Available online at : http://josi.ft.unand.ac.id/

Jurnal Optimasi Sistem Industri

| ISSN (Print) 2088-4842 | ISSN (Online) 2442-8795 |

Research Article

Enhancing Quality Control of Packaging Product: A Six Sigma and Data Mining Approach

Resty Ayu Ramadhani [a], Rina Fitriana [a,*], Anik Nur Habyba [a], Yun-Chia Liang [b]

[a] Departement of Industrial Engineering, Universitas Trisakti, Indonesia
[b] Department of Industrial Engineering and Management, Yuan Ze University, Taiwan

* Corresponding Author: rinaf@trisakti.ac.id

DOI: 10.25077/josi.v22.n2.p197-214.2023 **Submitted** : March 5, 2023 ; **Accepted** : November 20, 2023 ; **Published** : December 18, 2023

ABSTRACT

Six Sigma is of paramount importance to organizations as it provides a structured and data-driven approach, fostering continuous improvement, minimizing defects, and optimizing processes to meet and exceed customer expectations. In response to the increasing defects of packaging product in a cosmetics industry in Indonesia, surpassing the specified 3% tolerance limit, this research conducts a thorough investigation into the root causes, corrective measures, and improvement proposals to elevate product quality. By leveraging the Six Sigma method and data mining techniques, the study systematically addresses the complexities associated with defect reduction in packaging for cosmetics product. The research methodology encompasses defining the problem through SIPOC and Critical to Quality (CTQ) diagrams, measuring via control charts and sigma level calculations, and analyzing using tools like pareto diagrams, Apriori algorithms, fishbone diagrams, and Fault Mode and Effect Analysis (FMEA). Key findings reveal a notable correlation between spot defects and varying colors, leading to pearl defects as identified by the Apriori algorithm. FMEA identifies critical failures, including suboptimal printing plate conditions, clumpy ink usage, and insufficient operator attention to ink filling. The improvement stage proposes practical solutions, such as implementing alarms and buzzers, color-indicator-adjusted ink storage labels, and a structured form for cleaning and monitoring printing plates. These findings carry significant implications, providing a tailored roadmap for enhancing the quality of cosmetic packaging. The anticipated implementation of proposed improvements aims to elevate customer satisfaction by addressing specific pain points in the production process. Furthermore, the research contributes valuable insights to the broader cosmetics industry, offering effective methodologies for defect reduction and quality enhancement in packaging processes.

Keywords: Six Sigma, Data mining, Apriori algorithm, Failure Mode and Effect Analysis

INTRODUCTION

Successful companies thrive by ensuring customer satisfaction, primarily through the quality of their products [1]. Quality control is a critical aspect for companies, as it directly influences customer satisfaction and loyalty [2],[3],[4]. K.J.P Co., an offset printing company specializing in the production of packaging for cosmetic products, operates on a make-to-order system, necessitating stringent quality adherence to meet customer specifications in design and production. Despite efforts like gradual inspection, supervisor oversight, and manual ink dilution, the company faces challenges with a defect rate exceeding the accepted 3% threshold. This scenario indicates suboptimal quality control processes and underscores the need for a detailed analysis to enhance product quality and reduce defects.

Previous research [1] applied the Six Sigma method for quality control, achieving a notable 0.17 sigma improvement by identifying dominant defect factors. Another study by [5] utilized data mining, specifically the Apriori algorithm, to uncover frequent defect itemsets in production. This research builds upon these methodologies, combining Six Sigma's Define, Measure, Analyze, Improve, and Control framework [3],[6] with the Apriori algorithm's pattern recognition capabilities in data mining. The synergy of these methods is used to identify prevalent defects affecting product quality. To further evaluate potential failures and their impacts, Failure Modes and Effects Analysis (FMEA) is employed. FMEA offers a structured approach to problem identification and prioritizes risk numbers for quality improvement, making it a crucial tool in our analysis.

Quality, fundamentally, is the product's fitness for use, assessed against its intended specifications [2]. It is inherently linked to variability; as variability in product characteristics diminishes, the product's quality correspondingly escalates. This concept of quality is multifaceted, encapsulated by eight dimensions: performance, reliability, durability, serviceability, aesthetics, features, perceived quality, and conformance to standards. Each dimension provides a lens to evaluate a product's ability to satisfy customer expectations and adhere to manufacturing criteria [2],[7]. The Six Sigma method embodies a philosophy of perpetual improvement in product quality and production processes [8]. It is a systematic approach aimed at minimizing variability and reducing defect rates, with an ambitious goal of limiting failures to 3.4 per million opportunities, essentially pushing for near-perfect quality [9]. Defined by the DMAIC framework—Define, Measure, Analyze, Improve, and Control—Six Sigma is a cyclical process that iteratively advances towards excellence in process improvement and product quality [10]. This structured method emphasizes rigorous data analysis and problem-solving to achieve and maintain high standards of performance.

Data Mining is the investigative process of extracting novel and insightful information from large datasets. It involves discovering hidden patterns and relationships that can inform decision-making [11]. The field of data mining encompasses various tasks: description, estimation, prediction, classification, clustering, and association, each with specific goals and methods for analyzing data [5]. This process is integral to transforming raw data into meaningful, actionable insights. Association rules in data mining serve to uncover relationships between variables within datasets, identifying if the presence of one item influences the occurrence of another [12]. These rules are quantified using measures of support and confidence, providing a statistical basis for determining the strength of the associations found [11]. The Apriori algorithm is a key technique in this process, designed to discover itemsets that appear together with a frequency that meets user-specified criteria [13]. It involves iterative steps, starting with candidate itemset formation, support calculation for these itemsets, and concluding once no new frequent itemsets are found. These steps ensure that only the most relevant patterns are considered for analysis.

Our study is driven by the objective to enhance the quality control mechanisms at K.J.P Co. through the integration of Six Sigma and data mining techniques. Specifically, we aim to reduce the packaging defect rate below the current 3% threshold, identify the most frequent defect patterns, and recommend actionable strategies for quality improvement. This endeavor holds significant importance as it not only seeks to bolster operational efficiency but also to reinforce customer trust and satisfaction in the competitive field of beauty product packaging. The scope of this research is confined to the analysis of historical production data in existing quality control infrastructure of K.J.P Co. We limit our investigation to the packaging process of the Lightening Powder Foundation (LPF) product line. While our findings may offer valuable insights for similar manufacturing environments, they may not be directly transferable to different products, companies, or industries with distinct operational processes and constraints. Future studies may extend this research to broader contexts to validate the universality of the proposed methodology.

METHODS

The methodological flow of this study is encapsulated within the Six Sigma framework, specifically the DMAIC phases: Define, Measure, Analyze, Improve, and Control. Figure 1 is an explanation of the processing stages carried out using the framework. This structured approach aims to address and improve the quality issues of LPF packaging systematically. In the 'Define' phase, the critical aspects of the packaging quality issues are identified, and a SIPOC (Suppliers, Inputs, Process, Outputs, and Customers) diagram is constructed to provide a comprehensive view of the contributing factors and outputs. Moving into the 'Measure' stage, historical data is meticulously collected, employing control charts to track and measure the extent and nature of the packaging defects. This phase sets the foundation for data-driven decision-making. Transitioning to the 'Analyze' phase, the collected data undergoes a rigorous process of mining using the Apriori algorithm to detect common patterns among the defects. This analytical approach reveals the underlying causes that contribute to the quality issues.

 DOI: 10.25077/josi.v22.n2.p197-214.2023

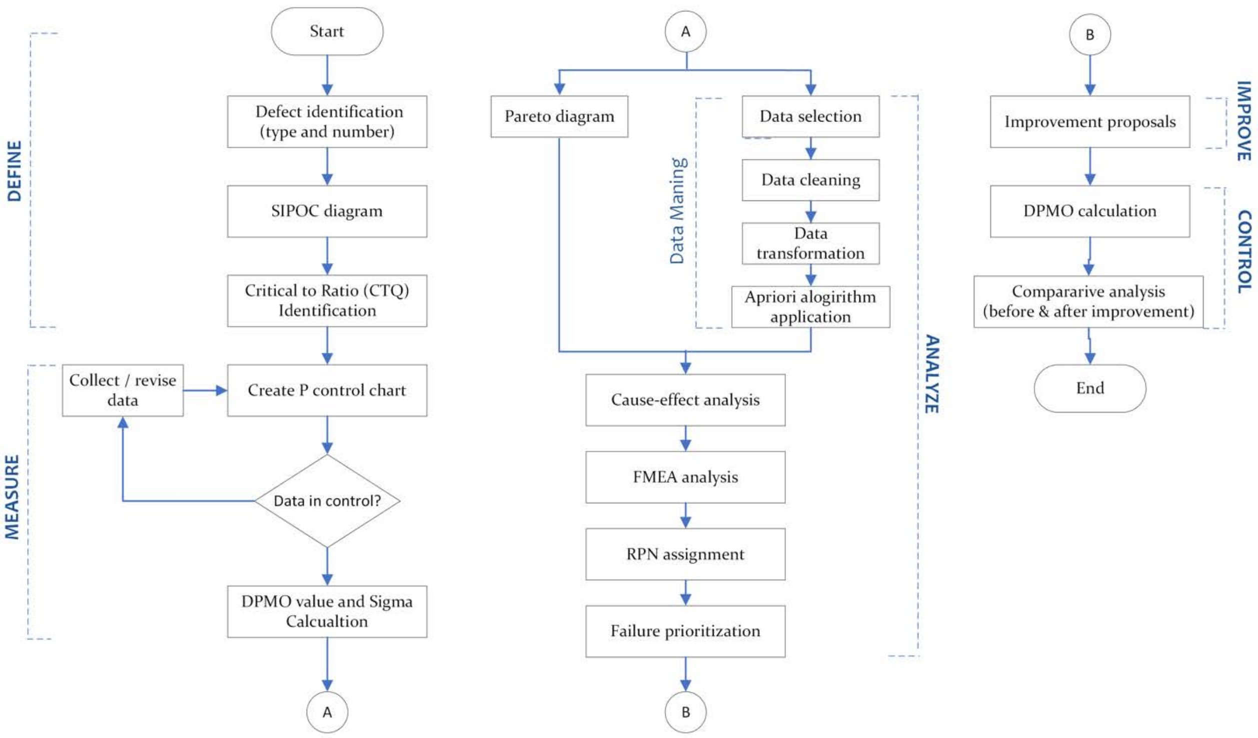

Figure 1. Proposed Six Sigma and Data Mining Framework

With the insights gained, the 'Improve' phase is initiated, employing FMEA to evaluate each potential failure mode's severity and occurrence. The Risk Priority Numbers (RPN) are calculated to prioritize interventions effectively. Strategies are then developed to mitigate the defects with the highest RPNs, ensuring targeted improvements. The final 'Control' phase is implemented to maintain the gains achieved by the improved processes. Continuous monitoring is set in place to ensure the sustained enhancement of product quality. The effectiveness of these improvements is quantified through the calculation of the sigma level, signifying the process capability and aligning with the overarching goal of Six Sigma—near perfection in quality standards. This comprehensive approach to quality improvement, rooted in data-driven decision-making, contributes to the enhancement of product quality, customer satisfaction, and loyalty.

RESULTS AND DISCUSSION

Stage 1: Define

This stage begins with collecting data on the production process and the output (LPF packaging). From these data, the identification of production activities is carried out using the SIPOC diagram (Supplier, Input, Process, Output, Customer) and identification of Critical to Quality (CTQ) to determine quality characteristics. A SIPOC diagram is identified starting from the raw materials acquisition until the product is ready to be sent to the customer [14]. The SIPOC diagram of LPF packaging can be seen in Table 1. In addition, Critical to Quality (CTQ) identification is carried out to determine, based on the production data obtained, which type of product is considered defective depending on the type of defect that occurs [15]. The packaging, i.e., cardboard packaging for cosmetic products, must be of good quality and must not have any defects that may affect the quality and aesthetics of the product.

The Quality Characteristics of LPF Packaging in good condition if it meets the characteristics of one of these characteristics:

a. There are no contaminations in the product that comes from the production process.
b. There are no torn parts on the surface of the product.

Table 1. SIPOC Diagram

Supplier	Input	Process	Output	Customer
PT Surya Pemenang, PT Cemani, PT Plastino Sinar Jati Jaya, *Glory*	Plano Paper, Plastic, Ink, Glue, Hologram	Incoming Material	Raw Material	Raw Material Warehouse
Raw Material Warehouse	Plano Paper	Taking material	Plano paper	Automatic cutting machine
Automatic cutting machine	Plano paper	Paper measuring and cutting	Ready to print paper	4-color print machine
4-color print machine	Ready to print paper, ink	Printing	The Print Result	Laminating machine
Laminating machine	The Print Result, Plastic	Laminating	Laminating result	Hot stamp machine
Hot stamp machine	Laminating result, hologram	Hot stamping	Hot stamping result	Cutting machine
Cutting machine	Hot stamping result	Cutting	Unit sheet packaging	Inspection Area
Inspection area	Unit sheet packaging	Inspection	Unit sheet packaging (OK)	Automatic glue machine
Automatic glue machine	Unit sheet packaging (OK)	Gluing	Packaging	Packing area
Packing area	Packaging	Packing	Box packaging	Warehouse
Warehouse	Box packaging	Shipping	Box packaging	Customer

c. Have a color that matches the standard color range that has been set.
d. Have a composition and design position following product specifications.
e. Completely and clearly printed design elements.
f. The side of the packaging is well-folded and perfectly attached.

Conversely, the Quality Characteristics of LPF Packaging fall into the category of defective products. Through direct observation, eight types of defects were identified, which include:

a. Hickies are small ring-shaped white spots on the surface of printed paper.
b. Dirty are stains or dirt attached to the surface of the printed paper.
c. Various colors are the printout color that is not within the specified color range
d. Miss prints are print images that do not fit in place or skewed.
e. Lopsided define the hot stamping results tend to be higher than the position they should be due to operator error.
f. Delamination is the adhesive on the product side that is loose or does not stick properly.
g. Shreds is parts of the packaging that are torn.
h. Spotting are splashes of ink in certain areas on the product's surface.

Stage 2: Measure

In the measure stage, a control chart is calculated to determine whether the product defect data from the production process of LPF Packaging is within the statistical control limits. Control chart calculations display graphs showing data outside the control limits [16]. Furthermore, control chart calculations are carried out to determine process capability by determining the DPMO value and sigma level.

 DOI: 10.25077/josi.v22.n2.p197-214.2023

Table 2. Calculation of P Control Chart – Initial Data of Defect

Date	Total Production	Defective Product	Proportion	UCL	LCL	Status
17/09/2022	24,540	911	0.037	0.043	0.036	In control
18/09/2022	25,680	955	0.037	0.043	0.036	In control
21/09/2022	23,810	894	0.038	0.043	0.036	In control
22/09/2022	25,700	965	0.038	0.043	0.036	In control
23/09/2022	27,460	1,025	0.037	0.043	0.036	In control
24/09/2022	31,810	1,185	0.037	0.043	0.036	In control
01/10/2022	22,580	905	0.040	0.043	0.035	In control
03/10/2022	26,670	1,104	0.041	0.043	0.036	In control
05/10/2022	28,700	1,094	0.038	0.043	0.036	In control
06/10/2022	27,880	1,163	0.042	0.043	0.036	In control
14/10/2022	22,580	915	0.041	0.043	0.035	In control
19/10/2022	30,510	1,215	0.040	0.043	0.036	In control
22/10/2022	24,080	983	0.041	0.043	0.036	In control
07/11/2022	31,360	1,173	0.037	0.043	0.036	In control
08/11/2022	23,005	1,269	0.055	0.043	0.035	Out of control
09/11/2022	27,730	1,123	0.040	0.043	0.036	In control
16/11/2022	25,450	963	0.038	0.043	0.036	In control
17/11/2022	27,300	1,037	0.038	0.043	0.036	In control
21/11/2022	22,355	858	0.038	0.043	0.035	In control
22/11/2022	31,800	1,152	0.036	0.043	0.036	In control

P-control Chart

A control chart is a statistical Process Control (SPC) tool that it can use for quality control processes. The control chart used in this study is the attribute control chart, namely the p control chart, to determine the proportion of product defects. Table 2 presents the proportion of defective product data from September to November 2022. An out-of-control data point was identified, indicated by an increase in defective products. To address this, the control chart in Table 2 was revised by excluding the out-of-control data, reflecting a state of in-control defect proportions (Figure 2).

Calculation of DPMO Value and Sigma Level

The steps determining the number of total productions, total defects, DPO (Defect per Opportunity), DPMO, and the sigma level.

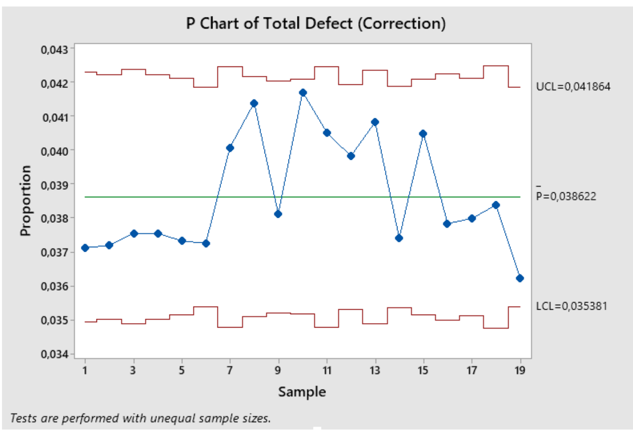

Figure 2. Visualization of Revised P Control Chart

a. Number of total production and defective products.
   These data were collected using historical data from September to November 2022, from which 507,995 unit and 19,620 unit for total production and defective product were obtained, respectively.

b. DPO Value (Defect per Opportunity)
   The calculation is based on the number of defects defined in the CTQ.
   $\text{DPO} = \frac{\text{Number of Defects}}{\text{Number of Production x CTQ}}$
   $\text{DPO} = \frac{19620}{507995 \text{ x } 8} = 0.0048278$

c. DPMO Value (Defect per Million Opportunity)
   DPMO = DPO x 1,000,000 = 4,827.8
   Based on the DPMO value obtained, the calculation is continued to determine the sigma level value in the process.

d. Sigma Level
   = NORM.S.INV ((1000,000-DPMO)/1000,000) +1.5
   = NORM.S.INV ((1000,000-4827,8)/1000,000) +1.5
   = 2.59+1.5
   = 4.09 sigma

Stage 3: Analyze

The analyze stage is the third step carried out within the DMAIC framework. This stage is carried out to conduct further analysis to determine the causes and effects that occur in the process and determine the source of failure in the production process [17]. At this stage, identification of the highest type of disability is carried out using a Pareto chart. This stage uses data mining studies in association rules with an Apriori algorithm to find the association patterns that are formed related to the defects that occur [5]. The results of the association formed will be used as a priority for making improvements at the improve stage. Furthermore, a fishbone diagram is used to identify the causes of defects that occur based on influencing aspects such as environmental factors, machines, operators, and so on [18].

Pareto Chart

The use of the Pareto chart has a goal, namely as a tool to find causal factors that have the highest frequency, so that they can be a reference in overcoming problems that arise [16]. Based on the pareto chart in Figure 3, it was found that the dominant type of defect was pearl defects at 33%, followed by spot defects and various colors, respectively, at 26.6% and 21.7%.

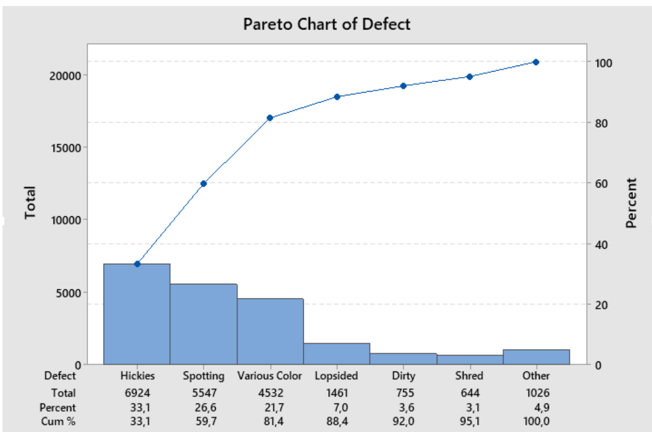

Figure 3. Pareto diagram of LPF Packaging Product

 DOI: 10.25077/josi.v22.n2.p197-214.2023

Table 3. Type of Defect Tabular Data

Transaction	Defect Type							
	Spotting	Dirty	Delamina-tion	Hickies	Miss Print	Lopsided	Various Color	Shred
1	0	1	0	1	1	0	1	0
2	1	0	1	0	0	1	0	0
3	1	0	0	1	0	0	1	0
4	1	0	0	0	0	1	0	1
5	0	0	0	1	0	1	0	1
6	1	0	0	1	0	0	1	0
7	1	0	0	1	0	0	1	0
8	1	0	1	1	0	0	1	0
9	1	0	0	1	0	1	1	0
10	0	0	0	1	0	1	1	0
11	0	1	0	1	0	0	0	0
12	1	0	0	1	0	1	0	0
13	1	0	0	1	1	0	0	0
14	0	0	0	1	0	0	1	1
15	1	0	0	1	0	0	0	0
16	1	0	0	0	0	0	1	0
17	0	1	0	0	0	1	1	0
18	0	0	1	1	0	0	1	0
19	0	1	0	1	0	1	0	0
20	1	0	0	1	0	1	1	0
Total	12	4	3	16	2	9	12	3

Apriori Algorithm

Analyze stage uses data mining studies in association rules with an Apriori algorithm to find the association patterns that are formed related to the defects that occur. The stages that can be carried out before data processing include data selection, cleaning, and transformation [19]. Data selection is a stage that is carried out to sort the data to be processed in a collection of database sets at the company. The data used in this research is defect data for LPF packaging products which were obtained during 20 days from September to November 2022 (Table 3).

The next stage is data cleaning which is carried out to clean the data to handle missing values and noise [5]. While the missing value is a condition where there is missing or incomplete data, noise is a data condition that does not match the character of the existing data, such as writing the wrong type of disability. Furthermore, the data transformation process is carried out, namely changing the shape of the disability data in the form of characters into a basket transaction data model, which is then used in data processing utilizing the Apriori algorithm. Data processing using the Apriori algorithm is done manually by calculating each combination of K-itemset data according to the minimum support and confidence values determined at the beginning [13]. Based on the results of identifying the types of defects in the company data, tabular data is generated to collect data on the types of defects that appear per day. Tabular data is the basis for manually calculating the a priori algorithm. This calculation used parameters such as minimum support value, namely the opportunity for the emergence of a type of disability from the total amount of existing data with a value of 0.15 and minimum confidence, which is a measure that can measure the strength of the relationship between items with a value of 0,8.

Table 4 is obtained from the number of defects that appear according to the characteristics of the existing defects. Furthermore, the calculation of the support value is exemplified for the Spotting type of defect data in the following way:

$$\text{Support} = \frac{\Sigma\ \text{transactions contain items}}{\text{Total transaction}}$$

$$\text{Support} = \frac{12}{20} = 0.6$$

Table 4. Calculation of Support Value for 1 Itemset – First Iteration

No.	Defect Type	Count	Support
1	Spotting	12	0.6
2	Dirty	4	0.2
3	Delamination	3	0.15
4	Hickies	16	0.8
5	Miss Print	2	0.1
6	Lopsided	9	0.45
7	Various Colors	12	0.6
8	Shred	3	0.15

Table 5. Calculation of Support Value for 3 Itemset – Third Iteration

No	Defect Type	Count	Support
1	Spotting, Hickies, Lopsided	3	0.15
2	Spotting, Hickies, Various Color	6	0.3
3	Spotting, Lopsided, Various Color	2	0.1
4	Hickies, Lopsided, Various Color	3	0.15
5	Hickies, Lopsided, Dirty	1	0.05
6	Hickies, Various Color, Dirty	1	0.05

In Table 4, data with a support value below the minimum threshold of 0.15 were excluded from the analysis. This led to the elimination of data number 5, which did not meet this criterion. Subsequently, the second iteration involved creating 2-itemsets by combining defect types that met the first iteration's criteria (see the details in Appendix A.1). The process continued through to the third iteration (Table 5), ultimately yielding three data patterns – data 1, 2, and 4. These selected data patterns emerged after discarding those that failed to meet the minimum support criteria.

The subsequent step involves calculating the confidence and lift ratio values for the previously established association rules. These calculations are crucial in identifying the most dominant rule and assessing the strength of the emerging association rules. An illustrative example of this process is provided, focusing on the calculation of confidence and lift ratio for the first data pattern within the 2-itemset association rules.

$$\text{Confidence} = \frac{\sum \text{Transaction contains A and B}}{\text{Transaction contatins A}} = \frac{9}{12} = 0.75$$

$$\text{Lift Ration} = \frac{\text{Confidence}}{\frac{\text{Transaction contains consequence}}{\text{Total transaction}}} = \frac{0.75}{\left(\frac{16}{20}\right)} = 0.938$$

The calculation of confidence and lift ratio values follows a process akin to that used for the 3-itemset association rules, factoring in both antecedent and consequent elements. The results of this calculation, which involve forming rules from item combinations, are detailed in Table 6 and Table 7. Subsequently, any data not meeting the minimum support and confidence values are eliminated. From this process, 2 rules are ultimately selected based on these calculations.

Table 8 presents the associations that fulfill the specified criteria and possess a lift ratio value greater than 1. According to the final associations derived, the occurrence of hickies defects is more likely when spotting and various color defects are present, as indicated by their higher lift ratio values. In addition to manual calculations, data processing was also conducted using R Studio software. Presented next is the R Studio code utilized for generating Apriori algorithm rules, following the data's pre-processing below.

 DOI: 10.25077/josi.v22.n2.p197-214.2023

Table 6. Two Itemset Association Rule Calculation

Rule	ΣA&B	ΣA	Confidence	Lift
If Spotting, Then Hickies	9	12	0.75	0.938
If Hickies, Then Spotting	9	16	0.563	0.938
If Spotting, Then Various Color	7	12	0.583	0.972
If Various Color, Then Spotting	7	12	0.583	0.972
If Hickies, Then Lopsided	6	16	0.375	0.833
If Lopsided, Then Hickies	6	9	0.667	0.833
If Hickies, Then Various Color	10	19	0.526	0.877
If Various Color, Then Hickies	10	12	0.833	1.042
If Spotting, Then Lopsided	5	12	0.417	0.926
If Lopsided, Then Spotting	5	9	0.556	0.926
If Hickies, Then Dirty	3	16	0.188	0.938
If Dirty, Then Hickies	3	4	0.75	0.938
If Lopsided, Then Various Color	4	9	0.444	0.741
If Various Color, Then Lopsided	4	12	0.333	0.741

Table 7. Three Itemset Association Rule Calculation

Rule	ΣA&B	ΣA	Confidence	Lift
If Spotting and Hickies, Then Various Color	6	9	0.667	1.111
If Spotting and Various Color, Then Hickies	6	7	0.857	1.071
If Hickies and Various Color, Then Spotting	6	10	0.6	1
If Spotting and Hickies, Then Lopsided	3	9	0.333	0.741
If Spotting and Lopsided, Then Hickies	3	5	0.6	0.75
If Hickies and Lopsided, Then Spotting	3	6	0.5	0.833
If Hickies and Lopsided, Then Various Color	3	6	0.5	0.833
If Hickies and Various Color, Then Lopsided	3	10	0.3	0.667
If Lopsided and Various Color, Then Hickies	3	4	0.75	0.938

Table 8. Final Association

Rule	Support	Confidence	Lift
If Various Color, Then Hickies	0.5	0.833	1.042
If Spotting and Various Color, Then Hickies	0.3	0.857	1.071

```
library(arules)
basket_rules <- apriori(txn, parameter = list(minlen = 2, support = 0.15, confidence = 0.8))
```

In R Studio, the processing of data using the Apriori algorithm begins with the command "library(arules)." The generation of rules is influenced by the parameters set within the Apriori algorithm, specifically the minimum support and confidence values. In this case, a minimum support value of 0.15 and a minimum confidence value of 0.8 are utilized. These parameters play a crucial role in determining the number of rules that will be generated. The subsequent step involves the use of the "inspect" command, which displays the association results. The output is organized to highlight rules with the highest lift ratio values, as outlined in the following coding sequence:

```
inspect(sort(basket_rules, by = "lift"))
```

Utilizing this command resulted in the formation of two rules, mirroring the outcomes of manual calculations. It was observed that if spotting and various color defects are present, there is a likelihood of hickies defects occurring, as evidenced by a support value of 0.2857, a confidence of 0.8571429, and a lift ratio greater than 1. This suggests a dominant value of this rule in the data set. Consequently, these three types of defects are interdependent, highlighting the need for a thorough analysis of factors influencing defect occurrence and the development of effective solutions.

	lhs		rhs	support	confidence	coverage	lift	count
[1]	{Spotting, VariousColor}	→	{Hickies}	0.2857143	0.8571429	0.3333333	1.12500	6
[2]	{VariousColor}	→	{Hickies}	0.4761905	0.8333333	0.5714286	1.09375	10

Fishbone Diagram

A fishbone diagram is used to identify the causes of defects based on influencing aspects such as environmental factors, machines, operators, etc.

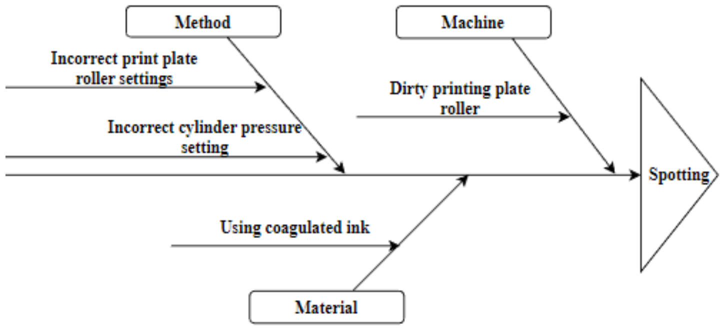

Figure 4. Fishbone Diagram of Spotting

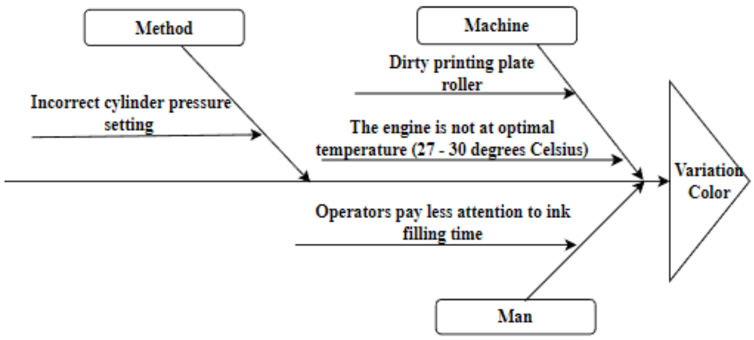

Figure 5. Fishbone Diagram of Various Color

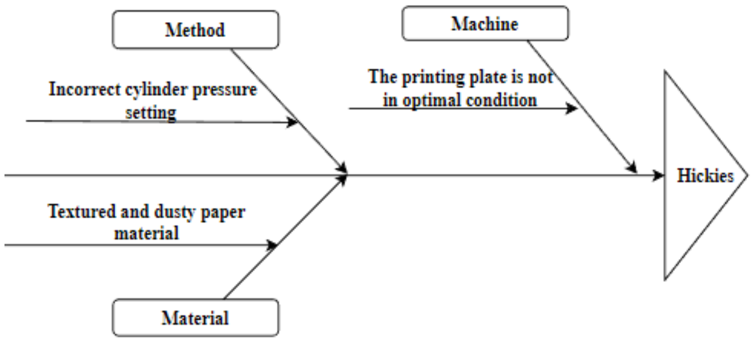

Figure 6. Fishbone Diagram of Hickies

 DOI: 10.25077/josi.v22.n2.p197-214.2023

Table 9. Failure Mode and Effect Analysis

Failure Type	Process	S	Cause of Failure	O	Executed Controls	D	RPN
Spotting	Printing	7	There is dirt on the plate	4	Clean the plate and replace the plate at a certain time	3	84
			Incorrect print plate rolling settings	3	Checking the condition of the printing plate installation when setting up the machine	2	42
			Incorrect cylinder pressure setting (impression)	3	Resetting after doing the first run approval	3	63
			Using coagulated ink	5	Perform ink dilution process	4	140
Color Variation	Printing	8	Dirty printing plate rolling	4	Clean the dirty area using a rag	2	64
			The engine is not at optimal temperature (27 - 30 degrees Celsius)	3	Resetting the temperature according to the results of the first run approval	4	96
			Operators pay less attention to ink filling time	4	Supervision of operators on a regular basis	4	128
			Incorrect cylinder pressure setting (impression)	2	Resetting after doing the first run approval	3	48
Hickies	Printing	7	The printing plate is not in optimal condition	7	Regular plate check	3	147
			Incorrect cylinder pressure setting (impression)	3	Resetting after doing the first run approval	3	63
			Textured and dusty paper material	2	Paper print test during first run approval	5	70

Failure Mode and Effect Analysis (FMEA)

After identifying the root causes of the issues using fishbone diagrams, a Failure Mode and Effect Analysis (FMEA) is constructed to elaborate on each cause of the identified defects (Table 9). This FMEA serves as a tool to evaluate the priority level of improvements, determined by the Risk Priority Number (RPN) value. The initial phase involves assigning values for Severity (S), Occurrence (O), and Detection (D). Subsequently, these three values are multiplied to calculate the RPN value for each identified cause of failure.

Stage 4: Improve

The 'improve' stage entails devising proposals for enhancements (Table 10), drawing upon insights gathered from the preceding Six Sigma stages. In collaboration with the company, this stage focuses on developing extensive solutions aimed at elevating product quality. This approach takes into account potential influences arising from the production process, ensuring a holistic and effective improvement strategy.

Table 12. Improvement Proposals

No.	Failure Type	Cause of Failure		Proposed Improvements
1	Spotting	Using coagulated ink	The ink has been stored for a long time and contaminated with the air	Making ink storage time labels that are differentiated by color indicators
2	Variation Color	Ink-filling on rolling print is irregular	Operators pay less attention to ink filling time	Installation of ink refill alarm
3	Hickies	Printing plate rolling is not in optimal condition	The plate is dirty, and there is dust attached	Making cleaning forms and checking the condition of the plates

Fixing Spotting Failure

The printing process involves machine components in a rotating cylinder to deliver ink from the roller to spread the ink onto the paper's surface. Before the ink manages to stick to the roller, the transmission process is carried out by automatic ejection on the machine, which originates from the ink storage roller. This process requires ink with optimal conditions so the ink transfer process can be carried out correctly. This label can help determine whether the remaining ink is still suitable for use. Therefore, it is necessary to monitor the use of ink with a suggestion in the form of making ink storage labels that are differentiated by color indicators (See Appendix A.2 for ink storage labelling display).

Fixing Color Variation Failure

The occurrence of color variation defects in the printing process can be attributed to irregularities in the ink filling process. This issue is linked to the mechanics of the machine, particularly the print roller, where the ink in the storage roller gradually diminishes with longer and faster rotations. Consequently, it becomes crucial for the operator to consistently monitor this during production. A practical solution is to implement tools such as alarms and buzzers. These devices serve as reminders for the operator to check and replenish the ink in the machine throughout the printing process. The specified alarm system not only prompts regular checks but also aids in timely ink reapplication on the printing press's ink roller. Additionally, the tool is enhanced with a luminous buzzer, designed to capture the operator's attention for immediate action on the printing press (See Appendix A.3 for Alarm and Buzzer Design and Specification).

Fixing Hickies Failure

Hickies failure in the printing process is often a result of a dirty printing plate. This dirt may accumulate from residual ink or dust that obstructs the printing mechanism. Given that each printing process utilizes a distinct plate corresponding to the desired pattern, it necessitates the operator's involvement in meticulously cleaning, storing, and readjusting the plate prior to its use. To address this, it is recommended to implement a rigorous cleaning protocol, ensuring the optimal condition of the printing plates for each process. This approach not only maintains the quality of the print but also minimizes the occurrence of hickies failure (See Appendix A.4 for Instruction form for Maintaining the Printing Plate)

Stage 5: Control

The control stage, as the final phase of the Six Sigma method, is pivotal for ensuring the sustainability of improvements in the production process. During this stage, the company executes the previously formulated enhancements. The effectiveness of these implementations is then evaluated through recalculations of control charts, DPMO (Defects Per Million Opportunities), and sigma values. A comparative analysis between the post-implementation results and the initial pre-implementation data is conducted to ascertain the impact of these improvements on product quality. Table 15 presents a detailed plan for the implementation of these proposed improvements.

Table 15 Implementation Plan Schedule

Activities	**PIC**
Explanation of research results and proposed improvements formulated (cleaning and checking plate forms, installing alarms and buzzers, ink labeling)	Resty Ayu Ramadhani
Confirm implementation schedule	Resty Ayu Ramadhani and Mr Awan
Implementation of implementation of improvement proposals	Resty Ayu Ramadhani and Mr Saiful
Collection of implementation results of improvement proposals	
Perform analysis of implementation results and recalculation of DPMO values and sigma levels	Resty Ayu Ramadhani

 DOI: 10.25077/josi.v22.n2.p197-214.2023

CONCLUSION

Based on the results obtained from the research, several significant conclusions can be drawn. The study meticulously examined the Wardah Lightening Powder Foundation Packaging products and identified eight distinct types of defects, ranging from miss prints to spotting issues. These findings provide a comprehensive overview of the quality challenges in the product line. In terms of process quality, the research revealed that the production process of Packaging Wardah Lightening Powder Foundation products had a DPMO (Defects Per Million Opportunities) value of 4,827.8, corresponding to a sigma level of 4.09. This sigma level indicates the current process capability and highlights areas where improvements are needed to meet higher quality standards. Moreover, a Pareto chart analysis shed light on the most dominant defects, with hickies at 33.1%, spotting at 26.6%, and various colors at 21.7%. These insights provide valuable guidance for prioritizing quality improvement efforts.

The study also utilized the a priori algorithm to uncover associations between different defect types. Specifically, it found that spotting and various color defects were linked, leading to the appearance of hickies defects with a confidence value of 0.8 and a lift ratio of 1.0714. These associations offer deeper insights into the interrelationships among defects, enabling more targeted quality enhancement strategies. Additionally, the Failure Modes and Effects Analysis (FMEA) identified three primary causes of failure with the highest Risk Priority Numbers (RPN): suboptimal printing plate condition (RPN value of 147), clumped ink usage (RPN value of 140), and operator inattentiveness during ink filling (RPN value of 128). These findings highlight critical areas in the production process that require immediate attention and improvement. To address these quality challenges, the study proposed a set of practical improvements, including the implementation of alarms and buzzers, the use of differentiated ink storage labels with color indicators, and the introduction of cleaning forms for checking the condition of the printing plates. These recommendations offer a roadmap for enhancing product quality and reducing defects in Wardah Lightening Powder Foundation Packaging products.

ACKNOWLEDGEMENT

The authors would like to extend my sincere thanks to the JOSI editorial team and reviewers for their insightful feedback and guidance, which significantly enhanced the quality of this work. Your expertise and dedication have been invaluable in the publication of this article.

CONFLICT OF INTEREST

The authors declare no conflict of interest regarding the publication of this paper. There are no financial or personal relationships with other people or organizations that could inappropriately influence or bias the content and outcomes of this research.

FUNDING

The authors received no financial support for the research, authorship, and/or publication of this article.

References

[1] R. Fitriana, J. Saragih, and S. D. Fauziyah, "Quality improvement on Common Rail Type-1 Product using Six Sigma Method and Data Mining on Forging Line in PT. ABC," in IOP Conf. Ser. Mater. Sci. Eng., vol. 847, no. 1, 2020, doi: 10.1088/1757-899X/847/1/012038.

[2] D. C. Montgomery, Introduction to Statistical Quality Control. Wiley, 2020. [Online]. Available: https://books.google.co.id/books?id=oh7zDwAAQBAJ

[3] C. I. Parwati, J. Susetyo, and A. Alamsyah, "Analisis Pengendalian Kualitas Sebagai Upaya Pengurangan Produk Cacat Dengan Pendekatan Six Sigma, Poka-Yoke Dan Kaizen," Gaung Inform., vol. 12, no. 2, pp. 2086–4221, 2019.

[4] R. Fitriana, J. Saragih, and D. P. Larasati, "Production quality improvement of Yamalube Bottle with Six Sigma, FMEA, and Data Mining in PT. B," in IOP Conf. Ser. Mater. Sci. Eng., vol. 847, no. 1, pp. 1–9, 2020, doi: 10.1088/1757-899X/847/1/012011.

[5] O. Pahlevi and A. Sugandi, "Penerapan Algoritma Apriori dalam Pengendalian Kualitas Produk," J. Penelit. Tek. Inform., vol. 3, no. 1, pp. 272–278, 2018.

[6] A. Ishak and N. Elizabeth Zalukhu, "Bolt Product Quality Control Using Six Sigma DMAIC Method (Case study: PT XYZ Company)," in IOP Conf. Ser. Mater. Sci. Eng., vol. 1003, no. 1, pp. 1–11, 2020, doi: 10.1088/1757-899X/1003/1/012094.

[7] A. Puspasari, D. Mustomi, and E. Anggraeni, "Proses Pengendalian Kualitas Produk Reject dalam Kualitas Kontrol Pada PT," Yasufuku Indones. Bekasi. Widya Cipta, vol. 3, no. 1, pp. 71–78, 2019, doi: https://doi.org/10.31294/widyacipta.v3i1.5088.

[8] I. Arizka, D. Hetharia, and A. N. Habyba, "Quality Improvement Proposal of Spun Pile Using Six Sigma Method at PT. Adhi Persada Beton," in Proc. Int. Conf. Sci. Eng. (ICSE-UIN-SUKA 2021), vol. 211, pp. 194–202, 2022, doi: 10.2991/aer.k.211222.032.

[9] D. Junianto, E. R. Arifianti, and N. Narto, "Peningkatan Kualitas Produk Shortening Menggunakan Pendekatan Dmaic Six Sigma Di Pt Best Gresik," J. Rekayasa Sist. Ind., vol. 7, no. 1, pp. 54–59, 2021, doi: 10.33884/jrsi.v7i1.4545.

[10] B. Setiawan, E. Rimawan, and D. Santoso Saroso, "Quality Improvement Using The DMAIC Method To Reduce Defect Product In The PVC Compounds Industry," Volatiles Essent. Oils, vol. 8, no. 4, pp. 5388–5405, 2021.

[11] W. Delrinata and F. B. Siahaan, "Implementasi Algoritma Apriori Untuk Menentukan Stok Obat," J. Sisfokom (Sistem Inf. dan Komputer), vol. 9, no. 2, pp. 222–228, 2020, doi: 10.32736/sisfokom.v9i2.875.

[12] A. Setiawan and F. P. Putri, "Implementasi Algoritma Apriori untuk Rekomendasi Kombinasi Produk Penjualan," Ultim. J. Tek. Inform., vol. 12, no. 1, pp. 66–71, 2020, doi: 10.31937/ti.v12i1.1644.

[13] E. H. Hermaliani et al., "Data Mining Technique to Determine the Pattern of Fruits Sales & Supplies Using Apriori Algorithm," J. Phys. Conf. Ser., vol. 1641, no. 1, pp. 1–7, 2020, doi: 10.1088/1742-6596/1641/1/012070.

[14] A. V. Rastiti, I. Wiyono, and I. W. Juliani, "Usulan Rancangan Perbaikan Untuk Meminimasi Defect Inklusi Pasir (IP) Pada Proses Pencetakan Shoulder For E-Clip di PT. Pindad Dengan Metode DMAIC," e-Proceeding Eng., vol. 6, no. 2, pp. 7610–7618, 2019.

[15] R. Fitriana, D. K. Sari, and S. Medina, "Quality Improvement on Welding Process of Colt Diesel Cabin Using Six Sigma Method," 2021.

[16] R. Fitriana, D. K. Sari, and A. N. Habyba, Pengendalian dan Penjaminan Mutu. Jakarta: Wawasan Ilmu, 2021.

[17] H. Kurnia, C. Jaqin, and H. Manurung, "Implementation of the Dmaic Approach for Quality Improvement At the Elastic Tape Industry," J@ti Undip J. Tek. Ind., vol. 17, no. 1, pp. 40–51, 2022, doi: 10.14710/jati.17.1.40-51.

[18] Y.-T. Jou et al., "Application of Six Sigma Methodology in an Automotive Manufacturing Company: A Case Study," Sustainability, vol. 14, no. 21, p. 14497, 2022, doi: 10.3390/su142114497.

[19] R. Takdirillah, "Penerapan Data Mining Menggunakan Algoritma Apriori Terhadap Data Transaksi Sebagai Pendukung Informasi Strategi Penjualan," Edumatic J. Pendidik. Inform., vol. 4, no. 1, pp. 37–46, 2020, doi: 10.29408/edumatic.v4i1.2081.

[20] M. Fauzi et al., "Usulan Perbaikan Proses Drawing Untuk Meminimasi Terjadinya Defect Pada Part Metal Fuel Filler di PT Sinar Terang Logamjaya (PT Stallion) Dengan Pendekatan DMAI," 2021.

APPENDIX

A.1. Calculation of Support Value for 2 Itemset – Second Iteration

No.	Defect Type	Count	Support
1	Spotting, Hickies	9	0.45
2	Spotting, Lopsided	5	0.25
3	Spotting, Various Color	7	0.35
4	Spotting, Dirty	0	0
5	Spotting, Delamination	2	0.1
6	Spotting, Shred	1	0.05
7	Hickies, Lopsided	6	0.3
8	Hickies, Various Color	10	0.5
9	Hickies, Dirty	3	0.15
10	Hickies, Delamination	2	0.1
11	Hickies, Shred	2	0.1
12	Lopsided, Various Color	4	0.2
13	Lopsided, Dirty	2	0.1
14	Lopsided, Delamination	1	0.05
15	Lopsided, Shred	2	0.1
16	Various Color, Dirty	2	0.1
17	Various Color, Delamination	2	0.1
18	Various Color, Shred	1	0.05
19	Dirty, Delamination	0	0
20	Dirty, Shred	0	0
21	Delamination, Shred	0	0

A.2 Ink Storage Labelling Display

Labels	Size	Function
 	9.6 cm x 6 cm	Used to indicate ink that is ± 8 months to the expiration date and has been used for the previous production process
 	9.6 cm x 6 cm	Used to denote inks whose shelf life is 10 to 16 months after they are manufactured
 	9.6 cm x 6 cm	Used to denote inks whose shelf life is 0 to 10 months after they are manufactured

A.3 Alarm and Buzzer Design and Specification

Name	**PNANWZ**
Type	*Controllable alarm*
Time Range	0,1 s – 99 H
Alarm Size	138 x 105 x 105 (mm)
Buzzer Size	87 x 160 (mm)
Voltage	220 V
Sound Intensity	110 dB

A.4 Instruction form for Maintaining the Printing Plate

	PT Kalingga Jaya Prima Cempaka Sari Street Number 7, Harapan Mulya, Jakarta	
INSTRUCTION FOR FILLING OUT THE CLEANING AND CHECKING PLATE CONDITION FORM		
CLEARANCE		
1	Operator fills in the product code and the plate type	
2	Operator fills in the day, date, and name of the operator who performs the plate cleaning	
3	Operator puts a check mark (✓) in the column that matches the checking conditions	
4	Operator fills in the action taken column if the operator finds conditions that are not suitable	
5	Operator signs at the bottom of the form	
CONDITION		
1	Operator fills in the day, date, and name of the operator who performs the plate cleaning	
2	Operator puts a check mark (✓) in the column that matches the checking conditions	
3	Operator fills in the action taken column if the operator finds conditions that are not suitable	
4	Operator signs at the bottom of the form	
Made By :	Approved By :	SAFETY FIRST
Resty Ayu Ramadhani	Arif Dwi Hernawan	

 DOI: 10.25077/josi.v22.n2.p197-214.2023

CLEANING AND CHECKING PLATE CONDITION FORM

PT Kalingga Jaya Prima

Product Code :

Plate Type :

PLATE CLEANING		Day / Date :		
		Operator :		
No	Checking Aspect	Suitability		Action Taken
		YES	NO	
1	Has the front plate been cleaned with cleaning fluid?			
2	Has the rear plate been cleaned with cleaning fluid?			
3	Is there liquid seeping into the front of the plate?			
4	Are there still traces of ink or dirt on the plate?			
5	Is there dust attached to the surface of the plate?			
6	Are there bits of paper stuck to the surface of the plate?			

PLATE CONDITION		Day / Date :		
		Operator :		
No	Checking Aspect	Suitability		Action Taken
		YES	NO	
1	Are there scratches on the plate?			
2	Is there a broken part on the edge of the plate?			
3	Is the pattern on the plate still visible?			
4	Does the plate need to be replaced?			

*Check under the appropriate conditions

Operator	*Supervisor*

AUTHORS BIOGRAPHY

Resty Ayu Ramadhani is a graduate from Industrial Engineering at Universitas Trisakti, Jakarta. She obtained his Bachelor's degree in the Department of Industrial Engineering, Faculty of Industrial Technology, Universitas Trisakti Jakarta, in 2022. She was a lecturer assistant at Quality Engineering Laboratory.

Rina Fitriana is an Associate professor and Head of Department in the Department of Industrial Engineering, Universitas Trisakti, Indonesia. Her educational background is a Bachelor of Industrial Engineering from Universitas Trisakti, a Magister of Management from PPM School of Management, and a Doctor of Agricultural

Industry Technology from IPB University. She has more than 21 years of teaching/ research in the field of Industrial Engineering. Her research interests include Quality Engineering, Analyze System analysis of information system design, Data Mining, and Business Intelligence. Rina can be contacted at email : rinaf@trisakti.ac.id

Anik Nur Habyba is a lecturer and Head of Quality Engineering Laboratory in the Department of Industrial Engineering, Universitas Trisakti, Indonesia. Her educational background is a Bachelor of Agricultural Industry Technology from Brawijaya University, a Master of Agricultural Industry Technology from IPB University. She has more than 5 years of teaching/ research in the field of Industrial Engineering. Her research interests include Statistic, Quality Engineering, Design of Experiment, and Technology-based entrepreneurship. Anik can be contacted at email anik@trisakti.ac.id

Yun-Chia Liang is Professor and Chair, Department of Industrial Engineering & Management, Yuan-Ze University, Taiwan, ROC. His Research & Interests are Meta-Heuristics, Intelligent Computing, Production Scheduling, Logistics Management, Artificial Neural Network Applications

 DOI: 10.25077/josi.v22.n2.p197-214.2023