Journal of Computers Vol. 35 No. 3, June 2024, pp. 327-343
doi: 10.53106/199115992024063503022

Research and Simulation Design of Lightweight Technology Approaches for Integrated Forming of New Energy Vehicles

Zhi Zhang[1,2], Wen-Tao Li[1*], Xiao-Bo Dong[1], Xiang-Yun Yi[1], Yan-Chao Sun[1], Liang-Gui Zhang[1]

[1] Department of Automobile Engineering, Hebei Institute of Mechanical and Electrical Technology, Xingtai City 054000, Hebei Province, China

{zhang_zhi5278, wentao3982, xiaobo9832, xiangyun7987, yanchao0986, lianggui3897}@163.com

[2] Xingtai New Energy Vehicle Lightweight Technology Research and Development Center, Xingtai City 054000, Hebei Province, China

Received 1 May 2024; Revised 1 June 2024; Accepted 19 June 2024

Abstract. Electric vehicle lightweighting is a new method for car molding. This article establishes an integrated molding model for car doors. The lightweight technology for car doors requires special structures and optimized parameters. The optimized parameters include inner plate thickness, outer plate thickness, door and window frame thickness, door lock installation surface thickness, door hinge installation surface thickness as design variables, first-order free mode frequency as the optimization function, second-order free mode frequency as the optimization function, sinking stiffness working condition displacement, torsional stiffness working condition displacement as the optimization object, and increasing the weight of the car door as the optimization object. To this end, a car door optimization model and finite element analysis model were constructed. In order to solve the optimal optimization parameters, this paper uses an improved Bayesian optimization algorithm and TabNet deep learning algorithm to solve, and finally obtains the optimal parameters for lightweight car doors. After analysis, it is found that the car doors can achieve significant weight reduction while improving stiffness.

Keywords: new energy vehicles, lightweight technology, topological optimization, deep learning

1 Introduction

In order to address climate change and energy conservation and emission reduction, China solemnly declared to the world at the 75th United Nations General Assembly that it aims to achieve "carbon peak" by 2030 and "carbon neutrality" by 2060. Among all carbon emissions, automobile carbon emissions account for about one-fifth of the global total, and achieving carbon neutrality has become a common challenge faced by the automotive industry. Automobile lightweighting is an important technological path to achieve energy conservation and consumption reduction, as well as to achieve the "dual carbon" goals. According to the research results of the World Aluminum Association, reducing the curb weight of fuel vehicles by 10% can reduce fuel consumption by 6% -8%, reduce carbon dioxide emissions by 13%, reduce the curb weight of electric vehicles by 10%, and increase the range by 5%-6% [1]. Therefore, automotive lightweight technology has become the only way and development direction for reducing energy consumption in automobiles.

Due to the significant reduction in oil consumption and environmental pollution caused by new energy vehicles, they will inevitably become a benchmark in the future automotive industry and a strategic pivot for China's economic development. The research content of this article is electric vehicles and electric vehicle lightweight technology. Electric vehicle lightweight refers to the use of lightweight materials, structural optimization, advanced technology, and other methods to reduce the curb weight of electric vehicles, while ensuring the driving safety, handling stability, riding comfort, and structural strength of the vehicle [2]. Automobile lightweighting not only reduces energy consumption, but also reduces adverse effects on the environment. At the same time, it can also normalize carbon dioxide content, making new energy vehicles an emerging strategic industry. With the support of the country and the continuous innovation of core technologies, new energy vehicles will inevitably achieve leapfrog innovative development and drive the development of other peripheral industries.

* Corresponding Author

Lightweight is a complex engineering project that requires consideration of multiple factors such as practical performance, stiffness, and strength when designing lightweight vehicles. On the premise of ensuring the performance of the entire vehicle, there are generally two ways to further improve the lightweight effect: selecting materials with higher strength to achieve thinning of parts; Design more optimized and advanced body structures, and improve production processes to minimize the overall weight of the vehicle [3]. This article focuses on lightweight design and explores automotive lightweight technology.

2 Related Work

Domestic and foreign scholars generally focus on the lightweight of vehicle body structural components and battery cladding structures. The car door is a part of the vehicle body structure. In terms of lightweight door structure, Yunkai Gao et al [4] constructed a joint welding car door Kriging and response surface approximation model, and used the Non unified Sorting Genetic Algorithm II algorithm to find the optimal solution for mass and sinking stiffness.

Binbin Ma et al [5] used RBF neural network approximation model method and simulated annealing optimization algorithm to achieve lightweight of car doors while meeting the requirements of lateral stiffness and sinking stiffness.

Zhenfang Hou introduced mesh deformation technology into multi-objective lightweight design of car door structures, constructed a Kriging approximation model, and used multi-objective genetic algorithm to optimize the calculation of car door mass and first-order modal frequency [6].

Tuolin Fang simplified the vehicle collision model, constructed a Latin hypercube design method and a Response Surface Model (RSM) approximation model, considering the first-order frequency, lateral stiffness, sinking stiffness, and side collision conditions of the car door. Without increasing the weight of the car door, the optimality of each response and the robustness of the car door structure were improved [7].

Yanfen Li, using the B-pillar of the vehicle frame as a lightweight object, established a side collision simulation analysis model based on side collision safety requirements and the relative position of people and vehicles. After analysis, it was found that the maximum deformation position of the local assembly of the body side wall during the side collision process was in the waist of the human body. After lightweight improvement, the intrusion amount was reduced from 243.6mm to 221.3mm, a decrease of 10.1% [8].

In terms of battery lightweighting, Chao Wang from Hunan University proposed a cross-sectional layout design method for aluminum alloy protective structures, established a simulation model of aluminum alloy protective beams, and carried out topology optimization. The two optimized aluminum alloy protective structure schemes reduced weight by 59.6% and 46.8% respectively compared to the original steel structure scheme, and the intrusion amount of battery modules met the requirements [9].

Jinliang Jiang established a finite element model of the frame of an electric commercial vehicle as the research object, and used structural design methods to redesign the longitudinal beam structure of the frame. The thickness of the longitudinal beam and crossbeam of the frame was used as design variables, and the maximum displacement of the loading point under bending conditions was used as constraint conditions at the first mode frequency. The objective function was to minimize the frame mass. The analysis results showed that the improved frame mass reduced by 174.40 kg (27.60%), achieving lightweight while ensuring the safety performance of the frame [10].

Zuoxuan Li from Beijing Institute of Technology, in order to meet the requirements of multi condition use, high maneuverability, and low-cost development of vehicles, adopts the idea of multi condition correlation design and lightweight optimization to optimize the structure of the vehicle truss body. Considering the large number of design variables and design space in multi working condition vehicle body structure design, and facing the problem of excessive simulation times, a lightweight optimization method for vehicle body structure based on multi working condition correlation is proposed. The design space is reduced by using design variable interval reduction strategy, and Gaussian process surrogate model replacement simulation analysis is introduced to achieve rapid evaluation of structural design scheme performance. Genetic algorithm is combined to optimize the scheme. The experimental results show that the final optimized scheme, after being validated through multidisciplinary performance simulations such as vehicle stiffness, strength, and modal, reduces mass by 14.12% compared to the initial scheme and 8.87% compared to the scheme optimized using only Gaussian processes [11].

Changyu Li, in order to reduce the weight of the white body of a certain SUV model, established its three-dimensional digital model and obtained its finite element model through mesh division processing. Dynamic and static analyses were conducted on the above model, and the first six natural frequencies and stiffness values were obtained. Based on the obtained natural frequency and stiffness values, a single objective size optimization method is adopted to reduce the weight of the white body, and the optimized results are compared with those before optimization. The results show that by optimizing the body in white, weight reduction is 23 1kg, with a weight loss ratio of 5.31%. And it ensures that the modal frequency and stiffness values are within the range required by the body design, achieving weight reduction without compromising the safety performance of the white body [12].

Pengxing Wu from Guilin University of Electronic Science and Technology used SFE-CONCEPT software to establish an implicit parameterized model of the white body of a commercial vehicle cab, and conducted static analysis of free modes and six typical working conditions. At the same time, an automatic analysis and optimization process is established. For 60 thickness, cross-sectional shape, and component displacement variable factors, the optimized design variable factors are selected through sensitivity analysis. The target response is quality and the maximum stress of 6 typical working conditions. A second-order response surface approximation model is fitted and accuracy verification is carried out. Using the second-generation non dominated sorting genetic algorithm (NSGA-II) to optimize the solution of the established approximate model and obtain the frontier optimal solution. The optimized white body model of the driver's cab has achieved a weight reduction of 16.9 kg and a lightweight rate of 5.49%, while ensuring reliable strength and modal performance, achieving a good lightweight effect [13].

In the field of new energy vehicles, integrated die-casting technology has begun to rise. Generally, we divide the body of the vehicle into two main parts, namely the body structural parts and the body cover parts. The lightweight technology of the body structural parts has been unprecedentedly improved with the improvement of integrated die-casting technology. The body covering parts mainly include "four doors and two covers", namely the car door and the front and rear machine top covers. The mechanism of the machine top cover is relatively simple and the material is relatively single. Therefore, the research object of this article is the lightweight technical approach of new energy vehicle doors, mainly completing the new structural design and optimization of the door to adapt to the die casting process. High quality aluminum alloy doors are obtained through the working characteristics of "high pressure and high flow rate" by pressure casting. Then, a mathematical model of the door is established to improve the design of the door structure. Based on this, the door structure is optimized according to the requirements of mechanical properties, and the optimized parameters of the door die casting are obtained as the main means of door lightweight.

Therefore, the work done in this article is as follows:

1) Firstly, based on the materials used for lightweight car doors, establish an analysis model for the car door, which includes a lightweight model and a stiffness model, and use this to conduct analysis.

2) Based on the established model, a structural topology optimization analysis was conducted on the car door, and a structural optimization model was established, which includes all parameters that determine the quality and weight of the car door.

3) Use improved Bayesian and TabNet algorithms to solve multiple parameters of the optimization model and obtain the optimal solution.

The main results of the article are as follows: Chapter 1 is the introduction section, which introduces the research background of this article; Chapter 2 is the relevant research results, summarizing the current research status of vehicle body lightweighting and the lightweighting methods adopted by researchers; Chapter 3 is the establishment and analysis process of vehicle door lightweighting model, which establishes a parameter model containing multiple optimization objectives; Chapter 4 is the optimization process, which establishes an optimization strategy based on artificial intelligence algorithms, uses improved Bayesian optimization algorithms and TabNet deep learning algorithms to solve the optimal solution of the optimal parameters; Chapter 5 establishes a simulation experimental environment, provides simulation optimization results to verify the scientificity of the method; Chapter 6 is the conclusion section, which summarizes the research innovation of this article. Point out and explain the shortcomings in the research process, At the same time, prospects for further research directions in the future were also presented.

3 Establishment of A Lightweight Model for Car Doors

The integrated door is a key component of the vehicle body cover, and the model structure of the door is shown in Fig. 1. Its structural design not only needs to meet the requirements of casting individual performance and manufacturing process, but also needs to consider the coupling effect between components and their impact on the performance of the entire vehicle body system. The door material selected for the integrated molding of the car door is ZL201A, and its material performance parameters are shown in Table 1.

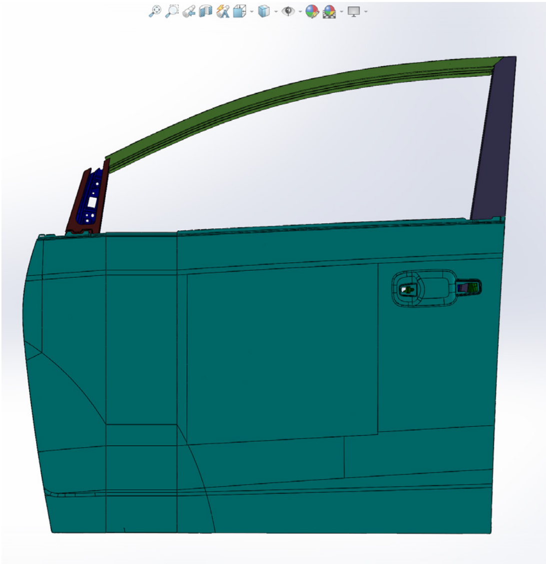

Fig. 1. Car door model

Table 1. Door material performance parameters

Stretching rate	Poisson's ratio	Elastic modulus	Density	Tensile strength
$\geq 8\%$	0.33	69GPa	$2800Kg/m^3$	$\geq 390MPa$

Before establishing the finite element model of the car door, it is necessary to establish a three-dimensional model of the car door. Without changing the boundary conditions of the car door, a three-dimensional model of an integrated aluminum door was established. The number of components in the aluminum model was significantly reduced, from 18 components in the steel model to 3. Compared to steel doors, aluminum doors eliminate multiple welding, riveting, or adhesive processes, making them simpler and easier to install. The discretization of the car door using shell elements can more accurately and efficiently simulate the mechanical characteristics of the car door, while improving computational efficiency and saving modeling time. Construct a finite element model of the car door structural shell element in the software SolidWorks [14], considering the accuracy of simulation results, and simulate the welding points using RIGID elements. The material density of aluminum car doors is 2800kg/m3, with an elastic modulus of 69GPa and a Poisson's ratio of 0.33.

3.1 Door Stiffness Model

After preliminary design, the model contains a large number of unit grids, and the performance analysis using the vehicle body system model is time-consuming. Therefore, the model structure is subjected to row reduction modeling and analysis. The car door system is a continuous structure, and the schematic diagram of the continuous structure is shown in Fig. 2.

The model object does not have inherent boundaries. This article proposes the principle of subsystem partitioning for continuum models to support further partitioning and reduction of vehicle subsystems. For a continuous structure with approximately equal cross-sections, it is assumed that the continuous structure is composed of a continuous body and a joint surface in series. The principles for subsystem partitioning are as follows: 1) Minimize the number of boundary nodes of the hyperelement as much as possible to achieve efficient reduction of the degrees of freedom of the hyperelement model; 2) Divide in an area with approximately equal cross-sections, where the joint surface is equivalent to a rigid element and the thickness of the joint surface is close to or equal to zero.

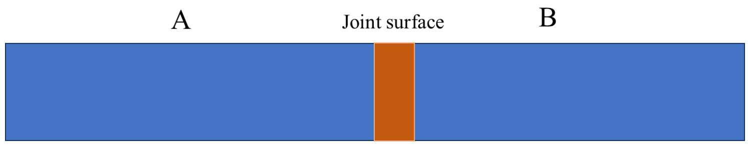

Fig. 2. The structural principle of continuous structures

The model object does not have inherent boundaries, so it is assumed that the continuous structure is composed of a continuum and a junction surface connected in series. The comprehensive stiffness of the structure of the car door is expressed as:

$$K_z = \frac{K_j \cdot K_l \cdot K_r}{K_r \cdot K_l + K_r \cdot K_j + K_l \cdot K_j}. \quad \textbf{(1)}$$

In the formula, K_z is the comprehensive stiffness of the car door, K_j is the equivalent stiffness of the car door joint surface, and K_l and K_r are the stiffness of the continuum on both sides of the joint surface. According to the principle of equal strain energy, the equivalent stiffness K of the joint surface and continuum can be expressed using the following formula:

$$K = \frac{ES}{h}. \quad \textbf{(2)}$$

In the formula, S is the cross-sectional area, h is the thickness, and E is the elastic modulus. By organizing Formula 1, it can be concluded that:

$$K_z = \frac{E_l \cdot E_j \cdot E_r \cdot E_s}{h_l E_j E_r + h_j E_l E_r + h_r E_l E_j}. \quad \textbf{(3)}$$

In order to facilitate the establishment of an accurate car door model, it is necessary to divide the car door structure area. When dividing the car door structure area, it is necessary to divide it in an area with approximately equal cross-sections. The joint surface is equivalent to a rigid element, and the thickness of the joint surface is close to or equal to zero. Therefore, the car doors are divided into inner door panels, outer door panels, and window frames [15]. To visualize the results of the door structure hyperelement model and read the information of key nodes, the boundary points, working condition loading points, and measurement points are sequentially connected and output results through PLOT elements. The finite element model of the final aluminum alloy car door is established as shown in Fig. 3.

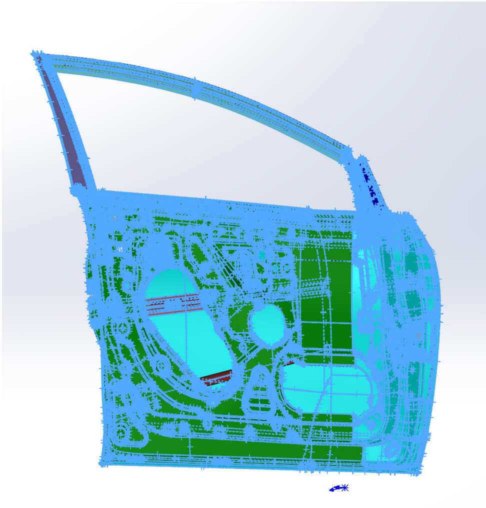

Fig. 3. Finite element model of car door

The number of outer door panel units is 167862, the number of inner door panel units is 97897, and the number of door and window frame units is 52332, which meets the modeling requirements. The model mass is 12.02kg. The window frame and inner panel of the cast aluminum car door form an integrated model of the window frame and inner panel through common nodes. Set adhesive surfaces at the edges of the inner plate, set 5 bolt connection bosses around the inner plate, and set 5 bolt connection surfaces at corresponding positions on the outer plate. The inner and outer panels are assembled through a combination of bolt connections and adhesive bonding.

3.2 Door Stiffness Analysis

The stiffness analysis of car doors mainly includes vertical stiffness analysis and torsional stiffness analysis. The vertical stiffness of the car door refers to the deformation ability of the car door to resist its own gravity and vertical load, which directly affects the gap size between the car door and the side wall components. During vehicle operation, the vertical stiffness of the door can effectively prevent excessive vibration and deformation caused by factors such as wind and road bumps, thereby improving the sealing and safety of the door. The vertical stiffness of car doors can usually be measured and evaluated through simulation or experimental testing. In the vertical stiffness condition, apply a sinking force of 900 N to the position of the door lock by constraining the six degrees of freedom of the bolt holes on the upper and lower hinges of the car door and the vertical degrees of freedom of the door lock position, namely the Z-axis rotational degrees of freedom. The direction of this force is vertical downward.

The stiffness of the car door determines the sealing and noise issues of the entire vehicle. According to the national standard GB15743-1995, when the car door is closed, a vertical downward load of 800N is applied to the lock cylinder position of the car door. The hinge mounting hole is fully constrained. The relevant settings in finite element analysis are shown in Table 2.

Table 2. Load situation

Working condition	Constraint	load
Vertical stiffness analysis	$DOF_i = 0$	800N

Post process the solved results in SolidWorks to obtain the vehicle displacement under vertical stiffness conditions, as shown in Fig. 4.

Fig. 4. Vehicle displacement model

After measurement, the vertical deformation at the position of the lock cylinder is 2.82mm. According to the calculation formula of the vertical stiffness K_c of the car door:

$$K_c = \frac{F_s}{S_s}. \tag{4}$$

In the formula, F_c represents the load at the lock core, and S_s represents the deformation at the lock core. After modeling and analysis, the deformation at the lock core is 2.07.

When the car door is closed, it is mainly constrained by the upper and lower hinges and the door lock, and over time, the car door will undergo asymmetric torsional deformation. This torsional deformation will have irreversible effects on the appearance and sealing of the car door [16].

The torsional stiffness of a car door refers to the resistance generated when the car door undergoes torsional deformation in its plane. When the car door is closed, its surface and interior may withstand forces and vibrations from vehicle movement and external environment. A higher torsional stiffness of the car door can effectively prevent excessive twisting during driving, thereby maintaining the stability and sealing of the car door. In addition, higher door torsional stiffness can also improve the safety of the vehicle and reduce the deformation and damage of the door in the event of a collision. In the upper torsional stiffness condition, apply a 900N vertical upper torsional force to the lower rear position of the window frame, with 6 degrees of freedom constraining the bolt hole positions of the upper and lower hinges of the car door and 3 degrees of translational freedom of the door lock position. The direction of this force is from the inner door panel to the outer panel.

Therefore, in the car door design stage, it is necessary to analyze the torsional stiffness of the car door to ensure that it has high initial torsional resistance characteristics. Using the same method, the values for setting the torsional stiffness of the car door are shown in Table 3.

Table 3. Load situation

Working condition	Numerical value	Enterprise limits	Result
Torsional stiffness	1.739	≤ 6	Qualified

4 Establishment of A Lightweight Model for Car Doors

The optimal Latin hypercube experimental design is based on the improvement of Latin hypercube [17], which can ensure that the occurrence of different levels of each treatment factor is equal, ensure a more balanced sample, reduce errors, improve experimental accuracy, and better explore the interaction between treatment factors while ensuring reliable experimental results, thereby improving experimental efficiency and accuracy. The Latin hypercube design and optimal Latin hypercube design sample point sampling are shown in Fig. 5.

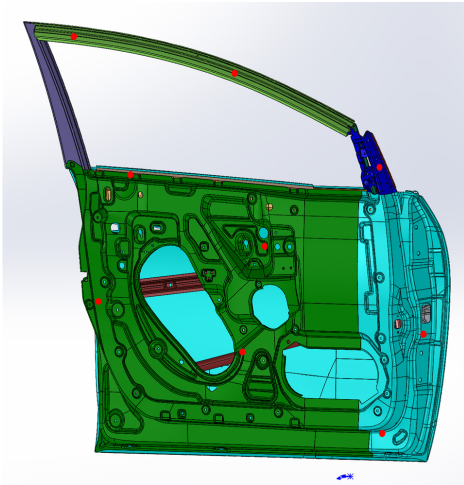

Fig. 5. Optimal Latin hypercube design sample point sampling

In order to obtain better structural parameters of the car door, the Latin hypercube sampling algorithm is used to perform multi-objective optimization on the geometric parameters of the constructed car door stiffness model. While ensuring the randomness of the samples, it can also avoid the occurrence of excessive redundancy in the samples. The specific steps include layering, sampling, and reordering.

1) Determine the number of samples to be extracted N and the dimension to be extracted D;

2) Divide each dimension into N equal parts and obtain N values, denoted as $V_1, V_2, \ldots, V_N$.

3) For the first dimension, randomly select a number from $V_1, V_2, \ldots, V_N$ as the first sample value, and then remove it from the list;

4) For the second dimension, randomly select another number from the column that removes the first sample as the value of the second sample, and repeat this operation until the value of the D-th dimension is extracted.

5) Finally, the obtained samples are arranged in columns to form a matrix of rows and columns, denoted as the Latin hypercube sample matrix.

The main idea of this algorithm is to stratify the probability distribution, with the aim of recreating the probability distribution with fewer samples. The advantage of achieving the same results as a large number of random samples with fewer sampling times is that the sampling range is uniform and there is no obvious clustering phenomenon. Each layer of samples is forcibly extracted, and by maximizing the layering of each edge distribution, it ensures full coverage within a variable range, which can reflect the comprehensiveness of the sample results. For situations with multiple variables and complex sampling environments, the sampling efficiency will be significantly improved. Therefore, the multi-objective optimization problem of car door structure is described as:

$$\min\left[A, B, \cdots N\right] = \begin{cases} 1 \le A \le x_1 \\ 0 \le B \le x_2 \\ \quad \vdots \\ 1 \le N \le x_n \end{cases}. \tag{5}$$

This plan uses the Latin hypercube algorithm to extract 200 sets of data from 5 optimization variables, with 200 sample points. The corresponding cogging torque and torque ripple size for each sample point are calculated, and the optimal parameters are selected.

4.1 Model of Car Doors

Taking the redesigned cast aluminum door as a deterministic optimization objective, the thickness of the inner panel T_1, outer panel T_2, door and window frame T_3, door lock installation surface T_4, and door hinge installation surface T_5 are design variables, with a thickness range of 1-3 millimeters.

Radial Basis Function (RBF) [18] neural network is a method of obtaining unknown function values by fitting discrete multivariate data. The radial basis function depends on the value function of the distance between the fixed value node and the coordinate origin. Simply put, it is necessary to define a fixed value node and determine the horizontal and vertical distance between the node and the coordinate origin; Secondly, using the obtained values as reference standards, measure the horizontal and vertical distances between other nodes and the coordinate origin; Then compare the measured values with the standard values. If the two are equal, the node and the original node are classified together. Finally, use the obtained node to define a function expression, which is the radial basis function. Under the condition that the grid space coverage does not change, the more node parameters that satisfy the same radial basis function expression, the stronger the capacity of the function condition to accommodate data information samples. Considering the diversity of data information sample sources, when solving the radial basis function expression, it is required that the position of the defined node and the coordinate origin cannot move.

RBE elements are established at the cross-section of the submodel, with interface nodes as RBE slaves and cavity centroids as the main points; The main points of the RBE units corresponding to each section of the two sub models are re stitched together through a common node to form a zero thickness joint surface. At this point, the main points of the RBE can be regarded as boundary nodes of the two sub models. In the RBF neural network model, if there is a set of known input values $x_1, x_2, x_3, \cdots, x_m \in A \subset R^m$, the output value of the design variable response is $y_1, y_2, \cdots, y_N \subset R$, and the difference model $I(x)$ of the unknown point is approximately estimated. The representation method is:

$$I(x) = \sum_{i=1}^{M} \lambda_i f_i(x) + \lambda_{M+1}. \tag{6}$$

In the formula, λ_j is the difference coefficient of the radial basis function, and the process of solving the coefficient is as follows:

$$\sum_{i=1}^{M} \lambda_i f_i(x_i) + \lambda_{M+1} = y_i, i = 1, 2, \cdots, M. \tag{7}$$

$$\sum_{i=1}^{M} \lambda_i = 0. \tag{8}$$

In the formula, $f_i(x)$ represents a set of radial basis functions. The representation method is as follows:

$$f_i(x) = f(x - x_i)^{1/c}. \tag{9}$$

c is the spline shape parameter.

4.2 An Approximate Model for Optimizing Response Surface of Car Doors

In the optimization process of car doors, there are multiple optimization objectives, so the optimization model should have the ability to model and effectively analyze multiple variables. Therefore, based on regression fitting and response surface drawing of the entire process, it is more convenient to obtain the corresponding response values of each factor level. The polynomial representation is as follows:

$$I(x)=T_0+\sum_{j=1}^{m}T_jx_j+\sum_{j=1}^{m}T_jx_j^2+\sum_{0\le j\le i\le m}T_{ji}x_jx_i. \tag{10}$$

In the formula, T_j is the polynomial coefficient, x_j is the design variable, and m is the variable coefficient. Therefore, using the car door thickness and stiffness obtained in the previous section as model variables, a quadratic polynomial is established as follows:

$$\begin{aligned}m=&\,0.08979+1.7682T_1+0.3656T_2+2.0981T_3+0.03981T_4+0.01982T_5\\&+0.00103T_1^2+0.0012T_2^2+0.00202T_3^2+0.0019T_4^2+0.0017T_5^2\\&-1.00137T_1T_2+0.00321T_1T_3+0.0912T_1T_4-0.09821T_1T_5\\&-0.0901T_2T_3-0.00801T_2T_4+0.0011T_2T_5.\end{aligned} \tag{11}$$

$$\begin{aligned}k_z=&\,28.9082-2.7821T_1-0.5026T_2-0.1211T_3-2.03981T_4-5.01982T_5\\&+0.20103T_1^2-0.0412T_2^2+0.00202T_3^2-0.1024T_4^2-0.3017T_5^2\\&-0.0216T_1T_2+0.5032T_1T_3-0.0612T_1T_4+0.03811T_1T_5\\&+0.0301T_2T_3-0.208T_2T_4-0.021T_2T_5.\end{aligned} \tag{12}$$

In the formula, m represents the mass of the car door, k_z represents the comprehensive stiffness of the car door, T_1 represents the thickness of the inner panel, T_2 represents the thickness of the outer panel, T_3 represents the thickness of the window frame, T_4 represents the thickness of the door lock installation surface, and T_5 represents the thickness of the door hinge installation surface. The above is an approximate model of the car door, As shown in Fig. 6.

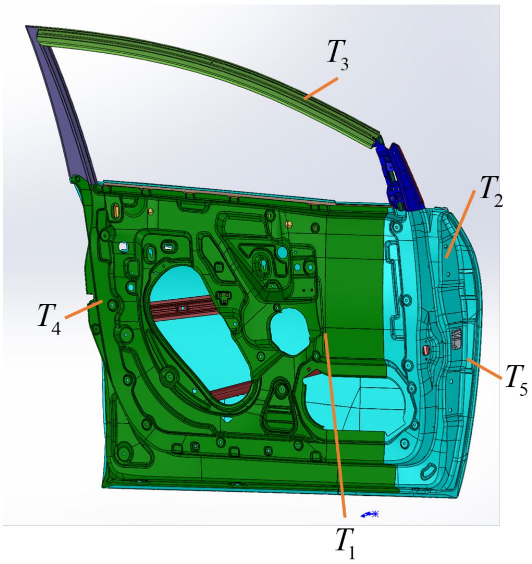

Fig. 6. Classification of door thickness

4.3 Establishment of an Optimization Model for Car Doors

For lightweight car doors, the most ideal result of optimization is to improve the modal and stiffness performance of the doors while reducing weight. Optimizing experimental design is essentially a multi-objective optimization problem, as it typically involves optimizing multiple indicators such as quality, stiffness, hardness, etc. Considering the performance of the car door structure and the coupling effect with other components, this section conducts multi-objective topology optimization of the car door working conditions to guide structural design. The car door design process involves the thickness of various parts of the car door, the stiffness of each structure, and the corresponding processing procedures and working conditions for each target. Therefore, in the optimization process, the compromise programming method is adopted as the optimization method in this article, and the optimization mathematical model is shown in the following equation:

$$\min : \theta(s) = \left[\sum_{g=1}^{l} q_g^{\omega} \left(\frac{\theta_g(s) - \theta_g^{\min}}{\theta_g^{\max} - \theta_g^{\min}} \right)^{\omega} \right]^{1/\omega} . \tag{13}$$

$\theta = (\theta_1, \cdots, \theta_n)^T$ - the design variable, n is the total number of units;

l -The total number of stiffness working conditions;

q_g - The weight of the g -th working condition;

ω - Punishment factor;

$\theta_g(s)$ - The flexibility objective function for the k -th working condition;

$\theta_g^{\min}$, $\theta_g^{\max}$ represents the maximum and minimum values of the flexibility objective function for the k -th working condition. Among them, it is necessary to handle the equivalent static load conditions of collisions. This article uses the reciprocal of weighted eigenvalues to define the modal condition optimization problem, and obtains a dynamic condition topology optimization mathematical model with the goal of minimizing the reciprocal of weighted eigenvalues:

$$\min : \varphi(s) = \frac{\sum_j \left(\frac{w_j}{\mu_j} \right)}{\sum_j (W_j)} . \tag{14}$$

μ_j -eigenvalues of the j -th mode;

B - weight coefficient.

4.4 Lightweight Solution for Car Doors

In order to determine the weight coefficients under various operating conditions, an improved algorithm combining Bayesian optimization algorithm [19] and TabNet deep learning algorithm [20] was used to solve the parameters and weight coefficients of the target model. For the convenience of description, in the following content, the algorithm is referred to as the iBS TabNet algorithm.

The Bayesian optimization algorithm uses past evaluation results to establish a probability model that reflects the probability distribution of hyperparameters on the objective function, which is used to guide the next parameter selection and avoid wasting a lot of time and computational resources on unnecessary sampling points. The optimization process mainly includes two aspects. One is the Gaussian process, which represents the distribution assumption of the optimized function and outputs the mean and variance of the Gaussian distribution; The second is the collection function, which is used to construct the utility function in the posterior distribution of the model.

The TabNet algorithm is based on the decision manifold of neural networks and can be regarded as a forward additive model. The model is constructed based on multiple repeated decision structures, each of which includes an attention converter layer, a mask layer, a feature converter layer, a splitting layer, and an activation function $\mathrm{Re}LU$ layer. Each step is sequentially connected to form an additive model The input data for each step is first normalized in batches through the regularization layer, followed by feature processing in the feature converter layer. Then, the splitting layer divides the data into two subsets, one of which is processed through the activation function $\mathrm{Re}LU$ layer as the output of the current step, and the other subset is used as the input for the next step. After receiving the processed data, each step is first subjected to feature filtering through the attention conversion layer and mask layer, and then the aforementioned data processing operation is repeated through the feature converter layer to complete feature processing. Finally, the output of each step is summed up as the final output result. The principle flowchart of using iBS-TabNet for solving is shown in Fig. 7.

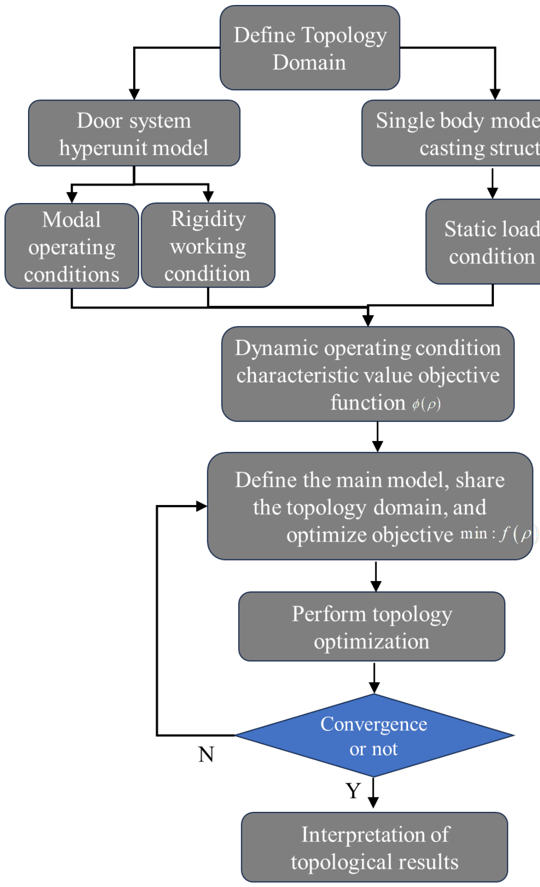

Fig. 7. Algorithm optimization process

After the above analysis, this article has established a car door simulation model and a car door optimization model, and established an algorithm for car door optimization. Through algorithm optimization, the lightweight parameters of the car door can be obtained. In the next chapter, use simulation to verify and provide optimized results.

5 Simulation Experiments and Result Analysis

For the optimization of the car door, the optimization object is first determined. After the analysis in Section 4, the thickness of the inner plate T_1, the thickness of the outer plate T_2, the thickness of the door and window frame T_3, the thickness of the door lock installation surface T_4, and the thickness of the door hinge installation surface T_5 are the design variables, the first-order free mode frequency f_1 and the second-order free mode frequency f_2 of the optimization function, the displacement d_1 of the sinking stiffness condition, and the displacement d_2 of the torsional stiffness condition are selected as the optimization objects. At the same time, the weight of the car door is added as the optimization object. The initial values of each optimization object are shown in Table 4.

Table 4. Optimization objectives and initial values

Parameter	Initial value	Parameter	Initial value
T_1	0.8 (mm)	f_1	48.09Hz
T_2	1.3 (mm)	f_2	76.28Hz
T_3	0.67 (mm)	d_1	4.307 (mm)
T_4	0.68 (mm)	d_2	2.398 (mm)
T_5	1.75 (mm)	m	17.9kg

Using an improved algorithm to solve the optimization results, firstly, in order to demonstrate the advantages of the proposed improved algorithm, the running situation of the algorithm is analyzed. The hardware environment of the algorithm is arranged as follows: the iteration cycle is 1000, and the number of waiting rounds for early stopping is 50 to prevent overfitting of the model; The training equipment is GPU; The number of worker threads during data loading is 8; The Adamax optimizer is used as the minimum loss function for adjusting model parameters, and the operating system is Windous11. The convergence effect of the algorithm is shown in Fig. 8.

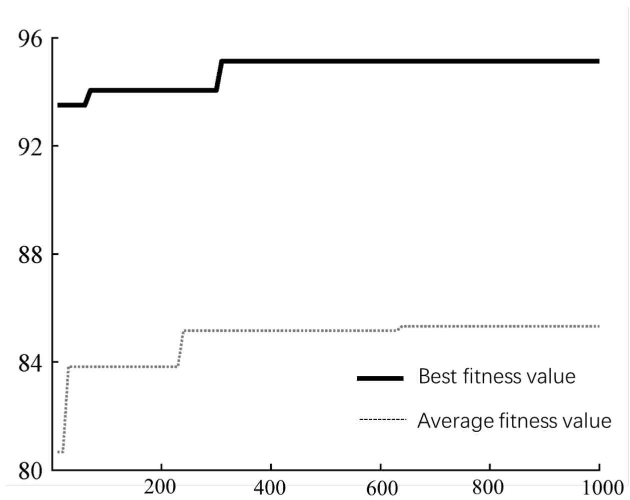

Fig. 8. Algorithm iteration times

From the graph, it can be seen that the population tends to explore the optimal fitness during the iteration process. It can be seen that after 1000 iterations, the average fitness of the algorithm's population has already reached the position of the best fitness of the population. The improved iBS-TabNet optimization algorithm actively explores other directions after finding the optimal solution, effectively avoiding getting stuck in local optima and finding other better solutions. After algorithmic solving, the optimization objective of the car door was obtained, and the results are shown in Table 5.

Table 5. Parameter optimization results

Parameter	Initial value	iBS-TabNet	Parameter	Initial value	iBS-TabNet
T_1	0.8 (mm)	3.296mm	f_1	48.09Hz	47.99Hz
T_2	1.3 (mm)	2.000mm	f_2	76.28Hz	63.29Hz

T_3	0.67 (mm)	1.980mm	d_1	4.307 (mm)	1.523mm
T_4	0.68 (mm)	4.003mm	d_2	2.398 (mm)	0.939mm
T_5	1.75 (mm)	3.987mm	m	17.9kg	14.498kg

Simulate and verify the thickness parameters of the RBF model after reliability optimization. At this time, the thickness of each part of the car door is T_1= 3.296mm, T_2= 2.0000mm, T_3= 1.980mm, T_4= 4.003mm, and T_5 =3.987mm. Based on the reliability optimization results, plot the Plane function fitting curves of the car door mass m with the inner panel thickness T_1 and outer panel thickness T_2, as well as the Plane function fitting curves of the car door sinking stiffness working condition displacement d_1 with the door lock installation surface thickness T_4 and hinge installation surface thickness T_5, as shown in Fig. 9.

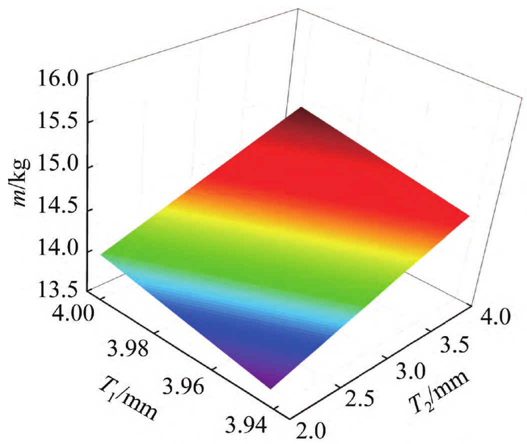

Fig. 9. Diagram of the relationship between weight and thickness of car doors

The fitting curve relationship between the sinking condition and the thickness of the car door is shown in Fig. 10.

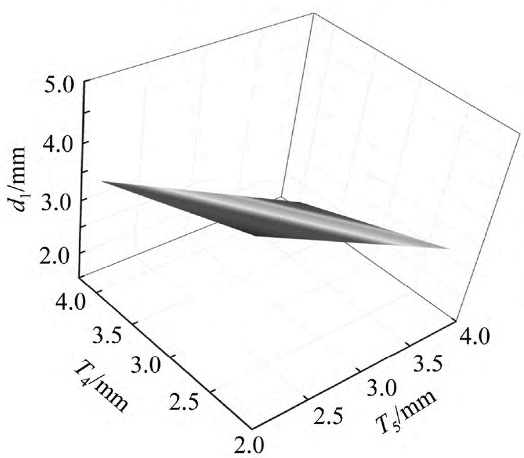

Fig. 10. Fitting curve between sinking condition and thickness

After optimization, the distribution pattern of various thicknesses of the car door was obtained, and the schematic diagram of the local thickness distribution of the car door is shown in Fig. 11.

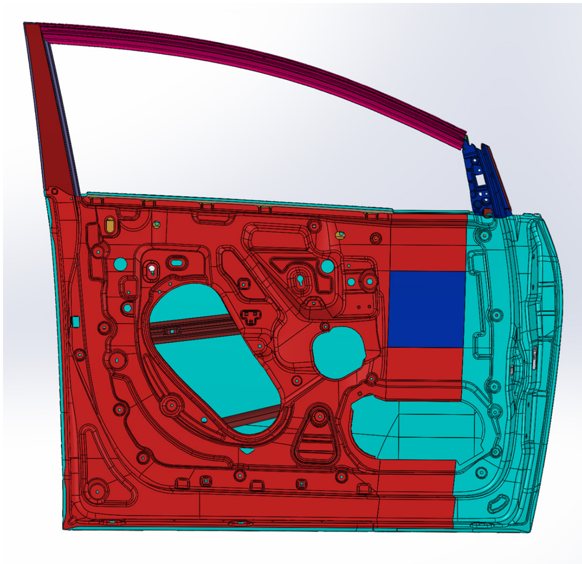

Fig. 11. Door thickness distribution

From the results in Fig. 11 and Table 5, it can be seen that the design scheme with medium thickness has been transformed into an engineering scheme with variable thickness, and all performances have been validated using finite element models. It can be found that:

1) Compared with before thickness optimization, the performance that did not meet the standards, such as second-order bending mode, static stiffness of door and window frame suspension points, and maximum equivalent static load force of section C, were all met after thickness optimization, and a weight reduction of 0.1kg was achieved;

2) Compared with the initial values, the performance of the optimized thickness scheme has been improved to varying degrees. The second-order bending mode has been increased by 108Hz, the equivalent static load bearing capacity has been increased by about 60%, and the static stiffness of the suspension point has been increased by about 30%. On the basis of meeting the performance goals, a weight reduction of 0.6kg has been achieved.

3) By constructing an optimization model and using the algorithm proposed in this article, the cast aluminum door achieved the best weight reduction effect. While ensuring that the first-order free mode frequency was greater than 40Hz, its mass was reduced by 19.006% compared to steel parts, and the displacement under sinking stiffness conditions was reduced by 64.64%. When paying more attention to the improvement effect of sinking stiffness, we choose to construct an RBF approximation model and optimize it with the algorithm in this paper.

6 Conclusion

After analysis, this article focuses on optimizing the doors of a certain car model. Based on the materials used for door lightweighting, an analysis model of the door was established, which includes a lightweight model and a stiffness model, and the analysis was carried out based on this. Then, based on the established model, a structural topology optimization analysis is conducted on the car door, and a structural optimization model is established, which includes all parameters that determine the quality and weight of the car door. Finally, the improved Bayesian and TabNet algorithms are used to solve multiple parameters of the optimization model and obtain the optimal solution. The obtained optimization results can guide car companies to optimize their vehicle structure, thereby reducing the weight of vehicle sound and improving the range of new energy vehicles.

Meanwhile, the further research direction of this article is the lightweight methods for the body structure and other attachments of the vehicle structure.

This article has conducted research on lightweight and finite element modeling of new energy vehicles. However, due to my limited abilities and experimental conditions, the following issues still need to be addressed:

(1) Due to limitations in experimental conditions and the actual funding situation of the research, the analysis in this article is based on the digital model of the frame and theoretical analysis, without conducting physical manufacturing and actual vehicle testing. It is basically theoretical research, lacking comparative analysis with actual experiments.

(2) Although it is a lightweight vehicle frame, the main research object is actually the car doors. Due to the complex composition and structure of the car, subsequent research should focus on lightweight research of all components of the vehicle body.

(3) For the optimization process of vehicle body parameters, due to the complexity and complexity of the experimental process, a series of experiments are required to obtain response values, which consumes a lot of time. This method still needs improvement. In addition, due to the existence of fitting errors in the fitting function of the constraint conditions, some parameters of the optimized frame exceed the range of the constraint conditions, and the fitting accuracy needs to be further improved. The solution result of nonlinear programming may not necessarily be the global optimal solution, and the solving algorithm still needs further research.

4) During the modeling process, the mesh refinement was carried out. Due to the complexity of the bus model, the mesh division work was too cumbersome, resulting in a total of millions of mesh elements. However, in the initial design of this article, the excessive pursuit of accuracy led to an excessive amount of mesh, which consumed a considerable amount of computational resources. Therefore, the mesh elements that needed structural optimization can be further refined in the future, and beam elements can be directly used to simplify the roof frame and surrounding frame beams.

References

[1] M.-M. Mo, Research on the Development of New Energy Vehicles under the Low-carbon Economy, Auto Time (20)(2023) 130-132+145.

[2] L.-N. Zhao, Application of Plastic and Carbon Fiber Composite in Automotive Lightweight, Plastic Additives (6)(2023) 72-74.

[3] X.-G. Gu, H.-L. Chen, L.-X. Yu, D.-S. Zhang, Integrated Design of Precision Aluminum Castings Parts and Its Application in Lightweight Vehicle Body, Automotive Engineering 46(1)(2024) 179-186.

[4] Y.-K. Gao, Z.-Y. Shen, Z.-Y. Feng, Y.-J. Li, Application of Multi-objective Optimization in Vehicle Door Lightweight, Journal of Tongji University (Natural Science) 45(2)(2017) 275-280+308.

[5] B.-B. Ma, J.-J. Tan, Y.-Q. Lin, A Research on Lightweight Car Door Design Based on RBF Neural Network, Chinese Journal of Automotive Engineering 5(2)(2015) 136-143.

[6] Z.-F. Hou, H.-O. Hu, A.-B. Zhang, H.-L. Li, J.-Y. Huo, Multi-objective lightweight research of a door structure, Journal of Mechanical & Electrical Engineering 37(4)(2020) 359-364.

[7] Z.-L. Fang, L.-J. Wang, Z.-Y. Chen, S.-S. Huang, J.-T. Sun, Study of multi-objective optimization design based on the vehicle door structure, Journal of Machine Design 31(8)(2014) 60-64.

[8] Y.-F. Li, H.-L. Cui, Y.-F. Liu, T.-Z. Yang, Lightweight Design of Electric Vehicle Carbody B-Pillar Based on Side Impact Analysis, Machinery Design & Manufacture (6)(2023) 27-30+36.

[9] C. Wang, A.-G. Cheng, C.-L. Zhang, W.-Y. Yu, Z.-C. He, Lightweight Design of Protective Structures of Battery Packs for Bottom-scraping Safety, China Mechanical Engineering 34(19)(2023) 2343-2353.

[10] J.-L. Jiang, C.-Y. Gan, W.-L. Zhou, Z.-M. Xu, Lightweight improvement of the frame structure for an electric commercial vehicle, Modern Manufacturing Engineering (2)(2022) 64-69.

[11] Z.-X. Li, L.-Y. Jia, J. Hao, C. Wang, G.-X. Wang, Z.-J. Ming, Y, Yan, Lightweight Optimization Design of Unmanned Vehicle Body Structure Based on Multi-working Conditions Correlation, Acta Armamentarii 44(11)(2023) 3529-3542.

[12] C.-Y. Li, J.-P. Lin, Y.-C. Qian, H.-Y. Dai, Lightweight Design of a Car Body in White Based on Finite Element Analysis, Computer Simulation 39(9)(2022) 144-149.

[13] P.-X. Wu, F.-Y. Liu, C. Song, Lightweight design of BIW based on NSGA-II implicit parameterization, Journal of Machine Design 39(2)(2022) 95-100.

[14] G. Li, Y.-L. Xin, T. Zhao, Design and Analysis of Assembled Bridge Electric Lifting Platform Attached Wall Frame Based on SolidWorks Simulation, Science Technology and Industry 23(24)(2023) 255-261.

[15] J.-F. Zhang, L.-C. Hu, J.-B. Wen, Y.-P. Geng, J. Li, Stiffness Matrixes of Elastic Connection Elements in Finite Element Method, Structural Engineers 39(6)(2023) 28-34.

[16] J. Guo, B. Song, M.-Z. Wang, Stiffness Analysis of Hot-formed Steel Body-in-white for Lightweight, Metal World (5) (2023) 48-52.
[17] J. Ding, W.-G. Jiang, Design Optimization of Permanent Magnet Synchronous Motor Based on Latin Hypercube Algorithm, Electric Machines & Control Application 50(8)(2023) 66-72.
[18] Z.-Q. Li, Y.-J. Liu, J.-F. Lai, W.-H. Lyu, Inversion Control of Flexible Manipulator Based on RBF Neural Network, Machine Building & Automation 52(6)(2023) 168-172.
[19] J. Chai, R.-X. Zhang, Y.-B. OuYang, D.-D. Zhang, R.-P. Wang, Z.-C. Tian, H.-R. Liu, Z.-C. Han, CatBoost mine pressure appearance prediction based on Bayesian algorithm optimization, Journal of Mine Automation 49(7)(2023) 83-91.
[20] G.-Q. Dong, P. Wang, L.-Y. Xia, Forest Cover Type Prediction Method Based on TabNet, Microcomputer Applications 39(9)(2023) 129-133.