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Design of Drawing Die for Rear Wheel Cover Outer Panel and Optimization of Wear Process Parameters

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Key words: die wear; drawing die, process parameter optimization, whale algorithm

ABSTRACT

Aiming at the problem of the wear caused by the mutual movement between the convex die and the sheet material in the stamping process, which results in a decrease in the die service life. In the paper, the three-dimensional design of the drawing die for the outer plate of the rear wheel cover was carried out by using UG, the simulation of the die stamping process was carried out by using Deform-3D, the main wear positions of the die were determined, the four process parameters of die clearance, friction coefficient, stamping speed and die hardness were selected as the test factors, the amount of die wear was used as the evaluation index to establish an orthogonal test, the multiple linear regression analysis of the test results was carried out by using SPSS software, and the empirical formula for the surface wear of the drawing die was established. Finally, the BP neural network model between process parameters and wear amount was constructed using MATLAB. The weights and thresholds of the nodes in the implicit layer of the model were optimized by using the whale algorithm to obtain the optimal combination of process parameters with minimum wear amount predicted based on the optimized WOA-BP neural network model. The minimum wear amount of the optimized convex die was 1.02×10^{-6} mm. The optimal combination of process parameters was friction coefficient 0.12, stamping speed 22mm/s, die hardness 62HRC, and die clearance 0.88mm, which completes the design of the automotive rear wheel cover outer plate drawing die and optimizes its surface wear process parameters.

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INTRODUCTION

Automobile covering parts are characterized by many curved surfaces, thin sheet material and complex spatial structure. In the process of forming automotive cover parts, drawing is the most important step. The current research mainly focuses on the simulation analysis of the forming process of parts. Still, there is less research on the wear analysis and life prediction of the drawing die for the outer plate of the rear wheel cover, and the wear formula for this type of die is not uniform. If we can find a formula that can reasonably predict the wear of the die, it will help to improve the service life of the drawing die. With the continuous development and improvement of CAE technology, it is meaningful to combine simulation technology with parameter optimization based on artificial intelligence algorithms to improve the quality of part forming and reduce the amount of die wear.

Michal Krzyzanowski et al. (2018) validated the main model assumptions, such as the assumed material flow stress curve and the damage criteria. Taguchi method is utilized to effectively model and analyze the relationship between process parameters. Roll-over and burr formation for a given punch-die clearance and cutting radius have been discussed and analyzed in terms of tool wear reduction for different materials. Fan et al. (2022) applied Deform-3D to numerically simulate the sheet stamping process in order to reduce the die wear during the stamping process of automotive-shaped stainless steel sheet parts and optimized the stamping process parameters based on the response surface method with the wear depth of convex and concave dies as the optimization target. At the same time, the life of the stamping die was predicted according to the maximum wear depth results, and finally, it was proved by stamping practice that the die life was significantly improved by using the optimal combination of stamping process parameters. E. Falconnet et al. (2012) investigated the punch wear resulting from the blanking of copper alloy thin sheet has been conducted by means of experimental and numerical analyses. Firstly, the experimental method has consisted in measuring punch worn profiles from replicas, and secondly in obtaining the wear coefficient by using a specific tribometer. The numerical modelling of blanking process has been developed with the finite element method to compute the mechanical fields necessary to calculate wear. Thus, the Archard formulation for abrasive wear has been programmed to compute the wear depth and the resulting punch geometry. Finally, the simulation results of wear prediction have been compared to experimental ones. Byung-Min Kim et al. (2015) evaluated the wear and fatigue characteristics of a new die material that has been developed for stamping ultra-high-strength steel. Through pin-on-disk wear testing and rotating bending fatigue testing, it is found that both the wear and fatigue characteristics of the die are improved by using this new material. And die wear is evaluated by FE analysis and experiment for ultra-high-strength steel stamping. A. Ghodke et al. (2016) researched work involved in the prediction of life of deep drawing die using artificial neural network (ANN) is described. The parameters affecting the life of deep drawing die were investigated through finite element (FE) analysis based on FE analysis results, stress amplitude (S) vs cycles to failure (N) approach is used for prediction of a number of cycles of deep drawing die. The number of cycles gives the number of sheet metal parts that can be produced with the deep drawing die before its failure. Cheng et al. (2018) established a new die wear prediction method by studying the wear characteristics of automotive panel stamping dies. The method considers the variation of contact pressure, wear coefficient and material hardness along the thickness direction of the treated layer and designs a new frictional wear device that can simulate the wear environment of the blank die interface in actual stamping. The prediction results of the new method and the traditional Archard method are compared with the actual wear conditions, and the results show that the die life prediction method used in this study is closer to the actual situation. Bernard F. Rolfe et al. (2016) examined the effect of sliding speed and surface temperature on the wear behavior of an unlubricated mild steel – tool steel contact pair using the pin-on-disc test. It will be shown that, while adhesive wear is dominant at the tool steel surface for all sliding speeds examined, the adhesive wear rate is very sensitive to sliding speed during slow speed conditions but relatively insensitive to sliding speed during higher speed conditions. Lemu H G et al. (2019) had an investigation that focused on the finite element-based analysis of wear of stamping tool for forming an axisymmetric drawpiece has been reported. The analyses were carried out for deep-drawing quality steel sheet with a sheet thickness of 2 mm. The implementation of an Archard's wear model in the numerical simulation proved the possibility of tool wear simulation in sheet metal forming. As a result of the conducted tests, the places of the stamping die potentially exposed to quick wear were determined. It was found that the most exposed region on accelerated wear is the upper part of the die radius.

In this paper, a three-dimensional model of an automobile rear wheel cover outer plate drawing die was designed by using UG, the die stamping process was simulated by using Deform-3D, the four process parameters of die clearance, friction coefficient, stamping speed and die hardness were utilized as test factors, the amount of die wear was used as evaluation index to design and complete an orthogonal test, and the SPSS software was used to conduct multiple linear regression analysis on the test data to establish an empirical formula for surface wear of drawing dies, and to verify the accuracy of the empirical formula. Then MATLAB is used to build a BP neural network model between the process parameters and the wear amount. The weights and thresholds of each node in the BP neural network model are optimized using the whale algorithm. The optimization results are reassigned to the BP neural network model. The minimum die wear value is predicted using the optimized neural network model to complete the design of the automotive rear wheel cover outer plate drawing die and optimize its surface wear process parameters.

REAR WHEEL COVER OUTER PLATE DRAWING DIE STRUCTURE DESIGN

As an outer covering part, the forming process of the rear wheel cover outer plate is not a one-step process but often requires multiple processes before it can be formed successfully. In the stamping process of outer covering parts, the drawing process is generally the first step after the drop process. The sheet blank material used in this paper is DC05 low strength steel, with a thickness of 0.7mm,and its basic mechanical parameters are shown in Table 1. The flat sheet can be made into box-shaped, stepped, cylindrical, and other irregularly shaped thin-walled parts through the drawing process, and the complex surface shape features of the parts can be obtained in the process and only when the shape features of the parts are successfully obtained in the drawing process can subsequent operations such as punching and trimming be performed. Therefore, the design of the drawing tool will affect the part's overall processing and forming quality, so the design of the drawing tool is particularly important.

Table 1 DC05 Sheet metal performance parameters

yield strength （MPa）	tensile strength （MPa）	strain hardening index n	hardening paramete K	elongation （%）

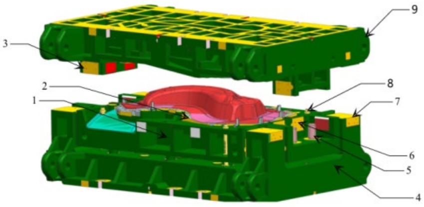
269	149	0.226	472	33.9

The drawing die is mainly composed of upper and lower die base, convex and concave die, blank holder, insert and guide pillar and guide bush. Figure 1 shows the assembly diagram of the drawing of the rear wheel cover outer plate designed by UG software. Combined with the actual application scenario of engineering and the design standard of the drawing die, the set of drawing die was designed with the following specific requirements:

(1) The rear wheel cover outer plate drawing die consists of upper and lower die base and blank holder, the convex die kernel is positioned by the positioning key, and then mounted on the lower die base by screws; the concave die adopts the block structure, which is made of 13 blocks, using pins for block positioning, and is mounted on the upper die base by screws; the blank holder also adopts the same block structure, using 13 blocks together, using pins for block positioning, and installed by screws. The design dimensions of the die are: L×W×H=2290mm×1550mm×900mm, where 900mm is the die closing height.

(2) The die is positioned when the die is closed through the guide pillar and guide bush on both sides and the guide plate. There are four guide pillars installed on both sides of the blank holder, and the corresponding guide bush is installed on both sides of the upper die; the guide plate is installed on the outer edge of the blank holder at the four corners and on the inner wall of the guide pillar slot to complete the positioning work when the die is closed together with the guide pillar and guide bush, there is a top bar at the bottom to provide the ejecting force when the blank holder moves, and the stamping stroke of the blank holder is 190mm.

(3) The positioning plate is installed around the blank holder to ensure the correct feeding of the sheet and to ensure that the sheet is in the correct position in the die during the drawing process, to position the sheet so that it does not move during the drawing process and to ensure the correct flow of material.



1-blank holder 2-convex die kernel 3-guide plate 4-lower die holder 5-guide pillar 6-upper die guide plate 7-limit block 8-limit screw 9-upper die holder

Fig. 1 Three-dimensional drawing of the rear wheel cover outer plate drawing die

SIMULATION OF WEAR PROCESS OF REAR WHEEL COVER OUTER PLATE DRAWING DIE

At present, there are few studies on the wear analysis and its life prediction of the drawing dies for the outer plate of the rear wheel cover, and the wear equations for this type of dies are not uniform, and it is difficult to predict the minimum wear of the dies. In this section, orthogonal tests will be used to complete the analysis of the process parameters of the drawing die for the rear wheel cover outer plate and get the best combination of parameters. The experimental data combined with the multiple linear regression equations were used to derive the empirical equation for die wear, and the derived empirical equation was used for die life prediction.

Establishment of the drawing die model

In the working process of the drawing die, the main wear position of the die is in the cutting edge part because of the violent friction between the sheet and the die, and the most complicated load situation in the fillet forming part during the stamping process. Due to the large size of the rear wheel cover drawing die itself and the significant features of the part shape, in order to simplify the analysis process and highlight the main wear situation, the stamping analysis is carried out locally to analyze the working condition of the main wear location.

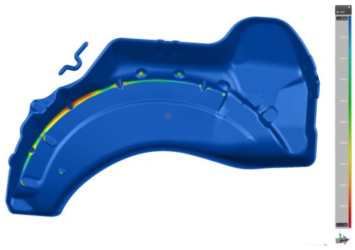


Fig. 2 Major wear locations

As shown in Figure 2, the analysis diagram of the main wear position of the convex die shows that the die wear is less at the smooth surface, while the die wear is more severe at the edge of the convex die. The main reason is that the material flow at the edge is more intense, and the load is more complex, leading to the most severe wear. In order to simplify the analysis process, this paper takes the location with more serious wear as the analysis object and takes the die shape in pieces. The area with severe wear was used for simulation analysis, and the wear condition was observed.

Figure 3 shows the 3D model of the die designed by using UG. The blue part of the figure is the convex die, the green part is the blank holder, the yellow part is the sheet material, and the red part is the concave die. The size of the rounded corner of the convex die is the same as the size of the rounded corner of the main wear position of the actual rear wheel cover outer plate drawing die. The original die is a flip-fitting die, but in Deform-3D, the front-loading die is generally used for analysis, so the assembly relationship of the front-loading die is also used in the 3D model.

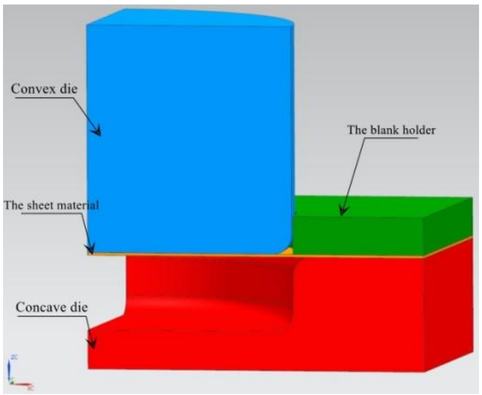


Fig. 3 Schematic diagram of the 3D model of the die

Mesh partitioning and irrelevance analysis

The stamping stroke of the die model in this study is set to 19mm, which makes the analysis more accurate on the premise of ensuring reasonable analysis time, so the number of steps is set to 100 in this paper, and the data is stored every 10 steps, so the step increment is defined as the displacement of the upper die, and the displacement is 0.19mm/step.

The quality of mesh delineation is an important factor that affects the wear simulation results of the rear wheel cover outer plate drawing die. Poor mesh quality and a small number of meshes will make the analysis results inaccurate, but too many meshes will cause the analysis time to be too long. In Deform-3D, the setting value of the step is generally one-third of the minimum mesh size. According to the displacement setting of 0.19mm/step, we know that the part's minimum mesh size should be no more than 0.57mm, and the absolute method is used to qualify the mesh size and set the minimum element size to 0.5mm. The grid size ratio is set to 2, and the maximum element size is set to 1mm. The system can calculate the number of grids for each tool body according to the set element size, and the specific division parameters are shown in Table 2.

Table 2 Grid division result table of each tool body

Tool body name	Types of grids	Minimum Element Size	Maximum element size	Number of grids
Convex die	Tetrahedral Mesh	0.5mm	1mm	265516
Concave die	Tetrahedral Mesh	0.5mm	1mm	350564
Sheet material	Tetrahedral Mesh	0.5mm	1mm	210600
blank holder	Tetrahedral Mesh	0.5mm	1mm	177868

In Deform-3D, the mesh size has an important influence on the analysis results and analysis time. If the number of meshes is small, the analysis time is less, but the accuracy of the analysis results decreases; if the number of meshes is large, the analysis time is longer, but the analysis results are more accurate. In order to save calculation time on the premise of ensuring the accuracy of calculation results, it is necessary to set a more appropriate number of meshes in advance. The data in Table 1 are the number of grids derived from the step size, and the method is used for most engineering calculations. In order to verify the reasonableness of the grid, comparison experiments were conducted using 0.8 times, 1.5 times, and 2 times of the grid parameters to ensure that the other set conditions are consistent, and the results are shown in Table 3.

Table 3 Simulation results under different grid numbers

Groups	die wear amount (mm)	Calculation time
Control group	0.00000231	/
0.8 times the number of grids	0.00000215	the shorter
1.5 times the number of grids	0.00000231	the longer
2 times the number of grids	0.00000231	the longest

As can be seen from Table 2, when the number of grids is small, the maximum and minimum element sizes will change accordingly, where the minimum element size will be larger than three times the step size, resulting in inaccurate analysis results, so the number of grids cannot be smaller than the original set number; when the number of grids reaches 1.5 times and above, the analysis results do not change. Therefore, it can be concluded that the analysis result of the original set number of meshes is close to the real value, but due to the dense grid number, it will cause the software analysis time to be longer.

In summary, the mesh size and number calculated from the step size are sufficient to meet the required accuracy of the analysis, and the software analysis time is moderate. Under the same conditions, a more detailed mesh does not significantly impact the analysis results. Therefore, the number of divided meshes is irrelevant to the final analysis results, provided that a certain accuracy is achieved.

Simulation of wear process of drawing die

As shown in Figure 4, the symmetry surface boundary is set for the concave die. The red surface is selected as the symmetry surface, the blue part is set as the heat exchange surface, and the remaining three tool bodies are aligned with the concave die. According to the movement of the drawing die, the convex die will contact the sheet downward and press the sheet into the concave die for forming under the action of the press. The edge of the sheet will be controlled by the blank holder during the forming process to ensure the forming process. Therefore, according to the above motion process, it can be seen that the plate material makes contact with the convex die, concave die, and blank holder respectively during the drawing process, and the above three sets of relations need to be set when defining the contact boundary conditions.

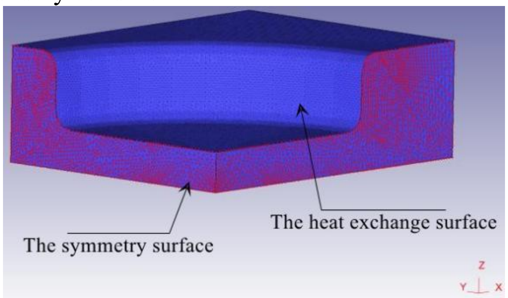


Fig. 4 Setting of symmetry surface of concave die

The boundary contact relationship is shown in Figure 5. According to the theoretical analysis of the sheet forming process of the drawing die, the main friction between the sheet and the convex and concave die during the forming process is shear friction, so the shear friction model is chosen, and the friction coefficient is set to 0.12. Since heat is generated by friction between the sheet and the die during the forming process, heat exchange surfaces are added to the surface of the convex and concave die and the front and back of the sheet, so the heat transfer coefficient in the contact relationship is set to 0.004.

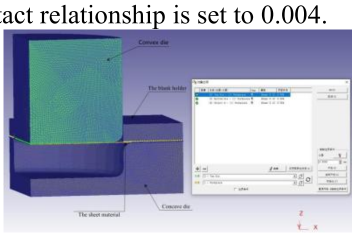


Fig. 5 die wear model contact condition setting

Finally, the wear model is defined. According to the commonly used wear model as the classical Archard wear model, so the wear model is equivalently replaced and integrally deformed in Deform-3D.

The Archard wear model is the most commonly used model in the metal plastic forming process. Its expression is shown in Equation (1). The model considers that the wear volume V of the die is proportional to the normal pressure P of the contact surface and the slip distance L between the workpiece and the die. H is the hardness of the contact surface die, and K is the wear coefficient of the corresponding material.

$$dV = K\frac{dPdL}{H} \quad (1)$$

In formula (1), dV, dP, dL can be converted to into formula (2).

$$\begin{cases} dV = dWdA \\ dP = \sigma_n dA \\ dL = vdt \end{cases} \quad (2)$$

In the formula : W is the wear dept; A is the corresponding contact surface area ; σ_n is the normal pressure of the corresponding contact surface ; v is the sliding speed between the die and the contact surface in stamping forming ; t is time. The formula (2) is substituted into the formula (1), the simplified formula (3) is obtained, and the formula (3) is integrated to obtain the wear amount calculation formula (4). Among them, a, b, c are constants, steel takes a = 1, b = 1, c = 2, wear coefficient K is different according to the different working conditions and the general value range is $10^{-3} \sim 10^{-7}$, steel takes K = 0.000002.

$$dW = K\frac{\sigma_n vdt}{H} \quad (3)$$

$$W = \int K\frac{P^a V^b}{H^c}dt \quad (4)$$

In the formula : W — wear depth (m).

P — the normal stress between the contact surface of the sheet and the tool body (MPa).

v — relative slip velocity (m/s).

H — die hardness (HRC).

dt — time increment (s).

It can be seen by equation (1), the theory that the wear amount is positively related to the stress load on the die and the sliding speed of the plate material, and negatively related to the die hardness.

After setting the boundary conditions, it is necessary to add the corresponding process parameters and characteristics to the convex die. Firstly, the stamping direction is selected as -Z direction, the stamping speed is set to 10mm/sec, and the hardness of the die is set to 55HRC.

Analysis of simulation results of the wear process of drawing dies

As shown in Fig. 6, the load curve of the cam die stroke during the drawing process is shown, and its ordinate is the load on punch along the Z direction, that is, the punching direction. As the figure shows, the sheet metal is formed along the die fillet within 0~0.968 seconds, and the flow resistance of sheet metal is the largest at this stage. Therefore, with the advance of the drawing process, the Z-direction load on the punch also increases and reaches the peak value at 0.968 seconds. At this stage, the punch surface also produces intense friction with the sheet metal surface. The punching pressure is used to complete the sheet metal forming in the concave die. At the end of the forming process, the main forming parts of the sheet metal are formed, and the force on the edge part is small, so its force decreases until the end of the forming process, the punch force is reduced to 0.

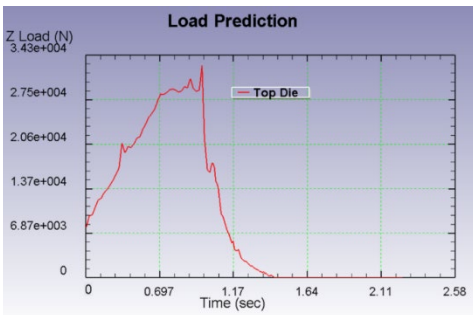


Fig. 6 Load curve of convex die stroke

FIG. 7 shows the sheet metal forming results of the drawing die model. The sheet metal has good formability under the drawing die, and its bottom is smooth and well-extended. Because the boundary condition of the symmetric surface is set, the sheet can be formed completely within the boundary range to fit the set boundary perfectly. The size of the lower surface is almost the same as that of the inner surface of the concave die. The sheet metal can be fitted to the surface of the die at the rounded corner transition, and there is no wrinkling or thinning cracking caused by uneven material flow at this position, which has a better forming effect and material flow process. Because the flange is provided with a blank holder, the excess unformed sheet material can flow to the forming area under the action of the blank holder, and in the forming process of the flange did not cause the phenomenon of edge warping due to local pressure, sheet forming successfully.

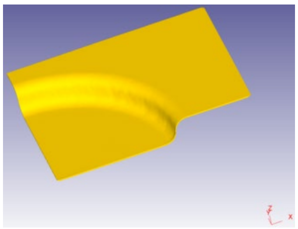


Fig. 7 Model sheet forming effect

As shown in Fig. 8, the distribution of the wear amount of the convex die after a single drawing, the highest wear amount of the convex die is 2.31×10^{-6} mm after a complete drawing and stamping process, and the main wear location appears at the rounded corner transition. It can be seen from the comparative analysis that the simulation results of the two software show that the wear occurs at almost the same location, so it can be assumed that the main wear location of the drawing die for the outer plate of the rear wheel cover is the location shown in the figure. The model follows the dimensions of the shape and rounded corners of the drawing die, so the wear amount here can be approximated as the wear amount of the drawing die during the processing and production process.

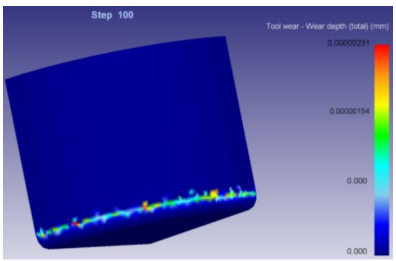


Fig. 8 Distribution of convex die wear amount

Study and analysis of wear factors of drawing dies

(1) Determination of the evaluation index of drawing die wear

Through the aforementioned contents, it is determined that the rounded corner of the convex die is the most severely worn area during the production process of the part processing. This location is the location where the die is most likely to be scrapped, so the wear amount of a single press at this location is chosen as the evaluation index of the wear condition of the drawing dies.

(2) Selection of test factors and orthogonal test design

Analysis of the influence of die clearance on die wear:

The size of the die gap not only affects the quality of the part being stamped and formed, but also the life of the die. If the gap is too small, the resistance to the flow of the sheet in the stamping process increases and the friction between the sheet and the convex and concave die increases, resulting in increased die wear and affecting die life. When the gap is large, although it can effectively reduce the wear of the die and prolong the service life, the forming defects such as stacking and wrinkling will occur in the local position.

Analysis of the influence of friction coefficient on die wear:

In the stamping process of the die, the lubrication condition is not good enough to lead to the friction coefficient is too large, so the flow of the sheet metal will be hindered, which will lead to the process of the sheet metal extending to the inside to be hindered, which is easy to cause the cracking phenomenon in the middle or round corner of the sheet metal. Secondly, insufficient lubrication conditions will lead to severe friction between the sheet metal and the the convex and concave die, which not only affects the forming quality of the parts, but also reduces the service life of the die due to friction heat generation.

Analysis of the influence of stamping speed on die wear:

With the increase of stamping speed, the wear of the die increases, but when the stamping speed exceeds a certain limit value, the increase of stamping speed makes the wear of the die decrease. However, in the actual blanking process, it is found that with the increase of stamping speed, the wear of the die is significantly increased.

Analysis of the influence of die hardness on die wear:

For stamping die, hardness is a very important parameter, which not only affects the quality of stamping products, but also affects the life of the die. The higher the hardness, the better the wear resistance and the longer the die life. Usually, the mold material, heat treatment and coating conditions will affect the hardness.

According to the research analysis, the factors affecting the amount of die wear mainly include die clearance, the friction coefficient between the plate material and the tool body, stamping speed, and die hardness, so these four process parameters were selected as the analysis factors for the orthogonal test. In order to comprehensively study the influence of each test factor on the test results, the range of parameters for the test analysis was expanded, and four levels were selected for each factor to be explored. The levels were chosen as shown in Table 4.

Table 4 Table of test factors and level settings

Factors	Level 1	Level 2	Level 3	Level 4
Friction coefficient	0.12	0.13	0.14	0.15
Stamping speed/ ($mm \cdot s^{-1}$)	10	20	30	40
die hardness/HRC	55	58	61	64
die clearance/mm	0.7	0.77	0.84	0.91

The orthogonal test table of $L_{16}(4^4)$ was established, and the wear simulation experiments were conducted against the parameter combinations in the table respectively. The wear results of each group were obtained, as shown in Table 5. To simplify the table, the friction coefficient is set as factor A, the stamping speed as factor B, the die hardness as factor C, and the die clearance as factor D. The amount of die wear is used as the evaluation index.

Table 5 Statistical table of simulation results of orthogonal test

Serial number	A	B ($mm \cdot s^{-1}$)	C (HRC)	D (mm)	Wear amount ($\times 10^{-6} mm$)
1	0.12	10	55	0.7	2.13
2	0.12	20	58	0.77	1.49
3	0.12	30	61	0.84	1.39
4	0.12	40	64	0.91	1.97
5	0.13	10	58	0.84	1.86
6	0.13	20	55	0.91	1.13
7	0.13	30	64	0.7	1.60
8	0.13	40	61	0.77	2.84
9	0.14	10	61	0.91	1.74
10	0.14	20	64	0.84	1.55
11	0.14	30	55	0.77	2.99
12	0.14	40	58	0.7	2.30
13	0.15	10	64	0.77	1.83
14	0.15	20	61	0.7	2.25
15	0.15	30	58	0.91	2.40
16	0.15	40	55	0.84	2.82

(3) Analysis of test results

Combining the 16 sets of test data obtained in Table 5, the effect of process parameters on the amount of die wear was investigated using the extreme difference analysis method. The analysis results are shown in Table 6.

Table 6 Table of extreme difference analysis of each parameter on the amount of die wear

Serial number	A	B	C	D
K_1	6.98	7.56	9.07	8.28
K_2	7.43	6.42	8.05	9.15
K_3	8.58	8.38	8.22	7.62
K_4	9.30	9.93	6.95	7.24
k_1	1.745	1.89	2.2675	2.07
k_2	1.8575	1.605	2.0125	2.2875
k_3	2.145	2.095	2.055	1.905
k_4	2.325	2.4825	1.7375	1.81
R	0.58	0.8775	0.53	0.4775

The extreme difference can reflect the degree of influence of each process parameter on the amount of die wear, and it can be seen through Table 5 that, $R_B > R_A > R_C > R_D$, that is, the degree of influence of each process parameter on the maximum thinning rate is: stamping speed > friction coefficient > die hardness > die clearance. In order to reflect more intuitively the trend of each process parameter's influence on the part's maximum thinning rate at different levels, a graph of the influence of each process parameter on the maximum thinning rate is produced in Figure 9.

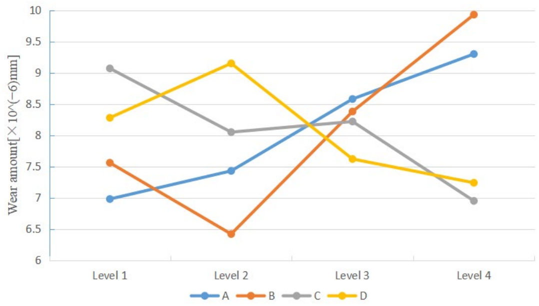


Fig. 9 Trend of the influence of each process parameter on the amount of die wear

Through Figure 9, orthogonal test and extreme difference analysis table, it can be seen that within a certain range, with the increase of friction coefficient, the die wear amount has been increasing; with the increase of stamping speed, the die wear amount decreases first and then increases, when the stamping speed is 20mm / s, the die wear amount is the smallest; with the increase of die hardness, the die wear amount first decreases, then fluctuates slightly, and then decreases continuously; with the increase of die clearance, the die wear amount increases first and then decreases, when the die clearance is 0.77 mm, the die wear amount is the largest.

It can be clearly seen through Figure 9 that if you want to minimize die wear, the combination of process parameters that should be selected as $A_1B_2C_4D_4$, that is, the friction coefficient is 0.12, the stamping speed is 20 mm/s, the die hardness is 64 HRC, the and die clearance is 0.91 mm. The simulation results using this combination of parameters are shown in Fig. 10.

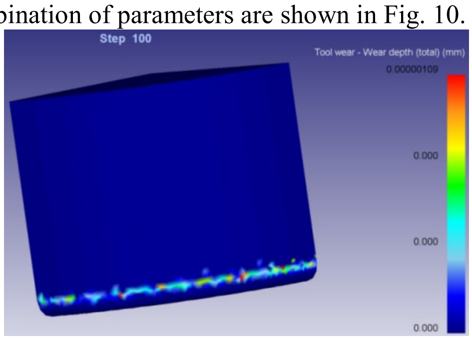


Fig. 10 Distribution of die wear under $A_1B_2C_4D_4$ combination

With this combination of process parameters, the wear of the convex die is reduced to 1.09×10^{-6} mm, and the main location of wear is still at the die edge. Therefore, this analysis's results align with the theoretical analysis and the processing reality. According to the general wear limit formulated by the factory, the surface wear of the drawing die should be less than 0.5mm, within which the die needs to be regularly maintained or repaired, etc. If the wear amount exceeds the limit, it will cause the production of parts with low dimensional accuracy, substandard surface roughness, or even inferior products, and will cause major accidents such as die failure. Using this wear limit, the life of the die can be found to be about 458,715 cycles under the $A_1B_2C_4D_4$ combination.

Wear empirical equation based on multiple linear regression

From section 3.5, it can be seen that the dependent variable die wear is jointly determined by the four independent variables, and it is known through the extreme difference analysis that the influence weight of each variable on the dependent variable is different. In order to determine the mathematical relationship between the independent variable and the dependent variable, and establish the corresponding mathematical formula to guide the subsequent processing production, so the multiple linear regression model is proposed to be used to derive the mathematical model between the independent variable and the dependent variable.

The multivariate linear model is simple in form and easy to model, and is generally a function that makes predictions through linear combinations of multiple attribute elements, as shown in equation (5).

$$f(x) = \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + b \quad (5)$$

Where: β_i — The weight coefficient of the ith attribute element, $i = 1,2,3 \cdots, n$;.

x_i — The value of the ith attribute element. $i = 1,2,3 \cdots, n$.

b — Free regression coefficient.

The data in Table 5 were entered into SPSS with the amount of wear as the dependent variable and the four process parameters as independent variables for regression analysis. The data entry method was selected as the forced entry. The results of the data analysis are shown in Table 7.

Table 7 Table of model complex correlation coefficient test

Models	R	R^2	Adjusted R^2	Error in standard estimation
1	0.756	0.571	0.415	0.42116

It can be seen from the data in Table 7, R represents the degree of correlation between the independent and dependent variables in the regression model, and its value ranges from 0 to 1. The closer the R-value is to 1, the higher the correlation of the regression model. The R-value of 0.756 in this table indicates that the model has an excellent correlation. The standard estimation error represents the degree of deviation between the actual value and the calculated value of the model, and the smaller the value, the higher the prediction accuracy. The error in this table is 0.42116, indicating that the regression model has a high computational prediction accuracy.

Table 8 Variance analysis table of regression model

Models	quadratic sum	Degree of freedom	Mean Square	F	Significance
Regression	2.600	4	0.650	3.664	0.039
Residuals	1.951	11	0.117		
Total	4.551	15			

Table 8 is the variance analysis table of the regression model, in which the main judgment is the F value and the final significant Sig value, F is the value of the constructed statistic, and the Sig value represents the significance level, which should generally be less than 0.05. It means that the regression model is significant and useful, the Sig value in this table is 0.039, so the regression model is constructed successfully.

Table 9 Table of regression coefficients for each factor

Regression coefficient	b	β_A	β_B	β_C	β_D
standardization coefficient	0	0.425	0.475	-0.324	-0.244
Non-standardized coefficient	3.120	20.275	0.025	-0.052	-1.661

Table 9 shows the regression model coefficients of the four independent variables, using the standardized coefficients to analyze the elements. The magnitude of their absolute values represents the degree of influence of the elements on the regression model results. The coefficients can be obtained that the degree of influence in this regression model is: stamping speed > friction coefficient > die hardness > die clearance, which is consistent with the results of the orthogonal test analysis. And the positive and negative coefficients are also consistent with the influence relationship, where the friction coefficient and stamping speed are positively correlated with the wear amount, and the die clearance and die hardness are negatively correlated with the wear amount, which is consistent with the results of the extreme difference analysis. The model is built by using non-standardized coefficients. The linear regression model of die wear is shown in equation (6), where the calculated results are in units of ($\times 10^{-6}$mm).

$$f(x) = 3.120 + 20.275x_A + 0.023x_B - 0.052x_C - 1.661x_D \quad (6)$$

The experimental values of the statistical orthogonal test and the calculated value based on the mathematical model of Equation (6) were counted. In order to unify the two results, the significant digit of the calculated value was reserved to two decimal places, and the results are shown in Table 10.

Table 10 Error statistics table of the test value and calculated value

Serial number	Test value/$\times 10^{-6}mm$	Calculated value/$\times 10^{-6}mm$	Error/$\times 10^{-6}mm$
1	2.13	1.76	-0.37
2	1.49	1.72	0.23
3	1.39	1.68	0.29
4	1.97	1.63	-0.34
5	1.86	1.57	-0.29
6	1.13	1.84	0.71
7	1.60	1.95	0.35
8	2.84	2.22	-0.62
9	1.74	1.50	-0.24
10	1.55	1.70	0.15
11	2.99	2.51	-0.48
12	2.30	2.70	0.4
13	1.83	1.78	-0.05
14	2.25	2.29	0.04
15	2.40	2.32	-0.08
16	2.82	2.83	0.01

In order to more visually express the accuracy of the prediction calculated by the regression model and to show the error relationship between the experimental and calculated values, a line graph was created using the data in the table above. The comparison graph between the experimental and calculated values is shown in Figure 11, and the error graph is in Figure 12.

Fig. 11 Comparison diagram of test value and calculated value

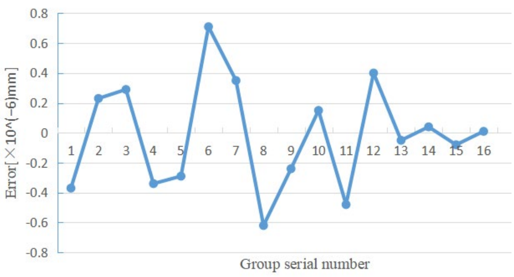


Fig. 12 Error diagram

PROCESS PARAMETER OPTIMIZATION BASED ON BP NEURAL NETWORK AND WHALE ALGORITHM

The friction between the sheet and the die surface during the drawing process varies nonlinearly, so it is difficult to find the exact function to express the linear relationship between the four process parameters and the amount of die wear. The function model obtained in the previous section using multiple linear regression can only obtain local minima and does not ensure that the solution found is a global minimum. In this section, we build a BP neural network model with process parameters as input and die wear as output, and optimize the weights and thresholds of the implicit layer of the neural network model using the whale algorithm to obtain the global minimum die wear and its corresponding combination of process parameters.

Processing of experimental data

The construction of the BP neural network requires certain experimental data as the learning object. Its prediction accuracy will increase with the increase of experimental data, so it is necessary to select the better three levels from the four levels of four process parameters in section 3.5 for a full-scale test. From section 3.5, it is known that the better combination of process parameters is friction factor 0.12, stamping speed 20mm/s, die hardness 64HRC, and die clearance 0.91mm, so the levels were selected as shown in Table 10, and the factors and levels in Table 11 were used to conduct the full-scale test.

Table 11 Table of test factors and level settings

Factors	Level 1	Level 2	Level 3
Friction coefficient	0.12	0.13	0.14
Stamping speed/ （$mm \cdot s^{-1}$）	10	20	30
die hardness/HRC	58	61	64
die clearance/mm	0.77	0.84	0.91

Construction of BP neural network model

The linear regression model between test factors and evaluation indexes obtained from section 3.6 is the result of statistical analysis using a small amount of test data, and its available range has certain limitations, and the prediction accuracy is not very high. In order to further find the combination of process parameters for minimum wear, the BP neural network model with four inputs and one output is established in this section.

BP neural network is a multilayer feed-forward neural network trained according to the error backpropagation algorithm, which generally consists of three or more neuron levels, a single input and output layer, and multiple hidden layers. A three-layer BP neural network is built to describe the relationship between process parameters and die wear based on the content of Section 3. The model input layer is the four process parameters of friction coefficient, stamping speed, die hardness, and die clearance, and the output layer is the die wear, and the model results are shown in Figure 13.

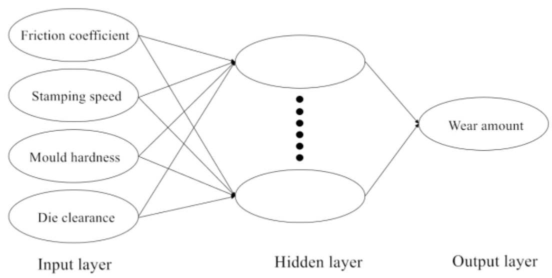


Fig. 13 BP neural network structure

Validation of BP neural network model

The process parameter item is set as X, and the die wear amount is set as Y. Use the BP neural network toolbox of MATLAB to build a neural network, set X as the input quantity and Y as the target quantity. The neural network includes an input layer, implicit layer, and output layer, in which the model determines the input layer and output layer. The input layer is the process parameters, 4, and the output layer is the evaluation index, 1. In order to achieve the predetermined mapping relationship to improve the network accuracy, the number of implicit layers is finally determined to be 20 for the best effect through several tests. The constructed model is shown in Figure 14.

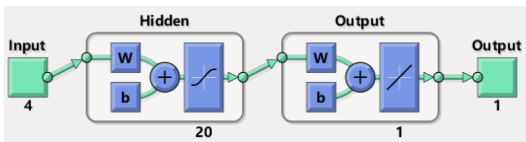


Fig. 14 Neural network model structure diagram

The training curve of the BP neural network is shown in Figure 15. It can be seen from Figure 15 that the verification performance of this neural network reaches the best at the 18th iteration, and the mean square error of the verification set is 0.066359. In the subsequent 19th to 24th iterations, the mean squared error of the training set gradually decreases until it becomes stable. In contrast, the mean squared error of the validation set and the test set becomes stable. At this time, it is considered that the BP neural network training is complete, and there is no precocious or overfitting phenomenon.

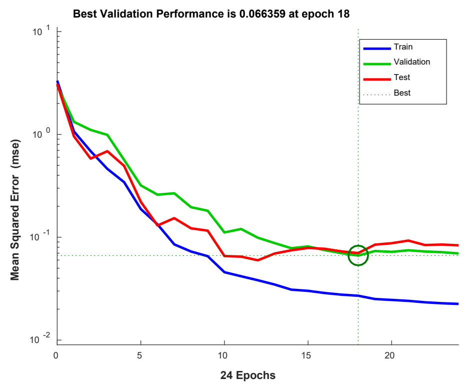


Fig. 15 BP neural network training curve diagram

As shown in Figure 16, the BP neural network training results fit curve can fully reflect the prediction accuracy of the built neural network model on the data, and the error between the predicted value and the test value can be visually displayed by the degree of line offset. The content of Figure 15 shows that the fitted regression R-value for the training set of this neural network is 0.92554, the fitted regression R-value of the validation set is 0.8294, the fitted regression R-value of the test set is 0.82295, and the integrated fitted regression R-value is 0.88396, which is a excellent fitting effect.

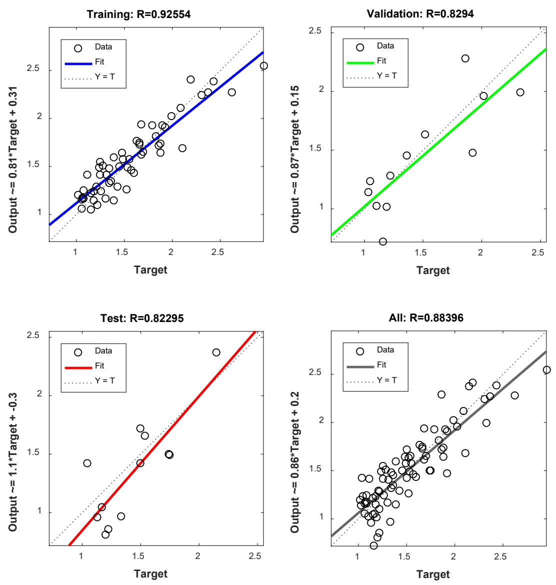


Fig. 16 BP neural network fitting curve diagram

The BP neural network error histogram is shown in Figure 17, whose error is calculated as the difference between the target value and the output value. It can be seen from the figure that the overall error of the neural network model is between [−0.09931~0.1181]. The multiple linear regression model was built in Section 3.6, its overall prediction error is between [−0.4~0.4], and the prediction error is significantly lower. Hence, this BP neural network's overall prediction error value is small.

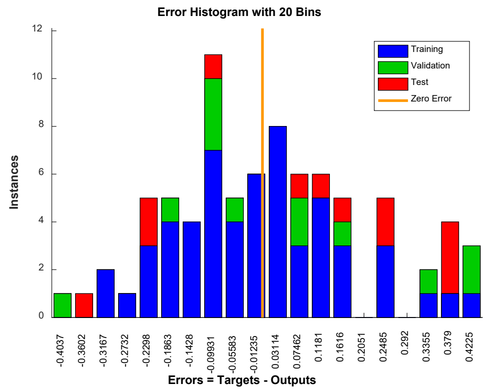


Fig. 17 BP neural network error histogram

In summary, it can be seen through each curve analysis graph that the neural network training process is complete, the numerical fit is high, the numerical prediction is accurate and meets the prediction requirements, and the BP neural network model is successfully built.

WOA Optimized BP Neural Network Model

The Whale Optimization Algorithm (WOA) is a meta-heuristic optimization algorithm that simulates the hunting behavior of humpback whales. The code sets the number of populations and the maximum number of iterations to ensure the accuracy of the whale algorithm for finding the optimal value, which has the characteristics of few optimization parameters, simple operation, and fast convergence and is widely used in engineering. The whale algorithm is used to optimize the weight values and thresholds of the BP neural network to obtain the WOA-BP neural network model with accurate prediction and stable structure. The model predicts the minimum die wear value and derives the optimal combination of process parameters using back calculation.

FIG. 18 shows the iterative evolution process curve of the whale algorithm optimization neural network. The optimization process has evolved for 50 generations and becomes stable after iteration to 16 generations, and the fitness value reaches the best, which verifies that the optimization model can converge quickly and complete the optimal search within the specified number of iterations.

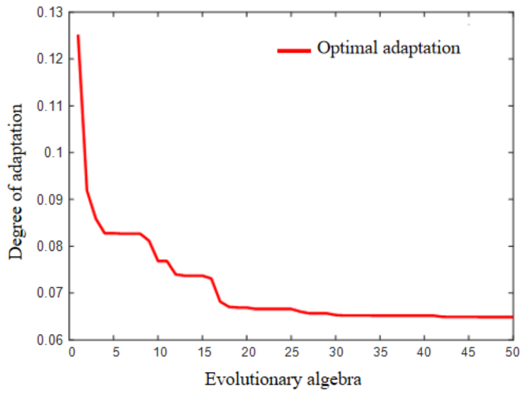


Fig. 18 Iterative curve diagram of optimal fitness

By optimizing the BP neural network using the WOA algorithm, the overall parameters of the model were significantly improved, the training of the neural network was completed after only 9 iterations, and the efficiency was significantly improved. The mean square error was reduced from the initial 4.33271×10^{-2} to 1.60163×10^{-2}, and the integrated regression R-value was improved from 8.8396×10^{-1} to 9.5588×10^{-1}. The optimization effect was obvious, and the fit curve is shown in Figure 19.

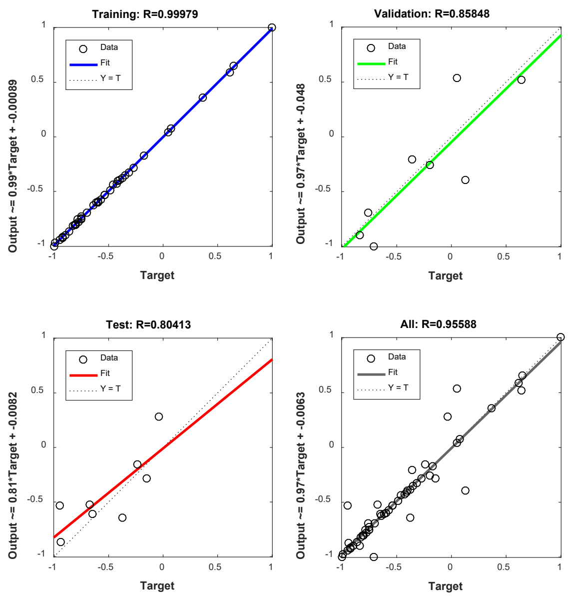


Fig. 19 WOA-BP neural network fitting curve diagram

As can be seen by the graphical content, compared with the initial BP neural network, the optimized neural network has a significant improvement in the degree of fitting, and the comparison of the fitted regression coefficient values before and after optimization is shown in Table 12.

Table 12 Comparison of R-values of neural network fitting regression before and after optimization

	Training	Validation	Test	All
Initial BP Neural Network	0.92554	0.8294	0.82295	0.88396
WOA-BP Neural Network	0.99979	0.85848	0.80413	0.95588

Figure 20 shows the comparison diagram between the predicted value and the actual value of the BP neural network before and after WOA optimization. The test data of the test set is used for statistical analysis, and the distance between the test value and the actual value judges the accuracy of data prediction. The graph shows that the predicted values of the WOA-BP neural network have higher prediction accuracy than the initial BP neural network, the error floating range is smaller, and the prediction results are more stable.

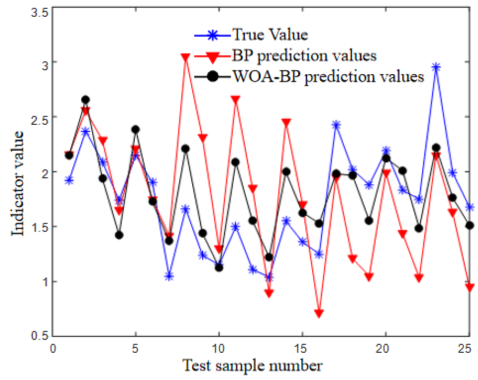


Fig. 20 Before and after comparison diagram of WOA optimized BP neural network

In summary, the neural network optimized by the whale algorithm has faster convergence speed, minor fitting error and more stable prediction accuracy, which indicates that the whale optimization algorithm optimizes the BP neural network well and the WOA-BP neural network is built successfully.

Optimization of process parameters based on WOA-BP

The parameter range set in Section 4.1 was converted to input X values into the WOA-BP neural network, and the output Y value was set to be the minimum. The prediction using the WOA-BP neural network yielded a convex die wear of 0.99×10^{-7} mm, a friction coefficient of 0.12, a stamping speed of 22 mm/s, a die hardness of 62 HRC, and a die clearance of 0.88 mm. The wear distribution of the convex die obtained by inputting each process parameter into Deform for verification is shown in Figure 21.

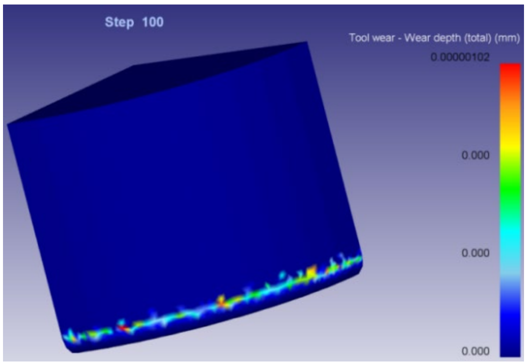


Fig. 21 Distribution diagram of convex die wear under WOA-BP neural network prediction

As verified by Deform, The minimum wear of the convex die for this combination of process parameters is 1.02×10^{-6} mm, which is not much different from the predicted result. As shown in Table 13, comparing the wear amount of the convex die before and after optimization and the analysis of the process parameter combination, the wear amount of the convex die was reduced from 2.31×10^{-6}mm to 1.02×10^{-6}mm. The die life was increased to 490,196 times, so the optimization effect was obvious.

Table 13 Comparison table of results analysis before and after optimization

Optimization methods	Process Parameters				Simulation results
	Friction coefficient	Stamping speed/ （$mm\cdot s^{-1}$）	die hardness/HRC	die clearance/mm	Wear amount（$\times 10^{-6}$mm）
No optimization method	0.12	10	55	0.77	2.31
Orthogonal test	0.12	20	64	0.91	1.09
WOA-BP	0.12	22	62	0.88	1.02

CONCLUSION

In this paper, we completed the three-dimensional design of the drawing die for the outer plate of the rear wheel cover of an automobile, selected four process parameters: friction coefficient, stamping speed, die hardness and die clearance as the test factors, and the amount of wear of the drawing die as the evaluation index, designed and completed an orthogonal test, and optimized the stamping process parameters of the outer plate of the rear wheel cover of an automobile using the method of BP neural network optimized by the whale algorithm, and the results showed that:

(1) Deform was used to complete the simulation of the stamping process of the rear wheel cover outer plate drawing die, determine the main wear position of the die, and obtain the initial simulation result of a single wear amount of 2.31×10^{-6} mm. With wear amount as the evaluation index, 16 groups of test data were obtained by the orthogonal test with friction coefficient, stamping speed, die hardness and die clearance as influencing factors. The influence trend of each process parameter on the evaluation index was analyzed by using the extreme difference analysis method. The final optimized combination of process parameters was obtained as a friction coefficient of 0.12, stamping speed of 20 mm/s, die hardness of 64 HRC, and die clearance of 0.91 mm. The minimum wear of the convex die under this combination was 1.09×10^{-6} mm, and the die life was about 458715 times.

(2)Using SPSS combined with orthogonal test data, the empirical equation for die wear within the set process parameters was obtained using multiple linear regression equations. The accuracy of the calculated values of the empirical formula for wear was analyzed by comparing the test values with the calculated values. The accuracy of the prediction of the empirical formula was verified by graphical analysis.

(3)The whale algorithm was used to optimize the BP neural network model and to optimize the wear amount of the convex die. The minimum wear amount of the convex die after optimization is 1.02×10^{-6} mm. The corresponding process parameters are friction coefficient 0.12, stamping speed 22mm/s, die hardness 62HRC, and die clearance 0.88mm, and the lifetime of the drawing die of the rear wheel cover outer plate of the car after optimization is increased to 490,196 times, which effectively improves the service life of the die.

(4)The optimal combination of process parameters based on the orthogonal test reduces the wear of the rear wheel cover outer plate drawing die by 1.22×10^{-6} mm. The optimization based on the BP neural network and the whale algorithm, the wear of the rear wheel cover outer plate drawing die was reduced by 1.29×10^{-6} mm. Compared with the orthogonal test, the process parameters are optimized by the WOA-BP neural network algorithm, and the die life is improved by 31,481 times. Therefore, using the BP neural network and whale algorithm is conducive to reducing the amount of die wear and improving the service life of dies, which can play a role in the development of stamping dies.

AUTHOR CONTRIBUTIONS

Guoqing Gong had made substantial contributions to design, experimental research, data collection and result analysis; Youmin Wang made critical changes to important academic content; Kefan Yang made the final review and finalization of the articles to be published.

DATA AVAILABILITY

The data used to support the findings of this study are included within the article.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest to report regarding the present study.

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NOMENCLATURE

W — wear depth (m).
P — the normal stress between the contact surface of the sheet and the tool body (MPa).
v — relative slip velocity (m/s).
H — die hardness (HRC).
dt — time increment (s).
β_i — The weight coefficient of the ith attribute element, $i = 1,2,3 \cdots$，n ;.
x_i — The value of the ith attribute element. $i = 1,2,3 \cdots$，n .
b — Free regression coefficient.

後輪罩外板拉延模具設計及其磨損工藝參數優化

宮國慶 王幼民 楊克帆
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摘要

針對衝壓過程中模具凸模與板料之間相互運動而造成的磨損，造成模具使用壽命降低的問題。本文利用 UG 對後輪罩外板拉延模具進行三維設計，利用 Deform-3D 進行模具衝壓過程模擬模擬，確定了模具主要磨損位置，選取模具間隙、摩擦係數、衝壓速度及模具硬度四個工藝參數作為試驗因素，以模具磨損量作為評價指標建立正交試驗，運用 SPSS 軟體對試驗結果進行多元線性回歸分析，建立了拉延模具表面磨損經驗公式。最後運用 MATLAB 搭建工藝參數與磨損量之間的 BP 神經網路模型，利用鯨魚演算法優化模型隱含層節點的權重和閾值，得到了基於優化後的 WOA-BP 神經網路模型預測出的磨損量最小時的最優工藝參數組合，優化後的凸模最小磨損量為 1.02×10^{-6}mm，最優的工藝參數組合為摩擦係數 0.12、衝壓速度 22mm/s、模具硬度 62HRC、模具間隙 0.88mm，完成了汽車後輪罩外板拉延模具的設計並優化了其表面磨損工藝參數。