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Quality Control Analysis of Porcelain Products Using Overall Equipment Effectiveness and Statistical Quality Control Methods

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Abstract
This study uses statistical quality control (SQC) and overall equipment effectiveness (OEE) to examine quality at a porcelain production firm. The study is motivated by the most frequently broken machines in 2019, is the Jigger 01 machine. This paper aims to evaluate the machine's effectiveness using the OEE method. The OEE determines the scope of the problem to be solved using the SQC method. The average OEE value in 2019 was 70%. Based on the SQC method, the product defect produced is still under control. However, the average defect is still above the company's tolerance limit of 10%. Consequently, this study offers enhancements utilizing the Failure Mode Effect Analysis (FMEA) technique. The results indicate that human resources and machines caused defective products. This paper contributes to providing several improvements that the company can apply to maximize its quality control analysis. After implementing the improvement, the OEE value increases to 74%.

Keywords
Porcelain manufacturing; Overall equipment effectiveness; Statistical quality control; Tolerance limit; Failure mode and effects analysis.

Introduction

In Indonesia, the development of manufacturing industries has flourished, leading to a rapidly growing market and competitive level. Industries must optimize production activity while maintaining the top-notch quality customers value to adapt to the continuously increasing market competitive level. In addition, it is imperative to sustain long-term performance production at a minimum cost (Kulkarni et al., 2023). As a result, every firm must continually utilize resources to provide high-quality products at competitive rates, because quality and productivity are critical aspects of corporate survival (Jimenez et al., 2019; Nurprihatin et al., 2022).

This study is focused on the production of porcelain in Indonesia. The production process begins with raw material scaling using the scaling filling machine 01. Then, the weighted materials are transferred to the body preparation division and transformed into hollowed ceramics using the ball mill body and mixing body machines. The hollowed ceramics are moved to the Jigger machine to be formed into greenware. This machine is designed to form ceramics into plates, bowls, mugs, and glass. Then the greenware is heated at 800°C before being glazed using the mixing glazed machine 02 and reheated using the kiln glost 01 machine under *12 000° C–13 000° C*.

With the increasing complexity emerging in industries, companies are more at risk of facing short-term disruptions (Bergs et al., 2021). Manufacturing disruption always impacts product quality (Andry et al., 2022). As mentioned in the porcelain production process, the company has been using modern machines to accelerate production to meet market demand. However, the company has never assessed any effectiveness analysis of their machine. The company only records machine breakdown data, including machine loading time and downtime.

This study is conducted in a well-known porcelain manufacturing industry to implement the overall

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equipment effectiveness (OEE) and statistical quality control (SQC) methods as a part of the quality control approach of porcelain products. These methods were chosen due to the absence of any evaluation activity regarding the effectiveness of the most frequent breakdown machine, Jigger 01. This machine has the highest breakdown frequency compared to other machines, up to 421 times a year. This breakdown has been detrimental to the company's performance because the Jigger machine is vital to transform ceramics into greenware.

The machine effectiveness assessment is carried out using the OEE method to evaluate machine capability, minimize the impact of six big losses, and overcome the breakdown problem. In its implementation, OEE regards three measurement indicators: availability, performance efficiency, and quality rate (Solikhah & Nusraningrum, 2022). The results of the OEE will be the reference in determining the scope of improvement needed for the machine. Integrated with OEE, the SQC method is implemented as the quality management approach to control process and product quality. By integrating OEE with SQC, this study aims to increase the effectiveness of SQC utilization in solving problems by limiting the problem based on the OEE results. Herewith, this study is conducted to control the quality of porcelain products, suppress product defects, and provide suggestions for improvements that could be implemented to eliminate issues.

The literature review is carried out to gain references from similar studies. The references used in this part are based on the problem identified in the introduction. Then, after the quality control analysis method is determined through a literature study, the research method is presented using a flow chart to understand how this study is conducted step by step. The findings are presented in the results and discussion and summarized in the conclusion. In addition, this paper also provides suggestions for the company's further improvement and future studies.

Literature review

The main contribution to the scientific community is to reduce the manufacturing disruption that always impacts product quality. This manufacturing uses a machine that is designed to form ceramics into plates, bowls, mugs, and glass. This paper also contributes to a new study on how overall equipment effectiveness (OEE) and statistical quality control (SQC) methods can be implemented to present the quality control analysis of a porcelain manufacturing industry.

These two methods are chosen based on the study's objective of integrating SQC as a part of quality control assessment in increasing the OEE value, specifically for the quality factor of the OEE. Failure Mode and Effect Analysis (FMEA) is implemented in optimizing these methodologies as a systematic approach used to analyze and prevent potential issues. In Table 1, four papers are used as the primary references in making this paper. These papers are chosen based on the same objective function. It has been made sure that these objective functions are the same as the objective of this paper. Other references besides the ones mentioned in Table 1 are also used to make this paper more valid and comprehensive.

OEE is a comprehensive key performance indicator that measures machine performance and capability during optimal manufacturing implementation (Anusha & Umasankar, 2020; Thiede, 2023). FMEA is a risk assessment method used to control a process by providing a formal and detailed description of how severe failures could affect a system, the likelihood for it to happen, and the probability for it to be detected (Appollis et al., 2020; Mascia et al., 2020). OEE and FMEA are two methods with different objectives. However, systematic research has shown that FMEA creates a significant impact on OEE value; it is shown that low RPN generates high OEE (Ahire & Relkar, 2012). Therefore, FMEA can be used as the approach to increase OEE value. In addition, a study showed that Fishbone Diagram is used to identify problems that cause a company to be unable to achieve the ideal OEE (Solikhah & Nusraningrum, 2022).

Besides OEE and FMEA, the SQC approach is also implemented to increase the OEE value's quality factor. As its name implies, SQC is a statistical method to monitor process and quality standards at a minimum cost level (Dwiartono et al., 2020). There are seven tools in SQC. The usage of each tool is adjusted to the needs and conditions of the observed system. Studies have proved SQC's success as the statistical quality control technique in identifying and understanding issues in different types of industries. SQC was also applied in the condom manufacturing industry (Subin & Sudheer, 2019). This study created a roadmap of how SQC can be implemented to improve reliability, increase productivity, and enhance customer satisfaction (Subin & Sudheer, 2019). The study's main takeaway for this paper is the *p*-chart and fishbone diagram implementation for the analysis technique of one of the defect types found (Subin & Sudheer, 2019). Lastly, SQC and FMEA methods were implemented in a steel manufacturing company to minimize the percentage of deformed bar product defects; it is shown that the percentage is decreased

Table 1
Literature review

Author(s)	Industry	OEE	Statistical quality control		FMEA	Objective function
			Control chart	Other tools		
Ahire & Relkar (2012)	Process industry	Yes	No	No	Yes	Establish the correlation between OEE and FMEA parameters
Solikhah & Nuraningrum (2022)	Pipe manufacturing	Yes	No	Fishbone diagram	No	Increasing production capacity
Subin & Sudheer (2018)	Condom manufacturing	No	*p*-chart, R-chart, $\bar{x}$ chart	Process flow, scatter plot, check sheet, Fishbone diagram	Yes	Process performance assessment, quality control
Mislan & Purba (2020)	Steel manufacturing	No	No	Histogram, Pareto analysis, scatter plot, Fishbone diagram	Yes	Quality control, minimize defect
This paper	Porcelain manufacturing	Yes	*p*-chart	Check sheet, scatter plot, Fishbone diagram, Pareto analysis, histogram	Yes	Machine effectiveness assessment, quality management, minimize defect

Source: Author's own conception

by 0.06%, suppose the recommended solutions are implemented (Mislan & Purba, 2020).

This shows the integration of overall equipment effectiveness (OEE) and statistical quality control (SQC) methods is appropriate for improving the quality of a porcelain manufacturing company. Therefore, through this literature review, it is decided to use FMEA and OEE to maximize the SQC result. In addition, other tools including check sheet, scatter plot, Fishbone diagram, Pareto analysis, and histogram are utilized along with FMEA and OEE.

Materials and methods

Figure 1 shows the research methodology carried out in this study. In the early phases, this study is focused on problem identification and a literature review. Then, a literature study is carried out to determine the best solution to overcome the problem. It is found that OEE and SQC are the best solutions for resolving machine downtime and defect problems, respectively. The SQC approach is integrated within the OEE framework to obtain an optimal result, specifically in the quality factor approach. The next stage after data collection is data processing. In this phase, the OEE calculation was carried out for each OEE factor: availability, performance, and quality. Lastly, the conclusion and recommendations were made for the company. Table 2 shows the data collected for this research and the calculation for which this data will be used. For this study, this research limitation is the limited amount of data gathered after the recommendations are implemented, which is only limited to 10

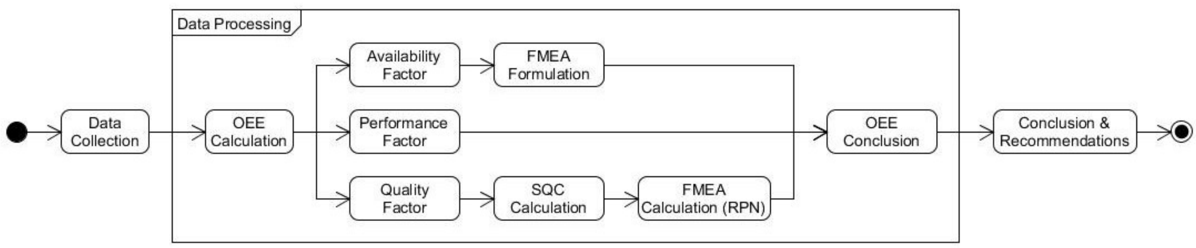

Fig. 1. Research method. Source: Author's own conception

Table 2
Data collected

OEE calculation	SQC calculation	FMEA calculation
1. Idle time 2. Machine cycle time 3. Total production 4. Total defect	1. Total sample 2. Defect type 3. Defective samples	1. Loading time 2. Machine downtime 3. Standard time available 4. Set up time

Source: Author's own conception

days. In addition, the research limitation is related to the limited quality control analysis carried out, which only used OEE, SQC, and FMEA.

Figure 1 and Table 2 show three calculations conducted in this study: OEE, SQC, and FMEA. The data collection process was conducted through a historical database and sampling. For sampling, the data is collected during observation on the manufacturing floor. Idle time, total sample, machine cycle time, and defective samples are the type of data collected through sampling while others are gathered from the company's historical data.

In addition, there is an additional calculation related to DPMO to determine the sigma level. The formula of each calculation is elaborated as follows:

Overall Equipment Effectiveness (OEE)

As its name implies, OEE is an overall measurement used to benchmark, analyze, and evaluate machine effectiveness utilized in the observed process (Nurprihatin et al., 2019). In its implementation, OEE is utilized through six big losses observation that provides a beneficial point of view in decision-making activity related to production lines and machinery (Sari & Darestani, 2019). The OEE calculation is first divided into three ratios: availability, performance efficiency, and quality rate. The final value of OEE is obtained by multiplying these ratios into one. The OEE calculation is elaborated as shown in Equation (1)–(4) (Nurcahyo et al., 2018).

1. As shown in Equation (1), the availability ratio describes the use of available time for machine or equipment operation activities.

$$A = \frac{\text{Loading time-Downtime}}{\text{Loading time}} \times 100\% \tag{1}$$

2. As Equation (2) explains, performance efficiency is the production quality ratio multiplied by the ideal cycle time to the available time (operation time).

$$P = \frac{\text{Cycle Time} \times \text{Processed Amount}}{\text{Operating Time}} \times 100\% \tag{2}$$

3. Product quality rate describes the ability of equipment to produce products according to standards.

$$Q = \frac{\text{Processed Amount-Defect Amount}}{\text{Processed Amount}} \times 100\% \tag{3}$$

4. OEE is obtained by multiplying the three main ratios; this is done to determine the effectiveness of using the machine.

$$\text{OEE} = A \times P \times Q \tag{4}$$

Statistical Quality Control (SQC)

Statistical Quality Control is a quality management approach essential to improve quality and processes. This approach starting from process analysis, continued with standards determination, performance comparison, deviation verification, and providing solutions (Andrade et al., 2017). Dr. Kaoru Ishikawa, a well-known quality guru, elaborates on seven vital tools in quality management applications: check sheet, scatter plot, Ishikawa diagram, Pareto analysis, stratification, histogram, and control charts (Antony et al., 2017). These tools are elaborated as follows:

- A check sheet is a form used to gather and analyze data related to any type of discrepancy found in a process (Dwiartono et al., 2020).
- The scatter plot is used to assess the correlation and analyze the relation between two variables (cause and effect) identified (Ginting & Supriadi, 2021).
- The Ishikawa diagram is the cause-and-effect presentation that visualizes the causes of a problem occurring in a process (Coccia, 2017).
- Pareto analysis is based on the utilization of the Pareto Chart to prioritize and sort data from the most to the least frequent problems identified in a system (Subin & Sudheer, 2019).
- Stratification is a grouping activity to categorize data based on its characteristics (Ginting & Supriadi, 2021).
- Histogram is a bar chart used to visualize the distribution of data that has been categorized into

different classes based on its size (Dwiartono et al., 2020).

- A Control chart is used to measure the stability of the observed system and determine whether the production process is in control or not (Syamsul et al., 2022). A Statistical Process Control (SPC) needs to monitor the trend behavior of production control (Viharos & Jakab, 2021). In selecting a control chart, it is crucial to determine the appropriate control chart based on the data analysis and distribution (Reynolds et al., 2021). Therefore, it has been determined that the best control chart that can be used for the specific data types gathered is a p-chart due to its ability to support extreme quality levels (Chukhrova & Johannssen, 2023). The steps in making a p-chart are shown in Equation (5)–(8) (Syamsul et al., 2022).

1. Defect percentage calculation

$$P = \frac{np}{n} \tag{5}$$

2. The average product defect calculation to obtain Central Line (CL)

$$\text{CL} = p' = \frac{\sum np}{\sum n} \tag{6}$$

3. Upper Control Limit (UCL) calculation

$$\text{UCL} = P' - 3\sqrt{\frac{p'(1-p')}{n}} \tag{7}$$

4. Lower Control Limit (LCL) calculation

$$\text{UCL} = P' + 3\sqrt{\frac{p'(1-p')}{n}} \tag{8}$$

Failure Modes and Effect Analysis (FMEA)

FMEA is a measurement method that combines quantitative and qualitative approaches to identify or measure hazards in a system (Qin et al., 2020; Subriadi & Najwa, 2020). It is a comprehensive and systematic approach utilized in any manufacturing process to define, identify, and eliminate potential failures (Ahire & Relkar, 2012). The steps in implementing FMEA include (Stamatis, 2019):

1. Determine the label on each process or system.
2. Explain the function of each process.
3. Identify the types of defects that occurred.
4. Identify the consequences of defects.
5. Determine the severity value ranging from 1-10. The more severe the impact of the defect, the higher the severity value given.
6. Identify the cause of the defect.
7. Determine the frequency value ranging from 1-10. The more frequent defects occur, the higher the rating value given.
8. Identify the controls performed.
9. Determine the detection value ranging from 1-10. The more difficult the cause of the defect is to be detected, the higher the rating value given.

The observed failures will be prioritized based on the Risk Priority Number (RPN) derived after considering the severity (S), occurrence (O), and detectability (D) characteristics of each failure category (Li et al., 2023). The formula of RPN is presented in Equation (9).

$$\text{RPN} = \text{severity} \times \text{occurrence} \times \text{detection} \tag{9}$$

Defect Per Opportunities (DPO) dan Defect Per Million Opportunities (DPMO)

A defect is a product's failure to meet customer requirements. In six sigma, process variation should be minimized to obtain 3.4 Defects Per Million Opportunities (DPMO) (Thakur et al., 2023). The result calculated from DPMO can be used to determine the sigma level. Having a high sigma level means the higher the capability of a process to meet Critical Customer Requirements (CCR). After calculating the DPMO, the sigma level of the current system can be known using the conversion table (Table 3). The DPMO calculation is shown in Equation (10)–(13) (Mittal et al., 2023):

1. Defect Per Unit (DPU) is the average number of defects that occur in every product unit.

$$\text{DPU} = \frac{\text{Total Defect}}{\text{Total Production}} \tag{10}$$

2. Defect Per Opportunity (DPO) is failure per one opportunity. The CTQ value is based on the total processes that can cause defects or product defects.

$$\text{DPO} = \frac{\text{DPU}}{\text{CTQ}} \tag{11}$$

3. DPMO calculation determines the opportunities for a defect to occur during production.

$$\text{DPMO} = \text{DPO} \times 1000.000 \tag{12}$$

4. The Sigma Level (SL) can be obtained by converting the previous DPMO value.

$$\text{SL} = \text{NORMSINV}\left[\frac{(1,000,000 - \text{DPMO})}{1,000,000} + 1.5\right] \tag{13}$$

Table 3
SL and DPMO (Sutrisno et al., 2019)

Sigma	DPMO	Notes
1-Sigma	691,462	–
2-Sigma	308,538	Average industries in Indonesia
3-Sigma	66,807	–
4-Sigma	6,210	Average industries in the USA
5-Sigma	233	Average industries in Japan
6-Sigma	3.4	World-class industries

Source: Sutrisno et al., 2019

Results and discussion

In this part, there are two sections of data processing carried out. The first part is for the OEE calculation and continues to the second part, where the SQC approach is implemented. The SQC is implemented within the scope of problems determined by the OEE analysis results. As mentioned, several machines are used in the production process of porcelain in this company. However, this study will only focus on the Jigger 01 machines that transform ceramics into greenware. Figure 2 shows the downtime data for all machines that led to this study's decision to focus on the Jigger 01 machines.

OEE calculation and analysis

In this study, OEE will be used as a guide to select the appropriate scope of problems to be solved using the SQC method. The calculation of OEE is obtained from the multiplication of three components: availability, performance, and quality. From this multiplication, the OEE value of the company is equal to 70%. According to the world-class performance standard, the ideal OEE values 85%, with 90%, 95%, and 99% for availability, performance efficiency, and quality, respectively (Jaqin et al., 2020). Figure 3 compares the Jigger 01 machine OEE value with the international standard. From this figure, it is known that the OEE value of the machine is 13% lower compared to the ideal value. Of all the OEE factors, the highest difference is 15% in the quality value. Regarding this concern, the scope of the problem to be solved is quality.

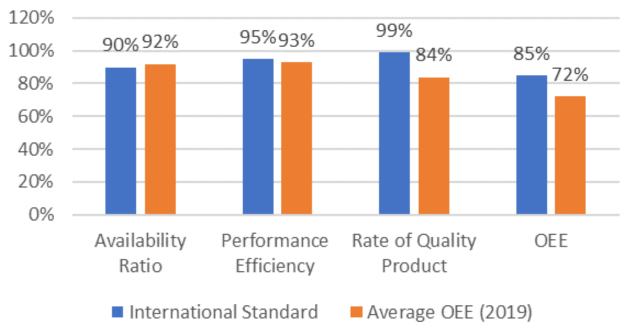

Fig. 3. OEE Comparison. Source: Author's own calculation

SQC implementation

From the OEE assessment, the quality aspect has the most significant negative gap among the other two indicators of OEE. Herewith, SQC is implemented to improve the quality value of the machine.

Collecting data using check sheet

The check sheet is one of the Six Sigma tools used as a statistical approach to evaluate process performance based on the predetermined standards (Karthik, 2020). Based on observations and the data collected in the check sheet, it is known that there are four types of defects found: black spots, unevenness, screen printing misplacement, and color discrepancy. The results of the check sheet show that the number of porcelain production used as research samples from January 2019 to December 2019 was 363,917 pieces. From this sample, there are 59,259 porcelains classi-

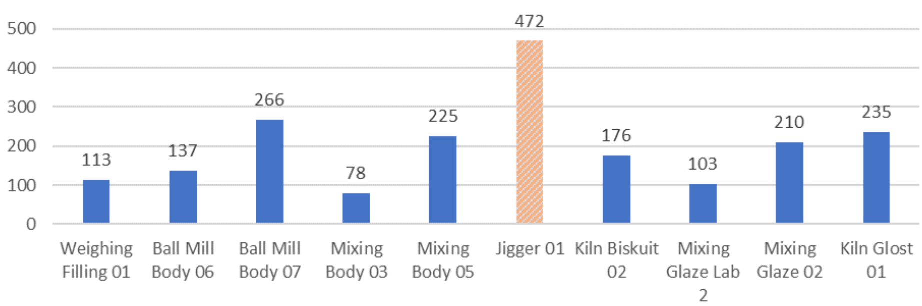

Fig. 2. Machine Downtime Data Jan–Dec 2019. Source: Company's historical data

fied as defective. The number of porcelains that were defective due to black spots, unevenness, screen printing misplacement, and color discrepancy is 14,847, 15,102, 14,524, and 14,786 pieces, respectively.

Histogram

Figure 4 visualizes the number of defective porcelains based on their defect type. From this histogram, the most defect that occurs is the presence of some rough parts, followed by black spots. The data shown in the histogram will be processed further using Pareto Chart to identify problems and prioritize them from the most to the least occurrence frequency (Dejene & Gopal, 2021).

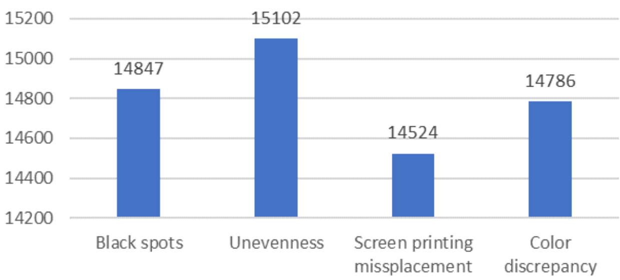

Fig. 4. Number of Defect Histogram. Source: Author's own calculation

Control chart (p-chart)

The control chart assesses to what extent the defects identified are within the statistical control limits. Figure 5 shows the p-chart after going through the calculation process of the central line (CL), the upper control limit (UCL), and the lower control limit (LCL). From Figure 5, it is shown that the number of defects remains in control, which is verified by all points of the defect proportion that falls within the boundaries of the UCL and LCL lines. However, because the value of the center line is still above the company's tolerance limit of 10%, the company still requires continuous quality control to reduce the occurrence of product defects.

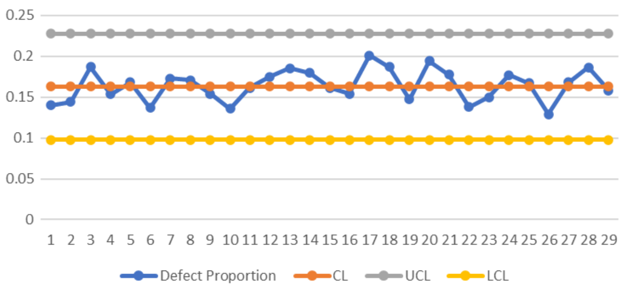

Fig. 5. Control Chart (p-chart). Source: Author's own calculation

DPMO and Sigma value calculation

Defect Per Opportunity (DPO) equals one failure per opportunity. The DPO value is obtained from the number of defective samples divided by the number of productions multiplied by the type of defect (CTQ). The CTQ identification is carried out based on processes that can cause defects or cause the product to be defective. Defects Per Million Opportunity (DPMO) is a failure measure that shows the number of defects or failures per one million opportunities. The DPMO value is obtained from the DPO value multiplied by 1,000,000, while the Sigma value equals the standard deviation of the random variable around the mean. Table 4 shows the results of DPO, DPMO, and sigma values.

Table 4
Data processing for DPO, DPMO, and Sigma value

Date (2019)	Total production	Total defect	CTQ	DPO	DPMO	Sigma value
3 Jan–14 Jan	11160	1577	4	0.0353	35327.06	3.31
15 Jan–25 Jan	12570	1815	4	0.0361	36097.85	3.3
26 Jan–7 Feb	11570	2166	4	0.0468	46802.07	3.18
8 Feb–19 Feb	12700	1950	4	0.0384	38385.83	3.27
20 Feb–2 Mar	12980	2184	4	0.0421	42064.71	3.23
4 Feb–15 Mar	15350	2100	4	0.0342	34201.95	3.32
16 Mar–27 Mar	11120	1922	4	0.0432	43210.43	3.21
28 Mar–9 Apr	11570	1976	4	0.0427	42696.63	3.22
10 Apr–22 Apr	13451	2076	4	0.0386	38584.49	3.27

Table 4 [cont.]

Date (2019)	Total production	Total defect	CTQ	DPO	DPMO	Sigma value
23 Apr–4 May	14562	1978	4	0.034	33958.25	3.33
6 May–16 May	12160	1965	4	0.0404	40398.85	3.25
17 May–28 May	11570	2025	4	0.0438	43755.4	3.21
10 Jun–20 Jun	12700	2354	4	0.0463	46338.58	3.18
21 Jun–2 Jul	11200	2015	4	0.045	44977.68	3.2
3 Jul–13 Jul	12440	2006	4	0.0403	40313.5	3.25
15 Jul–25 Jul	14350	2212	4	0.0385	38536.59	3.27
26 Jul–6 Aug	11120	2234	4	0.0502	50224.82	3.14
7 Aug–19 Aug	10670	1998	4	0.0468	46813.5	3.18
20 Aug–20 Aug	13621	2006	4	0.0368	36818.15	3.29
31 Aug–11 Sep	11562	2245	4	0.0485	48542.64	3.16
12 Sep–23 Sep	11260	1999	4	0.0444	44382.77	3.2
24 Sep–4 Oct	13550	1870	4	0.0345	34501.85	3.32
5 Oct–16 Oct	13470	2017	4	0.0374	37435.04	3.28
17 Oct–28 Oct	11680	2067	4	0.0442	44242.29	3.2
29 Oct–8 Nov	12670	2116	4	0.0418	41752.17	3.23
11 Nov–21 Nov	15350	1980	4	0.0322	32247.56	3.35
22 Nov–3 Dec	13120	2207	4	0.0421	42054.12	3.23
4 Nov–14 Dec	11770	2198	4	0.0467	46686.49	3.18
16 Dec–28 Dec	12621	2001	4	0.0396	39636.32	3.25
Total	**363,917**	**59259**	**116**	**Average**	**41,068.5**	**3.24**

Source: Author's own calculation

Based data calculation shown in Table 2, the production process of this company has low process capability with an average sigma value of 3.24 in 2019. The DPMO value is high, 50,224.82, from July 26, 2019, until August 6, 2019. This value can be interpreted that, in one million opportunities, there will be 50224.82 chances that the production process will produce a defective product.

Diagram Pareto

Figure 6 shows the Pareto Chart for the defective products based on their type. The chart shows the defect that occurs from the most to the least, from unevenness to screen printing misplacement, respectively. In the Pareto Chart, it has been calculated that the type of defect caused by unevenness is equal to 25%. Added to the number of defects caused by black spots, the percentage increased to 51%. From this, continued to be added to the color discrepancy defect, the percentage is increased to 75%. Lastly, the final sum of the last defect type makes the total percentage equal to 100%.

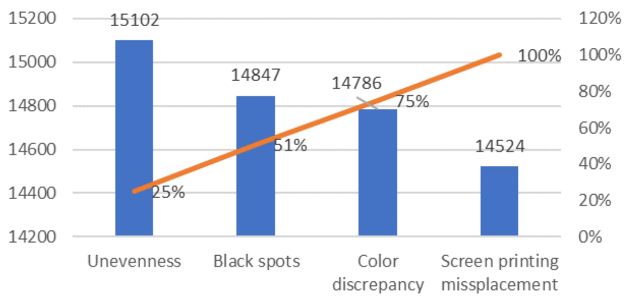

Fig. 6. Pareto Chart. Source: Author's own calculation

Fishbone diagram

The Fishbone Diagram or the Root Cause Analysis (RCA) diagram is used to identify the root causes of a defect in a process. The root causes identification is classified based on the defect type: black spots, screen printing misplacement, color discrepancy, and unevenness. Figures 7 to 10 show a causal diagram for each porcelain defect type identified. In general, five factors influence the cause of product defects. These factors include:

1. Humans or workers who carry out the production activity.
2. Machines that are used to produce goods.
3. Method or instructions that must be done.
4. Raw materials or components are to be processed into finished goods.
5. The environment around the place of production.

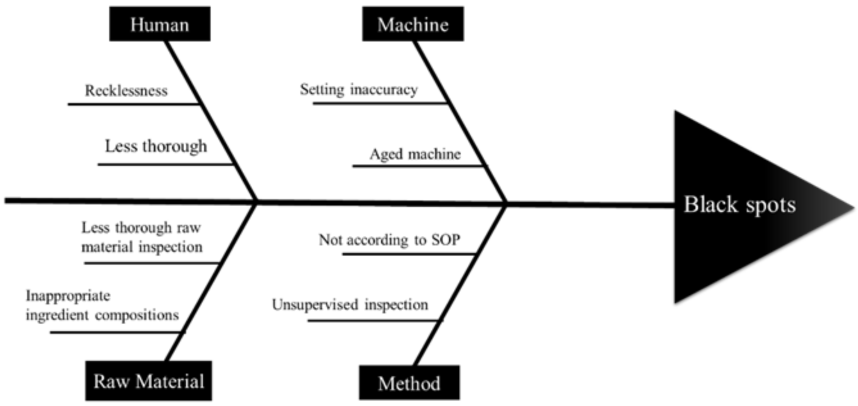

Fig. 7. RCA for Black Spots. Source: Author's own conception

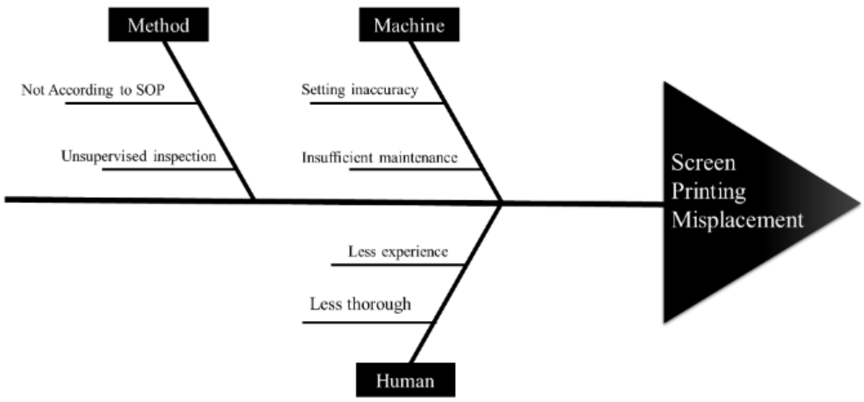

Fig. 8. RCA for Screen Printing Misplacement. Source: Author's own conception

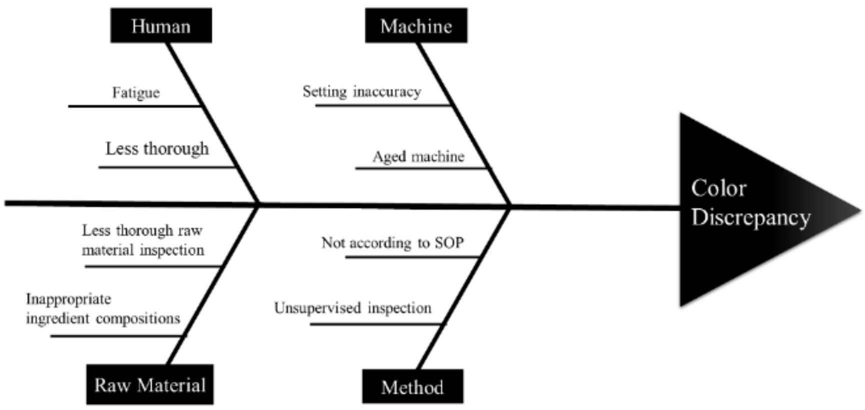

Fig. 9. RCA for Color Discrepancy. Source: Author's own conception

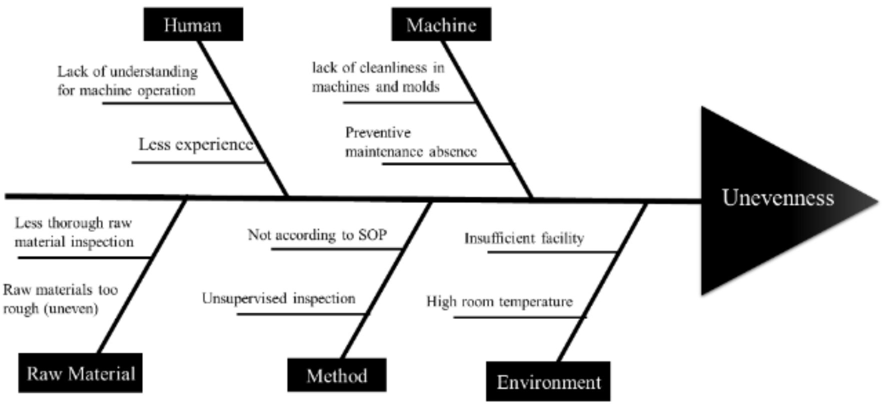

Fig. 10. RCA for Unevenness. Source: Author's own conception

Proposed improvements using the FMEA method

FMEA is a method used to analyze the severity of failure that affects the system, the opportunity for that failure to happen, and the probability that failures might not be detected (Appollis et al., 2020). Based on the cause-and-effect diagrams, five factors cause defects: humans, machines, raw materials, methods, and the environment. For each type of defect, the RPN is calculated based on the severity, opportunity, and detection scores identified. These scores are elaborated as follows:

1. Opportunity – The frequency or number of disturbances that can cause a failure in the production process.
2. Severity – The level of defect or influence magnitude of the failure on the system performance.
3. Detection – The level of detection of failure can be identified prior.

After these three scores are determined, the RPN value is calculated by multiplying these scores at once. The analysis results show that two factors have the most significant RPN values, namely human and machine factors, with RPN values of 210 and 175, respectively. Herewith, the proposed improve-

Table 5
FMEA calculation

Defect type	Effect	Factor	Cause of defect	S	O	D	RPN
Black spots	Products do not meet standard specifications	Human	Recklessness	4	4	5	80
			Less Thorough	4	6	5	120
		Machine	Setting inaccuracy	5	7	5	175
			Aged machine	7	5	5	175
		Raw material	Less thorough raw material inspection	4	5	5	100
			Inappropriate ingredient compositions	5	4	6	120
		Method	Not according to SOP	5	4	4	80
			Unsupervised inspection	4	5	5	100
Screen printing misplacement	Price deduction	Human	Less experience	5	7	6	210
			Less thorough	5	7	6	210
		Machine	Setting inaccuracy	6	5	5	150
			Insufficient maintenance	6	5	5	150
		Method	Not according to SOP	4	6	6	144
			Unsupervised inspection	4	6	6	144

Table 5 [cont.]

Defect type	Effect	Factor	Cause of defect	S	O	D	RPN
Color discrepancy	Products cannot be sold	Human	Less thorough	5	6	3	90
			Fatigue	5	5	3	75
		Machine	Setting inaccuracy	4	5	6	120
			Aged machine	6	6	3	108
		Raw material	Less thorough raw material inspection	6	6	4	144
			Inappropriate ingredient compositions	4	6	6	144
		Method	Not according to SOP	5	6	4	120
			Unsupervised inspection	6	5	4	120
Unevenness	Production targets are not achieved	Human	Lack of understanding of machine operation	4	6	6	144
			Less experience	6	4	6	144
		Machine	Lack of cleanliness in machines and molds	4	5	4	80
			Preventive maintenance absence	5	5	4	100
		Raw material	Raw materials too rough (uneven)	4	4	5	80
			Less thorough raw material inspection	5	4	4	80
		Method	Not according to SOP	6	4	4	96
			Unsupervised inspection	6	3	4	72
		Environment	Insufficient facility	5	5	6	150
			High room temperature	5	6	5	150

Source: Author's own conception and calculation

ments will focus on the system's human and machine factors.

Improvement implementation recommendation

As mentioned, the improvement recommendation focuses on the system's human and machine factors. The company started implementing the proposed improvement recommendation on June 22, 2020. The data obtained after the improvement was implemented from June 22, 2020, to July 2, 2020. The recommendations are elaborated as follows:

1. Limiting working hours to 8 hours a day.
2. Perform periodic maintenance and repair for all machines used.
3. Regular checks and repairs are intensified for machines with high breakdown frequency.
4. Provide additional facilities to enhance employee performance and reduce machine breakdown.

Analysis of OEE value after improvement

The company improves the OEE value from the data-collecting activity after implementing the recommendations. Figure 11 compares the OEE value before and after the improvement. From this bar chart, it can be concluded that the proposed improvement increases the quality value from 82% to 86%, and the OEE value increased from 70% to 74%. With this

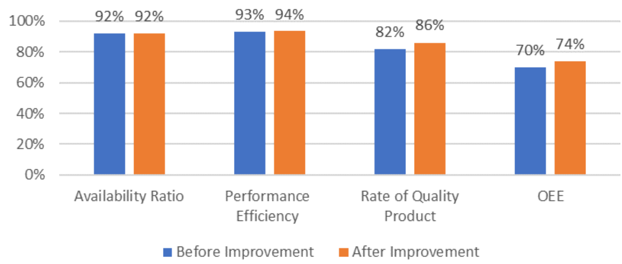

Fig. 11. OEE Comparison Before and After Improvement. Source: Author's own calculation

result, the proposed recommendations are expected to continue to be applied to achieve world-class OEE value.

Conclusions

Based on the OEE calculation for the Jigger 01 machine, the value of the quality aspect has the most significant gap compared to the other two factors, namely availability, and performance. From the OEE analysis, the implementation of improvements to the quality aspect is focused on the application of SQC for the machine. In the SQC implementation, the control chart (p-chart) shows that the number of defects that occurred is still within the control limits. Although the results show that this company's defects are still under control, the center-line value is still above the company's tolerance limit of 10%. Because of this, the company still requires further quality control assessment to minimize defects. Herewith, the DPO, DPMO, and sigma values are calculated. As a result, the process capability is 3.24, lower than the ideal value. In addition, the DPMO is relatively high, with a value of 50,224.82 defects in one million production opportunities.

Thus, the cause-and-effect diagram is used to identify the root cause of why defects occur. From the diagram, it is concluded that there are five main factors causing defects: human, machine, method, raw material, and environment. After knowing the root causes of each type of defect, FMEA is implemented. Through FMEA, it can be concluded that priority improvements can be made by conducting more stringent and scheduled supervision, warning employees who made mistakes, performing routine maintenance on the machines/equipment used, and providing additional facilities for employees to improve their performance. A previous study discussed the heuristic methods' performance for pure flow shop scheduling under certain and uncertain demands (Nurprihatin et al., 2020). These proposed improvement recommendations act as proof that the value of the quality indicator on OEE increased by 4% right after the proposed recommendation was implemented.

For further research, it is suggested that the improvement recommendation is implemented in the long term so that the impact of this study can be analyzed further. After the recommendations are implemented in the long term, the economic aspect of the study including profitability, timesaving, and moneysaving can be analyzed. In addition, this paper also recommends other studies conducted as an extension of this study. It is suggested that a study related to human resources compliance toward the priority improvements elaborated prior. This research will help the company learns about its working culture and employees' involvement in creating efforts to maximize its quality control activities.

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