MINIMIZING NUMBER OF DEFECTS IN NICKEL PLATING PROCESS USING FACTORIAL DESIGN

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ABSTRACT: Product defects may have a serious problem in any manufacturing company because they may increase the production cost due to rework, delays, waste of time and material. The purpose of this study was to investigate significant factors and their interactions in order to find the optimal setting that could reduce the number of defects in nickel plating line. Factorial design has been used as the experimental design technique to identify the critical factors to be controlled. This experiment investigated three different factors using full factorial design. The results were analyzed using Design Expert software. Analysis of variance (ANOVA) was utilized to find the most significant factors. The finding suggested that only one main factor Brightner Correction Solution (BCS) and one interaction factor (BCS and hot COT temperature) affected the number of defects in nickel plating line. The optimum process setting was attained at 22 g/L of BCS and 50°C of hot COT (Cream or Tartar) temperature. A confirmation run using these new settings approved a reduced number of defects in nickel plating process.

KEYWORDS: *Factorial design, Design of Experiment, Product Defects, ANOVA, Nickel Plating Process.*

1.0   INTRODUCTION

Design of experiments (DOE) has been used widely in industries to model and optimize manufacturing processes. This method focuses on minimizing the amount of required experiments for an analysis, while maintaining high quality results [1]. Factorial design, an instrument of DOE, is an excellent statistical method for quality improvement, that is, the optimization of heat treatment variables to eliminate wobbling of gears [2].Using factorial experiment to analyze industrial problems can provide a good result within shortest periods of time with the least costs [3].

The nickel plating process encounters a problem of high reject or defect rate especially in nickel plating production line number five. The Full

Factorial Design experiment was implemented in this study to reduce the number of defective products. This study involved three factors, each with two different levels which is lower and higher. These factors are suspected to have high impact on the number of defects.

A previous study on eliminating wobbling of gears has shown the gear wobbling defects in the gears assemblies can be reduced to less than 1% when applying factorial design [2]. The wobbling of gears can be removed by finding the optimum setting between three heat treatment variables because it causes the multi speed gear assemblies become defective. Factorial design considers a response at every possible combination and set up factors at different levels [2]. The advantage of factorial experiment compared to the conventional experimentation is that all levels of a given factor are combined with all levels of every other factor in the experiment, hence, a possible interaction between factors can be verified.

This study investigated factors and their interactions that had significant contribution to the number of defects in the nickel plating process. The development of regression model helped to explain the relationship between the number of defects of the process and their significant factors or interactions. Moreover, another crucial contribution of this study was to find the optimum setting of parameters which minimized the number of defect products.

2.0   METHODOLOGY

2.1   Determination of the response variable and parameters

Originally, seven factors are assumed to have impact on the number of defects in nickle plating line. However, only three variables were allowed to be adjusted to avoid disruption in production operation. The input variables, therefore, include BCS (Brightner Correction Solution), hot COT (Cream or Tartar) temperature and nickel plating solution temperature.

To prepare the BCS, several steps should be followed and the analysis was performed everyday to ensure the density level as required. The preparation involved titration process as in Figure 1.
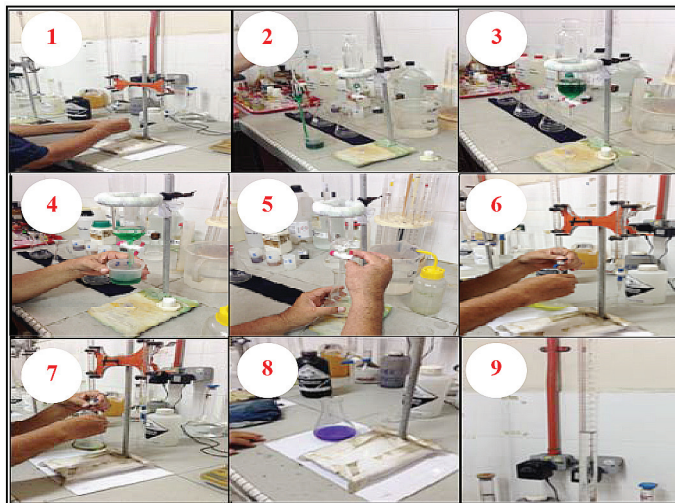
Figure 1: Analysis process of Brightener Correction Solution (BCS)

There are three types of defects in nickel plating process. The first is called yellowish which occurs when color of the product does not meet the required specification. Other types of defects are dull (unbrightened) and rusty. The initial setting parameters can be seen in Table 1.

Table 1: The Initial Settings of the Parameters

Parameters	Level	
	Low	High
Brightener correction solution density (BCS) (g/L)	17	22
Nickel Plating solution Temperature (^{0}C)	52	58
Hot COT Temperature (^{0}C)	50	60

2.2 Data collection and measurement of defects

In this study, data were collected from the result of one shift production run which consisted of 40 lots for every shift. The number of defects in nickel plating process was determined by inspections. Currently, there is no technical method to measure defects for plating process. The inspector was using visual examination by visually looking at the parts and judged whether the parts were rejected or not. This method involved experience whereby every inspector was well trained before they are qualified to do inspection. To avoid variation in the results, only two inspectors were allowed to analyze and detect reject parts. Figure 2 illustrates the conceptual framework on the relationship between independent variables and a dependent variable.
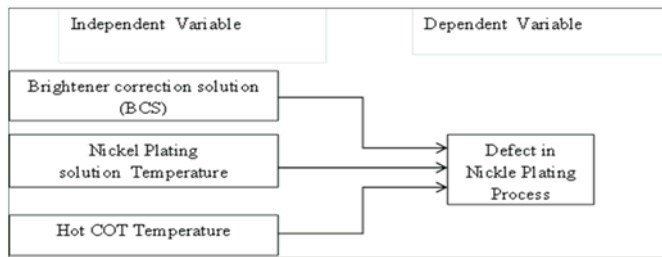
Figure 2: The Conceptual Framework

2.3　Design of experiment

In this experiment, full factorial design was used to study the effect of three independent variables. As the number of factors increases, the number of runs required for a complete replication of the design outgrows the resources of the experiment [5]. Hence, it is practical to use full factorial design when less than five factors are being investigated [2]. This experiment was designed to use a full factorial design that consisted of three factors. Each has two levels which were low and high. With this arrangement, a full factorial design would need 2^3 or equivalent to 8 treatment combinations. This study used the *Yates Standard Order* which was developed by Frank Yates [6] as a method to generate experimental designs in a consistent and logical fashion.. Design matrix in Table 2 shows the 2^3 factorial designs with treatment combinations in Yate's order.

Table 2: Design matrix for 23 full factorial design

Standard Order	Factors		
	(Factor A) Brightener correction solution Density (BCS) (g/L)	(Factor B) Nickel Plating solution Temperature (^{0}C)	(Factor C) Hot COT Temperature (^{0}C)
1	17	52	50
2	22	52	50
3	17	58	50
4	22	58	50
5	17	52	60
6	22	52	60
7	17	58	60
8	22	58	60

Pilot experiment was done simulataneously as the conduct of replicate 1. The purpose of the pilot test was to verify problems that might appear during the experimental run. This was accomplished by running

different random numbers. When the problems were solved, the real experiment could be further conducted on replicate 2 and replicate 3.

In this experiment, ANOVA was applied to identify the most significant variables that influenced the result. This statistical analysis was then applied to the experimental results in order to determine the percent contribution of each factor and factor interactions [6]. This analysis also helped to determine factors which needed to be controlled and not be controlled.

3.0   RESULTS

3.1   Parameter Screening

A visual inspection on the number of defects after the plating process shows different response from different treatment combinations. Table 3 presents the percentage of defect products for three replication.

Table 3: Full Factorial Experimental Results

Standard Order	Factor			Result (% of Defect)		
	A	B	C			
	(Brightener correction solution (BCS) (g/L)	Nickel Plating solution Temperature (^{0}C)	Hot COT Temperature (^{0}C)	Replicate 1	Replicate 2	Replicate 3
1	17	52	50	26.31	35.00	35.13
2	22	52	50	10.00	8.57	20
3	17	58	50	48.50	37.50	10.81
4	22	58	50	7.50	27.50	2.63
5	17	52	60	27.27	25.64	19.44
6	22	52	60	17.50	8.10	22.5
7	17	58	60	10.52	13.88	15
8	22	58	60	17.50	28.00	5.71

According to the results, run order number 3 in replicate 1 produced the highest percentage of defect which was 48.5%. Run order number 3 was a combination of 17 g/l of BCS, 58°C of Nickle Plating Solution Temperature and 50°C of Hot COT Temperature. The run order number 4 in replicate 3 produced the lowest percentage of defect which was 2.63%. Run order number 4 involved 22 g/l of BCS, 58°C of Nickle

Plating Solution Temperature and 50°C of Hot COT Temperature. In order to know the significant factor of the model, the data were analyzed using Design Expert software to determine the analysis of variance (ANOVA), regression model and graphical data.

3.2   Half Normal Plot

Figure 3 shows the resulting plot generated by Design Expert software for number of defect products with all big effects selected according to hierarchy. In this plot, five of the effects (B, C, AB, BC and ABC) fell on or close to the line. On the contrary, the effects of A and AC were relatively separated from the other effects. They, obviously, did not fall on the line. Therefore, both effects should be assumed as significant factors. In other words, both factors A and AC were important and needed to be investigated and analyzed further to see how they influenced the response of variable namely the number of defects.
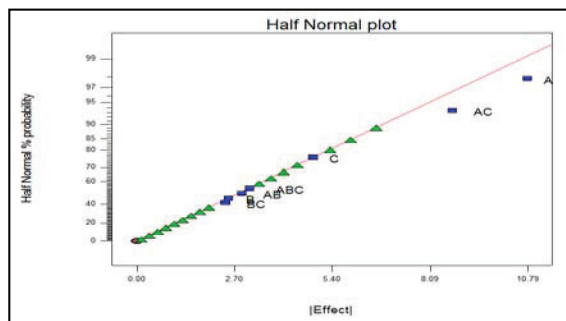

Figure 3: Half-normal Plot Effects for Number of Defects

3.3   Analysis of Variance

Analysis of variance was applied to confirm which factors and their interaction contributed significantly to the number of defects. Figure 4 demonstrates the ANOVA summary for each factor that consists of BCS density, nickel plating solution temperature, hot COT temperature and all interactions among the factors.

ANOVA for selected factorial model

Analysis of variance table [Partial sum of squares - Type III]

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	1296.68	3	432.23	4.77	0.0114	significant
A-BCS	698.65	1	698.65	7.72	0.0116	
C-Hot COT 1	142.06	1	142.06	1.57	0.2248	
AC	455.97	1	455.97	5.04	0.0363	
Residual	1810.73	20	90.54			
Lack of Fit	182.73	4	45.68	0.45	0.7717	not significant
Pure Error	1627.99	16	101.75			
Cor Total	3107.41	23				

Figure 4: ANOVA result for Number of Defects (all big effects selected)

"Prob>F" often reported on a scale from 0 to 1. If the p-value was less than 0.05 , then, the factor has significant effect on the response, providing at least 95% confident for all results [5]. In this case, A (BCS) with p-value of 0.0116 and AC (BCS and Hot COT Temperature) with p value of 0.0363 were significant since both of p-value were less than 0.05. Even though AC was significant, the main factor C was not significant.

3.4   Regression Model

In addition to graphical analysis, regression analysis was used to find the regression coefficient. According to the results of ANOVA in Figure 6, two factors (A and AC) were statistically significant (p-value < 0.05). However, to maintain hierarchy, factor C should be included to the model. Therefore, the regression model in terms of coded factors is

$$Y = 20.02 - 5.40\ X_1 - 2.43\ X_3 + 4.36\ X_1X_3.$$

Whereby,
Y is the number of defects,
X1 is the brightener correction solution (BCS) density (g/L),
X3 is the hot COT temperature (^{0}C)

According to the regression coefficient above, the number of defect was low if the BCS was at the high level (+1) and Hot COT was at the low level (-1) which produced the total number of defects of 12.69%.

3.5 Model Validation (Residual Analysis)

Residual is a discrepancy between the predicted value and the actual (observed) value [2]. Figure 5 shows the Normal Plot of Residual.

It is essential to diagnose the residuals and validate the statistical assumption from normal line. According to the Figure 5, the resulting plot is approximately linear. The plot showed no abnormalities and there was no signs of any problem in this data. Therefore, the data satisfied the normality assumption because there was no significant deviations.
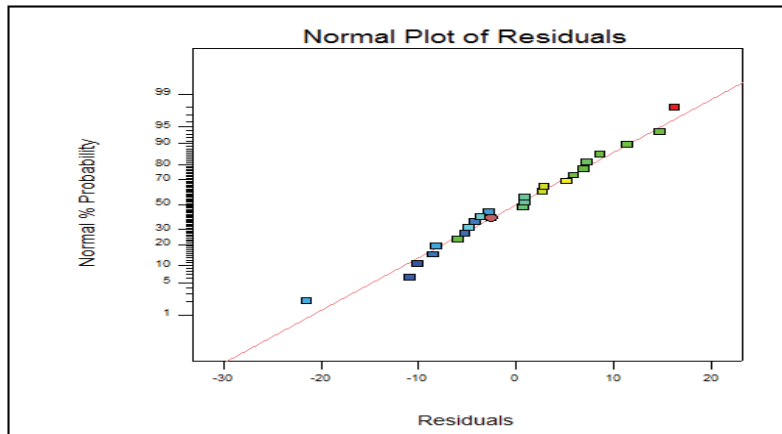

Figure 5: Normal Plot of Residual

3.6 The Optimum Setting of Parameters

One factor plot was used to present the main effect plot of the result. Figure 6 shows the main Effect Plot for BCS. The number of defects would be reduced when the BCS was set for high.
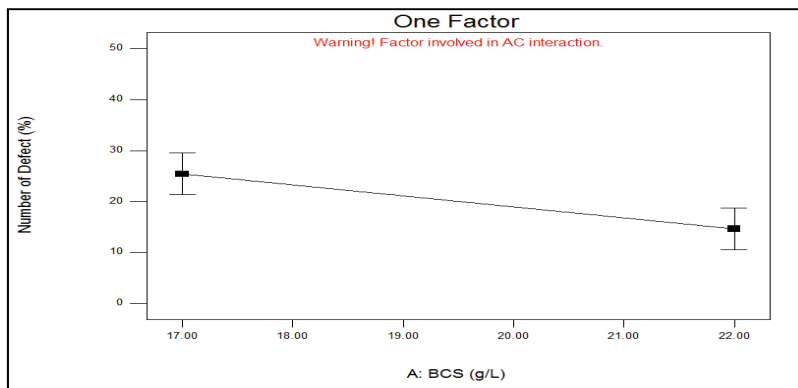

Figure 6: Main Effect Plot for BCS

Furthermore, the highest number of defects (25.42%) was achieved when BCS was at 17 g/L. Then the graph started to decrease to lower level which was 14.63%, when BCS was at 22 g/L. Hence, the optimal condition was achieved when BCS was set at 22g/L.
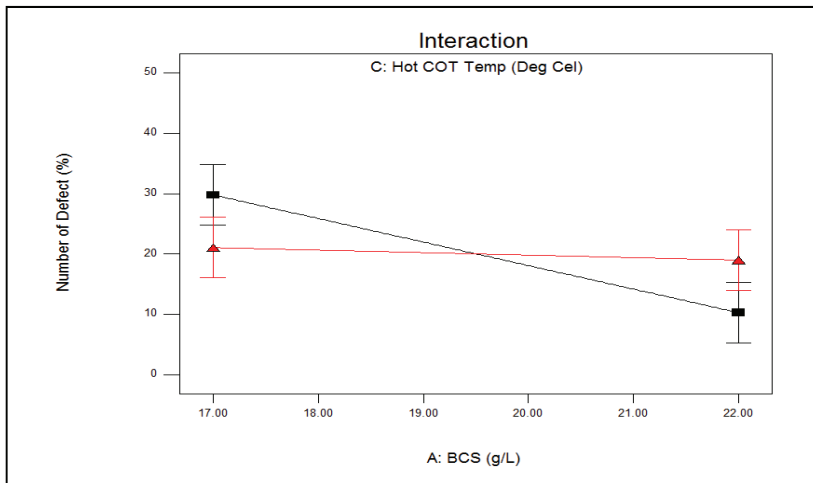

Figure 7 : Interaction Plot of BCS and Hot COT Temperature Vs Number of Defect

According to Figure 7, an interaction exists between BCS and Hot COT Temperature.The two lines overlapped with each other,indicating that the result from one factor was influenced by another factor. From the interaction plot, the lowest number of defect could be achieved when the BCS was 22 g/L (high) and the hot COT was 50 ^{0}C (low). On the contrary, the highest number of defects occured when the BCS was 17 g/L (low) and the hot COT was 50 ^{0}C (high).

If these optimum values were inserted into the regression coefficient model $Y = 20.02 - 5.40 X1 - 2.43 X3 + 4.36 X1X3..$, the lowest number of defects would be achieved, which was 12.69%, when X1 was replaced by +1 (high level) and X3 was replaced by -1 (low level).

In this study, confirmation run was conducted using these optimum values to see the difference. Within two weeks, there was a reduction in the number of defects. However the production cost also increased because the new setting required high quantity of BCS compared to the usual production run and the cost to buy the BCS was quite high.

For manufacturing firm, producing good quality of product is important to comply with customer requirement. However, they also need to make sure that the production cost does not exceed the budget

because their target is to reduce number of defects without increasing the production cost. Therefore it is hard to continue using the new setting if it may affect the production cost in the long term unless they can find very cheap raw material compared to the current usage. In this case, pre and post comparison cannot be made because the number of defects is analyzed every month and the confirmation run for this study can only be carried out for 2 weeks.

4.0   CONCLUSIONS

In conclusion, an interaction occurs between the two factors which shows that the combination of high level of BCS with the low level hot COT temperature can reduce the number of defects in nickel plating process. In short term, this project has achieved its objectives which is to understand the problem magnitude, the source of the problem, analyze the factors involved and find the optimal setting that can solve the problem. Basically, two parameters are identified as having significant effect in reducing the number of defects in nickel plating process. However, the data collected in the confirmation run are considered as a short term capability. Due to the cost limitation, the company cannot proceed with the new process setting at the longer period of time.

This study is limited in terms of the number of factors involved as only three factors are allowed to be investigated because the company does not want to take a risk by adding other factors that may affect the production process. In order to get accurate results, all the factors or input of the process should undergo the screening experiment to see which factors have important effect to the number of defects. Once the major factors that affect the process have been identified, more complex or multi-level design experiment can be used to identify the optimal settings. For further improvement, the company should take a risk to consider more factors for the experiment. When screening process is done, the interaction of all factors involved can be known. This will facilitate the next phase which is to find the optimal results using Response Surface Methodology so that better and accurate output can be achieved.

ACKNOWLEDGMENTS

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