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The Optimization of Extrusion Process Parameters Utilizing the Taguchi Method

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Abstract: *The selection of process parameters in the extrusion process has a significant impact on the forming quality of the workpiece. Based on the finite element simulation software simufact. Forming, an orthogonal experiment was designed, and the Taguchi algorithm was used to optimize the extrusion parameters, including extrusion temperature, extrusion speed, and thinning rate, to achieve the best forming quality of the workpiece. Through the nine groups of experiments selected in this study, the Taguchi algorithm was used to optimize the experimental results and obtain a set of optimal process parameters. The experimental results show that when the optimal process parameter is the extrusion temperature of 200°C, the stretching speed of the workpiece is 9 mm/s, and the friction coefficient is selected as 0.3, the product quality and production efficiency are improved.*

Keywords: *Pressing Process; Taguchi Method; Signal-to-Noise Ratio*

1. Introduction

The Taguchi method, as an effective engineering optimization method, has been widely applied in the optimization of plastic forming process parameters. The Taguchi method explores the main factors affecting the process parameters through the design of orthogonal experiments and determines the optimal parameter combination through the analysis of experimental results, thus achieving process optimization. Li Zhong and others selected the factors of thickness reduction rate, wheel working angle, wheel corner radius, and feed ratio as the optimization experimental factors for the powerful swaging of the connecting rod copper liner, and optimized the swaging parameters using the Taguchi method, obtaining the optimized parameter combination [1]. Kong Wei-jing and others simulated the size accuracy of the connecting rod liner by finite element simulation and optimized the process parameters using the Taguchi method, obtaining the optimal inner diameter tolerance and circularity error [2]. Wu Ming-ming and others used the Taguchi experimental method to establish an L16 orthogonal array for experiments and studied the influence of cutting parameters on the surface roughness of mold steel milling, and determined that the radial cutting depth and radial and axial cutting depth are the key parameters affecting surface roughness [3]. In future research, the Taguchi method is expected to play a greater role in the field of engineering optimization. As the algorithm continues to develop and improve, we can expect it to play an important role in process optimization, product design, and quality control. This study applies Taguchi's method and uses an orthogonal experimental design to systematically optimize the extrusion process parameters. By comparing and analyzing the product parameters under different parameter combinations, this study verifies the effectiveness of Taguchi's method in optimizing extrusion process parameters and provides reference and guidance for optimizing extrusion process.

2. Finite Element Simulation Design

2.1 Finite element modeling

Finite element modeling is a crucial step in achieving engineering simulation as it enables the prediction of workpiece performance under actual working conditions by establishing accurate numerical models. In this study, the SolidWorks software was utilized to perform 3D modeling of the die, punch, and blank. The detailed structure of the die and punch was meticulously drawn based on design requirements and actual process parameters. The die model incorporated geometric features of critical parts such as the bottom, side walls, and corners within the die cavity. Similarly, the punch model considered overall shape and surface features to ensure optimal compatibility with the die. Additionally,

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a blank model was established to account for initial material shape and size, providing precise initial conditions for subsequent forming process simulation analysis. Figure 1 shows the specific dimensions used for modeling. After importing these component models into simufact. Forming software, further tasks including mesh division, material property setting, and boundary condition setting were performed to ultimately conduct forming process simulation analysis. Figure 2 shows the assembly of the parts after they has been imported into Simufact Forming. Through this analysis approach, deformation and stress distribution during the forming process can be simulated effectively while offering valuable reference data for optimizing process parameters.

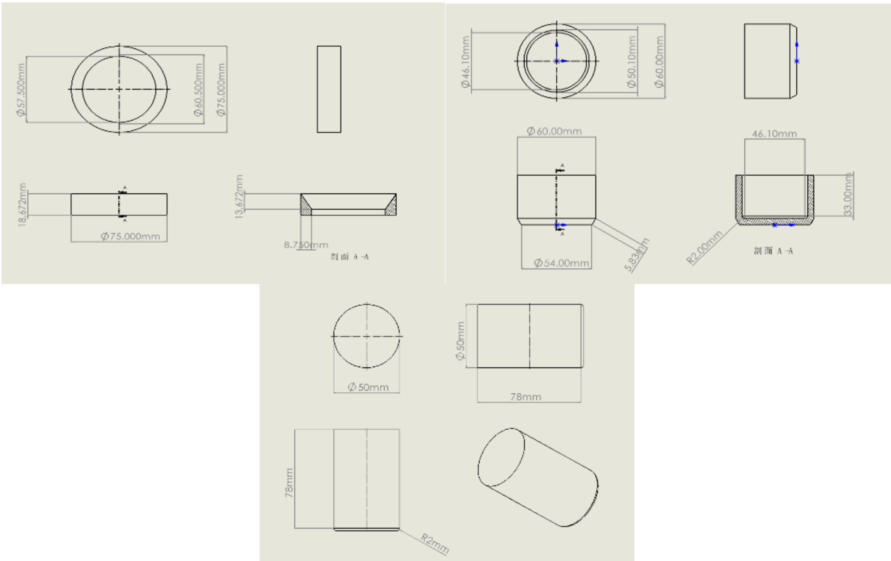

Figure 1: The dimensions of the recess die, blank, and punch

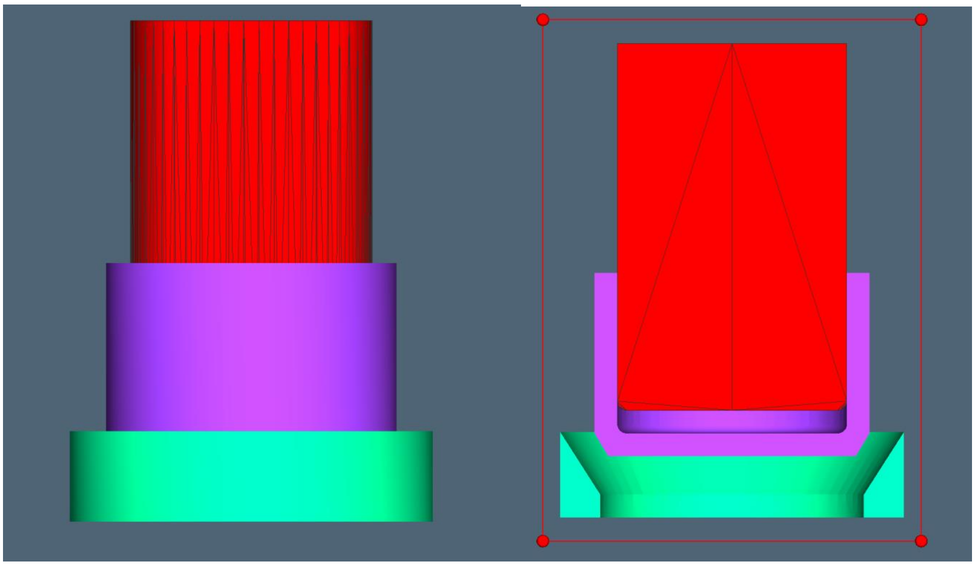

Figure 2: The assembled body after importing Simufact Forming

2.2 Grid discretization

In finite element analysis, mesh generation is a critical step that directly impacts the accuracy and computational efficiency of simulation results. For extrusion process simulations, accurate mesh generation plays a pivotal role in capturing essential information regarding workpiece deformation and stress distribution.

In this study, Simufact Forming software was employed for conducting finite element simulation analysis. During the mesh generation process, we utilized the Advancing Front Quad algorithm - an efficient quadrilateral mesh generation algorithm that ensures both suitable meshes for simulation and high-quality mesh structures. This algorithm generates meshes by continuously advancing forward: first

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determining boundary nodes and then gradually expanding inward to generate quadrilateral meshes. Figure 3 shows the grid-based results.

The resulting meshes generated by this algorithm exhibit excellent structural integrity and adaptability, making them highly suitable for simulating complex geometries and deformation conditions encountered in metal forming processes such as extrusion.

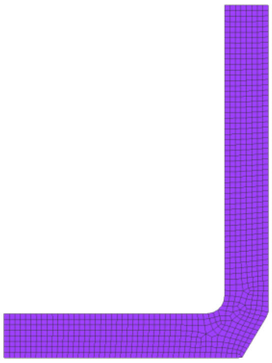

Figure 3: Grid discretization results

2.3 Orthogonal experimental design

The advantage of employing orthogonal experimental design lies in its ability to yield more precise results with fewer trial runs, thereby providing an effective means for optimizing the extrusion process parameters. The extrusion process parameters were optimized using the method of orthogonal experimental design, taking into consideration the key influencing factors. The process variables selected were extrusion speed, temperature, and friction coefficient, each set at three levels resulting in a total of 27 combinations. To simplify the experiment, nine groups of experiments representing these 27 combinations were chosen based on the principle of orthogonal experimental design as representative sets of process parameter combinations. Through analysis of the results from these nine groups of experiments, it is possible to determine the optimal combination for achieving superior quality in the extrusion process. By calculating and comparing both signal-to-noise ratio differences and total differences among factor levels' contributions to outcomes can be determined more accurately leading to further identification of optimal process parameter combination. The specific experimental plan is presented in Table 1 below.

Table 1: Orthogonal Experimental Design

Number	Stretching speed (mm/s)	Temperature (°C)	Coefficient of friction
1	3	80	0.1
2	3	140	0.2
3	3	200	0.3
4	6	80	0.3
5	6	140	0.1
6	6	200	0.2
7	9	80	0.2
8	9	140	0.3
9	9	200	0.1

3. Experimental Procedure and Results

In Simufact Forming 16.0 software, the initial step involved setting the press stroke to simulate pressure transfer and deformation during the pressing process. Following an orthogonal experimental design scheme, parameters were established for each group of experiments, encompassing contact stress, equivalent stress, and equivalent strain among others. Subsequently, the software was employed to simulate the forging process by replicating thinning and deformation occurrences during pressing.

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Through analysis of simulation results, contact stress, equivalent stress, and equivalent strain values were obtained for each parameter set; these data were subsequently utilized for optimization analysis in subsequent steps. The following Table 2 documents the experimental outcomes.

Table 2: Results record

Number	Contact stress (MPa)	Equivalent stress (MPa)	Equivalent strain
1	1768.26	1039.59	1.89
2	1978.92	971.51	2.16
3	1970.85	916.12	1.98
4	1706.34	949.35	2.06
5	1614.11	884.83	1.72
6	1451.15	839.71	1.71
7	1529.44	946.3	1.86
8	1594.11	913.46	1.71
9	1453.74	828.31	1.91

4. Optimization Analysis of Taguchi Method

4.1 Theoretical Principles

The Taguchi method is a systematic approach to optimizing product or process design through a limited number of trials, with the aim of determining the optimal parameter setting by minimizing system output variance in order to maximize or minimize system performance [4]. Taguchi method has the advantages of short computation period and multi-objective optimization design [5]. The core principle of the Taguchi method lies in signal-to-noise ratio (SNR) analysis. Initially, factors that influence system output and their corresponding levels are identified. Subsequently, a set of orthogonal experimental designs is developed to encompass all possible combinations of these factors. Through these experiments, measurements are taken on the response values of the system output, and SNR for each factor level is calculated. SNR serves as an indicator for stability or quality of the system output and is typically expressed as logarithmic ratios between smaller signals (e.g., better product size deviation) and noise (e.g., experimental error). By analyzing SNR values, it becomes possible to determine which factor level has the greatest impact on system performance and subsequently identify the optimal parameter setting. The Taguchi method not only considers average effects but also takes into account variance in experimental data, resulting in more robust and reliable optimization outcomes.

4.2 Statistical analysis

According to the orthogonal experimental plan, the contact stress, equivalent stress, and equivalent strain were recorded during the orthogonal experimental test. For these three evaluation indicators, the smaller the value, the better. Therefore, the formula for calculating the smaller signal-to-noise ratio was selected:

$$S/N = -10\, lg(y_i^2) \tag{1}$$

Table 3: Calculation of signal-to-noise ratio for each group of tests

Number	Contact stress (MPa)	S/N	Equivalent stress (MPa)	S/N	Equivalent strain	S/N
1	1768.26	-64.95	1039.59	-60.34	1.89	-5.53
2	1978.92	-65.93	971.51	-59.75	2.16	-6.69
3	1970.85	-65.89	916.12	-59.24	1.98	-5.93
4	1706.34	-64.64	949.35	-59.55	2.06	-6.28
5	1614.11	-64.16	884.83	-58.94	1.72	-4.71
6	1451.15	-63.23	839.71	-58.48	1.71	-4.66
7	1529.44	-63.69	946.3	-59.52	1.86	-5.39
8	1594.11	-64.05	913.46	-59.21	1.71	-4.66
9	1453.74	-63.25	828.31	-58.36	1.91	-5.62

According to the results of the Table 3, the sum of the signal-to-noise ratio of each factor and its level,

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as well as the average value, were further calculated. For the three characteristics of the process, the larger the value of the signal-to-noise ratio, the better the effect of the process. Through the analysis of Table 4 to Table 6, it can be known that the average signal-to-noise ratio of the contact stress corresponding to the stretching speed, temperature, and friction coefficient is the maximum at level 3. The average signal-to-noise ratio of the equivalent strain corresponding to the stretching speed, temperature, and friction coefficient is the maximum at level 2, level 2, and level 1. The average signal-to-noise ratio of the equivalent force corresponding to the stretching speed, temperature, and friction coefficient is the maximum at level 2, level 3, and level 1.

Table 4: Average Contact Stress Signal-to-Noise Ratio

Level	1	2	3
Stretching speed	-65.59085288	-64.01140671	-63.66358314
Temperature	-64.42762759	-64.71253101	-64.12568412
Coefficient of friction	-64.11977328	-53.26289958	-53.22900264

Table 5: Average signal-to-noise ratio of equivalent stress

Level	1	2	3
Stretching speed	-59.7751	-58.98943679	-59.03274186
Temperature	-59.8021	-59.29997766	-58.69516396
Coefficient of friction	-59.2128	-59.25070294	-59.33378836

Table 6: Average equivalent strain signal-to-noise ratio

Level	1	2	3
Stretching speed	-6.050538304	-5.215945184	-5.223616146
Temperature	-5.732279792	-5.353188723	-5.404631119
Coefficient of friction	-5.286824122	-5.579752038	-5.623523473

4.3 Range analysis

The total range is obtained by taking the average maximum - average minimum value of a certain factor at each level. The greater the range, the more significant the factor's influence on the research object. According to Table 7: the coefficient of friction has the greatest influence on the contact stress, temperature has the greatest influence on the equivalent stress, and the stretching speed has the greatest influence on the equivalent deformation.

Table 7: Range analysis

	The range of contact stress signal-to-noise ratio	The range of equivalent stress signal-to-noise ratio	The range of equivalent strain signal-to-noise ratio
Stretching speed	1.927269743	0.785641428	53.81679668
Temperature	0.586846892	1.106951293	0.379091069
Coefficient of friction	10.89077063	0.12102278	0.336699351

Table 8: The proportion of segmented range variance among all factors

	Contact stress level 2-3	Equivalent stress level 2-3	Equivalent strain level 2-3
Stretching speed	0.180474772	0.055120654	0.000142538
	Contact stress level 2-3	Equivalent stress level 2-3	Equivalent strain level 2-3
Temperature	1	0.546377877	0.13569931
	Contact stress level 1-3	Equivalent stress level 1-3	Equivalent strain level 1-3
Coefficient of friction	1	1	1

Calculating the proportion of the range for each factor at each level relative to the total range can determine the factors and levels that have the greatest impact on the results, thereby guiding further design and optimization of the experiment. Since the optimal level for each of the three indicators corresponding to the stretching speed is level three, the optimal level for each of the three indicators corresponding to the temperature is level two, level three, and level one; and the optimal level for each of the three indicators corresponding to the friction coefficient is level two, level two, and level one, the

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Table.8 is used to determine the contribution of the range for each factor at each level to the total range. The analysis shows that the proportion of the range for friction coefficient at each stage is the same, Table.7. Friction coefficient has a greater impact on contact stress than on equivalent stress and equivalent strain. Therefore, we choose the friction coefficient level corresponding to the optimal contact stress. Therefore, when the stretching speed is 9 mm/s, the temperature is 200℃, and the friction coefficient is 0.3, the process parameter combination is the optimal one.

5. Conclusion

This paper uses Taguchi's method to optimize the process parameters in extrusion process by conducting nine orthogonal experiments. The following results were obtained:

(1) The order of significance of each experimental factor on the contact stress affected by the extrusion process test is: friction coefficient > stretching speed > temperature, and the order of significance of each experimental factor on the equivalent stress affected is: temperature > stretching speed > friction coefficient, while the order of significance of each experimental factor on the equivalent strain affected is: stretching speed > temperature > friction coefficient.

(2) When the stretching speed is 9 mm/s, the temperature is 200°C, and the friction coefficient is 0.3, there is an optimal contact stress, equivalent stress, and equivalent strain.

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