

Article

Multi-Objective Optimization of Automotive Stamping Process Based on Orthogonal Experimental Design and BPNN-NSGA-II-TOPSIS Framework

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Abstract

To address the multi-objective optimization of stamping process parameters for vehicle components, a hybrid framework coupling Dynaform simulations, Orthogonal Experimental Design, BPNN, NSGA-II, and TOPSIS was proposed. Taking car door accessories as a case study, OED was utilized to investigate the interacting effects of blank holder force, friction coefficient, stamping speed, and die clearance on the maximum thinning and thickening rates. The simulated data trained a BPNN to construct the highly non-linear mapping relationships. Subsequently, the NSGA-II algorithm generated the Pareto optimal frontier, and TOPSIS objectively selected the best compromise process parameters: a blank holder force of 43,113 N, a friction coefficient of 0.13, a stamping speed of 2496 mm/s, and a die clearance of 1.0 mm. Applying this combination effectively constrained the maximum thinning and thickening rates to 41.4% and 16.8% respectively. The BPNN relative prediction errors against numerical validation were merely 0.0691% and 6.9930%, fully verifying the high fidelity and effectiveness of the proposed optimization methodology.

Keywords: multi-objective optimization; stamping; BPNN-NSGA-II algorithm; orthogonal test; TOPSIS

1. Introduction

Stamping is a crucial process in automobile manufacturing. However, complex components are highly susceptible to defects such as local cracking and wrinkling during the forming process [1]. The stamping quality heavily relies on the optimal configuration of process parameters, which is inherently a typical multi-objective optimization problem (MOP). Specifically, core parameters such as stamping speed, friction coefficient, blank holder force, and die clearance exert significant non-linear effects on forming quality, with complex interactions existing among them [2]. Therefore, establishing a high-precision surrogate model to rapidly and economically obtain the global optimal combination of process parameters has become one of the primary challenges in stamping process optimization and quality control [3].

Traditionally, stamping parameter optimization has heavily relied on trial-and-error methods and the empirical knowledge of engineers, making it difficult to obtain global optimal solutions for complex parts [4]. With the rapid development of computer-aided engineering (CAE), numerical simulation techniques have been widely utilized to predict forming defects [5,6]. However, parameter optimization often involves thousands of iterative calculations. The frequent execution of finite element software incurs prohibitive



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time costs and computational loads [7]. To overcome this computational bottleneck, integrating surrogate models with heuristic algorithms has become a mainstream research direction [8–10]. Building upon the successful application of intelligent algorithms in practical engineering problems, such as industrial equipment evaluation and real-world energy consumption feature estimation [11,12], methods like response surface methodology (RSM) [13], Bayesian estimation [14], and artificial neural networks (ANNs) [15,16] have also been widely employed to construct mathematical mapping relationships between input parameters and forming quality indicators. Among these, neural networks exhibit superior fitting accuracy and generalization capabilities when dealing with highly non-linear problems [17–19]. In particular, the backpropagation neural network (BPNN), owing to its outstanding self-learning capability and fault tolerance, has become an ideal choice for processing complex non-linear data [20]. For instance, Xiao et al. [21] utilized a BPNN model to predict the forming angle and thickness thinning in the incremental sheet forming (ISF) process for AA5052 sheets, demonstrating a highly significant correlation between their predictions and experimental data. Similarly, Song et al. [22] and Zhou et al. [23] constructed hybrid BPNN models for steel corrosion evaluation and alloy strength prediction, respectively, effectively constraining prediction errors to within 3%.

Although high-precision predictions of forming indicators lay a solid foundation for process optimization, traditional single-objective optimization methods struggle to achieve an effective balance among multiple conflicting objectives. To resolve this dilemma, the Non-dominated Sorting Genetic Algorithm II (NSGA-II) has been widely adopted as an efficient multi-objective evolutionary algorithm, capable of identifying a uniformly distributed Pareto frontier. For example, researchers have utilized an improved NSGA-II algorithm to effectively optimize metal forming parameters [24], while other studies have proposed multi-objective algorithms combined with specific strategies to successfully address process matching issues in similar manufacturing scenarios [25]. Nevertheless, NSGA-II only provides a set of Pareto optimal solutions rather than a single definitive decision. Faced with numerous non-dominated solutions, decision-makers still confront the highly subjective challenge of selecting the parameter combination most suitable for actual production [26]. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) offers a robust multi-attribute decision-making method that can objectively evaluate and rank these non-dominated solutions based on their relative distance to the ideal solution, thereby effectively eliminating arbitrariness in decision-making [27]. Zhan et al. [28] combined AHP with TOPSIS to achieve a multi-criteria evaluation of construction schemes; Zhou et al. [29] introduced fuzzy TOPSIS to resolve multi-objective trade-off dilemmas in energy systems; and Deng et al. [30] scientifically screened the Pareto solution set for energy storage systems using TOPSIS. At present, research comprehensively integrating BPNN, NSGA-II, and TOPSIS for the holistic optimization of complex automobile component stamping processes remains scarce in the existing literature.

To address the challenge of multi-objective optimization for automobile component stamping process parameters, this paper proposes a comprehensive multi-objective optimization framework. First, by coupling an orthogonal experimental design with Dynaform simulations, representative sample data are efficiently collected to analyze the main effects of blank holder force, friction coefficient, stamping speed, and die clearance on the maximum thinning and thickening rates. Second, a high-precision BPNN surrogate model is trained to replace the computationally expensive CAE simulation process. Subsequently, the NSGA-II algorithm is utilized to perform a global search on the multi-objective functions, obtaining the Pareto frontier of the conflicting objectives. Finally, the TOPSIS method is applied to scientifically determine the most suitable compromise combination of process parameters from the Pareto solution set based on process priorities. The effectiveness of

this proposed optimization strategy is ultimately verified through Dynaform simulation, providing a reliable and highly efficient new paradigm for intelligent parameter optimization in the automotive stamping industry. The overall technical roadmap of this study is illustrated in Figure 1.

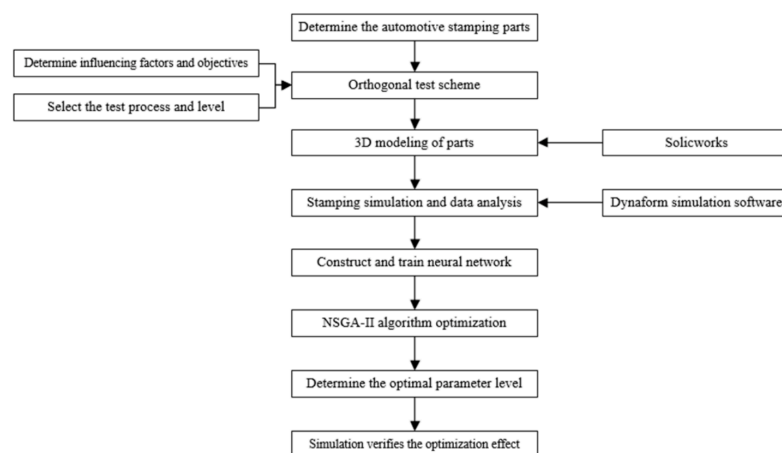


Figure 1. Technical roadmap.

2. Materials and Methods

2.1. Structural Characteristics and Process Analysis

The geometric structure of the automobile door accessory is intrinsically complex, characterized by sharp bending profiles, pronounced local gradients, and varying structural slopes, which severely escalate the difficulty of the stamping process. Owing to these challenging topography variations, the component is fabricated via a single-stage deep drawing process. Although the overall outer contour remains generally regular, the presence of distinct continuous slopes and numerous intricate small fillets significantly restricts the material flow. Notably, the maximum height variance between the opposing sides reaches up to 20 mm. Because the blank initially contacts a localized micro-area near the smaller fillet, this first-contact zone is highly susceptible to tensile rupture, whereas the later-contact areas exhibit a strong tendency to compressively wrinkle. Furthermore, the peripheral sharp corners are formed by transitioning fillets with varying diameters, creating substantial stress concentration zones highly vulnerable to fracture. The small-diameter semicircular topologies and adjacent localized holes at the top corners further aggravate the localized cracking risk during severe plastic deformation.

To mitigate these forming challenges and optimize production, the fabrication scheme utilizes a symmetric twin-cavity (double-row) joint deep drawing method. The integrated manufacturing routing sequence comprises one-time synchronous deep drawing, subsequent peripheral trimming, and final functional hole punching, wherein the twin components are eventually separated into two discrete, high-fidelity semi-finished products by removing the blank holder scrap material. This twin-cavity collaborative stamping strategy not only significantly enhances output efficiency and material utilization but also fundamentally reduces energy consumption per part. The detailed three-dimensional CAD geometry of the automobile door accessory is illustrated in Figure 2.



Figure 2. CAD model of car door accessory.

The macro-dimensions of the automobile door accessory exhibit a maximum length of 410 mm, a maximum width of 220 mm, and a drawing depth varying from 30 to 50 mm. The blank utilizes an 850 mm × 400 mm × 1 mm rectangular sheet fabricated from DC04 deep-drawing automotive steel, whose mechanical properties are detailed in Table 1.

Table 1. Material mechanical parameters of DC04.

Parameter	Numeric Value
Elastic modulus (GPa)	207
Tensile strength (MPa)	270
Yield strength (MPa)	210
Ratio	0.3
Plastic strain ratio	1.65
Index	0.18

The baseline manufacturing routing for this component primarily comprises sequential operations: blanking, single-action deep drawing, trimming, and functional hole punching. Among these stages, the deep drawing process is the most critical, as it fundamentally dictates the final forming quality. Due to the intricate local topography, the predominant forming defects are tensile cracking and compressive wrinkling, with the transitional fillets and continuous inclined walls exhibiting a high vulnerability to premature rupture. Consequently, this study concentrates explicitly on the deep drawing phase. The finite element simulation using Dynaform is decoupled into two continuous kinematic steps: the clamping process and the drawing process. In the initial clamping step, the tool and die remain spatially fixed while the blank holder dynamically translates toward the sheet specimen until the specified blank holder force is vertically applied. Subsequently, during the drawing step, the blank holder and die sustain their tightly constrained states while the punch forcefully advances toward the cavity at a prescribed velocity, thereby forcing the constrained sheet metal into severe plastic deformation to achieve the desired configuration.

Following the geometric design of the stamping process supplements within SOLIDWORKS, extraction of the theoretical neutral layer or direct construction of the exact upper and lower die mating surfaces became highly constrained due to the intricate local topography. To circumvent this, the mid-surface extraction module within Dynaform was utilized to generate the alternative working die surfaces via a precise normal offset approach.

The discretization quality of the finite element mesh fundamentally dictates both the multi-objective forming accuracy and the overall computational efficiency. Given that the minimum geometric fillet radius of the automobile door accessory is restricted to 2 mm, the element generation strategy was configured with a baseline element size of 8 mm, a refinement subdivision level of 4, and a minimum critical element threshold of 1 mm. To balance analysis time and capturing resolution, the sheet metal element size was designated to be adaptively smaller than that of the rigid tool meshes. The finalized discrete mesh configuration is illustrated in Figure 3. To ensure high fidelity and reliability, the DC04 blank was discretized utilizing Belytschko–Tsay shell elements, incorporating 6 integration points through the thickness direction to accurately capture the severe continuous bending and stretching deformations. The material plastic anisotropy was characterized by the Barlat-89 yield criterion, which is highly suitable for steel sheets. To mitigate the severe wrinkling tendency observed near the two large top-center corners, an equivalent drawbead model was strategically locked onto the die surface, providing a calibrated material flow resistance constraint equivalent to 54.4 MPa based on localized forming trials.

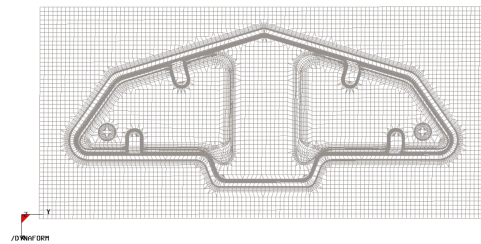


Figure 3. Meshing diagram.

Following the global mesh generation, rigorous topological validation and artifact healing (including automated boundary repair, gap filling, and localized reconstruction) were systematically executed. The geometric quality thresholds were strictly controlled, maintaining the element warping angle below 20 degrees. Comprehensive diagnostics—comprising surface normal alignment verifications, element overlap checks, and duplicate node eliminations—were performed to guarantee a mathematically sound and continuous finite element model.

Upon completing the boundary condition configurations for the deep drawing stage, the final assembled finite element simulation model was successfully established. As illustrated by the vertical spatial hierarchy from top to bottom in Figure 4, the fully integrated finite element assembly precisely comprises the working die, the sheet blank, the blank holder, and the lower forming punch.

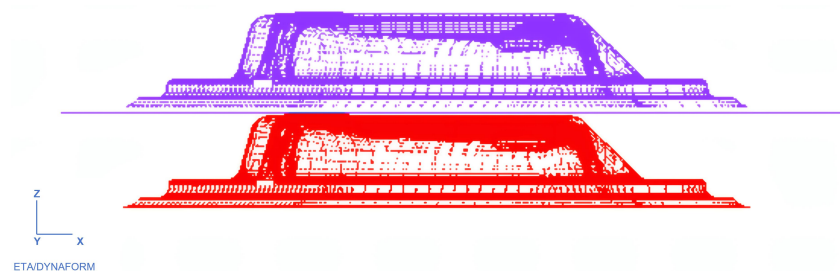


Figure 4. A finite element model.

2.2. Orthogonal Experimental Design Methods

In this paper, a standardized orthogonal table (selecting representative test points from comprehensive test) is used to test, which can effectively reduce the number of experiments and reduce the cost. The four variables of blank holder force, friction coefficient, stamping speed and die clearance were selected as orthogonal test factors. The evaluation indexes were the maximum thinning rate and maximum thickening rate. And the orthogonal table of 4 factors and 4 levels was used to design the orthogonal test. The determination of the blank holder force range is shown in Equation (1) with reference to the empirical equation.

$$F = q \times A \quad (1)$$

where F is the blank holder force (N); q is the unit pressure on the sheet (MPa), generally ranging from 2 to 2.5 MPa; and A is the blank holder area (mm²).

Although the theoretically calculated force is approximately 160,000 N, the actual required blank holder force depends highly on specific material properties. Based on preliminary simulations, a reasonable operating range was determined to be 30,000 to 45,000 N.

Regarding the friction coefficient, an excessive value impedes material flow during drawing, whereas an insufficient value exacerbates wrinkling risks. The existing literature indicates that for sheet thicknesses exceeding 0.5 mm, the optimal friction coefficient typi-

cally ranges from 0.10 to 0.15. Given the 1 mm sheet thickness in this study, the four levels were set to 0.10, 0.11, 0.12, and 0.13. For stamping speed, excessively high speeds increase the probability of fracture, while overly slow speeds compromise production efficiency. Therefore, the stamping speed was selected within the range of 1000 to 2500 mm/s. If the die clearance is too small, the material flow resistance will increase, leading to the risk of cracking of the stamping product. If the gap is too large, the material flow resistance will decrease, which will increase the risk of wrinkling of stamping products. The experiment showed that the effect is optimal when the die clearance is 10–15% of the plate thickness, so it was selected within the range of 0.9–1.2 plate thickness t . The orthogonal experiment scheme is shown in Table 2. The orthogonal table of 4 factors and 4 level was created by using the DOE module in Minitab 21. The data in the orthogonal table were converted to obtain the orthogonal test arrangement and simulation results for standard stamping forming, as shown in Table 3.

Table 2. Process parameters and levels.

Level	Parameter			
	Blank Holder Force (N)	Friction Coefficient	Stamping Speed ($\text{mm} \cdot \text{s}^{-1}$)	Die Clearance (mm)
1	30,000	0.10	1000	0.9 t
2	35,000	0.11	1500	1.0 t
3	40,000	0.12	2000	1.1 t
4	45,000	0.13	2500	1.2 t

Table 3. Orthogonal test arrangement and simulation results.

Test Number	Blank Holder Force (N)	Friction Coefficient	Stamping Speed ($\text{mm} \cdot \text{s}^{-1}$)	Die Clearance (mm)	Maximum Thinning Rate (%)	Maximum Thickening Rate (%)
1	30,000	0.10	1000	0.9	41.8	29.6
2	30,000	0.11	1500	1.0	41.7	26.6
3	30,000	0.12	2000	1.1	41.1	27.0
4	30,000	0.13	2500	1.2	41.5	22.8
5	35,000	0.10	1500	1.1	42.6	25.6
6	35,000	0.11	1000	1.2	41.6	24.5
7	35,000	0.12	2500	0.9	41.9	19.1
8	35,000	0.13	2000	1.0	40.5	21.0
9	40,000	0.10	2000	1.2	43.0	23.9
10	40,000	0.11	2500	1.1	41.9	11.2
11	40,000	0.12	1000	1.0	42.0	20.2
12	40,000	0.13	1500	0.9	41.7	21.1
13	45,000	0.10	2500	1.0	43.2	11.7
14	45,000	0.11	2000	0.9	42.0	19.9
15	45,000	0.12	1500	1.2	45.6	15.8
16	45,000	0.13	1000	1.1	46.5	11.7

From the table, it can also be seen that the empirical formula sometimes does not fully meet actual needs. The best value should be in the range of 30,000 to 45,000 N. but it is necessary to narrow the range of the orthogonal test and carry out the test design scheme to obtain a more reasonable parameter level range.

2.3. BP-NSGA-II Hybrid Optimization Algorithm

2.3.1. BPNN

In recent years, artificial neural networks and deep learning algorithms have demonstrated exceptional capability and reliability in handling complex non-linear mappings across diverse engineering applications, ranging from battery fault prognosis and vehicle range estimation to real-time cloud task scheduling [31–33]. Inspired by these successful implementations, a BPNN is utilized in this study.

The Backpropagation Neural Network (BPNN) is a highly effective feedforward neural network trained by the error backpropagation algorithm. It excels at mapping complex non-linear relationships between inputs and outputs. The standard architecture of a BPNN consists of three main components: an input layer, a hidden layer, and an output layer. The learning mechanism is primarily divided into two stages: the forward propagation of signals and the backward propagation of errors.

During forward propagation, the input data (such as blank holder force, friction coefficient, stamping speed, and die clearance) pass through the hidden layer to the output layer. The output of the j -th neuron in the hidden layer is calculated as

$$H_j = f_1 \left(\sum_{i=1}^n w_{ij} x_i + \theta_j \right) \quad (2)$$

Similarly, the predicted value at the k -th neuron in the output layer is expressed as

$$Y_k = f_2 \left(\sum_{j=1}^m w_{jk} H_j + \theta_k \right) \quad (3)$$

where x_i represents the input variables, w_{ij} and w_{jk} denote the connection weights between the layers, θ_j and θ_k are the bias terms, and f_1 and f_2 are the activation functions of the hidden and output layers, respectively.

If the predicted output deviates from the expected value, the network initiates the backpropagation stage. The loss function, typically defined by the Mean Squared Error (MSE), evaluates the prediction error:

$$E = \frac{1}{2} \sum_{k=1}^c (Y_k - \hat{Y}_k)^2 \quad (4)$$

where $\hat{Y}_k$ is the actual target value.

To minimize this error, the BPNN generally employs the gradient descent method to iteratively update the network weights:

$$w^{(t+1)} = w^{(t)} - \eta \frac{\partial E}{\partial w^{(t)}} \quad (5)$$

where η is the learning rate.

2.3.2. NSGA-II Algorithm

The NSGA-II algorithm, developed by Srinivas and Deb in 2000, significantly improves upon the original NSGA by enhancing computational efficiency and solution convergence. It overcomes previous practical limitations by introducing three core mechanisms:

Fast non-dominated sorting: The population is evaluated based on Pareto dominance. Individuals are compared against each other to determine their domination sets and counts. Through continuous sorting, the entire population is efficiently classified into distinct, hierarchical non-dominated fronts.

Crowding distance calculation: To maintain solution diversity, the algorithm calculates a crowding distance for individuals within the same front. Boundary individuals representing extreme objective values receive an infinite distance, while intermediate individuals are assigned a value based on the normalized objective differences of their adjacent neighbors. This mechanism allows the algorithm to prioritize solutions located in less crowded parameter regions.

Elitist selection strategy: The selection process strictly favors individuals from superior non-dominated fronts. If individuals share the same front rank, preference is given to the one with a larger crowding distance, thereby ensuring a uniformly distributed Pareto frontier.

In multi-objective optimization (MOO), traditional experimental designs sample discrete points, making it difficult to pinpoint the absolute global optimum due to parameter discontinuity. Unlike single-objective tasks, MOO simultaneously balances multiple conflicting objective functions. Since it is impossible to optimize all objectives concurrently, the algorithm identifies compromise solutions, culminating in a diverse set of non-dominated optimal outcomes known as the Pareto frontier. The complete workflow of the proposed BPNN-NSGA-II optimization algorithm is illustrated in Figure 5.

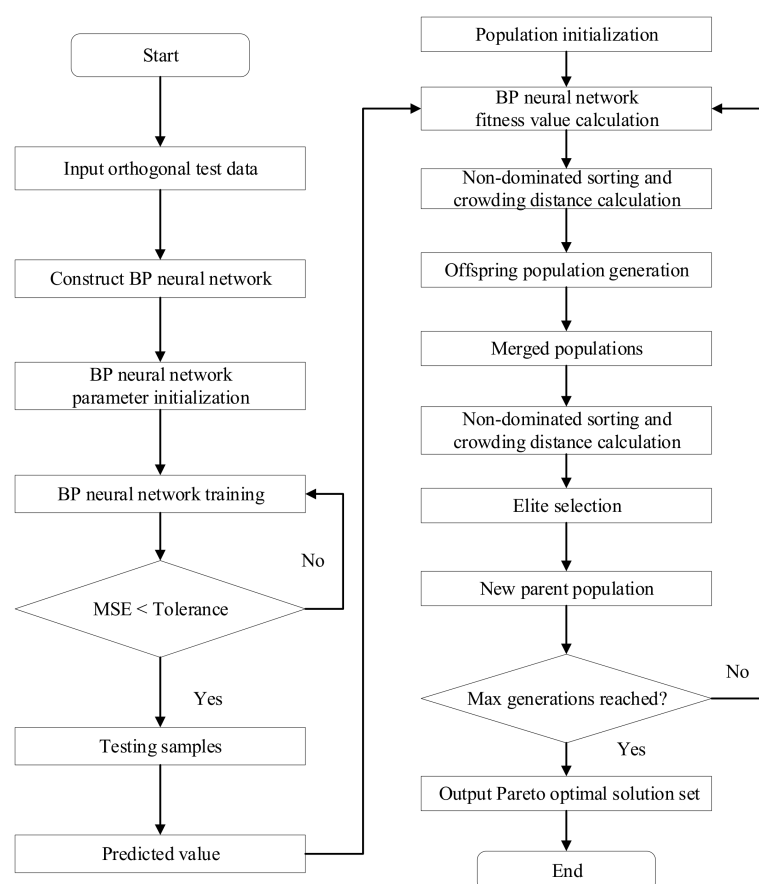


Figure 5. The BPNN-NSGA-II algorithm flow.

2.4. TOPSIS Method

For multi-objective decision-making problems, the TOPSIS method (Technique for Order Preference by Similarity to an Ideal Solution) is an intra-group comprehensive evaluation method proposed by C.L. Hwang and K. Yoon in 1981, also known as the superior-inferior solution distance method. The basic process is divided into unified index-type, standardized processing, determining the positive ideal solution and negative ideal solution, calculating the distance between each index and the positive ideal solution and the negative ideal solution, calculating the relative proximity, and taking the relative proximity as the evaluation of the index.

For multi-objective decision-making problems, the TOPSIS method is applied to evaluate and rank the non-dominated solutions. The specific mathematical implementation and weighting strategy are detailed as follows.

First, the Pareto optimal solutions obtained from the NSGA-II algorithm are normalized to eliminate the influence of different dimensions and magnitudes:

$$z_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^n x_{ij}^2}} \quad (6)$$

where x_{ij} is the j -th objective value of the i -th Pareto solution, and n is the total number of solutions.

Second, the weighted normalized decision matrix is constructed. The determination of criteria weights is the most critical step. In the stamping process for automobile door accessories, severe thinning (leading to fracture) and excessive thickening (leading to wrinkling) are both fatal defects that cause immediate part rejection. Therefore, evaluating these two defect indicators requires a strictly balanced trade-off. Although objective weighting methods such as the Entropy Weight Method (EWM) are widely used in multi-criteria decision-making, they allocate weights solely based on the mathematical variance of the data. To avoid subjective bias and objectively reflect the “pass/fail” engineering nature of these critical stamping defects, an equal weighting method is adopted in this study, where the weights for both objectives are set to $w_1 = 0.5$ and $w_2 = 0.5$. The weighted normalized value v_{ij} is calculated as

$$v_{ij} = w_j \cdot z_{ij} \quad (7)$$

Subsequently, the positive ideal solution V^+ and negative ideal solution V^- are identified. Since both the maximum thinning rate and maximum thickening rate are cost attributes, the ideal solutions are defined as

$$V^+ = (\min(v_{i1}), \min(v_{i2})) \quad (8)$$

$$V^- = (\max(v_{i1}), \max(v_{i2})) \quad (9)$$

The Euclidean distances from each candidate solution to the positive ideal solution D_i^+ and the negative ideal solution D_i^- are calculated using the following equations:

$$D_i^+ = \sqrt{\sum_{j=1}^2 (v_{ij} - V_j^+)^2} \quad (10)$$

$$D_i^- = \sqrt{\sum_{j=1}^2 (v_{ij} - V_j^-)^2} \quad (11)$$

Finally, the relative closeness C_i to the ideal solution is evaluated to rank the Pareto solutions:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad (12)$$

The solution with the maximum C_i value, representing the shortest distance to the positive ideal solution and the farthest distance from the negative ideal solution, is selected as the best compromise process parameter combination.

3. Results and Discussion

3.1. Simulation Results Cloud Diagram

In the 16 groups of experiments, the maximum thinning rate of the 8th group was the smallest, which was 40.5%, the corresponding blank holder force was 35,000 N, the friction

coefficient was 0.13, the stamping speed was 2000, and the die clearance was 1.0 mm, indicating that the risk of fracture was small at this process level. The maximum thickening rate of the 10th group was the smallest, which was 11.2%. The corresponding blank holder force was 40,000 N, the friction coefficient was 0.11, the stamping speed was 2500, and the die clearance was 1.1 mm, indicating that the risk of wrinkling at this process level was small. The thickness change rates of the 8th and 10th groups of tests are shown in Figure 6.

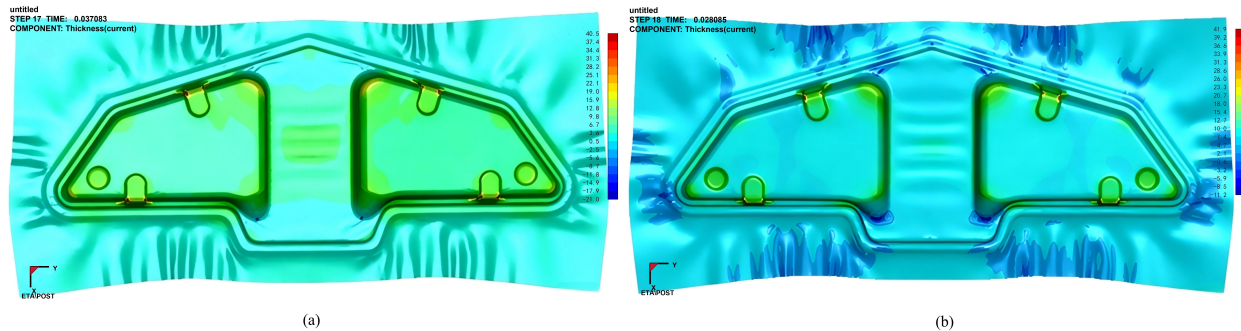


Figure 6. (a) Scheme 8 simulation thickness cloud map; (b) Scheme 10 simulation thickness cloud map.

3.2. The Influence of Process Parameters on Cracking and Wrinkling

Systematically exploring the impact of varying physical and process inputs on material and system responses is a fundamental analytical step. This methodology has been widely adopted across diverse engineering evaluations, such as understanding localized corrosion under bending deformation [34], optimizing dissimilar metal welding quality [35], and elucidating rock failure behaviors under complex stresses [36]. To quantitatively evaluate the specific influence of the four stamping parameters on the maximum thinning and thickening rates in this study, range analysis was utilized. Range analysis is an intuitive analysis of orthogonal test data, also known as the R method. It mainly includes two steps: calculation and judgment. The influence degree of factors is objectively evaluated by calculating the R value (factor range).

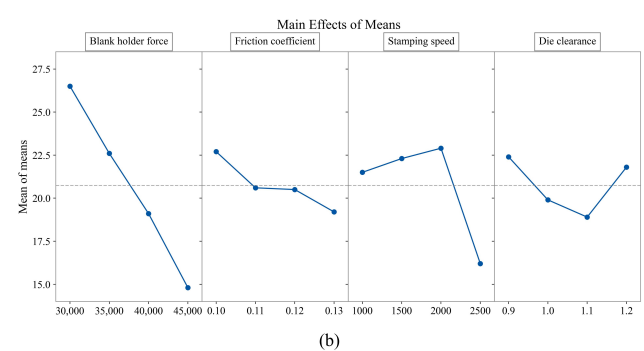
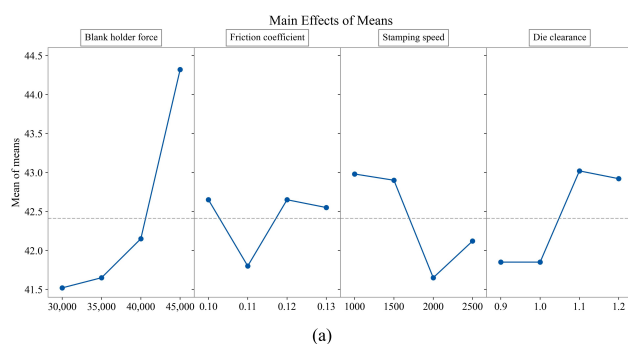
Through the range analysis of simulation results in Table 3, the range analysis results for the maximum thinning rate are as shown in Table 4, and the range analysis structure of the maximum thickening rate is as shown in Table 5. In the table, $\bar{T}_1$, $\bar{T}_2$, $\bar{T}_3$ and $\bar{T}_4$ represent the range levels of the four factors, respectively. Through the range sorting analysis, it was determined that the blank holder force > stamping speed > die clearance > friction coefficient. Both tables show that the blank holder force and stamping speed have the same degree of influence on the two targets. To visually illustrate the varying trends of each process parameter on the forming quality, the main effect plots for the maximum thinning rate and maximum thickening rate are presented in Figure 7a and Figure 7b, respectively.

Table 4. Range analysis of maximum thinning rate (%).

Level	Parameter			
	Blank Holder Force	Friction Coefficient	Stamping Speed	Die Clearance
$\bar{T}_1$	41.52	42.65	42.98	41.85
$\bar{T}_2$	41.65	41.8	42.9	41.85
$\bar{T}_3$	42.15	42.65	41.65	43.02
$\bar{T}_4$	44.33	42.55	42.13	42.92
range	2.8	0.85	1.33	1.18
sort	1	4	2	3

Table 5. Range analysis of maximum thickening rate (%).

Level	Parameter			
	Blank Holder Force	Friction Coefficient	Stamping Speed	Die Clearance
$\bar{T}_1$	26.5	22.7	21.5	22.43
$\bar{T}_2$	22.55	20.55	22.28	19.88
$\bar{T}_3$	19.1	20.52	22.95	18.88
$\bar{T}_4$	14.77	19.15	16.2	21.75
range	11.73	3.55	6.75	3.55
sort	1	4	2	3

**Figure 7.** (a) Main effect diagram of mean maximum thinning rate; (b) Main effect diagram of mean maximum thickening rate.

3.3. Correlation Analysis

Correlation analysis is utilized to quantify the linear relationship and impact direction between the input process parameters and the forming responses. In this paper, the correlation coefficient is used as an indicator to indicate the sensitivity between parameters and responses. The correlation coefficient between parameters and response is calculated from Equation (2) as follows.

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y} = \frac{E[(X - \mu_X)(Y - \mu_Y)]}{\sigma_X \sigma_Y} \quad (13)$$

where cov is the covariance between two datasets, E is the expectation of the data, μ is the average value, σ is the standard deviation, and $\rho_{X,Y} \in [-1, 1]$.

The correlation coefficient heat map of the parameters and the response is shown in Figure 8. The correlation coefficient of the first part is 0, indicating that the uniformity of the sampling points in the orthogonal test design is excellent. In the second part, it can be seen that the maximum thinning rate is positively correlated with the blank holder force, and the correlation coefficient is 0.654, indicating that the larger the blank holder force, the greater the maximum thinning rate. The maximum thickening rate is negatively correlated with the blank holder force, and the correlation coefficient is -0.783 , indicating that the larger the blank holder force, the smaller the maximum thickening rate. The maximum thinning rate was negatively correlated with the maximum thickening rate, and the correlation coefficient was -0.553 . The above analysis is also consistent with the actual situation.

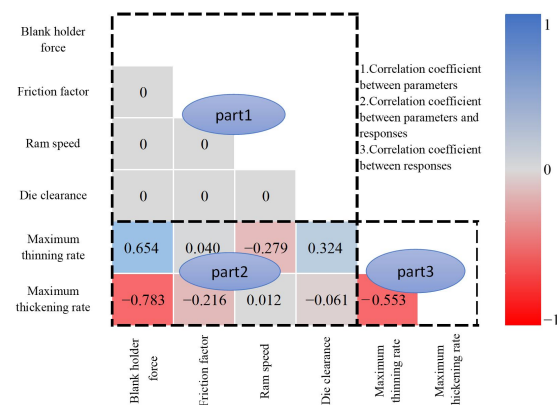


Figure 8. The relationship between parameters and response.

3.4. Multi-Objective Optimization of Process Parameters Based on BP-NSGA-II Algorithm

To construct a high-precision surrogate framework capable of capturing the complex multi-response forming quality, the topological configurations of the backpropagation neural network (BPNN) were meticulously established. Rather than employing a coupled multi-output network, a decoupled parallel single-output network topology was adapted to prevent cross-coupling errors between the conflicting forming objectives (i.e., tensile thinning and compressive thickening). Based on empirical neural network design paradigms, the optimal number of hidden layer nodes was determined to be 9, configuring each independent sub-network with a robust 4-9-1 architecture. To evaluate the multi-response forming performance, two independent BPNN surrogate models were executed in MATLAB R2021b to respectively predict the maximum thinning rate and maximum thickening rate. Given that the sample points systematically selected via the $L_{16}(4^4)$ orthogonal array naturally possess high representative and space-filling qualities across the multi-dimensional parameter domain, they provide a mathematically sufficient foundation for robust non-linear regression despite the compact dataset scale. For each individual surrogate model, the 16-group dataset was partitioned into 13 groups for network training and the remaining three groups as an independent testing set to rigorously monitor the convergence behavior and evaluate the true generalization capability. Prior to network execution, the sample data were normalized into the range of $[-1,1]$ via the `mapminmax` function to eliminate magnitude disparities. The `tansig` and `purelin` functions were applied as the activation transfer functions for the hidden and output layers, respectively, and the connection weights were iteratively optimized using the Levenberg–Marquardt backpropagation algorithm (`trainlm`). The hyperparameter configuration comprised a maximum threshold of 1000 epochs, an initial learning rate of 0.01, and a convergence error tolerance of 1×10^{-5} . To eliminate optimization bias stemming from stochastic initial weights and thresholds, the training procedure for each model was executed for five independent runs, with the statistical averages extracted to construct the final stabilized surrogate models. Following the execution of an inverse normalization process, the predictive performance was quantitatively validated using the Mean Absolute Percentage Error (MAPE) and the coefficient of determination. The sample data obtained from the orthogonal experimental design and the maximum thinning rate and maximum thickening rate obtained by simulation were used to train the BP neural network. The relevant information obtained is as follows.

The BP neural network training and testing results for the maximum thinning rate are shown in Figure 9a,b, while those for the maximum thickening rate are shown in Figure 9c,d.

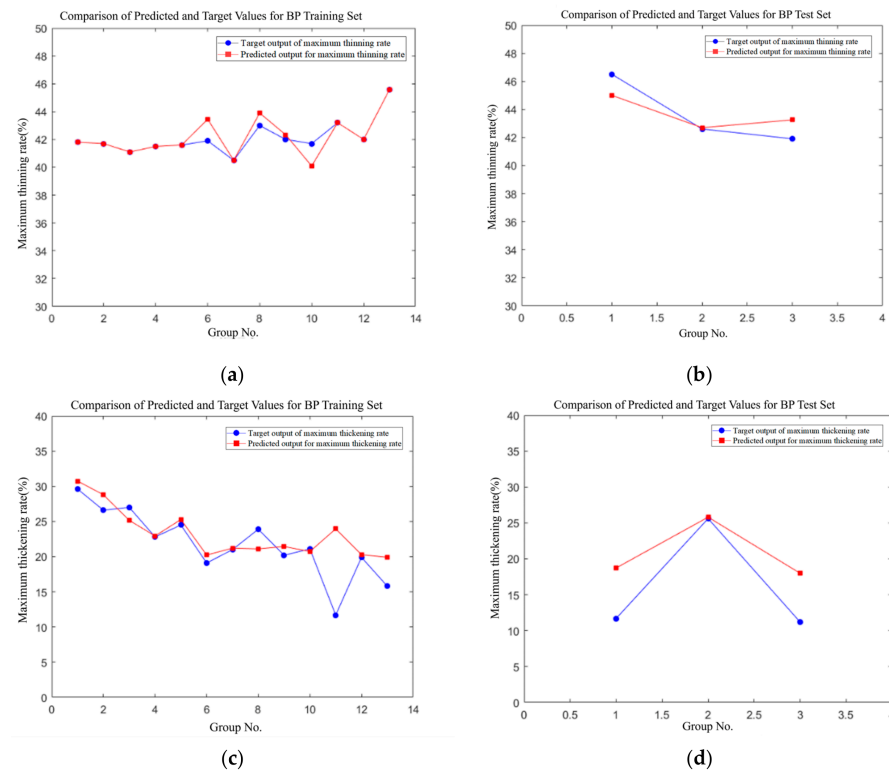


Figure 9. (a) Comparison of predicted and expected values for the maximum thinning rate training set. (b) Comparison of predicted and expected values for the maximum thinning rate test set. (c) Comparison between the predicted and actual values for the maximum thickening rate training set. (d) Comparison of the predicted and expected values for the maximum thickening rate test set.

The predictive performance and fitting accuracy of the trained parallel BPNN surrogate models are quantitatively summarized in Table 6. Specifically, the coefficient of determination between the four design variables and the maximum thinning rate reaches 0.93802, while the R^2 value for the maximum thickening rate achieves 0.9634. These high R^2 metrics demonstrate that the established networks possess excellent non-linear regression accuracy and successfully capture the complex mapping trends within the training domain. Furthermore, upon evaluation against the independent testing dataset, the Mean Absolute Percentage Error was calculated as 0.0098778 for the maximum thinning rate and 0.12125 for the maximum thickening rate. These low error distributions confirm that the established parallel surrogate models provide a sufficiently accurate mathematical foundation for the subsequent multi-objective optimization process.

Table 6. The BP neural network model performance.

Objective Function	RMSE	MAPE	R^2
Maximum thinning rate	0.5253	0.0098778	0.93802
Maximum thickening rate	2.3089	0.12125	0.93693

Root mean square error is RMSE, average relative error is MAPE, and coefficient of determination is R^2 .

To visually and quantitatively explore the coupled effects of the most significant process parameters on the thinning behavior, a three-dimensional response surface plot of the maximum thinning rate was constructed using the trained parallel BPNN surrogate model. Under the localized constraint of a constant stamping speed (2000 mm/s) and friction coefficient (0.11), the blank holder force (30,000–45,000 N) and die clearance (0.9–1.2 mm) were selected as the primary independent design variables. As illustrated by the response surface in Figure 10, the maximum thinning rate exhibits a prominent multi-dimensional

non-linear sensitivity to both process parameters. Specifically, the optimal response (the minimum peak thinning rate) is tightly constrained within the parameter window where the die clearance ranges from 1.1 to 1.2 mm and the blank holder force is maintained between 30,000 and 35,000 N.

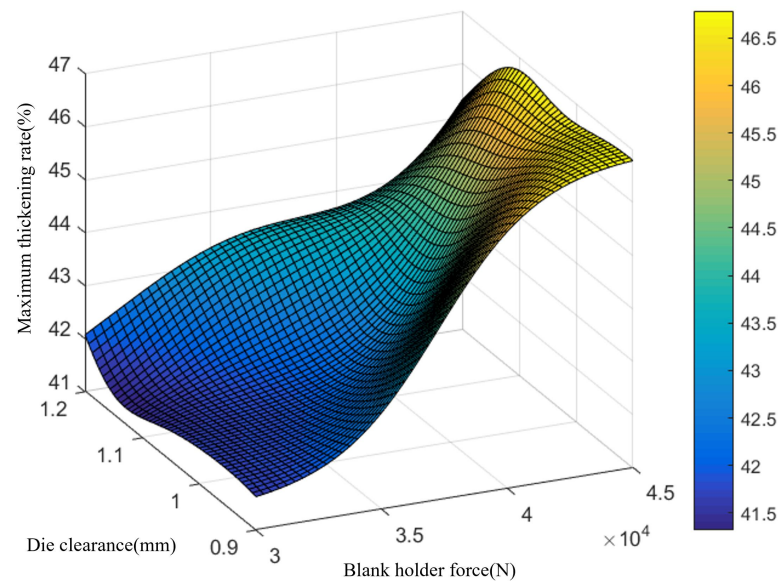


Figure 10. Three-dimensional diagram of the relationship between the maximum thinning rate and the die clearance and blank holder force.

Similarly, to characterize the non-linear influence of the process inputs on the thickening behavior, a three-dimensional response surface plot illustrating the relationships among the maximum thickening rate, blank holder force, and friction coefficient was constructed via the trained parallel BPNN model. Under the constant constraint of a maximum stamping speed (2500 mm/s) and a fixed die clearance (1.1 mm), the blank holder force (30,000–45,000 N) and friction coefficient (0.10–0.13) were evaluated as the independent design variables. As illustrated by the response surface in Figure 11, the maximum thickening rate exhibits high sensitivity to variations in the blank holder force. The quantitative results indicate that the maximum thickening rate is effectively minimized to its global optimum when the friction coefficient is maintained within the lower range of 0.10–0.11 and the blank holder force is optimized within the higher regime of 40,000–45,000 N.

In this paper, the NSGA-II optimization algorithm is used to optimize the two target values of maximum thinning rate and maximum thickening rate of the car door accessory after drawing. The mathematical optimization model of multi-objective optimization is established as shown in Equation (14).

$$\begin{aligned} & \min[y_1(x_1, x_2, x_3, x_4), y_2(x_1, x_2, x_3, x_4)] \\ \text{s.t.} & \begin{cases} 30000 \leq x_1 \leq 45000, & x_1 \in 1 \times \mathbb{N} \\ 0.1 \leq x_2 \leq 0.13, & x_2 \in 0.01 \times \mathbb{N} \\ 1000 \leq x_3 \leq 2500, & x_3 \in 1 \times \mathbb{N} \\ 0.9t \leq x_4 \leq 1.2t, & x_4 \in 0.1t \times \mathbb{N} \end{cases} \end{aligned} \quad (14)$$

where y_1 is the maximum thinning rate, y_2 is the maximum thickening rate, x_1 is the blank holder force, x_2 is the friction coefficient, x_3 is the stamping speed, x_4 is the die clearance, and N is a natural number.

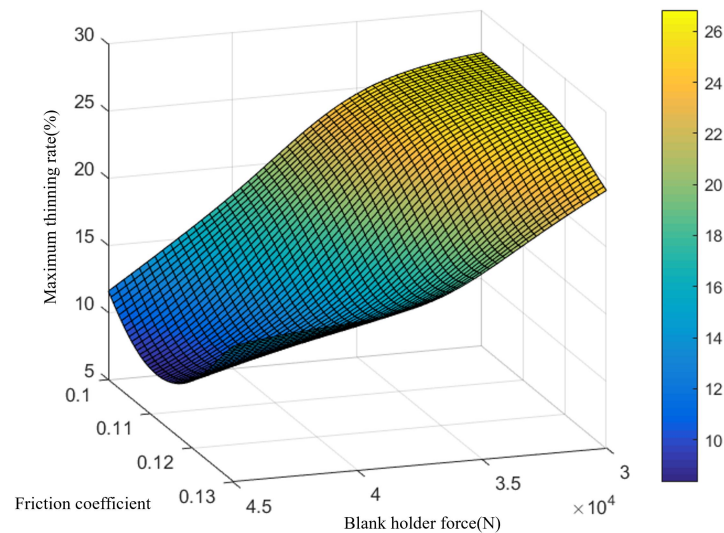


Figure 11. Three-dimensional diagram of the relationship between maximum thickening rate and stamping speed and friction coefficient.

Using the mathematical mapping constructed by the trained parallel BPNN models as the multi-objective fitness functions, the optimization loop was executed via a customized NSGA-II program implemented in MATLAB. The algorithmic hyperparameters configured within the main script were defined with a population size of 100, a maximum of 100 iterations, a crossover probability of 0.8, and a mutation probability of 0.05. To streamline computational execution and data management, preliminary empty matrices were initialized to store crucial algorithmic parameters, including the objective function vectors, design variable arrays, non-dominated sorting ranks, individual domination sets, crowding distances, and elite indices.

The global search process begins with initial population generation, where design variable sets are stochastically sampled within the bounded search space constraints defined in Equation (13). The parallel BPNN surrogate framework evaluates these candidate individuals to efficiently yield their respective thinning and thickening responses. Subsequently, the non-dominated sorting mechanism hierarchically classifies the population into progressive Pareto fronts based on dominance criteria. To preserve multi-objective solution diversity along each front, the crowding distance is computed. While the boundary individuals representing extreme target values are assigned an infinite distance, the crowding distance for any intermediate individual is quantified by the normalized objective difference between its adjacent neighbors. After executing the genetic selection, crossover, and mutation operators, the parent and offspring populations are merged into a combined pool. Non-dominated sorting and crowding distance calculations are systematically re-evaluated across the merged pool to execute the elitist selection strategy, discarding inferior candidates until a stable, uniformly distributed Pareto optimal front is successfully established. Based on this global search procedure, a diverse set of 100 non-dominated solutions was obtained, as illustrated in Figure 12.

As illustrated by the optimization outcomes in Figure 12, the Pareto non-dominated trade-off solutions are uniformly distributed across the objective space. Furthermore, a prominent competitive and conflicting relationship is observed between the two forming defects; specifically, the maximum thickening rate monotonically decreases with the continuous increase in the maximum thinning rate. This inverse distribution trend underscores the fundamental necessity of implementing a multi-objective trade-off framework, as si-

multaneously optimizing both attributes to their respective single-objective global minima is physically unfeasible within the tightly coupled stamping process constraints.

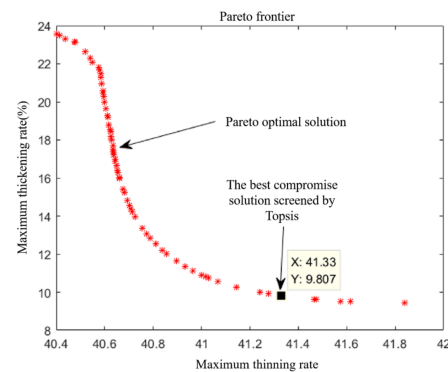


Figure 12. The Pareto front obtained by BP-NSGA-II algorithm.

3.5. TOPSIS Results

The dataset in the Pareto solution set is imported into the Excel software to select the best compromise solution by the constructed TOPSIS calculation function. Some results are shown in Table 7, and the maximum thinning rate and maximum thickening rate corresponding to the process parameters for No. 6 are shown in Table 8.

Table 7. Some results of TOPSIS screening.

Number	D_i^+	D_i^-	C_i	Ranking
1	0.1701	0.8299	0.8299	15
2	0.8299	0.1701	0.1701	83
3	0.8299	0.1701	0.1701	83
4	0.1701	0.8299	0.8299	15
5	0.1444	0.8228	0.8507	11
6	0.1221	0.7820	0.8649	1
7	0.1293	0.8070	0.8619	3
8	0.1421	0.7241	0.8360	13
9	0.1301	0.8084	0.8613	6
10	0.2995	0.5478	0.6465	30

Table 8. The best-compromise process parameters and corresponding maximum thinning rates and maximum thickening rates.

Blank Holder Force (N)	Friction Coefficient	Stamping Speed ($\text{mm} \cdot \text{s}^{-1}$)	Die Clearance (mm)	Maximum Thinning Rate (%)	Maximum Thickening Rate (%)
43,113	0.13	2496	1.0	41.3309	9.8070

To verify the prediction accuracy, a high-fidelity finite element simulation was executed in Dynaform using the selected optimal process parameters. As illustrated in Figure 13, the verified maximum thinning rate is 41.4%, and the maximum thickening rate is 16.8%. Correspondingly, the trained BPNN surrogate model predicts the maximum thinning and thickening rates to be 41.371% and 9.807%, respectively. The numerical deviation in the thickening prediction is primarily associated with the smoothing nature of the neural network regression when fitting localized, discrete peak profiles at unconstrained boundaries. Under a uniform full-domain evaluation baseline, however, the optimization framework demonstrates distinct efficacy; the maximum thickening rate is successfully suppressed from the worst-case initial design profile of 29.6% down to the optimized 16.8%,

which ensures the dimensional accuracy and service performance of the final formed car door accessory.

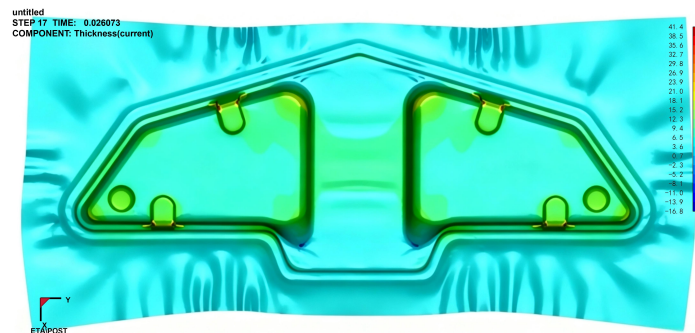


Figure 13. Cloud diagram of the best-compromise process parameters for thickness change.

4. Conclusions

This paper established a multi-objective optimization framework for the stamping process for complex automobile door accessories. By integrating Orthogonal Experimental Design (OED), BPNN surrogate modeling, the NSGA-II algorithm, and the TOPSIS strategy, the non-linear relationship between process parameters and forming defects was systematically investigated. The main quantitative conclusions are as follows:

- (1) The range analysis indicates that blank holder force and stamping speed are the dominant factors affecting forming quality, followed by die clearance and friction coefficient.
- (2) The proposed methodology successfully identified the best compromise process parameters: a blank holder force of 43,113 N, a friction coefficient of 0.13, a stamping speed of 2496 mm/s, and a die clearance of 1.0 mm. Compared to the worst-case boundaries of the initial orthogonal experiments, where the maximum thinning reached 46.5% and thickening reached 29.6%, the optimized FE results effectively constrained the thinning and thickening rates to 41.4% and 16.8%, respectively. This achievement significantly mitigates cracking and wrinkling risks.
- (3) This data-driven approach circumvents the prohibitive computational costs of iterative FE simulations, providing a rapid and scientifically quantified Pareto optimal solution for complex multi-objective stamping tasks.

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