Research Article

Research on the Injection Mold Design and Molding Process Parameter Optimization of a Car Door Inner Panel

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Received 24 April 2022; Revised 6 July 2022; Accepted 26 July 2022; Published 31 August 2022

Academic Editor: Achraf Ghorbal

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Numerical simulation of the injection molding of the inner panel of the car door and the optimization of its process parameters were completed. The inner panel and its injection mold were designed by UG software and simulated by the filling and cooling module of the Moldflow software. Different gate schemes were selected to compare quality indicators such as filling time, air pockets, and weld lines to obtain the optimal number of gates. We established the objective function model with gate position as the independent variable, and used a multi-population genetic algorithm to solve the optimal position of the function model to get the best gate position. The mold temperature, melt temperature, cooling time, holding pressure, and holding time were selected as the influencing factors, and volume shrinkage and warpage deformation were selected as the evaluation indicators to design and complete the orthogonal test. The test data were simulated by Moldflow, and the optimal combination of process parameters was determined by range and variance analysis. The BP neural network model related to the molding process parameters, volume shrinkage, and warpage deformation was built, and the trained network model was optimized with the ant colony algorithm. The optimal parameter combination was: mold temperature 76°C, melt temperature 205°C, cooling time 23.8s, holding pressure 54.7Mpa, and holding time 22.1s. The simulation results showed that volume shrinkage was 13.32% and warpage deformation was 4.315 mm. The design of an injection mold for the car door inner panel was completed and its molding process parameters were optimized.

1. Introduction

In the automobile manufacturing industry [1], replacing traditional steel components with plastic parts has become a significant trend. As an advanced processing method, injection molding production is widely used because of its advantages of short production cycle and high efficiency. However, there are also some quality defects in forming and manufacturing, such as volume shrinkage and warpage caused by uneven cooling, the insufficient flow of molten plastic leading to fusion marks, cavitation, and flying edges. These defects are mainly related to mold design, molding process parameter settings, material selection, and other factors. As a result, injection molding simulation is widely used in the production of automotive components.

Fan [2] proposed to build a BP neural network relationship between process parameters and warpage and optimize the BP neural network based on a genetic algorithm to reduce warpage deformation. Christoph et al. [3] investigated the deformation of injection-molded plastic parts, verified the quality of plastic parts based on laminated sheet-like parts, and found that crystalline conformal materials are prone to more significant warpage and shrinkage during the injection process. Marton Huszar et al. [4] reduced the deformation by selecting the optimal injection material and gate position; the research found that different injection materials produce different warpage, in which PP and PS produce the maximum and minimum deformation. Lu [5] pointed out that for the warpage deformation direction of injection-molded products, the magnitude of warpage deformation of stable warpage is proportional to volume shrinkage, and non-stable warpage is due to the bending of the product itself. Heidari Behzad shiroud et al. [6] reduced the values of warpage and contraction to 0.287222 mm and
Sateesh et al. [7] took the water meter top cover as the research object, optimized the injection molding parameters using the grey correlation analysis method, and obtained the optimal parameter combination. Saad [8] proposed an optimized injection molding process parameters under product defect constraints. They used MATLAB to build a function to solve the optimization problem and finally obtain the optimal combination of process parameters. Ramesh et al. [9] used matrix design and parameter group algorithms to investigate the variety combination of parameters for the automotive instrumentation injection molding process and verified this using processing experiments.

This study takes the car door inner panel as the research object; the inner panel and its injection mold are designed by UG software and simulated by the filling and cooling module of the Moldflow software. Different gate schemes are selected to compare the forming quality index and to obtain the optimal number of gates. We established the objective function model with gate position as the independent variable, and used a multi-population genetic algorithm to solve the optimal position of the function model to get the best gate position. The mold temperature, melt temperature, cooling time, holding pressure, and holding time are selected as the influencing factors, and volume shrinkage and warpage deformation are selected as the evaluation.
indicators to design and complete the orthogonal test. The test data are simulated by Moldflow, and the optimal combination of process parameters is determined by range and variance analysis. The BP neural network model related to the molding process parameters, volume shrinkage, and warpage deformation is built, and the ant colony algorithm is used to optimize the optimal process parameters. The design of an injection mold for the car door inner panel is completed and its molding process parameters are optimized.

2. Structure and Mold Design of the Car Door Inner Plate

The structural design of the car door inner panel is closely linked to its structural strength and stiffness. At the beginning of the parts design, the choice of material needs to be verified, and its thickness needs to be calculated and verified. Once the structural design is complete, the corresponding injection mold design needs to be carried out according to the door structure.

2.1. Structural Design of the Car Door Inner Panel

Plastic parts commonly used in automobiles are mainly modified plastics. PP plastic is one of the most widely used plastics, a comprehensive performance thermoplastic. Its heat resistance and rigidity strength meet the requirement of plastic instead of steel [10]. This paper uses modified polypropylene as the injection plastic combined with the use requirements and strength check of the car door inner plate. The modified PP composite (PP-LGF-30) has the advantage of high material stiffness and impact strength [11]. It can be remelted for remanufacturing after scrapping without wasting resources, and the material properties remain good through remanufacturing [12].

The three-dimensional car door inner panel model is modeled, as shown in Figure 1. Its surface area is 49698

![Gating compatibility = 1.000](a)

![Gating compatibility = 1.000](b)

![Gating compatibility = 1.000](c)

**Figure 5:** Matching cloud diagram of gates. (a) Matching cloud diagram of single gate. (b) Matching cloud diagram of two gates. (c) Matching cloud diagram of four gates.
mm², the projected area is 462648 mm², and the thickness is usually taken as 1.5mm–3 mm. When using modified PP material as the molding material of the car door inner plate, it is necessary to ensure that the structural strength of the door inner plate is not lower than that of the original steel parts. Too thick plastic parts will lead to a waste of resources, and too thin plastic parts will reduce the strength of the door inner plate and affect the safety of the regular use of the car [11]. Therefore, the thickness of the door inner plate is 3 mm.

2.2. Design of Injection Mold for the Car Door Inner Panel.
The injection mold design is an essential link in the production process of car door inner plates. The molding process of the door inner plate is based on the mold design, and the design of the mold structure directly affects the quality of the plastic parts. The design rationality of the mold structure is closely related to the durability, service life, production, and processing mode of the mold itself and the molding process of plastic parts. The injection mold is mainly composed of a moving mold and a fixed mold. The screw rod of the injection molding machine pressurizes the molten plastic into the mold cavity and takes out the plastic parts after pressure maintenance and cooling, completing a product manufacturing process. The assembly drawing of the die for the car door inner panel is shown in Figure 2.

1- Support plate; 2- Moving die base plate; 3- Cooling system; 4- Fixed template; 5- Fixing bolt; 6- Cavity; 7- Gate sleeve; 8- Locating ring; 9- Fixed die base plate; 10- Guide post; 11- Push rod fixing plate; 12- Push plate; 13- Moving die base plate; 14- Reset rod; 15- Push rod.

As shown in Figures 3 and 4, combined with the structural characteristics of the car door inner plate, the parting surface is selected. The axial and radial dimensions of the design core are 788.06 mm and 954.04 mm, respectively, and the cavity is 793.37 mm and 962.89 mm, respectively. Through calculation, it is obtained that the core pulling distance of the injection mold for the car door inner plate is 190 mm, the inclination angle is 20°, the diameter is 20 mm, the length of the inclined guide column is 555 mm, and the minimum mold opening stroke is 522 mm.

3. Research on the Optimal Gate Scheme of Injection Mold for the Car Door Inner Plate
Uneven filling and shrinkage deformation of plastic parts often occur in the process of injection molding, resulting in
defective products and waste of resources. These problems are due to the unreasonable design of the mold filling system and cooling system.

3.1. Study on the Optimal Number of Gates. Before the mold flow analysis, the location of the gates and the number of gates need to be determined [13], and the position of the gate will also change with the number of gates. In this paper, 1, 2, and 4 gates are mainly selected. The matching cloud diagram of the three gating solutions is shown in Figure 5, where the closer to the red area, the worse the matching; the more immediate to the blue area, the better the matching [14].

The injection molding filling process is simulated and analyzed based on Moldflow software. The results are presented in a simulation cloud diagram, mainly including process parameters such as filling time, clamping force, cavitation, and welding lines.

3.1.1. Filling Time. Filling time is an essential key index for the simulation analysis of most injection-molded parts. The simulation cloud diagram of filling time of three gate schemes is shown in Figure 6.

Figure 6 shows that the filling time is 6.443s for a single gate, 4.930s for two gates, and 3.783s for four gates. The shortest filling time is achieved when the number of gates is 4.

3.1.2. Clamping Force. In the process of melt flow, it will produce external torque to the die. If the clamping force is small, it will lead to the separation of the concave-convex die [15]. Therefore, we need to set a larger clamping force than the torque generated by the melt. Moldflow is used to simulate and analyze the clamping force, and the results are shown in Figure 7.

As shown in Figure 7, the maximum clamping force of single gate is 808.2t, that of two gates is 563.3t, and that of four gates is 350.7t. The three clamping forces meet the maximum injection pressure of the selected injection molding machine.

3.1.3. Welding Line. There may be multiple gates in the injection molding process, which will produce welding lines, resulting in the reduction of the surface quality of plastic parts. It is essential to minimize the number of welding lines.
when designing the gates. Moldflow is used to analyze the welding lines. The results are shown in Figure 8.

As shown in Figure 8, when the number of gates increases, the number of welding lines also increases. The rise in welding lines may lead to the decline of the quality of plastic parts and affect structural stability. Therefore, we should try to reduce the number of welding lines.

3.1.4. Cavitation. During the filling process of the plastic part, the flow rate of the melt, the cooling time, and the structural differences of the plastic part lead to the creation of cavitation in certain specific locations of the plastic part, and the number and position of cavitation have a significant impact on the quality of plastic parts. Moldflow carries out the simulation analysis of cavitation, and the results are shown in Figure 9.

It can be seen from Figure 9 that different gate positions and quantities will lead to different cavitation, which will reduce the quality and structural stability of plastic parts and increase warpage deformation and shrinkage deformation of plastic parts. Therefore, we need to select the location and number of gates that produce less cavitation for injection molding [16].

The analysis results of different gate schemes are listed in Table 1 for comparative analysis to select the best gate number and location.

It can be seen from Table 1 that the filling time of single gate is the longest, and the clamping force is the largest, which will lead to excessive injection time and reduce production efficiency. The filling time and clamping force of the four gates are the smallest, but the excessive number of fusion lines and cavitation have a significant impact on the product quality. This paper selects the two-gate scheme for injection molding of the car door inner plate. The positions of the two gates are verified by filling flow simulation, and the positions are shown in Figure 10. The initial coordinates are selected in $N_1 (20968)$ and $N_2 (14276)$. 
3.2. Study on Optimal Gate Position. The two-gate scheme is initially selected for the injection molding simulation of the car door inner panel by comparing the results of the filling flow simulation with single, two, and four gates. Further, optimization of the position is carried out on the basis of the two-gate scheme.

The selection of different gate positions has a significant influence on the maximum pressure at the injection port, the temperature difference between the surface of the molded part, the overheating unit, and the overpressure unit during the filling process [17]. Therefore, the above four main influencing factors need to be weighted by coefficients to finally determine the objective function model of gate position, as shown in equation:

$$
\min F(X) = \alpha \cdot P_{in} + \beta \cdot N_{novp} + \gamma \cdot N_{fth} + \lambda \cdot T_d,
$$

$$
T_d \leq 20, X \in \Omega, \alpha + \beta + \gamma + \lambda = 1, X = [X_1, X_2, X_3, \ldots, X_i]^T,
$$

where $F(X)$—Objective function model; $X_i$—Coordinates of gate position; $\Omega$—Feasible area; $P_{in}$—Maximum inlet pressure, Mpa; $N_{novp}$—Percentage of overvoltage units; $N_{fth}$—Percentage of overheating unit; $T_d$—Temperature difference, K; $\alpha, \beta, \gamma, \lambda$—Weights for $P_{in}$, $N_{novp}$, $N_{fth}$, and $T_d$ respectively.

Figure 9: Cavitation of three gate location schemes. (a) Single gate. (b) Two gates. (c) Four gates.

Table 1: Analysis results of three different intersection schemes.

| Number of gates | Filling time/s | Clamping force/t | Welding line | Cavitation |
|-----------------|----------------|------------------|--------------|------------|
| 1               | 6.443          | 808.2            | 5            | 2          |
| 2               | 4.930          | 563.3            | 7            | 2          |
| 4               | 3.783          | 350.7            | 9            | 4          |

Figure 10: Initial gate location diagram of two gate schemes.
The function value of the gate position optimization function needs to be calculated based on the Moldflow filling analysis module. The coordinates of the mesh nodes and the values of the various parameters are obtained through Moldflow, and the optimum node position is then recalculated in conjunction with the optimization function. However, the above function model has too many constraints and needs to be simplified to facilitate solution. Therefore, the following theorem is introduced [18].

If $\Psi$ is a positive variable, $G = \{g_K(X), K = 1, 2 \ldots q\}$, and $j$ is the set, then:

$$E_{(G)} = \frac{1}{\Psi} \ln \sum_{K=1}^{q} \exp \left[\Psi \cdot g_K(X)\right].$$  

Equation 2 is called PCE function, which is a constraint function with parameters as variables. Combining Equations (1) (2) yields the constrained optimization function equation:

$$\begin{aligned}
\min F(X), \\
\sum_{K=1}^{q} \exp \left[\Psi \cdot g_K(X)\right] \leq 0.
\end{aligned}$$  

The exact penalty function transforms equation 3 into a sequential unconstrained optimization function equation:
the objective function are within a reasonable range. In equation 4, the tightness principle, such that all the constraints in the objective function based on the constraints in the objective function, and the unconstrained objective function is shown to be optimized is

\[
\min \varphi(X) = F(X) + \frac{\alpha}{\Psi} \ln \left(1 + \sum_{k=1}^{m} \exp \left[\Psi \cdot g_k(X)\right]\right).
\]

The exact penalty function method automatically adjusts the constraints in the objective function based on the tightness principle, such that all the constraints in the objective function are within a reasonable range. In equation 4, \(\alpha\) is the penalty factor, and the function solution is in the feasible area when \(\alpha\) takes the value \([10^3, 10^5]\).

For a multi-population genetic algorithm, the constraint function needs to be transformed into an unconstrained function, and the unconstrained objective function is shown in equation:

\[
\max G(X) = C - \varphi(X),
\]

where \(G(X)\) is the adaptation value function after unconstrained processing, and \(C\) is taken to be a large enough positive number to ensure that the value of \(G(X)\) is positive. Using the multi-objective coefficient weighting method combined with equation 5, the evolutionary model is constructed as equation:

\[
\begin{align*}
\min A &= -\sum_{j=1}^{M} P_j G(X), \\
\min B &= -\sum_{j=1}^{M} P_j \ln P_j, \\
s \cdot t \cdot \sum_{j=1}^{M} P_j &= 1; P_j \in [0, 1],
\end{align*}
\]

where \(G(X)\) is the transformed unconstrained fitness objective function, and \(P_j(1, 2, \ldots, M)\) is the probability that the optimal solution is in the \(j\)th population, in equation 6, \(A\) is the feasible area of the optimal solution, and \(B\) is the uncertain region of the optimal solution. Using equation 6, the probability that the optimal solution falls in population \(j\), \(P_j\), can be expressed as:

\[
P_j = \frac{\exp \left[r \cdot G_j(X)\right]}{\sum_{j=1}^{M} \exp \left[r \cdot G_j(X)\right]},
\]

where: \(r = \alpha - 1/\alpha\); \(\alpha\) is the weight coefficient, taken as 0.6; \(R_j\) is the spatial contraction factor for each cluster; and \(R_j = 1 - P_j\).

When the optimal solution of the objective function is in the \(j\)th population, \(P_j = 1, P_i = 0, i \neq j, \) and \(\sum_{j=1}^{M} P_j G(X) = G(X^*)\); when optimization begins, \(P_j = 1/m, j = 1, 2, \ldots, M,\) and \(M\) takes the maximum value; when the optimization is completed, the uncertainty of the optimal solution is reduced to zero, i.e., \(\min B = 0\); in summary, the solution \(X^*\) of equation 7 is the solution of the original objective function.

Let the space at the beginning be \(C_0(0)\), contraction factor be \(R_{p_j, j = 1, 2, \ldots, M,}\) and \(M\) be the number. The contraction space is shown in equation:

\[
G_j(K + 1) = R_j C_j(K).
\]

The upper and lower limits of the variables are shown in equation:

\[
\begin{align*}
D_{ij}(K + 1) &= \max \left\{ \left[ X_{ij}(K) - \frac{C_j(K + 1)}{2} \right], D_{ij}(0) \right\}, \\
D_{ij}(K + 1) &= \min \left\{ \left[ X_{ij}(K) + \frac{C_j(K + 1)}{2} \right], D_{ij}(0) \right\},
\end{align*}
\]

where \(X_{ij}(k)\) is the value of the \(j\)th group and the \(i\)th design variable when iterating to the \(K\)-th generation. The iteration is completed when the space is reduced to the specified accuracy.

In the finite element model, the nodes are considered as each gate position to be marked, the gate position is regarded as \(N_p\), the number of nodes is \(N\), and the number of gates to be optimized is \(n\) as shown in equation:

\[
N_p = \frac{N(N - 1) \cdots [N - (n - 1)]}{1 \times 2 \times 3 \times \cdots \times n}.
\]

The melt temperature used for the injection molding process is 230°C, and the mold temperature is 70°C. Material parameters refer to the relevant data for the injection molding material polypropylene PP-LGF-30. The meshed parts have 117601 triangular elements and 58817 node elements. Set the \(\alpha, \beta, \gamma,\) and \(\lambda\) of the objective function to 0.3, 0.15, 0.4, and 0.15 respectively, the number of populations is taken as 10, the size is 20, the hybrid probability is 0.2, the variation probability is 0.03, and the initial gate positions are \(N_1(20968)\) and \(N_2(14276)\). After starting the algorithm to find the optimum, the objective function of the gate positions starts to converge after 900 iterations, as shown in...
Figure 11, where the horizontal coordinates are the number of iterations, and the vertical coordinates are the adaptation values.

As shown in Figure 12, by transcoding the binary coordinates after 900 iterations, the two gate positions obtained are \( N_3(28425) \) and \( N_4(46424) \).

Based on the optimized gate position, the filling flow module of Moldflow is used to simulate the optimized two gate parts. The optimized filling time is 4.840s, as shown in Figure 13, and the maximum clamping force is 551.0t, as shown in Figure 14.

The filling time and clamping force before and after optimizing the two gate positions are listed, as shown in Table 2.

It can be seen from Table 2 that the new gate position is obtained by establishing the objective optimization function.
for the gate position, which shortens the filling time and reduces the clamping force, achieving the optimization effect.

4. Process Parameter Optimization Based on the Orthogonal Test Design and the Ant Colony Neural Network

Warpage deformation and volume shrinkage of the car door inner panel are used as evaluation indicators, and the influence of the process parameters on the evaluation indicators is investigated based on orthogonal tests. Optimization of process parameters is based on ant colony neural network algorithms to obtain the optimal combination of parameters to reduce warpage and volume shrinkage and improve product quality.

4.1. Orthogonal Experimental Design and Data Analysis of the Car Door Inner Plate. This paper investigates five molding process parameters: mold temperature, melt temperature,
cooling time, holding pressure, and holding time; each experimental factor is uniformly selected at four levels, and the influence of each process parameter on warpage deformation and volume shrinkage of the car door inner panel is investigated through orthogonal tests. The division of experimental factors and levels is shown in Table 3.

As shown in Table 4, the orthogonal test principle is applied to establish the $L_{16}(4^5)$ orthogonal experiment table, and the simulation analysis is carried out for 16 sets of process parameter combinations in the table, respectively, to obtain 16 sets of warpage deformation and volume shrinkage.

4.1.1. Analysis of Volume Shrinkage. Volume shrinkage of the car door inner panel is studied by range and variance methods, respectively, as shown in Tables 5 and 6. Then use the data in Table 5 to make a line chart, as shown in Figure 15.

According to the data in Table 5, the influence degree of different parameters on volume shrinkage is as follows: melt temperature > holding pressure > mold temperature > cooling time > holding time. According to the corresponding F value of each parameter in Table 6, the analysis correctness of Table 5 can be verified. Therefore, combination A4B1C4D4E3 is the optimal combination for volume shrinkage.

4.1.2. Analysis of Warpage Deformation. Warpage deformation of the car door inner panel is studied by range and variance methods, respectively, as shown in Tables 7 and 8. Then use the data in Table 5 to make a line chart, as shown in Figure 16.

According to the data in Table 7, the influence degree of different parameters on warpage deformation is as follows: melt temperature > holding pressure > holding time > cooling time > mold temperature. According to the corresponding F value of each parameter in Table 8, the analysis correctness of Table 7 can be verified. Therefore, combination A2B1C1D1E3 is the optimal combination for warpage deformation.

Once the two sets of process parameters have been obtained, it is necessary to combine them. According to the analysis of variance, the melt temperature and holding pressure have the most significant influence on the comprehensive index; thus, the final process of selecting process parameters selects B1D4; for warping deformation, the influence of holding time and cooling time is more important, and thus the deformation of these two parameters is mainly small, i.e., C1E3 is selected; the mold temperature takes the median value, and the final combination is A4B1C1D4E3; the mold temperature of 90°C, melt temperature of 200°C, cooling time of 15s, holding pressure of 30Mpa, holding time of 22s, volume shrinkage, and warpage deformation are obtained by simulation analysis with Moldflow, as shown in Figures 17 and 18.

The process parameters obtained by range and variance analysis are simulated. The optimized volume shrinkage is 15.08%, and warpage deformation is 5.268 mm.
4.2. Establishment of the Ant Colony Neural Network. A three-layer BP neural network model is built to describe the relationship between process parameters and volume shrinkage and warpage deformation. The input layer takes five parameters, such as mold temperature as input neurons, and the output layer takes volume shrinkage and warpage deformation as neurons. The structure of the specific network model is shown in Figure 19.

The selection of samples usually follows the principle of average uniformity, using data derived from orthogonal tests and injection simulation as learning samples, using groups labeled 2–5, 7–10, and 12–15 to train the network, and 1, 6, 11, and 16 as validation groups. The model is trained by MATLAB programming and MATLAB toolbox, and the training of the BP neural network is stopped after 23 training sessions. The training results are shown in Figure 20, and the training error is 0.0111.

The training curve is shown in Figure 21, and the fitting degree is shown in Figure 22. It can be seen from the figure that the R-value of the training and test samples is 0.99978, indicating that the correlation between them is good.

Once the construction of the neural network is completed, its correctness needs to be verified by entering orthogonal experimental data into the software predictions and then calculating the results of the actual tests against the software predictions of shrinkage and deformation to obtain the errors, as shown in Table 9.

The fitting degree between the predicted and test results for volumetric shrinkage and warpage deformation is shown in Figures 23 and 24. After comparing the predicted value...
with the actual value, it is found that the maximum errors of the predicted value and the actual value of volume shrinkage and warpage deformation are 5.33% and 3.26%, respectively, the minimum errors are 0.77% and 0.14%, respectively, and the average errors are 2.285% and 2.115%, respectively, indicating the correctness of the neural network model.

Optimization of the built and validated neural network model is based on the ant colony algorithm called the ant colony neural network (ACO-BPNN) method [19]. Take the test data obtained in the above chapters as the test data to test the authenticity of this optimization method. The groups numbered 2–5, 7–10, and 12–15 in the orthogonal test table are selected for training the ant colony neural network, and 1, 6, 11, and 16 are used as the validation groups for the accuracy of the neural network. The sample is predicted and analyzed by MATLAB, and the volume shrinkage and

### Table 9: Error between the prediction and test results.

| Number | Volume shrinkage | Warpage deformation |
|--------|------------------|---------------------|
|        | Prediction result | Test result | Error | Prediction result | Test result | Error |
| 1      | 14.98            | 15.27              | 1.90% | 7.719            | 7.708      | 0.14% |
| 6      | 15.51            | 15.63              | 0.77% | 5.301            | 5.428      | 0.14% |
| 11     | 15.27            | 16.13              | 5.33% | 7.317            | 7.123      | 0.22% |
| 16     | 16.84            | 16.65              | 1.14% | 6.015            | 6.218      | 0.32% |

![Figure 22: Fitting degree diagram.](image-url)
warpage deformation obtained are compared with the test results to obtain the error between them, as shown in Table 10.

The fitting degree between the predicted and test results for volumetric shrinkage and warpage deformation is shown in Figures 25 and 26. After comparing the predicted value with the actual value, it is found that the maximum errors of the predicted value and the actual value of volume shrinkage and warpage deformation are 1.34% and 1.6%, respectively, the minimum errors are 0.68% and 0.04%, respectively, and the average errors are 1.37% and 1.605%, respectively; thus, the accuracy of the predicted value of ACO-BPNN model is verified.

4.3. Optimization of Molding Process Parameters Based on ACO-BPNN. The ant colony algorithm is used to optimize the established BP neural network model. The established neural network model is used as the fitness function, and the minimum value of volume shrinkage and warpage

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**Table 10: Error between the prediction and test results.**

| Number | Volume shrinkage | Warpage deformation |
|--------|------------------|---------------------|
|        | Prediction result | Test result | Error | Prediction result | Test result | Error |
| 1      | 15.13            | 15.27          | 0.92% | 7.711          | 7.708   | 0.04%  |
| 6      | 15.42            | 15.63          | 1.34% | 5.412          | 5.428   | 1.6%   |
| 11     | 16.24            | 16.13          | 0.68% | 7.139          | 7.123   | 0.22%  |
| 16     | 16.53            | 16.65          | 0.72% | 6.207          | 6.218   | 0.18%  |

**Figure 23: Volumetric shrinkage fit comparison.**

**Figure 24: Warpage deformation fit comparison.**
The deformation is used as the optimization goal of the ant colony algorithm to optimize factors such as die temperature [20]. The value range of the five process parameters is regarded as the constraint condition of the function, which is $x_1 \in [60, 90]$, $x_2 \in [200, 230]$, $x_3 \in [15, 30]$, $x_4 \in [20, 50]$, and $x_5 \in [10, 25]$. The fitness value is taken as the function value, and the minimum of fitness function is taken as the iterative optimization goal of the ant colony algorithm. The relevant parameter settings of the ant colony algorithm are shown in Table 11 [21].

Using MATLAB software to calculate the ant colony algorithm, the change of the optimal fitness value of the objective function can be obtained, as shown in Figure 27. It
can be seen from the function iteration diagram that convergence is reached about the 15th time. The comparative analysis of the predicted value and the actual value of the BP neural network before and after ACO optimization is shown in Figure 28.

As can be seen from Figure 27, the optimal adaptation value of ACO-BPNN is minimized after about 15 iterations, corresponding to the following molding process parameters: mold temperature of 76°C, melt temperature of 205°C, cooling time of 23.8 s, holding pressure of 54.7 MPa, and holding time of 22.1 s. By inputting the molding process parameters into Moldflow for filling flow analysis, volume shrinkage of the car door inner plate is 13.32% and warpage deformation is 4.315 mm, as shown in Figure 29 and Figure 30.

Comparing the orthogonal test optimization results with those based on ACO-BPNN, volume shrinkage is reduced from 15.08% to 13.32% and warpage deformation is reduced from 5.268 mm to 4.315 mm as shown in Table 12.

### Table 12: Result comparison table.

| Optimization method | Mold temperature/°C | Melt temperature/°C | Cooling time/s | Holding pressure/Mpa | Holding time/s | Volume shrinkage/% | Warpage deformation/mm |
|---------------------|----------------------|---------------------|----------------|----------------------|----------------|-------------------|-----------------------|
| Orthogonal test     | 90                   | 200                 | 15             | 50                   | 20             | 15.08             | 5.268                 |
| ACO-BPNN            | 76                   | 205                 | 23.8           | 54.7                 | 22.1           | 13.32             | 4.315                 |

5. Conclusion

(1) UG is used to model the car door inner panel, and then the injection mold is designed based on the mold design module of UG. Finally, the selection of the material and thickness of the car door inner panel and the design of the relevant parameters of the injection mold are completed.

(2) Based on the filling and cooling module of Moldflow, the mold flow of the door inner plate is analyzed. By selecting different gate positions and quantities for analysis, quality indexes such as filling time, cavitation, and welding line are obtained, so as to determine the optimal gate quantity. On this basis, the objective function about the gate position is established. Taking the objective function as the fitness function, the gate position is optimized based on the multi-population genetic algorithm, so as to obtain the optimal gate position.

(3) Warping deformation and volume shrinkage of the car door inner panel are selected as the evaluation indexes, and mold temperature, melt temperature, cooling time, holding pressure, and holding time are taken as the influencing factors to establish the orthogonal test. Through the analysis method of range and variance, the combination of process parameters is A4B1C1D4E3, i.e., the mold temperature is 90°C, the melt temperature is 200°C, the cooling time is 15 s, the holding pressure is 30 MPa, the holding time is 20 s, volume shrinkage is 15.08%, and warpage deformation is 5.268 mm.

(4) Finally, the BP neural network is established, in which parameters such as melt temperature are taken as the input layer and warpage deformation and volume shrinkage are taken as the output variables. The prediction results and the test results of warpage deformation and volume shrinkage are fitted and compared based on MATLAB to verify the accuracy of the neural network. The ant colony algorithm is used to optimize the established neural network model. The fitness value of ACO-BPNN reaches the minimum after about 15 iterations, with corresponding process parameters being: mold temperature of 76°C, melt temperature of 205°C, cooling time of 23.8 s, holding pressure of 54.7 MPa, and holding time of 22.1 s. Using Moldflow to simulate...
the filling flow, volume shrinkage is 13.32% and warpage deformation is 4.315 mm. The optimization of injection molding process parameters of car door inner plates is completed.

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.

Authors’ Contributions

Kf Y made substantial contributions to the design, experimental research, data collection, and result analysis; Ym W made critical changes to important academic content; and Gq W contributed to the final review and finalization of the articles to be published.

Acknowledgments

This article belongs to the major projects of the “The University Synergy Innovation Program of Anhui Province (GXXT-2019-004),” the project of the “Teaching Research Project of Anhui Education Department (2019jyxm0229),” and the project of the “Science and Technology Planning Project of Wuhu City (2021YF58).”

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