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Performance Enhancement in Injection Moulding Manufacturing: A Case Study Utilizing the DMAIC Methodology

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ABSTRACT

This study aims to enhance the performance of an injection moulding process at PT. XYZ, an Indonesian manufacturing firm, using the Define, Measure, Analyze, Improve, Control (DMAIC) methodology. The main issue identified was low Overall Equipment Effectiveness (OEE), averaging 66.47%, below the company's target of 85%. Through systematic application of DMAIC tools such as Supplier, Input, Process, Output, and Customer (SIPOC), Fishbone Diagram, Failure Mode and Effects Analysis (FMEA), and Root Cause Analysis, critical losses were identified, particularly in idle time and downtime. Targeted improvements, including preventive maintenance and process standardization, led to a significant performance increase. Post-implementation results showed that the OEE improved from 59.61% to 87.63%. These improvements also reduced idle time by 100% in December and stabilized run time. The study demonstrates how structured problem-solving frameworks like DMAIC can yield measurable operational benefits when consistently applied.

1. INTRODUCTION

Achieving high productivity without compromising product quality is a central objective for modern manufacturing industries [1, 2]. This objective compels companies to improve process efficiency in order to remain competitive, while simultaneously reducing reliance on imported equipment and components. In Indonesia, the injection moulding sector is experiencing increased demand, particularly for the production of medical devices.

Despite this growth, manufacturers often face significant operational challenges that hinder their ability to meet production targets. One such case is PT. XYZ, a local manufacturing company specializing in medical equipment using injection moulding technology. Based on internal production data, the company's average Overall Equipment Effectiveness (OEE) over the past year stands at 81.72%, which falls short of the company's performance target of 85%.

Preliminary analysis conducted at PT. XYZ revealed several key issues contributing to this suboptimal performance. The production data indicated that low OEE was primarily caused by high machine downtime, prolonged setup durations, and extended sample collection time. Frequent machine breakdowns occurred due to a lack of preventive maintenance and delayed corrective actions. Setup activities lacked standardization, leading to inconsistencies between operators and frequent delays in production start-up. Similarly, inefficient sample collection processes resulted in bottlenecks that delayed quality verification and disrupted production continuity. These inefficiencies not only reduced equipment utilization but also negatively impacted scheduling, throughput, and overall productivity. In addition, the lack of procedural standardization and poor documentation further contributed to inconsistencies in product quality. This situation highlights the need for a systematic, data-driven approach to process improvement.

To address these challenges, this research adopts the Define, Measure, Analyze, Improve, Control (DMAIC) methodology—an established framework within the Six Sigma approach [3]. DMAIC offers a structured and scientific process for identifying root causes, formulating corrective actions, and sustaining improvements over time [4, 5]. The primary objective of this research is to enhance the operational performance of the injection moulding process at PT. XYZ through the systematic application of DMAIC. The study aims to identify the root causes of low OEE, particularly those related to downtime, setup duration, and sample collection inefficiencies [6-10]. By utilizing analytical tools such as Supplier, Input, Process, Output, and Customer (SIPOC), Fishbone Diagram, Failure Mode and Effects Analysis (FMEA), and the 5-WHYs method, the research seeks to analyze process bottlenecks and implement corrective actions. Furthermore, it evaluates the impact of these interventions on performance indicators, with a focus on increasing OEE to meet or surpass the company's 85% target. Ultimately, this research demonstrates how data-driven continuous improvement methodologies can be effectively applied in real-world industrial environments to improve productivity and process reliability [3, 5, 11].

While DMAIC is a well-established methodology, the novelty of this study lies in its contextual application within an Indonesian injection moulding company that faces resource limitations and high production demands. The findings are expected to provide not only actionable insights for practitioners but also empirical evidence to support the use of structured improvement methodologies in similar manufacturing environments. This paper is organized to present the step-by-step application of DMAIC, supported by operational data and performance metrics, in order to demonstrate the practical value and effectiveness of continuous improvement initiatives in industrial settings.

2. LITERATURE REVIEW

This section reviews the literature on DMAIC approach, SIPOC, FMEA, 5WHY, Fishbone and gap analysis in the relevant literature. This literature review aims to provide a thorough understanding of recent advancements about research opportunities and trend of method.

2.1 DMAIC

DMAIC is a structured, data-driven methodology widely applied within the Six Sigma framework to drive process improvements and reduce variability. While originally developed for general quality management, DMAIC has found successful application across various manufacturing sectors, including automotive, electronics, and increasingly, injection moulding. Several studies have demonstrated the effectiveness of DMAIC in identifying inefficiencies, minimizing waste, and improving product quality in highly controlled manufacturing environments.

For instance, Mittal et al. [3] applied DMAIC to improve machining precision in a manufacturing firm, reporting a 27% increase in production yield and a reduction in defect rates by over 40% [3]. Similarly, Bhargava and Gaur [5] implemented DMAIC in a bearing production line, significantly reducing setup time and increasing OEE. More specifically to the injection moulding context, Maryani et al. [12] utilized DMAIC to improve aluminum casting operations and observed a measurable improvement in process capability. These studies affirm the adaptability of DMAIC to complex, repeatable, and quality-sensitive processes such as moulding operations.

However, while DMAIC has been widely used, most prior studies focused on general efficiency gains without detailed integration into OEE metrics or combining it with tools like FMEA and SIPOC in a comprehensive manner. There is still limited research that applies DMAIC holistically to injection moulding operations with a focus on quantifiable improvements in all components of OEE—Availability, Performance, and Quality/Yield. This gap presents an opportunity for research to explore how each phase of DMAIC can be linked to specific operational inefficiencies such as prolonged downtime, ineffective setup processes, and high defect rates, which are commonly encountered in moulding industries.

DMAIC's strength lies in its structured methodology [13]:

1. The Define phase helps clarify objectives and scope.
2. Measure focuses on quantifying current performance, often using metrics like Defects Per Million Opportunities (DPMO), calculated with the formula:

$$DPMO = 100000 \times \frac{\begin{array}{c}Total\ number\ of\ decfects\\ found\ in\ a\ sample\end{array}}{defect\ opportunities\ in\ a\ sample} \quad (1)$$

3. The Analyze phase uses tools like Fishbone Diagrams and Pareto analysis to identify root causes.
4. Improve recommends and implements targeted solutions.
5. Control ensures long-term sustainability of improvements.

2.2 SIPOC

The concept of SIPOC is a visual representation used in process improvement methodologies. This approach is used to make easily identified the resources involved in the company (Refer).

2.3 FMEA

FMEA is widely recognized as a proactive risk assessment tool used to identify potential failure modes within a process and prioritize them based on three factors: Severity (S), Occurrence (O), and Detection (D). These factors are combined into a Risk Priority Number (RPN = S × O × D) to determine which failure modes demand immediate attention.

In moulding industries, failure modes such as incorrect material loading, mold misalignment, or parameter deviation can cause defects or machine downtime. Prior studies [14] have demonstrated how FMEA significantly reduced downtime and enhanced safety in automated manufacturing environments.

In this study, FMEA is deployed not only as a scoring tool but as a bridge between the Analyze and Improve phases of DMAIC [15]. By evaluating failure modes tied to OEE loss (such as improper mold setup or drying errors), the research ensures that improvement efforts are not generic but prioritized based on operational impact. Moreover, this study applies corrective controls mapped from FMEA outputs to directly inform maintenance scheduling and operator instructions—closing the loop between diagnosis and implementation.

2.4 5-WHYs method

The 5-WHYs technique is one of the most preferred approaches to minimize or possibly eliminate the quality loss category of OEE [16]. This method was implemented successfully to eliminate loss [17].

In this study, DPMO and OEE are both used to measure performance and assess the impact of changes. OEE itself integrates Availability (operating time vs planned time), Performance (actual speed vs ideal speed), and Quality (good units vs total units produced), making it a comprehensive metric that aligns well with the DMAIC structure.

While methodologies such as Lean, Total Productive Maintenance (TPM), and Value Stream Mapping (VSM) are also effective in manufacturing improvement, DMAIC was chosen in this study due to its strong emphasis on data measurement and control, which are critical in high-precision environments like injection moulding. Additionally, DMAIC's integration with FMEA, SIPOC, and Root Cause Analysis tools allows for a more systematic identification and elimination of process inefficiencies.

3. METHODOLOGY

This study employs a case study approach within the framework of the DMAIC methodology. The case was conducted at PT. XYZ, an Indonesian injection moulding company that manufactures health devices. The purpose of this methodology is to identify process inefficiencies and implement targeted improvements to increase OEE [18, 19]. The implementation of each DMAIC phase is described as follows and is shown in Figure 1.

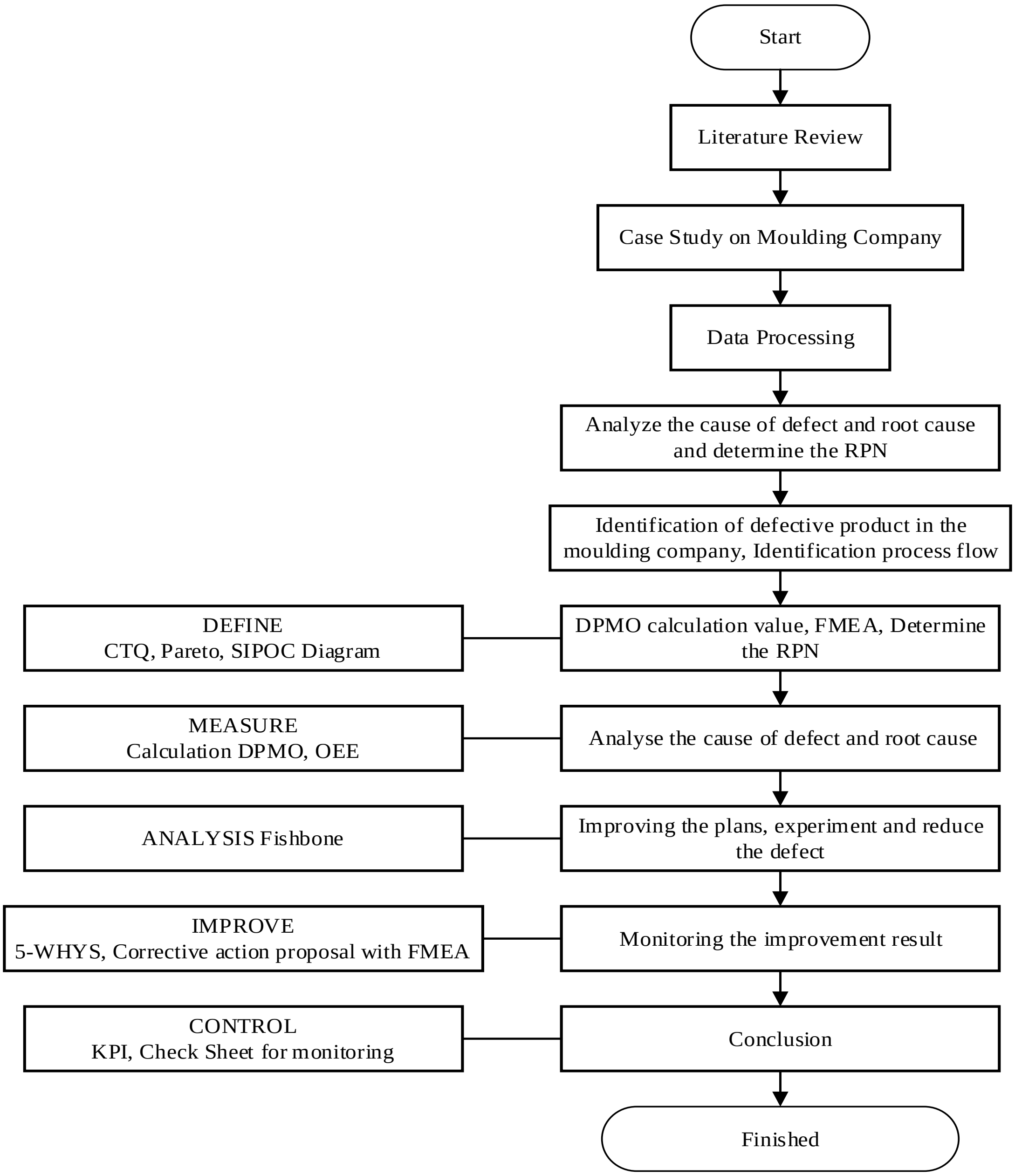

Figure 1. Research methodology flowchart

3.1 Define phase

The problem definition phase involved preliminary discussions with managers and engineers to identify the core performance issue. The main problem was defined as: *"OEE levels consistently below the company's 85% target, averaging only 81.72%."* To scope the problem, a SIPOC diagram was constructed to map the high-level process flow from suppliers to customers and to clarify inputs, outputs, and key stakeholders.

A Pareto analysis of historical rejection and downtime data was conducted to identify the most critical contributors to performance loss. Interviews and direct observations were used to refine the problem statement into measurable goals for the study.

3.2 Measure phase

In this phase, primary and secondary data were collected to establish baseline performance. Key performance indicators measured included Availability, Performance, Quality, and OEE for three different injection moulding machines (Fanuc, Arburg, Engel), using formulas derived from TPM literature.

Data sources included:

a. Monthly production reports (Jan–Dec),
b. Machine downtime logs,
c. Setup and cleaning records,
d. Sampling and inspection timelines.

Each OEE component was calculated according to the standard formula:

$$OEE = Availability \times Performance \times Quality$$

The Six Big Losses were categorized and quantified per machine. Data validation was conducted by triangulating logbook entries with supervisor interviews and visual observation of shop floor activities.

3.3 Analyze phase

The collected data were analyzed to identify root causes of low OEE. The Main tools used in this phase included:

a. Fishbone Diagram (to group causes into man, machine, method, and material),
b. 5-WHYs analysis (to drill down into the root of recurring issues),
c. FMEA (to prioritize failure modes using risk priority numbers).

The FMEA was applied to ten critical process steps, with validation sessions conducted through focus group discussions involving supervisors, maintenance teams, and QA personnel. Failure modes with RPN ≥ 48 were selected for intervention.

3.4 Improve phase

Improvement strategies were designed based on the findings from the Analyze phase. Interventions included:

a. Standardization of machine setup procedures,
b. Preventive maintenance scheduling (daily, weekly, and monthly),
c. Implementation of autonomous maintenance,
d. Operator training on drying temperature, mold verification, and product limit checks.

To validate these improvements, pilot tests were carried out over a 3-month period (Oct.–Dec.). Performance metrics before and after improvements were compared to assess effectiveness. Special focus was given to:

a. Changes in OEE across machines,
b. Reduction in idle and setup time,
c. Improvement in yield and reduction in defect rates.

3.5 Control phase

To sustain the improvements, Control Plans were developed, including:

a. Daily check sheets for critical parameters,
b. Weekly review of OEE trends, and
c. Audit checklists to monitor adherence to new standard operating procedures (SOPs).

Visual management tools such as performance dashboards and machine tagging systems were introduced. A Control chart (p-chart) was applied to monitor product quality stability over time. Feedback loops were created through monthly performance review meetings with operations staff.

The detailed flow diagram of the research methodology for this paper is shown in Figure 1.

4. CASE STUDY ON DMAIC IMPLEMENTATION

In the injection area, production disruptions caused by damage, shutdowns, and failures of the injection molding machine eventually happened, thus causing production to run inefficiently. There is too long downtime, machine setup time, sampling too long, and exceeding the targeted time. The amount of downtime resulted in missed production output. Other effects of downtime on the Injection Molding machine will increase the number of off-spec parts. The impact of this issues certainly makes the company can reach the determined target namely 85%. In this case study, the DMAIC methodology is categorized into the following five basic phases namely: Define, Measure, Analysis, Improve and Control.

Table 1 provides an analysis of the performance data for three different injection moulding machines: Fanuc, Arburg, and Engel (Figure 2). The analysis focuses on five key metrics: Availability, Performance, OEE, Utilization, and Yield. Table 1 presents trends in machine performance and suggest areas for improvement.

Table 1. The average of moulding performance

Moulding	Availability (%)	Performance (%)	OEE (%)	Utilization (%)	Yield (%)
Injection Moulding Fanuc	85.37%	93.82%	66.47%	23.01%	82.98%
Injection Moulding Arburg	88.30%	91.16%	74.56%	63.71%	92.63%
Injection Moulding Engel	84.07%	86.96%	59.61%	64.85%	81.54%

Figure 2. Product display

Availability (%)

Availability measures the percentage of time the machine was available for production. The Arburg machine had the highest availability at 88.30%**,** followed by Fanuc with 85.37%**,** and Engel had the lowest availability at 84.07%**.** Although the differences are not vast, this metric is crucial because higher availability leads to more potential production time.

Performance (%)

Performance reflects the actual production speed compared to the ideal or expected speed. Fanuc had the highest performance at 93.82%, followed by Arburg with 91.16%, and Engel with 86.96%. High performance indicates that the machines are running efficiently during production time.

OEE (%)

OEE is a combination of Availability, Performance, and Yield. It measures the overall effectiveness of the equipment. Arburg had the highest OEE at 74.56%, indicating superior overall efficiency, while Fanuc and Engel had OEE scores of 66.47% and 59.61%, respectively. This metric shows that the Arburg machine operates more effectively than the others.

Utilization (%)

Utilization measures how often the machine is being used during the available time. Engel and Arburg had much higher utilization rates at 64.85% and 63.71%, respectively, compared to Fanuc, which had a very low utilization rate of 23.01%. This indicates that Fanuc is significantly underutilized compared to the other machines, suggesting an opportunity for increased production time or scheduling optimization.

Yield (%)

Yield refers to the percentage of products that met quality standards on the first pass. Arburg had the highest yield at 92.63%, indicating fewer defects, followed by Fanuc with 82.98%, and Engel with 81.54%. Yield is an important metric because higher yield means less rework and waste.

5. DATA COLLECTION AND CALCULATION

5.1 Data collection

Before starting the DMAIC stage, it is essential to have a thorough understanding of the injection moulding production process flow being implemented. Figure 3 below illustrates the stages of the injection moulding process.

The DMAIC approach used is presented in this section.

(1) Define Phase

The define phase starting from identification of the problem and classification of objective.

a) Problem: the OEE rate and performance of moulding company lower than 85%.

b) Objective: The objective of the project was to increase rate of the moulding machine to minimum 85% by eliminating the critical factors resulting loss. The objective to ensures the quality and effectiveness of the company's products, as well as customer's satisfaction. In order to identified the process of moulding production, visualization in the form of SIPOC. The SIPOC for this case is presented in Table 2 below.

Table 2. SIPOC

Supplier	Input	Process	Output	Customers
Company A	LCD	Testing	Smartphones 5"	Distributors A
Company B	Battery	Assembly	Smartphones 5"	Distributor B
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
Company Z	Case	Moulding	Smartphones 5"	Distributor Z

(2) Measure Phase

The OEE is a very established key performance indicator that reflects the performance of a production machine in comprehensive manner. Figure 4 below is the OEE process and formula that illustrates how OEE is calculated, by multiplying the three main components [20].

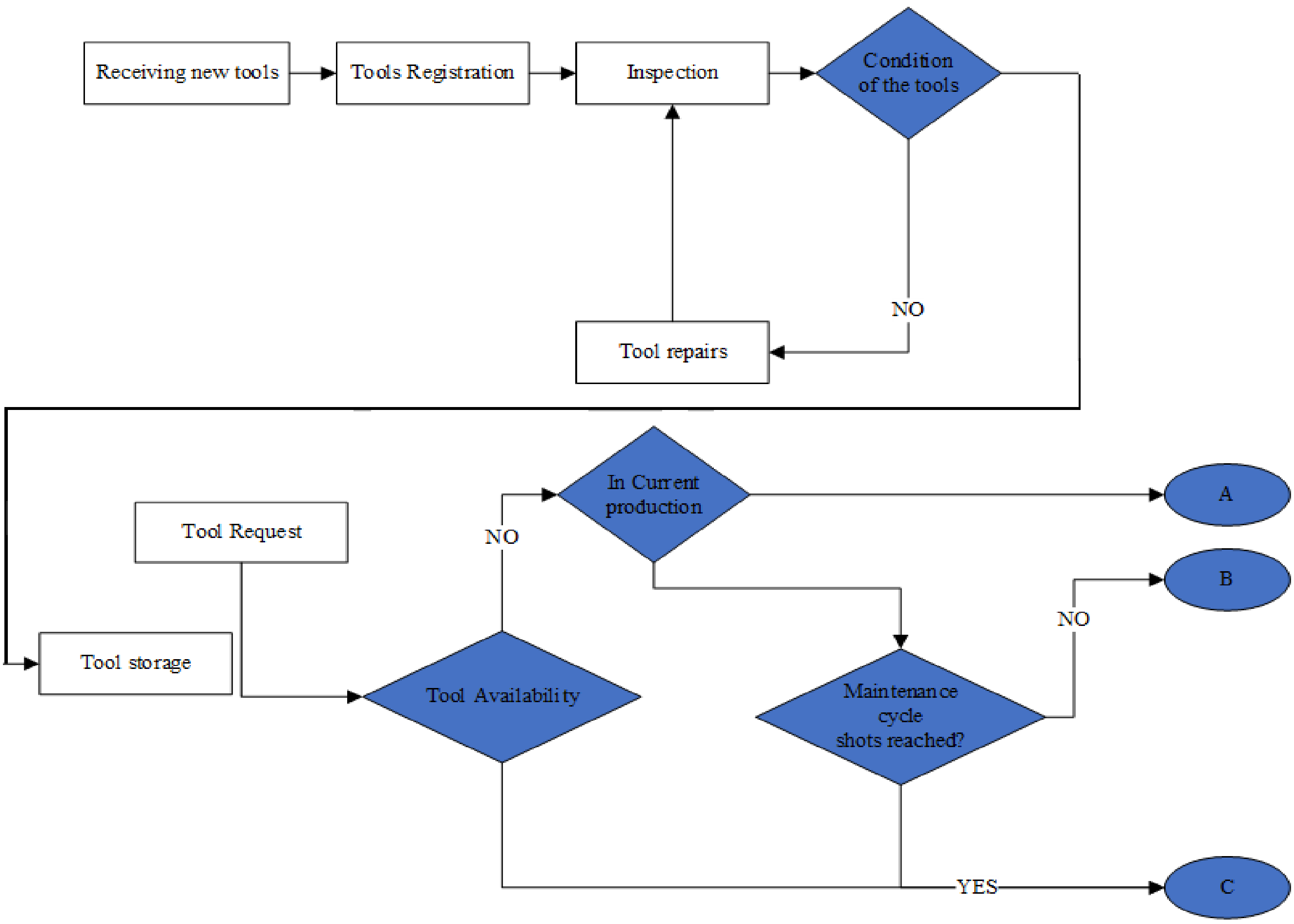

Figure 3. Process injection molding

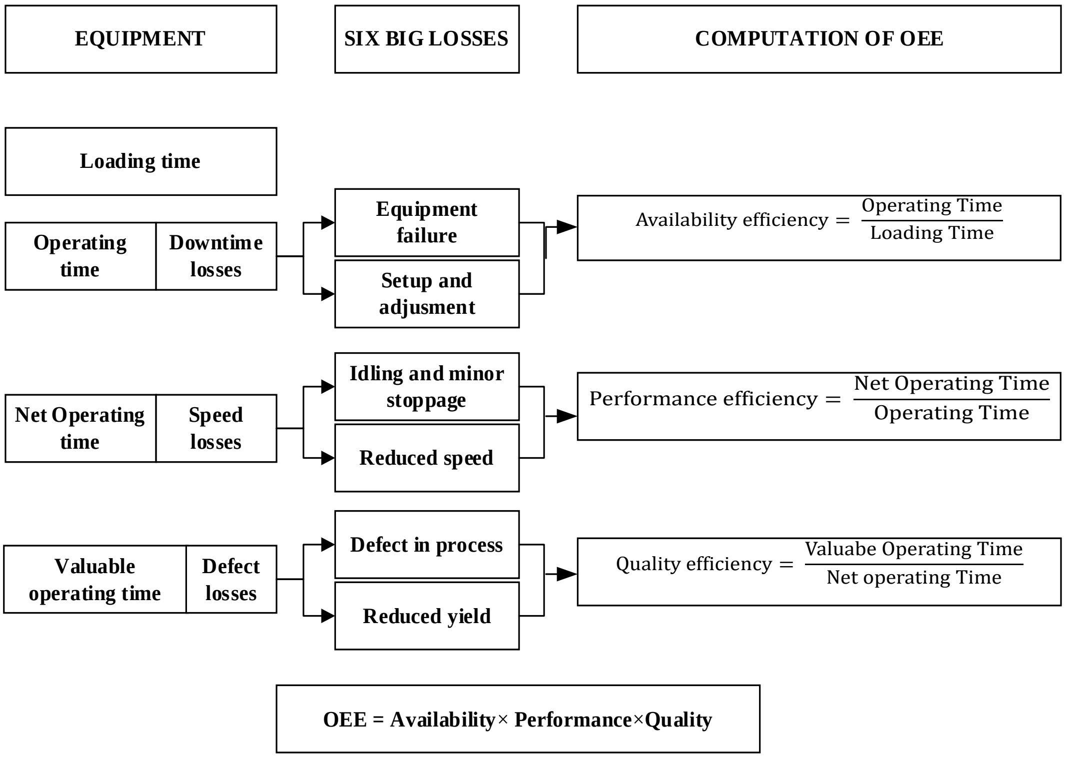

Figure 4. Modified OEE process and formula

Table 3. Six big losses for injection moulding Fanuc

Month	Run Time	Sample	Setup/Cleaning Time	Down Time	Idle Time	OEE (%)
Jan.	16.295	35	1.035	2.625	13.130	80.16%
Feb.	5.045	10	420	765	22.080	64.72%
Mar.	7.520	20	510	1.470	25.500	59.15%
Apr.	17.490	110	1.760	185	13.595	89.49%
May	9.795	20	290	45	19.610	94.50%
Jun.	14.515	55	840	910	17.280	30.26%
Jul.	11.410	490	120	850	17.370	83.61%
Aug.	11.830	490	30	860	18.470	74.93%
Sep.	11.560	910	240	1.750	17.700	74.77%
Oct.	5.380	420	1.080	540	23.300	66.90%
Nov.	16.955	650	1.740	305	12.900	80.69%
Dec.	22.225	540	630	2.955	5.760	70.29%
Total	150.020	3.750	8.695	13.260	206.695	66.47%

Table 4. Six big losses mesin injection moulding Arburg

Month	Run Time	Sample	Setup/Cleaning Time	Down Time	Idle Time	OEE (%)
Jan.	0	0	0	0	28.800	0%
Feb.	0	0	0	0	29.280	0%
Mar.	8.420	575	420	3.155	22.470	59.69%
Apr.	4.540	20	60	1.730	24.850	71.50%
May	6.935	405	600	640	22.120	78.38%
Jun.	19.000	310	1.320	1.080	12.818	62.17%
Jul.	3.750	20	60	40	14.073	88.90%
Aug.	3.170	0	450	220	27.840	79.91%
Sep.	0	0	0	0	31.680	0%
Oct.	3.900	90	140	0	26.110	80.12%
Nov.	11.980	330	450	2.120	17.760	71.04%
Dec.	31.030	60	600	1.430	0	87.47%
Total	92.725	1.810	4.100	10.415	257.801	74.19%

Table 3 provides performance data for a machine, broken down by month, with various metrics that assess machine efficiency and usage. Overall, the machine's OEE over the entire year is 66.47%, which is moderate but leaves room for improvement. The machine was idle for 206.695 hours, representing significant unused capacity, particularly in months like February, March, and October. A focus on reducing idle time and optimizing production scheduling could improve both run time and OEE in the future. The lowest OEE is in June with the percentage 30.26% and the highest is May 94.50%.

Table 5. Six big losses mesin injection moulding Engel

Month	Run Time	Sample	Setup/Cleaning Time	Down Time	Idle Time	OEE (%)
Jan.	0	0	0	0	31.680	0%
Feb.	0	0	0	0	28.800	0%
Mar.	0	0	0	0	33.120	0%
Apr.	0	0	0	0	30.240	0%
May	0	0	0	0	31.680	0%
Jun.	0	0	0	0	31.680	0%
Jul.	21.940	0	300	6.240	5.700	42.30%
Aug.	29.905	0	480	4.185	960	56.22%
Sep.	10.875	0	720	2.235	19.680	22.67%
Oct.	20.245	540	960	4.670	8.525	55.08%
Nov.	27.850	30	810	4.430	480	73.55%
Dec.	32.120	0	480	1.000	0	87.63%
Total	142.935	570	3.750	22.760	222.545	59.61%

Table 6. RPN calculation

No.	Process Description	Potential Failure	Potential Effect	Severity (S)	Potential Root Causes	Occurrence (O)	Current Process Control	Detection (D)	RPN
1	Moulding	Wrong material usage	Delay or stop production	6	No identification on raw material container	2	Attach material identification on container	4	48
2				6		2	Refill material when container empty & update the material identification tag	4	48
3		Different color	Part discoloration	6	Contamination from supplier	1	Use material batch by batch	4	23
4		Incorrect mold/tools preparation	Delay production	6	Technician overlook when collect mold	2	Identification in mold and verify with mold folder	4	48
5		Reject part	Increase reject rate	6	Insufficient drying material	1	Verify drying temperature & time with mold folder	4	24
6				6	Incorrect mold setting parameter	2	Verify mold setting parameter with mold folder	4	48
7				6	Broken tool or mold	2	Keep the first shot and last shot part	4	48
8				6	Erroneous dimension checking method	2	Alignment of measurement method with customer	4	48
9				6		2	Provide training for relevant personnel	4	48
10				6	Unclear product limit specification	2	Correspondence with BU manager for specification verification and brief to relevant personnel	4	48
11		Injection molding machine	Increase in machine	6	Unclear specifications of broken machine	2	leakage in the injection machine	4	48
12				6	Check the injection machine daily	2	Verify daily check sheet	4	48

Table 4 tracks the six big losses that impact the Arburg injection molding machine's OEE throughout the year. The six big losses include: setup and cleaning time, downtime, idle time, and run time, among other factors. These losses are crucial for identifying inefficiencies and bottlenecks that affect productivity.

a. Idle Time as the Major Contributor to Losses: Throughout the year, idle time was the largest source of inefficiency, with 257.801 hours of idle time. Addressing this could drastically improve productivity.
b. Significant Operational Gaps: The machine was completely idle in January, February, and September, and this contributed to major production losses. Production planning and scheduling should be re-evaluated to avoid long periods of inactivity.
c. Opportunities to Reduce Setup and Cleaning Time: With 4.100 hours spent on setup and cleaning, there is room for optimizing these processes to maximize run time.
d. Strong Efficiency in Productive Months: July and December demonstrated high OEE and efficient machine use. These months could serve as benchmarks for improving other months where OEE and run time were lower.

Table 5 outlines the six big losses for the Eagle machine, detailing run time, setup/cleaning time, downtime, idle time, and OEE for each month of the year. From January to June, the machine was completely idle, with 0 hours of run time and an OEE of 0%, leading to substantial idle time. Starting in July, the machine saw significant operation, with a run time of 21.940 hours and an OEE of 42.30%, though downtime was still high at 6.240 hours.

The run time peaked in December with 32.120 hours and the highest OEE of the year at 87.63%, showing optimal machine usage. Throughout the year, setup and cleaning time remained moderate, with a total of 3.750 hours, while downtime accumulated to 22.760 hours. Idle time, the largest contributor to losses, reached a total of 222.545 hours. The overall OEE for the year was 59.61%, showing room for improvement in machine efficiency and reduction of idle periods.

From the Table 6, one of the potential failures found is the use of the wrong material, which can cause delays or stoppages in production. The main cause of this problem is the lack of identification on the raw material container, with a severity level (S) of 6, a probability of occurrence (O) of 2, and a detection (D) of 4, resulting in an RPN value of 48. To reduce this risk, a control has been implemented in the form of providing identification labels on the material container.

In addition, there is a failure in the form of a difference in color in the product that can be caused by contamination from the supplier. Although it has the same severity level (S = 6), the probability of occurrence (O = 1) is lower, and the detection is quite good (D = 4), resulting in an RPN of 23. The preventive efforts made are to use materials in a batch system to avoid contamination.

Another failure analyzed is the preparation of the wrong mold or tool, which can cause production delays. This is generally caused by the technician's negligence in collecting the appropriate mold, with an RPN of 48. To overcome this, the mold identification and verification steps are implemented with the mold folder before use.

From this analysis, it can be concluded that risks with high RPN (≥48) such as the use of wrong materials and wrong mold preparation should be the top priority in process improvement. Improvement efforts can be made by ensuring a better identification system, improving technician training, and tightening raw material control. Meanwhile, risks with lower RPN, such as product color differences, must still be monitored even though they are not the top priority. With this approach, the effectiveness of the production process can be improved, and potential failures can be minimized.

(3) Analysis Phase

In this phase, the data collected has been analyzed using cause and effect diagram to identify major defects and their causes for addressing them in order to improve the process. Here’s a Fishbone (Ishikawa) diagram breakdown for the problem, highlighting the key causes in different categories as shown in Figure 5.

1. Man (People):
   a. Lack of proper training for operators, leading to inefficiencies in production.

2. Material:
   a. Poor quality of raw materials affecting product consistency.
   b. Slug weight variation causing defects in the final product.

3. Machine:
   a. Improper maintenance of machinery, leading to frequent breakdowns.
   b. Mold cleaning not done regularly, impacting product quality and cycle time.

4. Method:
   a. High speed of injection, causing defects due to insufficient control.
   b. No proper cycle time established, resulting in inconsistent product output.

These issues contribute to inefficiencies and quality problems in the production process.

(4) Improve Phase

In this phase, the primary objective is to develop, test, and implement solutions to address the root causes identified during the Analyze phase. In this phase, the main objective is to develop, test, and implement solutions to address the root causes identified during the Analysis phase. Recommendations for addressing the issues are presented in Table 7.

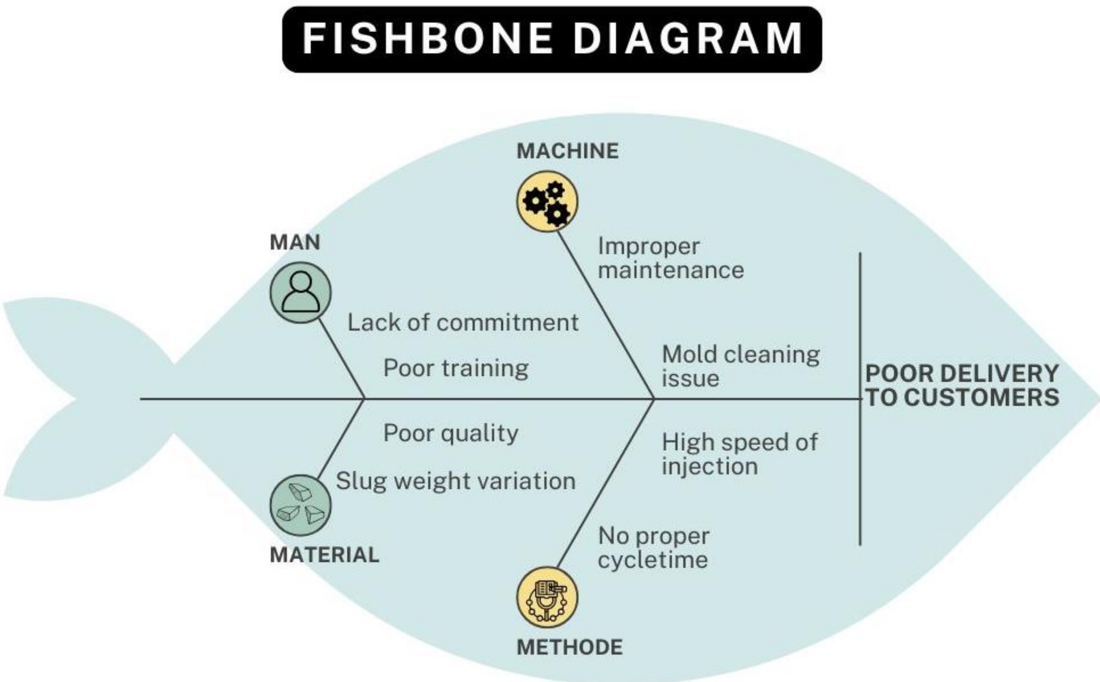

Figure 5. Fishbone Diagram

Table 7. Improvement recommendations

Type of loss	Failure Mode	Failure Cause	Current Control	Recommended Action
Reduce Speed Loss		Wear	Replacing worn-out machine components and performing machine maintenance by overhauling the machine once a month.	Create a schedule for the replacement of each machine component and routinely replace components based on the established replacement intervals, make sure high quality components are used to extend the service life.
		Old machine		Implementing autonomous maintenance aimed at enhancing operators' sensitivity to the condition of injection molding machines and improving their ability to perform self-maintenance, thereby maintaining the machines' performance.
		Not optimal maintenance		Implement preventive maintenance by enforcing a daily maintenance system (such as oil filling, checking oil temperature, inspecting nozzles for leaks, checking mold pressure, checking cooling circulation of the mold, checking hydraulic pump pressure, checking high-pressure clamp pressure, and checking the condition of the mold), weekly maintenance (such as changing oil, cleaning the oil tank, cleaning the clamping cylinder, and tightening hose bolts), and monthly maintenance (dismantling the barrel and nozzle to check the condition of parts and components, performing an overhaul, cleaning the cooling system, cleaning the chiller, and cleaning the heat exchanger) so that the machine can maintain stable performance.
Breakdown Loss	Damage in Mold	Lack of maintenance	Performing check mold every three months and repairing mold if there is a reject.	Do not use tools that can damage the mold, such as screwdrivers or hammers; it is recommended to use soft tools like pliers made of plastic, copper, or brass to avoid damaging the mold. Using clean water for cooling water. Avoid excessive clamp pressure and high injection pressure, as well as overproduction. Lubricate necessary components, and ensure the cleanliness of the work area and mold storage to prevent contamination. Routine checks of the mold should be conducted every month, and if necessary, repairs should be made as soon as there is minor damage to the mold, rather than waiting for the damage to worsen.
		Mistakes in the production process		
		Mistakes in installation		

5.2 Control

The objective of the control phase is to ensure the sustainability of the improved and modified system, making it more resilient and well-maintained to keep the process stable. It has been observed that without the implementation of restrictions, the system may become uncontrollable.

6. RESULT AND DISCUSSION

6.1 Results

The results presented in this case study offer an in-depth analysis of the moulding manufacturing operation's performance over a 12-month period. The evaluation focuses on key performance metrics, including run time, setup/cleaning time, downtime, idle time, and OEE. These metrics provide insights into the efficiency and effectiveness of the production process and highlight areas for improvement.

During the initial months, the plant faced operational challenges that resulted in no production output. However, starting in July, the application of the DMAIC methodology, along with continuous process improvements, led to gradual enhancements in equipment utilization and production efficiency. The significant increase in OEE towards the latter half of the year reflects the effectiveness of these improvements.

(1) Initial 6 Months (January - June):

a. OEE Performance: The OEE for the first six months (January to June) was consistently 0%, indicating no production activity during this period. This could be due to various factors such as downtime related to machine installation, preparation, or significant operational disruptions.

b. Idle Time: The operation showed significant idle time during these months, averaging around 31,000 hours per month, reinforcing the fact that production was not operational.

(2) Second Half of the Year (July - December):

a. OEE Improvement: Starting in July, production activities resumed, and the OEE began to increase, peaking at 87.63% in December. This indicates that significant improvements were made to both equipment and process utilization over the latter half of the year.

b. July: OEE began at 42.30%, with 21.94 hours of run time and 6.24 hours of downtime. The introduction of production activities and the gradual reduction of idle time demonstrate efforts to restart operations.

c. August: A further improvement in OEE to 56.22% was achieved, with a longer run time of 29.91 hours and less downtime, showing better utilization of equipment. However, idle time still accounted for 960 hours, which indicates room for further optimization.

d. September: OEE dropped to 22.67%, largely due to a sharp increase in idle time (19,680 hours), indicating that equipment was not being used effectively. This suggests potential issues with production planning, maintenance, or external disruptions.

e. October - December: These months marked a recovery, with OEE steadily rising:

f. October: OEE was 55.08%, with 20.25 hours of run time but higher setup and cleaning time (540 hours).

g. November: OEE improved significantly to 73.55%, with 27.85 hours of run time, and a substantial reduction in both downtime and idle time, highlighting improved operational stability.

h. December: Achieved the highest OEE at 87.63%, with minimal downtime and no idle time. The plant was running efficiently, and production processes had stabilized.

Analysis of Key Factors Influencing OEE:

(1) Run Time:

a. The run time started from 0 hours in the first half of the year to 32.12 hours in December. The gradual increase in run time reflects the ramping up of production, showing improved equipment reliability and operational consistency.

(2) Setup and Cleaning Time:

a. Setup and cleaning time fluctuated, peaking in October at 960 hours, which might have been due to a major changeover, cleaning, or preparation for a new product run. However, these times were well managed in other months, especially in November and December, where minimal setup and cleaning were needed, reflecting more streamlined processes.

(3) Downtime:

a. Downtime was a significant challenge early on, especially in July and October, but was effectively reduced to only 1,000 hours in December. The improvement in downtime management, especially through preventive maintenance and efficient planning, had a direct positive impact on OEE.

(4) Idle Time:

a. Idle time was extremely high in September (19,680 hours), indicating significant underutilization of machines. However, by December, idle time was reduced to 0, showcasing the successful optimization of resource utilization and capacity planning.

6.2 Discussion

The results from the DMAIC implementation demonstrate a significant improvement in OEE—rising from an initial 59.61% to 87.63%. This exceeds the company's target of 85% and aligns with the benchmarks suggested in Six Sigma literature [2, 4]. Similar studies, such as by Mittal et al. [3], reported a 27% yield increase using DMAIC, which supports the effectiveness of structured problem-solving approaches in complex manufacturing environments.

6.3 Impact of preventive maintenance and SOPs

The data indicates that preventive maintenance schedules and standardized operating procedures contributed most significantly to reducing downtime and idle time. This echoes findings from Bhargava and Gaur [5] who emphasized setup standardization as a key driver of OEE gains. The success of these interventions highlights the value of aligning FMEA insights with actionable improvements. For example, molds with high RPN values were prioritized, and corrective actions such as mold tagging and technician training directly targeted the root causes identified.

6.4 The role of contextual constraints

Interestingly, the improvement occurred despite constraints such as outdated machinery and limited automation. This supports DMAIC's flexibility and adaptability to low-resource environments—a point not deeply explored in prior literature.

6.5 Unexpected outcomes

One notable observation is the dramatic idle time reduction in December, which dropped to zero. While this is a positive outcome, the sudden nature of this change may reflect short-term efforts or over-scheduling, raising questions about long-term sustainability. Future studies should assess whether such gains are maintained.

6.6 Linking DMAIC phases to performance gains

Each DMAIC phase played a critical role:

a. *Define & Measure* clarified which losses were most severe.
b. *Analyze*—using Fishbone and 5-WHYs—prioritized man, method, and machine issues.
c. *Improve* translated these into clear action.
d. *Control* ensured routine monitoring and quick feedback loops.

6.7 Broader implications

These findings provide empirical evidence that structured continuous improvement strategies can transform operational performance even in environments with legacy systems. They also reinforce the importance of frontline involvement, as operator training and feedback loops were integral to success.

7. CONCLUSION

This study aims to address the issue of suboptimal performance in injection molding operations at PT. XYZ by applying the DMAIC methodology. The primary objective is to improve OEE by identifying and reducing the root causes of performance loss—especially those related to downtime, long setup times, and sampling inefficiencies.

Through a structured application of DMAIC, supported by various tools such as SIPOC, FMEA, Fishbone Diagram, and 5-WHYs, this study successfully identified the most critical failure modes affecting productivity. Targeted interventions, including the implementation of preventive maintenance, standardization of setup procedures, and enhanced operator training, resulted in a substantial increase in OEE to 87.63%, exceeding the company's performance targets.

These findings have significant practical implications for manufacturing companies operating in similar environments. This study demonstrates that a data-driven continuous improvement framework, when applied systematically and supported by cross-functional collaboration, can produce measurable performance improvements even in resource-constrained situations.

However, this study also encountered certain limitations. The scope of implementation was limited to a single plant and focused on three machines. Factors such as organizational culture, supplier variability, and human resource constraints were not explored in depth. These aspects may affect the scalability of the improvement strategy.

For future research, it is recommended to:

Expand the application of DMAIC across multiple facilities or product lines to test scalability and consistency, integrate advanced data analytics or IoT-based monitoring for real-time performance tracking, Investigate the long-term sustainability of various control measures through longitudinal studies, and explore the role of human factors, such as the effectiveness of training, motivation, and interdepartmental communication, in the success of operational improvements.

In conclusion, this study contributes to academic understanding and industry practice by demonstrating how a structured methodology such as DMAIC can deliver practical improvements in manufacturing performance. It also provides a replicable framework for other organizations seeking to improve efficiency and quality in complex production environments.

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