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A machine learning-driven Six Sigma framework for enhancing the quality improvement and productivity in the Aircraft Manufacturing

Dwi Adi Purnama[1]*, Alfiqra[2], Winda Nur Cahyo[1]
[1]Departement of Industrial Engineering, Universitas Islam Indonesia, Yogyakarta, 55584, Indonesia
[2]PT Astra Otoparts Tbk, Kelapa Gading, Jakarta, 14250, Indonesia

***Corresponding Author**: dwiadipurnama@uii.ac.id

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ABSTRACT
The aviation industry, a pillar of global transportation, is under constant pressure to increase productivity and efficiency while maintaining strict quality requirements. Airctraft defects in production can result in significant financial losses, lead to costly rework, delays, and even safety risks. This study proposes a framework to improve productivity and efficiency in aircraft manufacturing and analyze quality control using machine learning, Six Sigma, and the QCDSME (Quality-Cost-Delivery-Safety-Morale) method. The DMAIC (Define-Measure-Analyze-Improve-Control) stage is a reference in the implementation steps of the Six Sigma method of the Airbus A320. The sigma value in this study was obtained on average for 40 periods of 4.61 sigma and a DPMO of 1225.69. At the analyze stage, a fishbone diagram is used to find the root cause of the problem. Furthermore, a machine learning analysis was performed using the text mining method to identify the most common product components that frequently have defects in Airbus A320 and identify the main factors causing defects, by the human factor. The enhance stage suggests a rise in overcoming challenges with the QCDSME method. Overall, it was discovered that the number of defects fell while the sigma improved and this method can enhance industry performance.

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1. INTRODUCTION

The aviation industry, a cornerstone of global transportation, faces relentless pressure to enhance productivity and efficiency while maintaining stringent quality standards. As highlighted by Bhatia et al. [1], the aircraft production need to flexibility, adaptability, and data-driven decision-making has become increasingly apparent. Stringent safety regulations, complex supply chains, and the need for continuous innovation have intensified the pressure on manufacturers to deliver high-quality aircraft on time and within budget. The complex nature of aircraft manufacturing involves numerous processes, components, and suppliers, making it difficult to optimize the overall production flow. Inefficiencies can result in increased costs, longer lead times, and reduced customer satisfaction.

The aviation industry faces a critical challenge in ensuring the quality and reliability of aircraft products. Defects and low-quality components can lead to serious consequences, including safety risks, operational disruptions, and increased maintenance costs. According to a study by the International Civil Aviation Organization (ICAO), aircraft defects can result in significant financial losses for airlines, with an estimated global cost of over $100 billion annually. Defects and non-conformances can lead to costly rework, delays, and even safety risks. For instance, a study by the European Aviation Safety Agency (EASA) found that manufacturing errors are the leading cause of aircraft defects, accounting for approximately 40% of all incidents. Conventional quality control methodologies, such as manual inspections and basic statistical process control, are often time-consuming, labor-intensive, and susceptible to human error. These traditional approaches frequently prove inadequate for the rapid detection, complex root cause analysis, and proactive prevention of issues in today's data-rich, high-volume manufacturing environments. Addressing these multifaceted challenges therefore mandates a comprehensive strategy encompassing rigorous quality control, advanced manufacturing techniques, and continuous improvement initiatives.

To address these critical problems, this study proposes a novel framework designed to enhance productivity and efficiency in aircraft manufacturing while meticulously analyzing quality control through the strategic integration of Machine Learning (ML) and Six Sigma methodologies. The selection of Six Sigma stems from its proven track record as a data-driven, systematic problem-solving methodology, specifically designed to reduce defects and minimize process variability. Its structured DMAIC (Define, Measure, Analyze, Improve, Control) cycle provides a robust roadmap for process improvement, making it a foundational element for achieving near-perfect quality levels, which is paramount in aerospace. However, traditional Six Sigma often relies on manual data analysis and statistical tools that can be overwhelmed by the sheer volume, velocity, and variety of data generated in modern aerospace production.

This is precisely where Machine Learning becomes indispensable and highly relevant. Machine learning excels at processing vast, complex datasets, identifying intricate patterns, and making predictions that transcend the capabilities of human analysis or conventional statistical methods. Its application enables real-time monitoring, anomaly detection, and predictive analytics, which are crucial for moving from reactive defect identification to proactive prevention. Previous studies have consistently underscored the transformative potential of integrating sophisticated technologies, such as machine learning, into manufacturing processes to bolster performance and competitiveness [2]–[5]. By synergistically combining the data-driven analytical power of machine learning algorithms with the structured problem-solving approach of Six Sigma, unprecedented levels of process optimization, quality enhancement, and cost reduction can be achieved. For instance, machine learning algorithms are capable of predicting equipment failures, optimizing intricate supply chains, and identifying potential defects proactively at early stages of the manufacturing lifecycle. As highlighted by Theissler et al. [6], the application of predictive maintenance leveraging machine learning can substantially decrease operational downtime and significantly enhance overall equipment efficiency. This research delineates a framework that effectively harnesses these complementary capabilities to address the persistent quality and productivity challenges within the aviation manufacturing sector.

This paper presents a novel framework that leverages the powerful combination between Six Sigma and machine learning to revolutionize aircraft manufacturing. The framework is specifically tailored to the unique challenges and requirements of the aircraft manufacturing industry. This ensures that the proposed solutions are directly applicable and relevant to the industry's needs. The Six Sigma method has been widely used in various cases in the industry, such as the manufacturing industry [7]–[9], the drinking water industry [10], automotive industry [11], small and medium enterprises [12]–[14], food industry [15], [16], healthcare [17], laboratory [18], tin industry [19], textile industry [20],[21]. So far, quality improvement analysis using Six Sigma in the aviation industry has rarely been carried out.

In the other studies, the machine learning approaches can lead to significant improvements in manufacturing performance [22], [23]. Studies by Dalzochio et al. [3],[6] have highlighted the importance of data-driven decision-making in modern manufacturing environments. Text mining in machine learning is also often used for various cases in the industry, such as estimating job profiles and skills [19], services management [24], retail industry [25]. Furthermore, can enhance data-driven decision-making through the analysis of previous data to identify trends, patterns, and anomalies. The ability to make data-driven decisions is crucial for achieving competitive advantage in today's manufacturing environment. Although it is still rarely used for aircraft industry cases.

The contribution of the research and the novelty of the proposed framework lies in its synergistic integration of Six Sigma and machine learning to address the unique challenges of aircraft manufacturing. This gap is important because the amount and complexity of data in current aerospace production can be too much for traditional Six Sigma tools to handle. On the other hand, standalone ML apps generally don't have the structured, process-oriented framework needed for long-term quality control. In the aerospace manufacturing setting, there aren't many formal frameworks that clearly explain how to systematically use ML approaches in each step of the Six Sigma DMAIC cycle. In addition, this industry has not yet investigated or tested the full potential of advanced analytics for predicting defects before they happen and recognising complex patterns through Machine Learning (ML), combined with Six Sigma's analytical rigour. By integrating Six Sigma and machine learning, we can enhance decision-making, optimize processes, improve quality control, and increase efficiency. This novel approach offers a promising solution to the complex challenges faced by the aircraft manufacturing industry.

This paper proposes the specific applications of machine learning within the Six Sigma framework for aircraft manufacturing. This document is organised as follows. The subsequent section delineates the research methodology and recommended framework, followed by a case study description in section 2. Section 3 addresses the results and discussions. Section 4 delineates the conclusions.

2. MATERIALS AND METHODS

2.1. Aircraft Manufacturing Industry Profile

There is a company based in Indonesia that became the first aircraft manufacturer in both Indonesia and Southeast Asia. This company is also one of the original aircraft companies in Asia that has core competencies in aircraft design and development, aircraft structure manufacturing, aircraft assembly, and aircraft services for light and medium combat aircraft for civil and military. Furthermore, the company serves as a subcontractor for Airbus & Space, Airbus Helicopter, etc. The items manufactured include the Airtbus A380, CN235 Production Sharing, Boeing 747 for Korean Air, etc. This study analyzes the production system in the Assembly department of the A320 and A350 programs, with the object of research being the Airbus A320 aircraft wing skin component. Furthermore, this study's proposed method (Integrated Machine Learning and Quality-Cost-Delivery-Safety-Morale-Environment in Six Sigma) will also be validated based on a case study of one of the Aircraft products, the Airbus A320, to demonstrate its effectiveness in real cases.

2.2 DMAIC (Define-Measure-Analyze-Improve-Control)

Six Sigma has five steps in its implementation, namely DMAIC (Define-Measure-Improve-Control). In each step, there are criteria and tools for its implementation. The following is an explanation of each of the DMAIC processes according to previous studies [26]–[31]:

1. Define

   The Define phase is the initial operational stage in the Six Sigma quality improvement program. Prior to delineating essential processes and clientele in a Six Sigma initiative, it is imperative to understand the SIPOC (Supplier, Input, Process, Output, Customer) process model.
2. Measure

   Measure constitutes the second operational phase in the Six Sigma quality enhancement process.
   a. At this stage, quality characteristics are determined, along with specific customer needs. Quality characteristics (Critical to Quality) are the key that is determined because they are intimately associated with the special needs of customers, which stem from production and service requirements.
   b. Calculating the DPMO value

   A metric of failure in a Six Sigma quality enhancement initiative, signifying failures per million opportunities.

$$DPMO = \frac{Number\ of\ defect}{Total\ product\ \times Critical\ to\ Quality\ Potential} \times 1.000.000 \tag{1}$$

3. Analyze

   The Analyze phase is the third step of the Six Sigma as a quality improvement method, during which several activities are conducted.

   a. Determining the stability and efficacy of the process
   b. Determining the performance objectives for the critical quality characteristics (CTQ) to be enhanced in the Six Sigma initiative
   c. Identifying the underlying causes of defects or failures.

   During the Analysis phase of this study, a machine learning approach is integrated with the Six Sigma methodology with the primary objective of identifying dominant product defects in the components of the selected case study product. In addition to employing conventional fishbone analysis, this research utilizes a text mining approach to extract and explore nuanced insights regarding product defect characteristics. This comprehensive analytical strategy is instrumental in precisely determining effective improvement strategies for the most frequently occurring defective components, thereby ensuring that interventions are accurately targeted to optimize overall performance and production efficiency.
4. Improve

   Upon identifying the core cause of the quality issue, it is imperative to formulate an action plan for implementing quality enhancement. It implements quality improvement using QCDSME (Quality-Cost-Delivery-Safety-Morale-Environment).
5. Control

   Control represents the ultimate operational phase in a Six Sigma quality enhancement process. At this phase, quality enhancement outcomes are recorded and distributed, effective best practices for process improvement are standardised and utilised as standard operating procedures, and accountability for the process is established, signifying the conclusion of Six Sigma at this level [32].

2.3 *Machine Learning*

In this paper, we develop machine learning using text mining to identify the most critical defect in aircraft manufacture. Text mining is a powerful technique for extracting valuable insights from unstructured text data. When applied to aircraft maintenance records, it can help identify patterns, trends, and anomalies related to specific components. By combining text mining with machine learning, we can build predictive models to forecast potential failures and identify the most frequently affected components.

Text mining is a method of retrieving useful information from unstructured text data. It involves several steps: data collection and preprocessing to clean and structure the data, text classification to categorize documents based on their content, and visualization and interpretation. By applying these techniques, we can uncover patterns, trends, and anomalies within large volumes of text data, facilitating data-driven decision-making. For example, text mining has been applied to several studies in identifying dominant defect components [29], [33] the effectiveness of this approach in improving aircraft maintenance and safety.

In this study, we use a text mining approach to find dominant component defects in the wing skin components of an Airbus A320 aircraft. Information about product defects is collected; for example, defect data 1 provides the information "On Skin 2 STBD D57443568207B, Jidno, 2078382. Found Spot Drill 2.5 mm Dia, With Depth 0.4 mm for Set 353", defect data 2 "ON SKIN 2 PORT D57443568206B", and so on. This information will be helpful in implementing repair strategies on dominant product defect components so that it can be right on target in improving production performance and efficiency.

The step-by-step approach to applying this methodology are:

1. Data collection and preprocessing
   a. Gather the result of defect product from Six Sigma analysis
   b. Data cleaning: remove noise, inconsistencies, and irrelevant information. Such as the elimination of stop words, stemming (truncating words to their root form, e.g., "running" to "run"), lemmatisation (transforming words to their base form, e.g., "better" to "good"), and text normalisation (standardising text format, e.g., converting to lowercase).
2. Visualization and Interpretation:
   a. Data Visualization (e.g., table, bar charts, pie charts, word clouds) to illustrate the frequency of defects in different components.

b. Analyze the results to identify the most frequently affected components and potential root causes of failures.

2.4 QCDSME (Quality-Cost-Delivery-Safety-Morale-Environment)

QCDSME prioritizes consumer, employee, and corporate satisfaction [34]. The analytical values in QCDSME are described as follows [35], [36]. (1) Quality guarantees that a product consistently aligns with consumer expectations and improves product standards through strategic initiatives. (2) Cost refers to the efficiency of expenditures utilised in preserving product quality. (3) Delivery (Timeliness) refers to the efficiency of the time utilised in the manufacturing process from inception to the point at which the product is received by consumers, hence reducing a company's downtime. (4) Safety, which prioritizes the safety of all workers during industrial tasks. (5) Morale, which emphasizes the importance of satisfaction for all employees and participants in operations, particularly customers or consumers who are connoisseurs of a final product. (6) Environment, which focuses on sustaining the environment by avoiding waste disposal initiatives that harm the environment's health.

3. RESULT AND DISCUSSION

This study's initial research involves processing data through Six Sigma analysis (DMAIC) and Machine Learning, utilising information obtained from field observations, operator interviews, and direct verification with the production head and lean manufacturing manager.

3.1. Six Sigma-Define

In the Define stage, the steps describe the SIPOC (Supplier-Input-Process-Output-Customer) diagram. This diagram is helpful in describing the product to be studied, starting from the supplier, who provides raw materials or goods, to the customer, who buys the goods produced. Figure 1 is a picture of the SIPOC diagram in the Airbus A320 Aircraft Wing Skin production.

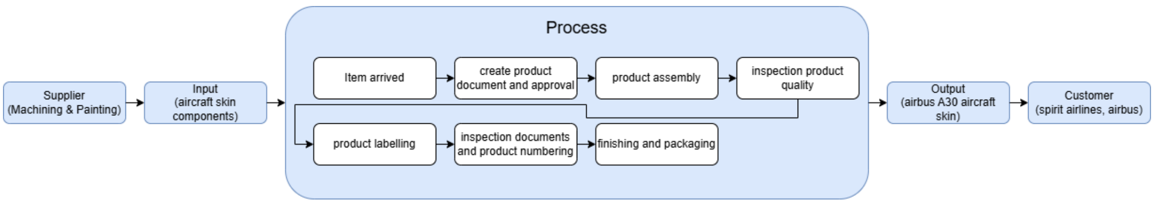


Figure 1.Diagram SIPOC aircraft wing skin

3.2. Six Sigma-Measure

The chart in Figure 2 shows the quantity of defects in the manufacturing procedure of Airbus A320 aircraft wing skins. The fluctuating nature of the chart indicates that the production process is not consistently stable. There are periods with high defect rates, likely due to issues like manufacturing process problems, material quality, or ineffective quality control. Conversely, periods with low defects suggest process improvements or positive factors. To address this, Airbus should conduct root cause analysis, optimize processes, enhance quality control, train employees, manage suppliers effectively, and leverage data-driven decision making.

Classification of defects and identification of Critical to Quality (CTQ) parameters. Various categories of errors arise during the production of skin products. The following is an explanation of each defect that arises:

1) Damaged (D)
   Changes in the product's shape cause this damage to the product. In addition, the criteria for damage to the product also occurs due to curvature and clumped paint on the skin product layer, untidy drilling marks, and marks from the tools used.
2) Corrosion (C)
   This is corrosion on the product that has been made. Poor material used or contamination of the product with other materials causes corrosion, which causes the product to enter the defect category.

3) Move Out (M)
   A move-out defect is a defect caused by inaccurate drilling of holes that does not comply with the desired specifications. It is also caused by mislocated and misaligned in the product assembly process, so the product cannot be used and becomes defective.
4) Over Size (O)
   This defect category is a size that does not match the desired specifications, such as the size cutting the product or the product hole that is too large so that it becomes a defective product and must be destroyed.
5) Wrong Installed (W)
   Product components in the assembly process sometimes have similarities that are almost similar but are different. Therefore, errors in installing components in assembly are a type of defect in the product.

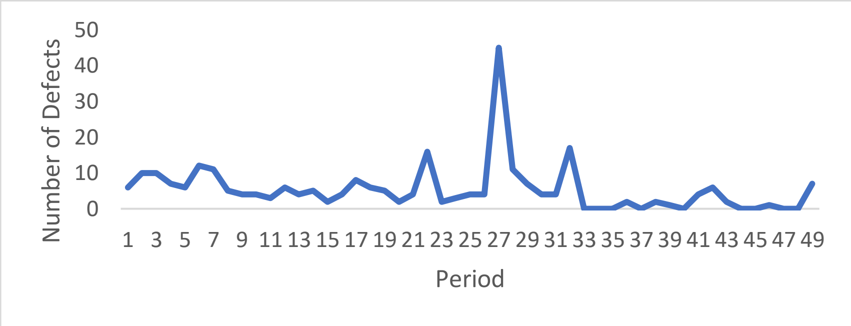


Figure 2. Number of product defect in Airbus A320 aircraft wing skin production

Based on identifying Critical to Quality (CTQ), Table 1 present data using a table of defect types and a Pareto diagram (Figure 3) regarding the number of defect types from highest to lowest. The predominant defect kind is Move Out (M), occurring 97 times, which constitutes 36.33% of the total. Subsequent to the classification of Damage (D) defect as many as 86 with a rate of 32.21%, then Oversize (O) as many as 49 with a percentage of 18.35%, Corrosion (C) as many as 22 with a percentage of 8.24% and finally Wrong Installed (W) as many as 13 with a rate of 4.87%. So, the number of CTQs is five types of defects.

Table 1. Frequency data of defect types in aircraft skin

No.	Defect Type	Frequency	Percentage (%)	Cumulative Percentage (%)
1	Move Out (M)	97	36.33%	36.33%
2	Damage (D)	86	32.21%	68.54%
3	Over Size (O)	49	18.35%	86.89%
4	Corrosion (C)	22	8.24%	95.13%
5	Wrong Installed (W)	13	4.87%	100.00%
Total		267	100.00%	

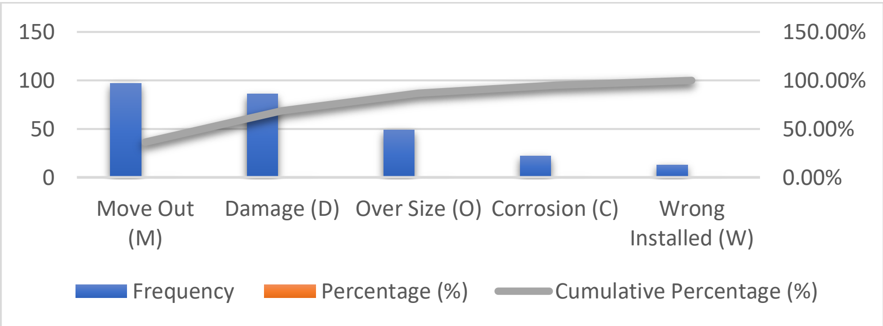


Figure 3. Pareto diagram of product defects

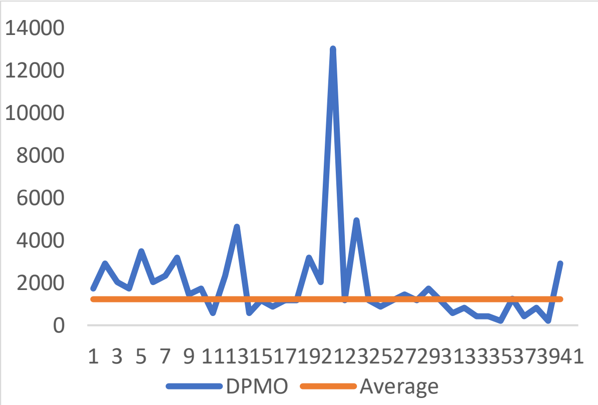
Computation of DPMO value and sigma level. Table 2 presents the results of the DPMO value and sigma level calculations:

Table 2. Calculation of DPMO and sigma level

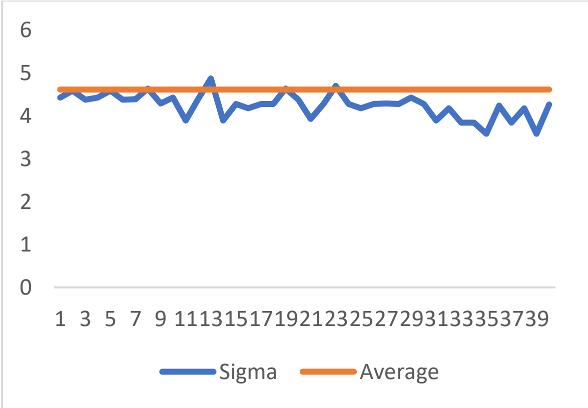
No	Total Production	Number of Defects	Number of CTQ	DPO	DPMO	Sigma
1	1152	6	5	0.005208333	1736.11	4.42
2	1152	10	5	0.008680556	2906.76	4.58
3	1152	7	5	0.006086957	2028.95	4.37
4	1152	6	5	0.005208333	1736.11	4.42
5	1152	12	5	0.010416667	3472.22	4.58
6	1152	7	5	0.006086957	2028.95	4.37
7	1152	8	5	0.006944444	2318.89	4.39
8	1152	11	5	0.009540278	3190.82	4.63
9	1152	5	5	0.004340278	1453.38	4.29
10	1152	6	5	0.005208333	1736.11	4.42
11	1152	2	5	0.001736111	582.06	3.89
12	1152	8	5	0.006944444	2318.89	4.39
13	1152	16	5	0.013888889	4637.78	4.87
14	1152	2	5	0.001736111	582.06	3.89
15	1152	4	5	0.003472222	1164.12	4.27
16	1152	3	5	0.002604167	873.08	4.18
17	1152	4	5	0.003472222	1164.12	4.27
18	1152	4	5	0.003472222	1164.12	4.27
19	1152	11	5	0.009540278	3190.82	4.63
20	1152	7	5	0.006086957	2028.95	4.37
21	1152	45	5	0.0390625	13020.8	3.92
22	1152	4	5	0.003472222	1164.12	4.27
23	1152	17	5	0.014772722	4951.39	4.7
24	1152	4	5	0.003472222	1164.12	4.27
25	1152	3	5	0.002604167	873.08	4.18
26	1152	4	5	0.003472222	1164.12	4.27
27	1152	5	5	0.004340278	1453.38	4.29
28	1152	4	5	0.003472222	1164.12	4.27
29	1152	6	5	0.005208333	1736.11	4.42
30	1152	4	5	0.003472222	1164.12	4.27
31	1152	2	5	0.001736111	582.06	3.89
32	960	4	5	0.004166667	833.33	4.18
33	960	2	5	0.002083333	416.67	3.84
34	960	2	5	0.002083333	416.67	3.84
35	960	1	5	0.001041667	208.33	3.58
36	960	6	5	0.00625	1250	4.24

No	Total Production	Number of Defects	Number of CTQ	DPO	DPMO	Sigma
37	960	2	5	0.002083333	416.67	3.84
38	960	4	5	0.004166667	833.33	4.18
39	960	1	5	0.001041667	208.33	3.58
40	480	7	5	0.014583333	2916.67	4.26
Average	1084.8	6.675	5	0.006128472	1225.69	4.61

The two graphs (Figure 4) show a lack of stability in the process. For example, in period 19, the greatest DPMO value was determined, It led to a low value at the sigma level. The production process for a product is more efficient the higher the sigma level. The table shows an average DPMO = 1225.69 and Sigma = 4.61.



(a)DPMO



(b) Sigma Level

Figure 4. Pattern of DPMO: (a) DPMO and (b) Sigma level

P control chart illustrates that the percentage of defects are placed in the uncontrolled group since it appears unstable during the procedure (Figure 5). In period 19, the percentage of faults is higher than the maximum. This is due to the fact that the number of flaws in one period is different from the others, which are often under the control limit.

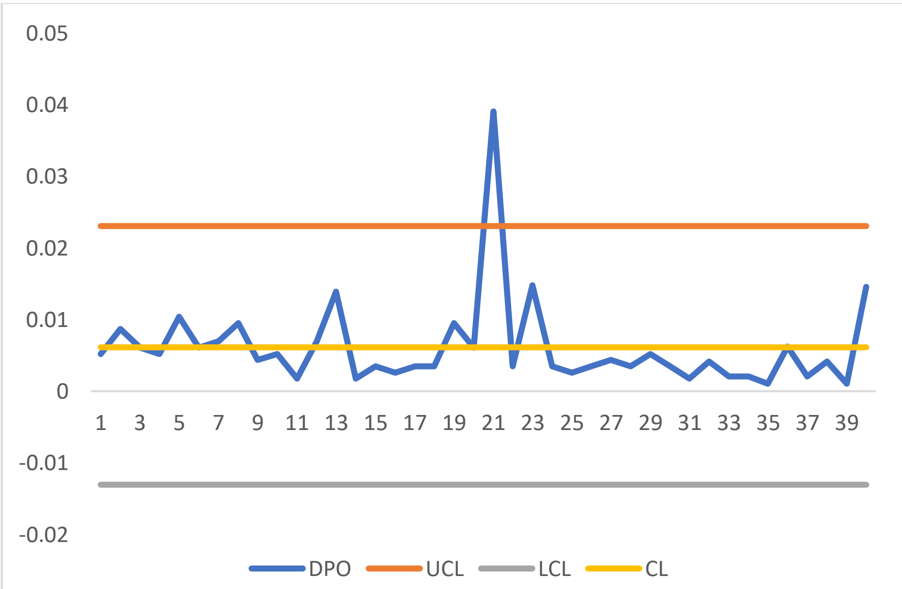


Figure 5. P control chart

3.3. Six Sigma-Analyze

3.3.1. DPMO and Sigma Values Data Analysis

Data on the quantity of Airbus A320 wing skin component product defects is used in this analysis. Five defects are potential CTQ characteristics: Move Out (M), Damage (D), Over Size (O), Corrosion (C), and Wrong Installed (W). These flaws, which are utilised as a guide to determine the DPMO value and sigma level, may arise during the production process.

In this study, calculations were carried out for 40 periods, indicating months, as many as 43392 items were studied, with 267 defects. Based on the Pareto diagram, the highest type of defect is the Move Out (M) defect, which accounts for 97 items and 36.33% of the total defects.

The average production amount, as determined by the computations, was 1084.8 pieces, with a sigma value of 4.61. Furthermore, the average DPMO score was 1225.69, meaning that 1225 units of skin products would be defective or not satisfy criteria out of a million skin items manufactured. This study obtained a sigma value of 4.61 with a DPMO value of 1225.9; this means that the skin product manufacturing process is already at the US industry average. It can be seen that the number of defective products in the skin product manufacturing process is not significant, given the large number of routine productions.

Based on Figure 4, the sigma level and DPMO value, an imbalance tends to be unstable. This suggests that there has been inconsistent execution of the production process. However, the skin production process is already classified as an outstanding category, considering that the DPMO and sigma values are good. Still, improving the production process to a zero-defect one would be better. With defective product control carried out consistently and continuously, the company can increase the Sigma value to become a world-class company.

3.3.2. Product Defect Cause Analysis

At this point, the reasons behind the skin product's flaws are examined. The Move Out (M) type of product problem will be examined to determine its underlying cause, with a total of 97 items of defects from a total of 267. A cause-and-effect diagram, often known as a fishbone diagram, is used to analyse the sources of faults. The outcomes of the cause-and-effect diagram of the reasons behind the Move Out (M), product defect in the Airbus A320 aircraft wing skin production process, are as follows based on Figure 6.

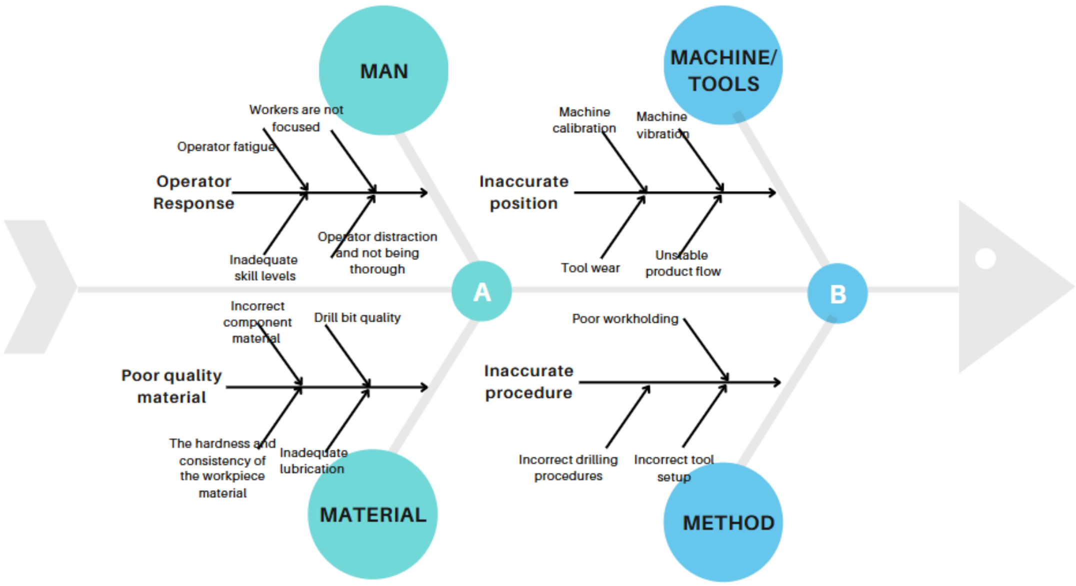


Figure 6. Fishbone diagram of move out defect

The following is an explanation of each of the causes of Move Out defects in the skin product:

1. Method

   The company requires all workers to see the drawing guide or working drawings when making or assembling a product. However, because most workers feel they have memorized and are experienced, not a few ignore the drawings, so product defects occur due to trivializing small things. Then, the cause in method is incorrect drilling procedures, such as using the wrong feed rate or speed, can result in inaccurate hole sizes and positions. Proper workholding and accurate tool setup are essential for precise drilling. Incorrect tool alignment or depth settings can result in deviations from the desired specifications. And proper workholding is crucial for maintaining workpiece stability during drilling, if the workpiece is not securely clamped, it can move, leading to inaccurate holes.

2. Machine / Tools

   Workers pay so much attention to making products and constantly improving quality that they forget the important thing, namely the equipment used. The tools must also be consistently maintained because most move-out defects are due to errors in the tools used. For example, the drill must be replaced but is still used, causing an imperfect hole and unwanted marks.

   Moreover, tool wear is a common cause of inaccurate drilling. As drill bits wear down, they become less precise, leading to deviations in hole size and position. Then, machine calibration and vibration can significantly impact drilling accuracy. If the machine is not calibrated correctly, it can result in systematic errors, such as consistently drilling holes that are too large or too small. And, vibration can cause the drill bit to chatter, leading to inconsistent hole quality and potential damage to the workpiece.

3. Human

   Product defects are caused by employees' ignorance and incompetence. Workers who are relatively new and not yet accustomed to the work can cause defects. In addition, sometimes workers are assigned to replace other workers who are absent, so the work they do is not as perfect as that done by their job desk; this can also cause defects. In addition, workers who are less focused and careful in their work are also the cause of product defects.

   Inadequate skills, operator fatigue, and operator distraction can also cause the cause-effect of the workforce. Operator training is essential to ensure operators have the necessary skills and knowledge to perform drilling operations accurately. Operator fatigue can reduce attention and increase the likelihood of errors. Moreover, operator distractions can lead to mistakes, such as forgetting to adjust settings or overlooking quality issues.

4. Material

   Materials sent from other divisions also often have errors. The skin component materials are many different types. Some materials have the same shape, but the product has a different use, so many workers misuse it. So, a solution is needed to overcome this and avoid product defects.

The quality of drill bits, the hardness and consistency, and lubrication can also cause the product defects. The quality of drill bits is a critical factor in drilling accuracy. Poor-quality drill bits can break, chip, or dull prematurely, leading to inaccurate holes. Then, the hardness and consistency of the workpiece material can affect drilling performance. Harder materials can increase tool wear and reduce drilling accuracy. Inconsistent material properties can lead to variations in drilling results. Moreover, lubrication is essential for reducing friction and heat during drilling. Inadequate lubrication can increase tool wear, reduce tool life, and lead to inaccurate holes.

In this study, we propose a machine learning approach used to find the dominant component defect of the product used as a case study. We have used a text mining approach that can see the part of the product defect of the Airbus A320 aircraft wing skin component. The text mining results are presented in Table 3. From the many aircraft skin component data, it was obtained that the most product defects were found in (1) ON SKIN 3 PORT D57443569264B, JD. 20093151, (2) ON SKIN 3 STBD D574435692658, JD. 20092181, (3) 2 (OFF) HOLES 2.50 MM DIA ON SKIN 13 PORT D5744358023202, JD 20140950. This will be useful for implementing improvement strategies on the dominant product defect components. So, it can be right on target in improving performance and production efficiency.

Table 3. Result of text mining to identify dominant product defect

Text Mining	
Dominant Defect	**Frequency**
ON SKIN 3 PORT D57443569264B, JD. 20093151. FOUND WAVING AND DENT	39
ON SKIN 3 STBD D574435692658, JD. 20092181. FOUND WAVING AND DENT	31
2 (OFF) HOLES 2.50 MM DIA ON SKIN 13 PORT D5744358023202, JD 20140950, FOUND MOVED OUT 1.60 MM	30

Furthermore, using text mining has also been found to be the most dominant defect-causing factor. Table 4 shows that among several factors that cause product defects, the percentage of man defect causes is the most dominant defect-causing factor, and around 60% of the total defect products found are caused by man factors. Other factors contributing to product defects are suppliers, tools, and materials. Product defects originating from suppliers are external factors and are the focus of product improvement. The results of the analysis of the defect-causing factors will be a reference in formulating strategies to increase productivity and efficiency.

Table 4. Result of text mining to identify dominan cause of product defect

Text Mining	
Dominant Defect	**Frequency**
Man	136
Supplier	67
Tool	15
Material	6

3.4. Six Sigma-Improve

The proposed improvements are based on the Fishbone Diagram, machine learning, and QCDSME results. The Move Out product defect's primary cause is seen in the fishbone graphic, that fell into the following groups: Material, Method, Machine/Tools, and Human. The results of text mining showed that the dominant types of product defects were (1) ON SKIN 3 PORT D57443569264B, JD. 20093151, (2) ON SKIN 3 STBD D574435692658, JD. 20092181, (3) 2 (OFF) HOLES 2.50 MM DIA ON SKIN 13 PORT D5744358023202, JD 20140950. In addition, machine learning also identified the leading causes of defects, namely man, supplier, tool, and material. Table 5 shows the proposed improvements by each problem cause and the appropriate improvement strategy. Referring to the text mining results in Table 4, the factors causing Man defects are the primary concern in improving performance and efficiency.

Table 5. Proposed improvement plan using QCDSME

QCDSME Strategy	**Man (Primary concern)**	**Material**	**Method**	**Machine**
Quality	▪ Conduct training for workers. ▪ Implement regular in-process inspections to identify and correct errors early on. ▪ Utilize Statistical Process Control (SPC) techniques to monitor process variability and identify potential issues. ▪ Improving the work environment to increase focus and address the lack of thoroughness in working.	▪ Selecting high-quality materials. ▪ Workers must be able to recognize component numbers well and distinguish components that are almost like their respective uses. ▪ Proper lubrication is essential to minimize friction and	▪ Create new work procedure standards. ▪ Intensive supervision, which will make employees understand how important it is to follow work drawing guides when creating or assembling a product.	▪ Proper machine calibration is essential to prevent systematic errors and maintain consistent drilling accuracy. ▪ Machine vibration can induce tool chatter, resulting in inconsistent hole quality and potential workpiece damage.

QCDSME Strategy	Man (Primary concern)	Material	Method	Machine
		heat generation during drilling.		
Cost	Recognize and reward workers who demonstrate excellent adherence to drawing guidelines and high-quality work.	Selecting high-quality, reasonably priced raw supplies as needed.	Direct instruction to operators.	Perform planned and routine equipment maintenance and inspections.
Delivery	Measure the workers' understanding of something so that mapping can be done on who needs training.	Routine checks are always carried out on incoming components to avoid material exchange or errors in material delivery.	Intensive supervision and reguler checks.	Equipment components that need to be replaced must also always be available. So, if the equipment component is damaged, it can be replaced quickly without product production delay.
Safety	Reduce over time with rotating breaks.	Choose materials that have been certified to safety standards.	Ensure a safe, comfortable, healthy work environment, including machinery and operators.	▪ Provide a printed warning sign on risky areas of the machine ▪ A cover to protect sharp regions.
Morale	▪ Encourage employee involvement in problem-solving and continuous improvement initiatives. ▪ Foster a positive and supportive work environment that values quality and safety.	Use of raw materials by provisions (SOP).	Create a comfortable working environment and methods, and pay attention to workers' mental health	Follow the prescribed standard operating procedures when operating the machine.
Environment	▪ The work environment, good lighting, and air space are the main factors that contribute to workers' comfort at work ▪ Provide ergonomic workstations to reduce operator fatigue and improve focus.	Choose materials with the most negligible negative environmental impact and create a mechanism for processing	Based on ergonomic work systems and environments.	Using eco-friendly machines.

QCDSME Strategy	Man (Primary concern)	Material	Method	Machine
	▪ Ensure proper lighting to aid in clear visualization of drawings and workpieces. ▪ The noise level in the work environment also needs to be considered.	waste materials.		

The proposed QCDSME (Quality-Cost-Delivery-Safety-Morale) framework also makes a contribution for all three pillars of sustainability: environmental, social, and economic. The framework's focus on improving quality leads to less harm to the environment because it leads to less material waste, less rework, and, as a result, less energy use. The Environment dimension, which calls for eco-friendly machinery, responsible waste processing, and the best working conditions in terms of noise and air quality, makes this environmental benefit even greater. From an economic point of view, initiatives that aim to lower costs, like reducing defects, planning maintenance, and using resources more efficiently, immediately save money and make the business more financially stable in the long run.

Moreover, the framework makes social sustainability much stronger, in addition to being good for the environment and the economy. Putting safety first by doing things like managing fatigue, making sure work conditions are safe, and using approved materials directly protects the health of employees and lowers the risks of accidents at work. Additionally, providing comfortable working conditions, comprehensive training, and encouraging employees to take part in problem-solving all help to build a stable, engaged, and ethical staff. This all-encompassing approach to human capital not only boosts productivity but also creates a responsible work environment, showing a strong commitment to the welfare of society.

As a result, combining an ML-driven Six Sigma approach with the QCDSME strategic framework creates a strong model for achieving operational excellence that is directly connected to long-term sustainability goals. This framework provides a comprehensive approach for the aviation manufacturing sector and other complex industries to operate ethically and efficiently, while significantly impacting the globe by emphasising Quality, Cost, Delivery, Safety, Morale, and Environment.

3.5. Six Sigma-Control

Work methods will be standardized during the control stage to reflects the recommended enhancements previous stage. Furthermore, the division head's new processes must be quickly communicated to all personnel in the area. In the control process, increasing production performance on human factors is also prioritized and becomes the focus; this aims to reduce the occurrence of product defects.

3.6. Practical Implications

This machine learning-driven Six Sigma approach offers significant practical implications beyond the Airbus A320 and the aircraft manufacturing sector, being highly adaptable for quality improvement and productivity improvements in different complex, high-stakes manufacturing contexts. The fundamental ideas and integrated methodology can be used on aircraft and sub-assemblies by retraining machine learning models with appropriate data. This was shown with the Airbus A320. Furthermore, industries characterized by high complexity, stringent quality requirements, large data volumes, and continuous improvement initiatives—such as automotive manufacturing, medical device production, heavy machinery manufacturing, and others—can profoundly benefit. Ultimately, this framework significantly changes from reactive to proactive, data-driven quality management. It allows organizations to find defects before they happen, spot hidden patterns, dynamically improve processes, and speed up root cause analysis. This leads to continuous improvement based on real-world evidence and predictive insights in a wide range of industries.

4. CONCLUSION

The study's contribution and the proposed framework's novelty lie in its synergistic integration of Six Sigma and machine learning to address the unique challenges of aircraft manufacturing. The findings of this study yielded a considerable performance improvement method based on the analysis of Six Sigma, machine learning, and QCDSME in the production process of Airbus A320 aircraft skin components. In the Six Sigma method's implementation processes, the DMAIC stage serves as a guide. The define process is carried out by mapping the process flow of making Airbus A320 aircraft wing skin products using the SIPOC diagram. Furthermore, the measuring step is carried out by calculating the sigma and DPMO values. Potential CTQ features include the following five defect types: Move Out (M), Damage (D), Over Size (O), Corrosion (C), and Wrong Installed (W). These flaws, which are types of errors that could occur in the production process, are used to calculate the DPMO value and sigma level. In this investigation, the average sigma value over 40 periods was 4.61 sigma, with a DPMO of 1225.69.

Then, the analyze stage was carried out using a fishbone diagram which aims to identify the underlying cause of the most significant product failure, namely move out defects. Furthermore, at the analyze stage, using the text mining approach, a machine learning study was conducted with the most promising outcomes (1) finding the most dominant product components that often have defects in Airbus A320 aircraft skin products, (2) finding the main factors causing defects based on the results of the text mining analysis, namely influenced by the man factor. Thus, by finding the root cause of the problem (fishbone) and the factors causing defects and components that are dominantly defective (machine learning), the improve stage proposes an increase in overcoming issues with the QCDSME approach. It was discovered that the number of defects dropped and the sigma level rose following the implementation of changes to product defects.

The research findings derived from actual case studies demonstrate the efficacy of the proposed approach, which identifies diverse product defect analyses and enhancements through the innovative combination of machine learning and QCDSME techniques inside the Six Sigma framework. This research offers an alternate way for identifying product flaws and facilitating continuous improvement, applicable to both the aviation industry and other complex sectors. Additionally, we have advocated the integration of QCDSME techniques into a comprehensive sustainability analysis.

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