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Analysis of the Six Sigma DMAIC Method to Reduce Product Defects in Reverse Engineering Components

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ABSTRACT

Purpose – This study is motivated by the occurrence of defects in the reverse engineering (RE) process of power plant components at PT PLN Pusharlis, both during the production stage and after the components are installed. To reduce defects RE products at PT. PLN Pusharlis, the Six Sigma method with the DMAIC approach is used in Non-Conformance Results (NCR) and after-sales. This method is effective in reducing defects and improving quality.
Methodology/approach – The research employs a mixed-methods approach by integrating quantitative and qualitative methods. Quantitative data are obtained from Non-Conformance Report (NCR) records and after-sales defect data for the period 2021–2024, which are analyzed to calculate CTQ, DPMO, and sigma levels. Qualitative data are collected through process mapping using SIPOC, cause-and-effect analysis with Fishbone 6M, and semi-structured interviews with relevant personnel involved in the production process.
Findings – A total of 274 NCR cases and 57 after-sales defect cases were identified during the 2021–2024 period. Pareto analysis showed that casting defects were the dominant defect category in the NCR data, accounting for 84 cases (30.66%), while drawing/design defects were the dominant category in the after-sales data, accounting for 23 cases (40.35%). Fishbone analysis revealed that the Method factor was the dominant root cause contributing to product defects. Process capability evaluation showed that the NCR DPMO decreased from 894 in 2021 to 19 in 2024, while the sigma level increased from 4.623 to 5.621. For after-sales defects, the DPMO decreased from 147 to 15, accompanied by an increase in the sigma level from 5.121 to 5.667. Based on these findings, improvement recommendations were developed in the form of a Casting Vendor Selection and Evaluation SOP and a Reverse Engineering SOP.

INTRODUCTION

PLN PUSHARLIS operates in the design and reverse engineering of electrical equipment. Manufacturing and repair of electrical equipment are a concrete manifestation of PLN PUSHARLIS commitment to supporting the reliability of PT PLN (Persero) electrical equipment. These four components (design, reverse engineering, manufacture, and repair) are integrated through rigorous quality control, resulting in high-quality and competitive products.

PLN PUSHARLIS flagship product is the reverse engineering (RE) of coal-fired power plant (PLTU) and hydroelectric power plant (PLTA) components through 3D scanning, 3D modeling, analysis, simulation, and manufacturing Product quality, in addition to price and distribution range, is one of the factors that can influence competitive advantage in winning global market competition. Therefore, every company strives to develop its products to compete with competing products in the market. The most important element in the product is quality. The quality of products (goods or services) produced by a company is the main factor that determines the performance of the company. The research from Usman et al. (2023) showed that service orientation has a significant and positive effect on company quality, consumer satisfaction, and company image (Usman et al., 2023). At the production stage, all components, namely people, process, and technology, must be well integrated. Management must implement a process that helps in finding, selecting, disseminating, and transferring important information and expertise to someone for activities such as problem solving, dynamic learning, strategic planning, and decision making. Knowledge is created, shared, and used to achieve a specific outcome such as shared knowledge, a higher level of innovation, or competitive advantage(Irjayanti & Azis, 2013).

The company needs to take quality improvement measures to reduce the level of product defects so that product quality increases. There are several methods for controlling and improving quality to reduce defect levels, one of which is using the Six Sigma (DMAIC) method (Pramono et al., 2021). In this study, researchers used the Six Sigma DMAIC approach to reduce the number of defects in the assembly process (Ahmad et al., 2024), (Nusraningrum, 2019). KM is a process that helps in finding, selecting, disseminating, and transferring important information and expertise to someone for activities such as problem solving, dynamic learning, strategic planning, and decision making. In Hendayani's research, problem identification is crucial for identifying phenomena occurring within a company. Hendayani's research focuses on determining the rating of sentiments and dimensions in order to measure the quality that needs to be prioritized based on customer opinions classified into nine dimensions of LSQ (Hendayani & Dharmawan, 2020).

In PT PLN PUSHARLIS, historical quality data from 2021–2024 shows recurring defects originating from design, welding, and casting processes, which have contributed to after-sales non-conformance findings and increased rework requirements. Although defect rates and DPMO have shown significant improvement over the years, persistent after-sales defects indicate that the production system has not yet achieved the expected performance benchmark of zero defects (Nusraningrum, 2019).
The Six Sigma method with the DMAIC (Define, Measure, Analyze, Improve, Control) approach is commonly used to minimize the level of defects in a product or packaging, as this method has proven effective in reducing defects and improving quality in various industries. DMAIC is a structured approach to identifying and eliminating the root causes of defects and minimizing variability in the manufacturing process (Mogatusi et al., 2025; Widodo & Soediantono, 2022). This study aims to implement the Six Sigma method with the DMAIC approach to minimize the level of defects.(Ahmad et al., 2024).

Based on previous research, it can be concluded that DMAIC is a methodology that consistently delivers significant results in improving process quality and efficiency, both internationally and nationally (Kurnia et al., 2021), (Baldah & Safitri, 2024). A commonality across nearly all studies is the focus on controlling process variation and strengthening a culture of data-driven decision-making. However, there remains a research gap regarding the application of Six Sigma DMAIC in the energy sector, particularly in the context of reverse engineering power plant components. Most studies focus on the automotive, healthcare, and general manufacturing industries, while there is limited research on integrating DMAIC with the technical characteristics of PLN PUSHARLIS components.

Therefore, this study seeks to address this gap by applying the Six Sigma DMAIC method to analyze and reduce product defect rates in the reverse engineering process at PT PLN PUSHARLIS. This research identifies two types of data, namely Non-Conformance Report (NCR) defect and after-sales defect. The objectives of this research are to (1) analyze defect characteristics within the reverse-engineering production process, (2) identify critical contributing factors through structured analytical tools, and (3) evaluate process capability to formulate targeted and sustainable quality improvement strategies.

LITERATURE REVIEW

Research by Anggamawarti et al., 2022 (Anggamawarti et al., 2022) demonstrated that the application of DMAIC can reduce defect rates and improve process quality consistency in the ammunition industry. Mittal et al. (2023) demonstrated that DMAIC can improve process performance through quantitative measurements of DPMO and sigma levels. Meanwhile, Adeodu et al. (2021) (Adeodu et al., 2021) demonstrated that DMAIC can improve process capability and reduce variation in the metal forming and machining industry (Mittal et al., 2023; Yu et al., 2022).

Unlike these studies, which were conducted in conventional manufacturing environments with relatively repetitive processes, this study applied Six Sigma DMAIC to the reverse engineering process of power plant components at PT PLN PUSHARLIS, which is characterized by make-to-order production, high product variation, and greater technical complexity.Most previous Six Sigma research has focused on mass production manufacturing industries such as automotive, electronics, and process industries that have standardized products and repetitive processes. Meanwhile, research on the application of Six Sigma DMAIC to the reverse engineering of power plant components is still very limited, particularly in the electricity industry and state-owned enterprises (SOEs) such as PT PLN PUSHARLIS.

Furthermore, previous research generally focused only on defects internal to the production process. This research contributes by integrating internal defect analysis (NCR) and after-sales defects to provide a more comprehensive picture of quality. This research not only measures CTQ, DPMO, and sigma levels but also develops Poka-Yoke-based improvement proposals through the Casting Vendor Selection and Evaluation Standard Operating Procedure (SOP) and Reverse Engineering Standard Operating Procedure (SOP) (Prabowo & Aisyah, 2020).

In conventional manufacturing, production processes are generally carried out based on existing designs, standardized specifications, and relatively high and repetitive production volumes. In contrast, reverse engineering processes often begin with existing components experiencing damage or wear, with limited original design data, engineering drawings, and material specifications. These conditions require companies to conduct needs identification, field surveys, dimensional measurements, remodeling, design validation, and material verification before production begins. Furthermore, the reverse engineering work at PT PLN PUSHARLIS is typically made-to-order with a high degree of variation, allowing each project to have different specifications, materials, dimensions, and technical requirements.

This complexity increases the potential for defects compared to conventional manufacturing systems, which have more stable and repetitive processes. Therefore, the application of Six Sigma DMAIC in a reverse engineering environment is crucial for systematically identifying the root causes of defects, measuring process capability using CTQs, DPMOs, and sigma levels, and formulating improvements tailored to the unique characteristics of the reverse engineering process at PT PLN PUSHARLIS.
Based on the theoretical studies and empirical phenomena outlined in the research background, this study formulates the following propositions as a conceptual basis for analyzing product quality and defect issues.

Six Sigma is a data-driven quality improvement methodology that aims to reduce process variation and the number of defects through the DMAIC (Define, Measure, Analyze, Improve, and Control) framework. In the Six Sigma approach, process capability is generally measured using Defects per Million Opportunities (DPMO) and Sigma Level indicators to evaluate quality consistency and process performance. In a reverse engineering environment, quality management has a higher level of complexity than conventional manufacturing due to limited initial design data, high product variation, and the characteristics of make-to-order production. Therefore, the implementation of defect prevention strategies and systematic quality control is essential to improve process reliability and product quality. Based on the theoretical studies and empirical phenomena outlined in the research background, this study formulates the following propositions as a conceptual basis for analyzing product quality and defect issues:

1. Proposition 1: Inconsistencies in the reverse engineering component production process at PT PLN Pusharlis reflect disruptions to the stability and capability of the production process.
2. Proposition 2: Recurrent and variable product defects reflect a condition in the production process that is not fully controlled
3. Proposition 3: Product defects in the reverse engineering process are manifestations of nonconformities stemming from the interaction of human factors, work methods, materials, machines, and operational environment
4. Proposition 4: Quality nonconformities and variations in product defects indicate the need for a systematic analysis of process characteristics and defect-causing factors to understand critical process areas.
5. Proposition 5: Recommendations for quality improvement and quality control are formulated based on the actual process conditions and the root causes of defects identified from the analysis

METHOD

Research Design

This study involved nine informants purposively selected based on their direct involvement in the reverse engineering process, quality control, NCR defect handling, and after-sales defect management at PT PLN PUSHARLIS.

For the NCR defect analysis, the study involved four informants:

Table 1. Informants for NCR defect analysis

Code of Informants	Position	Working Unit	Working Years
AA	Manager Assistant of Production	UP2W I	13 years
BB	Team Leader of Quality Control	UP2W VI	8 years
CC	QA Staff	Office Center	18 years
DD	Logistics Team Leader	UP2W III	22 years

or after-sales defect analysis, the research involved 5 informants consisting of:

Table 2. Informants for after-sales defect analysis

Code of Informants	Position	Working Unit	Working Years
EE	Manager Assistant of Production	UP2W III	13 years
FF	QA Staff	UP2W III	4 years
GG	QA Staff	Office Center	18 years
HH	Mechanical Team Leader	UP2W III	12 years
II	Drafter	UP2W III	4 years

The informant selection criteria included: direct involvement in the reverse engineering process of power plant components, experience in handling NCR defects and after-sales defects, understanding of quality control and production processes, technical experience or authority in QA, QC, Engineering, Production, Procurement, or other related functions, involvement in quality evaluation, defect investigation, or decision-making regarding corrective actions.

Informants were selected to obtain in-depth information regarding the root causes of defects and the effectiveness of the quality control system at PT PLN PUSHARLIS. Data validity was maintained using triangulation techniques. Triangulation was performed by comparing information obtained from various informants from different functions: Production, Quality Control, Quality Assurance, Procurement, Mechanical Team Leaders, and Drafters.

This study uses a mixed methods approach by combining quantitative and qualitative data within the Six Sigma DMAIC framework. Quantitative data in the form of NCR, after-sales defects, CTQ, DPMO, and Sigma Level are used to measure defect levels and process capabilities. Furthermore, qualitative data is obtained through semi-structured interviews with informants directly involved in the reverse engineering process to explain and validate the quantitative findings. The integration of both types of data is carried out at the analysis stage through triangulation of interview results with NCR, after-sales defects, CTQ, Pareto, and Fishbone 6M data to identify the root causes of defects and formulate quality improvement proposals.

In addition, interview results were validated through cross-checking with:

1. Non-Conformance Report (NCR) data for the 2021–2024 period.
2. After-sales defect data for the 2021–2024 period.
3. CTQ analysis results.
4. Pareto analysis results.
5. Fishbone 6M analysis results.

This approach was taken to ensure that interview results were not solely based on individual perceptions, but were also supported by empirical evidence and actual company data.

The reliability of qualitative analysis was maintained through a systematic analysis process. The coding process involved several stages:

1. Data reduction from interviews.
2. Identification of key themes and findings.
3. Clustering interview results based on the Fishbone 6M categories (Man, Machine, Method, Material, Measurement, and Environment).
4. Checking the consistency of the interpretation results with documented defect data.
5. Integrating interview results with Pareto and Fishbone analysis results.

RESULT AND DISCUSSION

The research results are structured based on the DMAIC stages outlined in Chapter III. The Define stage is used to establish the main problem and scope of the analyzed process. The Measure stage is used to measure process performance through SIPOC mapping, identifying Critical to Quality (CTQ) criteria, calculating the number of defects, Defects per Million Opportunities (DPMO), and sigma levels. Next, the Analyze stage is used to uncover the root causes of product defects based on data analysis and interview results. The Improve and Control stages are used to formulate improvement recommendations and quality control strategies to ensure the proposed improvements can be maintained sustainably.

Define Step

Figure 1 shows the process mapping using the SIPOC (Supplier, Input, Process, Output, Customer) approach in the reverse engineering component production process at PT PLN PUSHARLIS. This SIPOC mapping is used to describe the overall process flow, identify the parties involved, and understand the relationship between inputs, process stages, and outputs produced in the production system.

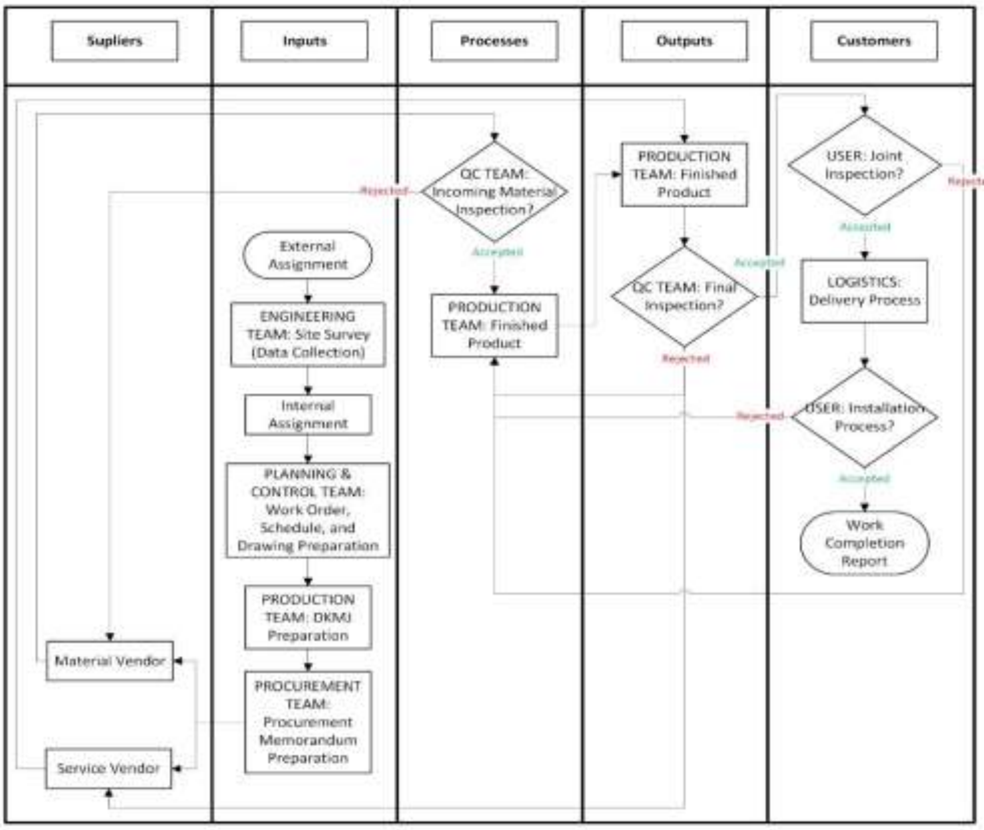


Figure 1. SIPOC of PLN Pusharlis

Measure Step

Critical to Quality (CTQ) determination at the Measure stage is based on the classification of defect types recorded in the Non-Conformance Report (NCR) for the 2021–2024 period. The approach used is a Pareto analysis with the 80/20 principle, which identifies the types of defects that cumulatively contribute most to the total quality nonconformities.

Table 3 Determination of Critical to Quality (CTQ) of NCR Based on Defect Type in 2021–2024

No	Type of Defect	Number of Defect	Percentage (%)	Cumulative (%)	Description
1	Casting Defect	84	30,66	30,66	Primary CTQ
2	Welding Defect	77	28,10	58,76	Primary CTQ
3	Dimension/Machining Defect	44	16,06	74,82	Primary CTQ
4	Process/Method Defect	27	9,85	84,67	Primary CTQ
5	Drawing/Design Defect	24	8,76	93,43	Secondary CTQ
6	Wiring/Electrical Defect	9	3,28	96,71	Non-CTQ
7	Material Defect	5	1,82	98,53	Non-CTQ
8	Testing Defect (IP34)	4	1,47	100,00	Non-CTQ
	Total	274	100,00		

source: PT PLN (Persero) Pusharlis, 2021, 2022, 2023, 2024 processed by the authors

NCR DPMO Calculation

The opportunity data used in this study was obtained from the recapitulation of quality inspections conducted by the Quality Control (QC) team and managed by the Quality Assurance (QA) team through the PT PLN PUSHARLIS Assignment Management Application (AMP). This data represents the accumulation of all defect opportunities originating from the quality characteristics examined in each reverse engineering project. Opportunity data recapitulation is conducted periodically based on daily inspection data recorded in the AMP system and subsequently used as part of the unit's year-end performance report. Therefore, the opportunity data used in this study represents the actual condition of the quality control process implemented by the company during the study period.

By using opportunity data sourced from the company's system, the DPMO calculation in this study is based on actual operational data used by the QA function in monitoring and evaluating quality performance, so that the results of the process capability measurement can reflect the true condition.

The DPMO calculation was performed using the number of defects and total opportunities obtained from the PT PLN PUSHARLIS AMP system using the following formula:

DPMO Formula

$$DPMO = \frac{Number\ of\ Defects}{Total\ Opportunity} \times 1{,}000{,}000$$

Research Data substitution:

Number of Defects (NCR) in 2021 = 176, Opportunities for defects per unit= 196.894.

$$\text{DPMO} = \frac{176}{196.894} \times 1.000.000$$

$$\text{DPMO} = 894$$

The calculation results show that the DPMO value in 2021 was 894. This value indicates that out of one million defect opportunities, an estimated 894 defects occurred during the reverse engineering process. The same calculation was then performed for the entire research period to obtain the DPMO value and annual sigma level, as presented in Table 4:

Table 4 Recapitulation of NCR DPMO 2021–2024

Year	Opportunity	Defect	DPMO
2021	196.894	176	894
2022	149.784	49	327
2023	368.560	27	73
2024	1.164.230	22	19

Source: PT PLN PUSHARLIS AMP data 2021-2024, processed by researchers.

NCR Sigma Level Calculation

The obtained DPMO value is then converted to a sigma level to statistically describe process capability. The higher the sigma level, the lower the likelihood of defects occurring in the reverse engineering process.

Table 5 NCR Process Performance Based on DPMO and Sigma Level

Indicator	2021	2022	2023	2024
DPMO	894	327	73	19
Sigma Level	4,623	4,909	5,297	5,621

Source: processed data

Based on Table 5, the NCR DPMO value shows a downward trend throughout the study period. In 2021, the DPMO value was recorded at 894, decreasing to 327 in 2022, then decreasing again to 73 in 2023 and 19 in 2024. This decline in the DPMO value indicates that the number of defects relative to the total defect opportunities is decreasing year by year.

In line with the decline in the DPMO value, the sigma level increased from 4,623 in 2021 to 4,909 in 2022, then to 5,297 in 2023 and reaching 5,621 in 2024. The increase in the sigma level indicates that the reverse engineering process capability is improving and further indicates improvements in process capability and product quality consistency.

Overall, the downward trend in the DPMO and the increase in the sigma level indicate an improvement in process quality throughout the study period. However, defects are still found in several main CTQ categories so that continuous improvement and quality control efforts are needed which will be further analyzed at the Analyze, Improve, and Control stages.

Table 6 Critical to Quality (CTQ) of Defect After-Sales 2021–2024 Period

No	Type of Defect	Number of Defect Case	Percentage (%)	Cumulative (%)	Description
1	Drawing/Design Defect	23	40,35	40,35	CTQ
2	Welding Defect	10	17,54	57,89	CTQ
3	Machining Defect	9	15,79	73,68	CTQ
4	Material Defect	6	10,53	84,21	CTQ
5	Casting Defect	4	7,02	91,23	Non-CTQ
6	Operation Defect	4	7,02	98,25	Non-CTQ
7	Press/Forming Defect	1	1,75	100,00	Non-CTQ
	Total	**57**	**100,00**		

Source: PT PLN (Persero) Pusharlis, 2021, 2022, 2023, 2024 processed by the authors.

After-sales DPMO Calculation

The opportunity data used in the after-sales defect calculation refers to the same opportunity data as the NCR defect calculation: opportunity data obtained from the recapitulation of quality inspections conducted by the Quality Control (QC) team and managed by the Quality Assurance (QA) team through the PT PLN PUSHARLIS Assignment Management Application (AMP). The use of the same opportunity data is because NCR defects and after-sales defects originate from the same population of reverse engineering jobs during the research period, but are differentiated by location and time of occurrence.

The difference lies in the number of defects used in the calculation. In NCR defects, defects are nonconformities discovered during the production process and internal company inspections. In after-sales defects, defects are nonconformities discovered after the product is used or operated by the customer. Therefore, the after-sales defect DPMO calculation is used to describe the external quality of the reverse engineered product received by the customer.

The DPMO calculation is performed using the number of after-sales defects and the total opportunity value obtained from the PT PLN PUSHARLIS AMP system using the following formula:

DPMO Formula

$$DPMO = \frac{Number\ of\ Defects}{Total\ Opportunity} \times 1{,}000{,}000$$

Research Data substitution:

- Number of after-sales defects in 2022 = 22, Opportunities for defects per unit= 149.784

$$\text{DPMO} = \frac{22}{149.784} \times 1.000.000$$
$$\text{DPMO} = 147$$

The calculation results show that the DPMO value for after-sales defects in 2022 is 147. This value indicates that out of one million defect opportunities, an estimated 22 defects are discovered after the product is used by customers. The same calculation is then performed for the entire study period to obtain the DPMO value and annual sigma level, presented in Table 7.

Table 7 Recapitulation of DPMO After Sales 2021–2024

Year	Opportunity	Defect	DPMO
2021	196.894	-	-
2022	149.784	22	147
2023	368.560	17	46
2024	1.164.230	18	15

Source: PT PLN PUSHARLIS AMP data 2021-2024, processed by researchers.

After-Sales Sigma Level Calculation

The obtained DPMO value is then converted into a sigma level to statistically describe process capability. The higher the sigma level, the lower the likelihood of defects occurring in the reverse engineering process.

Table 8 Aftersales Process Performance Based on DPMO and Sigma Level

Indicator	2021	2022	2023	2024
DPMO	-	147	46	15
Sigma Level	-	5,121	5,410	5,667

Source:processed by researchers

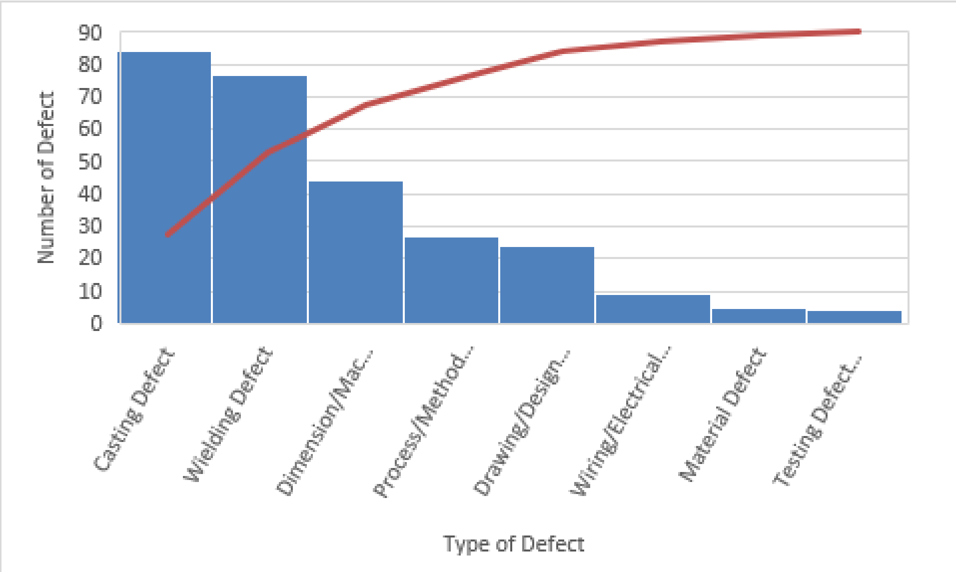
Table 8 shows that after-sales defect data was not yet available in 2021 due to the company's lack of systematically documented after-sales data recapitulation. Therefore, after-sales defect DPMO and sigma level measurements were conducted from 2022 to 2024.

Overall, the downward trend in DPMO and increasing sigma levels indicates an improvement in product quality and reliability during the study period. However, after-sales defects were still found in several key CTQ categories, necessitating continuous improvement and quality control efforts. Unlike NCR defects, which can still be identified and controlled within the company's internal processes, after-sales defects occur after a product has passed inspection and testing and is in use in a customer's generating unit.

Analysis Step

The Pareto diagram in Figure 2 shows that casting defects are the most dominant type of defect with a total of 84 NCRs (30.66%) of the total 274 NCRs during the 2021–2024 period. The high contribution of casting defects indicates that the material casting stage is a critical point in the reverse engineering component production process at PT PLN PUSHARLIS.

Figure 2 Pareto Diagram of NCR Defect Types 2021-2024



Source: Processed Data

The Pareto diagram in Figure 2 shows that casting defects were the most dominant defect type, accounting for 84 NCRs (30.66%) of the total 274 NCRs during the 2021–2024 period. The high contribution of casting defects indicates that the material casting stage is a critical point in the reverse engineering component production process at PT PLN PUSHARLIS.

The determination of the Method factor as the dominant cause of defects is not only based on the results of the 6M Fishbone analysis. Validation is carried out through a triangulation process by comparing the results of interviews with informants directly involved in the reverse engineering process with Non-Conformance Report (NCR) data, after-sales defect data, and the results of the Pareto analysis. In addition, the findings obtained from the interviews were verified using actual company data to ensure consistency and suitability between the results of the qualitative and quantitative analysis. The triangulation results show that problems related to work methods, reverse engineering procedures, and vendor controls consistently emerge as the main causes of defects.

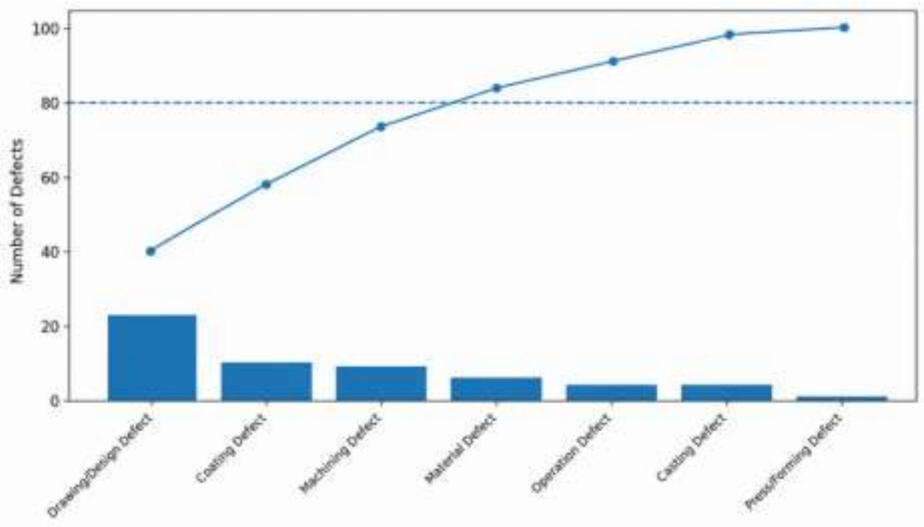
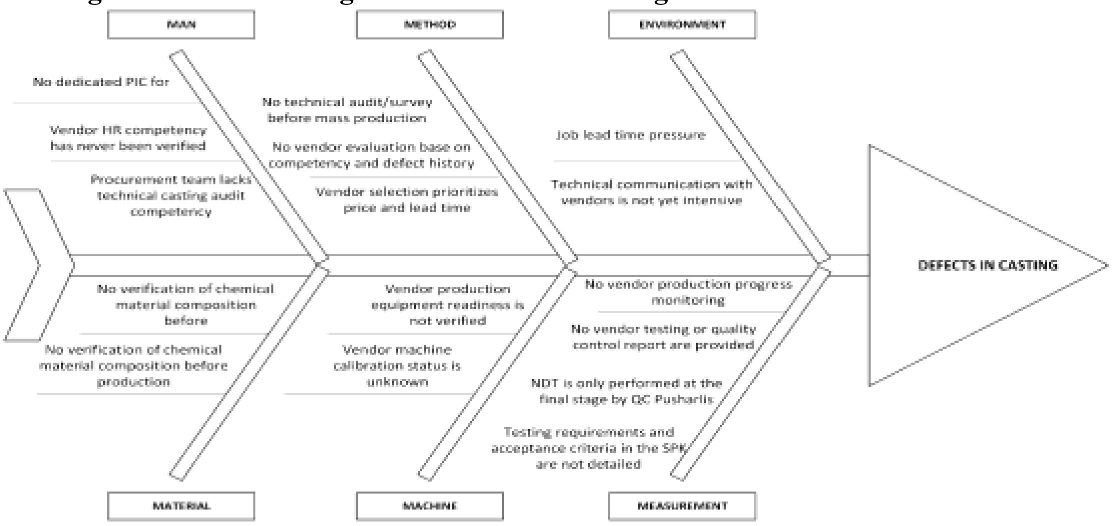


Figure 3 Pareto Diagram of After-sales Defect Types 2021-2024
Source: Processed Data

Based on the results of the Pareto analysis at the Analyze stage, design/drawing defects are the most dominant type of after-sales defects with 23 cases (40.35%) of the total 57 defects. The high contribution of design/drawing defects indicates that the design mismatch with the actual condition of the equipment at the customer site is still a critical problem in reverse engineering activities at PT PLN PUSHARLIS. Therefore, in the next analysis stage, this study focuses on the discussion of design/drawing defects as the main defect to conduct a more in-depth root cause analysis, in order to identify systemic factors that influence the occurrence of these after-sales defects.

Figure 4 Fishbone Diagram of Causes of Casting from NCR Defects Based on the 6M



Approach(Source: Processed Data)

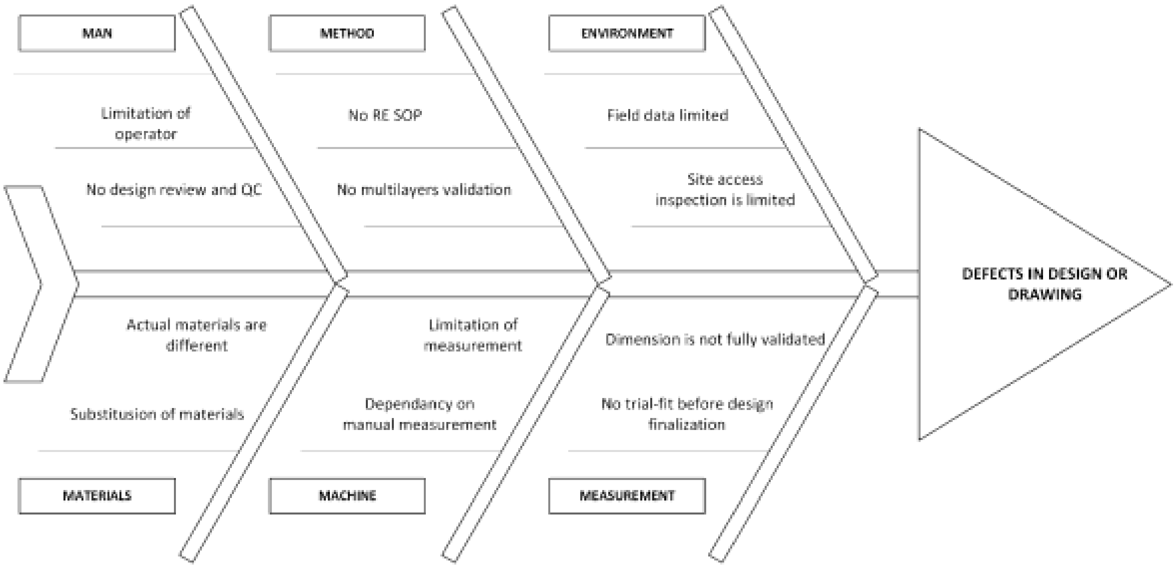


Figure 5 Fishbone Diagram of Causes of Drawing/Design Defects from After-sales Defects Based on the 6M Approach (Source: Processed Data)

Improvement Step

Improvement proposals are based on the dominant root causes identified in the Analysis phase, particularly those related to the Method factor. Proposed improvements include the development of SOPs for Casting Vendor Selection and Evaluation and Reverse Engineering to improve process standardization, consistency of work execution, and effectiveness of quality control. These improvements are based on the Poka-Yoke principle to prevent errors from the vendor selection stage, through field data collection, design validation, and the design approval process prior to production. Implementation of these SOPs is expected to improve vendor quality, strengthen the design validation process, ensure more accurate data verification, and reduce the potential for defects related to the casting and reverse engineering processes.

To ensure the sustainability of the proposed improvements, a control mechanism has been developed, including a vendor monitoring checklist, a reverse engineering design validation checklist, and a reverse engineering design database for ongoing quality monitoring and evaluation. Proposed indicators for monitoring include the number of vendor-related NCRs, the number of after-sales defects caused by design errors, the level of compliance with established SOPs, and the number of recurrent defects. These indicators are evaluated periodically to ensure the effectiveness of the improvement implementation and support continuous quality improvement.

Based on the analysis results, casting defects were identified as the most dominant type of NCR defect, accounting for 30.66% of the total defects. The Fishbone analysis and interview validation indicated that the dominant causes were related to the Method factor, particularly the absence of a structured vendor selection system, technical audits, trial casting procedures, and vendor performance evaluation. Therefore, a Casting Vendor Selection and Evaluation SOP was developed as a preventive quality control mechanism to ensure that selected vendors meet the required technical and quality standards before production begins. The proposed SOP covers the stages of casting requirement identification, initial vendor screening, technical audit, trial casting, and vendor approval. The stages of the proposed Casting Vendor Selection and Evaluation SOP are shown in Figure 6.

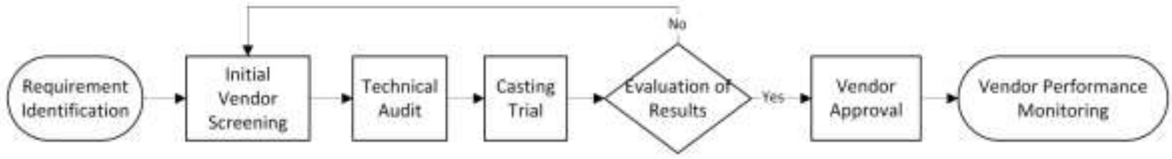
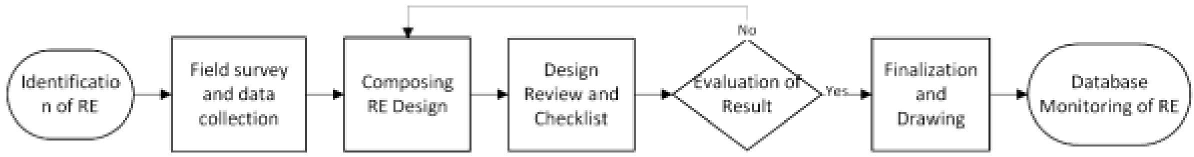


Figure 6. SOP for Casting Vendor Selection and Evaluation

Conceptually, this improvement applies the Poka-Yoke principle by preventing defects at the source through systematic vendor qualification and evaluation. Technical audits, trial casting activities, and vendor performance assessments are intended to identify potential quality issues before the production process begins. Through this approach, the risk of casting-related defects can be reduced, and the consistency of component quality can be improved.

Based on the analysis results in the Analyze stage, after-sales defects related to design or drawing errors indicate that problems occur not only in the production process but also in the design process, which lacks a structured control and documentation system. Therefore, a Reverse Engineering SOP was developed to improve process standardization, strengthen design validation, and ensure the completeness and accuracy of engineering data before production begins. This improvement applies the quality at source principle by implementing quality control from the early stages of the design process, thereby reducing the risk of design errors and after-sales defects. The stages of the proposed Reverse Engineering SOP are shown in Figure 7.

Figure 7 SOP for Reverse Engineering



The proposed Reverse Engineering SOP consists of several stages, including identification of reverse engineering requirements, field survey and data collection, reverse engineering design development, design review and validation, evaluation of results, and drawing finalization and release. This SOP is intended to ensure that all engineering data are properly verified, validated, and documented before production begins. Through a structured design process, the risk of design and drawing errors can be reduced, thereby improving product quality and minimizing after-sales defects.

Control Step

Based on the improvements made in the Improve phase, a control mechanism is needed to ensure that the casting vendor's quality is maintained and that the proposed improvements can be implemented sustainably. Therefore, in the Control phase, a data-based casting vendor performance monitoring system was designed to periodically control and evaluate vendor performance.

This Control phase focuses on monitoring vendor performance based on historical production data, specifically regarding production volume, number of defects, and type of defects. Furthermore, parameters from technical audits, trial casting results, and vendor evaluations are used as a basis for assessing the vendor's capability and performance consistency.

As an implementation of this control system, a casting vendor performance monitoring spreadsheet was developed to serve as a medium for recording and evaluating vendor performance, integrated with NCR (Non-Conformance Report) data. With this system, the quality control process is not only reactive but also preventive and data-driven. Vendor performance monitoring is conducted using key parameters, including production volume (casting quantity), number of defects, and defect rate (%) as the primary indicators for assessing the quality of vendor products. The defect rate is calculated as the ratio of the number of defects to total production, and therefore can be used as a quantitative measure for evaluating vendor performance.

In addition, dominant defects in each vendor are identified, such as cracks and dimensional mismatches, to identify problem patterns occurring in the vendor's production process. This information serves as the basis for further evaluation and corrective action for vendors with poor performance.

Other parameters used in monitoring include technical audit results, trial casting results, and the results of vendor evaluations conducted in the previous stage. This demonstrates that the monitoring system not only considers the final defect outcome but also considers the vendor's overall technical capabilities.

Based on the defect rate, vendor performance is classified into good, needs evaluation, and not recommended. Vendors with good performance continue to receive regular monitoring to maintain quality consistency, while vendors with the need for evaluation category undergo further analysis to determine the causes of defects. Vendors categorized as "not recommended" are not reused until a re-evaluation or improvement of their capabilities is conducted.

Furthermore, vendors are ranked based on their defect rate, with the vendor with the lowest defect rate having the highest ranking. This ranking is used as the basis for more objective and data-driven vendor selection decisions for subsequent projects.

With this spreadsheet-based vendor performance monitoring system, the vendor quality control process can be carried out in a more systematic, measurable, and sustainable manner. This system enables companies to conduct periodic vendor evaluations and detect potential quality declines early.

Conceptually, the implementation of this monitoring system is an implementation of the Control phase of the DMAIC method, which aims to maintain the sustainability of improvements made in the previous phase. Thus, this system functions not only as an evaluation tool but also as a continuous control mechanism that can improve the quality of the casting component procurement process and minimize the occurrence of NCR defects in the future.

Based on the analysis results from the Analyze phase, after-sales defects related to design or drawing errors indicate that problems occur not only in the production process but also in the design process, which lacks a structured control and documentation system. Therefore, the Control phase requires a mechanism to ensure that every reverse engineering design created can be monitored, evaluated, and traced back if problems arise in the field.

As part of this control effort, a reverse engineering design database monitoring spreadsheet was designed to serve as a medium for recording and controlling all design activities, from the survey phase, design process, validation, to implementation and after-sales evaluation. This system aims to ensure that each design has a clear documentation trail, including revision history, validation status, and its relationship to defects.

The research results indicate that the method factor is the dominant cause of defects in the reverse engineering process at PT PLN PUSHARLIS. This finding aligns with research by Anggamawarti (2022) and Adeodu (2021), which demonstrated that non-conforming work procedures and weak process control are the primary causes of defects in manufacturing environments. From a Six Sigma perspective, this situation indicates high process variation, potentially increasing the likelihood of product nonconformities (Adeodu et al., 2021; Anggamawarti et al., 2022). Therefore, process standardization through the development of standard operating procedures (SOPs) and the application of the Poka-Yoke principle is crucial to reduce process variation and improve product quality consistency.

Furthermore, the results of DPMO and Sigma Level measurements indicate that process capability is still suboptimal. This finding supports the concept of process capability in Six Sigma, which states that a high DPMO value and a low sigma level indicate a process that is unable to consistently meet quality requirements. These research results also align with Mittal et al. (2023), who demonstrated that DPMO and Sigma Level measurements can be used as quality performance indicators to systematically identify opportunities for process improvement.

These findings indicate that in a reverse engineering environment, product quality is influenced not only by technical production capabilities but also by the effectiveness of work procedures, quality control systems, and process validation mechanisms. Therefore, quality improvement needs to focus on strengthening the quality management system and standardizing processes across the board, not just the technical aspects of production.

CONCLUSION

Based on the results of research conducted using the Six Sigma method with the DMAIC (Define Measure, Analyze, Improve, and Control) approach on the reverse engineering process of components at PT PLN Pusharlis, the following conclusions can be drawn: The defect rate of reverse engineered component products at PT PLN Pusharlis during the 2021–2024 period consisted of 274 internal defects (Non-Conformance Reports/NCRs) and 57 after-sales defects. Measurement results indicate that the dominant type of defect in NCRs was casting defects, contributing 30.66%, while after-sales defects were dominated by design/drawing defects, contributing 40.35%. These findings indicate that there are still quality discrepancies that require attention in the reverse engineering process. The primary factor causing defects in the reverse engineering process at PT PLN Pusharlis is the method. For NCR defects, the dominant problem relates to the casting vendor selection and control system, such as the lack of vendor technical audits, trial castings, and systematic monitoring of the vendor's production process. Meanwhile, for after-sales defects, the dominant factor relates to the reverse engineering process, specifically design validation, field data collection, and design document control. The application of the Six Sigma DMAIC method has been proven to be systematically used to analyze and formulate solutions to defect problems in the reverse engineering process at PT PLN PUSHARLIS. Through the Define, Measure, Analyze, Improve, and Control stages, this study was able to identify priority defect types, measure process capabilities, determine root causes, and develop improvement proposals focused on the identified dominant causes. The evaluation results of Defects per Million Opportunities (DPMO) and sigma levels indicate an improvement in process quality during the study period. For NCR defects, the DPMO value decreased from 894 in 2021 to 19 in 2024, while the sigma level increased from 4.623 to 5.621. For after-sales defects, the DPMO value decreased from 147 in 2022 to 15 in 2024, with the sigma level increasing from 5.121 to 5.667. These results indicate that process capability and product quality have improved year-over-year. However, continuous improvement and quality control efforts are still needed to reduce the likelihood of defects, increase product reliability, and support the achievement of zero defects in the reverse engineering process of power plant components.

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