Multi-objective Optimization of Injection Process Parameters Based on EBFNN and NSGA-II

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Abstract. Taking the process parameters and quality index data obtained from the optimal Latin hypercube test of a front hood inner panel as sample data, this paper constructs an EBFNN approximate model by combining the NSGA-II multi-objective optimization algorithm to perform multi-objective optimization of injection molding process parameters, obtained Pareto solution set for volume shrinkage and warp during ejection. Comparing the Moldflow numerical simulation results of the four relatively optimized Pareto solutions, the optimal combination of process parameters is obtained. The optimized volume shrinkage and warp deformation reduced by 50.518% and 39.845% respectively, which verified the reliability and practicability of this method, and had certain practical reference significance for the optimization of injection molding process of other plastic parts.

1. Optimized Experimental Design of Injection Molding Process

1.1. Experimental Model
As the optimized model, the inner panel of a car’s front cover is as shown in Figure 1.

![Figure 1. Three-dimensional structure](attachment:image1.png)  
Figure 1. Three-dimensional structure

![Figure 2. Finite element model](attachment:image2.png)  
Figure 2. Finite element model

The wall thickness of the main body of the plastic part is 2.4mm, and the size is 1338mm×688mm×64mm. The finite element model established in Moldflow is shown in Figure 2.

The model of the experimental material is GFPP-30, which is produced by Jinfa Technology. Under the initial process parameters, this paper simulated and analyzed the inner panel of the front cover and obtained the volume shrinkage rate at ejection. And volume shrinkage rate and the Warp deformation rate are 13.51% and 5.175mm respectively, and the results of the warp deformation are shown in Figure 3.
Deformation, all effects deformation
Scale Factors:1.000 Scaling(1000 mm)

Figure 3. Warp simulated by initial process parameters

1.2. Design of OLHD
An optimization mechanism was added to the Optimal Latin Hypercube Experimental Design (OLHD) [7] on the basis of LHD, which could minimize the integrated mean square error, maximize the entropy[8-9] and improve its consistency and robustness. Compared with LHD, the sample points obtained can evenly cover the entire design space, which makes sufficient model information obtained and can make up for the missed model information in some areas of LHD. The approximate model that adopts OLHD has high accuracy and the second-order or higher-order nonlinear relationship can be obtained. Therefore, this paper chooses OLHD to design the plastic injection molding experiment of the inner panel of the front cover.

In this paper, the volume shrinkage volume Vs and the maximum warp deformation Wd of the plastic part during ejection are used as the experimental indexes of OLHD, and the volume shrinkage and warp deformation during ejection are reduced by optimizing the process parameters. According to the relevant experience of plastic injection molding and the research on the process parameters of plastic parts in plastic injection molding, this paper preliminarily selects the mold temperature Tw, temperature of the melted part Tm, injection time Tin, holding pressure (the percentage of filled pressure is used as holding pressure) Pp, time of holding pressure Tp and cooling time Tc as the experimental factors for the experimental design of OLHD. Generally, the value range of process parameters in plastic injection molding should be as wide as possible, so that the best process parameters can be better obtained in the subsequent optimization process[10]. Based on the injection molding experience and the recommended range of process parameter, the value range of each test factor studied in this paper is shown in Table 1.

| Factors          | Range  |
|------------------|--------|
| Mold temperatureTw(°C) | 20-60  |
| Melt TemperatureTm(°C) | 200-260|
| Injection timeTin(s)    | 1-20   |
| Holding pressurePp(%)   | 80-120 |
| Holding time Tp(s)      | 5-40   |
| Cooling time Tc(s)      | 10-50  |

1.3. Results of OLHD Experiment
100 training samples and 20 experimental samples were collected respectively for the establishment of subsequent approximate models, and the 120 sets of experimental sample points collected were put into the process parameter setting interface of Moldflow to simulate the experimental index of the inner panel of the front cover. The numerical simulation results of the 120 sets of process parameters collected and their corresponding volume shrinkage Vs and warp deformation Wd during ejection are shown in Table 2.
2. Analysis of the Result of the Experiment

| No. | Tw/°C | Tm/°C | Tm/s | Pp/% | Tp/s | Tc/s | Vs/% | Wd/mm |
|-----|-------|-------|------|------|------|------|------|-------|
| Training samples | | | | | | | | |
| 1 | 27.68 | 215.76 | 10.98 | 115.56 | 16.31 | 10.4 | 8.926 | 4.248 |
| 2 | 43.43 | 241.21 | 13.28 | 95.35 | 5 | 27.78 | 15.64 | 6.274 |
| 3 | 51.52 | 256.97 | 14.24 | 90.51 | 33.99 | 34.24 | 14.86 | 6.527 |
| 4 | 59.6 | 243.64 | 17.7 | 98.59 | 17.73 | 20.51 | 15.23 | 6.396 |
| 5 | 38.59 | 201.21 | 14.43 | 84.44 | 21.62 | 40.3 | 9.014 | 4.138 |
| 6 | 51.11 | 250.3 | 3.88 | 112.32 | 36.82 | 33.43 | 10.79 | 6.316 |
| 7 | 47.07 | 256.36 | 10.02 | 113.13 | 7.47 | 43.54 | 16.35 | 7.414 |
| 8 | 38.18 | 225.45 | 10.6 | 80 | 18.79 | 23.74 | 9.736 | 6.644 |
| 9 | 41.01 | 259.39 | 19.42 | 104.65 | 19.49 | 32.22 | 16.71 | 4.508 |
| 10 | 25.25 | 223.64 | 17.12 | 85.25 | 9.24 | 35.86 | 12.5 | 3.696 |
| 11 | 57.58 | 224.85 | 16.55 | 82.42 | 27.27 | 33.03 | 13.79 | 6.566 |
| 12 | 22.02 | 240 | 15.39 | 114.75 | 27.63 | 21.31 | 12.51 | 3.429 |
| 13 | 39.8 | 213.33 | 6.95 | 88.48 | 5.71 | 39.49 | 14.27 | 7.782 |
| 14 | 35.76 | 249.7 | 16.74 | 109.49 | 13.13 | 10.81 | 14.48 | 4.213 |
| 100 | 22.42 | 255.76 | 13.67 | 95.76 | 14.19 | 28.18 | 12.84 | 3.959 |
| Tested samples | | | | | | | | |
| 1 | 43.16 | 200 | 9 | 107.37 | 19.74 | 10 | 9.318 | 6.669 |
| 2 | 57.89 | 241.05 | 1 | 103.16 | 21.58 | 20.53 | 13.54 | 6.968 |
| 3 | 51.58 | 256.84 | 13 | 111.58 | 16.05 | 45.79 | 14.76 | 6.96 |
| 4 | 36.84 | 222.11 | 4 | 113.68 | 5 | 35.26 | 14.4 | 7.838 |
| 5 | 47.37 | 209.47 | 17 | 94.74 | 12.37 | 47.89 | 12.18 | 4.45 |
| 6 | 28.42 | 231.58 | 6 | 84.21 | 32.63 | 12.11 | 11.26 | 6.498 |
| 7 | 34.74 | 253.68 | 20 | 86.32 | 25.26 | 31.05 | 16.8 | 4.016 |
| 8 | 22.11 | 215.79 | 14 | 88.42 | 8.68 | 22.63 | 11.66 | 3.903 |
| 9 | 30.53 | 225.26 | 19 | 120 | 17.89 | 28.95 | 13.19 | 3.445 |
| 10 | 20 | 234.74 | 11 | 101.05 | 23.42 | 50 | 9.248 | 4.325 |
| 11 | 32.63 | 206.32 | 18 | 96.84 | 38.16 | 33.16 | 11.36 | 3.57 |
| 12 | 45.26 | 250.53 | 7 | 92.63 | 40 | 43.68 | 11.85 | 7.101 |
| 13 | 24.21 | 260 | 8 | 105.26 | 14.21 | 18.42 | 14.11 | 5.993 |
| 14 | 41.05 | 244.21 | 5 | 80 | 10.53 | 37.37 | 15.23 | 8.038 |
| 15 | 60 | 218.95 | 12 | 82.11 | 28.95 | 24.74 | 11.72 | 8.383 |
| 16 | 26.32 | 228.42 | 3 | 115.79 | 34.47 | 26.84 | 8.655 | 5.468 |
| 17 | 49.47 | 247.37 | 15 | 109.47 | 36.32 | 14.21 | 14.14 | 5.544 |
| 18 | 38.95 | 203.16 | 2 | 90.53 | 27.11 | 41.58 | 8.263 | 6.103 |
| 19 | 53.68 | 237.89 | 16 | 98.95 | 6.84 | 16.32 | 15.21 | 6.186 |
| 20 | 55.79 | 212.63 | 10 | 117.89 | 30.79 | 39.47 | 9.255 | 7.293 |
2.1. Analysis of Variance
Based on analysis of variance (ANOVA), it is believed that the total variance of the response originates from the polynomial model and its fitting error. And according to the results of analysis of variance, it can be judged whether the conclusion is of statistical significance[11]. The closer the fitting accuracy $R^2$ of ANOVA is to 1, the more accurate the polynomial model fitting will be. The optimal Latin hyper cube test data was imported into the DOE component of Isight software to analyze variance. The results are shown in Table 3.

| Test index                  | SSModel | SSError | SSTotal | $R^2$  |
|-----------------------------|---------|---------|---------|--------|
| Rate of volume shrinkage $V_s$ | 204.81  | 18.383  | 223.20  | 0.91764|
| Warp $W_d$                  | 485.48  | 42.155  | 527.63  | 0.92010|

It can be seen from Table 3 that the fitting accuracy $R^2$ of the volume shrinkage rate $V_s$ and warp deformation $W_d$ at the time of ejection are all greater than 0.9, therefore, we can conclude that the polynomial regression model fitted accurately, and the Pareto graph analysis of the test index for the subsequent test factors provided a basis for constructing approximate models with higher accuracy instead of numerical simulation programs.

2.2. Analysis of Pareto Chart
The Pareto chart, also known as the arrangement chart of major and minor factors, reflects the contribution degree of each item in the polynomial model of the fitting test sample to each test index. A large contribution indicates that the test factor had great impact on the test index. This paper analyze the Pareto graph using the linear regression analysis sequence. The blue color represents the positive effect while the red one represents the negative effect. The analysis of the contribution of each test factor to the test index is shown in Figure 4.

![Figure 4. Contribution of test factors to test index](image)

As is shown in Fig. 4, the test factors that contribute greatly to the volume shrinkage rate $V_s$ are melt temperature $T_m$ (33.11%), holding pressure time $T_p$ (25.77%), injection time $T_i$ (20.46%), and mold temperature $T_w$ (15.40 %); The test factors that contribute significantly to the warp deformation $W_d$ are injection time $T_i$ (38.48%) and mold temperature $T_w$ (35.6%). Therefore, the factors that contribute greatly to the test index are the mold temperature, melt temperature, injection time, and holding pressure time.

3. Construction of EBFNN Approximate Model and Error Verification
The construction of the EBFNN approximate model in this paper will be implemented in the
multidisciplinary optimization design software Isight. The training sample and test sample data are imported to Table 2 to establish an EBFNN approximate model and evaluate its fitting error. The error analysis methods included in the software include mean error, Root mean square error, maximum error, and complex correlation coefficient $R^2$. The closer the complex phase relation number $R^2$ is to 1, the more accurate the approximate model fitting will be. Usually, only the complex correlation coefficient $R^2$ is greater than 0.9 can the engineering needs be met. The error analysis results of each output response of the established approximate model are shown in Table 4.

| Output response         | Mean error | Root mean square error | Maximum error | Complex correlation coefficient $R^2$ |
|-------------------------|------------|------------------------|---------------|-------------------------------------|
| Volume shrinkage rate $Vs$ | 0.03509    | 0.04368                | 0.08772       | 0.97617                             |
| Warp deformation $Wd$    | 0.03746    | 0.05342                | 0.17732       | 0.96913                             |

As is shown in Table 4, the EBFNN approximate model complex correlation coefficients $R^2$ established for the volume shrinkage $Vs$ and warp $Wd$ during ejection are 0.97617 and 0.96913, respectively, and the accuracy of approximate model fitting is above 0.96. The comparison of the error analysis result between the predicted value of the established approximate model and the calculated value of the finite element is shown in Figure 5. From the figure, the predicted value and the true value of each output response are distributed near the straight line $y=x$, indicating the constructed predicted value of the approximate model of the EBFNN and the calculated value of the finite element is very close, and the accuracy of the approximate model can meet the engineering requirements, which is enough to replace the Moldflow injection simulation program for the numerical simulation of the volume shrinkage and warp deformation of the inner panel of the front panel.

4. NSGA-II Algorithm Optimization and Experimental Verification

4.1. Mathematical Model of Multi-Objective Optimization Problem

Although the experimental factors that have a significant effect on the volume shrinkage and warp deformation during ejection have been obtained based on the Pareto chart, the effect of the holding pressure $Pp$ and the cooling time $Tc$ on the volume shrinkage and warp deformation during ejection cannot be ignored. Therefore, the mold temperature $Tw$, melt temperature $Tm$, injection time $Tin$, holding time $Tp$, holding pressure $Pp$ and cooling time $Tc$ are still the design variables of the multi-objective optimization mathematical model, and the volume shrinkage rate $Vs$ at ejection, Warping deformation $Wd$ is the optimization goal, and an optimization mathematical model is constructed:
4.2. Establishment of Multi-Objective Optimization Model

On the basis of establishing the EBFNN approximate model, we can enter the Optimization component interface to select the NSGA-II multi-objective optimization algorithm, the algorithm parameters are set, as shown in Table 5, and the design variables and objective functions are defined. The established multiple objective optimization model is shown in Figure 6.

Table 5. NSGA-II algorithm parameter setting

| Index                        | Value |
|------------------------------|-------|
| Population Size              | 32    |
| Number of Generations        | 30    |
| Crossover Probability        | 0.9   |
| Crossover Distribution Index | 10    |
| Mutation Distribution Index  | 20    |
| Initialization Mode          | Random|

4.3. Analysis of Optimization Results and Experimental Verification

After 960 iterations of optimization by Isight software, the iteration process of each objective function is shown in Figure 7, and the distribution of Pareto solution of the optimization index is shown in Figure 8.
Based on the distribution of Pareto solution, the theory of Pareto solution and the particularity of the requirements for the design and process of the inner panel of the front cover, this paper selects the corresponding four sets of process parameters with relatively optimal warp deformation and volume shrinkage ratio. The numerical simulation results in Moldflow software are as shown in Table 6. It can be seen from Table 6: the warp deformation and volume shrinkage rate of each group have been optimized conspicuously compared with that of the the initial process, but while improving the quality of warp deformation, the quality of volume shrinkage will be reduced., which pushed us to choose a compromised plan; the deviation between the prediction results of the multi-objective optimization and the numerical simulation results is small, the maximum error of the volume shrinkage rate is 15.767%, and the maximum error of the warp deformation is 9.952%, indicating that it is reliable to optimize the process parameters by combining EBFNN approximation model with NSGA - II algorithm.

Table 6. Partial Pareto optimal solutions Predictive Numerical Simulation

| Category | Tw/°C | Tm/°C | Tin/s | Pp/%  | Tp/s  | Tc/s  | Vs/%  | Wd/mm | Vs/%  | Wd/mm |
|----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| 1        | 20.6  | 201.4 | 12.5  | 117.7 | 21.7  | 45.2  | 7.565 | 3.045 | 7.131 | 2.943 |
| 2        | 20.0  | 200.1 | 13.4  | 114.8 | 23.8  | 45.6  | 7.739 | 2.834 | 6.685 | 3.113 |
| 3        | 20.9  | 200.1 | 12.9  | 119.2 | 20.0  | 43.9  | 7.650 | 2.912 | 7.129 | 3.177 |
| 4        | 20.1  | 200.5 | 13.5  | 118.7 | 20.3  | 45.7  | 7.777 | 2.748 | 6.761 | 3.052 |
| Initial value | 50    | 210.0 | 4.3   | 90.0  | 10.0  | 20.0  | 13.132| 8.748 | 13.51 | 5.175 |

This paper mainly discusses the dimensional accuracy of plastic parts, therefore, the second group of Pareto solutions in Table 6 is selected as the optimal solution for forming quality optimized by the process parameters of the front hood inner panel. The corresponding optimal process parameters are: mold temperature 20.0°C, melt temperature is 200.1°C, the injection time is 13.4s, the holding pressure is 114.8%, the holding time is 23.8s, and the cooling time is 45.6s. The comparison of the results of the optimized molding quality is shown in Figure 9.
We can see from Figure 9 that the volume shrinkage rate and warp deformation of the plastic parts after ejection have been significantly improved. The optimized volume shrinkage rate is evenly distributed, with a maximum of 6.685%, decreased by 50.518%, and a maximum warp deformation of 3.113 mm, decreased by 39.845%, the warp deformation of plastic parts is relatively small and evenly distributed, which didn’t exceeding the target value of 5mm, and can be better assembled with the outer panel.

Volume shrinkage rate at injection equals 6.685%

5. Conclusion
(1) Based on the analysis of variance, it is found that the fitting accuracy of each test index $R^2$ is greater than 0.9, which provides a foundation for constructing a highly precise approximate model that can replace the numerical simulation program.

(2) Based on Pareto graph analysis of the test index, this paper carries out quantitative analysis of the contribution of each test factor to the test index, and obtains the main factors affecting the test index, which laid the foundation for multi-objective optimization of process parameters.

(3) By constructing EBFNN approximate model combining NSGA-II multi-objective optimization algorithm, this paper performs multi-objective optimization on the injection molding process parameters of the inner panel of the front cover to obtain the optimal combination of process parameters. The optimization results showed that: Moldflow numerical simulation results are close to the predicted values of the optimization model; compared with the results of the initial process, the volume shrinkage and warp deformation during ejection after optimization reduced by 50.518% and 39.845% respectively, which verifies the reliability and practicality of the method, and provide a reference for the optimization of injection molding process of other plastic parts.

6. Reference
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