# Optimization of Injection Molding Process Parameters for Medical Two-Color Test Boxes Based on Standard Particle Swarm Optimization Algorithm

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**Abstract:** Aiming at the difficulty in coordinating and optimizing multiple quality indicators in the two-color injection molding process and the complexity of the established model due to the large number of process parameters, an injection molding process parameter optimization method integrating multi-objective normalization processing, key process parameter screening, response surface model and particle swarm optimization (PSO) is proposed. Firstly, the rough optimization of process parameters is completed through orthogonal experiments. The critic method and the topsis method are combined to normalize and weight the three injection molding quality indicators, and the comprehensive quality score of the product is obtained. Then, the variance analysis is used to screen out four key parameters with higher significance from eight process parameters, and a second-order response surface model of key parameters and comprehensive quality score is established based on the central composite design (CCD). Finally, the particle swarm optimization algorithm is used to iteratively optimize the model, and the obtained optimal parameter combination is imported into Moldflow for simulation verification. The results show that the quality of the optimized product is significantly better than that of the orthogonal rough optimization result, and the proposed method can provide an effective reference for the optimization of two-color injection molding process parameters.

***Keywords*:** two-color medical test box; TOPSIS method; response surface methodology; standard particle swarm optimization.

## 1. Introduction

With rapid economic development and rising living standards in China, medical devices are increasingly expected to satisfy both functional and aesthetic requirements. Two-color injection molding [1] is a mature manufacturing process in which plastics of two different colors or materials are injected into a mold during one production cycle. The process produces a complete component in which the two plastics are closely bonded, providing an appearance, function, or tactile quality that may not be achievable with a single material. It also eliminates secondary processing and improves production efficiency. Optimizing two-color injection molding process parameters is an effective way to improve product quality, and extensive research has been conducted in this field.

Early studies used orthogonal experiments in combination with Moldflow simulation to optimize process parameters. Jiang et al. [2] investigated the effects of process parameters on warpage and volumetric shrinkage in two-color automotive components using Moldflow and orthogonal experiments. Their results showed that orthogonal experiments can identify a local optimum for process parameter optimization. Guo et al. [3] used an improved orthogonal experimental method to study the effects of mold temperature, melt temperature, filling pressure, filling time, injection time, cooling temperature, and cooling time on the molding quality of a polymer–metal hybrid automotive front panel. They obtained an optimal set of injection molding parameters to guide production. Although orthogonal experiments can achieve optimization to some extent, they evaluate only discrete points within the experimental space and cannot provide a functional relationship between experimental factors and responses across the entire region. More efficient and reliable mathematical methods are therefore needed for engineering optimization. To this end, some researchers have proposed approaches based on response surface methodology.

Response surface methodology is more effective at addressing interactions among multiple factors. Jiang et al. [4] used response surface methodology to optimize the process parameters for an automotive gear lever and compared the results with those obtained from orthogonal experiments. Compared with the orthogonal method, response surface methodology further reduced volumetric shrinkage and warpage. Luo et al. [5] combined the entropy weight method and TOPSIS to aggregate injection molding quality characteristics and identify key process parameters. By combining response surface methodology with a central composite design, they proposed a multiobjective optimization method for thin-walled plastic

parts and improved warpage and volumetric shrinkage. Kitayama et al. [6] combined the Taguchi method with response surface methodology to study the effects of melt temperature, mold temperature, injection time, holding time, and cooling time on dimensional shrinkage and warpage of a wire-harness connector. Yao et al. [7] proposed a multiobjective optimization method for injection molding process parameters based on a response surface model and comprehensive entropy weights, and successfully optimized the molding parameters of a thin-walled propeller blade. These studies demonstrate that response surface methodology can further improve process parameters. Because two-color injection molding includes a first shot and a second shot, it generally involves a relatively large number of quality characteristics and process parameters. To reduce the number of coefficients to be estimated and improve the fitting accuracy of the response surface with a limited number of experiments, multiple quality characteristics can be combined into a single comprehensive quality index, and significant process parameters can be selected from the full set of parameters. This approach can improve response surface modeling and optimization for two-color injection molding. However, response surface methodology alone may still struggle to achieve global optimization. With advances in artificial intelligence, intelligent manufacturing has increasingly become a research focus.

Researchers have applied intelligent algorithms to the optimization of injection molding process parameters, often in conjunction with computer-aided engineering simulations. Xue et al. [8] investigated the effects of material temperature, injection pressure, holding time, mold temperature, and other molding parameters on the tensile stress (σ) and Young's modulus (E) of a PC/ABS blend, and then used the sparrow search algorithm to optimize overall product quality. Their results indicated that injection pressure and material temperature had the greatest effects on the mechanical properties and microstructure of the blend, and that the final optimization results were satisfactory. Xu et al. [9] sought to optimize volumetric shrinkage, warpage, and weight. They first established an optimal neural network model based on Latin hypercube sampling to predict the complex relationships between metal injection molding parameters and quality characteristics, and then used NSGA-II and a CRITIC-based fuzzy decision-making method to optimize the parameters. Hong et al. [10] investigated the key factors and mechanisms responsible for birefringence and warpage, using both as optimization objectives, and applied differential evolution to obtain a suitable parameter combination for lens micro-injection molding. Hu [11] selected lens shape accuracy as the optimization objective and identified significant factors through Taguchi experiments and analysis of variance. An artificial neural network and a genetic algorithm were then used for further optimization, and experiments were conducted to verify the proposed approach. Guo et al. [12] showed that the optical quality of a lens depends largely on the processing parameters used in injection molding. Taking the birefringence characteristics of a symmetric biconvex Fresnel lens as the optimization objective, they established gray relational grades for the experiments using a Taguchi-based gray relational analysis and combined the results with a genetic algorithm to obtain an optimal parameter set that balanced two competing objectives. Wang et al. [13] addressed the difficulty of injection molding ultrathin backlight panels for LCD modules by optimizing the dimensions along the panel axes. They identified the main process parameters using gray relational ranking, established a fuzzy neural network approximation model based on orthogonal experiments, and used a multiobjective genetic algorithm to determine the optimal molding parameters.

These intelligent algorithms have substantially improved the search for suitable parameter combinations. Commonly used methods include NSGA-II, the sparrow search algorithm, and differential evolution. Compared with other algorithms, particle swarm optimization offers fast searching, high efficiency, and a simple structure. The standard PSO algorithm with an inertia weight can search a broad region efficiently during the early iterations and concentrate on promising regions during later iterations. The addition of the inertia weight also helps address premature convergence, thereby improving the optimization of process parameter combinations. Standard PSO was therefore selected for this study [14].

Based on the above analysis, the research procedure was established as follows. First, the product was modeled and the number and locations of the gates were determined. Next, orthogonal experiments were designed to generate data samples. The entropy weight method and TOPSIS were combined to normalize and aggregate three injection molding quality characteristics into a comprehensive quality index. Analysis of variance was then used to identify four significant parameters from eight process parameters. A second-order response surface model relating the key parameters to the comprehensive quality index was established using a central composite design. Finally, PSO was used to iteratively optimize the model and identify a globally optimal combination of key process parameters. Production trials were conducted to verify the results, yielding a two-color medical test box with good quality. On this basis, a method for optimizing two-color injection molding parameters using standard PSO was developed.

# 2. Product Modeling and Gate Analysis

## 2.1 Product Modeling

A two-color medical test box from a commercial brand was selected as the research object, and a finite element model was established in Moldflow. The product measured 165 mm × 70 mm × 50 mm, had a relatively uniform wall thickness, and featured smooth structural contours. Its three-dimensional model is shown in Figure 1. The model was discretized using a three-dimensional mesh in Moldflow, with a mesh size of 2 mm and a total of 657,853 elements. Considering the product's service environment and injection molding requirements, polyetherimide (PEI HU1010) was selected for both shots. For aesthetic purposes, gray was selected for the first shot and white for the second.



**Figure 1. Three-dimensional model of the product.**

## 2.2 Gate Analysis

The first- and second-shot sections of the test box were imported separately into Moldflow for meshing and gate-location analysis. The results are shown in Figure 2. The blue regions indicate the preferred gate locations for both shots. Taking practical requirements into account, a rectangular edge gate was selected for the first shot and a pin gate for the second. The actual gate locations are shown in Figure 2. Filling, packing, overmolding filling, and overmolding packing analyses were performed; the results are shown in Figure 3.

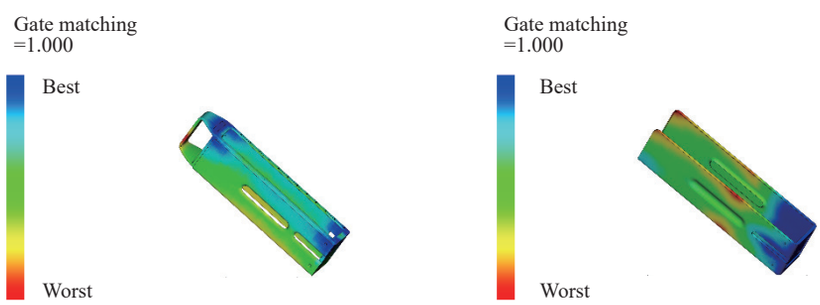



**Figure 2. Analysis of preferred gate locations for the first and second shots.**

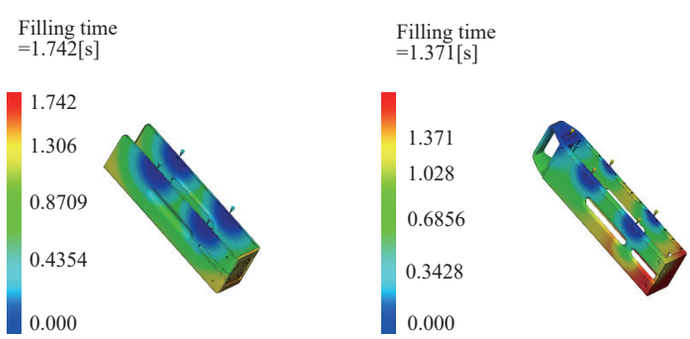



**Figure 3. Filling times for the first and second shots.**

As shown in Figure 3, the filling times were 1.371 s for the first shot and 1.742 s for the second. Filling proceeded relatively smoothly, and the material filled the cavity uniformly. The results satisfied the product requirements, indicating that the gate design was reasonable.

# 3. Comprehensive Quality Index and Selection of Key Process Parameters

## 3.1 Orthogonal Experimental Design and Comprehensive Quality Index

(1) Orthogonal experimental design. Eight principal process parameters were selected as experimental factors: first-shot mold temperature (A), first-shot melt temperature (B), second-shot mold temperature (C), second-shot melt temperature (D), first-shot holding pressure (E), first-shot holding time (F), second-shot holding pressure (G), and second-shot holding time (H). Three characteristics were selected to evaluate product quality: average first-shot volumetric shrinkage ($Y_1$), average second-shot volumetric shrinkage ($Y_2$), and total warpage ($Y_3$). An eight-factor, three-level experimental design was adopted. The factor levels were determined from Moldflow's recommended values, as shown in Table 1.

**Table 1. Factor levels for the eight-factor, three-level experiment.**

| | A/℃ | B/℃ | C/℃ | D/℃ | E/Mpa | F/s | G/Mpa | H/s |
|---|---|---|---|---|---|---|---|---|
| 1 | 60 | 230 | 50 | 230 | 50 | 15 | 90 | 20 |
| 2 | 70 | 255 | 75 | 265 | 60 | 25 | 105 | 30 |
| 3 | 80 | 280 | 100 | 300 | 70 | 35 | 120 | 40 |

An $L_{27}(3^8)$ orthogonal array was used to arrange the experiments. Moldflow simulations were performed to obtain the average volumetric shrinkage of each shot and the total warpage. Because the three characteristics contribute differently to the overall assessment of product quality, their weights were determined using the entropy weight method, and TOPSIS was then used to calculate the comprehensive quality index. To eliminate the influence of different units, the data were normalized using Equation (1).

$$Y_{ij} = \frac{Y_{jmax} - Y_{ij}}{Y_{jmax} - Y_{jmin}} \tag{1}$$

Here, $Y_{ij}$ is the jth quality characteristic for the ith sample, where i = 1–27 and j = 1–3. $Y_{jmax}$ and $Y_{jmin}$ are the maximum and minimum values, respectively, of the jth characteristic. The weights calculated from the $L_{27}(3^8)$ orthogonal experiment and Moldflow simulation data were 0.326 for first-shot average volumetric shrinkage, 0.350 for second-shot average volumetric shrinkage, and 0.324 for total warpage.

(2) Comprehensive quality index. TOPSIS was used to calculate the comprehensive quality index. The orthogonal experimental results and calculated indices are presented in Table 2.

**Table 2. Results of the $L_{27}(3^8)$ orthogonal experiment and calculated comprehensive quality indices.**

| Experiment No. | First-shot volumetric shrinkageY1/% | Second-shot volumetric shrinkageY2/% | Total warpage $Y_3$/mm | Comprehensive quality indexY |
|---|---|---|---|---|
| 1 | 6.221 | 4.644 | 1.113 | 0.5844 |
| 2 | 5.437 | 4.761 | 0.893 | 0.6233 |
| 3 | 4.582 | 5.502 | 0.723 | 0.6126 |
| 4 | 6.223 | 6.721 | 1.034 | 0.3992 |
| 5 | 5.992 | 4.371 | 1.123 | 0.4421 |
| 6 | 7.983 | 4.663 | 1.352 | 0.3112 |
| 7 | 7.941 | 6.772 | 1.324 | 0.2543 |
| 8 | 8.032 | 7.723 | 1.421 | 0.2731 |
| 9 | 7.972 | 5.734 | 0.993 | 0.5822 |
| 10 | 8.875 | 6.384 | 0.973 | 0.5422 |
| 11 | 6.974 | 4.773 | 1.232 | 0.4921 |
| 12 | 5.352 | 5.832 | 1.187 | 0.5438 |
| 13 | 6.244 | 4.657 | 1.582 | 0.6611 |
| 14 | 6.044 | 4.668 | 1.283 | 0.6731 |
| 15 | 5.734 | 4.621 | 1.231 | 0.6142 |
| 16 | 4.382 | 3.785 | 1.114 | 0.6723 |

| Experiment No. | First-shot volumetric shrinkageY1/% | Second-shot volumetric shrinkageY2/% | Total warpage $Y_3$/mm | Comprehensive quality indexY |
|---|---|---|---|---|
| 17 | 6.112 | 3.558 | 1.003 | 0.6657 |
| 18 | 6.347 | 4.893 | 1.448 | 0.6532 |
| 19 | 5.148 | 6.561 | 1.438 | 0.6322 |
| 20 | 5.338 | 5.702 | 1.874 | 0.5328 |
| 21 | 4.539 | 4.926 | 1.324 | 0.6938 |
| 22 | 6.382 | 7.224 | 0.842 | 0.6821 |
| 23 | 6.339 | 5.731 | 1.842 | 0.4321 |
| 24 | 5.382 | 7.112 | 0.995 | 0.4821 |
| 25 | 7.104 | 4.121 | 1.847 | 0.5442 |
| 26 | 7.392 | 5.663 | 1.638 | 0.3211 |
| 27 | 6.034 | 3.721 | 0.984 | 0.4121 |

Among the 27 experiments in Table 2, experiment 21 had the highest comprehensive quality index, at 0.6938. Its corresponding process parameters were a first-shot mold temperature of 70°C, first-shot melt temperature of 225°C, second-shot mold temperature of 50°C, second-shot melt temperature of 230°C, first-shot holding pressure of 50 MPa, first-shot holding time of 20 s, second-shot holding pressure of 120 MPa, and second-shot holding time of 20 s. The orthogonal experiment thus yielded a preliminary optimal combination; however, because it represents only a local optimum, further optimization was required.

## 3.2 Selection of Key Process Parameters

To assess the significance of the effects of different process parameters on the comprehensive quality index, range analysis was performed on the simulation and calculation results from the $L_{27}(3^8)$ orthogonal array. The results are shown in Figure 4. Analysis of variance was then used to further assess the significance of each factor; the results are presented in Table 3.

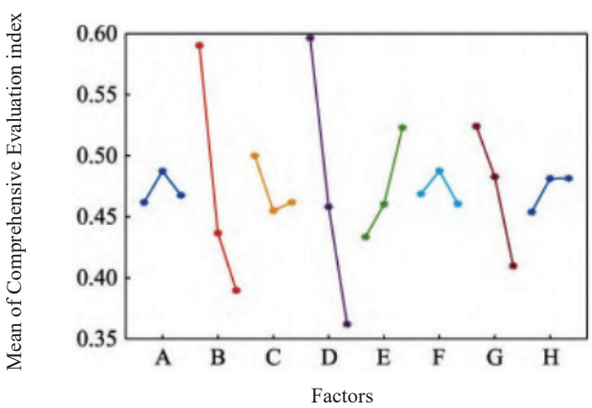



**Figure 4. Range analysis of the comprehensive quality index.**

**Table 3. Analysis of variance.**

| | | Sum of squaresss | Degrees of freedom | Mean squareMs | F value | P value |
|---|---|---|---|---|---|---|
| Molding process Parameter | A | 0.003258 | 2 | 0.001629 | 0.74 | 0.500 |
| | B | 0.198413 | 2 | 0.099206 | 45.32 | 0.000 |
| | C | 0.010563 | 2 | 0.005281 | 2.41 | 0.140 |
| | D | 0.249703 | 2 | 0.124852 | 57.03 | 0.000 |
| | E | 0.037921 | 2 | 0.018961 | 8.66 | 0.007 |
| | F | 0.003467 | 2 | 0.001733 | 0.79 | 0.479 |
| | G | 0.060343 | 2 | 0.030171 | 13.78 | 0.001 |
| | H | 0.004545 | 2 | 0.002272 | 1.04 | 0.389 |
| Error sum of squares | $S_E$ | 0.02189 | 10 | 0.02189 | | |
| Total sum of squares | Sr | 0.590104 | | | | |

In the range analysis, the mean index value indicates the average performance obtained at a particular factor level. A higher mean indicates a better comprehensive quality index and a more favorable parameter level, whereas a lower mean indicates a weaker improvement. As shown in Figure 4, first-shot melt temperature (B), second-shot melt temperature (D), first-shot holding pressure (E), and second-shot holding pressure (G) had relatively large ranges and significant effects. The remaining factors had less significant effects.

In the analysis of variance, the F-value is the ratio of the mean square for a factor to the mean square for error. A larger F-value indicates that the variation associated with the parameter is more substantial relative to random experimental error and therefore suggests a stronger effect on the index. The P-value indicates whether the effect is statistically significant; a smaller P-value suggests that the observed effect is less likely to be attributable to random error. Together, these values can be used to assess the relative importance and significance of the parameters. As shown in Table 3, the F-values for first-shot melt temperature (B), second-shot melt temperature (D), first-shot holding pressure (E), and second-shot holding pressure (G) were all greater than $F_{0.05}(2, 10) = 4.1$, and their P-values were below 0.05. These four parameters therefore had significant effects on the comprehensive quality index, whereas the effects of the other parameters were not significant.

Based on these results, first-shot melt temperature, second-shot melt temperature, first-shot holding pressure, and second-shot holding pressure were selected as the four key parameters for evaluating the comprehensive quality index.

# 4. Development and Validation of the Response Surface Model

## 4.1 Central Composite Design

Based on the experimental results, the four significant factors—first-shot melt temperature (B), second-shot melt temperature (D), first-shot holding pressure (E), and second-shot holding pressure (G)—were selected as evaluation variables. First-shot average volumetric shrinkage ($Y_1$), second-shot average volumetric shrinkage ($Y_2$), and total warpage ($Y_3$) were used as the quality characteristics. A central composite design (CCD) was used to plan the experiments. The levels of the optimization variables are shown in Table 4, where $X_1$, $X_2$, $X_3$, and $X_4$ represent B, D, E, and G, respectively.

The nonsignificant process parameters were fixed at their optimal levels: first-shot mold temperature (A) at 70°C, second-shot mold temperature (C) at 50°C, first-shot holding time (F) at 25 s, and second-shot holding time (H) at 40 s. The entropy weight method was applied to the CCD data in Table 5. The resulting weights were 0.399 for first-shot average volumetric shrinkage ($Y_1$), 0.373 for second-shot average volumetric shrinkage ($Y_2$), and 0.228 for total warpage ($Y_3$). TOPSIS was then used to obtain the comprehensive quality index. The CCD results and calculated indices are shown in Table 5.

**Table 4. Levels of the optimization variables.**

| Key parameter | Factor level | | | | |
|---|---|---|---|---|---|
| | -2 | -1 | 0 | 1 | 2 |
| $X_1$ | 230 | 242.5 | 255 | 200 | 72.5 |
| $X_2$ | 230 | 247.5 | 260 | 282.5 | 300 |
| $X_3$ | 50 | 55 | 60 | 65 | 70 |
| $X_4$ | 90 | 97.5 | 105 | 112.5 | 120 |

**Table 5. Central composite design results and calculated comprehensive quality indices.**

| Experiment No. | Key parameter | | | | Quality characteristic | | | Comprehensive score |
|---|---|---|---|---|---|---|---|---|
| | $A_2$ | $B_2$ | $C_2$ | $D_2$ | $X_1$/% | $X_2$/% | $X_3$/mm | X |
| 1 | 1 | -1 | -1 | 1 | 5.462 | 4.336 | 1.645 | 0.3211 |
| 2 | -1 | 1 | 1 | -1 | 5.322 | 5.322 | 1.436 | 0.3934 |
| 3 | 1 | 1 | 1 | -1 | 5.334 | 4.234 | 1.653 | 0.4124 |
| 4 | -1 | -1 | 1 | 1 | 5.752 | 4.116 | 1.667 | 0.6231 |
| 5 | 0 | 0 | 0 | 0 | 5.113 | 4.065 | 1.295 | 0.7412 |
| 6 | -1 | 1 | -1 | -1 | 5.072 | 4.032 | 1.132 | 0.7734 |
| 7 | -1 | 1 | 1 | 1 | 5.521 | 5.241 | 1.485 | 0.6721 |
| 8 | 1 | 1 | 1 | 1 | 5.922 | 5.115 | 1.448 | 0.4421 |
| 9 | 1 | -1 | -1 | -1 | 6.253 | 5.632 | 1.328 | 0.3714 |

| Experiment No. | Key parameter | | | | Quality characteristic | | | Comprehensive score |
|---|---|---|---|---|---|---|---|---|
| | $A_2$ | $B_2$ | $C_2$ | $D_2$ | $X_1$/% | $X_2$/% | $X_3$/mm | X |
| 10 | 0 | 0 | 0 | 0 | 5.326 | 4.532 | 1.561 | 0.3819 |
| 11 | 0 | 0 | 0 | 0 | 5.432 | 5.743 | 1.671 | 0.7232 |
| 12 | -1 | -1 | -1 | -1 | 5.513 | 4.662 | 1.601 | 0.4152 |
| 13 | -1 | 1 | 1 | 1 | 5.117 | 5.713 | 1.574 | 0.4431 |
| 14 | -1 | -1 | -1 | 1 | 5.492 | 5.932 | 1.568 | 0.8943 |
| 15 | 1 | -1 | -1 | 1 | 5.623 | 5.012 | 1.552 | 0.6143 |
| 16 | 1 | 1 | 1 | -1 | 5.932 | 4.992 | 1.379 | 0.5211 |
| 17 | 1 | 1 | 1 | 1 | 6.227 | 5.428 | 1.257 | 0.5314 |
| 18 | 1 | -1 | -1 | -1 | 5.719 | 5.021 | 1.445 | 0.5121 |
| 19 | 0 | 0 | 0 | 0 | 5.012 | 4.742 | 1.582 | 0.4261 |
| 20 | -1 | -1 | -1 | -1 | 5.621 | 5.632 | 1.437 | 0.4226 |
| 21 | 0 | 0 | 0 | 2 | 4.953 | 5.744 | 1.466 | 0.5714 |
| 22 | 0 | 0 | 0 | 0 | 6.635 | 5.221 | 1.332 | 0.3233 |
| 23 | 0 | 0 | 0 | 0 | 6.775 | 5.932 | 1.576 | 0.3913 |
| 24 | 0 | 2 | 2 | 0 | 6.031 | 5.116 | 1.412 | 0.3367 |
| 25 | 0 | 0 | 0 | 0 | 5.682 | 5.773 | 1.442 | 0.3752 |
| 26 | 2 | 0 | 0 | 0 | 5.603 | 5.642 | 1.632 | 0.5324 |
| 27 | -2 | 0 | 0 | 0 | 6.132 | 5.791 | 1.543 | 0.4115 |
| 28 | 0 | -2 | -2 | 0 | 5.743 | 5.511 | 1.474 | 0.4723 |
| 29 | 0 | 0 | 0 | -2 | 5.643 | 4.331 | 1.422 | 0.5732 |
| 30 | 0 | 0 | 0 | 0 | 5.852 | 4.012 | 1.401 | 0.5221 |

As shown in Table 5, experiment 14 had the highest comprehensive quality index, at 0.8943. The corresponding process parameters were a first-shot mold temperature of 65°C, first-shot melt temperature of 227.5°C, second-shot mold temperature of 55°C, second-shot melt temperature of 230°C, first-shot holding pressure of 50 MPa, first-shot holding time of 20 s, second-shot holding pressure of 120 MPa, and second-shot holding time of 20 s. This combination performed better than the best orthogonal experimental combination in Table 2, indicating improved overall product quality. A response surface model was subsequently introduced for further optimization.

## 4.2 Construction of the Response Surface Model

Response surface methodology combines experimental design with mathematical statistics to analyze responses affected by multiple variables. In this study, the four evaluation variables were used as model inputs, and the comprehensive quality index was used as the response. The general second-order regression equation is given in Equation (2).

$$Y = b_0 + \sum_{i=1}^{m} b_i X_i + \sum_{i=1}^{n} b_{ii} X_i^2 + \sum_{i}^{m-1} \sum_{j=i+1}^{m} b_{ij} X_i X_j \tag{2}$$

Here, $b_0$, $b_i$, $b_{ii}$, and $b_{ij}$ are regression coefficients; m is the number of evaluation variables; Y is the comprehensive quality index; and $X_i$ and $X_j$ are evaluation variables. The response surface model contains 15 coefficients to be determined. Quadratic multiple regression was performed using the CCD and comprehensive evaluation results in Table 5, yielding the second-order equation:

$$\begin{aligned} Y = {} & 0.2341 - 0.346X_1 - 0.0453X_2 + 0.231X_3 + 0.0723X_4 \\ & + 0.023X_1X_2 + 0.0065X_2X_2 + 0.0032X_3X_2 + 0.0026X_4X_2 \\ & + 0.0231X_1X_2 + 0.0861X_1X_3 + 0.0127X_1X_4 + 0.0415X_2X_3 \\ & + 0.0611X_2X_4 + 0.0427X_3X_4 \end{aligned} \tag{3}$$

## 4.3 Validation of the Response Surface Model

The adequacy of the second-order regression equation was assessed using the coefficient of determination $R^2$, adjusted coefficient of determination $R^2adj$, and nonlinear coefficient of determination RNL, calculated using Equations (4), (5), and

(6), respectively.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_i - \widehat{Y}_i\right)^2}{\sum_{i=1}^{n}\left(Y_i - \overline{Y}_i\right)^2} \tag{4}$$

$$R_{adj}{}^2 = 1 - \left(\frac{n-1}{n-k}\right)\frac{\sum_{i=1}^{n}\left(Y_i - \widehat{Y}_i\right)^2}{\sum_{i=1}^{n}\left(Y_i - \overline{Y}_i\right)^2} \tag{5}$$

$$R_{NL} = 1 - \sqrt{\frac{\sum_{i=1}^{n}\left(Y_i - \widehat{Y}_i\right)^2}{\sum_{i=1}^{n} Y_i^2}} \tag{6}$$

Here, $Y_i$ denotes the observed value for a sample; the fitted value and its mean are defined in the original equations; n is the number of samples; and k is the number of factors.

Using the CCD and comprehensive evaluation results, the calculated values were $R^2 = 0.9303$, $R^2adj = 0.8556$, and RNL = 0.9090. The adjusted coefficient of determination exceeded 0.85, while the other two measures exceeded 0.9, indicating a good fit. The response surface regression equation can therefore effectively represent the effects of process parameters on the comprehensive quality index.

# 5. Process Parameter Optimization Using Standard Particle Swarm Optimization

## 5.1 Optimization Procedure

The response surface model was used as the basis for standard PSO. The swarm's collective search capability was employed to seek a global optimum and provide a basis for adjusting injection molding parameters. The velocity and position update equations are:

$$v_{mn}(t+1) = wv_{mn}(t) + c_1 \cdot r_m \cdot \left(pbest_{mn}(t) - x_{mn}(t)\right) + c_2 r_2 \cdot \left(gbest_n(t) - x_{mn}(t)\right) \tag{7}$$

$$x_{mn}(t+1) = x_{mn}(t) + v_{mn}(t+1) \tag{8}$$

Here, m identifies a particle and n identifies a dimension. $v_{mn}(t)$ and $x_{mn}(t)$ are the velocity and position, respectively, of particle m in dimension n at iteration t. $pbest_{mn}(t)$ is the best position found by particle m in that dimension, and $gbest_n(t)$ is the best position found by the swarm in that dimension. $c_1$ and $c_2$ are learning factors; $r_1$ and $r_2$ are random numbers in the interval [0, 1]; and w is the inertia weight. Previous research indicates that favorable results can be obtained when w decreases from 0.9 to 0.4. The algorithm was implemented in MATLAB. Its parameters are listed in Table 6, and its flowchart is shown in Figure 5.

**Table 6. Parameters of the standard particle swarm optimization algorithm.**

| Population size | Iterations | Number of variables | Inertia weight | Learning factors |
|---|---|---|---|---|
| 200 | 100 | 4 | [0.4,0.9] | c1=c2=2 |

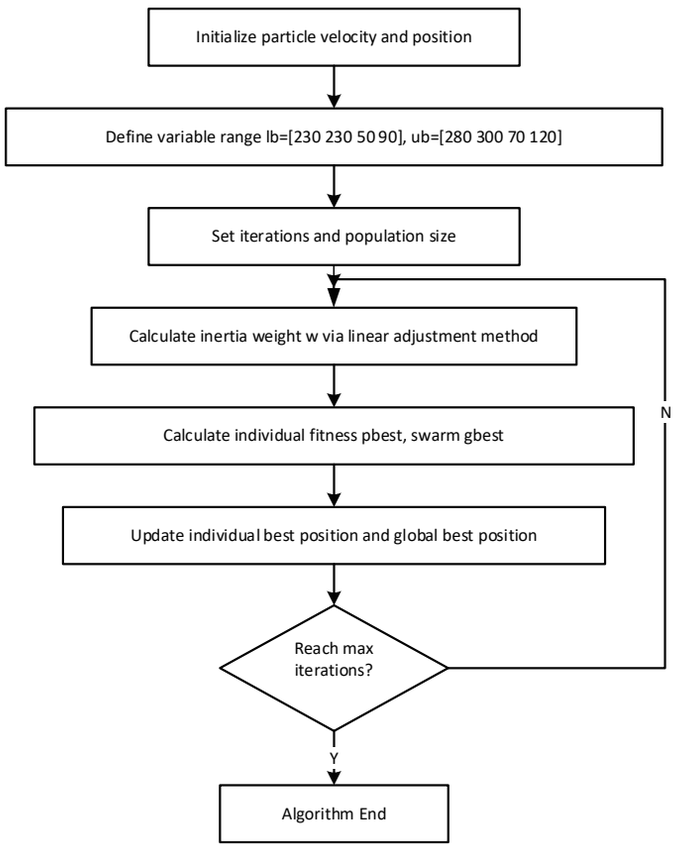



**Figure 5. Flowchart of the standard particle swarm optimization algorithm.**

The variable ranges and optimization objective were specified according to Moldflow's recommended injection molding values and practical experience, as shown in Equation (9).

$$\begin{cases} Y = \mathrm{Y}_{\min} \\ Range \begin{cases} 230 \le B \le 280 \\ 230 \le D \le 300 \\ 50 \le E \le 70 \\ 90 \le G \le 120 \end{cases} \end{cases} \tag{9}$$

After 100 iterations, the convergence history shown in Figure 6 was obtained. The slope of the global-best convergence curve was relatively stable, indicating satisfactory algorithm performance. The resulting globally optimal process parameter combination is presented in Table 7.

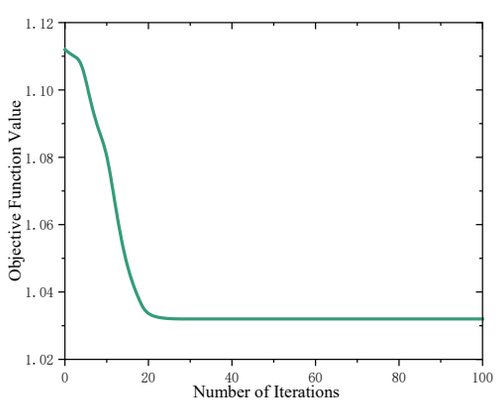



**Figure 6. Convergence history of the standard particle swarm optimization algorithm.**

**Table 7. Optimization results obtained using standard particle swarm optimization.**

| Comprehensive quality index | First-shot melt temperature | Second-shot melt temperature | First-shot holding pressure | Second-shot holding pressure |
|---|---|---|---|---|
| 1.1129 | 242°C | 260°C | 55Mpa | 95Mpa |

The best comprehensive quality index was 1.1129. The original manuscript reports that, compared with the preliminary optimization result of 0.8943 in Table 5, this represented a 16.322% improvement in overall product quality. The result indicates that standard PSO can be applied to injection molding parameter optimization to improve product quality. The optimized parameters in Table 7 were a first-shot melt temperature of 242°C, second-shot melt temperature of 260°C, first-shot holding pressure of 55 MPa, and second-shot holding pressure of 95 MPa. This combination was subsequently evaluated in Moldflow.

## 5.2 Moldflow Verification

The parameter combination obtained by PSO was analyzed in Moldflow. As shown in Figure 7, the average first-shot volumetric shrinkage ($Y_1$) was 4.682%, the average second-shot volumetric shrinkage ($Y_2$) was 5.031%, and the total warpage ($Y_3$) was 0.8476 mm.

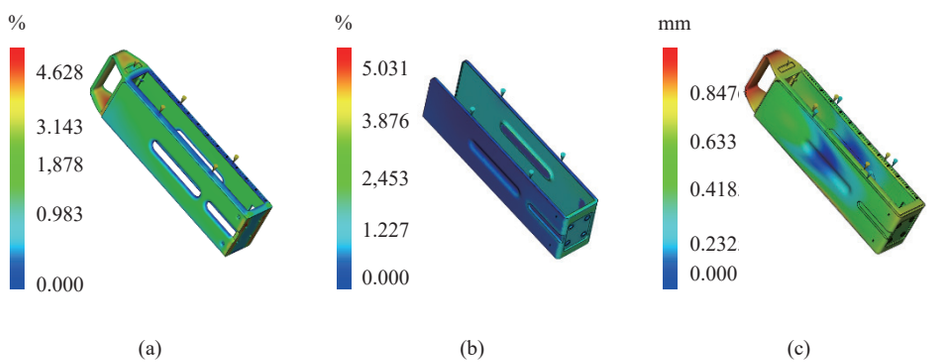



**Figure 7. Simulation results for the optimized parameter combination: (a) average first-shot volumetric shrinkage; (b) average second-shot volumetric shrinkage; and (c) total warpage.**

Weighted aggregation of the three simulated quality characteristics yielded a comprehensive quality index of 1.0514. The original manuscript reports a relative error of 1.44% between this value and the predicted index of 1.1129, indicating good model agreement. The analysis also showed that both shots exhibited relatively good flow during filling and that the weld-line strength was satisfactory, supporting the overall strength and appearance of the product. The reported two-color injection molding process time was 3.37 s, contributing to production efficiency. No flash was observed, and the results met practical production requirements.

## 5.3 Production Verification

An HT-250ton rotary-table multicolor injection molding machine was used for production verification. The optimal process parameter combination obtained using standard PSO was entered into the machine, producing a two-color medical test box with good surface quality, as shown in Figure 8. This result indicates that standard PSO can effectively optimize process parameters for two-color injection molding.



**Figure 8. Manufactured two-color medical test box.**

# 6. Conclusions

(1) A response surface model was established to provide the basis for parameter optimization using standard PSO. The

entropy weight method and TOPSIS were combined to aggregate three product quality characteristics—first-shot volumetric shrinkage, second-shot volumetric shrinkage, and total warpage—into a comprehensive quality index. Range analysis and analysis of variance were used to select four key process parameters from eight candidates. A response surface model relating the comprehensive quality index to the key parameters was then established and its adequacy was assessed.

(2) Standard PSO was used to optimize the process parameters of a two-color medical test box. The optimal key parameters were a first-shot melt temperature of 242°C, second-shot melt temperature of 260°C, first-shot holding pressure of 55 MPa, and second-shot holding pressure of 95 MPa. The predicted comprehensive quality index was 1.1129. The original manuscript reports an improvement of 16.322% over the preliminary optimization result of 0.8943 and states that first-shot volumetric shrinkage, second-shot volumetric shrinkage, and total warpage were improved. Production verification yielded a medical two-color injection-molded box with good quality, indicating that standard PSO can effectively optimize two-color injection molding parameters.

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