Quality improvement of DB-CDP with integration of CRISP-DM and six sigma method

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ARTICLE INFO

Article history
Submission: 26th April, 2023
Revised: 1st August, 2024
Accepted: 8th August, 2024

Keywords
CART Algorithm
CRISP-DM
FP-Growth Algorithm
Six Sigma

https://doi.org/10.22219/oe.2024.v16.i2.110

ABSTRACT

The DB-Customer Display Product (CDP) is a product that has a high level of defects with the type of attribute that the display light is off. The quality improvement is carried out using the integration of the Cross-Industry Standard Process Data mining (CRISP-DM) method with Six Sigma. The technique using classification technique with the CART algorithm to identify the leading causes of defects in the CDP and association processes using the Frequent Pattern-Growth Algorithm to make association rules between the combination of production support data sets. The results of both algorithms known attributes that cause high rejects are poor solder and solder Short. Implementation of proposed improvements made at the deployment stage, there are work instructions for re-soldering, tip checking forms, and Standard Operating Procedures for solder tip replacement. The result from implementation, was decrease in the value of Defects per unit to 0.0541, where previously it was worth 0.0628, and the value of Defects per million Opportunities decreased from 32.636 to 27.020, and converted into sigma level and obtained sigma value 3.80, before the implementation was at 3.74 sigma. The three indicators of DPU, DPMO, and Sigma level indicate that the proposed quality improvement is successful.

1. Introduction

PT. Delameta Bilano is a company engaged in transportation payment control technology in Indonesia, which produces a set of tools for automatic toll gates (GTO). DB-Customer Display Panel (DB-CDP) is a product that has the highest number of tiers. The types of products observed include attributes, and the lights on the panels are off. The data used in this study are production data and data on defective products from June 2021 to September 2021 (see Fig. 1). For CDP products, the percentage is high, between 6% to 12%.

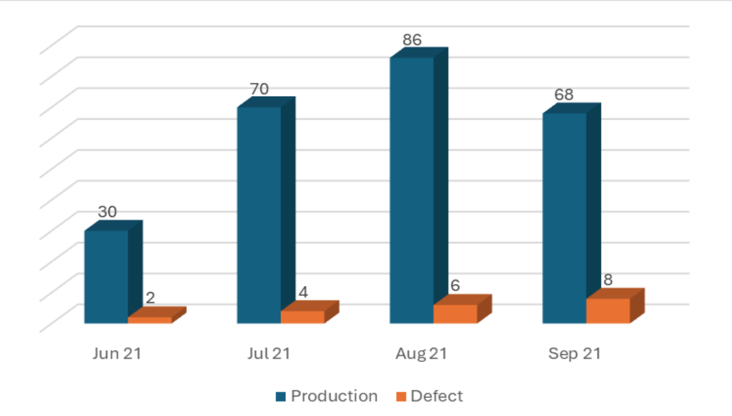

Fig. 1 Graph of CDP production amount and product defects june – sep 2021

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In this study, we are using the integration of CRISP-DM (Cross-Industry Standard Process for Data Mining) with Six *Sigma*. CRISP-DM provides a standard data mining process as a general problem-solving strategy in a business or research unit (Meeting & Chapman, n.d.). The integrating between the two methods results in a data mining study and can be processed using quality tools (Franziska Schäfer, 2018). The mindset used through CRISP-DM, with the algorithm used, namely the CART Decision Tree Algorithm (classification technique), and FP-Growth (association technique) will produce rules that identify the cause of high rejects (Schäfer, 2018).

Quality is one of the most crucial consumer decision factors in selecting competitive products or services (D. C. Montgomery, 2013). Quality has a traditional sense of quality based on the view that products and services must meet the requirements of those who use them or fitness for use (D. C. Montgomery, 2013). Six Sigma (6 σ) is a methodology to improve processes to reduce the percentage of rejects to product defects. It can be interpreted that Six Sigma is a methodology used to make efforts to improve and improve continuous production processes (Joseph C. S, 2018).

Data mining is a process of finding something meaningful from existing relationships, patterns, and trends by selecting large data stored in a repository, using pattern recognition technology as well as mathematical and statistical techniques (Liu & Sun, 2009). CRISP-DM (Cross-Industry Standard Process for Data Mining) is a standard that was developed in 1996, and intended when conducting an industrial analysis process as a form of strategy for solving business problems (Schäfer, 2018).

Business Understanding includes project analysis, understanding, and definition, to understand what the customer wants to achieve (P. Chapman & Clinton, 2000). Data understanding is an understanding of the data to be studied. The next stage is data preparation. The process in this stage are data cleaning, data reduction, and data transformation. In the modeling stage, data modeling is carried out based on data sets through techniques in data mining. The first technique used is the Frequent Pattern-Growth Algorithm. This algorithm is used to find the frequent itemset from the transaction dataset and get the association rules. After the frequent itemset is obtained, then produces association rules with confidence greater than or equal to the minimum confidence specified by the user (Shaukat Dar et al., 2017). The CART (Classification and Regression Tree) algorithm is one of the methods with data exploration techniques, and decision tree (Steinberg, 2009). CART was developed to perform classification analysis. After the two techniques are carried out, and evaluation of this technique is carried out by calculating the accuracy value. And continued with the deployment phase, as a result of the proposed improvement implementation. The QM-based CRISP-DM cycle become the DMAIC cycle (Define, Measure, Analyze, Improve, and Control. Problem-solving can be solved by using the quality management, and the world of six *sigma* (da Silva et al., 2019).

The purpose of the research conducted at PT. Delameta Bilano is to reduce the number of defective products and reduce the level of *sigma* in the case of DB-Customer Display Panel (DB-CDP) product defects. This can be achieved through:

1. Identify business objectives and data mining objectives at the business understanding stage.
2. Determine the level of *sigma* of the Customer Display Panel (CDP) production process based on the data understanding stage.
3. Determine the identification of the causes of defects through the results of the Frequent Pattern-Growth and CART algorithms on Customer Display Panel (CDP) products.
4. Determine the accuracy value of the modeling results with the decision tree on the CART algorithm of the CDP product.
5. Formulate quality improvement proposals in the DB-Customer Display Panel (CDP) production process to improve product quality based on analysis of data modeling results.

Determine the capability of the production process and the level of sigma of the DB-Customer Display Product (DB-CDP) production process after implementation.

2. Methods

Research requires accurate and systematic steps to achieve good results. The study underwent several stages of implementation, including preliminary research, problem identification, literature review, research objectives, data collection, data processing, and results analysis. To clarify the data processing procedure, create a flow chart that includes the data processing phases shown in Fig. 2.

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This figure details the data processing based on the CRISP-DM phase. Business understanding, data understanding, data preparation, modeling, scoring, and deployment (Ayele, 2020).

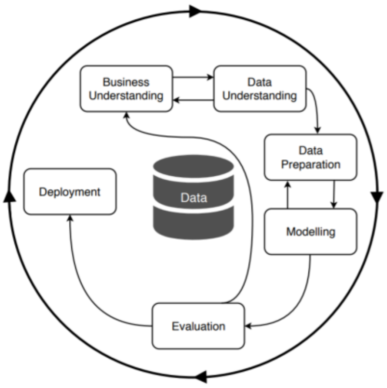

Fig. 2 Process of CRISP-DM (Schäfer, 2018).

The CRISP-DM framework used (Cross-Industry standard process for data mining) is as follows:

1. The business understanding phase consists of definitions of business goals and data mining, to identify suppliers, inputs, processes, outputs, customers (SIPOC) diagrams to define production process activities. It has a critical toe quality (CTQ). This represents a limitation on the quality characteristics of the Character Display Panel (CDP).
2. Understanding the data is the phase of data acquisition, and data selection, which includes process stability with P control charts and calculation of DPU, DPMO, and *sigma* values.
3. In the Data Preparation stage, there are preprocessing stages consisting of data cleaning, data reduction, and data transformation. With a new dataset output ready to be modeled.
4. In the Modeling stage, data modeling is carried out using two techniques, namely the classification technique with the Decision Tree CART algorithm with MINITAB, and the Association technique with the Frequent PatternGrowth Algorithm using RapidMiner.
5. In the evaluation phase, the accuracy level is calculated based on the obtained model results, and Ishikawa and the FMEA diagram tool are used to further analyze the main causes of high rejection.

The deployment is the phase of implementing improvement proposals based on data analysis.

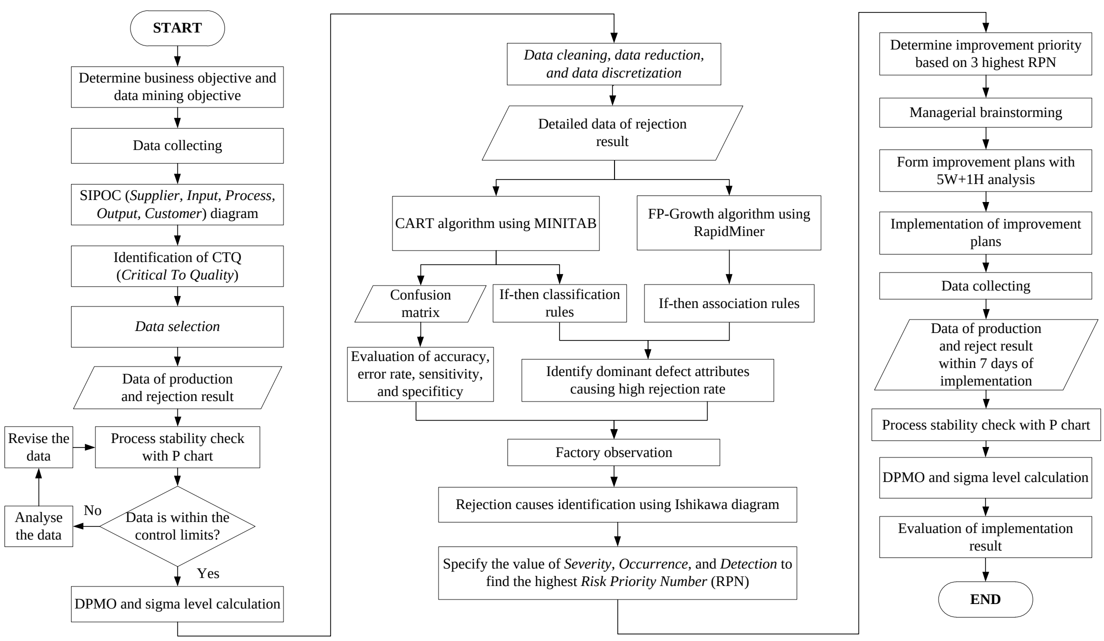

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Fig. 3 Methodology

3. Results and Discussion

Business Understanding

In this study, the business objective was determined to be to reduce the number of rejected products, while the objective of data mining was to explore the knowledge of defect patterns that cause high rejection (Theodora et al., n.d.). In addition, the SIPOC diagram showed ten production processes for DB-CDP, namely material inspection, taking solder paste to PCB, Soldering, Drying, Sub Assembly, inspection for Assembly, Inspection for Casing CDP, Assembly, and Final Inspection. CTQ or Critical to Quality Characteristics is a factor or parameter that is the main driver of quality in a process. In Table 1, the types of defects in CDP products show five types of attribute defects, based on the type of defect and a description of the defect.

Table 1 CTQ

No	Defect Attributes	Details
1	Short Solder	Overflow Tin
2	Peeled	Leadless Soldered PCB
3	Poor Solder	Less solder
4	LED Blink	Different IC maker
5	Shifting	Moving Chip

Data Understanding

At this stage, the function is to understand the data so that the data can be identified related to quality improvements that will be carried out on CDP products, and process control calculations are carried out with P control charts (Fig. 4). In its use, the P control chart serves to determine the stability of the processes that occur in the production process of CDP products from June to September 2021.

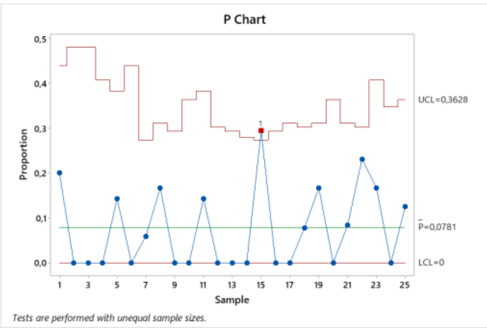

Fig. 4 P chart.

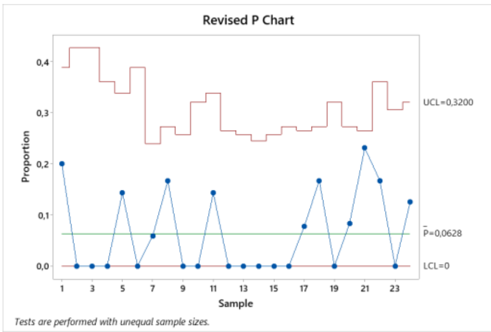

Fig. 5 Revised P chart.

From the calculation results, the DPU value is 0.16317, so the chance of a defect in the CDP (character display product) product is 1.63% per unit. The DPMO value 32.636, which means that every 1 million CDP products have a probability of 32.636 defects. The sigma value is 3.74, where this value shows that the existing process is still at the level above the industry average in Indonesia, which is generally in the range of values of 2 to 3 sigma, while the sigma level is below the average USA industry which is generally at levels above four sigma.

Data Preparation

At this stage, using data preprocessing, there are three steps used in this study, namely starting with data cleaning, then data reduction, and data transformation (Adrita et al., 2021).

Modeling

The model development is carried out with the help of RapidMiner and MINITAB software, because in both software no coding is needed. RapidMiner is used to get the results of association rules using FP-Growth or Frequent Pattern – Growth which functions to be able to run the association rule technique (Andi & Utami, 2018). This operator will calculate the combination of the occurrences of itemsets from the data set. To run this operator, there is a rule that the data is of the binomial type or

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only consists of two decisions, such as "YES" and "NO" , or "Reject low" and "Reject high". After the process is run, it will produce output in the form of Association rules as follows:

```
1.   [% ACTUAL REJECT] --> [Solder Short, Poor Solder] (confidence: 0.567)
2.   [Solder Short] --> [% ACTUAL REJECT, Poor Solder] (confidence: 0.594)
3.   [Solder Short] --> [Poor Solder] (confidence: 0.656)
4.   [Poor Solder] --> [% ACTUAL REJECT, Solder Short] (confidence: 0.667)
5.   [% ACTUAL REJECT] --> [Poor Solder] (confidence: 0.716)
6.   [% ACTUAL REJECT, Solder Short] --> [Poor Solder] (confidence: 0.731)
7.   [Poor Solder] --> [Solder Short] (confidence: 0.737)
8.   [% ACTUAL REJECT] --> [Solder Short] (confidence: 0.776)
9.   [% ACTUAL REJECT, Poor Solder] --> [Solder Short] (confidence: 0.792)
10.  [Solder Short] --> [% ACTUAL REJECT] (confidence: 0.812)
11.  [Poor Solder] --> [% ACTUAL REJECT] (confidence: 0.842)
12.  [Solder Short, Poor Solder] --> [% ACTUAL REJECT] (confidence: 0.905)
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The support value is a value to determine the possibility of an item appearing together with other items, and the confidence parameter determines how often the If-Then Rules rule appears. Based on the results of the association rules, there are 12 association rules from 56 attribute items, namely five types of defects, and one attribute of reject decisions. In addition, the results of the rule have a combination pattern of 2 dominant disability attributes, namely Poor Solder, and Solderan Short, and are associated with the % Actual Reject item. The confidence value obtained has the smallest value of 0.567, and the largest confidence value of 0.905. So that it can be concluded that if there is a Poor solder defect, a short solder defect will also appear, and this will result in a high reject rate.

The decision tree is a decision tree graph to classify the types of attributes from a data set. The use of tree graphs can also make it easier for readers to understand. This technique will produce a binary branch, which means that in sorting the data, the data collected will be selected in a space called a node or node. These nodes will create two children called child nodes. This procedure is done recursively, where the separation is repeated until it meets certain criteria. Partitioning is also carried out in this method, the classification process is carried out by sorting some data into several parts.

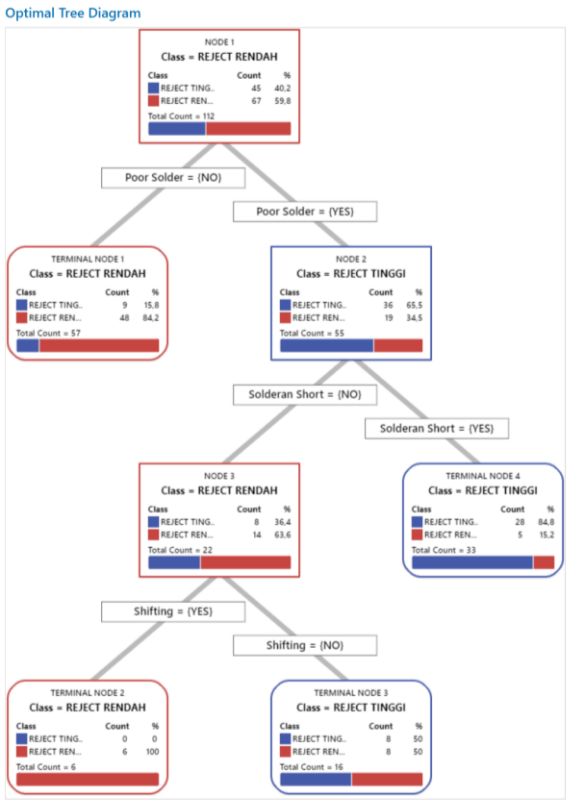

Fig. 6 Decision tree CART algorithm.

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Based on the modeling performed using the decision tree and FP-Growth, it can be concluded that there are two dominant attributes, namely Poor solder, and Solderan Short in the Decision Tree, and these two attributes are contained in the FP-Growth association rules (Andi & Utami, 2018). So that the two disability attributes, namely Poor solder, and Solderan Short in the Decision Tree, have the potential to result in high rejection, so the problem analysis is focused on these two types of defects.

Evaluation

This evaluation can be calculated through the performance obtained and the level of accuracy. This calculation requires the results of the confusion matrix obtained from the MINITAB software.

Table 2 Confusion matrix

		Predicted Class (Training)			Predicted Class (Test)		
Actual Class	Count	REJECT TINGGI	REJECT RENDAH	% Correct	REJECT TINGGI	REJECT RENDAH	% Correct
REJECT TINGGI (Event)	45	36	9	80,0	36	9	80,0
REJECT RENDAH	67	13	54	80,6	13	54	80,6
All	112	49	63	80,4	49	63	80,4

Statistics	Training (%)	Test (%)
True positive rate (sensitivity or power)	80,0	80,0
False positive rate (type I error)	19,4	19,4
False negative rate (type II error)	20,0	20,0
True negative rate (specificity)	80,6	80,6

Based on these calculations, the values for accuracy, error rate, sensitivity, specificity, precision, and recall are obtained. The accuracy value is a measure of the specifications used for the general standard of size from the classification model used, in this study, namely the Decision tree. In the calculation, the accuracy value is 80.3%, which shows that the model has high accuracy with an error rate of 19.7%. The error rate value is the percentage of errors that can occur in the model used, and this value can also be calculated through 1 minus the accuracy value. Furthermore, the Sensitivity value is 80%, this value is the ability to correctly predict high rejects (Morlock & Boßlau, 2021), so even though the accuracy of the obtained accuracy is 80.3%, the correct prediction value is obtained for high rejects, which has a slightly smaller percentage. Precision is the value of the percentage of accuracy between the requested data is positive, namely high rejects with the prediction results obtained by the model, and the percentage value of precision is 80.5%. Specificity and recall are true rates, namely the ability to correctly predict low and high rejects, and obtained a value of 80% for high rejects and 80.6% for low rejects, so the testing data is considered predictable correctly.

Based on the modeling stage, it is found that defect attributes are capable of causing high rejects, but have not explained the causes of the existing problems, so the results from these stages need to be analyzed using six *sigma* tools, namely Ishikawa diagrams and FMEA (Failure Mode and Analysis), with the aim of using tools This can identify the causes of the existing disability attributes (Bhargava & Gaur, 2021). Based on the results obtained at the Modeling stage, it has two types of dominant disability attributes, namely Poor Solder and Solder Short.

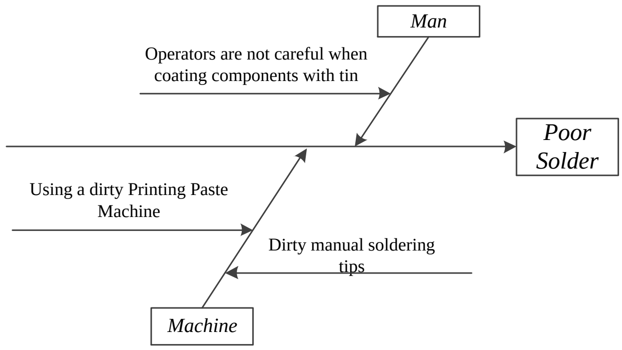

Fig. 7 Ishikawa diagram for poor solder.

Ishikawa diagram on the machine factor is caused by using a dirty printing paste, and dirty manual soldering tips. These two factors cause the tin paste used to be used unevenly throughout the components on the PCB (Printed Circuit Board), because the tin cannot flow perfectly and is blocked by the existing impurities. In the man factor, poor soldering can occur because the operator is not careful when coating components with tin, so some components are not coated with tin.

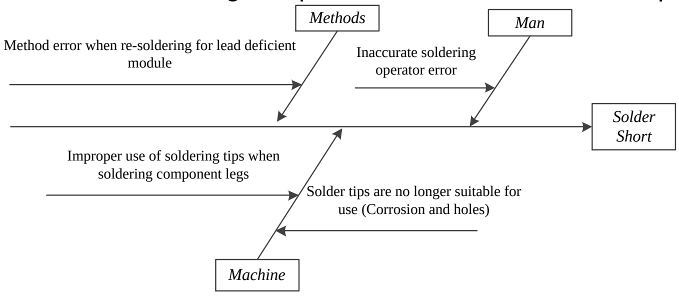

Fig. 8 Ishikawa diagram for solder short.

On the machine factor, it is caused by the use of solder tips that are not precise when soldering the component legs and the soldering tips are not suitable for the use marked by corrosion and holes. These two factors cause the tin paste to overflow, because the tin during soldering is excessive, so the tin hits other components. In the man factor, the operator was not careful so he was excessive when soldering components, especially when re-soldering a module that previously experienced a lack of solder (Poor solder), which resulted in excess of lead.

The identification result on the Ishikawa diagram are then analyzed using the FMEA table. Failure Mode and Effect Analysis (FMEA) is a tool for analyzing Quality Management (QM), to find the Risk Priority Number (RPN), so that it can determine the priority of solving the causes of existing defects (D. C. Montgomery, 2013). FMEA has three values, namely Severity (S), Occurrence (O), and Detection (D) (Saxena, 2021). The 3rd score is filled in based on an interview with the head of SMT production, namely Mr. Bambang, and is made in the form of a reference table for filling out the FMEA.

Tables 3 FMEA Analysis

Failure Type	Process	S	Cause Of Failure	O	Control	D	RPN
Poor Solder	Soldering	7	Using a dirty Printing Paste Machine	4	Printing Paste machine cleaning	5	140
			Operators are not careful when coating components with tin	3	Conducting training on Operators	5	105
			Dirty manual soldering tips	6	Solder tip checking and cleaning	5	210
Solder Short		6	Inaccurate soldering operator error	4	Conducting training on Operators	4	96
			Improper use of soldering tips when soldering component legs	6	More precise soldering tip replacement	6	216
			Solder tips are no longer suitable for use (Corrosion and holes)	5	Solder Tip Replacement	6	180
			Method error when re-soldering for lead deficient module	7	Manual re-soldering	6	252

Poor solder has a severity value (S) of 7, and this value is included in the high category, this is because the type of disability attribute is included in the critical category (D. C. Montgomery, 2013), which makes customers dissatisfied, and the product takes a long time when reworked. This defect is caused by three factors, namely the use of a dirty printing paste machine, dirty manual soldering tips, and the operator is not careful when coating components with tin. In calculating the RPN value, the RPN value is 210.

This type of defect soldering Short has a severity value (S) 6. This is because this type of defect is caused by the use of imprecise soldering tips during the soldering process for component legs at very close distances, solder tips are not suitable for the use which are marked by corrosion and holes, and the operator is not careful so that it is excessive when soldering components. This type of defect has the second-highest RPN value with a value of 216 for the cause of defects in the use of imprecise soldering tips, and the highest RPN value is on the cause of method errors during re-soldering for modules experiencing lead deficiency with an RPN value of 252, due to With this type of defect, the production process will take longer, because the work is carried out three times, namely at the time of the first and second failed to solder, then the extraction of the spilled tin is carried out, and manual re-soldering is carried out.

Deployment

At this stage, present the knowledge obtained based on the evaluation of the model from the entire data mining, so that the data that has previously been evaluated and modeled can provide clear information on the resulting knowledge (Franziska Schäfer, 2018). Where the modeling, and evaluation stages produce the causes of problems that need to be resolved, the causes of these problems are dirty manual soldering tips that are not even suitable for use, the use of inappropriate tips and method errors when re-soldering for modules that have a lack of leadership. The cause of this problem causes defects in the form of Poor soldering and Short soldering. The formulation of improvement proposals with the aim of reducing the number of defective CDP, is carried out through a brainstorming approach with the factory production party, resulting in a comprehensive improvement proposal and can be a solution to the problems that occur. Brainstorming is a discussion activity about possible options that can be made for proposed improvements, especially in order to improve product, and not hamper the ongoing production process.

Based on the results of the use of Poor solder and Solderan Short are the types of defects found in the PCB module soldering process. After discussions with the operator and the head of SMT production, it was found that the existing checks and replacements were carried out without data records or had standard working procedures. Poor solder rework is caused by a lack of tin that does not have a standard working procedure, so during soldering, it can result an excess tin. The work at the time of soldering requires precise accuracy. Even though the SMT has checked, it is possible that when the module arrives on the assembly side and is installed on the product, it can cause the CDP product not to turn on. it takes a long time to rework, because the components on the PCB module are very small and have the number is large, so it must be checked one by one the components that are the cause of the death of the CDP product. Therefore, through brainstorming, it was agreed that the quality inspection could be improved by seeking suggestions for improving the work instructions for re-soldering lead shortages, filling out check forms and SOPs for changing soldering tips to be filled out by the operator.

Table 4 Improvement proposal

Failure Type	Cause of Failure	Improvement Proposal
Poor Solder	Dirty manual soldering tips	Making checking forms and SOPs for changing Soldering Tips
Solder *Short*	Improper use of soldering tips when soldering component legs	
	Method error when re-soldering for lead deficient module	Preparation of work instructions for re-soldering of lead-deficient modules

4. Conclusion

Based on data processing and analysis in research, the following conclusions are obtained. Based on the Business Understanding stage, the business objective in this research is to reduce the number of defective CDP (Character Display Panel) products. The objective of data mining in this study is to gain knowledge about the relationship patterns of the types of product defects using the Frequent Pattern Growth algorithm in data mining and reject product classification using the decision tree on the CART algorithm. At the data understanding stage, the DPU value is 0.068. The DPMO value is 12560. The *sigma* value is 3.74, where this value shows that the existing process is still at the level above the industry average in Indonesia. In the modeling using Decision Tree and FP-Growth, it can be concluded that there are two dominant attributes, namely Poor solder, and Solder Short in the

ISSN-p: 2085-1431
ISSN-e: 2654-5799

Decision Tree, and both attributes are contained in the if-then-else rules of the FP-Growth association. So it has the potential to result in a high Reject. The accuracy value measures the specifications used for the general standard of size from the classification model used, namely the Decision tree. In the calculation of the evaluation stage, the accuracy value is 80.3% showing that the model has good accuracy with an error rate of 19.7%. At the deployment stage, to improve product quality, implementation was formulated in the form of work instructions for re-soldering components that experienced a lack of leadership, instructions for checking solder tips, forms for checking soldering tips, and SOP (Standard Operating Procedures) replacement for soldering tips.

Acknowledgments

The authors pay homage to the Magister of Industrial Technology, Universitas Trisakti. This paper is the research funded by Universitas Trisakti in the academic year 2023/2024.

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Please cite this article as: Alfiandi, A., S.D., T., & Fitriana, R. (2024). 8D methodology implementation to quality improvement: study case PT. XYZ. Operations Excellence: Journal of Applied Industrial Engineering, 16(3), 309-318. doi:http://dx.doi.org/10.22441/oe.2024.v16.i2.110