

Research Article

Study on Automotive Back Door Panel Injection Molding Process Simulation and Process Parameter Optimization

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A plastic back door car panel was considered as the research object. In order to obtain optimal injection molding simulation parameters, Moldflow2018 is used to simulate injection molding process of plastic back door car panel. Orthogonal experiment is conducted to analyze the influence of injection process parameters on the evaluation index. Melt temperature, mold temperature, cooling time, packing pressure, and packing time are selected as process parameters. Warpage and volumetric shrinkage are taken as evaluation indicators. Test groups are designed to obtain data, and range analysis method is employed to analyze warpage and volumetric shrinkage. Warpage range analysis shows that optimal warpage is 9.3 mm for volumetric shrinkage rate of 14.3%. Range analysis of volumetric shrinkage rate indicates that the best warpage is 8.3 mm for the corresponding volumetric shrinkage rate of 15.05%. A comprehensive evaluation index is established using the gray relational analysis. This analysis shows that warpage is 8.3 mm and volumetric shrinkage rate is 14.2%. Taguchi method is employed to obtain signal-to-noise ratio, while range and variance methods are used for the analysis. Optimal warpage is obtained as 8.2 mm, while the volume shrinkage rate is 10.3%. For a single evaluation index warpage, least squares method and artificial fish swarm algorithm are used to find the optimal parameter combination. Moldflow2018 is employed for simulation verification, and minimum warpage is obtained as 6.405 mm.

1. Introduction

Due to an increase in demand of plastic products, injection molds have been rapidly developing. A relatively large number of plastic products are used in automobile industry. As the requirements for lightweight and low energy consumption of automobile are getting higher, steel parts are more frequently being replaced with plastic ones. In recent years, many scientific researchers have employed CAE technology for simulation of injection molding processes in automotive industry. BP neural network was used by Kejian et al. [1] to establish the relationship between process parameters and warpage. The authors reduced warpage via genetic algorithm optimization. In order to reduce warpage, Yan et al. [2] predicted deformation trends of plastic parts through Moldflow and corrected the molding parameters related to plastic parts. Li et al. [3] observed that the amount of stable warpage deformation was proportional to the volume shrinkage. Furthermore, the authors concluded that

unstable warpage was caused by the bending of the product itself. The aforementioned researchers used algorithms to optimize the relationship between parameters and warpage. In addition, the authors modified relevant parameters of injection molding to reduce warpage, where they demonstrated the relationship between warpage and volume shrinkage. In addition, the authors pointed out main causes of warpage. However, there is no detailed study on correlation optimization between volume shrinkage and warpage. Doerffel et al. [4] studied deformation of injection molded parts and validated the quality of plastic parts based on laminated sheet parts. Through experimental investigations, the authors found that crystalline conformable materials were prone to large warpage and shrinkage during the injection molding process. Huszar et al. [5] minimized the warpage by selecting the optimal injection material and gate positions. The authors found that PP and PS materials produced the largest and smallest warpings, respectively, while the warpage of polypropylene was mainly determined

by the gate position and injection pressure. Shiroud et al. [6] employed simulation and variance analyses of important components of artificial skeletal joints to control optimal values of warpage and volume shrinkage at 0.287222 mm and 13.6613%, respectively. Sateesh et al. [7] considered the top cover of water meter as the research object. The authors used gray correlation analysis method to optimize injection molding parameters. The above-mentioned researchers analyzed various types of injection molding materials, pointed out the influence of different injection molding materials on warpage, and optimized the injection parameters using the gray correlation degree. However, for the selection of optimization methods, a combination of multiple optimization methods had not yet been employed. In this paper, vehicle plastic back door is taken as the research object. Injection molding simulation is performed, for which five injection molding process parameters are selected: melting temperature, mold temperature, pressure holding time, pressure holding pressure, and injection time. By taking warpage and volume shrinkage as evaluation indicators, process parameters that affect injection molding are studied based on the orthogonal test method. Furthermore, degree of influence of each parameter on evaluation indicators is obtained by employing different analysis methods. Least two multiplication and artificial fish school algorithms are employed to optimize process parameters during injection molding process.

2. Process Simulation of Back Door Outer Panel Injection Molding

In this section, injection molding process is simulated. Next, influence of gate positioning and number on process parameters during the injection molding process is investigated based on Moldflow. Finally, the best gate position is determined.

2.1. Introduction to Injection Molding Process Theory

2.1.1. Filling Stage. This stage plays an important role in plastic parts molding. The following mathematical model is used to describe the process:

$$\eta = \frac{\eta_0}{1 + A(\eta_0\gamma)^{1-n}}, \quad (1)$$

$$\eta_0 = B \exp\left(\frac{T_0}{T} + \beta p\right),$$

where η_0 stands for zero shear viscosity, p stands for injection pressure, n stands for flow index, γ represents shear rate, and T denotes melting temperature.

2.1.2. Packaging Stage. Continuity equation is as follows:

$$\frac{\partial p}{\partial t} + \frac{\partial(\rho\mu)}{\partial x} + \frac{\partial(\rho v)}{\partial y} + \frac{\partial(\rho\omega)}{\partial z} = 0. \quad (2)$$

Equation of motion is as follows:

$$\frac{\partial P}{\partial x} - \frac{\partial}{\partial z} \left(\eta \frac{\partial x}{\partial z} \right) = 0. \quad (3)$$

Energy equation is as follows:

$$\rho C_p (T) \left(\frac{\partial T}{\partial t} + \mu \frac{\partial T}{\partial x} + v \frac{\partial T}{\partial y} \right) = \frac{\partial}{\partial z} \left[K(T) \frac{\partial T}{\partial z} \right] + \eta \gamma^2. \quad (4)$$

2.1.3. Cooling Phase. Simplified conduction equation of temperature field is as follows:

$$\rho c_p \left(\frac{\partial T_p}{\partial t} \right) = \frac{\partial}{\partial z} \left(K_p \frac{\partial T_p}{\partial z} \right), \quad (5)$$

where T_p stands for plastic parts temperature, T stands for time, K_p denotes thermal conductivity, ρ represents plastic parts density, and C_p denotes equivalent specific heat capacity.

2.2. Mesh Division of the Outer Panel of the Back Door. CATIA is employed to design the outer panel structure of the plastic back door, as shown in Figure 1. The part is imported into Moldflow for mesh division. Mesh side length is set to 5 mm [8], mesh type is set to double-layer, mesh division is shown in Figure 2, and mesh division results are shown in Table 1.

According to Table 1, the matching percentage of grid analysis is equal to 97.1%, which is suitable for a double-layer analysis. However, maximum aspect ratio of the grid is 11.57. Thus, maximum aspect ratio has to be reduced to approximately 6 through grid repair [9]. Analysis results following the reparation are shown in Table 2.

According to the results from Table 2, maximum aspect ratio is now equal to 6.59, while the grid matching percentage is 97.2%. Thus, the repaired grid meets the requirements and analysis can be continued.

2.3. Selection of Injection Materials. PP-LGF-30 is selected as the material of the inner panel and PP-EPDM-T30 is selected as the material of the outer panel. Some basic material parameters are shown in Table 3 [10].

2.4. Selection of Gate Location. The outer panel of the plastic rear door is a large car cover. Based on actual production experience, number of gates is set to four, six, and eight. Moldflow is used to simulate and analyze three gate positions, and the results are shown in Figure 3.

Main process parameters during injection molding are the clamping force, filling time, flow front temperature, air pockets, and welding line. The effect of these parameters is investigated in the following sections.

2.4.1. Clamping Force. Clamping force must be greater than the thrust generated by the melt flow. Moldflow is used to analyze the clamping force, and the results are shown in Figure 4. It can be observed that maximum clamping forces

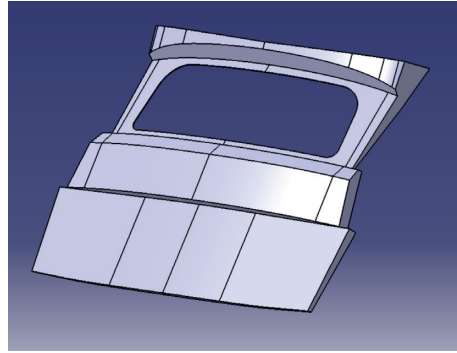


FIGURE 1: 3D parts design.

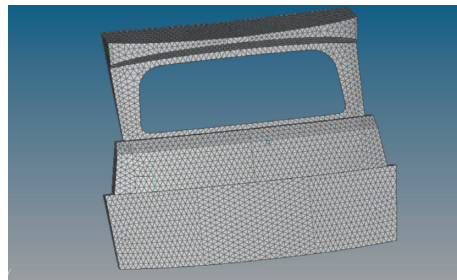


FIGURE 2: Meshing diagram.

TABLE 1: Meshing results.

Number of free edges	Number of multiple sides	Incorrectly aligned unit	Intersecting and fully overlapping cells	Grid matching percentage (%)	Average aspect ratio	Maximum aspect ratio
0	0	0	0	97.1	1.64	11.57

TABLE 2: Result of mesh repair.

Number of free edges	Number of multiple sides	Incorrectly aligned unit	Intersecting and fully overlapping cells	Grid matching percentage (%)	Average aspect ratio	Maximum aspect ratio
0	0	0	0	97.2	1.62	6.59

TABLE 3: Basic properties of two modified PP.

Material	Elastic modulus (MPa)	Poisson's ratio	Shear modulus (MPa)	Maximum shear stress (MPa)	Density (g/cm ³)
PP-LGF-30	6502.3	0.387	1482.5	0.25	1.1443
PP-EPDM-T30	2005.3	0.365	660	0.25	1.0314

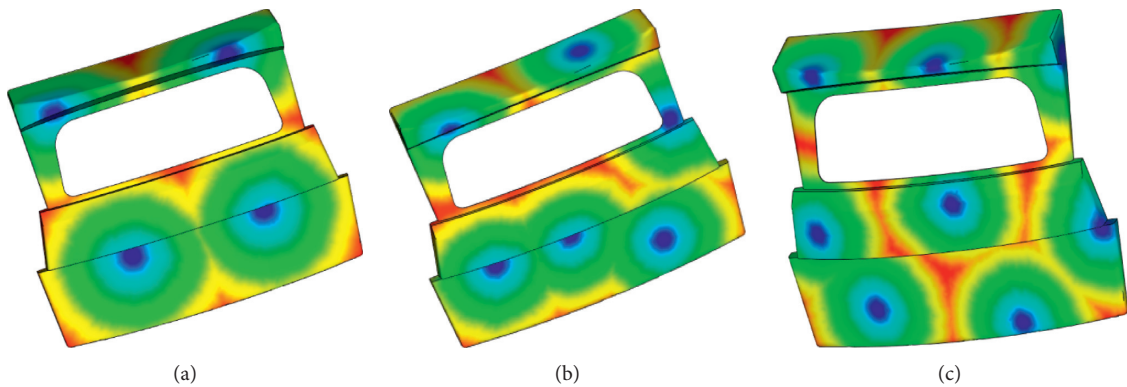


FIGURE 3: Gate location with (a) four gates, (b) six gates, and (c) eight gates.

of three gate positions are 969.7 t, 1167.9 t, and 1159.8 t, respectively. It is found that clamping forces between three gates demonstrate negligible differences.

2.4.2. Filling Time. Filling time is an important key result. Filling times of three different gate solutions are shown in Figure 5. It can be observed that the filling times of four-gate and six-gate schemes are approximately the same, while the filling time of the eight-gate scheme is longer.

2.4.3. Flow Front Temperature. Flow front temperature differences should not be significant, with generally allowable difference being less than 20°C. Analysis result is shown in Figure 6. Temperature differences of three gate scheme models are 9.3°C, 10.7°C, and 12.2°C, respectively. Moreover, all temperatures meet the difference requirement. Lastly, it should be noted that the leading edge temperature should be as high as possible within a reasonable range.

2.4.4. Welding Line. Weld marks directly affect the surface quality of plastic parts. Therefore, they should be reduced when possible. Analysis results are shown in Figure 7. It can be seen that the number of weld lines is increased with the number of gates.

In Table 4, results of the above conducted analysis are shown.

It can be seen from Table 4 that six gates are selected.

3. Optimization of Process Parameters Based on the Orthogonal Experiment

The influence of each process parameter on evaluation index is analyzed via orthogonal experiment.

3.1. Introduction to Orthogonal Experiment. Orthogonal test is an experimental method that studies the influence of multiple factors and multiple levels on experimental results [11]. When designing an orthogonal experiment, it is necessary to first determine objectives of the experimental research. Then, experimental measurement indicators are formulated according to objectives of the experimental research. Lastly, influencing factors of the experiment are selected. The general design is as follows:

(1) Selection of evaluation indicators

First step of the orthogonal test is to reasonably select evaluation indicators according to the actual situation

(2) Selection of test influence factors and determination of influence factors test levels

In the orthogonal experiment, letters A, B, C, D, and E are used to represent influencing factors of the experiment. Generally, the number of influencing factors is 3-6, and

numerical difference between each level should be determined according to the calculation and difference of field conditions. Moreover, numerical difference should conform to a certain interval range.

3.2. Orthogonal Design. Basic steps of orthogonal test are as follows:

- (1) Determining the value range of each process parameter
- (2) Obtaining a reasonable evaluation index for adequate orthogonal test table design
- (3) Simulation of combined process parameters via CAE software

3.2.1. Influencing Factors and Evaluation Options. Based on actual production experience, five factors are selected: melting temperature, mold temperature, cooling time, packing pressure, and packing time. Two evaluation indicators of product warpage and volume shrinkage are selected. Based on actual process parameter values, the level of each factor should be selected according to Table 5.

Selected level value of each influencing factor is placed into the orthogonal table. The system automatically generates 16 sets of process parameter combinations. Moldflow is used to simulate 16 sets of process parameter combinations and evaluate each set of tests. Index results are shown in Table 6.

3.2.2. Orthogonal Test Table Data Analysis. (1) Analysis of warpage results: Range analysis method is used to analyze test data of a single warpage. The analysis results are shown in Table 7 and Figure 8.

Based on the presented results in Table 7 and Figure 8, degree of influence of various factors on warpage can be ordered as follows: packing pressure > packing time > melting temperature > mold temperature > cooling time. Through warpage range analysis, a better combination of process parameters A4B1C3D4E1 can be obtained. After analyzing and verifying combination of process parameters, the final result is shown in Figure 9. The warpage is 9.3 mm, while the volume shrinkage rate is 14.3%.

(2) Volume shrinkage result analysis: Range analysis method is also used to perform range analysis on a single volume shrinkage rate, as shown in Table 8.

According to data presented in Table 8 and Figure 10, degree of influence of various factors on volume shrinkage rate can be ordered as follows: melting temperature > mold temperature > cooling time > packing pressure > packing time. Favorable process parameter combination A1B1C4D4E4 can also be obtained via volume shrinkage range analysis. The group is verified, and final results are shown in Figure 11. The warpage is 8.38 mm, and the volume shrinkage rate is 15.05%.

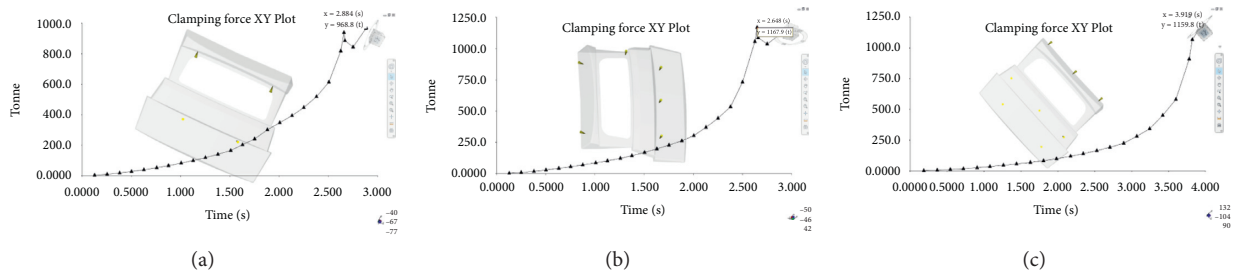


FIGURE 4: Clamping force with (a) four gates, (b) six gates, and (c) eight gates.

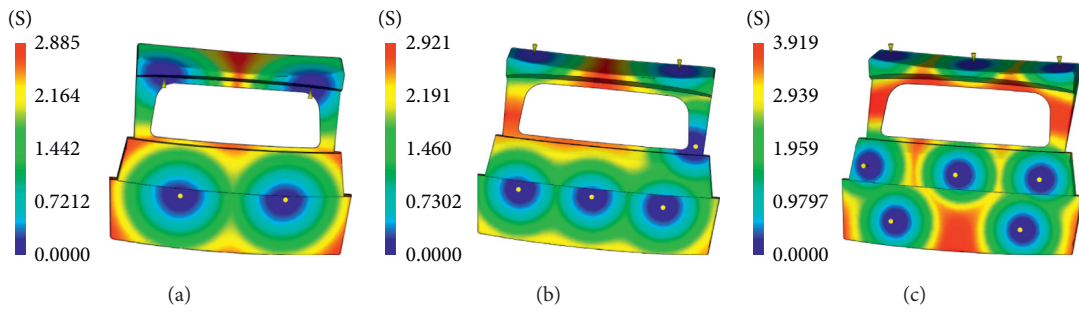


FIGURE 5: Filling time with (a) four gates, (b) six gates, and (c) eight gates.

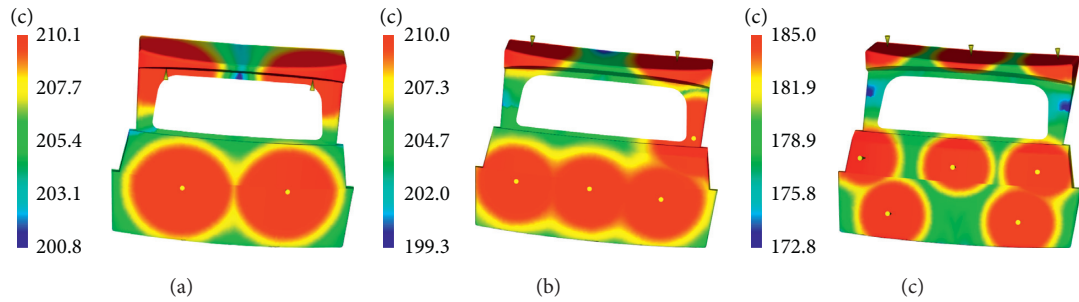


FIGURE 6: Flow front temperature with (a) four gates, (b) six gates, and (c) eight gates.

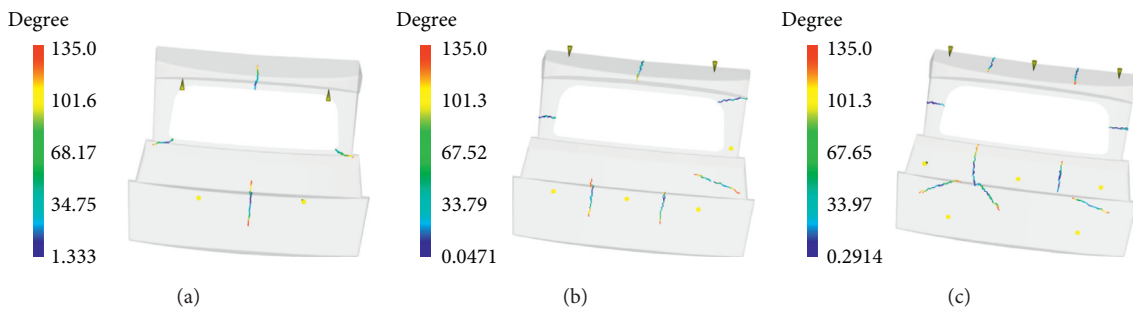


FIGURE 7: Welding line with (a) four gates, (b) six gates, and (c) eight gates.

TABLE 4: Analysis results of three different gate schemes.

The number of gates	Clamping force (t)	Filling time (s)	The difference of temperature (°C)	The number of welding lines
4	969.7	2.885	9.3	4
6	1167.9	2.921	10.7	6
8	1159.8	3.919	12.2	8

TABLE 5: Level factor settings.

Level	Factor				
	A Mold temperature (°C)	B Melt temperature (°C)	C Cooling time (s)	D Packing pressure (MPa)	E Packing time (s)
1	40	185	20	65	15
2	50	200	25	75	20
3	60	215	30	85	25
4	70	230	35	95	30

TABLE 6: Tests and results.

Numbering	Factors					Index	
	A	B	C	D	E	Warpage (mm)	Volumetric shrinkage (%)
1	40	185	20	65	15	10.35	14.26
2	40	200	25	75	20	10.35	15.05
3	40	215	30	85	25	11.35	14.86
4	40	230	35	95	30	10.59	12.35
5	50	185	25	85	30	10.33	14.29
6	50	200	30	95	25	9.10	15.05
7	50	215	35	65	20	11.44	15.85
8	50	220	20	75	15	10.27	16.64
9	60	185	30	95	20	7.84	14.24
10	60	200	35	85	15	8.27	15.05
11	60	215	20	75	30	12.01	15.85
12	60	230	25	65	25	13.52	16.63
13	70	185	35	75	25	8.84	14.24
14	70	200	20	65	30	11.41	15.05
15	70	215	25	95	15	8.61	15.86
16	70	230	30	85	20	1.91	16.63

TABLE 7: Warpage range analysis (mm).

Level	A	B	C	D	E
Mean value 1	10.66	9.34	11.01	11.68	8.826
Mean value 2	10.29	9.79	10.15	10.37	11.04
Mean value 3	10.41	10.30	9.67	10.09	10.71
Mean value 4	9.26	11.19	9.79	8.487	11.09
Range analysis	1.4	1.85	1.344	3.2	2.264

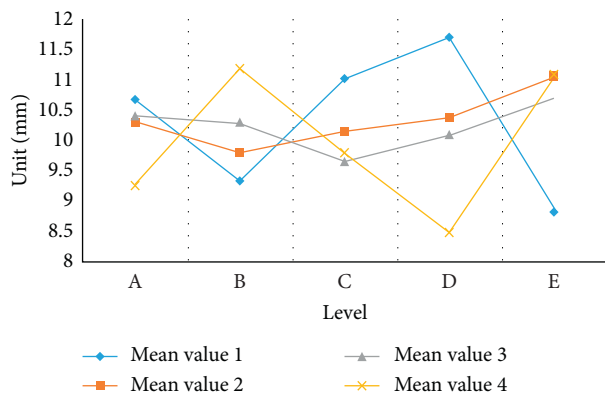


FIGURE 8: Warpage mean analysis.

4. Parameter Optimization Based on Gray Correlation Degree and Taguchi Algorithm

The further optimization of influence of process parameters on evaluation index via dual-index analysis of gray correlation degree and Taguchi algorithm based on SNR (signal-to-noise ratio) is conducted.

4.1. Dual-Index Analysis Based on Gray Correlation. Orthogonal experiment is employed to analyze single warpage or volume shrinkage rate. It is impossible to determine whether there is an inherent connection between two evaluation indicators due to changes in process parameters. Therefore, the concept of gray correlation is introduced. Moreover, gray correlation integration and in-depth analysis are conducted [12].

4.1.1. Gray Correlation Theory. Calculation of gray relation theory is as follows:

- (1) Initial value sequence is determined through nondimensionalization:

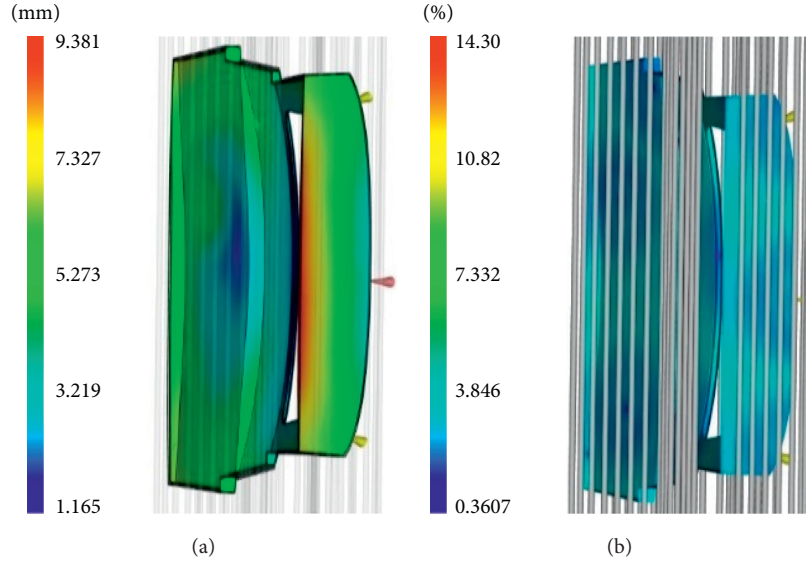


FIGURE 9: A4B1C3D4E1 combined simulation results with (a) warpage and (b) volume shrinkage.

TABLE 8: Range analysis of volume shrinkage (%).

Level	A	B	C	D	E
Mean value 1	14.13	14.26	15.45	15.45	15.45
Mean value 2	15.45	15.05	15.46	15.44	15.44
Mean value 3	15.44	15.61	15.20	15.21	15.20
Mean value 4	15.45	15.56	14.37	14.37	14.39
Range analysis	1.32	1.35	1.09	1.08	1.06

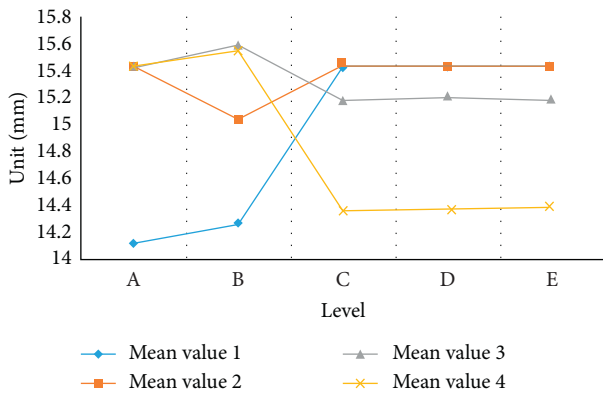


FIGURE 10: Mean analysis of volume shrinkage.

$$y_i = x_i D = (y_i(1), y_i(2), y_i(3) \dots y_i(n)), \quad (6)$$

$$i = 0, 1, 2, 3 \dots m.$$

(2) Sequence difference is obtained:

$$\Delta_{0,i}(k) = |y_0(k) - y_i(k)|, \quad (7)$$

$$i = 1, 2, 3 \dots m; \quad k = 1, 2 \dots n.$$

(3) Range value between indicators is found:

$$M = \max_i \max_k \Delta_{0i}(k), m = \min_i \min_k \Delta_{0i}(k). \quad (8)$$

(4) Correlation coefficient is obtained:

$$r_{0i}(k) = \frac{m + \rho M}{\Delta_i(k) + \rho M}, \quad (9)$$

where ρ represents resolution coefficient, $i = 1, 2, \dots, m$, $k = 1, 2, \dots, n$, and $\rho \in [0, 1]$, $\rho = 0.5$.

(5) Gray correlation degree between indicators is calculated:

$$r(x_0, x_i) = \frac{1}{n} \sum_{k=1}^n r_{0i}(k); \quad (i = 1, 2, 3 \dots m). \quad (10)$$

Actual experimental data and equations (6)–(10) are combined, and correlation coefficient between two indicators is calculated.

4.1.2. Gray Correlation Calculation. A series of numerical values, such as the range of gray correlation degree and correlation coefficient, are calculated. Gray correlation degree for two different evaluation indicators is calculated according to equation (10). Results are shown in Table 9. Range analysis method is used to postprocess gray correlation data, and the results are shown in Table 10. Two evaluation indicators are integrated via gray correlation degree. Therefore, a set of improved combination parameters can be obtained by employing gray correlation degree range analysis results. Improved combination parameters are denoted as A1B1C4D4E1. Simulation analysis results of parameter combination are

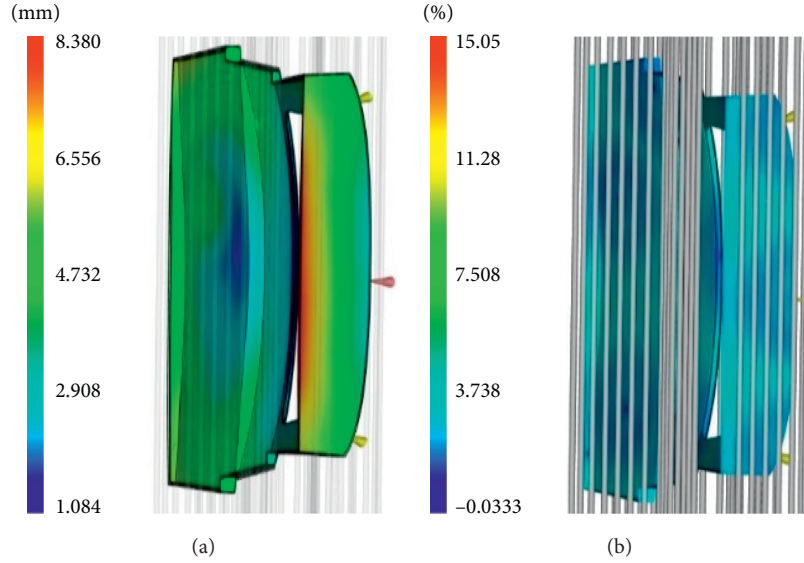


FIGURE 11: A1B1C4D4E4 combined simulation results with (a) warpage and (b) volume shrinkage.

TABLE 9: Gray correlation results.

Numbering	Correlation	Numbering	Correlation
1	0.51	9	0.62
2	0.46	10	0.55
3	0.44	11	0.39
4	0.73	12	0.34
5	0.51	13	0.57
6	0.51	14	0.43
7	0.40	15	0.69
8	0.41	16	0.41

TABLE 10: Gray correlation range analysis.

Level	A	B	C	D	E
Mean value 1	0.54	0.55	0.44	0.42	0.54
Mean value 2	0.46	0.49	0.5	0.46	0.47
Mean value 3	0.48	0.48	0.5	0.48	0.47
Mean value 4	0.53	0.47	0.57	0.64	0.52
Range analysis	0.08	0.08	0.13	0.22	0.07

shown in Figure 12. Warpage is equal to 8.37 mm, while the volume shrinkage rate is 14.26%.

4.2. Taguchi Algorithm Data Processing Based on SNR. Contrary to the orthogonal experiment method, Taguchi algorithm introduces the concept of SNR on the basis of orthogonal experiment. In Taguchi algorithm, the index for measuring test results is no longer warpage or volume shrinkage rate. Instead, SNR is employed [13].

4.2.1. SNR Calculation. For the injection molding process considered in this paper, numerical evaluation index should be as small as possible but within a reasonable range. In other words, the smaller the chosen index, the better the SNR

calculation. SNR is calculated according to the following equation:

$$\eta = -10 \log_{10} \left(\frac{1}{n} \sum_{j=1}^n S_j^2 \right). \quad (11)$$

Minimum characteristic warpage value is set to Y_1 and SNR to η_1 . Minimum volume shrinkage characteristic value is set to Y_2 with the corresponding SNR value of η_2 . The overall SNR is obtained as

$$\eta = 0.5\eta_1 + 0.5\eta_2. \quad (12)$$

Equations (11) and (12) are used to calculate SNR, and the results are shown in Table 11.

4.2.2. Analysis of SNR Calculation Results

(1) SNR sum and its average are found:

$$N = \sum_{j=1}^{16} \eta_j. \quad (13)$$

Data in Table 11 is substituted into equation (13):

$$\begin{aligned} N = \sum_{j=1}^{16} \eta_j &= -(21.6906 + 21.8109 + \dots + 21.9005 + 21.9329) \\ &= -349.6783. \end{aligned} \quad (14)$$

SNR sum is equal to -349.6783 , and the mean value is equal to -21.8549 .

(2) Mean value and range of each SNR factor are calculated.

According to Table 11, SNR mean value and range corresponding to each process parameter are calculated, and the results are shown in Table 12.

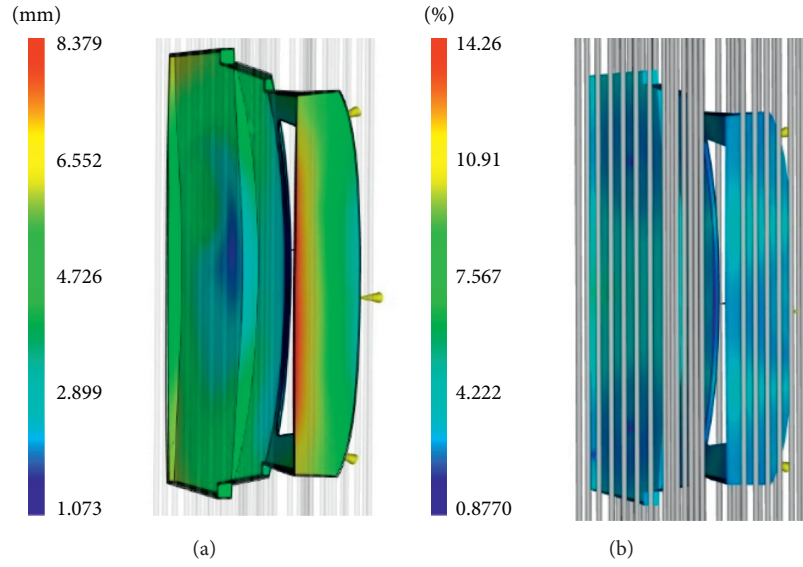


FIGURE 12: A1B1C4D4E1 combined simulation results with (a) warpage and (b) volume shrinkage.

TABLE 11: SNR calculation results.

Numbering	SNR η_1	SNR η_2	SNR η
1	-20.2988	-23.0824	-21.6906
2	-20.2988	-23.3229	-21.8109
3	-20.5826	-23.3624	-21.9725
4	-20.5616	-23.0276	-21.7946
5	-20.5071	-23.0423	-21.7747
6	-20.3133	-23.1313	-21.7223
7	-20.4463	-23.2666	-21.8565
8	-20.4200	-23.4292	-21.9246
9	-20.2016	-23.3907	-21.7962
10	-20.0489	-23.4070	-21.7280
11	-20.2140	-23.4644	-21.8392
12	-20.4739	-23.5524	-21.0132
13	-20.3732	-23.5171	-21.9425
14	-20.4332	-23.5196	-21.9764
15	-20.2472	-23.5537	-21.9005
16	-20.2526	-23.6131	-21.9329

Sum of SNR squared total fluctuations can be obtained as

$$S_N = \sum_{j=1}^{16} (N_j - \bar{N})^2 = 0.15. \quad (15)$$

SNR sum of squared fluctuations of each influencing factor is calculated as

$$S_i = \frac{1}{4} (N_1^2 + N_2^2 + N_3^2 + N_4^2) - \frac{1}{16} N^2. \quad (16)$$

According to Table 12 and the above data, equation (16) is employed for calculation:

$$S_1 = 0.0393; S_2 = 0.0403; S_3 = 0.0039; S_4 = 0.0166; S_5 = 0.0218.$$

(3) Variance analysis

In variance calculation, degree of freedom f has to be first determined. Degree of freedom f is the number of influencing factors lowered by one. Variance V is equal to the square sum of S_i /degree of freedom f of each influencing factor SNR fluctuation. Parameter F is equal to variance error of the influencing factor. When the error variance does not exist, value with the smallest SNR fluctuation square and influencing factor S_i can be selected as the error variance for calculation (e.g., factor C), and the variance can be calculated based on the above data. Volatility sum of squares, degrees of freedom, variance, and F value are all calculated, and the results are shown in Table 13.

According to Table 13, influence of A and B on quality fluctuation characteristics can be observed. Therefore, the two can be regarded as stable factors. Factors C, D, and E,

TABLE 12: SNR range analysis.

Level	A	B	C	D	E
Mean value 1	-21.8172	-21.8017	-21.8577	-21.8842	-21.8109
Mean value 1	-21.8195	-21.8094	-21.8748	-21.8800	-21.8491
Mean value 1	-21.8442	-21.8922	-21.8560	-21.8520	-21.9133
Mean value 1	-21.9388	-21.9163	-21.8311	-21.8034	-21.8426
Range analysis	0.1216	0.0304	0.0438	0.0808	0.1024

TABLE 13: Variance data analysis.

Level	Fluctuation square sum S	Degree of freedom f	Variance V	Value F
Factor A	0.0393	3	0.0131	10.1
Factor B	0.0403	3	0.0134	10.1
Factor C	0.0039	3		
Factor D	0.0166	3	0.0055	4.2
Factor E	0.0218	3	0.0073	5.6

TABLE 14: Warpage SNR analysis of factors C, D, and E.

Numbering	Cooling time	Packing pressure	Packing time
1	-81.366	-81.6522	-81.0149
2	-81.527	-81.306	-81.1993
3	-81.3501	-81.3912	-81.743
4	-81.43	-81.3237	-81.7159

are set as adjustable factors. For stable factors A and B, corresponding levels are A1 and B1, respectively. Factors A and B are kept constant, while the warpage SNR of factors C, D, and E is analyzed. Analysis results are shown in Table 14.

In Table 14, only influence of factors C, D, and E on warpage is analyzed. Furthermore, the best combination of process parameters is selected as C3D4E1. Combination of this set of process parameters is simulated, and the results are shown in Figure 13. The warpage is equal to 8.21 mm, and the volume shrinkage rate is equal to 10.3%.

4.3. Comprehensive Analysis. Warpage and volume shrinkage of the orthogonal experiment are analyzed via extreme difference. In addition, influence trend and degree of the injection molding process parameters on the evaluation index are obtained for two cases. Simultaneously, gray correlation analysis method and SNR Taguchi method are used to perform a simple optimization analysis on data obtained from the orthogonal experiment. Moreover, the influence trend and degree of the injection molding process parameters on the evaluation index are obtained for each case. Comprehensive analysis is shown in Table 15.

According to Table 15, the warpage is 8.2 mm and the volume shrinkage rate is 10.3% when Taguchi method is employed. Compared with previous analysis methods, improved process parameter combination is obtained by Taguchi method.

5. Parameter Optimization Based on Least Squares and Fish School Algorithm

In this section, least square method is employed to fit the obtained orthogonal test data for a single evaluation index warpage. Then, the fitted curve is optimized via fish school algorithm.

5.1. Least Squares Method. When each group of X and Y data is known, the fitting curve can be obtained using mathematical formulas or computer-aided methods [14].

5.2. Least Square Curve Fitting

5.2.1. Set Weight. When excessive amount of influencing factors is present in the process of injection molding parameter optimization, setting weights method is used to integrate five factors into one. Considering the actual situation during injection molding process, weight of each factor is set as follows:

$$\omega = (\omega_1, \omega_2, \omega_3, \omega_4, \omega_5) = (0.4, 0.3, 0.1, 0.1, 0.1). \quad (17)$$

5.2.2. Numerical Calculation. The weight value is used to weigh 16 sets of process parameter combinations. Parameter X in the least square method is obtained as the result, with its values being 81.5, 88, 90, 94, 94.5, 95, 96.5, 97, 97.5, 99.5, 100, 101, 101.5, 104.5, 106.5, and 110.5. Evaluation index in this chapter is the warpage. Thus, the Y value during least square

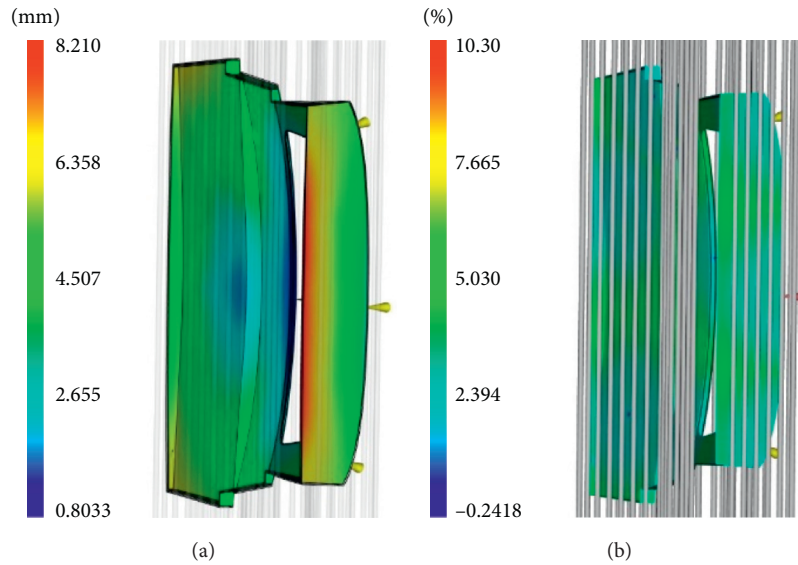


FIGURE 13: A1B1C3D4E1 combined simulation results with (a) warpage and (b) volume shrinkage.

TABLE 15: Comprehensive analysis and comparison.

Influencing factors		Parameter combination	Warpage (mm)	Volume shrinkage (%)
Warpage analysis	Packing pressure > packing time > melt temperature > mold temperature > cooling time	A1B1C3D4E1	9.3	14.3
Volume shrinkage analysis	Melt temperature > mold temperature > packing pressure > cooling time > packing time	A1B1C4D4E4	8.38	15.05
Gray relational analysis	Melt temperature > packing pressure > packing time > mold temperature > cooling time	A1B1C4D4E1	8.37	14.26
Taguchi method analysis	Melt temperature > mold temperature > packing time > packing pressure > cooling time	A1B1C3D4E1	8.21	10.3

fitting is the value of 16 warpage groups in the orthogonal test table. These values can be obtained by referring to Table 6.

5.2.3. *Curve Fitting.* In order to increase the accuracy of curve fitting, weighted data is imported into MATLAB and discrete points are connected. In Figure 14, data distribution obtained after using automatic import via

MATLAB software is shown. Then, the software is used to simulate the curve of this discrete data set. After multiple attempts and optimizations, the final fitted curve is shown in Figure 15.

According to Figures 15 and 16, sets of imported data sets are distributed on the fitted curve. Analytical equation with various corresponding parameter values fitted by the software is as follows:

General model *sin 4*:

$$F(x) = a1 * \sin(b1 * x + c1) + a2 * \sin(b2 * x + c2) + a1 * \sin(b2 * x + c2) + a3 * \sin(b3 * x + c) + a4 * \sin(b4 * x + c4)$$

其中:

$$\begin{aligned} a1 &= 11.41; b1 = 0.0006434; c1 = 7.279 \\ a2 &= 1.414; b2 = 0.3507; c2 = -11.73 \\ a3 &= 2.096; b3 = 0.8195; c3 = -18.83 \\ a4 &= 3.388; b4 = 1.646; c4 = -12.89. \end{aligned}$$

(18)

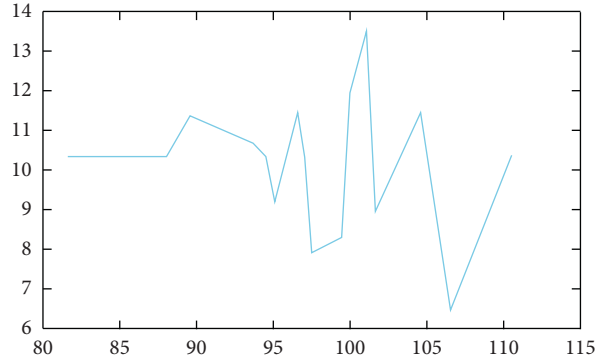


FIGURE 14: Data import.

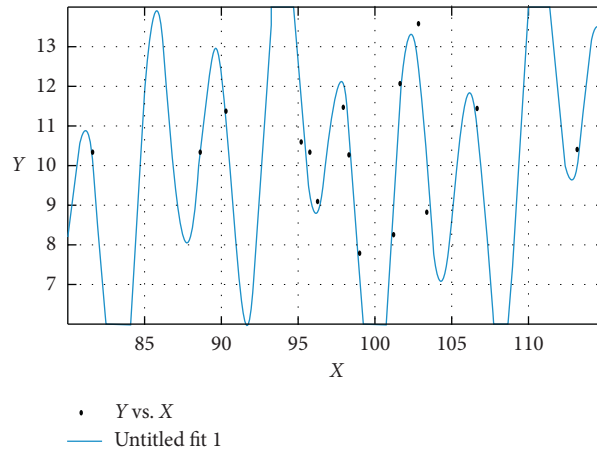


FIGURE 15: Curve fitting.

Least square method is employed for the above-presented data fitting. Next, the algorithm is used to optimize the analytical equation.

5.3. Optimization of Injection Process Parameters Based on Fish School Algorithm. In water, the place with the highest fish density is considered the most food abundant place. Artificial fish are constructed based on fish characteristics to imitate the behavior of fish schools. Each fish corresponds to an optimized solution. Virtual water area corresponds to optimization problem solution space. Food concentration corresponds to the value of the objective function. Therefore, the best optimization is obtained by swimming in virtual waters with schools of fish [15, 16].

5.3.1. Introduction to Fish School Algorithm

- (1) Foraging behavior: the current state of the artificial fish is assumed as X_a , while X_b represents a randomly selected state within its field of view:

$$X_b = X_a + \text{Visual} \cdot \text{Rand}(). \quad (19)$$

If the food concentration is $Y_a > Y_b$, one step forward in that direction is equal to

$$X_a^{t+1} = X_a^t + \frac{X_b - X_a^t}{\|X_b - X_a^t\|} \text{Step} \cdot \text{Rand}(). \quad (20)$$

- (2) Grouping behavior: current artificial fish state is set to X_a , while the number of partners in its neighborhood is nf . If $nf/N < \delta$, the partner center has more food, and it is not overly crowded. Therefore, $Y_a > Y_c$ and the fish moves forward to the center position X_c :

$$X_a^{t+1} = X_a^t + \frac{X_c - X_a^t}{\|X_c - X_a^t\|} \text{Step} \text{Rand}(). \quad (21)$$

- (3) Tail-catch behavior: current state of the artificial fish is X_i , while the best neighbor is X_{MAX} . If $Y_a > Y_{\text{MAX}}$, number of partners in the neighborhood of X_{MAX} is nf , and $nf/N < \delta$ criteria are met. If it is indicated that more food exists in X_{MAX} and it is not too crowded, one step towards X_{MAX} is taken:

$$X_a^{t+1} = X_a^t + \frac{X_{\text{max}} - X_a^t}{\|X_{\text{max}} - X_a^t\|} \text{Step} \text{Rand}(). \quad (22)$$

If the aforementioned is not true, foraging behavior is performed.

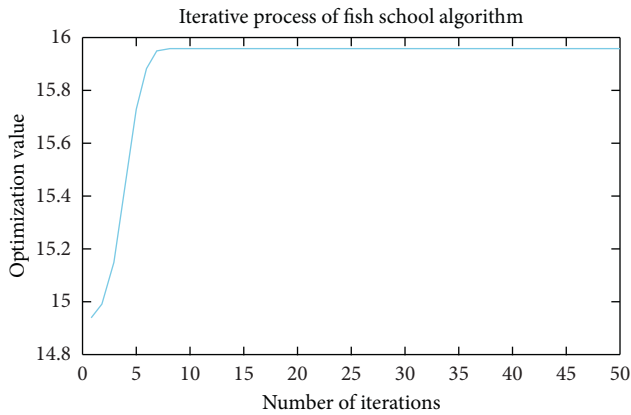


FIGURE 16: Number of iterations.

- (4) Random behavior: the essence of random behavior is a default behavior of foraging behavior:

$$X_a^{t+1} = X_a^t + \text{Visual Rand}(). \quad (23)$$

- (5) Bulletin board: optimal artificial fish state is recorded during the optimization process.

5.3.2. Fish School Algorithm Optimization Process

- (1) Mathematical model input

Mathematical model obtained after using curve fitting method is written into the artificial fish school algorithm.

- (2) Initialization setting

Before performing algorithm optimization, necessary parameter values in addition to analytical ones are determined.

In this paper, the number of artificial fish is set to 50 to ensure an adequate number of samples without increasing the complexity of the analysis. Maximum number of iterations is set to 50, while the maximum number of trials is set to 100. Perception distance is chosen as one, congestion factor is 0.618, and optimal step length is set to 0.1.

- (3) Analysis and calculation

Following the completion of initial settings, the algorithm is activated. The computer performs internal calculations according to predetermined parameters to solve the fitness value of the individual fish school. The best artificial fish state is selected by mutual comparison and assigned to the bulletin board.

- (4) Behavior selection

Each individual is evaluated separately, and various above-described fish school behaviors are selected.

- (5) Iterative optimization

Iterative optimization is carried out. Algorithm evaluates all individuals. When the result of an individual is better than the result shown on the

bulletin board, this individual is used to replace the individual of the original bulletin board. This process is repeated in the form of iterative analysis. The iteration stops when the specified error range is reached.

5.3.3. *Fish School Algorithm Optimization Results of the Injection Process Parameters of the Automobile Back Door Outer Panel.* According to initial settings described in Section 5.3.2, parameters required for the algorithm execution process are input into the algorithm program. Then, the fish school algorithm program is imported into MATLAB for optimization analysis.

After debugging and inspections, the results are shown in Figures 16 and 17. Figure 17 shows that the optimization result has stabilized after 10 times.

The results are presented in Figure 17. It can be concluded that the optimal solution X obtained by the artificial fish school algorithm optimization is 92.88298, which is approximately equal to 93.

5.3.4. Analysis and Verification of Optimization Results.

In Section 5.3.3, fish school algorithm is used to optimize weighted parameters for process parameters that affect the warpage. Final optimal solution is 92.88298. A total of 16 data sets are analyzed and optimal process parameter combination weighted value is obtained as 93.

Five process parameters corresponding to the value of 89.5 are as follows: mold temperature of 50°C, melting temperature of 185°C, cooling time of 25 s, packing pressure of 85 MPa, and packing time of 30 s. Five process parameters corresponding to the value 94 are as follows: mold temperature of 60°C, melting temperature of 185°C, cooling time of 30 s, packing pressure of 95 MPa, and packing time of 20 s. Orthogonal experiment is used to simulate the process combination with the weighted value between 90 and 94. Thus, six other verification test sets are conducted via Moldflow simulation analysis. The obtained results are shown in Table 16.

The group with the smallest warpage is the fifth group, with the corresponding deformation amount of 6.405. Weighted combination of process parameters of this group is 93, which is basically in line with the prediction. Warpage amount is compared with previous orthogonal test results, gray correlation results, and Taguchi SNR results (comparison in Table 6). The fifth group demonstrates the least amount of deformation. It can be concluded that the best combination of process parameters is obtained for the verification test group in the fifth group. Simulation results are shown in Figure 18.

It can be concluded that the results obtained via artificial fish swarm algorithm for injection molding process parameters optimization are better than the results obtained by previous methods such as range analysis, gray correlation analysis, and Taguchi SNR analysis using orthogonal experiments. Process parameters were successfully optimized.

The final optimal combination of process parameters is as follows: mold temperature of 60°C, melting temperature

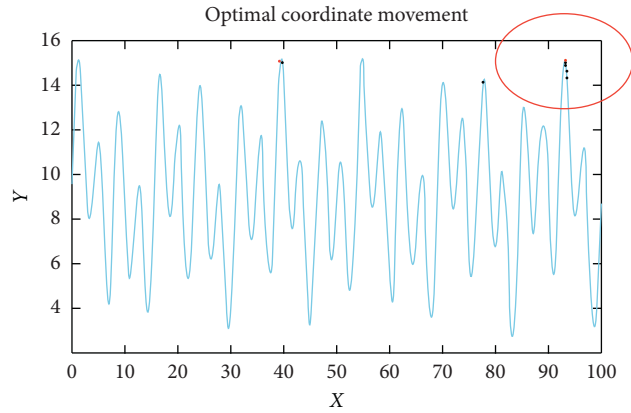


FIGURE 17: Optimal solution location.

TABLE 16: Verification test group.

Numbering	Factors					Index Warpage/mm
	A	B	C	D	E	
1	50	185	20	95	15	10.041
2	50	185	25	95	20	11.345
3	50	185	30	95	25	10.312
4	60	185	20	85	20	8.275
5	60	185	25	85	25	6.405
6	60	185	30	85	30	7.845

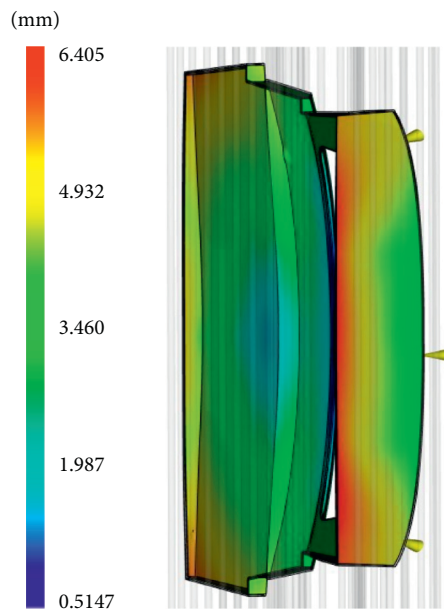


FIGURE 18: Warpage after optimization.

of 185°C, cooling time of 25 s, holding pressure of 85 MPa, and holding pressure time of 25 s. Corresponding deformation is obtained as 6.405 mm.

6. Conclusions

In this paper, outer panel of the plastic back door was considered as the research object. Moldflow2018 was used to

simulate the injection process of plastic back door outer panel. The orthogonal test method was used to study injection molding process parameters. Taguchi algorithm and manual are used. Fish school algorithm was used to optimize injection molding process parameters. The main research work and contributions of this paper can be summarized as follows:

- (1) Filling, packing, and cooling stages of back door outer panel injection molding process were

introduced. PP-EPDM-T30 was selected for the back door outer panel, and plastic parts were meshed using Moldflow and repair option. The best spur location was determined through injection molding process parameters analysis.

- (2) An orthogonal experiment was designed. Moldflow was used for simulation, while the effect of five test factors was considered: melting temperature, mold temperature, packing time, packing pressure, and injection time. Warpage and volume shrinkage rate were selected as evaluation indicators. Different analysis methods were used to obtain degree of influence of each test factor on the evaluation index. The results show that Taguchi method obtained better values, and the best combination of process parameters was A1B1C3D4E1: mold temperature of 40°C, melting temperature of 185°C, cooling time of 30 s, packing pressure of 95 MPa, and packing time of 15 s. The warpage was 8.2 mm, and the volume shrinkage rate was 10.3%.
- (3) Based on the orthogonal test data and warpage as the evaluation index, the mathematical model was found by the least square method. Furthermore, based on the established mathematical model, fish school algorithm was used to optimize process parameters that affect the warpage. The best combination of process parameters was as follows: mold temperature of 60°C, melting temperature of 185°C, cooling time of 25 s, packing pressure of 85 MPa, and packing time of 25 s. Minimum corresponding deformation was 6.405 mm. It is concluded that the best results are obtained after algorithm optimization.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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