21	120	8,605	1.3945%
	22	75	8,585	0.8736%
	23	80	8,580	0.9324%
	24	61	8,520	0.7160%
	25	65	8,605	0.7554%
June	26	70	8,605	0.8135%
Total		995	111,746	0,8904%
Average		76.54	8,595.85	0.8904%

4.3.6. Setup & Adjustment (Changeover/CIP) Losses

Table 10 shows that setup & adjustment losses range from 0.29% to 1.74% of loading time per week. with an average of ≈0.95%. The peak loss occurred in week 21 (1.74%). in line with a changeover duration of 150 minutes. while the lowest value was in week 24 (0.29%). For the total period. the accumulated changeover/CIP = 1.060 minutes against the total loading time = 111.746 minutes. resulting in a contribution of ≈ 0.95%. These findings indicate that although planned losses are relatively small compared to breakdowns. their variation still affects availability and weekly capacity.

Table 10. Set-up and adjustment calculation

Month	Week	Cange Over (min/unit)	Loading Time (min/unit)	Setup & Adjustment Losses (%)
April	14	122	8,630	1.41
	15	65	8,625	0.75
	16	130	8,635	1.51
	17	80	8,635	0.93
May	18	65	8,565	0.76
	19	60	8,601	0.70
	20	60	8,555	0.70
	21	150	8,605	1.74
June	22	75	8,585	0.87
	23	43	8,580	0.50

Month	Week	Cange Over (min/unit)	Loading Time (min/unit)	Setup & Adjustment Losses (%)
	24	25	8,520	0.29
	25	105	8,605	1.22
	26	80	8,605	0.93
	Total	1.060	111,746	12.32
	Average	81.54	859,585	0.95

4.3.7. Idling & Minor Stoppages

As shown in Table 11, idling & minor stoppages ranged from ≈0.12%–0.58% of loading time per week, with an average of ≈0.24% (a total of 269 minutes out of 111,746 minutes). The highest value occurred in week 23 (≈0.58%), while the lowest was in week 26 (≈0.12%). Although the proportion is small, micro-stops tend to fragment the flow and reduce actual speed, thereby contributing to Reduced Speed Losses and a decrease in the Performance component of OEE.

Table 11. Idling & minor calculation

Month	Week	Stop Line (min/unit)	Loading Time (min/unit)	Idling & Minor Stoppages (%)
April	14	21	8,630	0.24
	15	20	8,625	0.23
	16	15	8,635	0.17
	17	13	8,635	0.15
May	18	25	8,565	0.29
	19	13	8,601	0.15
	20	12	8,555	0.14
	21	30	8,605	0.35
June	22	26	8,585	0.30
	23	50	8,580	0.58
	24	11	8,520	0.13
	25	23	8,605	0.27
	26	10	8,605	0.12
Total		269	111,746	21.74
Average		20.6923	8,595.8462	0.24

4.3.8. Reduced Speed Losses

As shown in Table 12, reduced speed was in the range of 26.71%–30.79% of loading time per week, with an average of ≈28.48%. The highest value occurred in week 24 (30.79%), even though the downtime at that time was the smallest, indicating the dominance of actual speeds below the rated 125 units/minute and/or micro-stoppages that fragmented the flow. The lowest value was recorded in week 21 (26.71%). This pattern is consistent with the performance (average 70.92%) and idling & minor (≈0.24%) components, making reduced speed the largest contributor to the decline in OEE during the study period.

Table 12. Reduced speed calculation

Month	Week	Operating Time (min/unit)	Ideal Cycle Time (min/unit)	Total Product (bottle/unit)	Loading Time (min/unit)	Reduced speed (%)
April	14	8,417	0.008	750,217	8,630	27.99
	15	8,440	0.008	753,229	8,625	27.99

Month	Week	Operating Time (min/unit)	Ideal Cycle Time (min/unit)	Total Product (bottle/unit)	Loading Time (min/unit)	Reduced speed (%)
May	16	8,415	0.008	755,189	8,635	27.49
	17	8,440	0.008	750,150	8,635	28.24
	18	8,399	0.008	733,286	8,565	29.57
	19	8,493	0.008	735,727	8,601	30.31
	20	8,417	0.008	755,586	8,555	27.73
	21	8,305	0.008	750,791	8,605	26.71
June	22	8,409	0.008	741,265	8,585	28.87
	23	8,407	0.008	746,374	8,580	28.39
	24	8,423	0.008	724,954	8,520	30.79
	25	8,412	0.008	762,455	8,605	26.87
	26	8,445	0.008	740,099	8,605	29.33
Total		109,422	0	9,699,322	11,746	370.30
Average		8,417.077	0	746,101.7	8595.8462	28.48

4.3.9. Defect Losses

As shown in Table 13, defect losses ranged from ≈0.041% to 0.190% of loading time per week, with an average of ≈0.0895%. The highest value occurred in week 22 (2,034 units rejected → ≈0.190%), while the lowest was in week 24 (432 units rejected → ≈0.041%). In aggregate for the period, the total reject of 12,505 units is equivalent to ≈100.0 minutes of lost time out of 111,746 minutes of loading time, resulting in total defect losses of ≈0.0895%. With stable product quality and low defect losses, the quality component is not a major constraint on OEE in this study period.

Table 13. Defect losses calculation

Month	Week	Reject Product (bottle/unit)	Ideal Cycle Time (min/unit)	Loading Time (min/unit)	Defect Losses (%)
April	14	1,005	0.008	8,630	9.30
	15	908	0.008	8,625	8.40
May	16	974	0.008	8,635	9.00
	17	899	0.008	8,635	8.30
	18	765	0.008	8,565	7.10
	19	704	0.008	8,601	6.50
	20	565	0.008	8,555	5.30
June	21	1,560	0.008	8,605	10.07
	22	2,034	0.008	8,585	13.19
	23	1,143	0.008	8,580	7.43
	24	432	0.008	8,520	4.10
	25	932	0.008	8,605	8.70
	26	584	0.008	8,605	5.40
Total		12,505	0.104	11,746	1.163
Average		961,9231	0.008	8,595.85	0.0895

4.4. Discussion

Measurements taken at beverage company bottling line show an average OEE of ≈ 69.35% with high availability (≈97.9%), very stable quality (≈99.9%), and relatively low performance (≈70.9%). The six big losses decomposition confirms that reduced speed is the dominant loss (≈26.7–30.8% of loading time; average ≈28.48%), while breakdown (≈0.89%), setup & adjustment (≈0.95%), idling & minor stoppages (≈0.24%), and defect losses (≈0.0895%) are relatively small. This profile means that the main bottleneck in performance is in the actual line speed (especially in the pacemaker Filler) and micro-stops that fragment the flow, not in availability or quality. In terms of its position relative to the benchmark, the OEE achievement of approximately 69% is below the "world-class" target of 85% commonly referenced in modern TPM/OEE literature; this target is also confirmed in a study by Luozzo et al. [28], as an aspirational value across sectors (85%), making it reasonable to use as a reference for gradual improvement.A comparison with studies in the beverage company shows a consistent pattern. A study conducted by Junaedi et al. [29] on beverage filling lines reported a monthly OEE of 53–63% and concluded that the main losses stemmed from slow speed/operation and downtime (thus performance became a limiting factor), exactly as was the case with this line. In addition, a study conducted by Danaish et al. [30] on packaging lines applied the OEEML metric and successfully improved line performance by approximately 14% after focusing on improving speed coordination and machine synchronization, reinforcing the importance of the "line level" perspective rather than just single machine OEE.

From a state-of-the-art perspective, a systematic review by Corrales et al. [8], confirmed that Performance is often the most variable component of OEE, and encourages the integration of Lean–Industry 4.0 approaches to reduce speed loss and micro-stops—in line with our findings that reduced speed dominates. Supplementary evidence comes from a 2024 case study in research conducted by ALMashaqbeh and Hernandez [14], which found that speed losses accounted for 58.1% of total losses on production lines, indicating that the dominance of speed losses is a recurring phenomenon in process manufacturing. At the methodological level, Dobra and Jósvai [31], demonstrated how supervised machine learning-based OEE prediction/monitoring can target improvements precisely at the weakest components (the context is different—assembly—but relevant to OEE analytics architecture). For the beverage company in particular, Phukapak et al. [32] compared OEE vs. desirability function in juice processing and emphasizes the need for simultaneous optimization of speed and quality when pursuing output—the implication is consistent with our results: pursuing speed without process stability will "pay off" in quality or micro-stops. Meanwhile, Bekar [33], suggested a fuzzy-based TPM performance evaluation framework (FCOPRAS/FDEA) to prioritize the most material sources of loss—an approach relevant for formalizing the priority of reduced speed and micro-stop improvements in this case.

Our minor findings are also consistent with the literature on energy and operations in bottling lines: Osterroth and Voigt [34] showed that operational status/availability affects energy consumption per machine in bottling plants; high availability without speed stability does not automatically equate to efficiency—reinforcing the focus on speed stability and reducing micro-stops rather than simply pursuing uptime.

Practical implications of this comparison for beverage company:

1. Prioritize Performance: tune the speed of the Filler as a pacemaker, line balancing & buffer management, foaming/nozzle/back-pressure control, and short-stop logging (<10 seconds) to capture unrecorded micro-stops. This recommendation is in line with empirical evidence from various studies that reduced speed/micro-stops are commonly the biggest contributors.
2. Maintain stable availability: despite minor breakdowns (≈0.89%), predictive maintenance on the Washer/Filler maintains weekly variability; the TPM prioritization approach as suggested by Bekar [33] facilitates risk ranking.
3. Real-time monitoring/analytics integration: research experience by Dobra & Jósvai [31], and digital OEE implementation studies in the food industry by Sumargo and Makmur [35], showed that data-driven monitoring accelerates the handling of speed loss and micro-stops.

Limitations & future agenda. This discussion is based on weekly data from a single line within a limited range; cross-SKU/packaging format generalizations require additional verification. Moving forward, multi-objective modeling/optimization (output–quality–energy) as highlighted by the 2024 study on beverage processes could be a powerful extension to elevate OEE while maintaining quality and energy efficiency [32]; [34].

5. CONCLUSION

The performance assessment of the bottling line at beverage company shows that the average OEE during weeks 14–26 was approximately 69.35%, with high Availability (≈97.9%), moderate Performance (≈70.9%), and very high Quality (≈99.9%). Weekly OEE values ranged from 68.03% to 70.79%, indicating relatively stable performance throughout the observation period. Despite the high Availability and Quality levels, the overall

OEE remains below the commonly cited world-class benchmark of approximately 85%, highlighting the need for targeted improvement strategies.

The analysis of the Six Big Losses reveals that the Performance component is the primary limiting factor of OEE. Reduced Speed losses dominate the loss structure, accounting for approximately 26.7–30.8% of loading time (with an average of ≈28.48%), followed by smaller contributions from Setup and Adjustment (≈0.95%), Breakdown (≈0.89%), Idling and Minor Stoppages (≈0.24%), and Defect losses (≈0.0895%). These findings indicate that the main bottlenecks in the bottling line are related to line speed instability, particularly at the Filler acting as the pacemaker, as well as frequent micro-stoppages that disrupt continuous flow.

Availability and Quality were not identified as major constraints during the study period. Availability remained stable in the range of 96.51–98.86% due to relatively low and well-controlled downtime, while Quality consistently exceeded 99.7%, resulting in negligible quality-related losses to OEE. Variations in weekly OEE values were therefore driven primarily by changes in actual operating speed and the occurrence of micro-stoppages rather than by long-duration downtime or product defects.

From a practical perspective, improving the Performance component represents the most effective pathway to increasing overall OEE while maintaining the already high Availability and Quality levels. Priority improvement actions include optimizing Filler speed settings, improving infeed and outfeed synchronization, controlling back-pressure, guide rail alignment, foaming, and nozzle conditions, and enhancing buffer management to reduce starved and blocked states. In addition, systematic logging of short stops (less than 10 seconds) is essential to capture unrecorded micro-stoppages, while predictive maintenance of critical equipment such as the Bottle Washer and Filler can help reduce performance fluctuations and prevent unplanned breakdowns.

This study is subject to several limitations. The analysis is based on weekly aggregated data from a single bottling line and specific product formats, and startup losses were not analyzed separately. Future research is therefore recommended to incorporate real-time data acquisition, predictive analytics for performance and loss estimation, and integrated financial and energy impact evaluations. Such extensions would enable a more comprehensive prioritization of improvement actions based on return on investment and long-term operational sustainability.

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