

Case Study on the Application of Six Sigma DMAIC for Reducing Product Rejects in VRLA Battery Production

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Abstract - The high reject rate in the VRLA battery production process has become a critical issue affecting both efficiency and product quality. This study aims to reduce the reject rate by applying the Six Sigma methodology through the DMAIC approach (Define, Measure, Analyze, Improve, Control). The tools utilized include the Pareto diagram, DPMO and Sigma Level trend charts, and the 5 Why Analysis to identify root causes. The implementation results demonstrate a reduction in product mismatch rate from 4.2% to 1.1%. The average weekly DPMO decreased from 23,544.74 to less than 5,000, while the Sigma Level improved from 3.5 to above 4.0. The application of the Six Sigma methodology proved effective in enhancing process capability and reducing product defects.

Keywords: Six Sigma, DMAIC, VRLA battery, DPMO, defect reduction.

I. INTRODUCTION

Amidst increasing global competition in the manufacturing industry, companies are required to continuously improve product quality and production process efficiency. This poses a unique challenge in manufacturing sectors such as battery production, where complex and stringent processes demand high-quality standards. One of the widely produced battery types today is the VRLA battery (Figure 1). This battery is also commonly referred to as a dry battery or Sealed Maintenance Free (SMF) battery. The VRLA battery is a type of sealed lead-acid battery designed for minimal maintenance and is widely used in vehicles, UPS systems, and telecommunications applications.

The advantages of VRLA batteries include minimal electrolyte leakage, low evaporation rates, and a design that withstands tilted positions. This technology enables more stable and safer usage compared to conventional wet-cell batteries [9].

The production process of VRLA batteries involves several critical stages: grid manufacturing (lead framework), active paste filling, curing, assembling (plate and separator assembly), electrolyte filling, terminal welding, initial

charging (formation), testing, and sealing. Each stage must meet strict quality parameters to prevent defects such as leakage, capacity mismatches, and physical damage [6]. Although battery manufacturing technology continues to advance, quality issues like product rejects still frequently occur, resulting in losses for the company [1].

Product rejects represent a significant form of waste in the production process because they require rework or even disposal, leading to wastage of raw materials, labor, energy, and time [2]. The high reject rate in VRLA battery production indicates process inconsistencies that need to be identified and addressed. Addressing these quality problems is crucial due to their impact on productivity, production costs, and customer satisfaction.



Figure 1: A Valve Regulated Lead-Acid (VRLA) battery

To address these challenges, data-driven quality management approaches such as Six Sigma have become strategic solutions widely implemented in the manufacturing industry. Six Sigma is a methodology aimed at reducing process variation and improving capability to achieve only 3.4 defects per million opportunities (DPMO). This method is recognized as effective in significantly enhancing process performance [3].

One of the main approaches within Six Sigma is the DMAIC cycle (Define, Measure, Analyze, Improve, Control). DMAIC provides a systematic framework for analyzing root causes of quality problems and implementing data-based

solutions. The application of DMAIC successfully reduced the reject rate in motorcycle battery production from 3.32% to 1.6%, demonstrating the effectiveness of this method in complex production environments [4].

The effectiveness of the DMAIC methodology in reducing defects in automotive component manufacturing processes reached 52%. Implementation of DMAIC in the manufacturing industry resulted in a product defect rate reduction of up to 48.7%. In a relevant context, applying Six Sigma in the battery manufacturing industry achieved a 63% reduction in product rejects while simultaneously improving production efficiency [5].

Moreover, the DMAIC approach has been applied to various other manufacturing processes. The use of DMAIC was able to reduce the reject rate in the automotive component industry from 1.75% to 0.80% within one year, while simultaneously improving production process efficiency [6]. In medium-scale manufacturing sectors, the implementation of Lean Six Sigma successfully lowered the rejection rate from 5.3% to 1.2% by utilizing analytical tools such as Pareto Charts and cause-and-effect diagrams [7].

The application of Six Sigma is not limited to automotive products but is also employed in quality control for components such as telecommunication cabinet doors, showing significant results in reducing defects caused by welding errors [8]. All these studies demonstrate that the implementation of Six Sigma using the DMAIC approach can deliver tangible results in reducing product reject rates and enhancing process performance.

Building upon this background, this study aims to apply the Six Sigma DMAIC methodology in the VRLA battery production process at a leading battery manufacturing company in Indonesia to reduce the product reject rate. The analysis process will utilize tools such as Pareto diagrams, DPMO and Sigma Level trend charts, and the 5 Why Analysis to identify root causes and develop sustainable solutions.

Six Sigma is a data-driven quality improvement methodology aimed at reducing process variation and achieving near-perfect quality with a defect level of only 3.4 Defects Per Million Opportunities (DPMO). Six Sigma utilizes statistical tools to analyze processes and eliminate the root causes of defects [10].

The DMAIC methodology is the core approach within Six Sigma, consisting of five main phases: Define (identifying the problem and objectives), Measure (assessing current performance), Analyze (examining root causes), Improve (developing and implementing solutions), and Control (sustaining the improvements). DMAIC is considered

effective in enhancing process capability and reducing product rejects in manufacturing [11][12].

Several tools commonly used in the DMAIC methodology include Pareto diagrams, cause-and-effect diagrams (Fishbone), control charts, DPMO trend graphs, and 5 Why Analysis. These tools have proven effective in systematically identifying and resolving production problems [13][14].

The application of DMAIC has been successful in the lead-acid battery industry to reduce defects such as terminal leakage and paste rejection. For example, DMAIC implementation in the motorcycle battery industry reduced the reject rate from 3.32% to 1.6% [8].

Other studies also demonstrate significant success in reducing reject rates across various manufacturing industries. These include reducing process variability and improving quality in the metal industry [10], and lowering defect rates from 7.7% to 2% in the textile industry [15].

With the DMAIC approach, this study is expected to deliver measurable, sustainable improvements and significantly enhance the production quality of VRLA batteries.

II. METHODOLOGY

This study employs the Six Sigma methodology using the DMAIC model (Define, Measure, Analyze, Improve, Control) as the main framework to reduce the reject rate in the VRLA battery production process. Each phase of the DMAIC cycle is implemented systematically and structurally, utilizing appropriate tools based on the characteristics of the data and the specific issues in the production process. This approach aims to identify the root causes of defects, implement measurable improvements, and ensure sustainable quality control.

In the Define phase, this study focuses on identifying the main problems contributing to the high reject rate in the production process. To prioritize the most significant types of defects, a Pareto Chart is used to map the contribution of each defect type to the total number of rejected products. This analysis provides an initial overview of the key areas requiring improvement within the process.

Rejects in VRLA battery production are categorized into two types: half battery rejects (Figure 2) and sealing rejects (Figures 3 to 5). The difference lies in the fact that half battery rejects can still undergo rework, but they still cause time losses that ultimately impact production costs.

In contrast to half battery rejects, batteries that experience defects during the sealing stage cannot be reworked. This is because the sealing process is permanent, and reopening the joint can damage the overall structure of the battery. As a result, batteries that are defective at this stage are immediately classified as scrap products, representing a total loss in terms of materials, labor, and production overhead costs. Therefore, rejects occurring during the sealing process result in significantly higher losses and require special attention in quality improvement efforts.



Figure 2: Half battery defect (separator mismatch)

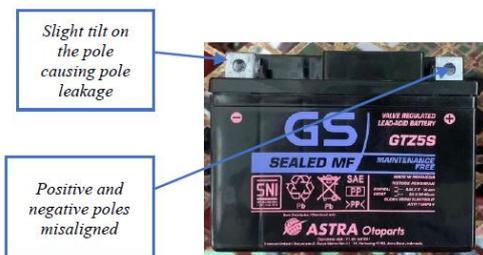


Figure 3: Pole Leak Defect



Figure 4: Cell Leak Defect



Figure 5: Sealing defect (collapsed)

The Measure phase aims to evaluate the current performance of the production process using several quantitative tools. The Defects per Million Opportunities (DPMO) formula is employed to calculate the defect rate based on the number of defect opportunities and the actual production volume. DPMO is a key metric used in Six Sigma to quantify the number of defects per one million opportunities. It is calculated by dividing the number of rejects by the product of total production and the number of defect opportunities. The DPMO value can be determined using Equation 1.

$$DPMO = \frac{(Defects)}{[(Units) \times (Opportunities)]} \times 1,000,000 \quad (1)$$

The Sigma Level is a statistical metric that indicates a process's capability to produce defect-free products. In Six Sigma, the ideal target is 6sigma, which corresponds to only 3.4 defects per million opportunities (DPMO). The Sigma Level is converted from the DPMO value using Six Sigma conversion tables or calculators [16]. The DPMO and Sigma Level data are then visualized in weekly trend charts to monitor fluctuations in production performance. The results of this phase form the basis for assessing the extent of improvement required in the process.

In the Analyze phase, the study focuses on identifying the root causes of defects using the 5 Why's Analysis. This method is applied iteratively to uncover the underlying causes of the most frequent defects, such as separator mismatch or sealing process errors. By repeatedly asking "why," a deeper understanding of the primary sources of nonconformities in the production process is achieved.

The Improve phase involves formulating corrective action recommendations based on the analysis results. Each proposed solution is documented in an Improve-Implementation Table, which outlines the suggested improvements along with their corresponding implementation actions. The improvement efforts are concentrated on processes identified as the main contributors to product rejects, such as reconfiguring machine parameters and retraining operators at critical process points.

Finally, in the Control phase, control measures are implemented to ensure that the improvements achieved can be sustained over the long term. To support this, the company develops and formalizes a new Standard Operating Procedure (SOP) as an updated guideline for operational activities. This SOP is designed to maintain a low reject rate and preserve the achieved Sigma Level. In addition, regular monitoring is conducted to ensure that the implemented improvements are consistently and sustainably applied throughout the production process.

III. RESULTS AND DISCUSSION

The implementation of the Six Sigma methodology using the DMAIC approach at the VRLA battery company can be described as follows, aligned with the sequential stages of DMAIC.

3.1 Define

In the Define phase, defect or reject data was collected over a one-month period and presented in a weekly format (Table 1 and Table 2).

Table 1: Half Battery Defect or Reject Data

Week	Production Target	Actual Production	Mismatch	Damb	Barri
1	9.300	9.349	485	133	87
2	9.300	9.383	423	104	80
3	9.300	9.365	438	96	77
4	9.300	9.315	492	142	85

Table 2: Sealing Defect or Reject Data

Week	Production Target	Actual Production	Pole Leak	Cell Leak	Collapsed
1	9.225	8.917	2	23	4
2	9.225	9.154	3	15	2
3	9.225	9.179	1	12	1
4	9.225	9.888	5	19	2

The data is visualized using Pareto diagrams (Figures 6 and 7) illustrating the frequency of occurrence for each type of defect or reject. The analysis reveals that the most dominant defect is the half battery reject, accounting for nearly 60% of the total product failures. Therefore, improvement efforts will be focused on this type of reject due to its significant contribution to overall product losses.

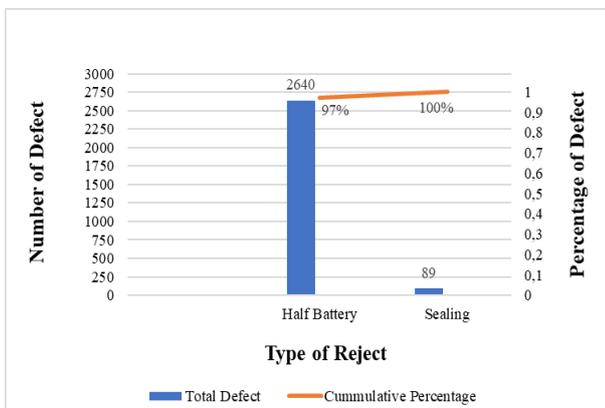


Figure 6: Pareto chart of defect types in VRLA battery products

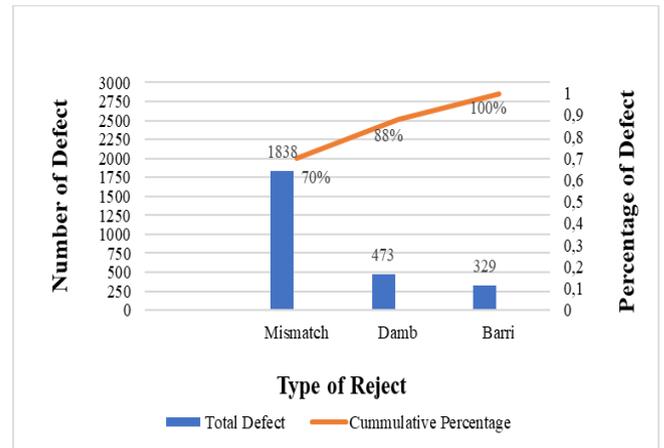


Figure 7: Pareto chart of half battery defect

Based on the data in Figures 6 and 7, the reject rate for half batteries is relatively high, with an average monthly reject rate of around 7%, compared to sealing rejects which are only at 0.25%. Furthermore, the data also indicates that 70% of the half battery rejects are due to separator mismatch.

3.2 Measure

After identifying the main problems, the production process performance was measured by calculating the Defects Per Million Opportunities (DPMO) and sigma level for each type of defect. The measurements were conducted over a one-month period with weekly intervals, and the results are presented in Table 3 and Table 4, as well as Figures 8 and 9.

Table 3: DPMO and Sigma Level on Half Battery Defects

Week	Productions Total	Rejects Total	Opportunities	DPMO	Sigma Level
1	9.349	705	3	25.136	3,5
2	9.383	607	3	21.564	3,5
3	9.365	611	3	21.748	3,5
4	9.315	719	3	25.729	3,5

Table 4: DPMO and Sigma Level on Sealing Defects

Week	Productions Total	Rejects Total	Opportunities	DPMO	Sigma Level
1	8.917	29	3	1.084	4,6
2	9.154	20	3	728	4,7
3	9.179	14	3	508	4,8
4	8.888	26	3	876	4,6

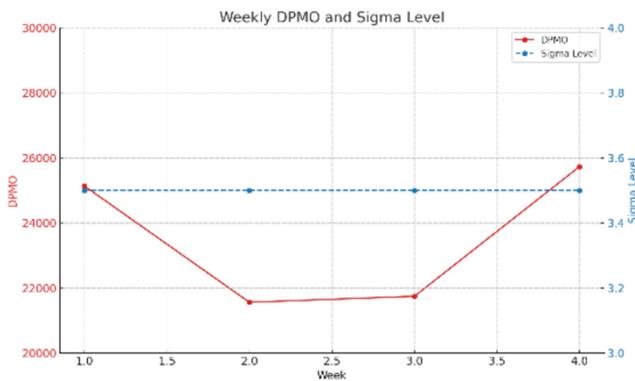


Figure 8: Trend graph of DPMO and sigma level on half battery defect

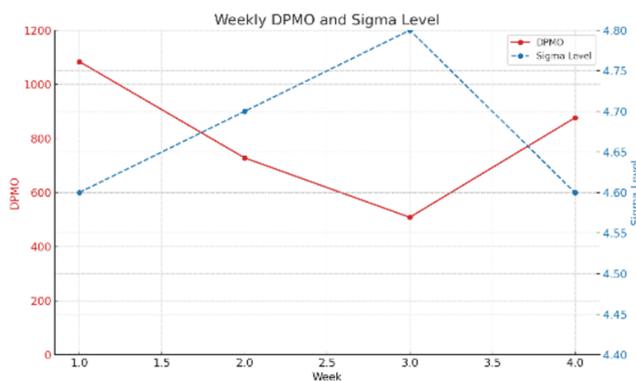


Figure 9: Trend graph of DPMO and sigma level on sealing defect

3.3 Analyze

The analysis focused on the highest type of reject/defect, namely the half battery, with particular emphasis on the mismatch defect in the separator. The approach used was the 5 Why's Analysis method to identify the root cause of the problem (Figure 10).

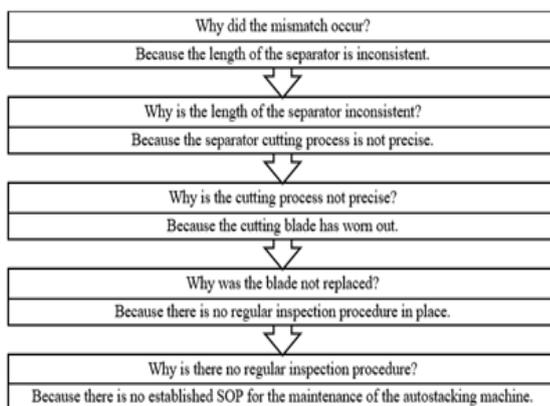


Figure 10: Searching for root causes using the 5 Why's Analysis method

It was identified that the root cause of the problem stemmed from the absence of a Standard Operating Procedure (SOP) for the maintenance of the auto-stacking machine. This machine is responsible for automatically cutting the

separators; however, due to aging and machine degradation, the cutting precision has declined, resulting in mismatched separator dimensions. This issue is further exacerbated by the lack of a preventive maintenance system and scheduled routine inspections.

3.4 Improve

Based on the analysis results, a series of improvement plans were developed with the objective of reducing reject rates and enhancing process capability. Several improvements were systematically designed and implemented, with their outcomes validated accordingly. Examples of the implemented actions include the realignment of separator cutting blades using optimal angle analysis, replacement of worn blades with OEM-standard components, and adjustment of cutting pressure to match the material specifications. These improvement activities were carried out over a four-week period, and the results are presented in Table 5.

Table 5: Measurement Data Before and After Cutting Blade Readjustment

Parameter	Before improvement	After Improvement	Change
Number of mismatch defect/week	324 units	97 units	↓ 70.1%
Standard deviation of dimensions	±2.7 mm	±0.8 mm	↓ 70.4%

The length sensor was recalibrated using a traceable standard device, followed by the installation of a laser-based stack depth sensor with an accuracy of ±0.2 mm. The integration of data from these sensors into the real-time monitoring system generated the results presented in Table 6. The data in Table 6 were obtained through the following calculation process.

Sigma Level Calculation:

Before Calibration:

$$\begin{aligned}
 \text{DPMO} &= 22.750 \\
 \text{Yield} &= \left(\frac{1-22.750}{1,000,000} \right) \times 100\% = 97,73\% \\
 \text{Sigma Level [16]} &= 3.5\sigma
 \end{aligned}$$

After Calibration:

$$\begin{aligned}
 \text{DPMO} &= 4.350 \\
 \text{Yield} &= \left(\frac{1-4.350}{1,000,000} \right) \times 100\% = 99,57\% \\
 \text{Sigma Level [16]} &= 4.12\sigma
 \end{aligned}$$

$$\text{Sigma Level Enhancement} = 4.12 - 3.5 = 0.62\sigma$$

Table 6: Pre- and Post-Calibration Condition Comparison

Parameter	Before Calibration	After Calibration	Improvement
DPMO	22.750	4.350	↓ 80.9%
Sensor Accuracy	92.3%	99.1%	↑ 6.8%
Sigma Level	3.5	4.12	↑ 0.62σ
Yield	97.73%	99.57%	↑ 1.84%

The implementation of a daily audit system using sampling based on the Acceptable Quality Limit (AQL) method, combined with the use of digital measuring instruments, has proven effective in consistently reducing the DPMO throughout the observation period. The detailed results of this implementation are presented in Table 7.

Table 7: Effectiveness of Daily Audits in Reducing DPMO

Period	Initial DPMO	Final DPMO	Reduction
Week 1	23,544	5,870	↓ 75.1%
Week 2	22,980	4,980	↓ 78.3%
Week 3	24,100	4,350	↓ 82.0%
Week 4	23,150	3,850	↓ 83.4%
Average	23,544	4,200	↓ 82.2%

The Standard Operating Procedures (SOPs) were updated by reviewing and revising critical parameters based on the findings from the Failure Mode and Effects Analysis (FMEA). The revised SOPs were then incorporated into a training program delivered to 25 operators from a single production line, divided into three separate training batches. The evaluation results of the SOP updates and training sessions are presented in Table 8.

Table 8: Evaluation Results of SOP Updates and Operator Training

Parameter	Before Training	After Training	Change
Procedure understanding score	72.4/100	94.3/100	↑ 30.2%
Machine setup time	25.7 minutes	14.2 minutes	↓ 44.7%
Process result variation (CV)	8.5%	3.2%	↓ 62.4%
Setup error rate	7.3%	1.2%	↓ 83.6%

The Poka-Yoke system was implemented by integrating visual sensors and an automatic dimensional inspection

mechanism, operating prior to the assembly stage of the separator. This approach aims to prevent errors at an early stage and ensure consistent product quality. The results of the Poka-Yoke implementation are summarized in Table 9.

Table 9: The Results of the Poka-Yoke Implementation

Parameter	Before Poka-Yoke	After Poka-Yoke	Change
Defect detection rate	82,3%	99,7%	↑ 21.1%
Deviarion identification time	35 minutes	2,5 miuntes	↓ 92.9%
Defect passed to next proces	48 units/week	2 units/week	↓ 95.8%

The implementation of the Poka-Yoke system successfully eliminated the need for manual recording, which was often overlooked in the past, thereby reducing the risk of errors caused by operator negligence. With the digitization of deviation data records, root cause analysis can now be conducted more quickly and accurately. Table 10 presents a summary of the improvement plan along with the results of its implementation.

Table 10: Improvement Steps and Their Implementation along with the Results Achieved

No	Improvement Plan	Implementation Result
1	Readjustment of separator cutting blades	Reduced mismatch defects by up to 70%
2	Recalibration of length sensors and addition of stack depth sensors	Increased sigma level from 3,5 to 4,12
3	Daily audit of separator cutting results with digital measuring instruments	Reduced average DPMO from 23.544,24 to 4.200
4	SOP updates and operator retraining	Reduced process variability and increased result consistency
5	Implementation of Poka-Yoke system for early detection of separator errors before assembly	Reduced potential for human error and accelerated deviation identification

3.5 Control

To sustain the improved results achieved, new Standard Operating Procedures (SOPs) have been developed and implemented as part of the ongoing control phase. These SOPs address key aspects of the process, as detailed in Table 11.

Table 11: New Standard Operating Procedure

No	Description
1	Weekly and monthly maintenance schedule for auto stacking machines, including sensor calibration and cutting angle inspection.
2	Daily separator inspection checklist, complete with allowable separator dimension tolerances.
3	Visual work instructions for operators, including how to identify non-conforming separators before assembly.
4	Weekly quality audits that record DPMO and sigma levels to ensure production result stability.
5	Operator retraining every 3 months to maintain quality awareness and technical competence.

IV. CONCLUSION

Based on the results of the analysis and application of the Six Sigma method in the VRLA battery production process, several conclusions were obtained as follows:

1. The main problem causing product rejects and battery leaks is the inaccuracy of the separator cutting by the auto-stacking machine. This results in the separator dimensions not being in accordance during the assembly process, which contributes significantly to product defects and leaks.
2. Before the application of the Six Sigma method, the level of VRLA battery rejects and leaks was relatively high and exceeded the company's target, which resulted in increased production losses.
3. Through the DMAIC (Define, Measure, Analyze, Improve, Control) approach, the following were carried out:
 - a. Identification of the root cause of the problem,
 - b. Measurement of the defect rate,
 - c. Analysis of the root cause,
 - d. Process improvements, such as standardization of separator cutting and maintenance and replacement of critical components on the auto-stacking machine,
 - e. Strict process control.
4. The results of the Six Sigma application showed success in reducing process variation and significantly reducing the defect rate. This has an impact on increasing the stability of the production process and overall operational efficiency.

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Citation of this Article:

Norman Iskandar, Afif Nashafa Al Qauma, & Sulardjaka. (2025). Case Study on the Application of Six Sigma DMAIC for Reducing Product Rejects in VRLA Battery Production. *International Research Journal of Innovations in Engineering and Technology - IRJIET*, 9(5), 246-253. Article DOI <https://doi.org/10.47001/IRJIET/2025.905033>
