The Adoption of the Response Surface Methodology within the DMAIC Process to Achieve Optimal Solutions in Reducing Product Defect

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Abstract. The high number of defective products can cause the company to receive many complaints. This research aimed to apply the quality improvement approach i.e., the DMAIC methodology (Define-Measure-Analysis-Improve-Control), to reduce product defect. The object of discussion was the black-color cloth hangers produced by the injection machine. The absence of definite standards regarding the parameter settings for the injection machine was suspected to be a reason for the high number of defective products. Therefore, adopting the Response Surface Methodology (RSM) into the DMAIC phases can bring the optimization result. when the experimental design called-as Box-Behnken was applied. The measurement of the initial condition before improvement showed that the sigma level of the injection process was 3.64 (out of 6), with the dominant types of product defects being flash, short mold, and lack of the color black. By implementing the RSM, the experiment produced the optimum setting of the injection machine: 180°C for barrel temperature, 35 bars for injection pressure, and 41% for injection speed index. After implementing the proposed improvements, the sigma level was increased to 3.90.

Keywords: DMAIC, RSM Experimental Design, Injection Process, Sigma Level.

1 Introduction

Product quality is one of the competitive edges to satisfy customer needs [1]. The high number of defective products can cause the company to have many rework activities, consuming the working time and causing the customer to be late in receiving the product. The low product quality can also cause the company to get complaints whenever the customer receives poor quality products. A manufacturer of plastic products, called-as Miwa Plastik, located in East Java – Indonesia, found many defective products in its injection process of the cloth hangers. Therefore, the quality improvement methodology, i.e., the Define-Measure-Analyze-Improve-Control (DMAIC) cycle was proposed to reduce product defects.

DMAIC is a structured and systematic thinking framework from Six Sigma methodology that supports the implementation of continuous improvement. Six Sigma is the organizational vision of improving quality towards the target of 3.4 defects per million opportunities (DPMO) and the effort towards a zero-defect level of perfection

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[2]. DMAIC supports a data-driven analytical approach to ensure the analysis process is done thoroughly and has an accurate baseline.

The process from the injection molding machine is the primary production process for clothes hangers. The initial observations found that the parameters setting of the injection molding machine had not been determined so the operators often used the pre-determined range of machine settings which may increase the probability of defective products. Thus, this study adopted the Response Surface Methodology (RSM), proposing a particular experimental design to determine the optimal combination of machine parameter settings. RSM is a collection of statistical and mathematical techniques that are useful for developing, improving, and optimizing processes, which responses are influenced by several factors called independent variables [3]. The use of RSM adheres to statistical assumptions to make the optimization results unbiased [4]. RSM can also provide directions for shifting the factor levels toward the area with optimum response conditions with the steepest ascent or steepest descent, so the obtained result can be closer to the global optimum point.

This research focused on the black-color cloth hanger because of the highest demand and number of defects. This research aims to reduce the number of defective clothes hangers and determine the optimum combination of machine parameter settings by adopting Box-Behnken Design (BBD) experimental design into the DMAIC cycle. Several studies have integrated DMAIC with different experimental design methods for different research objects. For instance, a 3-factor full-factorial experimental design was used to reduce the rejection rate of electronic product [5], a 3-factor RSM experimental design with Central Composite Design was used to improve the brick production process in [6], and a 4-factor Taguchi experimental design with Signal-to-Noise Ratio was used to design a water-based paint quality improvement model [7]. Meanwhile, this research uses a 5-factor RSM experimental design with Box-Behnken Design to reduce the number of defective clothes hangers. Besides its more efficient design, BBD was selected to avoid extreme treatment combinations as it would result in too many defective products. The role of the experimental design as an optimization tool was applied in the phase of Improve in the DMAIC cycle.

2 Research Methodology

The Define-Measure-Analyze-Improve-Control (DMAIC) methodology structured the overall research steps as shown in Figure 1. In the Define stage, the research activities included defining the raised problems, quality criteria, and critical-to-quality, as well as identifying the types of product defects that occur in the production process. In the phases of Measure and Analyze, the calculation of the sigma level for the initial condition as a baseline measure and the identification of the dominant types of defects were carried out; the usage of the Ishikawa diagram and Failure Mode and Effect Analysis (FMEA) was to identify the root causes and priorities of critical defects.

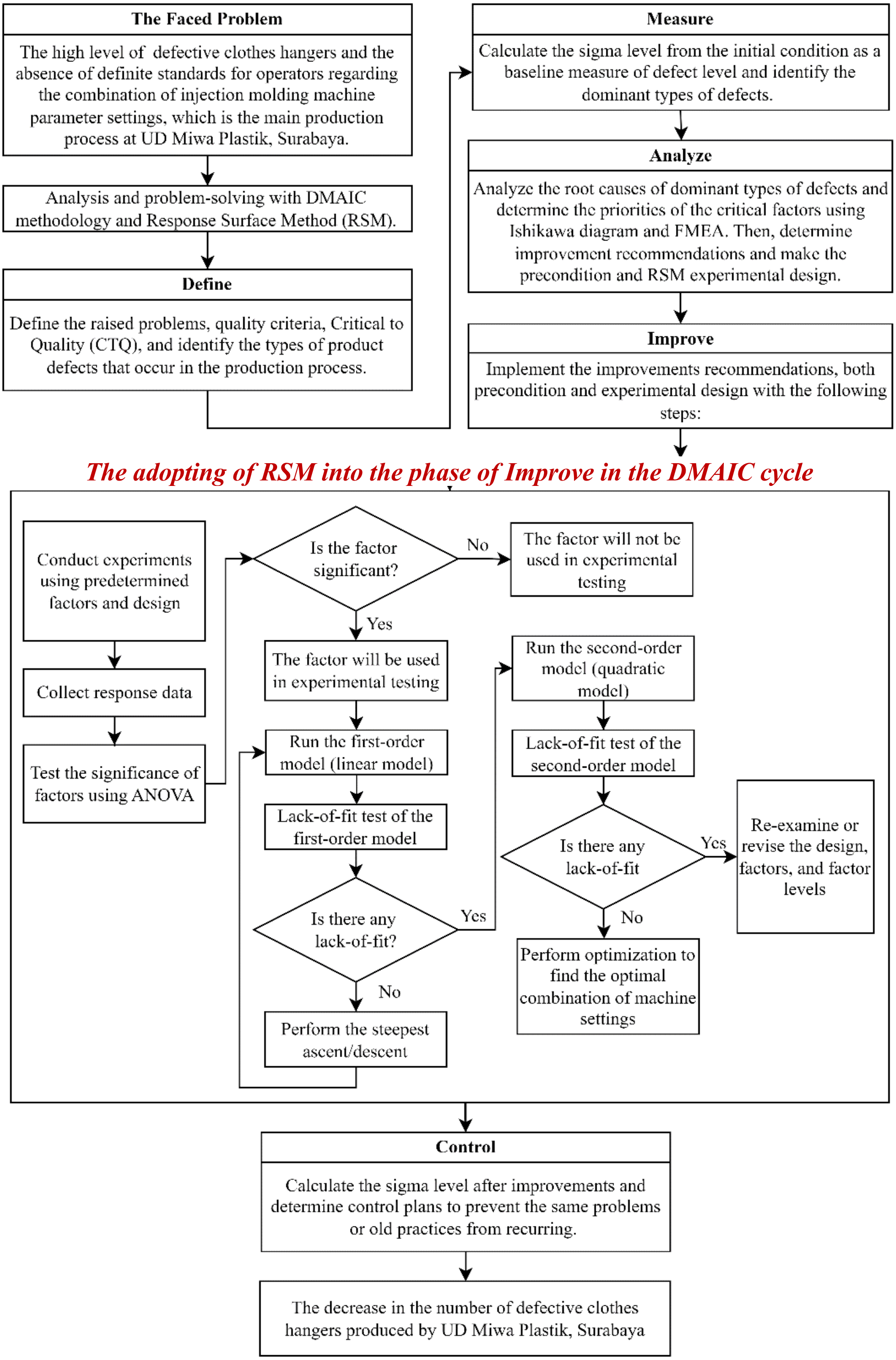

Fig. 1. The DMAIC methodology for improving the product quality

Recommendations for improvement, including precondition and experiment designs, were determined and then implemented in the Improve stage to reduce the number of defective clothes hanger products and obtain the optimum combination for the injection molding machine settings. This was the phase where the Response Surface Methodology (RSM) was adopted for experimental design, from the design to the implementation to obtain optimal benefits in defect reduction.

In the Control stage, the designed improvements were evaluated by calculating the sigma level of the new condition to confirm whether the improvements could significantly reduce the number of defective products. Finally, control plans based on the improvements are determined to prevent same problems from recurring.

3 Results

3.1 Define-Measure-Analyze Phases

The observation on voice of customer undertaken in the Define stage yielded information pertaining to quality criteria or standards for clothes hangers. Specifically, these criteria include the good shape of the hangers, solid black color, smooth surface, not easily broken, and good appearance. These were then translated into 5 Critical-to-Quality (CtQs) and 6 types of defects, which can be seen in Table 1.

Table 1. CTQs and types of defects for the black-color cloth hanger product.

Critical to Quality (CtQ)	**Types of Defects**
All parts are well-molded	Short mold
The color is solid black	Lack of the color black (gray)
No rough surface	Rough wrinkled surface
	Flash
Not easily broken	Easily broken if bent
The appearance is good	Dirty
	Rough wrinkled surface
	Flash

Based on the number of CtQs and production data collected in the data collection process, a DPMO (defects per million opportunities) number of 16,091.77 and a sigma level of 3.64 were obtained. These two values indicate that there was an opportunity to improve process capability and reach higher sigma level.

Furthermore, the identification of the dominant defects was accomplished by the use of the Pareto principle, a concept positing that 80% of issues arise from a mere 20% of underlying factors. According to the data presented in Figure 2, the dominant defects observed in the study were flash, short mold, and lack of the color black; collectively accounting for 81.64% of the total.

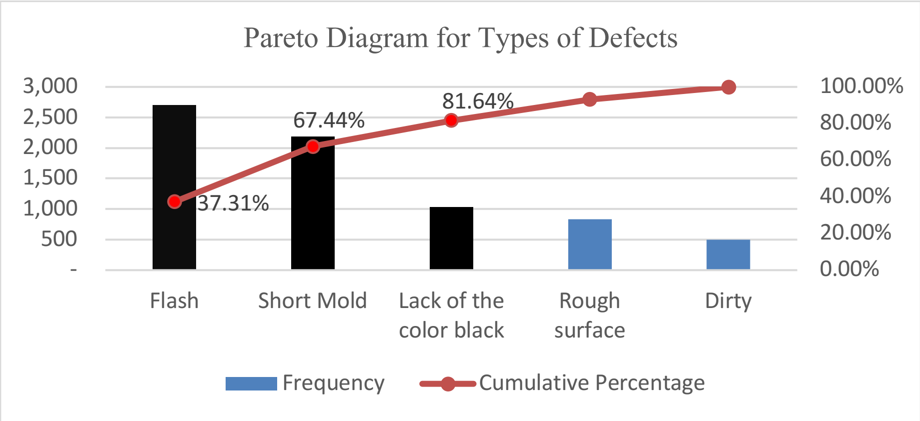

Fig. 2. Pareto diagram for types of defects.

In the Analyze stage, an analysis was carried out to identify the root causes of each type of dominant types of defects using Ishikawa diagram, which can be seen in Figure 3 to 5. The further analysis using the Failure Mode and Effect Analysis (FMEA) as shown in Figure 6 was performed to determine the critical root causes of the dominant defect types.

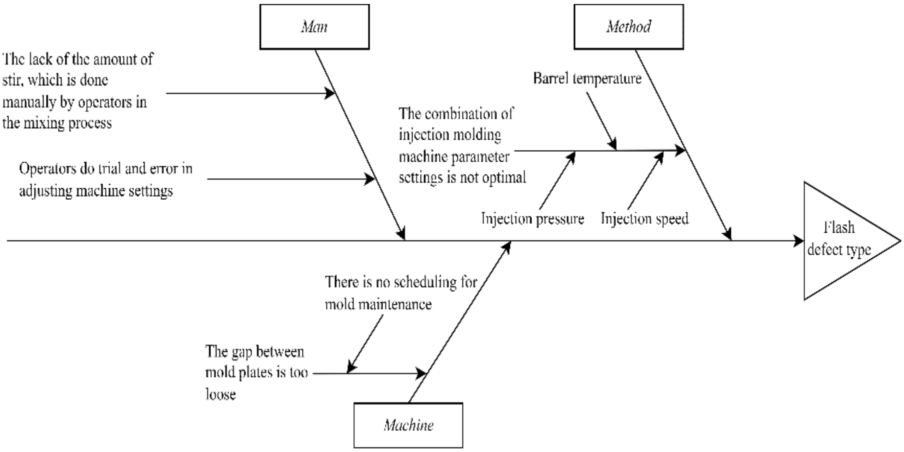

Fig. 3. Ishikawa diagram for flash defect type.

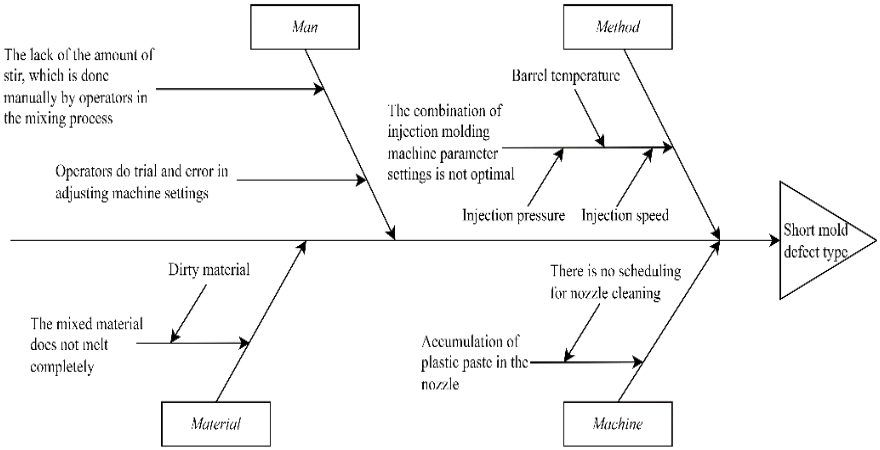

Fig. 4. Ishikawa diagram for short mold defect type.

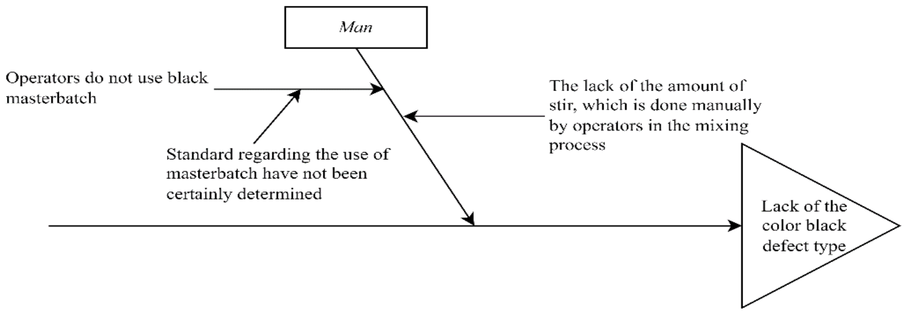

Fig. 5. Ishikawa diagram for lack of the color black defect type.

Based on the findings presented in Figure 6, it can be inferred that the key root causes were attributed to various components, as indicated by their respective Risk Priority Number (RPN) values exceeding the average threshold of 65.

Process Step	Potential Failure Mode	Potential Failure Effect	S	Factor	Potential Causes	O	Current Process Control	D	RPN
Mixing process, injection molding machine setting process, and injection process	Flash	The product's appearance is not good and causes the sides to become rough, which has the potential to damage the clothes	3	Man 1	Operators do trial and error in adjusting machine settings	4	Operators visually inspect the finished product	9	108
				Man 2	The lack of the amount of stir, which is done manually by operators in the mixing process	1			27
				Method 1	The combination of injection molding machine parameter settings is not optimal	3			81
				Machine 1	The gap between mold plates is too loose because there is no scheduling for mold maintenance	1			27
Mixing process, injection molding machine setting process, and injection process	Short mold	There is a portion of the product that is missing, so the product can not function properly	5	Man 3	Operators do trial and error in adjusting machine settings	3	Operators visually inspect the finished product	9	135
				Man 4	The lack of the amount of stir, which is done manually by operators in the mixing process	2			90
				Method 2	The combination of injection molding machine parameter settings is not optimal	2			90
				Material 1	The mixed material does not melt completely due to dirty material	1			45
				Machine 2	Accumulation of plastic paste in the nozzle because there is no scheduling for nozzle cleaning	1			45
Mixing process	Lack of the color black	Slight dissatisfaction because the color does not match the customer's request	1	Man 5	Operators do not use black masterbatch because the standard regarding the use of masterbatch has not been certainly determined	4	Operators visually inspect the finished product	9	36
				Man 6	The lack of the amount of stir, which is done manually by operators in the mixing process	3			27

Fig. 6. The Failure Mode and Effect Analysis (FMEA) for dominant defects.

3.2 The adoption of RSM in the Improve Phase

Hence, the recommended improvements included the identification of the optimal combination of injection molding machine parameter settings from the experimental results, the formulation of comprehensive guidelines for production operators to optimize the material mixing procedure, the implementation of a more strict supervision of production operator, the reinforcement of quality inspection protocols for raw material batches procured from suppliers, and the development of instructions and schedules for production operators to effectively clean the injection molding nozzle.

The proposals for improvement were categorized into two sections: precondition and experimental design. Preconditions should be design in advance and implemented prior to the experimental procedure in order to prevent any potential interference with the outcomes of the experiment. The experimental design was developed with the purpose of identifying the optimal combination of parameter setting for injection molding machines. The five factors in the experimental design were defined as: segment 1, 2 and 3 of barrel temperature, injection pressure, and injection speed. The levels for each factor are listed in Table 2.

The Box-Behnken Design (BBD) design of experiment was selected, this design incorporated predetermined factors and corresponding responses. The selection of BBD as the experimental design was motivated by its enhanced efficiency, characterized by a reduced number of tests. Additionally, BBD was preferred over other experimental designs to mitigate the issue of extreme treatment combinations, which would otherwise lead to an excessive occurrence of defective goods.

Table 2. Factors and factor levels for experimental design.

Factors		**Factor Levels**		
		1	**2**	**3**
x_1	Segment 1 barrel temperature	180°C	195°C	210°C
x_2	Segment 2 barrel temperature	185°C	190°C	195°C
x_3	Segment 3 barrel temperature	180°C	185°C	190°C
x_4	Injection pressure	35 bars	40 bars	45 bars
x_5	Injection speed	35%	40%	45%

The response measured in this experiment was the percentage of products that have flash or short mold defects. Experimental data were processed using ANOVA with the help of Minitab.

From the results of the ANOVA test in Figure 7, it is obtained that x_1, x_3, x_4, and x_5 are the factors that statistically have a significant influence on the response because they each have a p-value smaller than $\alpha = 5\%$. Further testing, it is obtained that x_1, x_3, x_4, and x_5 still have a significant influence on the response even without x_2. Thus, these four factors are used in the experimental analysis.

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
X1	2	0,033480	0,016740	4,83	0,014
X2	2	0,005035	0,002517	0,73	0,491
X3	2	0,035017	0,017509	5,05	0,012
X4	2	0,107948	0,053974	15,57	0,000
X5	2	0,275807	0,137903	39,78	0,000
Error	35	0,121347	0,003467		
Lack-of-Fit	30	0,120038	0,004001	15,28	0,003
Pure Error	5	0,001310	0,000262		
Total	45	0,696539			

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
X1	2	0,03295	0,016473	4,82	0,014
X3	2	0,03491	0,017457	5,11	0,011
X4	2	0,10790	0,053950	15,79	0,000
X5	2	0,30608	0,153041	44,80	0,000
Error	37	0,12638	0,003416		
Lack-of-Fit	24	0,10429	0,004345	2,56	0,041
Pure Error	13	0,02209	0,001699		
Total	45	0,69654			

Fig. 7 The results of factors significance test on the response. A complete of 5-factor **(left)** and 4-factor without x_2 **(right)**.

The initial choice for testing is the first-order model (known as the linear model), due to its inherent simplicity. The adequacy of the model can be assessed through the lack-of-fit test (ANOVA test). According to the data presented in Figure 8, the p-value for lack-of-fit was found to be less than $\alpha = 5\%$. This indicates that the overall first-order model was not appropriate for accurately explaining the relationship between the components and the response. Because the first-order model was inadequate, the model fit analysis is continued for the second-order model.

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	4	0,124608	0,031152	2,23	0,082
Linear	4	0,124608	0,031152	2,23	0,082
X1	1	0,013983	0,013983	1,00	0,323
X3	1	0,002149	0,002149	0,15	0,697
X4	1	0,107900	0,107900	7,74	0,008
X5	1	0,000577	0,000577	0,04	0,840
Error	41	0,571932	0,013950		
Lack-of-Fit	28	0,549841	0,019637	11,56	0,000
Pure Error	13	0,022091	0,001699		
Total	45	0,696539			

Fig. 8. Lack of fit test results for the first-order model (linear model).

Based on the findings presented in Figure 9, it can be inferred that the p-value for lack-of-fit exceeds the predetermined significance level of $\alpha = 5\%$. Consequently, it can be deduced that the overall second-order model, namely the quadratic model, is better suited for accurately representing the association between the factors and the answer. But there are some insignificant terms that need to be removed, namely x_4^2, x_1x_3, x_1x_4, x_1x_5, x_3x_4, and x_3x_5, so as not to weaken the prediction or estimation capability of the model [8]. However, it is necessary to include x_3 and x_5 in order to preserve the hierarchical structure of the model.

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	14	0,612313	0,043737	16,10	0,000
Linear	4	0,124608	0,031152	11,47	0,000
X1	1	0,013983	0,013983	5,15	0,030
X3	1	0,002149	0,002149	0,79	0,381
X4	1	0,107900	0,107900	39,71	0,000
X5	1	0,000577	0,000577	0,21	0,648
Square	4	0,445549	0,111387	41,00	0,000
X1*X1	1	0,018963	0,018963	6,98	0,013
X3*X3	1	0,032765	0,032765	12,06	0,002
X4*X4	1	0,000000	0,000000	0,00	0,996
X5*X5	1	0,305505	0,305505	112,44	0,000
2-Way Interaction	6	0,042156	0,007026	2,59	0,038
X1*X3	1	0,000233	0,000233	0,09	0,772
X1*X4	1	0,000020	0,000020	0,01	0,933
X1*X5	1	0,001262	0,001262	0,46	0,501
X3*X4	1	0,000002	0,000002	0,00	0,978
X3*X5	1	0,000555	0,000555	0,20	0,654
X4*X5	1	0,040084	0,040084	14,75	0,001
Error	31	0,084226	0,002717		
Lack-of-Fit	18	0,062136	0,003452	2,03	0,099
Pure Error	13	0,022091	0,001699		
Total	45	0,696539			

Fig. 9. Lack of fit test results for the second-order model (quadratic model).

As shown in Figure 10, the p-value of lack-of-fit is still greater than $\alpha = 5\%$, so the overall new model is suitable for describing the relationship between factors and the response and can be used in the optimization process with RSM. The obtained first-order model equation is:

$$\boldsymbol{y = 0{,}2913 + 0{,}0296x_1 + 0{,}0116x_3 + 0{,}0821x_4 + 0{,}0060x_5 - 0{,}0449x_1^2 - 0{,}0590x_3^2 + 0{,}1800x_5^2 + 0{,}1001x_4\,x_5}.$$

Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	8	0,610241	0,076280	32,70	0,000
Linear	4	0,124608	0,031152	13,36	0,000
X1	1	0,013983	0,013983	5,99	0,019
X3	1	0,002149	0,002149	0,92	0,343
X4	1	0,107900	0,107900	46,26	0,000
X5	1	0,000577	0,000577	0,25	0,622
Square	3	0,445549	0,148516	63,68	0,000
X1*X1	1	0,019890	0,019890	8,53	0,006
X3*X3	1	0,034361	0,034361	14,73	0,000
X5*X5	1	0,320148	0,320148	137,26	0,000
2-Way Interaction	1	0,040084	0,040084	17,19	0,000
X4*X5	1	0,040084	0,040084	17,19	0,000
Error	37	0,086299	0,002332		
Lack-of-Fit	24	0,064208	0,002675	1,57	$\boxed{0,199}$
Pure Error	13	0,022091	0,001699		
Total	45	0,696539			

Fig. 10. Lack of fit test results for the second-order model without insignificant terms.

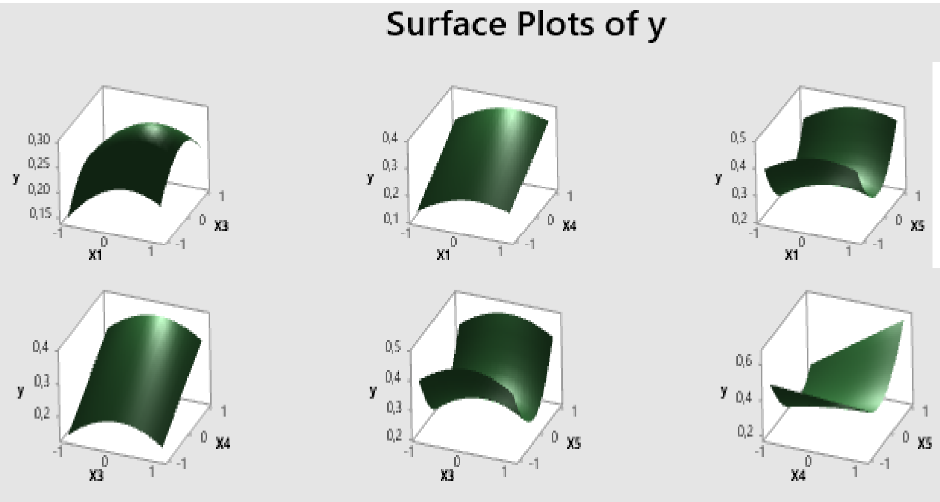

Fig. 11. Surface plot.

With the help of the Response Optimizer from Minitab 19, which as shown in Figure 11 and 12, the optimization findings had yielded a combination of factor levels that can generate the lowest response values (the percentage of defective products, ***y***). Specifically, these levels are -1 for x1, -1 for x3, -1 for x4, and 0.2616 for x5. Therefore, the optimal factor level combinations are 180°C for x_1, 180°C for x_3, 35 bars for x_4, and 41% for x_5.

In the Improve stage, precondition design and the optimal setting levels of machine parameters are implemented. As the segment 2 barrel temperature does not statistically have a significant effect on the response, then the factor is set at the low level, which is 185°C, because using a low factor level tends to be more economical. After the improvement recommendations are implemented, production data is collected again to calculate the new sigma level.

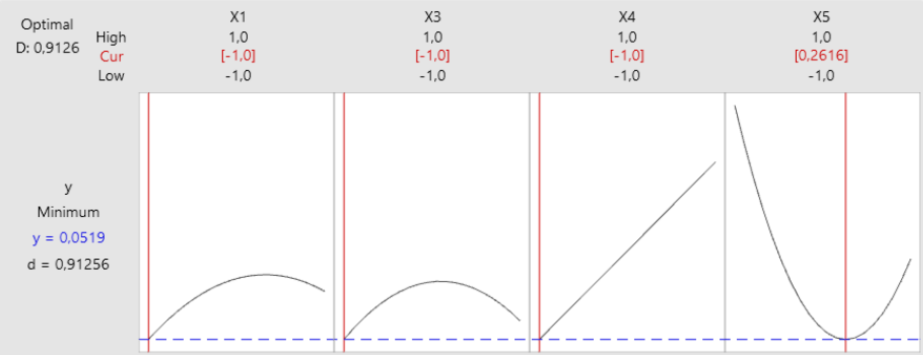

Fig. 12. Optimal result to minimize the defective products

3.3 The Control Phase

According to the data presented in Table 3, it showed that a decline in the Defects Per Million Opportunities (DPMO) and a corresponding increase in the sigma level. This empirical evidence proved the effectiveness of the implemented improvements in reducing the occurrence of defective products and enhancing the overall capability of the production process.

Table 3. Comparison of DPMO and sigma level for the initial vs the improvement.

	Initial Condition	After Improvement
DPO	0,01609177	0,00819672
DPMO	16.091,77	8.196,72
Sigma Level	3,64	3,90

Control plans are made to monitor production operators so that operators implement the designed improvements properly and for the injection molding machine so that the parameters continue to operate at the optimal level. The determined control designs are a visual reminder so that production operators carry out the mixing process properly, the nozzle cleaning in the injection machine and the checking form to ensure that production operators routinely clean the nozzle every morning, a positrol plan to ensure injection molding machine parameters operate at the optimal level, and a checklist for resetting the machine parameter levels to ensure that production operators routinely reset the machine's parameter settings every two hours.

4 Conclusions

The research was conducted using the DMAIC framework. The focus of this study was on the black-colored hangers that were manufactured using an injection machine. The initial three phases, namely Define-Measure-Analysis, yielded the following outcomes: (i) there were six types of defects, namely short mold, lack of the color black, rough wrinkled surface, flash, easily broken if bent, and dirty, (ii) the current injection process has achieved a sigma level of 3.64. The Pareto diagram was utilized to identify the primary types of defects, which were found to be flash, short mold, and lack of the color black, accounting for a cumulative proportion of 81.64%, (iii) by using Ishikawa diagram and FMEA, improvement priorities for critical root causes can be determined.

The preconditioning stage was intended to facilitate the mixing process, ensure the quality of materials received from suppliers, and establish a plan for nozzle cleaning. The experimental design is aimed to determine the optimal combination of injection molding machine parameter settings. The experimental design was done by using the Response Surface Methodology (RSM). The adoption of RSM into DMAIC framework was done in the stage of Improve. The Box-Behnken Design (BBD) was chosen as the preferred response surface methodology (RSM) in order to mitigate the occurrence of excessive treatment combinations, which could lead to a higher number of defective goods.

The BBD experimental design included five machine parameters, specifically segment 1, 2 and 3 of barrel temperature, injection pressure, and injection speed. The measured reaction pertained to the proportion of flash and short mold defects. The application of Analysis of Variance (ANOVA) revealed that certain parameters exhibit statistically significant effects on the reduction of defective products. The optimal combination of parameter levels for the injection machine was determined to be 180°C for segment 1 barrel temperature, 180°C for segment 3 barrel temperature, 35 bars for injection pressure, and 41% for injection speed.

By implementing the designed improvements, a decrease in DPMO to 8,196.72 and an increase in sigma level to 3.90 were obtained. These proved that the designed improvements can actually reduce the number of defects as well as increase the capability of injection process.

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