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# PRODUCT QUALITY IMPROVEMENT THROUGH RESPONSE SURFACE METHODOLOGY : A CASE STUDY

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## ABSTRACT

***Purpose*** *– The paper aims to improve the key quality performance of the terminal of earphone in an electronic company.*
***Design/methodology/approach*** *– Sequential experimental designs are employed. Significant input variables are found trough a full factorial design. Then a response surface model is constructed considering curvature in the linear model.*
***Findings*** *– Optimized key input variables' parameters are found using the response surface model. The key quality performance, coplanarity of the terminal of earphone has been improved.*
***Research limitations/implications*** *– Instead of running a full factorial design in the first stage, a fractional factorial may be used to reduce experimental runs.*
***Originality/value*** *– The methodology used in this case can be easily extended to similar cases.*

**Keywords** quality improvement, design of experiments, response surface methodology, central composite design, parameter optimization

## INTRODUCTION

Response surface methodology (RSM) is a collection of statistical and mathematical techniques useful for developing, improving, and optimizing products and processes. The most extensive applications of RSM are particularly in situations where several input variables have potentially influence on some performance measures or quality characteristics of the product or process. RSM initiates from design of experiments (DOE) to determine the factors' values for conducting experiments and collecting data. The data are then used to develop an empirical model that relates the process response to the factors. Subsequently, the model facilitates to search for better process response, which is validated through experiments. The above procedure iterates until an optimal process is identified or the limit on experimental resources is reached. RSM is a very important tool for product and process improving in the improvement phase of Six Sigma Management.

Company A is an electronics enterprise in Tianjin, which engaged in supplying many kinds of electronic connectors for Motorola mobile phone division. In the supplying process, the company often received feedback complaints from customers. One kind of earphone named AJR45 had defect of bad echo caused by large coplanarity of the terminal. In order to improve the quality of products and reduce quality cost, the company adopted the one-factor-at-a-time (OFAT) approach and just selected the best existing experiment conditions as the optimal operating conditions. As we know, OFAT does not work well for process optimization if there are interactions among input variables. The solution by OFAT was not optimal in practice. The article presents a systematic solution to this problem through sequential use of experimental design to minimize the coplanarity and thus improve product quality.

## LITERATURE REVIEW

Experimental design is widely used in manufacturing (Mukherjee & Ray, 2006; Sharma & Yadava, 2013; Koleva and Luchkov, 2005). C F Jeff Wu and Michael S Hamada(Wu & Hamada, 2009) classify experimental problems in to five broad categories according their objectives: treatment comparisons, variable screening, response surface exploration, system optimization and system robustness. RSM is a critical technology in developing new processes, optimizing their performance and improving the design and/or formulation of new products (Box et al,2005; Myers and Montgomery, 1995; Sefa-Dedeh, et al 2003). Myers and Montgomery (1995) also point out that most applications of RSM are sequential in nature. A screening experiment or a first order model is conducted first to identify important input factors. If the there is strong curvature exists and the first order model is not adequate, a second model or response surface model is needed. Cihan M.T. et al construct response surface for compressive strength of concrete through sequential design of a $2^{7-4}$ fractional factorial and then a D-optimal design (Cihan, Güner & Yüzer, 2013). He et al (2009) use sequential experimental design to improve the isolation of the fused biconical taper wavelength division multiplexer. In this paper, we design a full factorial experiment to find the important factors and a response surface model to optimize process parameters to improve coplanarity of the terminal of earphone.

## THE FIRST STAGE EXPERIMENT

Most applications of response surface methodology are sequential in nature. That is, at first some ideas are generated concerning which factors or variables are likely to be important in the response surface study. This usually leads to an experiment designed to investigate these factors with a view toward eliminating the unimportant ones. This purpose of the experiment at this stage is to screen important factors or input variables.

Before starting experiment, we need to identify factors that affect coplanarity of the terminal by cause and effect analysis using fishbone diagram and cause and effect matrix. The coplanarity is mainly affected by the operating conditions of the gas riveting end machine. The factors are cylinder pressure, block height, decent speed, slot width. Table 1 gives factors and their levels in the experiment.

**Table 1. Factors and their levels in experiment**

| Factors | Types | Levels | Are there center points |
|---|---|---|---|
| A (cylinder pressure) | variable | 6-8 Pa | Yes |
| B (decent speed) | variable | 2-4 s/mm | Yes |
| C (block height) | variable | 13.1-13.7 mm | Yes |
| D (slot width) | variable | 40-60 mm | Yes |

Because there are less than five factors, we can use full factorial design in order to screen significant factors. We choose the $2^4$ design with four center points to check the possible curvature. Table 2 shows the experimental arrangement. Note that the run order of the experiment has been randomized.

**Table 2. Experiment arrangement for the $2^4$ design (coded variables)**

| Run order | Center pt | A | B | C | D | Y |
|---|---|---|---|---|---|---|
| 1 | 1 | 1 | -1 | -1 | -1 | 0.069 |
| 2 | 1 | -1 | -1 | -1 | 1 | 0.087 |
| 3 | 1 | 1 | 1 | -1 | 1 | 0.071 |
| 4 | 1 | -1 | 1 | 1 | -1 | 0.095 |
| 5 | 0 | 0 | 0 | 0 | 0 | 0.082 |
| 6 | 1 | -1 | 1 | 1 | 1 | 0.093 |
| 7 | 1 | -1 | 1 | -1 | -1 | 0.086 |
| 8 | 1 | 1 | 1 | 1 | 1 | 0.083 |
| 9 | 1 | 1 | -1 | 1 | -1 | 0.081 |
| 10 | 1 | 1 | 1 | 1 | -1 | 0.082 |
| 11 | 1 | -1 | -1 | -1 | -1 | 0.088 |
| 12 | 1 | -1 | -1 | 1 | 1 | 0.094 |
| 13 | 0 | 0 | 0 | 0 | 0 | 0.081 |
| 14 | 1 | 1 | -1 | -1 | 1 | 0.072 |
| 15 | 0 | 0 | 0 | 0 | 0 | 0.079 |
| 16 | 1 | -1 | 1 | -1 | 1 | 0.085 |
| 17 | 1 | -1 | -1 | 1 | -1 | 0.093 |
| 18 | 0 | 0 | 0 | 0 | 0 | 0.081 |

| Run order | Center pt | A | B | C | D | Y |
|---|---|---|---|---|---|---|
| 19 | 1 | 1 | 1 | -1 | -1 | 0.073 |
| 20 | 1 | 1 | -1 | 1 | 1 | 0.084 |

The experimental data in Table 2 were analyzed by Minitab. Table 3 shows the estimated effects and coefficients for response Y. From Table 3 we can find that factor A and C are significant with p-value<0.05, the interaction of A*C is significant with p-value=0.05.

**Table 3. Estimated regression coefficients for Y (coded units)**

| Term | Effect | Coef | SE Coef | T | P |
|---|---|---|---|---|---|
| Constant | | 0.083500 | 0.000315 | 265.44 | 0.000 |
| A | -0.013250 | -0.006625 | 0.000315 | -21.06 | 0.000* |
| B | -0.000000 | -0.000000 | 0.000315 | -0.00 | 1.000 |
| C | 0.009250 | 0.004625 | 0.000315 | 14.70 | 0.001* |
| D | 0.000250 | 0.000125 | 0.000315 | 0.40 | 0.718 |
| A*B | 0.000750 | 0.000375 | 0.000315 | 1.19 | 0.319 |
| A*C | 0.002000 | 0.001000 | 0.000315 | 3.18 | 0.050* |
| A*D | 0.001000 | 0.000500 | 0.000315 | 1.59 | 0.210 |
| B*C | 0.000250 | 0.000125 | 0.000315 | 0.40 | 0.718 |
| B*D | -0.001250 | -0.000625 | 0.000315 | -1.99 | 0.141 |
| C*D | 0.000500 | 0.000250 | 0.000315 | 0.79 | 0.485 |
| A*B*C | -0.001000 | -0.000500 | 0.000315 | -1.59 | 0.210 |
| A*B*D | -0.000500 | -0.000250 | 0.000315 | -0.79 | 0.485 |
| A*C*D | 0.000250 | 0.000125 | 0.000315 | 0.40 | 0.718 |
| B*C*D | -0.000000 | -0.000000 | 0.000315 | -0.00 | 1.000 |
| A*B*C*D | 0.000750 | 0.000375 | 0.000315 | 1.19 | 0.319 |
| Ct Pt | | -0.00275 | 0.000703 | -3.91 | 0.03 |
| S = 0.00125831, R-Sq = 99.57%, R-Sq(adj)=97.29% | | | | | |

Note: * means that the p-value is less than 0.05, and the corresponding term is significant

To reduce the regression model, we need to delete those insignificant terms and keep A, C and A*C in the model. Table 4 shows the estimated effects and coefficients for response Y of the reduced model, and Table 5 shows the results of analysis of variance.

**Table 4. Estimated regression coefficients for Y (coded units)**

| Term | Effect | Coef | SE Coef | T | P |
|---|---|---|---|---|---|
| Constant | | 0.08350 | 0.000331 | 252.480 | 0.000* |
| A | -0.01325 | -0.006625 | 0.000 | -20.03 | 0.000* |
| C | 0.00925 | 0.004625 | 0.000 | 13.98 | 0.000* |
| A*C | 0.00200 | 0.001000 | 0.000 | 3.02 | 0.009* |
| Ct Pt | | -0.002750 | 0.001 | -3.72 | 0.002* |
| S = 0.00132288, R-Sq = 97.64%, R-Sq(adj)=97.01% | | | | | |

Note: * means that the p-value is less than 0.05, and the corresponding term is significant

**Table 5. Analysis of variance for Y (coded units)**

| Source | DF | Seq SS | Adj SS | Adj MS | F | P |
|---|---|---|---|---|---|---|
| Main effects | 2 | 0.0010445 | 0.0010445 | 0.0005223 | 298.43 | 0.000* |
| 2-way interactions | 1 | 0.0000160 | 0.0000160 | 0.0000160 | 9.14 | 0.009* |
| Curvature | 1 | 0.0000242 | 0.0000242 | 0.0000242 | 13.83 | 0.002* |
| Residual error | 15 | 0.0000263 | 0.0000263 | 0.0000018 | | |
| Pure error | 15 | 0.0000263 | 0.0000263 | 0.0000018 | | |
| Totol | 19 | 0.0011110 | | | | |

Note: * means that the p-value is less than 0.05, and the corresponding term is significant

Figure 1 shows the Pareto chart of the standardized effects, and Figure 2 shows the normal probability plot of the standardized effects. Both of them indicate that the effects of A, C and A*C are significant. But the curvature term is also significant. That means the first order model is not adequate. A second-order model for the significant variables A and C needs to be designed, and more experiments need to be done to fit the model.

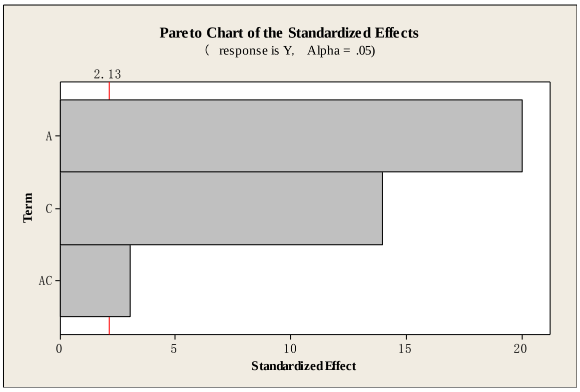


**Figure 1 Pareto chart of the standardized effects**

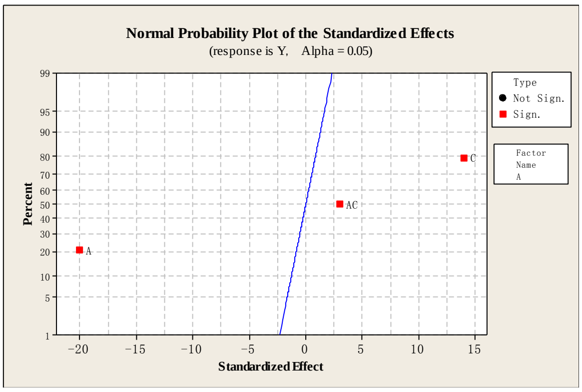


**Figure 2 Normal probability plot of the standardized effects**

## EXPERIMENTAL DESIGNS FOR FITTING RESPONSE SURFACES

The first stage experiements results also shows that the lower pressure (factor A) and higher Height may yield possible lower coplanarity. Based on the engineering experience and steepest ascend analysis, we choose the high level of pressure to the high end of operating range, and the low level of height to the low level of operating end. Coplanarity was significantly reduced through the first stage experiement. Since there is possible curvature, a composite face-centered design (CCF) is used for the second stage experiments as shown in Figure 3, for two variables, there are four factorial points, five centre points and four axial points in the design.

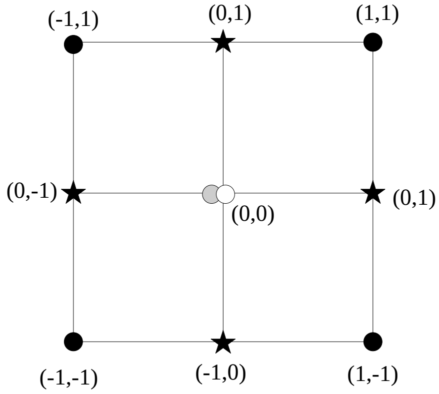


**Figure 3 CCF design for two factors**

Table 6 shows the experiment arrangement and results. In the second column, Pt type is the type of the experiment run. 1 stands for corner point, -1 stands for axial point, and 0 stands for center point. Also the run order of the experiment has been randomized.

**Table 6. Experiment arrangement for the CCF (coded units)**

| Run order | Pt type | A | C | Y |
|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0.029 |
| 2 | -1 | 0 | 1 | 0.036 |
| 3 | -1 | 1 | 0 | 0.022 |
| 4 | 1 | -1 | -1 | 0.031 |
| 5 | 1 | 1 | 1 | 0.039 |
| 6 | -1 | 0 | -1 | 0.022 |
| 7 | 0 | 0 | 0 | 0.024 |
| 8 | 0 | 0 | 0 | 0.029 |
| 9 | 1 | 1 | -1 | 0.018 |
| 10 | 0 | 0 | 0 | 0.027 |
| 11 | 0 | 0 | 0 | 0.027 |
| 12 | -1 | -1 | 0 | 0.030 |
| 13 | 1 | -1 | 1 | 0.033 |

Tables 7 and 8 show the analytical results. It can be seen from Table 7 that two-order term A*A is not significant and deleted from the model. The new results are shown in Table 9 and 10.

**Table 7. Estimated regression coefficients for Y (coded units)**

| Term | Coef | SE Coef | T | P |
|---|---|---|---|---|
| Constant | 0.026862 | 0.000856 | 31.368 | 0.000 |
| A | -0.002500 | 0.000842 | -2.969 | 0.021 |
| C | 0.006167 | 0.000842 | 7.324 | 0.000 |
| A*A | -0.000017 | 0.001241 | -0.014 | 0.989 |
| C*C | 0.002983 | 0.001241 | 2.404 | 0.047 |
| A*C | 0.004750 | 0.001031 | 4.606 | 0.002 |
| S = 0.00206235, R-Sq = 92.81%, R-Sq(adj)=87.68% | | | | |

Note: * means that the p-value is less than 0.05, and the corresponding term is significant

**Table 8. Analysis of variance for Y (coded units)**

| Source | DF | Seq SS | Adj SS | Adj MS | F | P |
|---|---|---|---|---|---|---|
| Regression | 5 | 0.000385 | 0.000385 | 0.000077 | 18.08 | 0.001 |
| Linear | 2 | 0.000266 | 0.000266 | 0.000133 | 31.23 | 0.000 |
| Square | 2 | 0.000029 | 0.000029 | 0.000014 | 3.36 | 0.095 |
| Interaction | 1 | 0.000090 | 0.000090 | 0.000090 | 21.22 | 0.002 |
| Residual Error | 7 | 0.000030 | 0.000030 | 0.000004 | | |
| Lack-of-Fit | 3 | 0.000013 | 0.000013 | 0.000004 | 1.03 | 0.469 |
| Pure Error | 4 | 0.000017 | 0.000017 | 0.000004 | | |
| Total | 12 | 0.000414 | | | | |

Note: * means that the p-value is less than 0.05, and the corresponding term is significant

**Table 9. Estimated regression coefficients for Y (coded units)**

| Term | Coef | SE Coef | T | P |
|---|---|---|---|---|
| Constant | 0.026857 | 0.000729 | 36.833 | 0.000 |
| A | -0.002500 | 0.000788 | -3.174 | 0.013 |
| C | 0.006167 | 0.000788 | 7.830 | 0.000 |
| C*C | 0.002976 | 0.001073 | 2.773 | 0.024 |
| A*C | 0.004750 | 0.000965 | 4.924 | 0.001 |
| S = 0.00192918, R-Sq = 92.81%, R-Sq(adj)=89.22% | | | | |

Note: * means that the p-value is less than 0.05, and the corresponding term is significant

**Table 10. Analysis of variance for Y (coded units)**

| Source | DF | Seq SS | Adj SS | Adj MS | F | P |
|---|---|---|---|---|---|---|
| Regression | 4 | 0.000385 | 0.000385 | 0.000096 | 25.83 | 0.000 |
| Linear | 2 | 0.000266 | 0.000266 | 0.000133 | 35.69 | 0.000 |
| Square | 1 | 0.000029 | 0.000029 | 0.000029 | 7.69 | 0.024 |
| Interaction | 1 | 0.000090 | 0.000090 | 0.000090 | 24.25 | 0.001 |
| Residual Error | 8 | 0.000030 | 0.000030 | 0.000004 | | |
| Lack-of-Fit | 4 | 0.000013 | 0.000013 | 0.000003 | 0.77 | 0.596 |
| Pure Error | 4 | 0.000017 | 0.000017 | 0.000004 | | |
| Total | 12 | 0.000414 | | | | |

Note: * means that the p-value is less than 0.05, and the corresponding term is significant

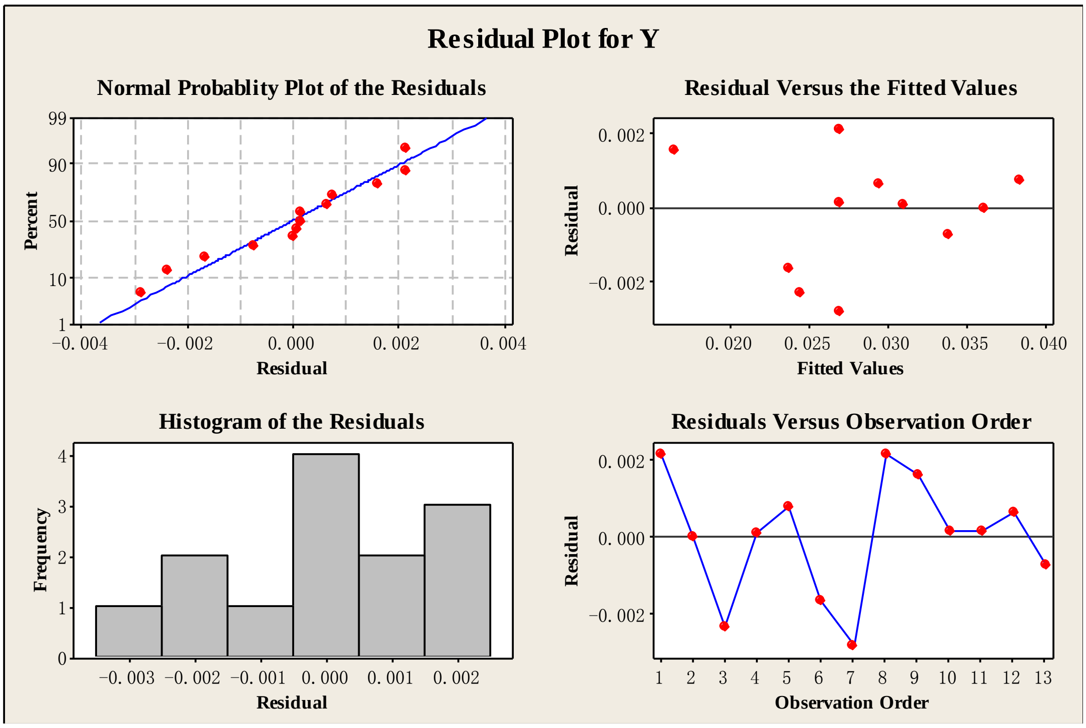


**Figure 4 Four-in-One residual plots for response Y**

The second-order model fit to the coded variables is

$$\hat{y} = 0.0269 - 0.0025A + 0.00617C + 0.00298C^2 + 0.00475A \times C \quad (1)$$

The model is fit well since R-Sq=92.81% and R-Sq(adj)=89.22%.

To check the validity of the fitted model we also conducted residual analysis (see Figure 4).

Results show that the residual is normally distributed, and equal variance and independence hold true.

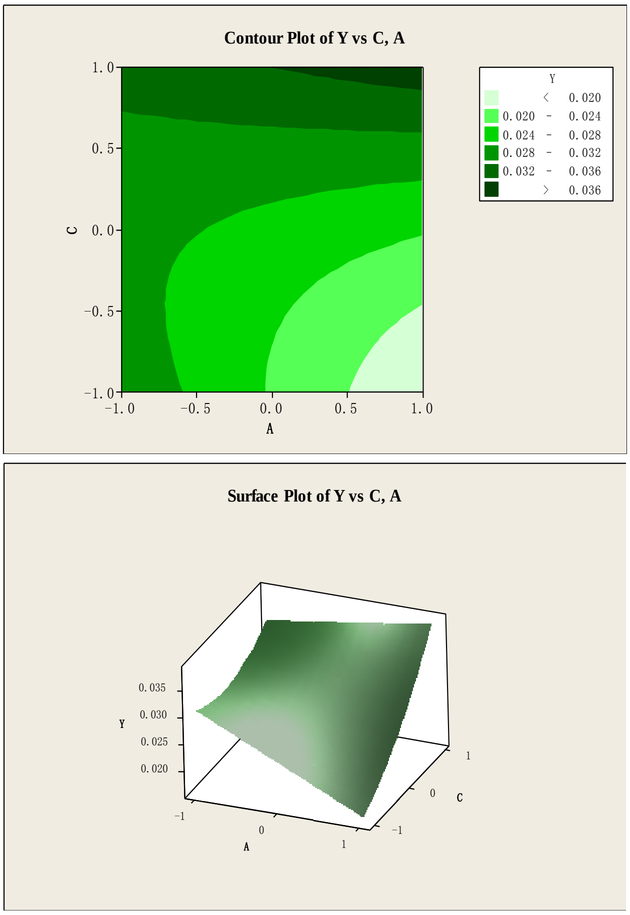


**Figure 5 Contour plot and response surface**

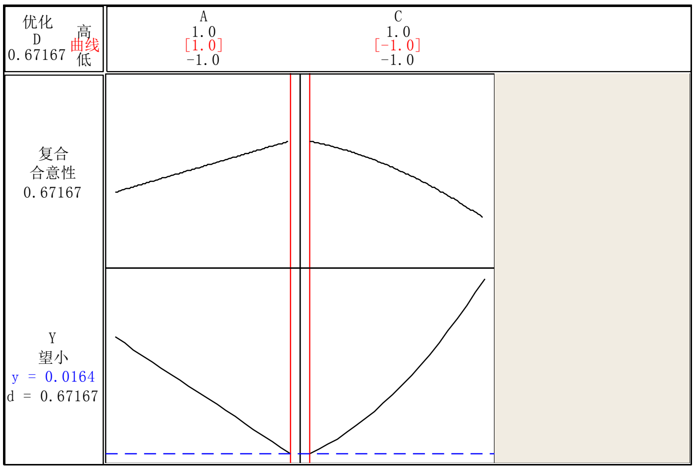


**Figure 6 Response optimizer output**

We can obtain the minimum point from model (1) directly, unfortunately, the minimum point is not at the region of operability. Hence we use computer to search the optimal point using "response optimizer" of Minitab automatically. As shown in Figure 6, the optimal point is at A=1.0, C=-1, with the response Y=0.0164. At the same time, we estimate that at the optimal point the prediction confidence interval at $\alpha$=0.05 is (0.0126, 0.0203). The coplanarity had a mean 0.0975 mm with a standard deviation 0.01mm before optimization, while it is 0.012-0.0203 mm after optimization. It is obvious that the coplanarity has been significantly improved. The experimental result is confirmed by confirmation runs.

## CONCLUSION

The article presents a solution to optimize the coplanarity of the terminal of earphone, using designed experiments and response surface methodology. By designing experiments and analyzing experimental data, the optimum technical condition has been found, and the coplanarity has been improved.

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