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Defect Analysis of R8 Cover Products Using the Six Sigma Method at PT Amtek Engineering

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Abstract. Quality consistency is a critical requirement in automotive component manufacturing, particularly in precision stamping processes where visual conformity, product identification, and physical integrity directly influence customer acceptance. This study investigates quality defects in R8 Cover production at PT Amtek Engineering using the Six Sigma DMAIC (Define–Measure–Analyze–Improve–Control) framework. A descriptive quantitative and observational approach was employed using production and reject records collected from 5–17 May 2024. The Define phase utilized SIPOC and Critical-to-Quality (CTQ) mapping to identify key quality characteristics. Process capability was evaluated through Defect per Unit (DPU), Defect per Opportunity (DPO), Defect per Million Opportunities (DPMO), process yield, and sigma level measurements. Pareto analysis and fishbone diagrams were applied to determine dominant defect categories and their potential root causes. The results indicate that 82,843 units were produced with 4,533 rejected units, resulting in a DPU of 0.0547, a DPO of 0.0109, a DPMO of approximately 10,900, a process yield of 98.91%, and a sigma level of 3.8. Missing and damaged identification was identified as the most significant defect, contributing 33% of total defects, followed by missing lettering at 23%. Root-cause analysis revealed that defect occurrence was associated with operator practices, machine and tooling conditions, inspection procedures, material conformity, and workplace environment. The study proposes improvement actions focused on setup verification, preventive maintenance, tooling management, inspection standardization, operator competency development, and incoming material control. These findings provide an empirical basis for enhancing process capability and strengthening quality assurance in precision stamping operations.

Keywords: Defect Analysis; DMAIC; Pareto Analysis; Quality Control; Six Sigma.

1. INTRODUCTION

Product quality is a strategic requirement in precision automotive manufacturing because customers evaluate components through dimensional accuracy, surface conformity, identification clarity, and low rejection rates (Conde et al., 2023; Mittal et al., 2023). Metal stamping requires stable coil feeding, accurate tooling setup, reliable press-machine performance, and disciplined operator inspection. Prior studies in railcar assembly, microlens production, and wind-blade manufacturing show that DMAIC helps convert process variation into measurable defect-reduction targets when each improvement stage uses operational evidence (Wang et al., 2025).

Lean Six Sigma applications in can manufacturing, automotive production, and Indonesian automotive SMEs further show that defect reduction becomes stronger when This insight matters for R8 Cover production because the process must meet visual quality requirements while maintaining stable capability under repeated production cycles (Widiwati et al., 2025). Defect-sensitive production often faces rejection caused by surface damage, painting failure, process instability, tooling wear, and inconsistent inspection response. Cases in filter manufacturing and hood outer panel production demonstrate that DMAIC can separate dominant defects from secondary problems and translate the results into operational controls

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(Guleria et al., 2021; Pranavi & Umasankar, 2021).

Indonesian manufacturing studies emphasize that DMAIC becomes more useful when it combines statistical tools with labor-performance analysis, FMEA thinking, and routine inspection discipline. These findings justify the evaluation of human, machine, method, material, and environmental sources of variation in R8 Cover production (Montororing et al., 2022; Nurprihatin et al., 2023). Recent Six Sigma applications in cylinder block production, MBNQA-based quality improvement, and automotive painting defects indicate that defect reduction depends on clear baseline measurement, strong prioritization, and practical control mechanisms. These studies support the use of DPMO, sigma level, Pareto analysis, and standardized follow-up actions in the present research (Rinawati & Sriyanto, 2024; Saputra, 2025; Setiawan et al., 2025). Other current studies combine Six Sigma with seven quality tools, FMEA, and product-quality control in manufacturing contexts. Their findings support the integration of visual defect classification, cause-and-effect analysis, and improvement planning for products that must satisfy strict customer inspection requirements (Merjani et al., 2024; Rochmatullah & Rusindiyanto, 2025).

Defect analysis in packaging bottles, patient beds, and ceramic products confirms that Six Sigma applies across sectors when the problem involves recurring reject patterns and measurable defect opportunities. These studies are useful as methodological references, but they do not explain R8 Cover defects in a precision stamping process for an automotive power steering component (Muttaqin & Aryanny, 2024; Okstevia & Sumiati, 2024; Ridwan et al., 2024).

Research on railway manufacturing and Six Sigma project selection highlights the need to prioritize the most influential defect mode before corrective action begins. This study follows that logic by identifying the largest defect contributors before developing 5W+1H improvement actions (Sumasto et al., 2022; Syamil et al., 2023).

PT Amtek Engineering operates in metal stamping, tooling, and precision part manufacturing. One of its products is the R8 Cover, which forms part of an automotive power steering system. The production process still records several defect categories, including Color NG, white dots, slug mark, missing and damaged identification, missing lettering, and crack or damage. These defects reduce production efficiency, increase internal rework pressure, and create a risk of customer rejection when visual identification and surface conformity do not meet inspection standards (Conde et al., 2023; Syamil et al., 2023).

This study addresses the identified gap by applying an integrated DMAIC framework to the R8 Cover stamping process at PT Amtek Engineering. By combining SIPOC analysis, Critical-to-Quality (CTQ) mapping, process capability measurement, Pareto prioritization, fishbone analysis, and 5W+1H improvement planning, the study provides a comprehensive evaluation of quality performance using actual production data. Particular attention is given to identification-related defects, which are examined as a consequence of interactions among operator practices, tooling conditions, inspection procedures, material conformity, and workplace environment. The analysis aims to quantify process capability, determine dominant defect categories, identify potential root causes, and develop improvement strategies to support defect reduction and continuous quality improvement.

This study contributes by demonstrating that identification-related defects can become a major source of quality loss in precision stamping processes. Through the integration of capability measurement, root-cause analysis, and control planning, the findings provide a practical basis for improving traceability, reducing defects, and strengthening process capability in automotive component manufacturing.

2. LITERATURE REVIEW

Six Sigma and DMAIC Methodology

Six Sigma is a data-driven quality improvement methodology that aims to reduce process variation and minimize defects in products and services. The methodology focuses on improving process capability through systematic measurement, analysis, and continuous improvement. One of the most widely used Six Sigma frameworks is DMAIC, which consists of five phases: Define, Measure, Analyze, Improve, and Control. This framework provides a structured approach for identifying quality problems, measuring process performance, analyzing root causes, implementing corrective actions, and sustaining improvement results. Recent studies have shown that DMAIC effectively improves manufacturing quality performance by reducing defects and increasing process stability (Conde et al., 2023; Mittal et al., 2023).

Process Capability Measurement

Process capability refers to the ability of a manufacturing process to consistently produce products that meet predetermined quality specifications. In Six Sigma applications, process capability is commonly evaluated using Defect per Unit (DPU), Defect per Opportunity (DPO), Defect per Million Opportunities (DPMO), and sigma level indicators. DPMO measures the number of defects that occur per one million opportunities, while the sigma level indicates the overall performance and consistency of the production process. Higher sigma levels represent lower process variation and improved quality performance. Therefore, these indicators are widely used to assess manufacturing effectiveness and identify opportunities for continuous improvement (Daniyan2022; Wang et al., 2025).

Pareto Analysis and Fishbone Diagram

Pareto Analysis and Fishbone Diagram are important quality management tools frequently applied within the Six Sigma framework. Pareto Analysis is based on the 80/20 principle, which suggests that a small number of causes often contribute to the majority of quality problems. This tool helps organizations prioritize improvement efforts by identifying the most significant defect categories. Meanwhile, the Fishbone Diagram, also known as the cause-and-effect diagram, is used to systematically identify potential root causes of defects from factors related to human resources, machines, methods, materials, and the work environment. The integration of Pareto Analysis and Fishbone Diagram enables more effective root-cause identification and supports data-driven decision-making for quality improvement initiatives (Enache et al., 2023; Guleria et al., 2021).

2. RESEARCH METHOD

This study adopted a quantitative observational design to evaluate the quality performance of the R8 Cover stamping process at PT Amtek Engineering. The investigation focused on defect occurrence in a precision metal stamping component used in automotive power steering systems. Production and reject data were collected from 5 to 17 May 2024 through daily production reports, reject records, visual inspection documents, and direct shop-floor observations. These data sources provided the basis for assessing process capability and identifying dominant sources of quality variation.

The analytical procedure followed the DMAIC (Define Measure Analyze Improve Control) framework, which provides a structured approach for process evaluation and continuous quality improvement. Previous studies have demonstrated the effectiveness of DMAIC in reducing process variation, identifying dominant sources of defects, and supporting data-driven decision-making in manufacturing environments (Daniyan et al., 2022; Enache et al., 2023; Mittal et al., 2023).

During the Define phase, the production process was mapped using SIPOC analysis, while Critical-to-Quality (CTQ) characteristics were established to represent key customer-oriented quality requirements. The Measure phase evaluated current process performance through Defect per Unit (DPU), Defect per Opportunity (DPO), Defect per Million

Opportunities (DPMO), process yield, and sigma level calculations. The performance indicators were calculated using the following equations:

DPU = total defects / total units produced .... (i)

DPO = total defects / (total units produced × CTQ opportunities) .... (ii)

DPMO = DPO × 1,000,000 .... (iii)

Process yield **(%)** = (1 − DPO) × 100 .... (iv)

Five CTQ opportunity groups were incorporated into the DPMO calculation in accordance with the company's inspection criteria. Subsequently, Pareto analysis was employed to determine the most influential defect categories and establish improvement priorities.

The Analyze phase utilized fishbone analysis to investigate potential root causes associated with human, machine, method, material, and environmental factors. Based on these findings, improvement initiatives were formulated using the 5W+1H approach to define corrective actions, implementation procedures, responsible personnel, and expected outcomes. The proposed actions focused on operator competency, process discipline, preventive maintenance, tooling management, inspection standardization, and incoming material control.

Finally, the Control phase emphasized the development of sustainable monitoring mechanisms through documentation, standardized inspection procedures, maintenance scheduling, and periodic performance evaluation. These measures were intended to support process stability and reduce the likelihood of recurring defects.

3. RESULT AND DISCUSSION

The results and discussion are presented based on the DMAIC framework to show the relationship between process definition, defect measurement, root-cause analysis, improvement planning, and control recommendations.

Define Phase

The Define phase established the boundaries of the quality problem by mapping the R8 Cover production flow and translating customer requirements into Critical to Quality characteristics. The SIPOC analysis showed that the process begins with incoming coil material, followed by feeder preparation, progressive-press tooling setup, stamping, inspection, product arrangement in ESD trays, and delivery to the customer. This sequence indicates that final product conformity is generated through several interdependent control points rather than by the stamping operation alone. Consequently, nonconformity may originate from incoming material, setup conditions, tooling performance, process execution, inspection practices, or post-stamping handling.

The CTQ assessment identified quality requirements related to surface appearance, identification clarity, lettering conformity, and physical integrity. The relationship between these CTQ aspects, the observed defects, and their implications for product quality is summarized in Table 1.

Table 1. CTQ and observed defect categories.

CTQ aspect	Defect category	Quality implication
Surface appearance	Color NG, white dots, slug mark	Reduces visual conformity and product appearance quality
Product identification	Missing and damaged identification	Causes unclear numbering and weakens traceability
Lettering conformity	Missing lettering	Indicates incomplete stamping or poor marking clarity
Physical integrity	Crack and damage	Indicates structural damage and direct rejection risk

The CTQ results indicate that R8 Cover quality is determined not only by surface and structural conformity but also by the clarity and completeness of product identification. Five CTQ opportunity groups were used for DPMO calculation: color conformity, surface cleanliness, formed-surface conformity, identification and lettering conformity, and physical integrity. However, six operational defect categories were retained for Pareto analysis because missing and damaged identification and missing lettering represent different failure manifestations that require separate corrective actions.

Based on production records and direct visual observation, six defects were identified: Color NG, white dots, slug mark, missing and damaged identification, missing lettering, and crack or damage. Representative examples of these defects are presented in Figure 2.

Figure 2. Types of defects in R8 Cover products

As illustrated in Figure 2, Color NG, white dots, and slug marks affect visual and surface conformity, whereas missing identification and missing lettering affect traceability. Crack and damage represent physical nonconformity that may directly lead to rejection. Similar manufacturing studies have shown that SIPOC and CTQ mapping are effective in linking customer requirements with process inputs, production controls, and inspection points (Enache et al., 2023; Shamsuzzaman et al., 2023).

The present findings extend this perspective by showing that permanent identification must be treated as a critical product requirement. Identification failure may not reduce mechanical function, but it can weaken product genealogy, batch tracking, and customer verification. Therefore, quality control should be distributed across incoming inspection, tooling preparation, first-piece approval, stamping verification, and identification inspection rather than concentrated only at the end of production (Conde et al., 2023; Daniyan et al., 2022).

Measure Phase

During the observation period, 82,843 units were produced and 4,533 units were rejected. The average daily production and rejection were 6,904 and 378 units, respectively. The resulting DPU, DPO, DPMO, process yield, and sigma level are presented in Table 2.

Table 2. Process capability measurement of R8 Cover production.

Measurement indicator	Formula	Result
Average production	Production output per day	6,904 units
Average reject	Rejected products per day	378 units
DPU	378 / 6,904	0.0547
DPO	378 / (6,904 x 5)	0.0109
DPMO	0.0109 × 1,000,000	10,900
Process yield	(1 − 0.0109) × 100	98.91%
Sigma level	Six Sigma conversion	3.8

As reported in Table 2, the process generated a DPU of 0.0547, a DPO of approximately 0.0109, and a DPMO of approximately 10,900. The opportunity-based yield reached 98.91%, while the corresponding sigma level was 3.8. The DPU indicates that approximately 5.47 defects occurred for every 100 units produced. The higher opportunity-based yield should not be interpreted as evidence that the process has already achieved strong capability because each unit contains several CTQ opportunities. In high-volume production, a relatively small probability of failure can still create a substantial rejection burden.

The sigma level of 3.8 is derived from the DPMO result. A DPMO of approximately 10,900 corresponds to a short-term normal-distribution value of approximately 2.29. After applying the conventional 1.5-sigma long-term shift, the estimated process level becomes approximately 3.79 and is rounded to 3.8. This value indicates intermediate capability: the process performs better than a low-capability operation but remains below the quality level expected from a mature Six Sigma system. According to conventional Six Sigma benchmarks, world-class manufacturing performance is generally associated with a six-sigma process capability corresponding to approximately 3.4 defects per million opportunities. Previous automotive-manufacturing studies reported improvement from 3.4 to 4.0 sigma after critical process variables were controlled (Conde et al., 2023). Other evidence reported sigma levels above 5 after improvements in inspection methods, supplier control, workforce capability, and operator training (Jou et al., 2022). Compared with these findings, the R8 Cover process has a clear capability gap, although direct comparison should remain cautious because sigma performance depends on CTQ definition, inspection criteria, product complexity, and defect classification.

The current value should therefore be treated as a baseline rather than a final capability statement. Because statistical control charts were not applied, the study cannot yet confirm that the process is statistically stable. Subsequent measurement after implementation is required to determine whether the proposed improvements reduce DPMO and increase sigma performance (Daniyan et al., 2022; Mittal et al., 2023).

Pareto Analysis

The distribution of defects was analyzed to determine which categories contributed most significantly to total rejection. The number, percentage, and cumulative percentage of each defect category are presented in Table 3.

Table 3. Pareto analysis of R8 Cover defects.

Defect category	Number of defects (pcs)	Percentage (%)	Cumulative percentage (%)
Missing and damaged identification	1,502	33	33
Missing lettering	1,025	23	56
Crack and damage	610	13	69
White dots	525	12	81
Slug mark	450	10	91
Color NG	421	9	100

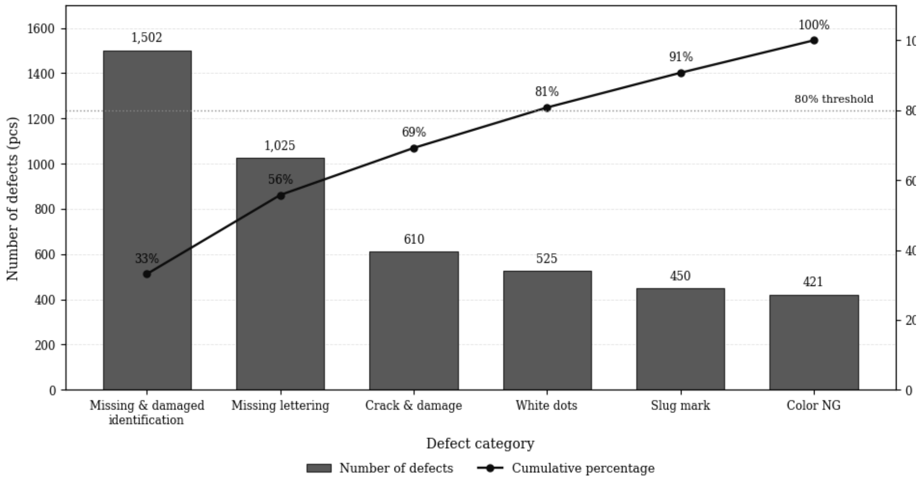

Figure 3. Pareto chart of R8 Cover defects.

Figure 3 shows that missing and damaged identification and missing lettering jointly accounted for approximately 56% of total defects. This concentration indicates that the principal quality loss is associated with the identification-forming mechanism rather than being evenly distributed across all product characteristics. The dominance of identification-related defects may be associated with tooling alignment, stamping pressure, tool contamination, wear, material positioning, and inspection consistency. Minor deviations in these conditions may still produce a dimensionally acceptable component while generating incomplete, shallow, distorted, or damaged markings.

This pattern differs from studies in which dimensional defects, cracks, machining parameters, or material deformation were the main causes of rejection (Conde et al., 2023; Singh et al., 2023). In the present case, crack and damage represented only 13%, whereas identification-related defects represented 56%. This comparison confirms that improvement priorities are highly process-specific and should be based on actual defect distribution rather than generic assumptions.

Identification defects also have broader implications for traceability. Permanent markings support the association of a component with its part number, production batch, tooling condition, and production date. Reliable identification systems have been shown to strengthen product tracking, process visibility, and containment activities in industrial operations (Gomes et al., 2023). Therefore, incomplete identification may complicate customer-complaint investigation, increase the scope of product segregation, and weaken product genealogy. The Pareto result provides a rational basis for prioritizing identification-related defects. However, Pareto analysis establishes frequency priority rather than causality. Further verification through defect stratification by machine, shift, operator, tooling age, and production batch is required before determining which process variable has the greatest causal influence.

Fishbone and Root-Cause Analysis

Following Pareto prioritization, fishbone analysis was conducted to identify the probable causes of missing and damaged identification. The potential causes were classified into human, machine, method, material, and work-environment factors, as illustrated in Figure4.

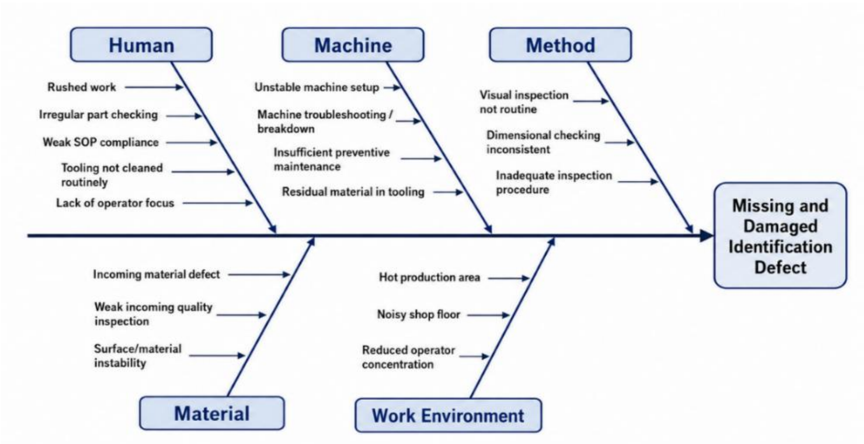

Figure 4. Fishbone diagram for missing and damaged identification defect.

The principal problems identified in each category and their improvement focus are summarized in Table 4.

Table 4. Root-cause analysis and improvement focus

Root-cause factor	Main problem identified	Improvement focus
Human	Operators work in a hurry, do not check parts regularly, and show weak SOP compliance	Strengthen supervision, operator training, and inspection discipline
Machine	Machine troubleshooting occurs and setup is not always stable	Implement preventive maintenance and setup verification
Method	Visual and dimensional inspection are not performed consistently	Standardize inspection intervals and check sheets
Material	Incoming material may already contain nonconformity	Strengthen incoming material quality control
Work environment	Hot and noisy production area reduces operator concentration	Improve workplace comfort and reduce inspection error risk

The fishbone analysis indicates that the dominant defect is likely to result from interactions among operator behavior, tooling condition, machine setup, inspection procedures, incoming material, and workplace conditions. The human category includes rushed work, irregular checking, weak SOP compliance, and reduced concentration. These conditions should not be interpreted solely as operator negligence because human error in manufacturing is influenced by task design, workload, procedures, training, supervision, and workplace conditions (Alqahtani et al., 2023; Torres et al., 2021).

Accordingly, rushed work and irregular inspection may reflect production pressure, insufficient inspection time, unclear acceptance criteria, or weak supervisory controls. Operator training is necessary, but it should be supported by standardized work instructions, reference samples, first-piece approval, defined inspection intervals, and escalation procedures when marking quality deteriorates.

Machine and tooling factors provide another plausible explanation. Tooling wear, contamination, misalignment, and unstable press settings may alter the depth and clarity of identification marks. Previous sheet-metal-forming research has shown that progressive tooling wear can reduce product quality and increase downtime, while periodic manual inspection may detect deterioration only after significant wear has occurred (Kubik & Becker et al., 2023; Kubik & Molitor et al., 2023).

These findings justify the use of preventive maintenance as a quality-control mechanism rather than merely a downtime-reduction activity. Preventive control should include tooling-cleaning frequency, tool-life monitoring, setup verification, marking-depth inspection, and maintenance records linked to defect occurrence. This approach is consistent with Total Productive Maintenance principles, which connect equipment reliability with quality, productivity, safety, and operator involvement (Wolska et al., 2023).

The method category highlights inspection reliability. Visual inspection may vary according to lighting, viewing angle, inspection duration, operator fatigue, and the clarity of defect criteria. Previous stamping studies have shown that reflective surfaces and unstable lighting can reduce the consistency of manual defect detection (Singh et al., 2023). Therefore, inspection reliability should be strengthened through controlled lighting, standardized viewing distance, defect catalogues, inspector qualification, and periodic agreement testing.

Image-based inspection may also be considered as a future control option. Recent research has demonstrated that machine-vision systems can support defect detection and tooling-wear classification in high-speed stamping and blanking processes (Kubik & Molitor, et al., 2023; Singh et al., 2023). Such systems may complement manual inspection by reducing subjectivity and detecting gradual deterioration.

Material and environmental factors further confirm that the defect system is multicausal. Incoming material variation may affect surface response during stamping, while heat and noise may reduce operator concentration and visual-inspection accuracy (Alqahtani et al., 2023).

However, the fishbone diagram remains a qualitative diagnostic tool. It identifies plausible causes but does not quantify their relative contribution. Therefore, it would be premature to state that the human factor is statistically dominant. Further validation should use defect stratification, FMEA, measurement-system analysis, maintenance-record correlation, or controlled experiments. The fishbone analysis should be interpreted as a set of testable causal hypotheses rather than as definitive proof of causality.

Improve and Control Recommendations

Based on the dominant defect and root-cause analysis, improvement actions were formulated using the 5W+1H framework. The proposed actions, responsible units, and implementation procedures are presented in Table 5.

Table 5. Proposed improvement actions based on 5W+1

Problem focus	What should be improved	Responsible unit	Recommended action
SOP compliance	Operator discipline during setup and inspection	Production supervisor	Conduct routine supervision and operator briefing
Tooling condition	Cleanliness and readiness of tooling	Production and maintenance	Inspect and clean tooling before and after production
Machine stability	Press machine reliability	Maintenance	Create preventive maintenance schedule
Inspection method	Visual and dimensional checking consistency	Quality control	Use standardized inspection check sheets
Material quality	Incoming coil conformity	Incoming quality control	Strengthen material inspection before production

As summarized in Table 5, the improvement priorities include machine-setup verification, tooling cleaning, preventive maintenance, operator training, standardized inspection, and incoming-material control. These actions are consistent with the identified causes, but their effectiveness has not yet been empirically demonstrated.

Previous DMAIC studies have reported measurable improvements after corrective actions were implemented, including increases in sigma level and substantial reductions in scrap (Conde et al., 2023; Enache et al., 2024; Jou et al., 2022). . In contrast, the present study concludes at the recommendation stage. Therefore, it cannot yet claim that the proposed actions reduce DPMO or increase sigma performance.

The Improve phase should prioritize tooling alignment, marking-depth verification, first-piece approval, tooling-cleanliness checks, and periodic in-process inspection. Each action should have a responsible unit, implementation frequency, verification method, and measurable target. The Control phase should include standardized check sheets, maintenance records, operator competency evaluation, first-piece inspection documentation, and periodic review of defect trends, DPMO, process yield, and sigma level. Sustainable Lean Six Sigma implementation requires not only technical controls but also management commitment, employee training, communication, and adequate resources (Tampubolon & Purba, 2021).

Overall, the findings show that the opportunity-based yield of 98.91% conceals a concentrated identification and traceability problem. Effective defect reduction requires coordinated control of operator practices, tooling condition, inspection reliability, material conformity, and preventive maintenance. Post-implementation measurement is required before the proposed actions can be causally associated with improved process performance.

4. CONCLUSION

This study applied the Six Sigma DMAIC framework to evaluate the quality performance of the R8 Cover stamping process at PT Amtek Engineering. The process produced a DPMO of approximately 10,900, a sigma level of 3.8, and an opportunity-based yield of 98.91%. Missing and damaged identification was the dominant defect, accounting for 33% of total rejection, followed by missing lettering at 23%. Together, these identification-related defects represented approximately 56% of total defects, indicating that the main quality problem was concentrated in the marking and traceability process rather than evenly distributed across all product characteristics.

The main contribution of this study is the integration of SIPOC, CTQ mapping, capability measurement, Pareto analysis, fishbone analysis, and 5W+1H improvement planning within a single DMAIC-based diagnostic framework for precision stamping. The findings provide an empirical baseline for R8 Cover quality performance and demonstrate that identification defects should be treated not only as visual nonconformities but also as traceability risks. Practically, the results imply that improvement efforts should prioritize tooling alignment, machine setup verification, tooling cleaning, preventive maintenance, first-piece approval, standardized visual inspection, operator competency, and incoming-material control.

This study is limited by the relatively short observation period and the absence of post-implementation evaluation. The fishbone analysis also identifies probable causes qualitatively and does not quantify the contribution of each factor. Therefore, the study cannot yet confirm that the proposed improvements will directly reduce DPMO or increase the sigma level.

Future research should extend the observation period, conduct before-and-after performance evaluation, and verify the proposed root causes using control charts, Failure Mode and Effects Analysis, measurement-system analysis, or controlled experiments. Further studies may also evaluate image-based inspection and tooling-condition monitoring to improve defect detection reliability and support more sustainable process control.

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