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Proceedings of the Pacific Rim Statistical Conference for Production Engineering

Big Data, Production Engineering and Statistics

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ICSA Book Series in Statistics

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Preface

The Pacific Rim area is one of the key manufacturing sites in the world, and applications of statistical thinking and methods for production engineering have never been more important with big data. To address the need, a statistical conference for production engineering was first proposed by Prof. George Tiao, The University of Chicago, during his opening remarks at 2014 Joint Applied Statistics Symposium of the International Chinese Statistical Association and Korean International Statistical Society in Portland. The first conference was held at Shanghai Center for Mathematical Sciences located in Fudan University in December 2014. The main goal was to bring researchers and practitioners in statistics and engineering from academe and industry to promote collaborations and exchange the latest advancements in methodology and real-world challenges among participants. Following the success of the first conference, the 2nd Pacific Rim Statistical Conference for Production Engineering was held at Seoul National University in December 2016. These proceedings present the selected papers based on the presentations at the first and second Pacific Rim Statistical Conferences for Production Engineering. We hope that this effort can stimulate further collaborations between academe and industry in production engineering.

The conference series has become a major joint event of the International Chinese Statistical Association and Korean International Statistical Society. We welcome those who are interested in this endeavor to join the third conference that will be held at National Tsing Hua University in Taiwan in 2018.

Portland, USA — Dongseok Choi
Busan, Korea (Republic of) — Daeheung Jang
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Gainesville, USA — Peihua Qiu
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Chapter 2
The 62% Problems of SN Ratio and New Conference Matrix for Optimization: To Reduce Experiment Numbers and to Increase Reliability for Optimization

Teruo Mori

Abstract Robust design has been widely adopted during product design to reduce variation and improve quality. However, based on our survey of 171 published case studies using the L_{18} orthogonal array in Japan, 62% of the signal-to-noise ratios (SN) of the optimal design cases concluded from the main effects plots were worse than the best combinations of the existing 18 runs of the L_{18} orthogonal array. This means that current robust design based on SN ratios and the L_{18} cannot predict the optimal conditions accurately and needs further work to improve the analytical prediction accuracy and optimization efficiency. We will show the six causes of 62% problems. Now, we have understood to face the serious problems like global warming, food amounts for increasing population. We need faster and more precise methodology for researching them, and it will be able to reduce experiment numbers and to increase reliability using conference matrix.

2.1 Introduction

The job range of engineers' assignments is wide and includes the basic research on invention and new product development through the improvement of current products and improvement of production processes, etc. They need to meet development goals and to find optimal conditions to reduce product and process performance variation at the same time (Mori 2011, 2009, 1992).

It is too late to conduct the troubleshooting activities to change product design or production conditions to resolve product defect issues after those products are

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manufactured and shipped to the market and to customers. It is common to use the recall and warranty activities to resolve quality problem issues. Also, it will be happened at a loss to customers. Of course, company guarantees the product and service quality as top priority and is willing to take action to reduce customers' loss due to defective products (Mori 2014).

In this paper, we will review first the problems of the current robust design. Then, we will show to expect the new conference matrix for optimization methods.

2.2 Verification Assessment to Confirm the Optimal Condition to Exceed the Best of L_{18} Trials

After finding the optimal candidate condition, engineers will conduct experiments to confirm and verify that the results of the optimal candidate condition are reproducible. Table 2.1 shows the SN ratio results (Mori 2013) (a) of the optimal conditions for 171 case studies to compare the best SN ratio values (b) of the L_{18} trials. One hundred and six (62%) cases were a<b. Theoretically, the SN ratio results of (a) are as good as or better than (b), because the optimal condition candidates (a) are chosen from many more possible combinations of factor levels than (b).

Unfortunately, 62% of the optimal conditions of (a) are worse than the best values of (b) as illustrated in Table 2.1 (Japan Quality Engineering association 2003–2012).

Engineers who have been trained in statistical modeling of Taguchi may be surprised at the "prediction uncertainty of the optimal design candidates" shown in Table 2.1. Then, they will be requested the more advanced mathematical analysis for improving the prediction accuracy and reduce the uncertainty of the optimal design solutions.

2.3 Investigating the Root Causes for 62% Problems

Assume that the mean of the output response is μ; and that the main effects of four selected experimental factors (A, B, C, and D) are a, b, c, and d.

The interaction terms are expressed using a multiplication term such as ab, ac,…abc…, and abcd for the four factors. Let the summation of experimental error and measurement error be (e). The experimental output response (y) is expressed with the mean value μ, main effects, a, b, c, and d, and the quadratic, interaction and higher terms as shown here:

Experimental output response (Jeff Wu and Hamada 2009)

$y = \mu + a + b + c + d + aa + ab + ac + \cdots + cd + abc + \cdots + bcd + abcd + (e)$

$=$ Mean value + main effects + quadratic + interaction effects + higher terms + error

Table 2.1 Optimal condition comparison analysis

QES	Total # of case studies	# of case studies where (a<b)
2012	6	3
2011	9	6
2010	15	8
2009	7	6
2008	20	9
2007	14	9
2006	33	24
2005	23	11
2004	22	18
2003	22	12
Total	171	106
(%)	62.0	
QES→	Japan quality engineering symposium	

The optimal conditions (a) of Table 2.1 are selected based on the level averages which were calculated to divide the sum of response y with data numbers. The response graphs are made with the level averages.

On the other hand, orthogonal array tables like L_8, L_9, L_{18} as the design matrix have the linear effect structure, so that it will be expected that the response should consist of linearity components. If the response has nonlinear effect, the response graph will be shifted from the original by contaminating nonlinear effect. Nonlinear effect will consist of quadratic, and interaction between factors and higher other terms. We can estimate the nonlinear effects in the response with the empty column of the orthogonal array table. So, we tried to look for the nonlinear effect from start to finish of the robust process.

2.4 Causes Analysis for 62% Problems

We have done to analyze the causes of 62% problems related to nonlinear effects. We finally detected six nonlinear effects at robust process on Fig. 2.1. It has the marked ①–⑥ on nonlinear in Fig. 2.1.

We will introduce ①–⑥ at Fig. 2.1 to explain the complex mathematics background to get contaminated with nonlinear effects.

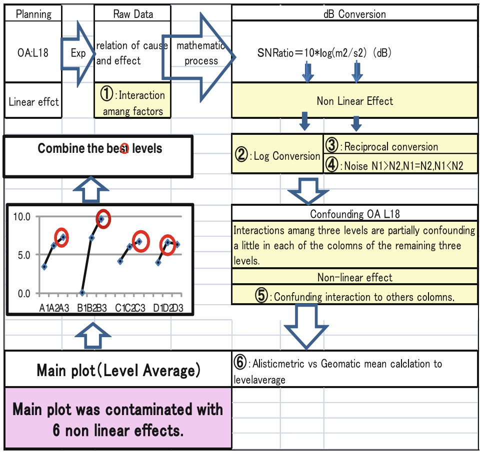

Fig. 2.1 Six nonlinear effects on robust design process

2.5 Multiple Contamination of Six Type of Nonlinear Effect

Six types of nonlinear effects were separately investigated as the cause of 62% problem. Actual optimum cases will be contaminated single or multiple of them. We cannot detect the real causes individually if columns were filled with factors.

However if there were empty columns in orthogonal array tables, we can make a diagnose the degree of contamination the with the empty column factor effects.

We selected the published typical three case studies with empty columns for SN ratio. We showed Figs. 2.2(BGA), 2.3(circuit), 2.4(straw) (Tanabe 2016).

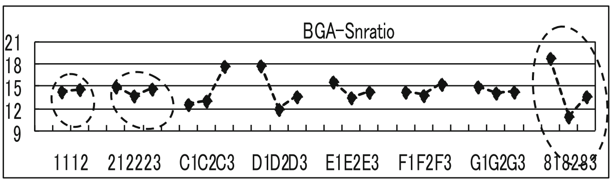

Fig. 2.2 BGA semiconductor structure

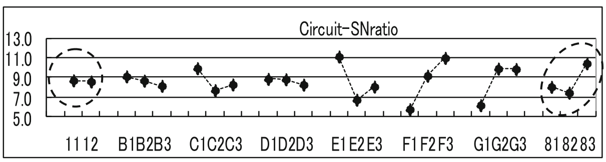

Fig. 2.3 Electro circuit case

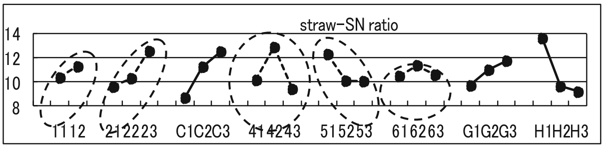

Fig. 2.4 Education training case

At Fig. 2.2 case, the empty column 8 is the largest effect. At Fig. 2.3, this case has six factors, the empty column 8 is fourth largest factor, and it is at middle class position. At Fig. 2.4, this case 3 factor and empty columns are 5 factors. The largest empty column 4 is in second largest position. The empty columns effects might be lower than the layouted columns. Those empty columns are gotten the multiple contaminations of six nonlinear effects. We cannot ignore such six nonlinear effects for contamination to other columns. The current robust design process will not be reasonable for engineering subjects. At least, SN ratio and L_{18} should be replaced the different way to get more reliability of optimization.

2.6 The New Design Matrix for the Next Generation

We started to create the new process to avoid six types of nonlinear effects for robust design. L_{18} has been long time recommended as standard tool at current robust design. Taguchi (1984) explored statistically the optimum condition like black box. The current robust design was not supported that reason is to demand too much experiment number like 108 at dynamic style. If statistician likes to recommend directly catching the optimal solution itself, the trial number might be naturally increased to avoid missing it. If a fisherman tries to catch a fish, he will select the net as much as largest size with the finest mesh to fear failures.

The scientist now is shifting the investing philosophy to confirm the tendency of factor effect to target in mix conditions with design matrix to make the less number trials and higher reliability. The best deign matrix might be "conference matrix." Conference matrix C_4 ($2^1 3^3$) is the minimum number for three-level matrix with

Table 2.2 $C_4(2^1 3^3)$ and linear term of $L_9(3^4)$

C_4	1	2	3	4
1	0	1	1	1
2	−1	0	−1	1
3	−1	1	0	−1
4	−1	−1	1	0
*	3	0	0	0
		3	0	0
			3	0
				3

L_9	1	2	3	4
1	−1	−1	−1	−1
2	−1	0	0	0
3	−1	1	1	1
4	0	−1	0	1
5	0	0	1	−1
6	0	1	−1	0
7	1	−1	1	0
8	1	0	−1	1
9	1	1	0	−1
*	6	0	0	0
		6	0	0
			6	0
				6

linear term. We compare linear term with $L_9(3^4)$ in Table 2.2. (*) is the sum of product of columns to confirm the orthogonality (Tanaka 2016).

The new process may not use SN ratio with log conversion to avoid six nonlinear effects, and we are testing to adapt the raw data themselves. It will be complete in 2017.

2.7 Conclusion

In this paper, author introduced 62% problems to the current robust design with L_{18} and SN ratio.

Based on author survey, 171 published case studies using the L_{18} orthogonal array (OA) in Japan, and 62% of the signal-to-noise ratios (SN) of the optimal design cases concluded from the main effects plots were worse than the best combinations of the 18 runs of the L_{18} orthogonal array.

Also, author detected six types of nonlinear effects.

①: Interaction among factors: ②: Log conversion for response

③: Reciprocal structure of SN ratio: ④: Diversion (S^2) size of SN ratio

⑤: Confounding type $L_{18}(2^1 3^7)$: ⑥: Geometric level average after log conversion.

Also, author is touching the conference matrix and new concept for new type robust design.

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