

Article

Comprehensive Analysis of the Injection Mold Process for Complex Fiberglass Reinforced Plastics with Conformal Cooling Channels Using Multiple Optimization Method Models

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Abstract

During the cooling phase of injection molding, the conformal cooling channel system optimizes the uniformity of mold temperature, diminishes warping deformation, and contributes substantially to heightened product precision. The injection molding process involves complex process parameters that may result in uneven cooling between components, leading to prolonged cycle times, increased shrinkage depth, and warping deformation of the plastic parts. These manifestations negatively impact the surface quality and structural strength of the final product. This article combined theoretical algorithms with finite element simulation (CAE) methods to optimize complex injection molding processes. Firstly, the characteristics of six different types of materials were examined. Melt temperature, mold opening time, injection time, holding time, holding pressure, and mold temperature were chosen as optimization variables. Meanwhile, the warpage deformation and shrinkage depth of the formed sample were selected as optimization objectives. Secondly, an L27 orthogonal experimental design (OED) was established, and the signal-to-noise ratio was processed. The entropy weight method (EWE) was used to calculate the weights of the total warpage deformation and shrinkage depth, thereby obtaining the grey correlation degree. The influence of process parameters on quality indicators was analyzed using grey relational analysis (GRA) to calculate the range. A second-order polynomial regression model was established using response surface methodology (RSM) to investigate the effects of six factors on the warpage deformation and shrinkage depth of injection molded parts. Finally, a comprehensive comparison was made on the impact of various optimization methods and models on the forming parameters. Analyze according to different optimization principles to obtain the corresponding optimal process parameters. The research results indicate that under the principle of prioritizing warpage deformation, the effectiveness ranking of the three optimization analyses is RSM > OED > GRA. The minimum deformation rate is 0.1592 mm, which is 27.37% lower than before optimization. Under the principle of prioritizing indentation depth, the effectiveness ranking of the three optimization analyses is OED > GRA > RSM. The minimum depth of shrinkage is 0.0312 mm, which is 47.21% lower than before optimization. This discovery provides strong support for the optimal combination of process parameters suitable for production and processing.

Keywords: conformal cooling channel; entropy weight method; grey relational analysis; response surface methodology; optimization objectives



Academic Editor: Sara Liparoti

Received: 22 July 2025

Revised: 23 August 2025

Accepted: 26 August 2025

Published: 1 September 2025

Citation: Zhao, M.; Tang, Z.Comprehensive Analysis of the Injection Mold Process for Complex Fiberglass Reinforced Plastics with Conformal Cooling Channels Using Multiple Optimization Method Models. *Processes* **2025**, *13*, 2803.<https://doi.org/10.3390/pr13092803>

Correction Statement: This article has been republished with a minor change. The change does not affect the scientific content of the article and further details are available within the backmatter of the website version of this article.

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1. Introduction

Injection molding (IM) injects completely melted plastic material into a mold cavity under high pressure at a specific temperature and obtains molded products after holding, cooling, and demolding [1,2]. Injection molding has been widely used in plastic molding technology, which can shape plastic products with complex shapes and structures, produce products with high dimensional accuracy, and has the advantages of a short molding cycle and low production cost [3]. The injection molding process starts with plastic particles entering the barrel and being converted into molten material through heating, compression, and other processes. Next, axial pressure is applied to the injection molding machine screw to hold and cool the mold [4,5]. Finally, the ejection mechanism ejects the plastic part to obtain the plastic product. The general mold opening time accounts for 15%, the injection molding time accounts for 5%, the holding time accounts for 10%, and the cooling time accounts for 70%, as shown in Figure 1 [6,7]. The temperature range of the molten material injected during the plastic molding process is 200 to 300 °C. To remove plastic parts from the mold, they must be cooled to temperatures of 60 and 80 °C, which takes up most of the molding cooling cycle. Excessive cooling time and uneven cooling can lead to deformation and warping. The cooling effect of injection molds significantly impacts the quality and productivity of products. Reducing the cooling time will improve production efficiency. To achieve the optimal cooling temperature, the temperature distribution of the mold needs to be uniform [8,9].

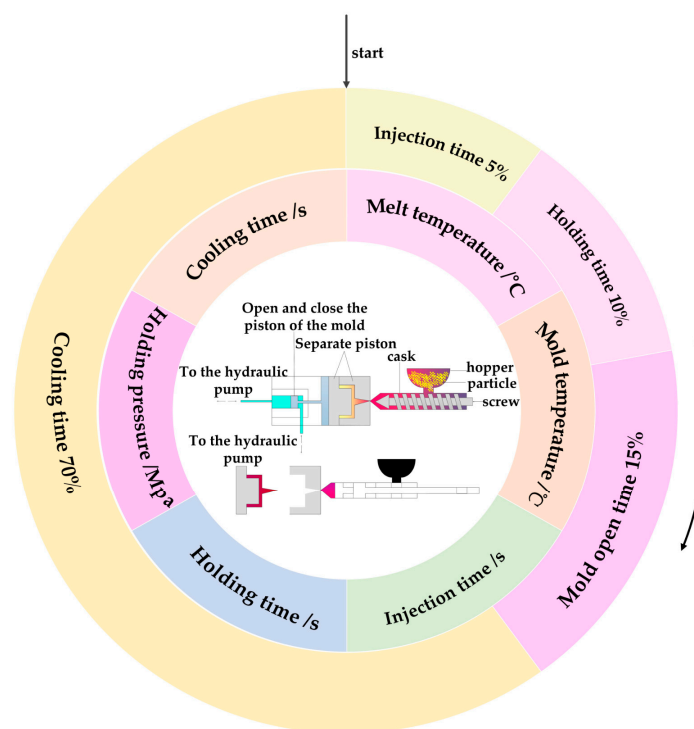


Figure 1. Injection molding process and main stages.

The purpose of designing cooling channels in molds is to reduce the temperature of the injected material. Conventional cooling channels consist of straight-drilled channels, which have limitations as they cannot provide the best cooling effect due to the complex shape of the plastic part, which restricts the channel's ability to fit the mold cavity's contour at equal distances. As a result, conventional cooling channels lead to uneven cooling between components, causing issues such as prolonged cycle time, warping, and scrap rates [10]. On the other hand, conformal cooling channels (CCCs) [11–13] offer a solution to this problem by achieving more uniform and efficient cooling of products, as shown in

Figure 2. This technology refers to a cooling water channel whose contour changes with the variation of the plastic cavity, effectively solving the problem of unequal distance between the conventional water channel and the cavity surface [14–16]. By maximizing heat transfer in injection molding [17–19], conformal cooling channels significantly enhance product quality [20–23].

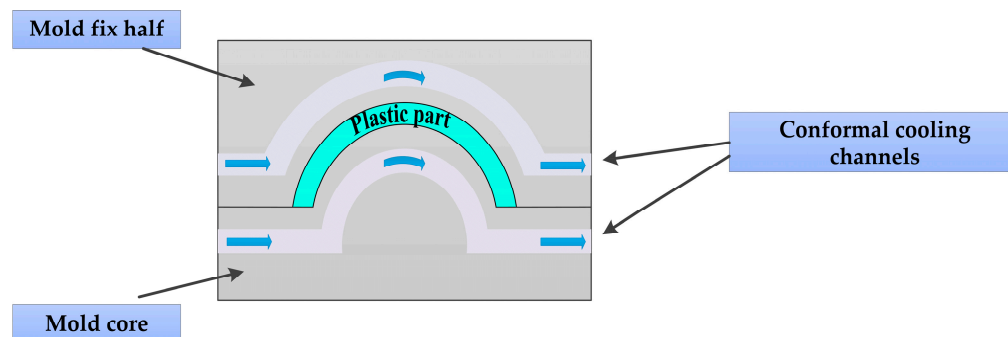


Figure 2. Conformal cooling channels.

The frequent occurrence of many defects during the injection molding process makes injection molding very difficult. The typical injection molding defects mainly include warping deformation, shrinkage marks, weld marks, bubbles, short shots, and burrs. Various factors, such as raw materials, mold structure, and injection molding equipment, can cause injection molding defects. In addition, differences in the composition of injection molded parts and molding process parameters can also lead to uneven shrinkage of plastic parts [24,25]. Especially for some complex plastic parts, it mainly relies on the experience of injection molding engineers. However, over time, the production quality of plastic parts has yet to be guaranteed, which limits the development of complex plastic products in the mold industry. To prevent problems such as warping, shrinkage marks, and uneven shrinkage, Zhai et al. [26] proposed analyzing the optimal combination of molding parameters through Taguchi grey correlation theory. They used six optimization algorithms and inverse deformation design (IDD) to reduce volume shrinkage and warping deformation. The results showed that the warping deformation of the plastic part (polycarbonate) was reduced, and the quality of the product was improved. Marinset et al. [27] evaluated the effect of injection parameters on bending and shrinkage using Taguchi's method and analysis of variance (ANOVA) with a polymeric copolymer and an acrylic butadiene styrene copolymer. The results indicate that the holding pressure and holding time significantly impact the warpage. Huang and Tai [28] demonstrated that the most significant factor affecting warpage during injection molding is holding pressure, followed by mold temperature, melt temperature, and holding time.

Meanwhile, the interaction between mold temperature and melt temperature is also an essential factor affecting the quality of plastic part forming. Ozcelik, B. and Eerzurunlu, T. [29] studied the effects of various process parameters on the quality of plastic parts using analysis of variance (ANOVA), artificial neural networks (ANN), and genetic algorithms (GA). The results indicate that the holding pressure is the most significant factor affecting warpage deformation. Youngjae Ryu et al. [30] validated the optimal combination of the Taguchi method and RSM using Glass Fiber Reinforced Polyamide 6 to minimize process factors and levels of shrinkage and warpage.

Ozcelik, B. [31] conducted a comparative study on the effects of melt temperature, holding pressure, and injection pressure on the mechanical properties of products with and without weld marks using polypropylene material. The Taguchi method was used to calculate plug specimens' maximum tensile load, elongation at break, and impact strength.

Experiments have shown that injection pressure has a more significant impact on the maximum tensile load and elongation at the break of specimens than melt temperature, which is the main factor affecting impact strength. Kitayama S. et al. [32] used polyacetal resin to determine the optimal process parameters in PIM through radial basis function sequential approximation optimization, to achieve high product quality and productivity. Subsequently, Kitayama et al. [33] used liquid crystal polymer and employed sequential approximation optimization (SAO) using radial basis function (RBF) networks to determine the optimal injection speed and pressure distribution through a small number of simulations, thereby improving product quality. Wang Qingwu [34] used Polyformaldehyde to analyze the relationship between key process parameters and optimization objectives in micro injection molded small modulus plastics through a second-order response surface model. Kitayama S. et al. [35] used Acrylonitrile Butadiene styrene for sequential approximation optimization in rapid thermal cycling using radial basis function networks to determine the optimal process parameters for improving product surface quality. Feng, Q. et al. [36] used acrylonitrile butadiene styrene/polyamide for data analysis through variance analysis and signal-to-noise ratio, and obtained the quality characteristics of plastic products, including warpage, welds, and clamping force, through simulation experiments. Hakimian, E. [37] studied the effects of process molding parameters and their interactions on the warpage and shrinkage of injection molded micro gears using three different types of thermoplastic materials (PC/ABS, PPE/PS, and POM) through the Taguchi method. Fu [38] optimized the process using the warpage defect of dual material products, where the melt temperature and holding pressure significantly impact the warpage defect. As the melt temperature and holding pressure increase, the warpage is improved.

Researchers utilize finite element analysis software to simulate injection-molded products and analyze their defects, such as shrinkage depth and warping deformation [39,40]. They explore the influence of different injection molding process parameters on defects through relevant experiments. By finding the optimal combination of molding process parameters, they aim to obtain the best process plan, reduce defects, improve product production quality, and shorten development cycles [41–44]. In recent years, computer-aided engineering (CAE) technology has rapidly developed [45,46], becoming a commonly used method in modern manufacturing engineering. The integration of advanced technologies such as computer-aided design (CAD) and computer-aided manufacturing (CAM) has laid the foundation for intelligent manufacturing. The application of response surface methodology (RSM) to injection molding can effectively reduce random errors generated in experiments and improve the accuracy of design schemes [47,48].

Based on the results mentioned above, the first step of this study involves designing the geometric structure of the conformal cooling water channel for the printer shell to evaluate its impact on the cooling performance of the injection mold being studied. The study also combines theoretical algorithms and CAE methods to optimize and research the injection molding process. Subsequently, the warpage deformation and shrinkage depth of the formed sample were selected as optimization objectives. Secondly, an L27 orthogonal experimental design (ODE) was established, and the signal-to-noise ratio was processed. The entropy weight method (EWE) was used to calculate the weights of the total warpage deformation and shrinkage depth, thereby obtaining the grey correlation degree. The influence of process parameters on quality indicators was analyzed using grey relational analysis (GRA) to calculate the range. A second-order polynomial regression model is established using Response Surface Methodology (RSM) to optimize and solve the model. Design Expert is used to analyze the experimental design data of RSM and explore the optimal combination of molding process parameters. Finally, a comprehensive comparison was made on the impact of various optimization methods and models on the forming

parameters. Moldflow 2023 is an injection moulding and compression moulding plastic simulation software developed by Autodesk, mainly used to optimise parts, moulds, and process design to improve product quality and reduce production defects. Design Expert 13 is a professional experimental design (DOE) and response surface analysis software developed by Stat-Ease Inc. (United States). This article uses the Moldflow 2023 version and the Design Expert 13 version, respectively.

According to previous reference descriptions, the existing cooling channel structure of injection molds is simple and cannot meet the processing and production of complex injection molded parts. This article uses orthogonal experimental design, grey relational analysis, and response surface methodology to optimize six forming process parameters of a complex structured conformal cooling channel for multi-objective optimization. Finally, the characteristics of different optimization methods under different principal priorities were discovered, providing a theoretical basis and technical support for the process optimization of complex structure injection molds.

2. Materials and Methodologies

This section details experimental methods. To fulfill the study's objectives, computer-aided engineering (CAE) technology, design of experiments (DOE), grey relational analysis (GRA), and response surface methodology (RSM) were used to optimize the target parameters in stages. Figure 3 illustrates the flowchart of the experimental procedure methodology.

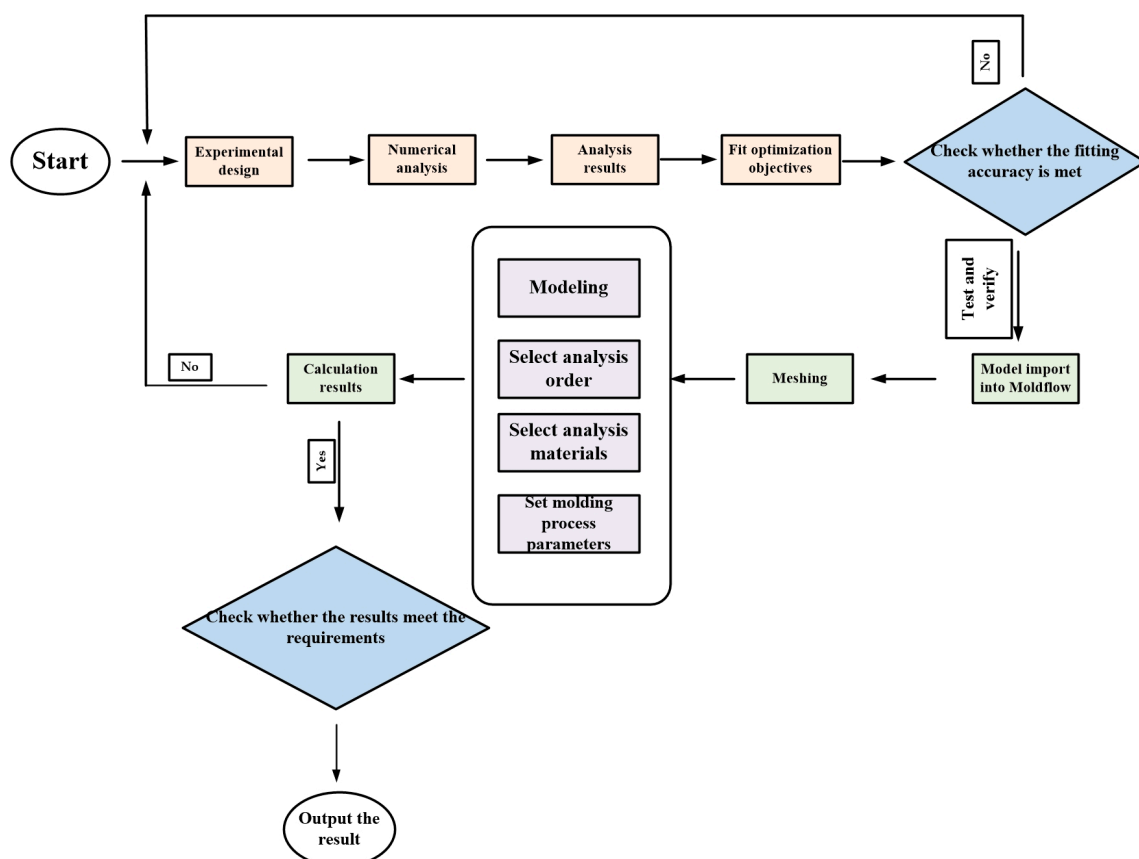


Figure 3. Flowchart of the experimental methodology.

2.1. Creation of Plastic Model and Conformal Cooling Channel

The plastic part has a complex geometric shape with thin-walled and thick-walled areas, which makes it difficult to achieve uniform cooling during the cooling process. The product was a printer drawer case shell, with dimensions and shape as displayed

in Figure 4, created using SolidWorks 2023 software to construct a plastic model. The dimensions of the part were 62 mm (L) × 49 mm (W) × 10 mm (H). Import the injection molded part model into Moldflow 2023 software and use the software to simulate and analyze the plastic part model. The materials are PP, PP + GF20%, PP + GF30% and PP + GF40%. The material manufacturer is A Schulman GMBH (Germany), and the material brand is POLYFLAM RIPP 3625 CS1. Table 1 shows the characteristics of four materials. Many curved pipes are used in the conformal cooling channel to better fit the surface of the plastic part. Therefore, a circular section is selected as the cross-sectional area of the conformal cooling channel, and the diameter of the conformal cooling channel was chosen as 10 mm, as shown in Figure 5. To improve the accuracy of subsequent analysis, the plastic parts were imported into Moldflow software to generate a double-layer mesh. The grid size is set to 2.5 mm. The total number of grid elements in the plastic component is 821,825, the total number of grid elements in the flow channel is 199,572, and the total number of grid elements in the mould is 2,126,359.

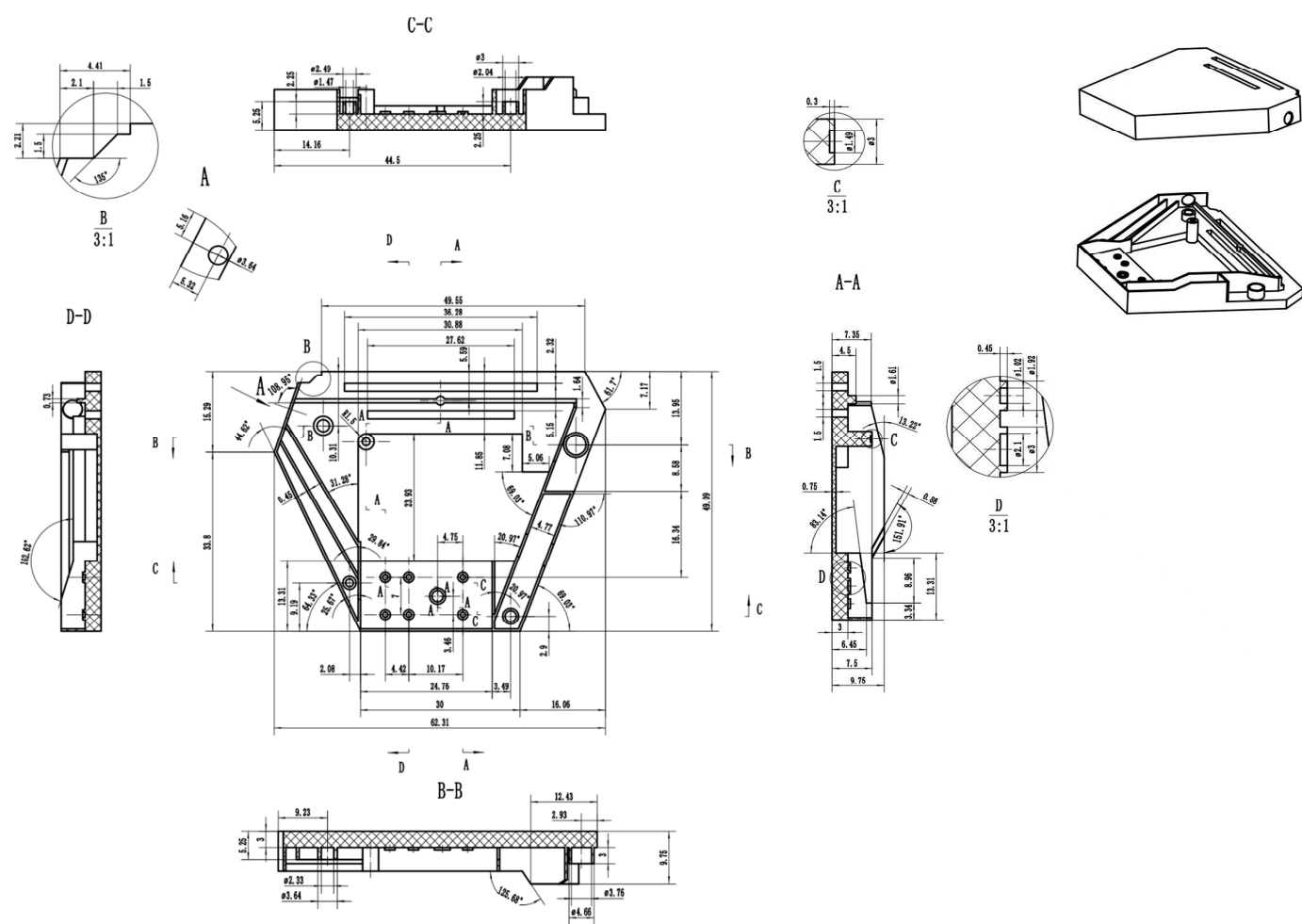


Figure 4. Injection parts structure diagram.

Table 1. Material characteristics.

Mechanical Properties	Numerical Value
Density (g/cm ³)	1.3717
Poisson's ratio	0.375
Modulus E (MPa)	2822
Shear modulus (MPa)	907

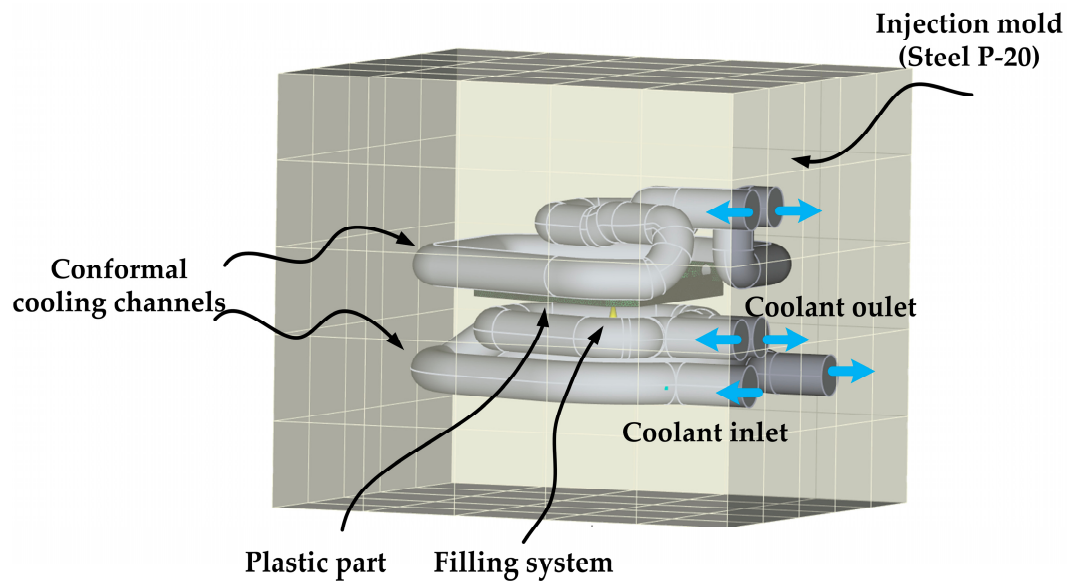


Figure 5. Design of the conformal cooling channel system.

2.2. Experimental Method

When the warpage deformation and volume shrinkage rate of plastic parts are small, it indicates an improvement in the quality of plastic parts. This belongs to the desirable small characteristic, and the signal-to-noise ratio expression is shown in Equation (1) [26].

$$S/N = -10 \lg(1/n \sum_{i=1}^n x_i)^2 \quad (1)$$

where S/N represents the signal-to-noise ratio, n is the number of repeated experiments, and x_i is the result of the i th experiment.

Before conducting grey relational analysis, it is necessary to normalize the data of the two target objects, the total amount of mold warping deformation and the volume shrinkage rate. This is because not only are their dimensions and units different, but there are also significant differences in the range of their numerical variations. To ensure the equivalence and orderliness of the data, normalization processing must be carried out as shown in Equation (2) [26].

$$y_i = \frac{y_{imax} - y_i}{y_{imax} - y_{imin}} \quad (2)$$

where y_i is the normalized value; i represents the number of experiments, $i = 1, 2, 3, \dots, 27$; y_{imax} and y_{imin} are the maximum and minimum values in the original data, respectively.

Based on the processed data series, the grey correlation coefficient can be calculated as shown in Equation (3) [26].

$$\delta_i = \frac{\min \min |y_i^0 - y_i| + \rho \max \max |y_i^0 - y_i|}{|y_i^0 - y_i| + \rho \max \max |y_i^0 - y_i|} \quad (3)$$

where y_i^0 represents the normalized ideal value of the data corresponding to the i -th experiment, ρ represents the resolution coefficient, ranges from 0 to 1, and takes a value of 0.5.

The response surface methodology replaces the response surface by fitting a global approximation of the output variables through a finite experimental design of a set of sample points within a specified design space [49,50]. In practical optimization design, response surface methodology can be applied to determine the relationship between re-

sponse objectives and design variables, as well as optimization schemes, to achieve the optimal combination of the objective function. Before constructing a response surface approximation model, it is essential to clearly define the relationship between the design variables and the analysis objectives. An appropriate function form should be selected to describe the relationship between the current design variables and the analysis objectives. The response surface optimization method is currently applicable for optimization experiments involving 2–5 factors. The Box Behnken Design (BBD) design method involves three levels for each factor, which are encoded as $(-1, 0, 1)$. The design table is arranged with 0 as the center point, and $+1$ and -1 are the high and low values corresponding to the cubic point, respectively [51]. The schematic diagram of the BBD experimental design is shown in Figure 6.

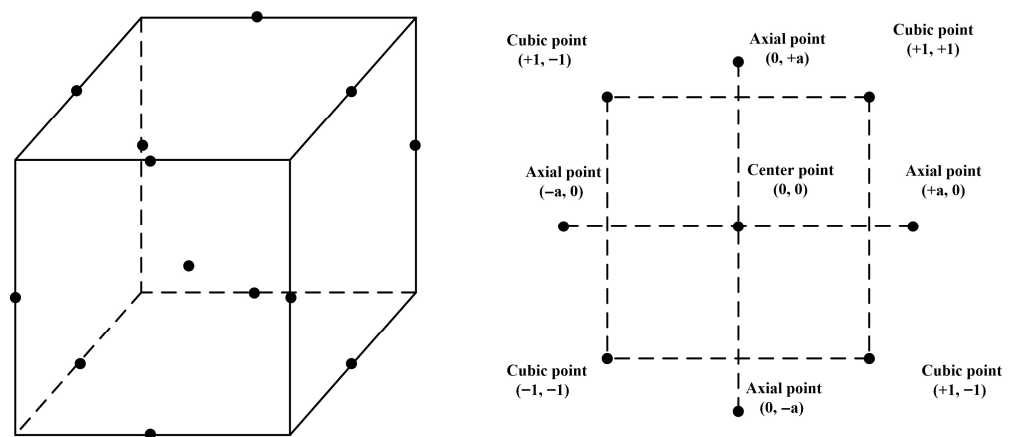


Figure 6. BBD Experimental Design Diagram.

Response Surface Methodology (RSM) is an optimization technique proposed by Box that combines experimental design and mathematical modeling to measure the response of a system to one or more variables [52–55]. It uses a quadratic polynomial model to verify the complex unknown function relationship between factors and results within the region. It obtains the optimal values of each factor to get the prediction model. This optimization method has been widely applied in machinery, materials, and environmental fields. According to the Weierstrass polynomial best approximation theorem, the general form of the predictive polynomial Equation (4) [50] for the system response Y and the design variable x is:

$$Y_{\beta} = \beta_0 + \sum_{i=1}^n \beta_i x_i + \sum_{i=1}^n \beta_{ii} x_i^2 + \sum_{i=1; j=1}^n \beta_{ij} x_i x_j + \varepsilon \quad (4)$$

where Y represents the response target values (warpage deformation, shrinkage depth, and cooling time), X_i and X_j are the independent variables ($i, j = 1, 2, 3, \dots, n$), β_0 , β_i , β_{ii} , β_{ij} , and ε are the regression constant coefficients, linear coefficients, second-order coefficients, interaction coefficients, and statistical error, respectively.

The uneven shrinkage of general plastic parts can result in uneven internal stress within the plastic parts. If the internal stress exceeds the material's strength limit, the plastic parts will warp and deform. Excessive warping deformation can cause difficulties in demolding the product, resulting in large dimensional deviations and low molding quality, which makes it challenging to meet the molding requirements in terms of both quality and appearance. In general, the deformation of plastic parts is optimized based on product wall thickness, material, cooling system, and injection molding process parameters to minimize significant warping deformation during the injection molding process. When

there are many factors in an experiment, it is necessary to conduct a screening experiment to select a few essential factors as the research object from the numerous factors. This type of experiment can usually be undertaken using response surface methodology. Draw response surfaces and contour plots using statistical testing to predict reactions or optimize processes, demonstrating the correlation between factors and response values, and generated data using a fitted model.

3. Results and Discussion

3.1. Comparison of Different Cooling Channels System Designs

Figure 7 shows the warpage deformation, shrinkage depth, and volume shrinkage of four engineering thermoplastic materials. Through a comparative evaluation of unfilled and glass fiber-reinforced polypropylene (PP) systems, it was found that adding 40% glass fiber reduced PP warpage by 55.85%, shrinkage depth by 73.77%, and shrinkage rate by 58.28%. This may be because fibers restrict the fluidity of polymer chains, enhance thermal conductivity, and reduce residual stress. These findings provide guidance for material selection in subsequent precision injection molding applications.

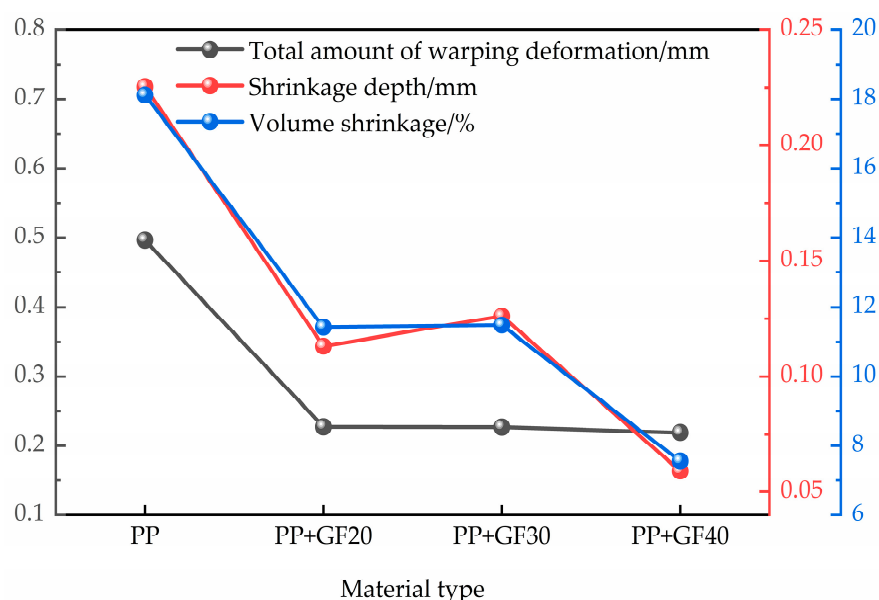


Figure 7. Performance analysis results of different types of materials.

3.2. Orthogonal Experimental Design Results

The conclusion drawn from reading some of the literature [26,56]. The six molding process parameters, namely melt temperature (A), injection time (B), mold opening time (C), holding time (D), holding pressure (E), and mold temperature (F), have the most significant impact on complex injection molded parts. Therefore, this factor was selected as the experimental parameter.

The research factors for the injection molding process include melt temperature (A), injection time (B), mold opening time (C), holding time (D), holding pressure (E), and mold temperature (F), as shown in Table 2. Selecting the total amount of warpage deformation and volume shrinkage rate as optimization objectives, a 6-factor 3-level orthogonal experimental factor table was designed, and 27 sets of injection molding process parameter simulation experiments were conducted. The results of the shrinkage depth and the total amount of warpage deformation are shown in Table 3.

Table 2. Orthogonal test factor level table.

Control Factors	Level		
	1	2	3
A. Melt temperature (°C)	220	230	240
B. Injection time (s)	3	4	5
C. Mold opening time (s)	1.0	1.5	2.0
D. Holding time (s)	10	12	14
E. Holding pressure (MPa)	80	90	100
F. Mold Temperature (°C)	60	70	80

Table 3. Orthogonal experimental design results.

No.	Process Parameters						Results	
	A	B	C	D	E	F	Total Amount of Warping Deformation/mm	Shrinkage Depth/mm
1	220	3	1	10	80	60	0.1868	0.0496
2	220	3	1	10	80	70	0.1871	0.0498
3	220	3	1	10	80	80	0.1718	0.0495
4	220	4	1.5	12	90	60	0.1661	0.0378
5	220	4	1.5	12	90	70	0.1683	0.0380
6	220	4	1.5	12	90	80	0.1677	0.0376
7	220	5	2	14	100	60	0.1620	0.0313
8	220	5	2	14	100	70	0.1624	0.0316
9	220	5	2	14	100	80	0.1594	0.0316
10	230	3	1.5	14	100	60	0.1694	0.0446
11	230	3	1.5	14	100	70	0.1717	0.0456
12	230	3	1.5	14	100	80	0.1780	0.0451
13	230	4	2	10	80	60	0.1650	0.0363
14	230	4	2	10	80	70	0.1650	0.0363
15	230	4	2	10	80	80	0.1678	0.0365
16	230	5	1	12	90	60	0.2069	0.0545
17	230	5	1	12	90	70	0.2070	0.0545
18	230	5	1	12	90	80	0.2061	0.0544
19	240	3	2	12	100	60	0.1739	0.0424
20	240	3	2	12	100	70	0.1700	0.0420
21	240	3	2	12	100	80	0.1781	0.0430
22	240	4	1	14	80	60	0.2191	0.0588
23	240	4	1	14	80	70	0.2212	0.0591
24	240	4	1	14	80	80	0.2195	0.0587
25	240	5	1.5	10	90	60	0.1896	0.0514
26	240	5	1.5	10	90	70	0.1903	0.0512
27	240	5	1.5	10	90	80	0.1891	0.0511

From the range results calculated in Table 3, the order of the influence of these six factors on the warpage deformation and volume shrinkage rate from small to large is: $F < B < E < D < A < C$.

The effects of various parameters on shrinkage depth and warping deformation at different factor levels are shown in Figure 8. From the figure, it can be seen that the combination of molding parameters A1-B1-C3-D1-E3-F3, using the OED method, has the smallest warpage deformation and shrinkage depth. When A1 is the melt temperature (220 °C), B1 is the mold opening time (3 s), C3 is the injection time (2 s), D1 is the holding time (10 s), E3 is the holding pressure (100 MPa), and F3 is the mold temperature (80 °C). The minimum warpage deformation is 0.1597 mm, a decrease of 26.61% compared to the

initial value. The minimum shrinkage depth is 0.0312 mm, a reduction of 47.21% compared to the initial value.

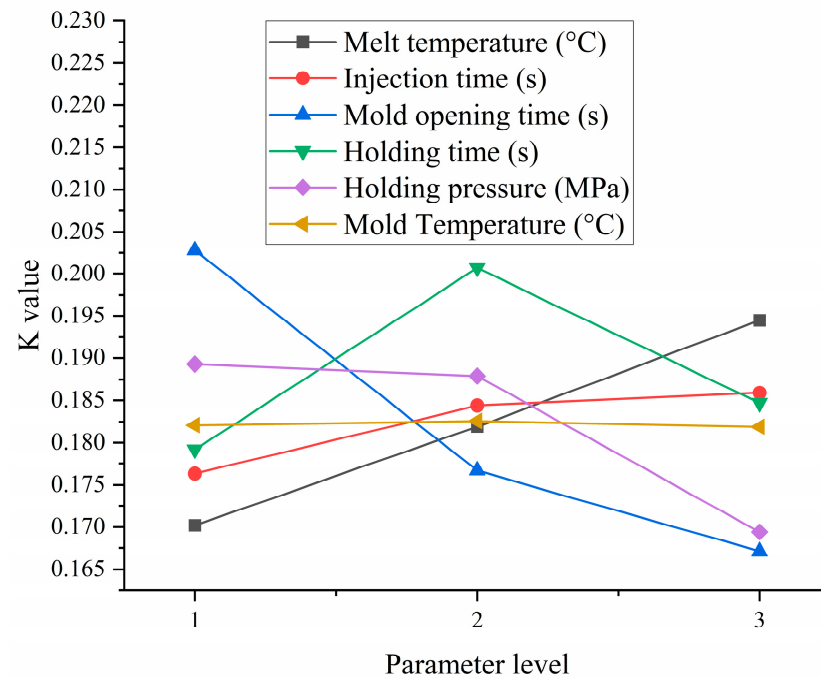


Figure 8. Performance analysis results of different types of materials.

3.3. Entropy Weight Method Grey Correlation Results

The total warpage deformation of the plastic part affects the tolerance value of the molding, thereby influencing the fit of the product. The volume shrinkage rate determines the surface quality. This article combines entropy weight analysis and grey relational analysis to establish weight coefficients based on entropy values. The higher the entropy, the smaller the variability, and the lower the weight coefficient. The steps of this method are summarized as follows:

Construct the decision matrix for determining the body mass index results from Table 2 as shown in Equation (5) [57].

$$X_{m \times n} = \begin{bmatrix} X_{11} & X_{12} & \dots & X_{1n} \\ X_{21} & X_{22} & \dots & X_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ X_{m1} & X_{m2} & \dots & X_{mn} \end{bmatrix} \quad (5)$$

where, m is the number of experiments ($m = 27$), n is the experimental index ($n = 2$).

Further regularize the decision matrix as shown in Equation (6) [57].

$$\lambda_{ij} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^m X_{ij}^2}} \quad (6)$$

where λ_{ij} is the regularization result of the j -th test indicator in the i -th experiment.

Calculate the entropy value by normalizing the data as shown in Equation (7) [57].

$$E_j = -\frac{1}{\ln m} \sum_{i=1}^m \frac{\lambda_{ij}}{\sum_{i=1}^m \lambda_{ij}} \ln \frac{\lambda_{ij}}{\sum_{i=1}^m \lambda_{ij}} \quad (7)$$

where J is the experimental index ($j = 2$), i is the number of experiments ($i = 27$), and m is the number of experiments ($m = 27$).

Calculate the weight coefficients using Equation (8) [57].

$$\omega_i = \frac{1 - E_j}{\sum_{j=1}^n 1 - E_j} \times 100\% \quad (8)$$

where, J is the experimental index ($j = 2$), n is the number of experiments ($n = 27$).

After obtaining the weight coefficients through the above calculation, the grey correlation degree is calculated as shown in Equation (9).

$$\gamma_i = \sum_{j=1}^2 \xi_{ij} \omega_j \quad (9)$$

where γ_i indicates a more consistent impact of the factor on the target object.

Substitute the results of determining the shrinkage depth and total amount of warping deformation in Table 3 into equations for calculation, and obtain the weight and grey correlation degree of the total amount of warping deformation and volume shrinkage rate as shown in Table 4. The weights of warping deformation and shrinkage index obtained are 44% and 56%, respectively.

Table 4. The data for calculating the grey correlation degree.

No.	Total Amount of Warping Deformation/mm					Shrinkage Depth/mm					γ_i
	S/N	y_i	δ_i	Entropy	Weight	S/N	y_i	δ_i	Entropy	Weight	
1	14.57	0.48	0.51			26.09	0.72	0.41			0.453
2	14.56	0.49	0.51			26.06	0.73	0.41			0.450
3	15.30	0.23	0.69			26.11	0.72	0.41			0.532
4	15.59	0.13	0.80			28.45	0.30	0.63			0.704
5	15.48	0.17	0.75			28.40	0.31	0.62			0.679
6	15.51	0.15	0.76			28.50	0.29	0.63			0.691
7	15.81	0.05	0.91			30.09	0.00	1.00			0.960
8	15.79	0.06	0.90			30.01	0.02	0.97			0.938
9	15.95	0.00	1.00			30.01	0.02	0.97			0.984
10	15.42	0.19	0.73			27.01	0.56	0.47			0.587
11	15.30	0.23	0.69			26.82	0.59	0.46			0.560
12	14.99	0.34	0.60			26.92	0.57	0.47			0.524
13	15.65	0.11	0.83			28.80	0.23	0.68			0.746
14	15.65	0.11	0.83	0.99	0.44	28.80	0.23	0.68	0.98	0.56	0.746
15	15.50	0.16	0.76			28.75	0.24	0.67			0.713
16	13.68	0.80	0.39			25.27	0.87	0.36			0.374
17	13.68	0.80	0.39			25.27	0.87	0.36			0.374
18	13.72	0.78	0.39			25.29	0.87	0.37			0.376
19	15.19	0.27	0.65			27.45	0.48	0.51			0.574
20	15.39	0.20	0.72			27.54	0.46	0.52			0.607
21	14.99	0.34	0.60			27.33	0.50	0.50			0.543
22	13.19	0.97	0.34			24.61	0.99	0.34			0.337
23	13.10	1.00	0.33			24.57	1.00	0.33			0.333
24	13.17	0.98	0.34			24.63	0.99	0.34			0.337
25	14.44	0.53	0.49			25.78	0.78	0.39			0.433
26	14.41	0.54	0.48			25.81	0.77	0.39			0.431
27	14.47	0.52	0.49			25.83	0.77	0.39			0.436

According to Table 5, the larger the range value of the grey correlation degree, the greater the influence of parameters on the grey correlation degree. The order of influence of each parameter on the grey correlation degree, from largest to smallest, is Mold opening time, holding pressure, melt temperature, holding time, injection time, and Mold Temperature. Figure 9 shows the trend of the mean gray correlation degree of parameters at different levels. In the data processing stage, the observation of small feature function is used, and the higher the gray correlation value of the parameter level, the more optimal the parameter is. Therefore, according to Figure 9, the optimal solution obtained using the GRA method is A1B3C3D3E1, with a melt temperature of 220 °C, an injection time of 5 s, a mold opening time of 2 s, a holding time of 14 s, a holding pressure of 100 MPa, and a mold temperature of 60 °C. The minimum warpage deformation is 0.1594 mm, a decrease of 26.75% compared to the initial value. The minimum indentation depth is 0.0316 mm, a decrease of 46.53% compared to the initial value.

Table 5. Range calculation of the grey correlation degree.

No.	Process Parameters					
	A	B	C	D	E	F
K1	0.2295	0.5367	0.3962	0.5489	0.5164	0.5741
K2	0.1718	0.5873	0.5605	0.5468	0.4997	0.5688
K3	0.1408	0.5895	0.7568	0.6178	0.6975	0.5706
R	0.0887	0.0529	0.3606	0.0710	0.1978	0.0053

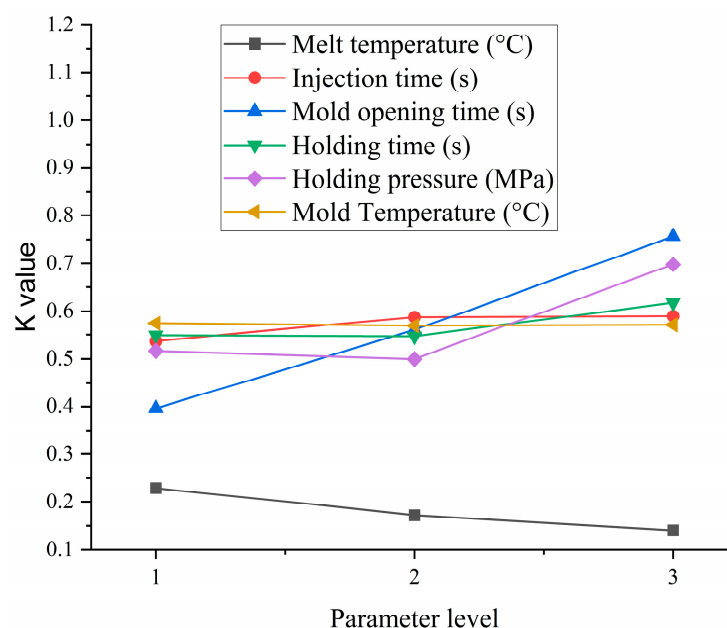


Figure 9. The average grey correlation degree of parameters at different levels.

3.4. Analysis of Response Surface Experiment Results

The BBD experimental design was used to optimize the injection molding process parameters, with the product wall thickness, material, cooling system, and other aspects remaining unchanged. Melt temperature (A), mold opening time (B), injection time (C), holding time (D), holding pressure (E), and mold temperature (F) were selected as factors, with plastic part warpage deformation and shrinkage depth as optimization objectives. The response surface experimental design method optimizes the model, with each factor taking three levels. A 3-level and 6-factor DOE-1 table was designed, as indicated in Table 6. Based on the results of single-factor experiments, Design-Expert software was

used to optimize the Box-Behnken design. An L54 orthogonal array was used to establish a quadratic polynomial response surface model, and the optimal values of the responses and corresponding factor values were calculated. The experimental data are displayed in Table 7.

Table 6. Design an experiment of a factor level table.

Control Factors	Level		
	−1	0	1
A. Melt temperature (°C)	220	230	240
B. Injection time (s)	3	4	5
C. Mold opening time (s)	1	1.5	2
D. Holding time (s)	10	12	14
E. Holding pressure (MPa)	80	90	100
F. Mold Temperature (°C)	60	70	80

Table 7. Response surface optimization, experimental design and results.

No.	Control Factors						Quality Index	
	A-Melt Temperature (°C)	B-Injection Time(s)	C-Mold Opening Time (s)	D-Holding Time (s)	E-Holding Pressure (MPa)	F-Mold Temperature (°C)	Y1-Warping Deformation (mm)	Y2-Shrinkage Depth (mm)
1	240	4	1	12	90	80	0.2014	0.0542
2	230	3	1	12	80	70	0.1995	0.0532
3	230	5	1.5	12	100	60	0.1685	0.0423
4	240	4	1	12	90	60	0.2009	0.0544
5	240	5	1.5	14	90	70	0.1810	0.0490
6	220	5	1.5	14	90	70	0.1631	0.0368
7	230	4	2	10	90	80	0.1598	0.0349
8	230	4	1	14	90	80	0.1990	0.0531
9	230	4	1.5	12	90	70	0.1687	0.0428
10	240	4	2	12	90	80	0.1688	0.0401
11	230	5	1	12	100	70	0.1941	0.0522
12	240	4	1.5	10	80	70	0.1708	0.0484
13	230	3	1.5	12	80	80	0.1706	0.0437
14	230	5	1	12	80	70	0.1997	0.0532
15	240	5	1.5	10	90	70	0.1792	0.0471
16	220	4	2	12	90	80	0.1601	0.0306
17	230	5	1.5	12	80	80	0.1701	0.0440
18	230	4	1.5	12	90	70	0.1710	0.0430
19	220	4	1.5	14	80	70	0.1657	0.0370
20	240	3	1.5	10	90	70	0.1744	0.0481
21	220	3	1.5	14	90	70	0.1665	0.0367
22	230	3	1.5	12	80	60	0.1704	0.0440
23	220	4	1.5	14	100	70	0.1660	0.0363
24	240	4	2	12	90	60	0.1722	0.0403
25	230	4	1	10	90	80	0.1769	0.0520
26	230	4	1.5	12	90	70	0.1739	0.0429
27	220	4	1.5	10	80	70	0.1666	0.0369
28	230	4	1.5	12	90	70	0.1665	0.0424
29	230	5	1.5	12	100	80	0.1667	0.0420
30	230	3	1.5	12	100	60	0.1684	0.0424
31	220	4	1.5	10	100	70	0.1619	0.0362
32	230	4	1	10	90	60	0.1956	0.0521
33	230	3	2	12	80	70	0.1614	0.0352

Table 7. *Cont.*

No.	Control Factors						Quality Index	
	A-Melt Temperature (°C)	B- Injection Time(s)	C-Mold Opening Time (s)	D- Holding Time (s)	E-Holding Pressure (MPa)	F-Mold Temperature (°C)	Y1-Warping Deformation (mm)	Y2- Shrinkage Depth (mm)
34	230	5	1.5	12	80	60	0.1725	0.0439
35	230	4	1.5	12	90	70	0.1696	0.0430
36	230	4	2	14	90	60	0.1601	0.0351
37	230	3	1	12	100	70	0.1946	0.0524
38	220	4	1	12	90	80	0.1806	0.0482
39	230	5	2	12	100	70	0.1592	0.0336
40	240	4	1.5	14	80	70	0.1738	0.0490
41	220	3	1.5	10	90	70	0.1616	0.0363
42	230	4	1.5	12	90	70	0.1674	0.0422
43	240	4	1.5	10	100	70	0.1736	0.0456
44	230	3	2	12	100	70	0.1607	0.0345
45	230	5	2	12	80	70	0.1620	0.0349
46	220	4	2	12	90	60	0.1606	0.0306
47	230	4	2	14	90	80	0.1596	0.0350
48	220	4	1	12	90	60	0.1783	0.0481
49	240	3	1.5	14	90	70	0.1833	0.0489
50	230	4	1	14	90	60	0.1985	0.0532
51	230	3	1.5	12	100	80	0.1716	0.0425
52	220	5	1.5	10	90	70	0.1606	0.0363
53	240	4	1.5	14	100	70	0.1784	0.0479
54	230	4	2	10	90	60	0.1617	0.0345

The experimental data from the response surface methodology were processed using Design-Expert software (Table 7) to investigate the effects of melt temperature, mold temperature, holding time, and holding pressure on warpage deformation and shrinkage depth.

Within the selected process parameter range, Design Expert was used to optimize and solve the problem, with the minimum warpage deformation as the optimization objective. The optimal combination of predicted process parameters is shown in Table 8. The average errors between the predicted minimum warpage deformation and shrinkage depth of the product and the actual numerical simulation values are 3.18% and 8.6%, respectively, confirming the accuracy of the response surface model numerical simulation. The optimal combination of molding process parameters is suitable for production and processing.

Table 8. Optimum process parameters and validation.

No.	A	B	C	D	E	F	Predicted Value		Simulation Value		Prediction Error	
							Y1	Y2	Y1	Y2	Y1	Y2
1	221	4.255	1.996	13.144	80.578	61.054	0.1570	0.030	0.1630	0.0319	3.82	6.33
2	221.162	3.865	1.945	10.458	94.614	78.359	0.1570	0.030	0.1614	0.0321	2.80	7.00
3	220.233	4.787	1.870	12.223	97.703	72.632	0.1570	0.030	0.1616	0.0330	2.93	10.0
4	221.697	3.844	1.966	12.209	97.351	60.128	0.1570	0.030	0.1633	0.0327	4.01	9.00
5	220.819	3.860	1.971	11.619	96.632	76.958	0.1580	0.029	0.1617	0.0321	2.34	10.69
Average											3.18	8.60

3.5. Comparison of Different Optimization Methods

Figure 10a shows the warpage deformation results analyzed using different optimization methods. From the figure, it can be seen that the RSM method performs the best, with significantly lower warpage deformation than the original method. The GRA and OED methods have similar effects and are both better than the original values. Under the principle of prioritizing warping deformation, the effectiveness ranking of the three optimization analyses is $RSM > OED > GRA$. The minimum deformation rate is 0.1592 mm, which is 27.37% lower than before optimization. Figure 10b shows the results of analyzing the depth of shrinkage using different optimization methods. From the figure, it can be seen that the OED method performs the best, followed by the GRA method, but it is still significantly better than the original method. Under the principle of prioritizing indentation depth, the effectiveness ranking of the three optimization analyses is $OED > GRA > RSM$. The minimum shrinkage depth is 0.0312 mm, which is 47.21% lower than before optimization. This discovery provides strong support for the optimal combination of process parameters suitable for production and processing.

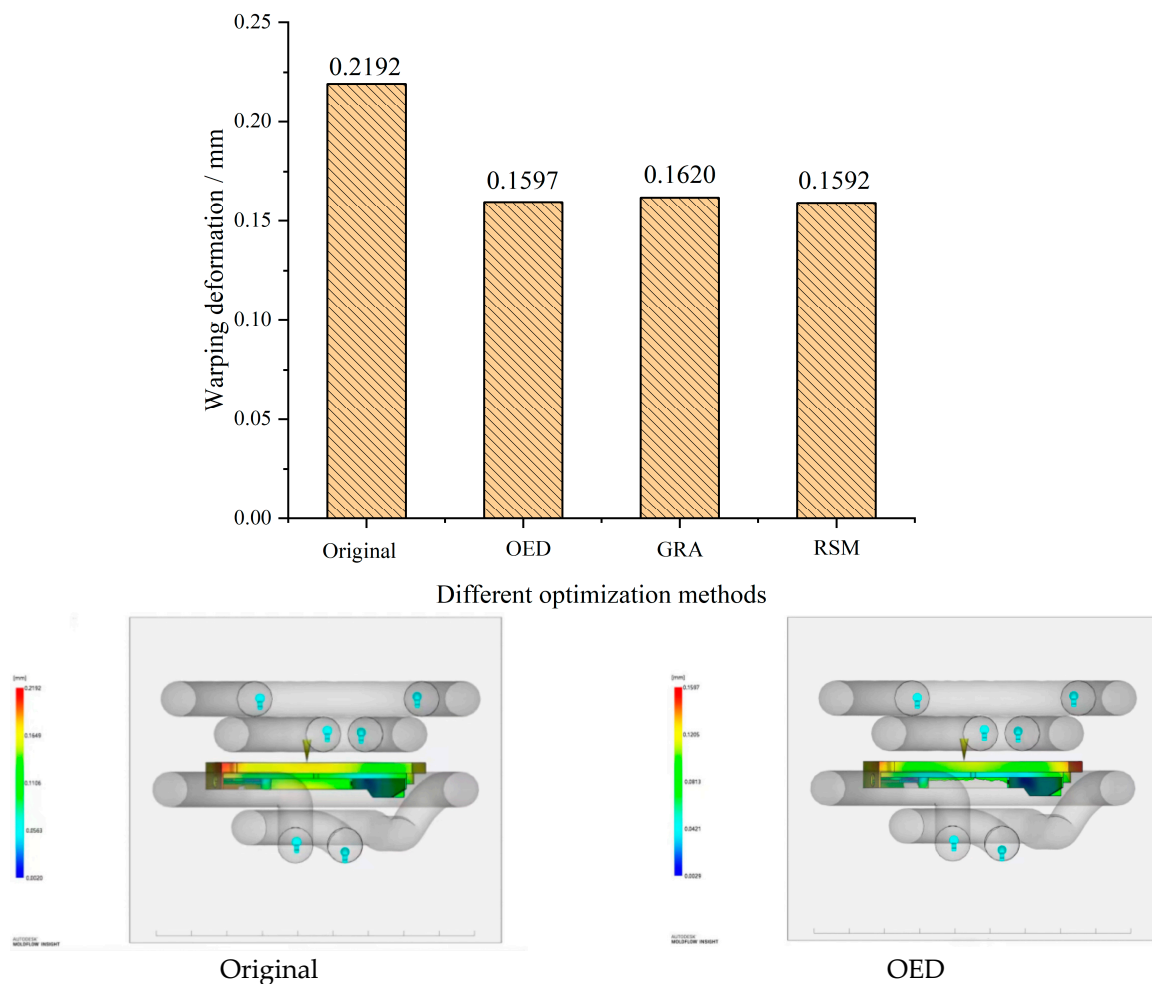


Figure 10. Cont.

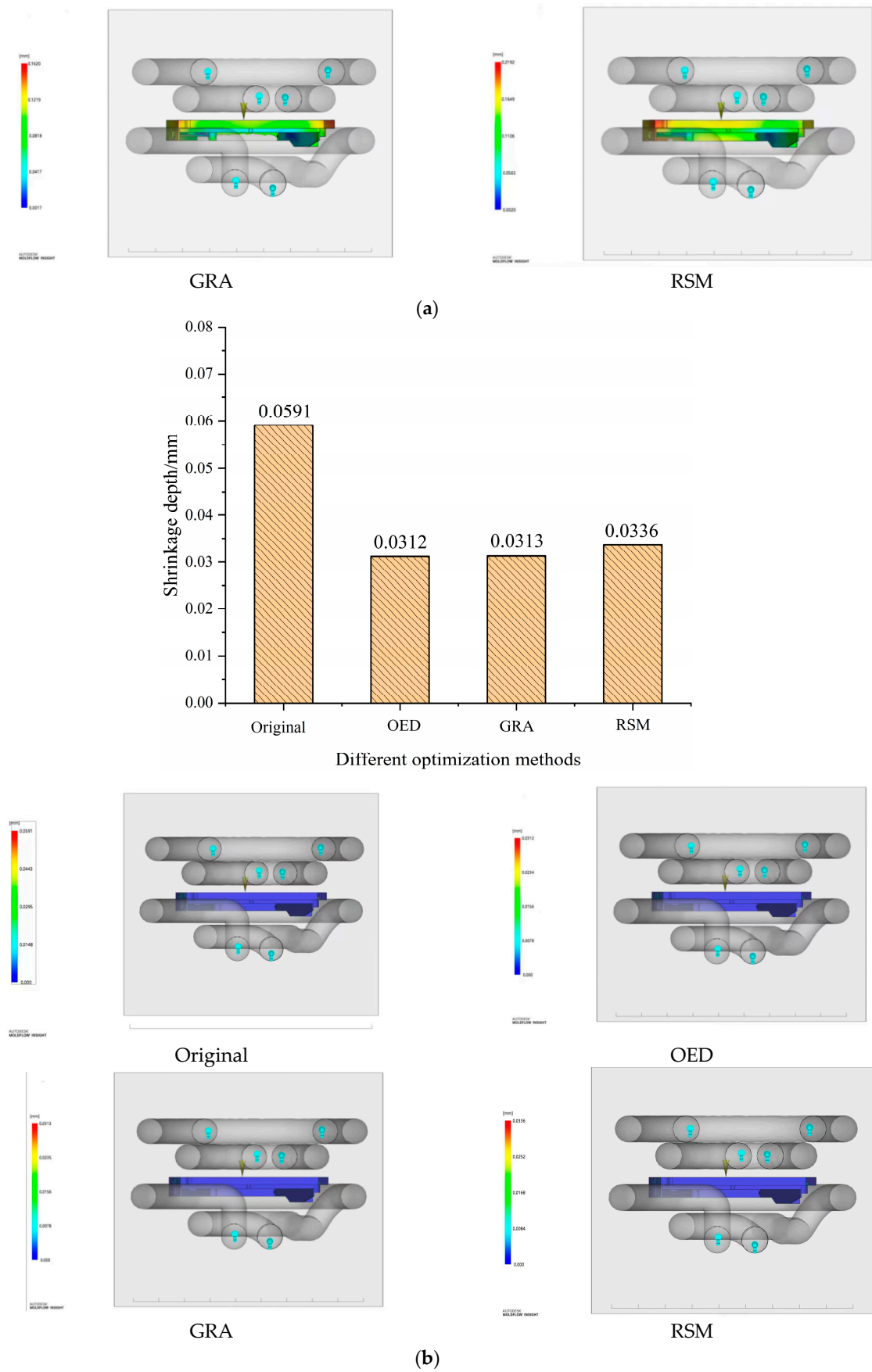


Figure 10. Optimize simulation results (a) Analysis of warpage deformation using different optimization methods; (b) Analysis of warpage deformation using different optimization methods.

4. Conclusions

The injection mold with the conformal cooling channel (CCC) can improve the uniformity of mold temperature, reduce warpage deformation, and significantly improve product accuracy. This article designs the geometric structure of the conformal cooling water channel for the printer shell, evaluates its impact on the cooling performance of the studied injection mold, and combines theoretical algorithms and CAE methods to carry out injection molding process optimization and research. The conclusions are as follows:

1. The combination of molding parameters A1-B1-C3-D1-E3-F3, using the OED method, has the smallest warpage deformation and shrinkage depth. When A1 is the melt temperature (220 °C), B1 is the mold opening time (3 s), C3 is the injection time (2 s), D1 is the holding time (10 s), E3 is the holding pressure (100 MPa), and F3 is the mold temperature (80 °C). The minimum warpage deformation is 0.1597 mm, a decrease of 26.61% compared to the initial value. The minimum indentation depth is 0.0312 mm, a reduction of 47.21% compared to the initial value.
2. The optimal solution obtained using the GRA method is A1B3C3D3E1, with a melt temperature of 220 °C, an injection time of 5 s, a mold opening time of 2 s, a holding time of 14 s, a holding pressure of 100 MPa, and a mold temperature of 60 °C. The minimum warpage deformation is 0.1594 mm, a decrease of 26.75% compared to the initial value. The minimum indentation depth is 0.0316 mm, a decrease of 46.53% compared to the initial value.
3. The average errors between the predicted minimum warpage deformation and shrinkage depth of the product and the actual numerical simulation values are 3.18% and 8.6%, respectively, confirming the accuracy of the response surface model numerical simulation. The optimal combination of molding process parameters is suitable for production and processing.
4. Under the principle of prioritizing warpage deformation, the effectiveness ranking of the three optimization analyses is RSM > OED > GRA. The minimum deformation rate is 0.1592 mm, which is 27.37% lower than before optimization. Under the principle of prioritizing indentation depth, the effectiveness ranking of the three optimization analyses is OED > GRA > RSM. The minimum depth of shrinkage is 0.0312 mm, which is 47.21% lower than before optimization.

Author Contributions: Conceptualization, M.Z. and Z.T.; methodology, M.Z. and Z.T.; software, M.Z. and Z.T.; validation, M.Z. and Z.T.; formal analysis, M.Z. and Z.T.; investigation, M.Z. and Z.T.; resources, M.Z. and Z.T.; data curation, M.Z. and Z.T.; writing—original draft preparation, Z.T.; writing—review M.Z. and Z.T.; visualization, M.Z. and Z.T.; supervision, Z.T.; project administration, M.Z.; funding acquisition, M.Z. and Z.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the 2023 Anhui Province Youth Teacher Training Action Project, grant number JNFX2023134, and the Science Research Program Projects of Universities of Anhui Province, grant number 2024AH051862.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Acknowledgments: The authors acknowledge the support of the Anhui Provincial Ministry of Education, Tongling Polytechnic, and Jiangsu University.

Conflicts of Interest: The authors declare no conflicts of interest.

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