REDUCING DEFECTIVE OF ROLL M-70 PRODUCT ON CASTING PROCESS

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ABSTRACT

Statistical process control (SPC) is a method of monitoring the production process with the goal of maintaining product quality during the production process. Thus, once the problems (variables)have resulted, the repair process can be immediately identified and carried out.However, in some cases, the application of SPC is not maximized. This was caused by the lack of a systematic procedure that was usedto guide the operator in applying statistical process control. Therefore, this study offers a systematic procedure to guide the operator in applying SPC. Systematic procedure is performed with the literature study and direct observation in manufacturing companies. In order to apply statistical process control, several statistical tools are accommodated according to their needs and objectives. Thus, it results systematic application of SPC procedure which consists of 15 steps and is divided into two concepts.Indicator is applied to determine the systematic procedure to qualify whether the test is applicable and can improve the ability of the process. Definition of applicable is able to guide the operator in applying SPC and stabilize the process. Systematic procedure have undergone testing at the casting factory. Systematic procedures otherwise applicable and may improve the ability of the improved process.

Keywords : Statistical process control, Design of Experiment, defective

INTISARI

Statistical Process Control (SPC) adalah metode pemantauan proses produksi dengan tujuan menjaga kualitas produk selama proses produksi. Dengan demikian, setelah masalah (variabel) telah diidentifikasikan, maka proses perbaikan dapat segera diidentifikasi. Namun, dalam beberapa kasus, penerapan SPC belum maksimal. Hal ini disebabkan oleh kurangnya prosedur yang sistematis yang digunakan untuk memandu operator dalam menerapkan pengendalian proses statistik. Oleh karena itu, penelitian ini menawarkan prosedur sistematis untuk memandu operator dalam menerapkan SPC. Prosedur yang sistematis dilakukan dengan studi literatur dan observasi langsung di perusahaan manufaktur. Dalam rangka menerapkan pengendalian proses statistik, beberapa alat statistik yang ditampung sesuai dengan kebutuhan dan tujuan mereka. Dengan demikian, hasil aplikasi sistematis prosedur SPC yang terdiri dari 15 langkah dan dibagi menjadi dua concepts.Indicator diterapkan untuk menentukan prosedur sistematis untuk lolos apakah tes ini berlaku dan dapat meningkatkan kemampuan proses. Definisi yang berlaku adalah mampu membimbing operator dalam menerapkan SPC dan menstabilkan proses. Prosedur yang sistematis telah menjalani pengujian di pabrik pengecoran. Prosedur sistematis dinyatakan berlaku dan dapat meningkatkan kemampuan proses perbaikan.

Kata Kunci : Statistical process control, Design of Experiment, defective.

INTRODUCTION

Quality control (QC) is an important function and critical success factor for the companies as it deals with product inspection before the product is shipped to customers. For this reason, an increasing emphasis on quality should be done continuously by reducing the defect rate. Hence, monitor and build quality into the process are ways to eliminate defects. Statistical process control (SPC) is one of the tools widely used in QC to monitor whether the production process is in control through the use of statistical control chart.

Montgomery, 2008 described that control chart used to the simplicity of its implementation and the ease of interpretation of the process status (in control or out of control). However, traditional control charts currently can show problems of performance or practical implementation, Other researchers also propose a systematic procedure concerning the application of SPC are Laosiritaworn and Bunjongjit, 2010. This research generates a systematic procedure for applying control chart. However, as a supporter of the application of SPC control charts, design of experiments required.

Design of Experiments (DoE) method, has been widely used by many researchers. Eriksoon , 2008 used any kind of experimental subjects that have emerged on system to check the theoretical results and also to obtain some practical information or to optimize its operation.

This research only showed the optimal results on the variable of parameter factor while other treatments such as calculation loss function have not been discussed. Based on those researches, it will be conducted further research with a systematic procedure concerning the application of SPC that is applicable and comprehensive so easily understood by operators on the production floor.

Several researches concerning to the quality improvement gathered more attentions in recent years. Due to the difficulties of control system in those industries, many methods are developed to maintain the production process. Mares and Sokolowski , 2010 mentioned that the integration of Statistical Process Control methods was developed to analyze casting component properties.

In the current Quality control, control chart as a featured tool of statistical process control has been used extensively by practitioners to monitor and even reduce process variation by identifying and eliminating sources of variation Montgomery, 2008. Yamamoto, H., et al , 2010 mentioned the P control chart is often used in manufacturing processes as a control tool for monitoring product qualities. Wu, et al. 2009 proposed the use of an np x chart to monitor a process mean by attribute inspection as an alternative to the use of an x chart. Tuerhong et al., 2014 proposed control charts can efficiently handle mixed data. Ho Wu and Chang, 2004 applied the Taguchi method to optimize the process parameters for the die casting of thin-walled magnesium alloy parts in computer, communications and consumer electronics industries.

Muzammil, et al, 2003 made a study for optimization of Gear Blank Casting Process by Using Taguchi's Robust Design Technique. In this study they demonstrated that casting process involve a large number of parameters affecting the various casting quality features of the product. The reduction in the weight of the casting as compared to the target weight was taken to be proportional to the casting defects. NoorulHaq, et al , 2009 in their study demonstrates optimization of CO_2 casting process parameters by using Taguchi's design of experiments method. The effect of the selected process parameters on casting defects and subsequent setting of the parameters are accomplished by using Taguchi's parameter design approach.

METHODOLOGY

The objective of this paper is a program development on quality improvement based on SPC and also optimizing the process parameters on casting process including optimum levels using Taguchi method while quality loss function are needed to balance the cost and quality of a product. The case study is conducted in a job foundry in Klaten, Central Java.

Research Model, The model of this research is the application of SPC to identify the defect in milling process in order to improve the performance for increasing quality of products. The model uses a formula that has been built by Laosiritaworn and Bunjongjit, 2010

Research Design, To solve the problem, this research applies SPC under systematic procedure. Systematic design is a systematic procedure in flowchart form that developed in order to facilitate the operator in applying statistical process control. The systematic flowchart is shown in Figure 3.1.

In these cases, the product or component are classified as conforming or non-conforming. Control charts for these features are called control charts for attributes. They demonstrate the data process collecting such as: amount of production, product accepted, and reject product number, then identify and categorize the data into attribute or variable data.

Determine Stastitical Control Chart, Hence, the data is attribute, need to differensial between the different type of control chart is required to measure proportion of rejected product in sample.

It already mentioned that p -chart control has been applied to measure the proportion of items in a sample that are defective. The purpose of this analysis is to compute the upper and lower control limits with formula is the p chart shown in Eq

$$UCL = \overline{p} + z\sigma \ , \ LCL = \overline{p} - z\sigma$$

Where, z = standard normal variable
$\overline{p}$ = mean value of sample proportion defective
$z\sigma$ = the standard deviation of the average proportion defective

As with the other charts, z is selected to be either 2 or 3 standard deviations, depending on the amount of data that wish to be captured in the control limits. Usually, however, they are set at 3. The sample standard deviation is computed as follows:

$$\sigma_p = \sqrt{\frac{\overline{p}(1-\overline{p})}{n}}$$

Where n is the sample size.

To all processing of 27 reject data, so the result of fraction defective, upper control limit and lower control limit which will be inserted and calculated into the Minitab software are shown in Figure 1

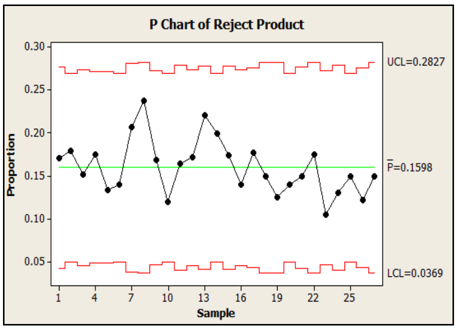

Figure1: *p -chart graph*

In Figure 4.2, it is showed that when the control limit and part of rejected samples mapped, there was no input data which was out of control however there are still many defects. So, this research will try to reduce the number of existing defects and make a high quality improvement but firstly, it is needed to identify the factors that cause product defect which will be explained in the next sub-section.

Identifying root cause, The purpose of this analysis is to identify the possible causes. The primary factors will become a parameter to determine the optimum setting. Based on the Figure. 2, there are four factors that affect the occurrence of product defects i.e. material, method, molding, production process.

As the core of this research, the production process has the most significant effect on the occurrence of defective products produced. This defect is caused by four factors: pouring time, pouring temperature, permeability, and

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water content. Therefore, Design of Experiment (DoE) will be applied to determine the optimum settings to these factors by considering the value of the parameter of each level.

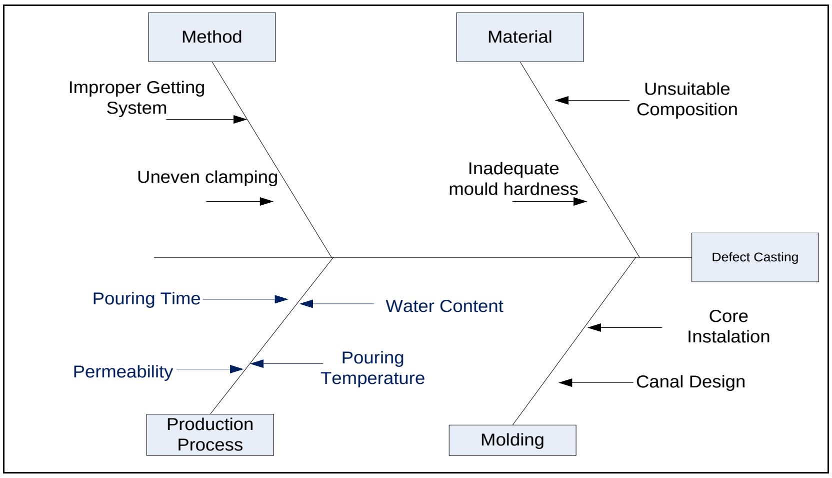

Figure 2: Ishikawa Diagram

The Taguchi method can be applied by using eight experimental steps that can be grouped into three major categories as follows Phadke, 1989:

Planning the experiment:

1. Identify the main function of casting process.
2. Identify the quality characteristic to be observed and the objective function to be optimized.
3. Identify the control factors and their alternate levels.
4. Identify noise factors and the testing conditions of the process.
5. Design the matrix experiment and define the data analysis procedure.

Performing the experiment:

1. Conduct the matrix experiment.
2. Analyzing and verifying the experimental results:
3. Analyzing the data, determining the optimum levels for the control factors, and predicting performance under these levels
4. Conducting the verification (also called confirmation) experiment and planning future actions

Furthermore, important factors were selected and used the DOE modelling involved in the experiment are Pouring temperature, Pouring time, Permeability, Water content.

For each process parameter, three levels and four factors are selected which define the experimental region is shown in Table 1.

Table 1: Factors and Level design

Factors	Level		
	1	2	3
Pouring Temperature	1320° C	1350° C	1380° C
Pouring Time	15sec	18sec	20sec
Permeability	75ml/cm²	80 ml/cm²	90 ml/cm²
Water Content	75%	8%	9%

Quality Characteristic**,** Casting defects was selected as a quality characteristic to be measured. The most common defects occurring in the foundry were monitored and recorded. The smaller the better number of casting defect implies better process performance. Here is the objective function to be maximized:

$SNratio\eta' = -10\log$ $meansquaresurfacedefects$
$S/Nratio\ (\eta') = -10\log\ (\Sigma yi\hat{}2)/n$

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Maximizing η leads to minimization of quality loss due to defects. Where *S/N* ratio is used for measuring sensitivity to noise factors, *n* is the number of experiments orthogonal array, and *yi* the i^{th} value measured.

Selection of orthogonal array, Selection of orthogonal array was adopted from Fowlkes and Creveling, [2] which will be processed using *Minitab software* to obtain the proper orthogonal arrays. The L9 Orthogonal Array can handle four factors at three levels L9 Because the DoF = 8, so, it can be separated into two DoF per column. This is because the Dof_f = (3-1) = 2 Columns 1 and 2 of the L9 make up the 32 full factorial. The orthogonal array is shown in Table 2.

Table 2: Orthogonal Array

Run	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
L	1	1	1	2	2	2	3	3	3
e	1	2	3	1	2	3	1	2	3
v	1	2	3	2	3	1	3	1	2
e	1	2	3	3	1	2	2	3	1
l									

The value factors in Table 2 Orthogonal Array will be entered into *Minitab software.* The results of data inputting into Orthogonal Array is shown in Table 3. Experimental Orthogonal Array consisting of 9 running experiments by testing all combinations of values in each factor.

Table 3: Experimental orthogonal array

Trial No	Pouring temperature	Pouring time	Permeability	Water Content
1	1320°C	15 sec	75 ml/cm^2	7%
2	1320°C	18 sec	80 ml/cm^2	8%
3	1320°C	20 sec	90 ml/cm^2	9%
4	1350°C	15 sec	80 ml/cm^2	9%
5	1350°C	18 sec	90 ml/cm^2	7%
6	1350°C	20 sec	75 ml/cm^2	8%
7	1380°C	15 sec	90 ml/cm^2	8%
8	1380°C	18 sec	75 ml/cm^2	9%

Due to the number of defects, 27 data will be divided into 3 levels, experiments, so there are 9 running experiments as shown in Table 4

Table 4: Experimental data

Experiment	Sample Size 1	2	3	Total Defect
1	15	12	10	37
2	18	14	14	46
3	14	16	13	43
4	17	19	14	50
5	13	20	10	43
6	14	15	11	40
7	17	13	15	45
8	19	16	11	46
9	16	12	12	40

Experiment Results and S/N Ratios, The static S/N Ratios are the most commonly used metrics in Robust Design. They relate directly to calculate mean square deviation. The computing example is presented as following:

$$MSD = \frac{(15^2 + 12^2 + 10^2)}{3} = 156.33$$

$$\frac{S}{N} = -10\log_{10}(156.33) = -21.94$$

Ratio calculation results of MSD and S / N are distributed to the major factor response and optimum variables can be determined by Minitab software. Figure 3 shows the response of the main factor calculations Main ratio S / N.

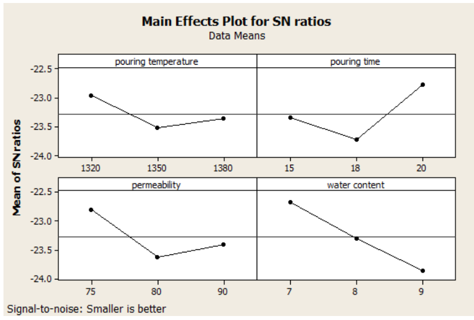

Figure .3 graphs of main factor response

Based on the above calculation, the selection of the optimum settings is the greatest value in each of the factors contained in the Figure 3. Then the optimum settings are Pouring Temperature: Level 1 (1320ºC), Pouring Time : Level 3 (20 sec), Permeability : Level 1 (75 ml/cm²), Water Content : Level 1 (7%)

Implementing the DoE result analysis into the process**,** The results from design of experiments provide the most optimum output of the variable compared with other tolerance values. So the value of the tolerance should be applied to the production process directly. Data collecting after implementation is needed to estimate the extent to which savings from improved quality.

Collecting and evaluate the new data process, Based on calculations of 27 Data from data after p -chart, then the data inputting process using Minitab software is executed and produces a graph as shown in Figure.4

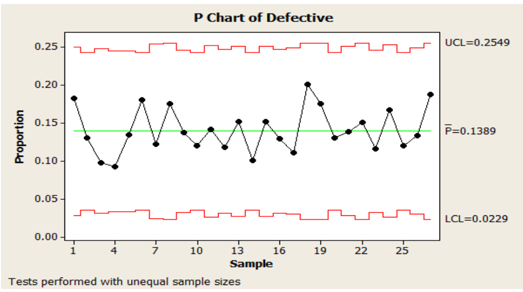

Figure 4 : *p -chart* of after data process

Based on the Fig. 4 we can conclude that there is no point outside of the limits and the defects result in milling products are decreasing if compared with the initial *p -chart.* In details, changes between the defect before and after the process capability will be analyzed.

Capability Process Analysis**,** Process capability can be analyzed as a ratio to determine whether a process fulfill design specifications. Figure 5 is process capability of initial defect data which the results will be compared with the before and after results of data defect analysis capability. Data processing will be analyzed using Minitab software in accordance with the steps following

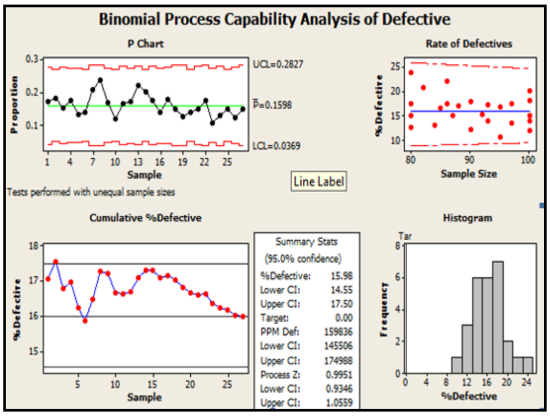

Figure 5 Capability proses for initial defect

This analysis resulting a *Process Z* = 0.995, and its *defective* percentage is15.98 %. The higher the z value process, the better ability of these processes to fulfill design specifications set by consumer demand. To see the analysis capability in data after, minitab software will be employed to process the data returned. The results are shown in Figure 6.

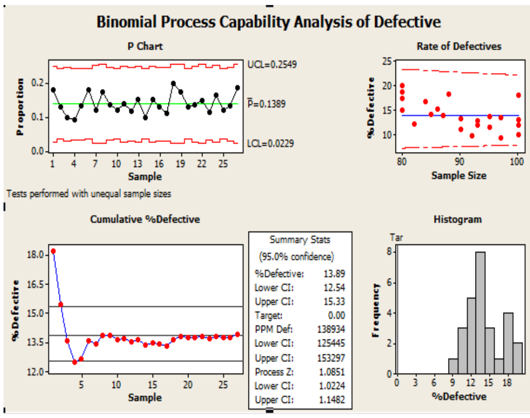

Figure 6. Result of *capability analysis* using *Software* Minitab with data after

The results of capability process analysis use data after with generating value = 1.0851 and Z Process defective with the percentage of 13.89%,

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increasing value of Z is an indicator of the increased ability process.

Process Improvement Analysis, The process can be terminated once the test is passed. This is due to the increase of Z of the process by 9.05% from the previous value of 0.995 to 1.0851. Process of Z represents the standard deviation of the data. Therefore, higher process Z value, the ability of these processes will also increase. This is also supported by stable process that has been improved.

Hypothesis test

$H_o : \mu_1 = \mu_2$; $H_o : \mu_1 \neq \mu_2$

$\alpha = 0,05$; Critical area $t < -2.05$ *and* $t > 2.05$

$$t = \frac{\bar{d} - d_0}{Sd / \sqrt{n}} \qquad With\ v = n - 1 = 27 - 1 = 26$$

$$Sd^2 = \frac{(27)(487) - (51)^2}{(27)(26)} = 15;$$

$$Sd = \sqrt{Sd^2} = \sqrt{15 = 3.8}$$ and

$$t = \frac{2-0}{3.8/\sqrt{27}} = 2.73$$

t < −2.05 and t > 2.05 so the results of the calculation (2.73 > 2.05) thus, Included in critical zone and concluded that there was significant difference between the number of defects before and after.

Total defect data before and after will be analyzed to determine the percentage of quality loss function. Percentages of defects before and after shown are in Table 6.

Calculation of k :

Cost (A_0) = 50000 IDR, and Upper limit (Δ)=0.95

$$k = \frac{A_0}{\Delta} + \frac{Rp\ 50.000}{0.95^2} = 55.401{,}662$$

Calculation before conducting research:

$y = \frac{390}{27} = 14{,}4$; $\sigma = 2{,}357$; σ^2=5,559;
$L_{(y)} = k(\sigma^2 + y^2) = 11.798.337$

Calculation after conducting research:

$y = \frac{339}{27} = 12{,}6$; $\sigma = 2{,}357$; σ^2=5,559;
$L_{(y)} = k(\sigma^2 + y^2) = 9.103.601$

With the proposed setting, then there is a cost savings of 2.694.736 IDR per year

Table 5 Hypothesis test calculation Paired T

No	Initial Defect	Defect After	d	d^2	No	Initial Defect	Defect After	d	d^2
1	15	16	-1	1	16	13	12	1	1
2	18	13	5	25	17	16	10	6	36
3	14	9	5	25	18	12	16	-4	16
4	17	9	8	64	19	10	14	-4	16
5	13	13	0	0	20	14	13	1	1
6	14	18	-4	16	21	13	12	1	1
7	17	10	7	49	22	14	12	2	4
8	19	14	5	25	23	10	11	-1	1
9	16	13	3	9	24	11	14	-3	9
10	12	12	0	0	25	15	12	3	9
11	14	12	2	4	26	11	12	-1	1
12	16	11	5	25	27	12	15	-3	9
13	19	13	6	36			**Total**	51	487

14	20	10	10	100	**Average**	2	18
15	15	13	2	4			

Table 6. Defect before and after

No	Defect initial	Defect after	Total Production	No	Defect initial	Defect after	Total Production
1	15	16	88	15	15	13	86
2	18	13	100	16	13	12	93
3	14	9	92	17	16	10	90
4	17	9	97	18	12	16	80
5	13	13	97	19	10	14	80
6	14	18	100	20	14	13	100
7	17	10	82	21	13	12	87
8	19	14	80	22	14	12	80
9	16	13	95	23	10	11	95
10	12	12	100	24	11	14	84
11	14	12	85	25	15	12	100
12	16	11	93	26	11	12	90
13	19	13	86	27	12	15	80
14	20	10	100				

DISCUSSIONS

To improve the quality, this research proposes a p-chart as a model for measuring the percentage of rejection in a sample of attribute, a small sample is mapped and then the characteristics of the resulting data tested to see whether the process is within control limits.

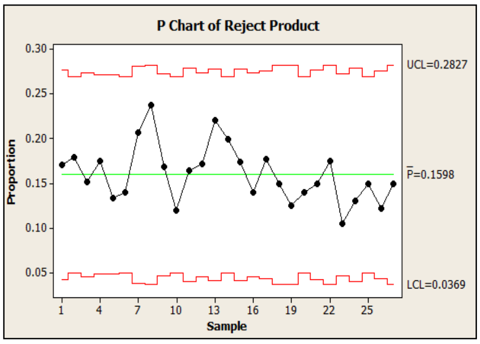

Figure 7: *p -chart* of initial defect

Figure 7, shows that a process is under control and capable of producing the specified control limit, however many defects that occur caused by factors in the casting process. Therefore, to reduce the number of defects, the implementation of optimum variables is required.

Design of experiment was used to determine the optimal parameter settings on the process performance to get the best combination on existing variables. In this experiment, the authors determine the four parameters that influence the occurrence of defects of the casting products. Those variables are pouring temperature, pouring time, permeability and water content. The combination of these four variable level values are processed by Minitab that generates optimum value which can be seen from the results of graph, indicates pouring temperature level 1 is -68.87, pouring time is -68.31 level 3, and level 1 is -68.41 permeability and water content levels 1 is - 68.00.

Based on analysis result, it can be seen that the optimal setting for pouring temperature are 1320^{0}C, pouring time of 20 cm, permeability of 75 ml/cm² and water content 7%. The water content is the most influential factor of each factor there, it can be concluded that the water in the molding sand is turning bentonite holding capacity so that it can be used to bind the molding sand. When the water content continuously improved it will affect fastener holding capacity, water content continues to be added to make the water that is added into the free water and fill the gap with the grain while the water is added continuously to the molding sand into a paste (defect).

The results of design of experiments analysis provide the most optimum output of the variable compared with other tolerance values. So the value of the tolerance should be applied to the production process directly. Significant reduction occurred in the new data can be displayed in the *p*-chart is shown in Table 6. Based on the graph above, it is concluded that there is coming out of the limits and the defects result in milling products are decreasing if compared to initial *p*-chart

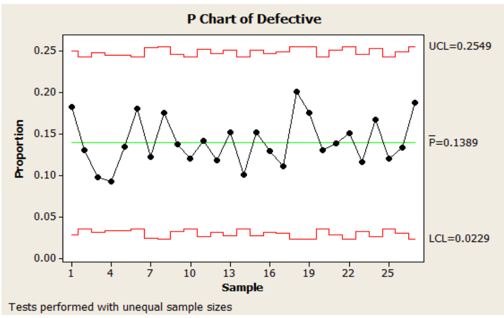

Figure 8: *p*-chart of data after

Based on the calculation results, it is showed that, the cost of losses before trial is 11.798.337 IDR. While the cost of losses after the trial is 9.103.601 IDR. Hence, it establishes cost savings for 2.694.736 IDR. Since the tremendous savings that can be obtained, it is necessary to generate the implementation of the optimum settings in this study as well as to conduct sustainable evaluations for the production process.

CONCLUSION

This study has successfully developed the SPC based quality improvement program in the form of a systematic procedure of statistical process control application so that can assist operators in implementing statistical process control. Systematic procedure can be applied and passed the test, with evidence of the testing results that form a new stable process, and the increasing value of Z of the process becomes 1.0851 and defective reduce become 13.89%. The result of optimal conditions using DoE (Design of Experiments) are 1320^{0}C in temperature, pouring time of 20 cm, permeability of 75ml/cm²and water content of 7%. It can be concluded that if this parameter implemented into real system, the defect will be decreased also. The profit of the company increases due to 2.694.736 IDR cost savings by calculating before and after defect loss cost.

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