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Optimization of Injection Molding Process Parameters for Automotive Brake Plug-in Based on CCD and PSO

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Abstract: Taking the amount of warpage deformation of automotive brake Plug-in as the research object, UG NX10.0 software was used to design the product model and Moldflow software was used for predictive analysis of the product model. The preliminary optimized parameters were obtained by using the response surface method - central composite experiment design (CCD) and combined with injection molding CAE technology. The mold temperature was 70°C, the melt temperature was 250°C, the holding pressure was 95 MPa, and the holding time was 10s. The warpage was 1.18 mm. Through the analysis of variance, the influence of four injection process parameters on product warpage was obtained, namely, holding pressure>holding time>melt temperature>mold temperature. Based on the fitted response surface algorithm model, the process parameters were optimized using particle swarm optimization (PSO) with the minimum warpage as the constraint condition, and the optimal combination of the optimized process parameters was obtained, that was, the mold temperature was 60°C, the melt temperature was 280°C, the holding pressure was 95 MPa and the holding time was 8.296 s. The minimum warpage was 1.057 mm. The optimization results showed that the minimum warpage was reduced by 10.85% compared with the initially optimized parameters, and the effectiveness of the proposed method was verified by using this parameter combination for actual injection production.

Keywords: Automotive Brake Plug-in, Response Surface, Injection Molding Process Parameters, Warpage, Particle Swarm Optimization

1. Introduction

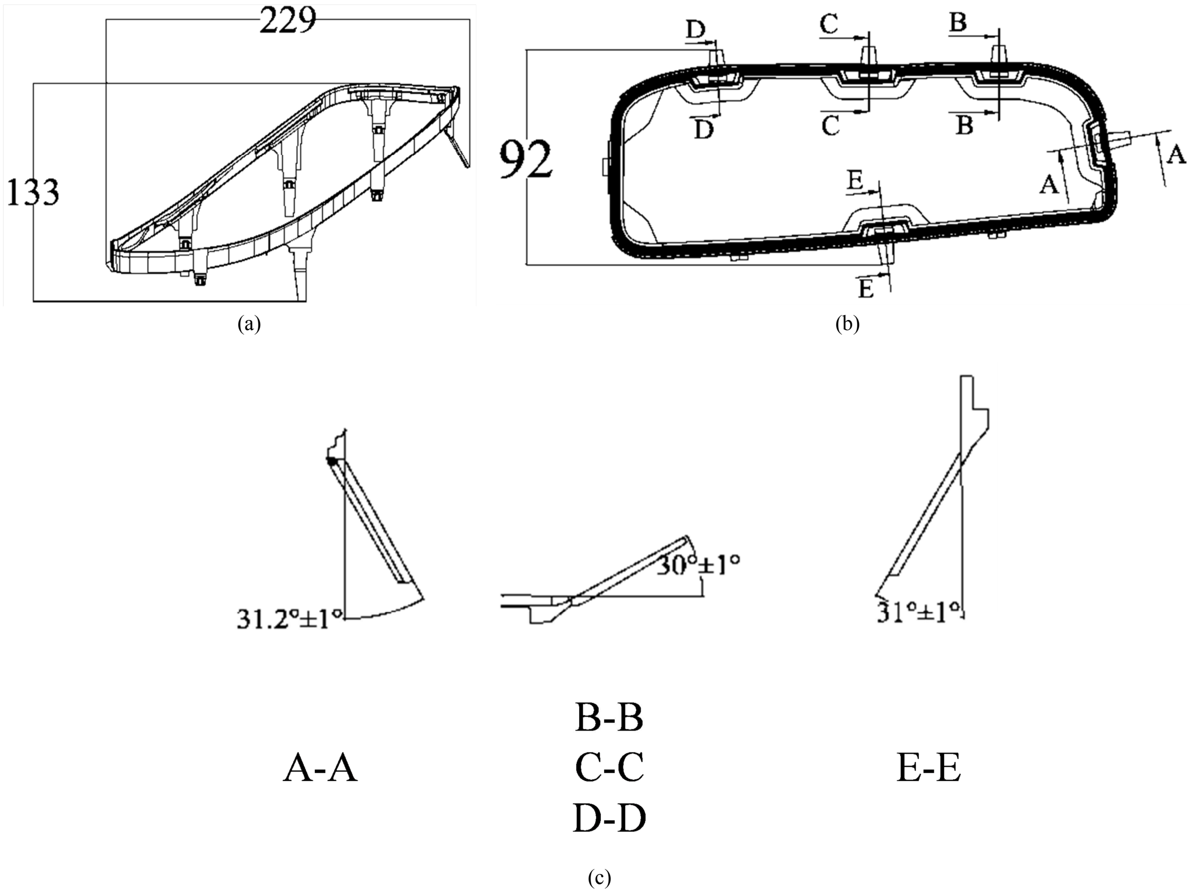
Automotive brake Plug-in has an auxiliary role in automotive braking devices. Automotive brake Plug-in for injection molded product, if its molding quality is poor, such as the occurrence of warpage deformation and other defects, will produce assembly stress in the assembly process, which will lead to its accelerated aging during use, resulting in cracking failure. The quality of injection molded products is mainly affected by the material, mold, and process. This paper discusses how to reduce the warpage of injection molding from the perspective of process parameter optimization. The injection molding process parameters have many complex nonlinear effects on injection molding warpage, and the optimization of the injection molding process has become one of the main challenges and research hotspots to reduce warpage. In process optimization, the more used is the orthogonal test method [1-3], which can only intermittently take points in the test space to find the optimal parameters and can not give a function expression between the test factors and response values on the whole area. To obtain an efficient and reliable mathematical planning method, which can also meet the optimization calculation in the engineering field, some scholars have studied the optimization of injection molding process parameters [5-7] using the response surface method [4], which can well solve the time-consuming and nonlinear optimization problems. Although the above-mentioned optimization method combined with injection molding CAE technology for simulation can help optimize the injection molding process parameters, the obtained injection molding process parameter combinations are only locally optimal parameters, and it is difficult to achieve global optimization. With the development of a new generation of artificial intelligence, making its application in various fields showing great potential, the development of industrial intelligence has also become a trend and focus of research. Currently, some scholars have studied the optimization of injection molding process parameters using intelligent algorithms and combined with CAE technology for numerical simulation, which is generally used for the optimization of injection molding process parameters such as genetic algorithm [8-15], firefly algorithm [16] or its improvement algorithm [17, 18] for multiple indexes seeking optimization. Among them, the particle swarm optimization (PSO) algorithm has the advantages of fast search speed, high efficiency, and simple algorithm compared with other algorithms, and the early convergence problem is effectively avoided by using the improved standard particle swarm optimization algorithm. Therefore, the injection molding process parameters can be better optimized.

In this paper, we take the automotive brake Plug-in as the research object and conduct a study on the warpage problem of injection molding. The mold temperature, melt temperature, holding pressure, and holding time were selected as the test factors, and the response surface method-central composite experiment design (CCD) combined with Moldflow software was used for CAE technology simulation analysis to establish a second-order response surface model [10] and determine the influence regularity of process parameters on warpage deformation through the analysis of variance. The standard particle swarm optimization algorithm combined with CAE technology is used to obtain the global optimal combination of injection molding process parameters with the minimum warpage, and the optimal combination of parameters is verified in production, which effectively reduces the cost of mold trial and improves production efficiency.

2. Moldflow Analysis of Product

2.1. Two-Dimensional and Three-Dimensional Models

The automotive brake Plug-in is a body injection molded part, the whole of which is composed of a shaped surface, with reinforcement ribs to enhance the structural strength of the product and some hooks for installation, and the end of the hooks in five places have a certain angle. The product size is 229 mm × 92 mm × 133 mm, and the average thickness is about 1.05 mm. Its two-dimensional and three-dimensional models are shown in Figure 1 and Figure 2. The product is required to have a bright and clean surface, without obvious air traps, weld lines, and other defects that affect the appearance or function.



(a) (b) (c)

Figure 1. *Automotive brake Plug-in 2D model (unit: mm) (a) Front view (b) Top view (c) Cross-sectional view.*

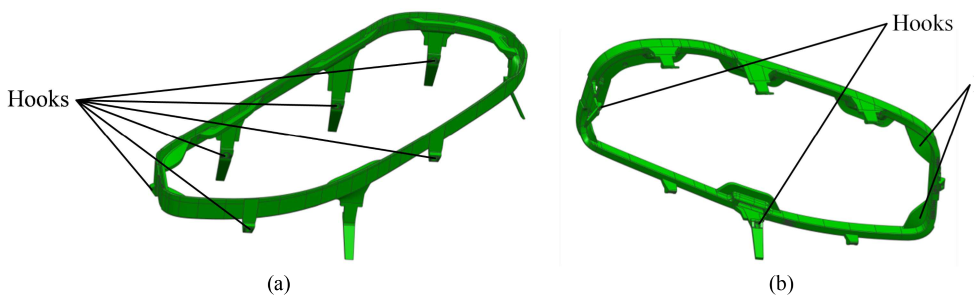


Figure 2. *Automotive brake Plug-in 3D model (a) Front view (b) Side view.*

2.2. Mesh Division

The 3D model of the automotive brake Plug-in designed by UG NX10.0 was imported into Moldflow CAD doctor 2015 software, and the model was pre-processed to repair features affecting the mesh quality such as chamfers, edges, and recesses. The repaired model has been imported into Moldflow 2015 software for meshing. Due to the thin wall thickness and small size of the product, the dual-domain mesh was used. The mesh side length is set to 2 mm. The number of meshes is 25806. The matching rate reaches 91%, and the average aspect ratio is 1.89, which meets the requirements of the mold flow analysis, as shown in Figure 3.

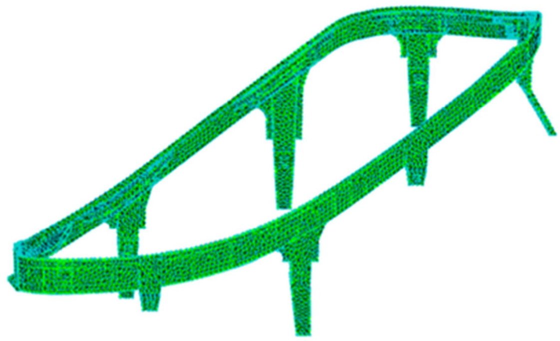


Figure 3. *Mesh model.*

2.3. Feed System Design

The feed system is the flow channel between the melt flowing from the beginning of the main flow runner through each branched runner and then to the gate, which can fill the melt into the cavity in a smooth and orderly manner to complete the product molding. As shown in Figure 4, the open hot-runner system to cold-runner system is used in the injection molding process, considering the structural characteristics of the mold kernel, to ensure the balance of melt flow and to minimize the waste generated by the cold-runner. From the flow resistance analysis, it is concluded that the left front side of the product has the lowest flow resistance and is the best location for the gate, but according to the molding requirements, the single design of the gate will lead to uneven pressure holding around the product, as shown in Figure 5a. The gate matching analysis is shown in Figure 5b. The dark area is the best area for product gate matching. The gate position should avoid interfering with the mold mandrel and insert and be located at the thicker part as much as possible, considering the factors such as melt flow balance, mold processing complexity, and customer's requirements for the product, so the 4-point feeding scheme is adopted. The best matching value of the side gate is selected to be about 0.7. The final scheme is shown in Figure 6.

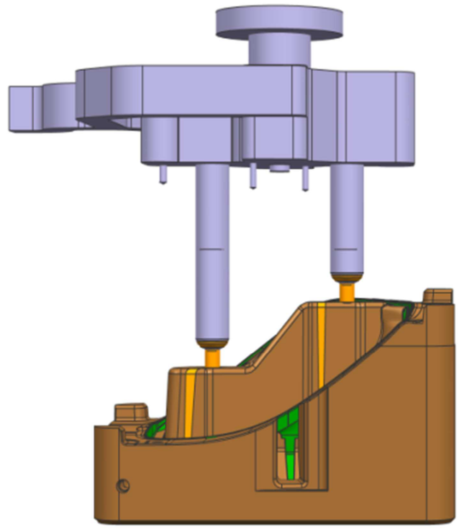
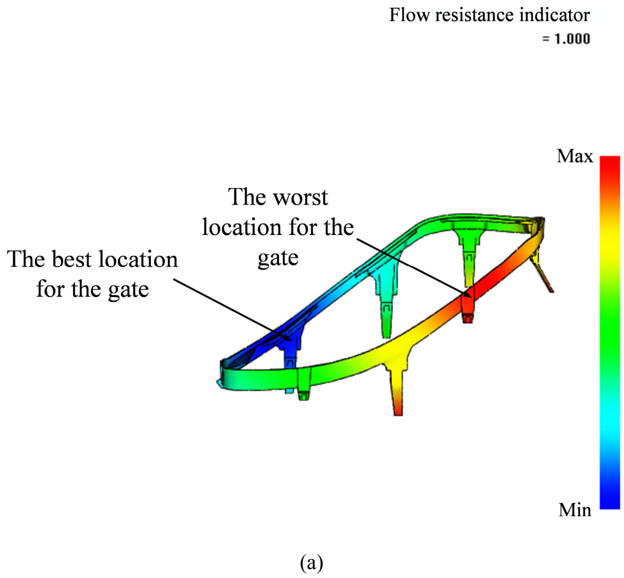
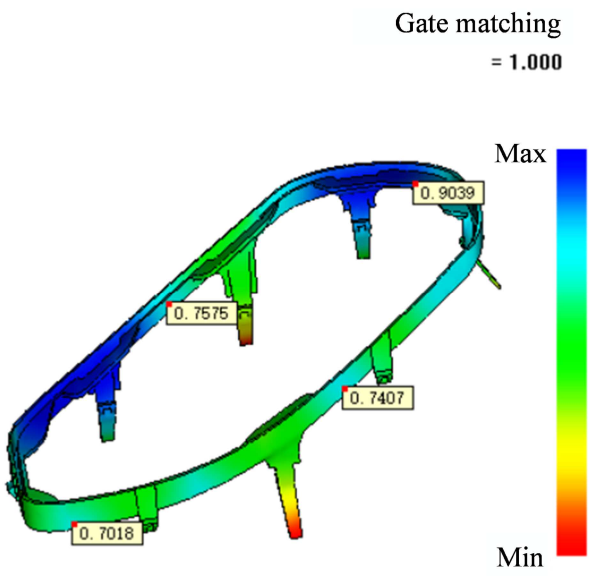


Figure 4. *Mold kernel structure and feed system.*





(b)

Figure 5. *Gate position (a) Gate flow resistance (b) Gate matching.*

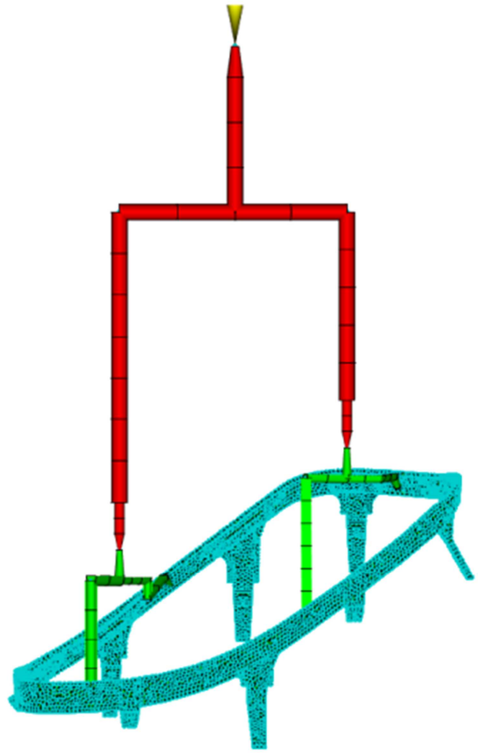


Figure 6. *Feed system.*

2.4. Cooling System Design

The cooling system controls the temperature of the mold through the water circuit to make the product cool evenly after molding, and the water circuit arrangement will directly affect the molding quality of the product. According to the structural characteristics of the product, six sets of cooling circuits are set to ensure uniform cooling of the mold and product, with a cooling pipe diameter of 8 mm and a cooling water well diameter of 10 mm, as shown in Figure 7.

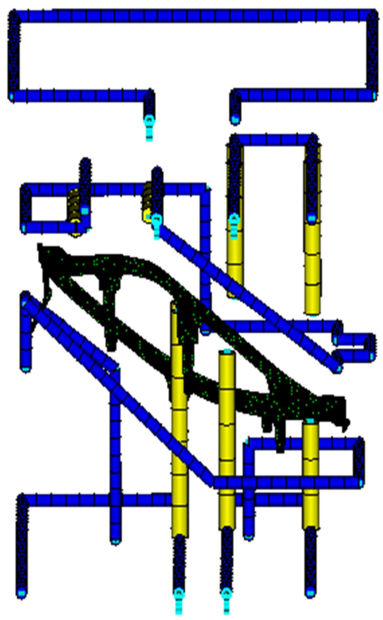


Figure 7. *Cooling system.*

2.5. Analysis Results

The filling and cooling analyses were performed on the feed system and cooling system models, and the default values were used for all injection process parameters to obtain the filling analysis results as well as the cooling analysis results, as shown in Figure 8 and Figure 9. As shown in Figure 8a, the melt is filled into the cavity from four gates, and the flow balance is maintained throughout the filling process. As shown in Figure 8b, the melt filling time is 1.357 s, which can ensure a better processing efficiency, and the plastic melt reaches the end of the cavity on both sides almost simultaneously. There is no gray part, indicating that the filling flow is balanced and there is no short shot or hesitation. As shown in Figure 8c, the air traps created by melt filling are located on the product surface, and air can be expelled through the gap between the cavity and the product. As shown in Figure 8d, most of the product weld lines are located on the surface of the product and distributed in the thicker part of the product. The length is short, which can ensure the strength and appearance of the product. Figure 9a shows the results of the circuit coolant temperature analysis. To ensure the cooling efficiency, the temperature difference is required to be less than 3°C. As can be seen from Figure 9a, the maximum temperature is 25.48°C and the minimum temperature is 24.99°C, and the temperature difference is only 0.49°C, which meets the requirements. As shown in Figure 9b, the minimum value of the loop Reynolds number in the cooling process is 10,000 and the maximum value is 12,266, and the Reynolds number is greater than 4,000. It is easier for the coolant to form turbulent flow in the cooling loop, so the cooling effect of the product is better and the molding quality of the product is higher. In summary, the product feed system and cooling system are reasonably designed and can meet the requirements of later process optimization.

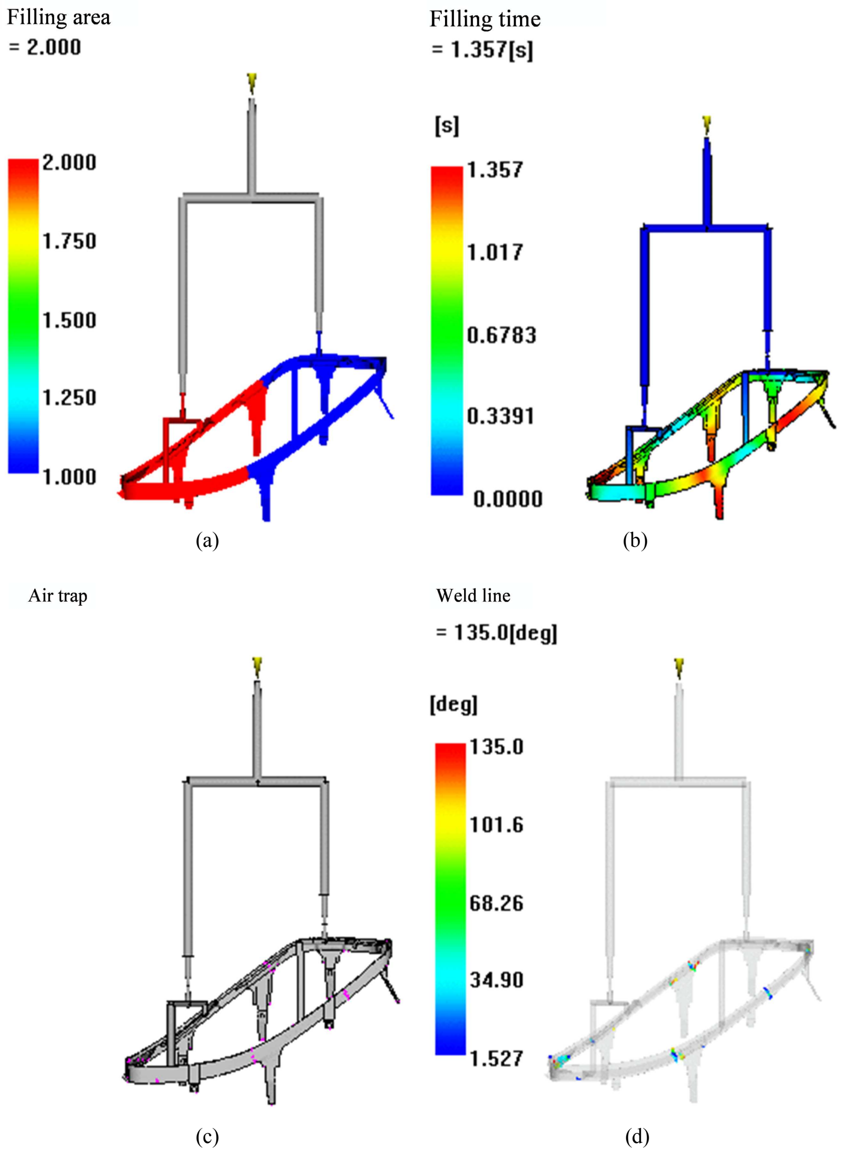


Figure 8. *Filling analysis (a) Filling area (b) Filling time (c) Air trap (d) Weld line.*

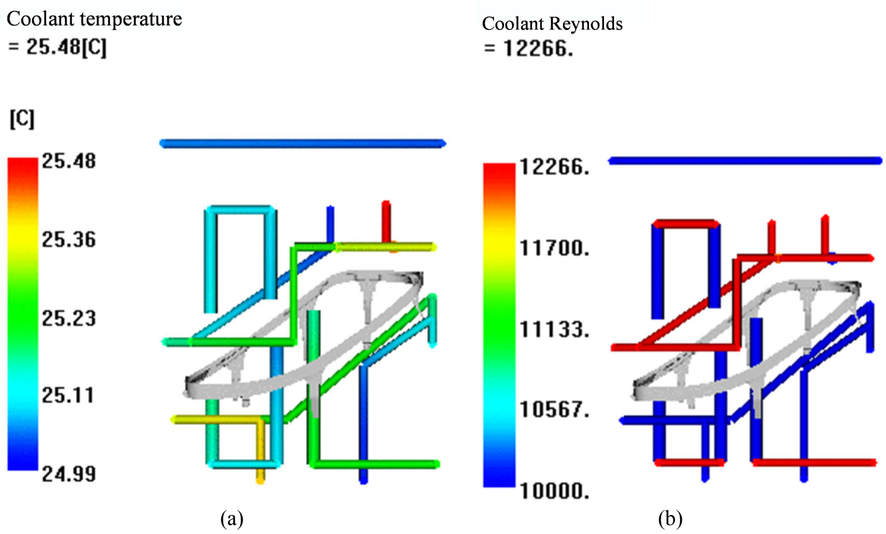


Figure 9. *Cooling analysis (a) Coolant temperature (b) Coolant Reynolds.*

3. Response Surface Method - Central Composite Experiment Design (CCD)

The automotive brake Plug-in injection material is Lustran Elite HH ABS 1827. ABS plastic products not only have excellent molding processability, good dimensional stability, and colorability, but also have good mechanical strength, and the material property parameters can be obtained by Moldflow software and production experience. In the injection molding process, to reduce the cost, the warpage of product can be reduced by optimizing the injection process parameters. In this paper, the mold temperature (A), melt temperature (B), holding pressure (C), and holding time (D) are selected as the test factors based on the production experience, and the cooling time is taken as the default value to analyze the warpage deformation of automotive brake Plug-in under different process conditions by selecting "filling + holding + cooling + filling + holding + warping".

In the central composite experiment design, if the number of factors is k, cubic points n_α are used to fit the primary and cross terms of the function, which constitute the factorial test part, the number of which is $n_\alpha = 2^k$ or $n_\alpha = 2^{k-1}$ (k⩾5). Axial points n_β, also known as asterisk points, have a total of 2k. The center point n_γ is the design center, which is the zero point on the coordinate axis. The test was designed according to the number of center points and the number of tests recommended by the central composite experiment design (CCD), as shown in Table 1. The test factors and levels are shown in Table 2.

Table 1. *Number of recommended test sites for CCD.*

Number of factors	Cubic points n_α	Axial points n_β	Center points n_γ	Number of tests
4	16	8	6	30

Table 2. *Test factors and levels.*

Test factors	Level range				
	-2	-1	0	1	2
Mold temperature A/°C	60	65	70	75	80
Melt temperature B/°C	220	235	250	265	280
Holding pressure C/Mpa	35	50	65	80	95
Holding time D/S	4	7	10	13	16

4. Analysis of Test Results, Discussion and Optimization of Process Parameters

4.1. Central Composite Test (CCD) Results

Thirty sets of experimental process parameters were simulated and analyzed using Moldflow 2015 software, and the results of the product warpage obtained from the simulation are shown in Table 3. From the results of the 24th group of tests, it can be concluded that the automotive brake Plug-in has the largest warpage, with a value of 1.77mm. The minimum warpage of 1.18 mm in the first group of test results corresponds to the following process parameters: mold temperature of 70°C, melt temperature of 250°C, holding pressure of 95 MPa, and holding time of 10s. The result of the first group of tests is shown in Figure 10, and it can be concluded that the maximum warpage is located at the edge of the product hook position.

Table 3. *Test results.*

Serial number	A	B	C	D	Warpage (mm)
1	0	0	2	0	1.18
2	-1	-1	1	-1	1.309
3	0	0	0	0	1.438
4	2	0	0	0	1.418
5	-1	1	1	1	1.338
6	0	0	0	0	1.438
7	-1	-1	1	1	1.291
8	-2	0	0	0	1.426
9	1	1	1	1	1.359
10	0	0	0	0	1.438
11	1	-1	-1	-1	1.582
12	1	1	-1	1	1.6
13	0	0	0	0	1.438
14	0	0	0	0	1.438
15	0	-2	0	0	1.371
16	1	-1	1	-1	1.31
17	0	0	0	0	1.438
18	0	-2	0	0	1.446
19	-1	1	-1	-1	1.676
20	1	-1	-1	1	1.442
21	1	1	1	-1	1.314
22	-1	-1	-1	1	1.443
23	0	0	-2	0	1.684
24	0	0	0	-2	1.77
25	-1	1	-1	1	1.569
26	-1	-1	-1	-1	1.578
27	0	0	0	2	1.398
28	1	-1	1	1	1.285
29	1	1	-1	-1	1.699
30	-1	1	1	-1	1.304

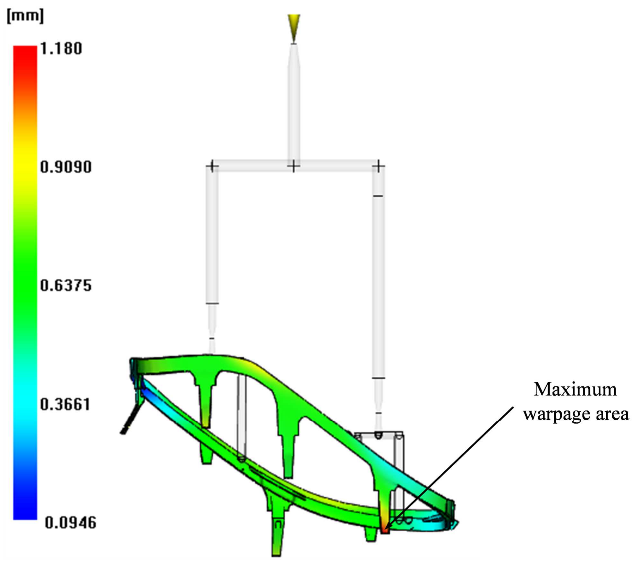


Figure 10. *Group 1 warpage test result.*

4.2. Automotive Brake Plug-in Warpage Model and Analysis of Variance

Response surface algorithm models are divided into first-order response surface models and second-order response surface models. The first-order response surface model only responds to the linear correlation problem, which is obviously not applicable to the warpage deformation of this product, so the second-order response surface model is used. The general expression is shown in eqn. (1).

$$y = b_0 + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} x_i^2 + \sum_{i<j}^{k} b_{ij} x_i x_j \tag{1}$$

Where y is the warpage objective function. k is the number of factors. x_i and x_j indicate the encoded levels for independent variables.

b_0 is a constant term. b_i, b_{ii}, b_{ij} are the partial regression coefficients.

Based on the 30 sets of test data, the second-order response surface model is obtained by ordinary least squares fitting, and the partial regression coefficients can be obtained by adopting the matrix form of the equation to construct a second-order polynomial model for predicting the minimum warpage, as shown in eqn. (2).

$$\begin{aligned} y = & -1.78278 + 0.022963A + 0.024284B + 0.014966C - 0.20602D + 7.25\times10^{-5}AB - 2.58333\times10^{-5}AC \\ & +2.91667\times10^{-5}AD - 1.05278\times10^{-4}BC + 2.65278\times10^{-4}BD + 7.18056\times10^{-4}CD - 2.79583\times10^{-4}A^2 \\ & -4.60648\times10^{-5}B^2 - 1.99537\times10^{-5}C^2 + 3.72338\times10^{-3}D^2 \end{aligned} \tag{2}$$

After the response surface model was established, the warpage was analyzed by ANOVA and the results are shown in Table 4.

Table 4. *Analysis of variance results.*

Error source	Sum of squares	Degree of freedom	Mean-square error	F	P
Model	0.55	14	0.039	21.76	<0.0001
A	1.870×10^{-4}	1	1.870×10^{-4}	0.10	0.7521
B	0.025	1	0.025	13.63	0.0022
C	0.40	1	0.40	219.70	<0.0001
D	0.059	1	0.059	32.59	<0.0001
AB	4.731×10^{-4}	1	4.731×10^{-4}	0.26	0.6164
AC	6.006×10^{-5}	1	6.006×10^{-5}	0.033	0.8578
AD	3.063×10^{-6}	1	3.063×10^{-6}	1.695×10^{-3}	0.9677
BC	8.978×10^{-3}	1	8.978×10^{-3}	4.97	0.0415
BD	2.280×10^{-3}	1	2.280×10^{-3}	1.26	0.2790
CD	0.017	1	0.017	9.24	0.0083
A^2	1.340×10^{-3}	1	1.340×10^{-3}	0.74	0.4028
B^2	2.947×10^{-3}	1	2.947×10^{-3}	1.63	0.2211
C^2	5.529×10^{-4}	1	5.529×10^{-4}	0.31	0.5884
D^2	0.031	1	0.031	17.04	0.0009
Residual	0.027	15	1.807×10^{-3}		
Lack of fit	0.027	10	2.711×10^{-3}		
$r^2 = 0.9531$ $r_{adj}^2 = 0.9093$					

The response surface model can be tested using a p-value test, when the smaller the p, the better the significance of the model. When the corresponding model parameter p is less than 0.05, then the corresponding process parameter has a significant effect on the warpage. When the parameter p is less than 0.01, the corresponding process parameter has an extremely significant effect on the warpage. When the parameter p is greater than 0.05, the effect of the corresponding process parameter on the warpage is not significant. From Table 4, the order of factors affecting the warpage is: holding pressure (C) > holding time (D) > melt temperature (B) > mold temperature (A). Among them, the holding pressure and holding time have an extremely significant effect on the warpage of the product. The main reason is that during the pressure-holding stage, as the mold cavity is full of melt, the screw of the injection molding machine moves forward a short distance. At this time, the melt flow is very slow and the flow no longer plays a dominant role. The holding pressure is the main factor affecting the product molding at this stage, so it is important to set the appropriate holding pressure and holding time. In summary, in the actual injection molding process, the holding time and holding pressure parameters can be adjusted to obtain good product quality.

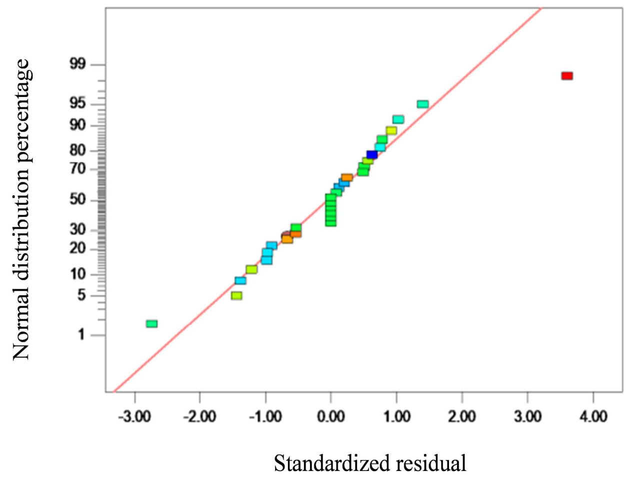


Figure 11. *Residual normal distribution.*

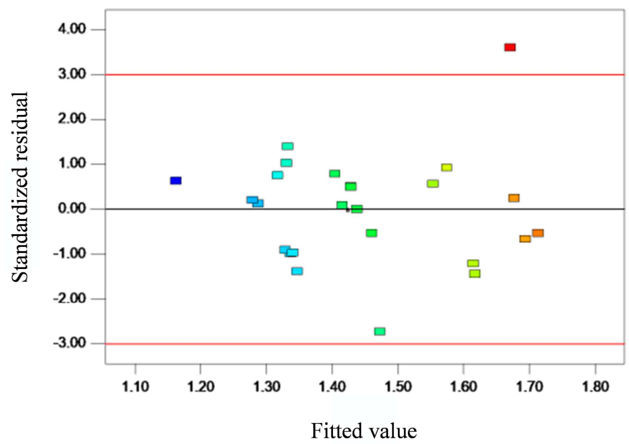


Figure 12. *Distribution of fitted values and residuals.*

The multi-correlation coefficient r^2 and modified multi-correlation coefficient r^2_{adj} were used to test the degree of fit of the established response surface model. From Table 4, it can be obtained that $r^2 = 0.9531$, $r^2_{adj} = 0.9093$. The closer the value is to 1, the closer the correlation between the variables is. Therefore, it can be judged that this model meets the requirements. As shown in Figure 11, the residual normal distribution plot is generated using Design-Expert software, and it can be seen that the model residuals are basically on a straight line, which conforms to the normal distribution regularity. As shown in Figure 12, the residuals are randomly distributed in the region above and below the zero line. The normal distribution and random distribution of the residuals also fully demonstrate the reliability of the developed response surface model.

4.3. Optimization of Process Parameters Based on Standard Particle Swarm Optimization

Due to the limitations of the response surface method and the limitation of the number of test points, the resulting warpage minimum is only a local optimum solution. Therefore, the model established by the response surface method is used as the standard particle swarm algorithm model, and the global optimal solution is obtained by using the population intelligence-seeking behavior of the algorithm, which further provides a basis for the adjustment of actual injection molding process parameters.

Particle swarm optimization (PSO) is widely used in different fields because they are simple in function and relatively easy to implement, while not requiring many parameters to be adjusted. In the PSO algorithm, particles are prone to fall into local extremes, early convergence, or stopping phenomena [19] due to inappropriate particle velocities as they continuously aggregate toward the individual optimum and the global optimum. In 1998, Shi [20] proposed to increase the inertia weighting coefficient to the velocity term $v_{mn}(t)$ in the equation to balance the local search and global search capabilities. The expressions are shown in eqn. (3) and (4).

$$\begin{aligned} v_{mn}(t+1) &= wv_{mn}(t)+c_1 \bullet r_1 \bullet (pbest_{mn}(t)-x_{mn}(t)) \\ &+c_2 \bullet r_2 \bullet (gbest_n(t)-x_{mn}(t)) \end{aligned} \tag{3}$$

$$x_{mn}(t+1) = x_{mn}(t)+v_{mn}(t+1) \tag{4}$$

Where $n=1,2,...,n$ presents the dimension. $m=1,2,...,N$ represents the particle index. N is the size of the swarm. c_1 and c_2 are called social scaling and cognitive parameters respectively that determines the magnitude of the random force in the direction of particle's previously best visited position ($pbest_{mn}(t)$) and best particle ($gbest_n(t)$). r_1,r_2 are the uniform random variable between [0,1]. w is the inertia weighting coefficient.

Table 5. *Parameters of the standard particle swarm optimization.*

Population size	**Number of iterations**	**Dimension of variables**	**Weighting coefficient**	**Learning factors**
200	100	4	[0.4,0.9]	$c_1 = c_2 = 2$

The particle swarm optimization algorithm was improved by increasing the inertia weight coefficient, which was later proven to be effective and widely accepted by scholars in various fields, and therefore became the standard particle swarm optimization algorithm. Shi [21] proposed to improve the performance of the algorithm by linearly decreasing the inertia weights. That is, at the beginning of the iteration, to enable the algorithm to search over a large range and have a strong search capability initially, the ability to perform a local search for better intervals can be improved in the later part of the iteration. It is shown that the algorithm can obtain optimal results when w decreases from 0.9 to 0.4. In using the standard particle swarm optimization algorithm to optimize the product warpage, MATLAB is used to write the program. The range of variables and optimization objectives of the algorithm are set according to Moldflow injection molding process recommendations and production experience as shown in eqn. (5). The algorithm parameters are shown in Table 5. The algorithm process is shown in Figure 13.

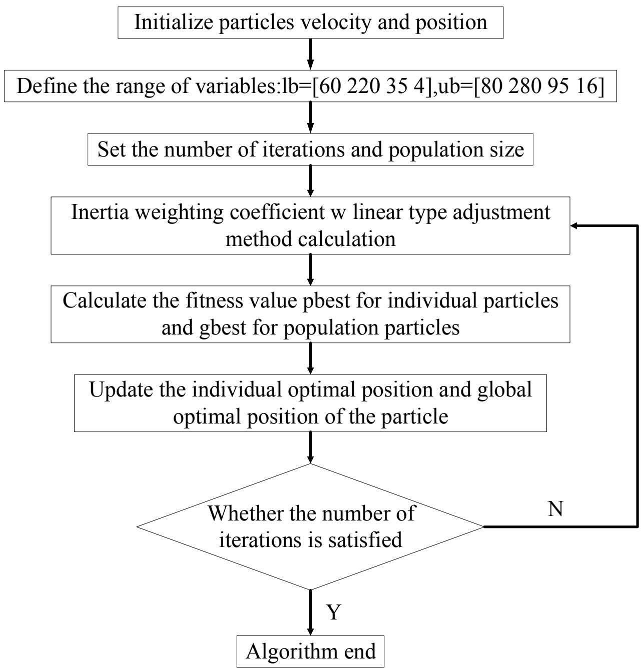


Figure 13. *Standard particle swarm optimization flowchart.*

$$\begin{cases} y = y_{\min}(mm) \\ \text{range}\begin{cases} 60 \le A \le 80 \\ 220 \le B \le 280 \\ 35 \le C \le 95 \\ 4 \le D \le 16 \end{cases} \end{cases} \tag{5}$$

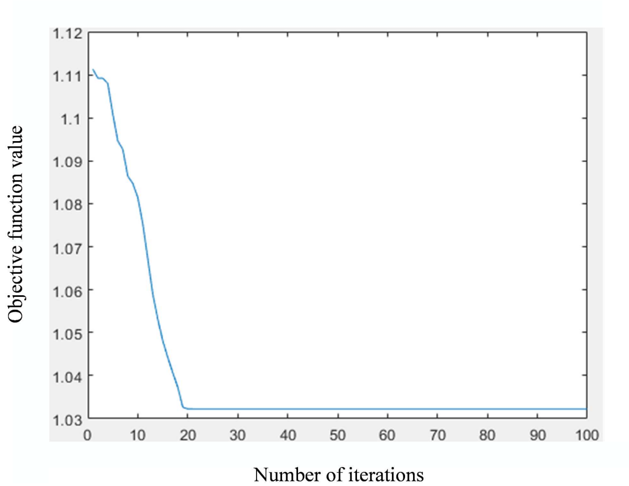


Figure 14. *Convergence plot of standard particle swarm optimization.*

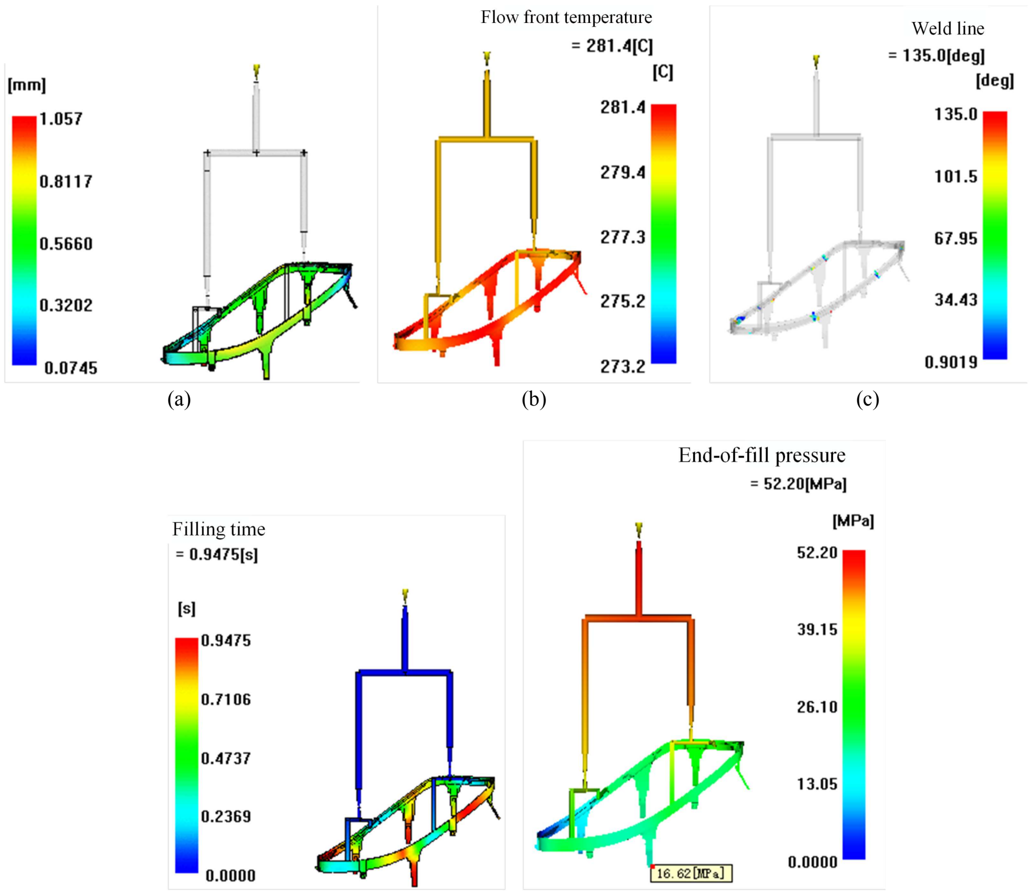
As shown in Figure 14, the convergence result is obtained after 100 iterations of operations. It can be concluded that the slope of the convergence process of the global optimum result is more stable in the process of finding the optimum using the standard particle swarm optimization, which proves that the algorithm calculation process is more effective. The final combination of process parameters for global minimum warpage of 1.0323 mm is obtained as shown in Table 6.

Table 6. *Standard particle swarm optimization results.*

Warpage /mm	**Mold temperature/°C**	**Melt temperature /°C**	**Holding pressure /°C**	**Holding time/s**
1.0323	60	280	95	8.296

4.4. CAE Analysis

As shown in Figure 15, the combination of the process parameters obtained by the particle swarm optimization algorithm is simulated and analyzed using Moldflow software, and the results show that the standard particle swarm optimization algorithm can effectively optimize the warpage of the product. From Figure 15a, the minimum warpage obtained by the particle swarm optimization reaches 1.0323 mm. The combination of the optimal process parameters of the algorithm is input into Moldflow, and the warpage obtained is 1.057 mm, which is reduced compared with the warpage of 1.18 mm analyzed by the response surface method, proving that the standard particle swarm optimization is more effective in optimizing the warpage deformation of the product. As shown in Figure 15b, when the temperature is higher, the weld line is less obvious. The maximum temperature of the flow front is 281.4°C, and the temperature of the flow front at other locations of the product is about 280°C, with a temperature difference of only 1.4°C. Therefore, during the filling process, the overall flow of the material is better and the strength of the weld line is higher, which can ensure the strength and appearance of the products. The distribution of the weld lines is shown in Figure 15c. As shown in Figure 15d, the melt filling time can be reduced to less than 1s, which ensures production efficiency. As shown in Figure 15e, there is no flash at the end of the product when the end-of-fill pressure reaches approximately 16 MPa. The optimal combination of process parameters was obtained according to the standard particle swarm optimization, namely, the mold temperature was 60°C, the melt temperature was 280°C, the holding pressure was 95 MPa, and the holding time was 8.296 s. The combination of the parameters was input into the injection molding machine for trial production, with good results, and the product is shown in Figure 16.



(a) (b) (c) (d) (e)

Figure 15. *Simulation results (a) Warpage (b) Flow front temperature (c) Weld line (d) Filling time (e) End-of-fill pressure.*

(a) (b)

Figure 16. *Qualified product (a) Front view (b) Side view.*

5. Conclusion

Through CAE mold flow analysis of automotive brake Plug-in and actual injection molding production, the following conclusions can be drawn:

1) Thirty sets of injection molding simulation tests with mold temperature, melt temperature, holding pressure, and holding time as parameters and warpage as the index was constructed by response surface-central composite experiment design (CCD). A response surface regression second-order polynomial model for predicting the minimum warpage deformation was established based on the 30 sets of experimental data. The analysis of the results shows that the model can better map the relationship between the process parameters and the minimum warpage deformation, and the preliminary optimized combination of process parameters for the product is obtained: mold temperature of 70°C, melt temperature of 250°C, holding pressure of 95 MPa, holding time of 10s, and the corresponding warpage of 1.18mm. The optimal combination of process parameters, namely, mold temperature of 60°C, melt temperature of 280°C, holding pressure of 95 MPa, and holding time of 8.296 s, was further optimized by using response surface model combined with standard particle swarm optimization algorithm (PSO). At this time, the corresponding minimum warpage deformation predicted value is 1.0323mm and the simulated value is 1.057mm, with a difference of 2.27% and a 10.85% reduction in the minimum warpage compared to the central composite experiment design. The proposed method has been effectively verified by actual injection production.
2) Practice shows that the optimal process parameters obtained by using the response surface method and standard particle swarm optimization (PSO) can ensure the molding quality of products. In the automotive industry, it has become a trend for plastic materials to replace metal materials. When producing automotive components by injection molding with other materials,

the research method of this paper can be referred to, so that the potential defects that will be generated by plastic parts can be excluded in advance, shortening the product production cycle and reducing the pollution to the environment.

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