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Application of statistical experimentation in manufacturing for process improvement

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Abstract
From the analysis of the available Quality Assurance data, one of the machine and/or process of a certain product in a manufacturing facility was found to be incapable because it consistently produces a high level of rejects everyday over months. Hence, an endeavor was undertaken to improve the machine/process in order to lower the reject rate thus improving quality and saving cost. A three-factor two-level full factorial statistical experiment was designed and carried-out in the manufacturing plant using real production units. Two reject types were chosen as responses and the data collected was analyzed using statistical techniques. The main and interaction effects of the variations in the factors was examined to arrive at a set of optimal machine settings. Challenges faced while running experiment under actual production environment and recommendations for further work are also discussed.

Keywords: Design of experiment, full-factorial experiment, process improvement, statistical techniques

Introduction

High quality and low cost have always been two of the most important considerations in the manufacturing industry. While there are many aspects to work on to raise quality level and lower production costs, one of the things that is always in the mind of any manufacturing engineer is the reject rate. A low reject rate not only directly reduces production costs, it will also inevitably elevate quality level.

To achieve a lower reject rate without relaxing the reject criteria, improving the machine/process capability is essential [5]. This, in turn, is achieved by properly design statistical experiment, correctly collected and accurately analyzed data which will reveal the optimum machine parameter settings.

A statistical experiment cannot be properly designed without a thorough study of past reject data and a deep understanding of the working of the machine which will enable an informed selection of machine parameters as factors [2, 5]. Conducting the experiment involves proper planning and coordination by the production manager and line leader as well as cooperation from the production supervisor and machine operators.

There was an academic-industry collaboration program in my institution called Faculty Industry Attachments. The arrangement is for the faculty to work on-site eight hours a day, two days a week for a total of six weeks continuously. This ninety six hours of practical work includes factory familiarization, project selection, team forming, design and running of experiment and data analysis. Due to the various constraints and delay in real-world production environment, ninety six hours is really quite a short time frame.

In order to protect the identity of the factory involved, the product name and nature as well as the machine and process are not mentioned and the defect types are coded.

Past Data Study

Defect Type

As the first step, all the previously collected data was congregated according to relevancy and been put in perspective before analysis is done on them. There are more than twenty five different types of defect but only two of them consistently showing an outstandingly high rate over the years. These two defects were coded as D and L. Type D defect is rejected through human inspection whereas type L defect is rejected from an automatic tester. Both of these defects constitute more than three quarters of the total defects in the months of March, April and May, and most likely in other months as well, as shown in the pie charts below.

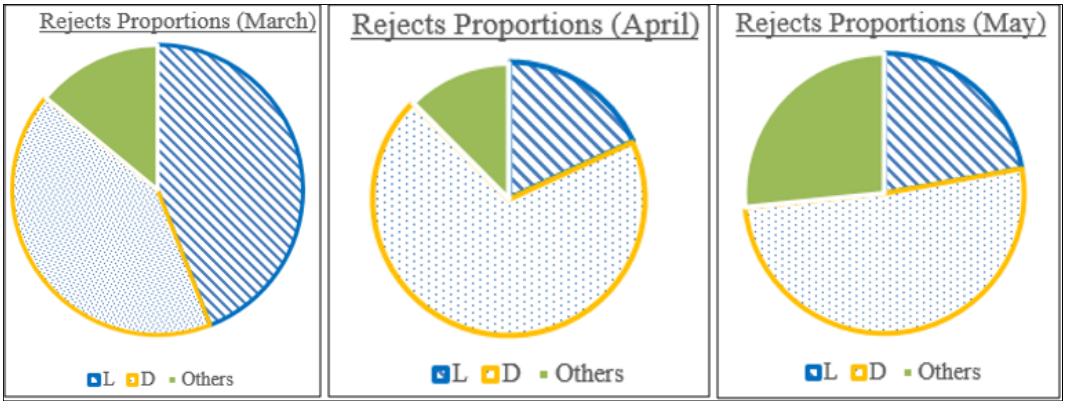


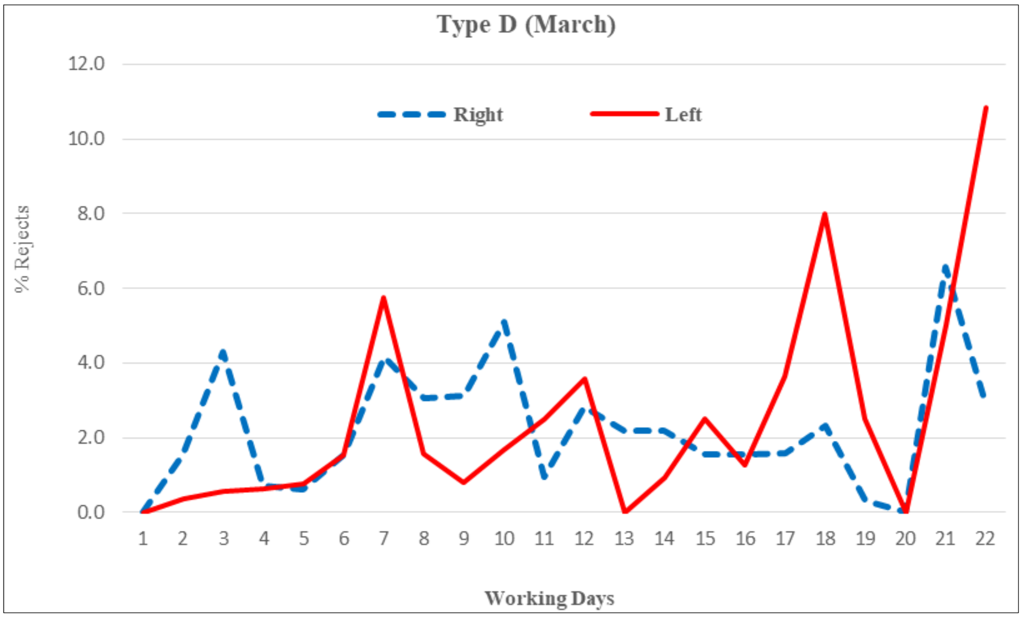
Fig 1: Reject Proportions

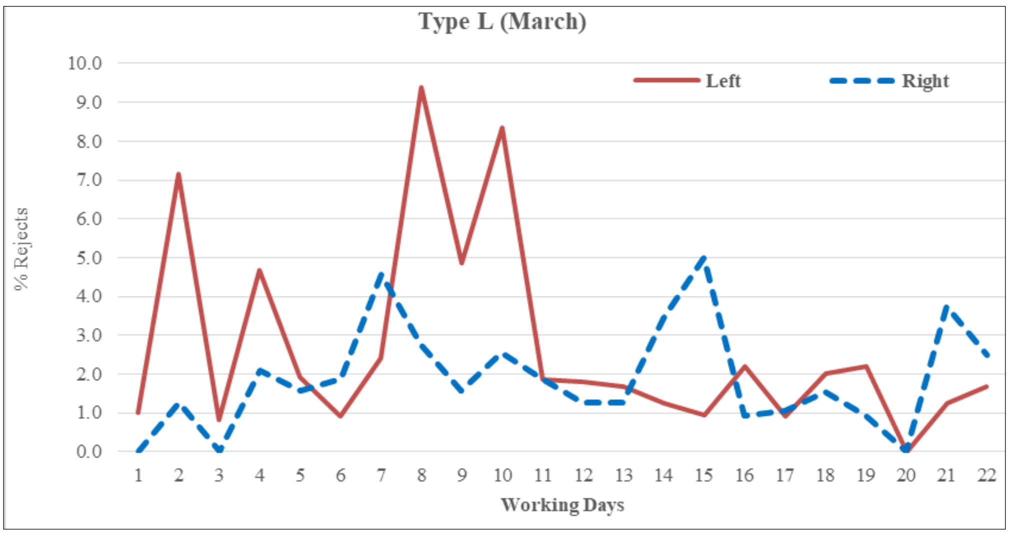
Defect Cause

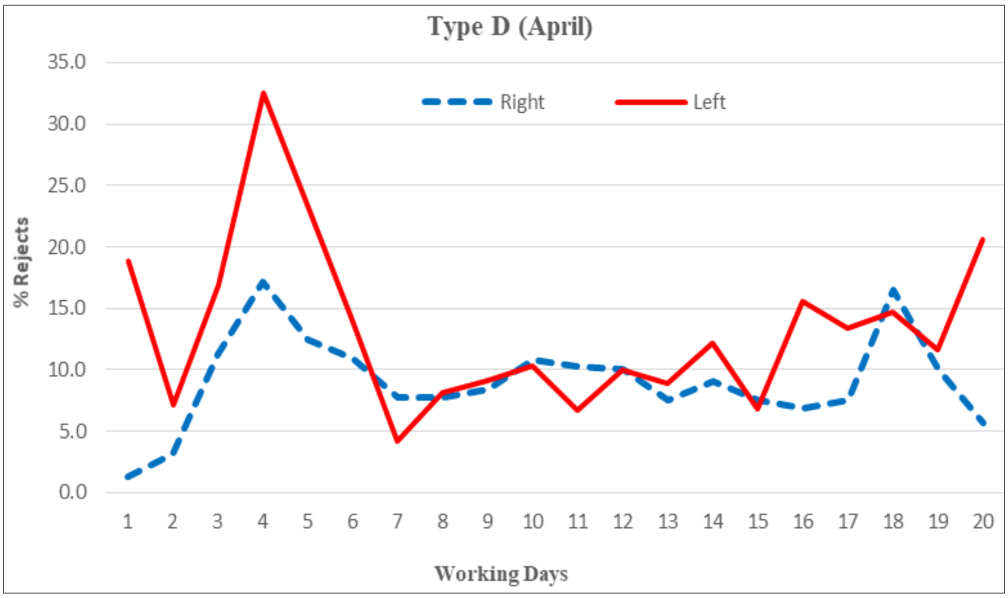
Type D defect may arise from the environment, come together with the piece-parts or originated from the manufacturing process itself, whereas Type L defect is believe to be caused by misalignment of the parts on the jig during the assembly process, surface irregularities on the piece-part or various machine parameters settings.

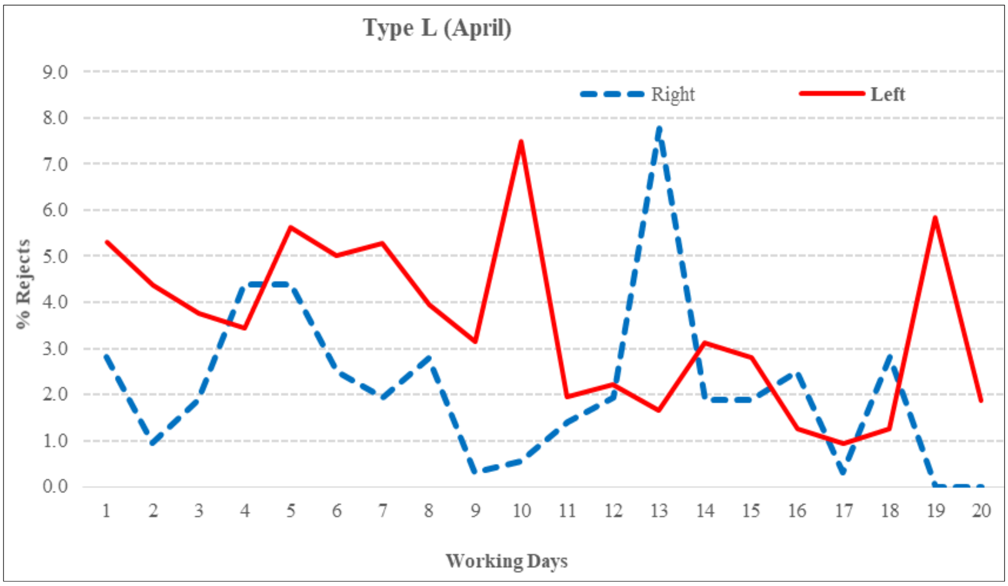
Past Reject Data

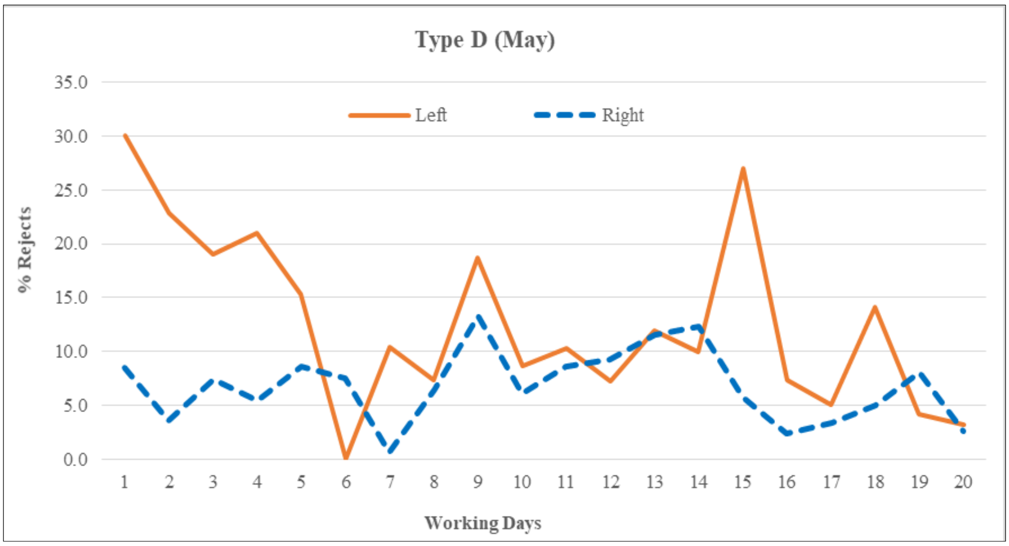
This product is always sold and used in pair, one for left side and the other for right. The reject rate, in percent, for both types of defects were plotted as line charts for the months of March, April and May as shown below.






Type D (April)
Right
Left
% Rejects
35.0
30.0
25.0
20.0
15.0
10.0
5.0
0.0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
Working Days


Type L (April)
Right
Left
% Rejects
9.0
8.0
7.0
6.0
5.0
4.0
3.0
2.0
1.0
0.0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
Working Days


Type D (May)
Left
Right
% Rejects
35.0
30.0
25.0
20.0
15.0
10.0
5.0
0.0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
Working Days

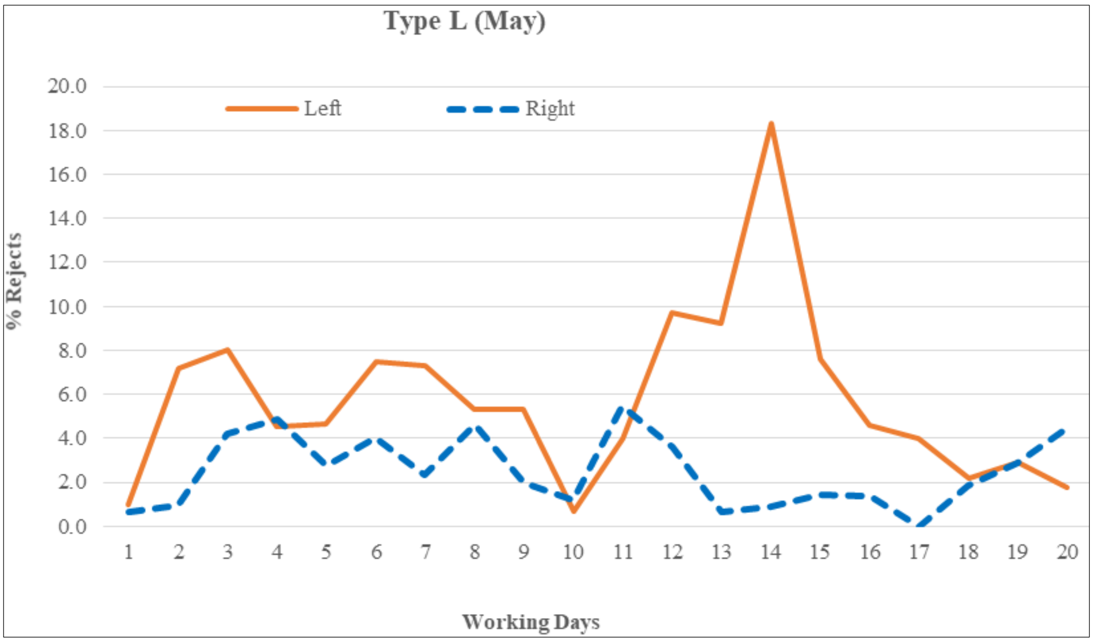


Fig 2: Reject Rate

These charts reveal the following points

- The defect rate changes wildly from day to day for both types.
- The left-side product has a higher reject rate than the right-side for most days.
- Type D defect has a higher reject rate than Type L.

The bar chart below shows the month-to-month variation for both types of reject. It can be seen that the month-to-month variation is large especially for Type D and the left product is worse than the right.

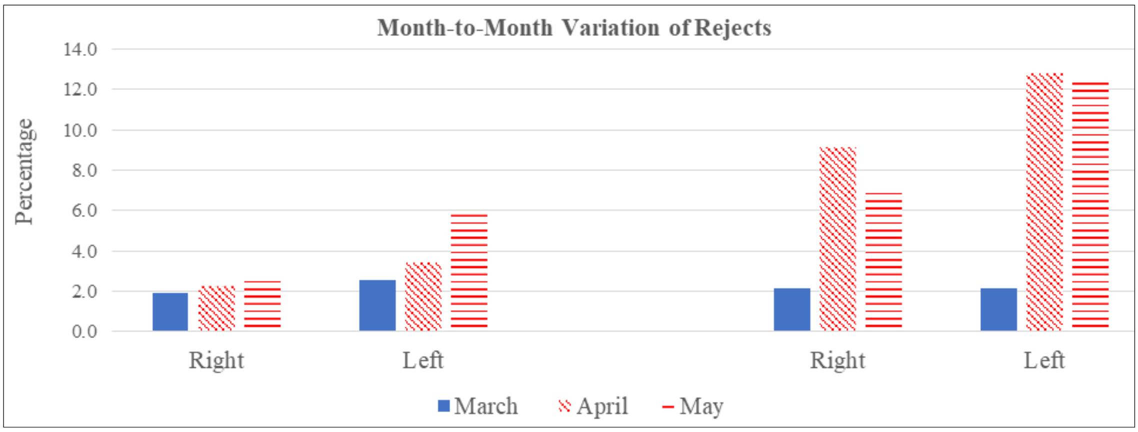


Fig 3: Month-to-month Variations

Design of Experiment

In a full-factorial experiment, the number of runs is equal to the number of levels raise to the power of the number of factors. A three-factor two-level experiment was designed, hence a total of eight experiments will be run in random order [3, 5]. Out of the many machine settings, three that were believed to play a vital role in this process were selected as factors, namely Amplitude (A), Hole Time (H) and Distance (D). The table below listed their specifications, current settings and the chosen high and low levels.

Table 1: Factors and Levels

Factors	Specifications	Current settings	Low (-)	High (+)
Amplitude	60-100%	60%	65%	80%
Hold Time	0.0-0.99 s	0.6 s	0.4 s	0.8 s
Distance	N/A	0.33	0.35	0.4

The primary response of interest is Type D defect and the secondary response is Type L. Each experiment was run over a one-day production time from 8:00 am to 5:45 pm. The production quantity, hence the sample size, varies on a day-to-day basis, ranging from 240 to 480 with an average of 340 over this 8-day period.

Data Analysis

The responses to the variations in the three selected factors were recorded and processed. The individual effect of the three factors as well as the effect of their interactions to the responses [1, 5] were calculated and tabulated as shown in Figure 5 below.

Table 2: Response Tables

Run Order	Exp Number	Main Effect A	H	D	Interaction Effect AH	AD	HD	AHD	Response Type D(%)
4	1	+	+	+	+	+	+	+	14.1
3	2	+	+	-	+	-	-	-	5.0
1	3	+	-	+	-	+	-	-	6.7
6	4	+	-	-	-	-	+	+	3.2
5	5	-	+	+	-	-	+	-	4.2
7	6	-	+	-	-	+	-	+	7.5
8	7	-	-	+	+	-	-	+	9.3
2	8	-	-	-	+	+	+	-	7.3
	S+	29.0	30.8	34.3	35.7	35.6	28.8	34.1	
	S-	28.3	26.5	23.0	21.6	21.7	28.5	23.2	
	Effect	0.2	1.1	2.8	3.5	3.5	0.1	2.7	

Run Order	Exp Number	Main Effect A	H	D	Interaction Effect AH	AD	HD	AHD	Response Type L(%)
4	1	+	+	+	+	+	+	+	2.2
3	2	+	+	-	+	-	-	-	4.0
1	3	+	-	+	-	+	-	-	1.4
6	4	+	-	-	-	-	+	+	1.8
5	5	-	+	+	-	-	+	-	2.9
7	6	-	+	-	-	+	-	+	0.8
8	7	-	-	+	+	-	-	+	0.7
2	8	-	-	-	+	+	+	-	4.6
	S+	9.4	9.9	7.2	11.5	9.0	11.5	5.5	
	S-	9.0	8.5	11.2	6.9	9.4	6.9	12.9	
	Effect	0.1	0.4	-1.0	1.2	-0.1	1.2	-1.9	

The numbers in the Response column were computed based on empirical data obtained directly from the experiment. The Interaction Effect were calculated based on the responses to the Main Effect [4, 5].

As can be seen from the table on the left for Type D defect, out of the three main factors, only factor D has significant effect on the response. However, the highest effects are from the interactions between AH and AD. The table on the right indicates that none of the selected main factors nor their interactions have any significant effect on Type L defect.

The response cubes shown in Figure 6 is a pictorial depiction of the responses to the Main Effect.

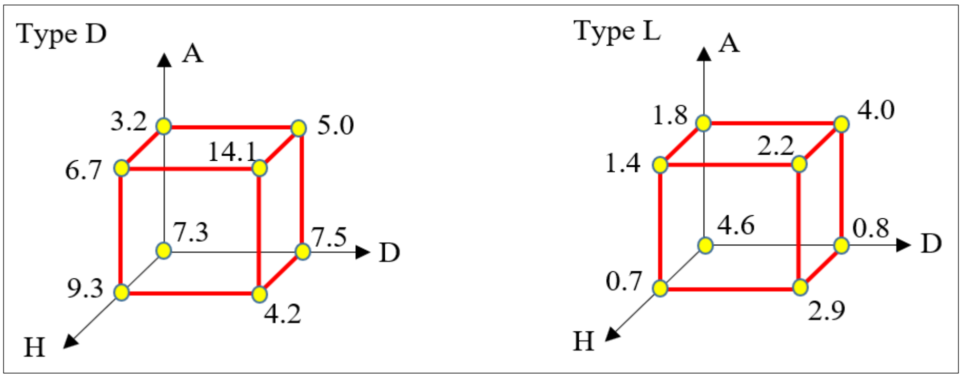
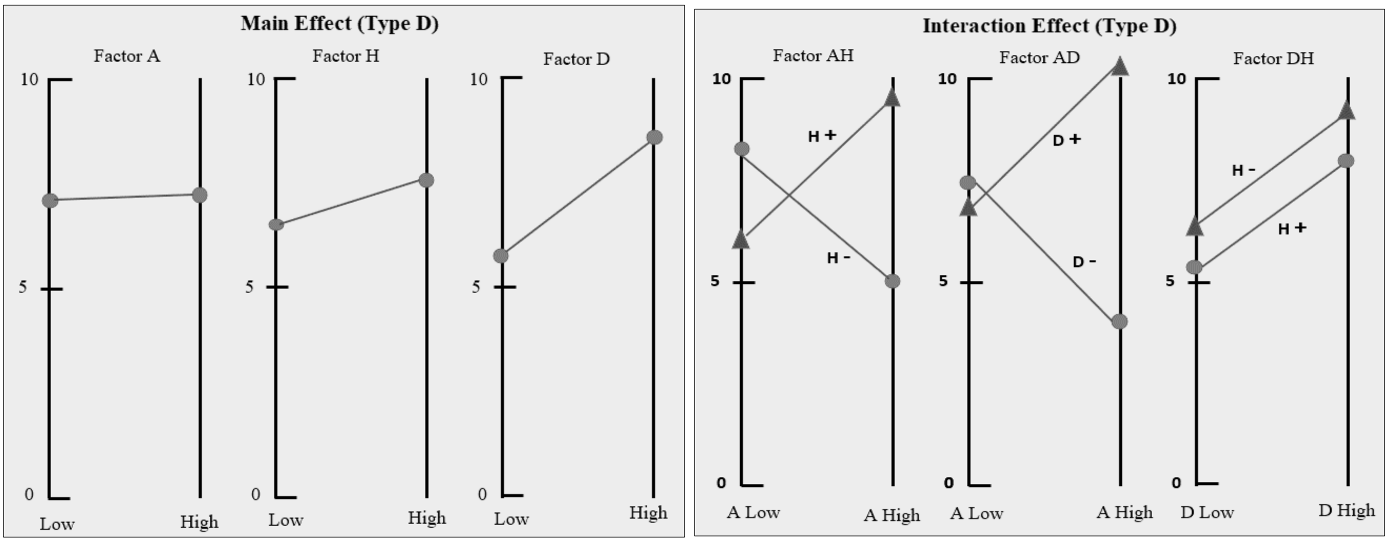


Fig 4: Response Cubes

Since the selected factors have insignificant effect on Type L defect, further analysis on this data will be done on Type D only.

Figure 7 below illustrates the effect of the three main factors, as well as their interactions, to the response Type D. From Graph (a), while the effect of A is negligible and H is insignificant, the effect of D is substantial. It is obvious that a level-low setting for D is desirable.



(a) Main Effect

(b) Interaction Effect

Fig 5: Effect Graphs

Graph (b) indicates that the interactions between AH and AD are significant while DH is negligible. In the first graph, the two lines cross each other, meaning A and H have inverse relationship to one and the other. If we set A low, then H must be high, and vice versa. Same thing can be construed from the second graph about A and D settings, only that this inverse relationship is not as strong compared to the previous pair. The third graph reveals that there is minimal interaction between D and H.

Let's investigate Figure 7(b) further. The second graph tells us that a low setting for D must be accompanied by a high setting for A. The first graph says if A is set high, then H must be set to low in order to achieve a lower reject rate. The third graph indicates that if D is low, H high or low does not really make too much difference because the two lines are almost parallel and quite close to each other. Nonetheless, the third graph reveals that setting H high would give us a reduction of around 1% in reject rate. However, the first graph shows that, with a high setting for A, H high would yield an increase in reject as much as 4.6% compared to H low. So, it is evidenced that setting H to low is a better choice

Now we have arrived at the optimum machine parameter settings as follow:

Table 3: Optimum Settings

Factor	Level	Setting
A	High	80%
D	Low	0.4 s
H	Low	0.35

The word "optimum" used here refers to the optimum settings for the current study and may not be the true optimum settings for this machine. We need to run more experiments to confirm the result, narrow the window and then use Response Surface Methodology to pinpoint the exact optimum settings for the chosen factors [5, 6].

Positional Variation of Defect

While collecting data, the Quality Assurance operators were instructed to note down the location of the defect on the schematic diagram provided. The duration was about two weeks and sample size was the production quantity of the day, which varies on a daily basis. The result of the positional variation of Type D defect is presented in Figure 6 below. It is obvious that the far right one quarter of the product suffers the least problem compared to the other three quarters. In fact, merely 8.5% of the Type D rejects appear in this zone.

Table 4: Positional Variation

52	66	64	17
26.1%	33.2%	32.2%	8.5%

Discussion

Due to the fact that the duration of the project was restricted to ninety six hours, we just did not have the luxury of time to conduct further studies. The conclusion would be more convincing if further experiments could be conducted as suggested below [5, 7].

- Run confirmation experiment.
- Run another similar experiment with either narrowed or expanded parameter windows.
- Conduct more experiments for other machine parameters.
- Use Response Surface Methodology to express the empirical relationship between Type D defect and the selected factors.

Challenges

The major challenge for this kind of project is to get full cooperation from the manager in giving authority, the technicians for changing machine parameters, and the machine operators for reliable data collection.

Solution

These challenges were foreseen from experience. Hence, when the team was formed, the manager, executive, supervisor and assembly leader of that process were invited into the team. They were informed with the Why When What Who How about the project.

Conclusion

The three-factor two-level full factorial experiment was successfully run and the collected data was analyzed for the main and interaction effects of the factors to the responses. However, only one of the two responses, Type D reject, shows significant response to the variation of the chosen factors while Type L reject's response is negligible. Based on the statistical analysis, the optimum parameter settings for the machine under study were obtained.

Acknowledgement

The names of the manager, executive, supervisor, assembly leader as well as the machine operators and quality assurance inspectors would not be mentioned here in order to protect the identity of the factory involved. Nevertheless, my sincere appreciation is directed to the above-said persons.

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